ABSTRACT

PALMER, JOSHUA MICHAEL. Geostatistical Modeling of Subclimatic Tropical Precipitation in the Carolinas. (Under the direction of Dr. Lian Xie.)

Demand for high-resolution, gridded interpretations of irregularly spaced point measurements is increasing at a significant rate. Unfortunately, due to many limitations inherent in point measurements of meteorological variables, spatial predictions must not only exhibit some skill in resolving small-scale features, but the methods employed must also be able to quantify the uncertainty in the prediction. Therefore, this research employs basic geostatistical methods to investigate the feasibility of empirical spatial modeling at subclimatic time scales. For this investigation, daily accumulations are employed from a widely-used climatological precipitation database maintained by the National Climatic Data Center. Tropical cyclone-induced accumulations from Hurricanes Floyd (1999), Frances (2004), and Ivan (2004) are sampled from a rectangular domain centered on North and South Carolina in order to study the robustness of the geostatistical model on highly-variable precipitation fields across a diverse geophysical region. Two geostatistical methods, ordinary kriging (OK) and kriging with external drift (KED), are studied. The KED technique assumes that the trend moment of the geostatistical model is not constant and must be modeled itself before the residual moment can be studied as a stationary random function. Therefore, this research incorporates basic geophysical and physical variables into various multivariate linear regression models in order to account for non-constant spatial trend and the limitations of the rain gauge network in resolving spatial variability. In addition to numerous sensitivity tests, the OK and KED methods are compared to IDW estimates and output from the ~4 km Multisensor Precipitation Estimator (MPE) in order to examine the costs and benefits of geostatistical modeling under the pre-specified constraints.

Overall, both OK and KED improve upon the accuracy of the predicted spatial field produced by IDW regardless of case. However, within this research the OK assumption of constant trend (i.e., stationarity) is violated; KED offers superior adherence to geostatistical model assumptions by producing a normalized and stationary residual dataset; reducing or eliminating anisotropy; producing more stable estimates of semivariance model parameters; and minimizing the bias and variance of the prediction error. Trend modeling is also shown
to add value to the spatial prediction given a subset of significant covariates. For example, comparison of first- through third-order Cartesian coordinate polynomials with a first-order trend model comprised of significant Cartesian, geophysical, and physical covariates suggests that the latter models produce better spatial accuracy and more realistic spatial fields when the maximum precipitation axes occur in the western Carolinas. The superior performance of the third-order coordinate polynomial in Hurricane Floyd, however, suggests that additional investigation is required into the spatial scale of the relationship between (geo)physical covariates and subclimatic precipitation. Furthermore, other (geo)physical covariates were investigated in an attempt to empirically represent orographic precipitation enhancement, but current results suggest that these covariates are desensitized by the large domain and would require complex domain disaggregation subsequently allowing orographic processes to better dominate the trend.

Additionally, this research reveals that root mean square error is not the best metric for model performance. Instead, the user should carefully assess model calibration and the root mean square standardized error in tandem with a knowledge-based evaluation approach. Sensitivity of semivariance model parameter estimation techniques was most dependent on the presence of non-stationarity, measurement error, and microvariability. Analysis suggests that when non-stationarity is left uncorrected, the potential for misapplication of semivariance modeling techniques significantly increases. While KED substantially mitigates the impact of user misapplication and misinterpretation, it does not eliminate inaccuracies associated with falsely assigning a classical semivariance model. These results therefore suggest that automation of KED for daily precipitation data across climatological scales will be a very challenging endeavor requiring a highly intelligent trend modeling and evaluation methodology.
Geostatistical Modeling of Subclimatic Tropical Precipitation in the Carolinas

by
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I was born in beautiful Central New York in the city of Syracuse on October 12, 1980. I grew up in Kirkville, a very small town about 20 miles northeast of Syracuse, until I left for undergraduate studies at the University of Oklahoma (OU) in Norman 17 years later. At an early age I became fascinated by the cold and snowy climate downwind of Lake Ontario. The reward for those brutal winters was the gorgeous summers and for most of my teenage years, I spent those summers on a nearby vegetable farm. The physical labor was probably some of the most rewarding and character-building work I have ever done. Graduating from East Syracuse-Minoa High School in June of 1998 and despite my love for the exciting winter months, I was anxious to try something new and the move to Oklahoma was about as dramatic a change as possible.

As a sophomore working on my bachelor of science in meteorology I was fortunate enough to be recommended to the National Severe Storms Laboratory (NSSL) for a student position. My main responsibility was the management of the in-house Weather Surveillance Radar 88 Doppler Level II Database; data for various research projects were stored on archive tape at NSSL and scientists would request additional data that I was required to order from NCDC and process for analysis. It was a humble position that gave me my first significant experiences in basic to intermediate UNIX and Perl scripting and prepared me for additional responsibilities in my undergraduate and graduate studies as well for my eventual employment with the National Weather Service (NWS).

My experiences at OU were life changing in many ways, the most significant of which being the meeting of my future wife Trisha in a meteorology class only two weeks into our freshman year. Upon graduation from OU in May of 2002 we married in Trisha’s hometown of Benton, Arkansas. Since Trisha was a student employee with the NWS, opportunities at the NWS Weather Forecast Office in Raleigh meshed nicely with our desire to attend graduate school and we began our graduate careers at NCSU in the fall of 2002.

Eventually, Trisha’s student employment in Raleigh became a permanent position and an opportunity for a promotion in Peachtree City, Georgia arrived in the summer of
2005. Though I was not yet ready for graduation, coursework for both my master’s degree and associated minor in statistics was already completed, allowing me to complete my research remotely. Thus, I had a narrow window of opportunity to begin realizing a long-standing dream: a career working in operational meteorology. Fortunately, several positions were available within the NWS and eventually I accepted a position as a hydrometeorologist at the Lower Mississippi River Forecast Center (LMRFC) in Slidell, Louisiana effective early September 2005. Unfortunately, the greater New Orleans region was tragically struck by Hurricane Katrina at the end of August 2005 and I was unable to begin my position due to an understandable lack of housing. Thus, the NWS detailed me to the Southeast River Forecast Center (SERFC) in Peachtree City for one month while housing could be secured in Slidell. In late October 2005, I finally began my position at the LMRFC, where, in addition to my main duties, I developed a monitoring system for malfunctioning rain-gauges that has since become instrumental in reducing workload and improving data quality.

Obviously, the eventual goal was to reunite with Trisha, but we realized doing so was going to take time as we waited for positions to become available at one NWS location. However, neither of us expected success after only eight months, when a hydrometeorologist position opened at the SERFC in the late spring of 2006. Since that time I have remained at the SERFC where my main responsibilities include precipitation forecasting for hydrologic modeling and the analysis and quality-control of precipitation estimates from radar, rain-gauge, and multi-sensor sources. However, the position also provides tremendous professional development opportunities in a variety of areas including tropical meteorology, multi-scale hydrology, climatology, and emergency management and preparedness. In order to fulfill future ambitions I am also grateful for the many occasions my current position allows for leadership roles and the enhancement of related skills.

Though education is a lifelong journey, I am looking forward to at least a temporary retirement from formal education. I will resume a long-dormant hobby in digital photography while advancing my passion for high-fidelity surround sound music and movies. Trisha and I are also looking forward to taking up several home improvement and landscaping projects where we currently reside in Senoia, Georgia.
ACKNOWLEDGEMENTS

First of all, I would like to thank my committee members Drs. Lian Xie, Montserrat Fuentes, and Gary Lackmann for their support and patience while I simultaneously completed my graduate research and began my career in operational meteorology. Despite the additional time required to attend to both responsibilities, I remained confident in my decision knowing my committee wanted to see me succeed in each endeavor.

Without certain individuals in the Department of Statistics, my climb up a steep learning curve would have been even more difficult. Therefore, I want to thank Dr. Fuentes for being available to answer my many questions and inquiries throughout the initial stages of this project. I would also like to thank Kristen Foley, for her assistance in clarifying certain concepts and for her encouragement during my initial studies. Finally, I would like to acknowledge Dr. Dave Dickey for his efforts in teaching a formal course in regression modeling; his teaching style and materials were instrumental in sharpening my previous understanding of these methods.

While extensive “from-scratch” development was required for data processing and analysis in this particular project, the entire process would have been far more difficult had it not been for the availability of the R statistical environment and several supplementary packages that allowed me to complete my research. Due to the thorough documentation and availability of the original source code I was able to modify various functions as needed and, over time, developed a solid level of skill sets. Special acknowledgement is needed for Drs. P. J. Ribeiro Jr. (developer of geoR) and Edzar Pebesma (developer of gstat) for their quick and friendly replies regarding their software.

Of course, I also need to thank my colleagues at the Southeast River Forecast Center for their support and encouragement throughout the past couple of years. They have always been supportive of my ambitions but during the final several weeks of my graduate career, they were especially patient and accommodating while they tolerated the bemused state of mind I often carried into the office.
Coming to NCSU led to the development of several wonderful friendships. We all were going through the same experiences and each of us benefited from the comfort and encouragement we provided each other. For all of that support I am especially grateful. Since leaving NCSU I have been fortunate enough to know many other wonderful individuals. I would like to thank Jason Caldwell especially; Jason was a unique source of support as he could directly relate to this challenging period in a way many others could not, having completed his graduate studies in a similar manner.

Each and every day I am blessed to have two wonderful parents persistently and enthusiastically cheering me on regardless of the endeavor. They instilled in me many invaluable principles, but perhaps none have been more significant than the importance of placing 100% into every goal, no matter how large or small. This insatiable desire for quality has motivated me in every element of my life. Throughout any experience, regardless of success or failure, their unconditional love has inspired me to never be satisfied, redefine my boundaries, and dream each dream better than the one before. I thank them both for always providing me the opportunities to aspire.

My wife Trisha has been, by far, the most instrumental in helping me realize the conclusion of my graduate studies. Her unwavering encouragement and guidance throughout each success and each failure gave me the strength to overcome each challenge, celebrate each accomplishment, and maintain my focus on the final goal. Her commitment to my success has required several years of patience and I know we both look forward to enjoying the rewards of this experience for many years to come. I am a stronger, more confident individual due her amazing friendship and love, and I cannot imagine my life being nearly as fulfilling without it.

Finally, this study was jointly supported by the National Oceanic and Atmospheric Administration (NOAA) Grant #NA07NWS4680002, NOAA subcontract UF-EIES-0704029-NCS through the University of Florida, National Science Foundation Grant #DMS-0706731, and by a federal salary from the National Weather Service. It was a tremendous privilege to have had the support of these agencies via the hardworking taxpayers of this wonderful country.
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Section 5.2 – Residual Performance

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Section 5.3 – KED Performance

Non-zero probability density histograms of KEDIDP for 16 September 1999 using the following techniques: (a) the 3LXYs trend model and an exponential SV model derived using REML; and (b) the 1Lia Max trend model and a spherical SV model derived using REML. The term “non-zero” refers to the removal of all zero values from the KEDIDP grid prior to derivation of the histograms.

Probability density histograms of KEDIDP for 8 September 2004 using the following techniques: (a) the 2LXY trend model and a spherical SV model derived using REML; and (b) the 1Liai Avg trend model and a spherical SV model derived using REML.

Probability density histograms of KEDIDP for 17 September 2004 using the following techniques: (a) the 3LXYs trend model and a spherical SV model derived using REML; and (b) the 1Liai Avg trend model and an exponential SV model derived using REML.

KEDIDP (mm) and rain gauge site locations for 16 September 1999 based on (a) the 3LXYs trend model and an exponential SV model derived using REML and (b) the 1Lia Max trend model and a spherical SV model derived using REML.

KEDIDP (mm) and rain gauge site locations for 8 September 2004 based on (a) the 2LXY trend model and a spherical SV model derived using REML and (b) the 1Liai Avg trend model and a spherical SV model derived using REML.

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<th>Description</th>
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<tr>
<td>%A</td>
<td>Percent of accepted gauges</td>
</tr>
<tr>
<td>%CI</td>
<td>Percent of actual values that lie within the 95% Confidence Interval</td>
</tr>
<tr>
<td>%R</td>
<td>Percent of rejected gauges</td>
</tr>
<tr>
<td>1LALL</td>
<td>First-order regression model for the logarithmically transformed DRP dataset using all available Cartesian and physical covariates and all associated interaction terms</td>
</tr>
<tr>
<td>1L</td>
<td>First-order regression model for the logarithmically transformed DRP dataset using all available Cartesian and physical covariates</td>
</tr>
<tr>
<td>1La</td>
<td>First-order regression model for the logarithmically transformed DRP dataset using all significant Cartesian and physical covariates</td>
</tr>
<tr>
<td>1Lia</td>
<td>First-order regression model for the logarithmically transformed DRP dataset using all significant Cartesian and physical covariates and their interaction terms</td>
</tr>
<tr>
<td>1LXY</td>
<td>First-order polynomial model for the logarithmically transformed DRP dataset using only Cartesian covariates</td>
</tr>
<tr>
<td>2LXY</td>
<td>Second-order polynomial model for the logarithmically transformed DRP dataset using only Cartesian covariates</td>
</tr>
<tr>
<td>3LXY</td>
<td>Third-order polynomial model for the logarithmically transformed DRP dataset using only Cartesian covariates</td>
</tr>
<tr>
<td>3LXYs</td>
<td>The 3LXY trend model using scaled Cartesian coordinates. The first-order covariates (X and Y) are scaled by $10^{-2}$ and all higher-order polynomial terms are calculated using the scaled coordinates.</td>
</tr>
<tr>
<td>AL</td>
<td>Alabama</td>
</tr>
<tr>
<td>AQC</td>
<td>Number of gauges available after removal of M, ND, and RT gauges</td>
</tr>
<tr>
<td>ASOS</td>
<td>Automated Surface Observing System</td>
</tr>
<tr>
<td>ASOS?</td>
<td>Number of gauges with reporting times of 2400 local time</td>
</tr>
<tr>
<td>BLUE</td>
<td>Best, Linear, and Unbiased Estimator</td>
</tr>
<tr>
<td>COOP</td>
<td>Cooperative Observer</td>
</tr>
<tr>
<td>CorEA</td>
<td>Correlation Coefficient between Error and Actual values</td>
</tr>
<tr>
<td>CorPA</td>
<td>Correlation Coefficient between Predicted and Actual values</td>
</tr>
<tr>
<td>CorSEA</td>
<td>Correlation Coefficient between Standardized Error and Actual values</td>
</tr>
<tr>
<td>DEM</td>
<td>Digital Elevation Model</td>
</tr>
<tr>
<td>DEMSlope</td>
<td>Rate of Change in DEM with Horizontal Distance</td>
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<tr>
<td>DFE</td>
<td>Error Degrees of Freedom</td>
</tr>
<tr>
<td>DFM</td>
<td>Model Degrees of Freedom</td>
</tr>
<tr>
<td>Abbreviation</td>
<td>Full Form</td>
</tr>
<tr>
<td>--------------</td>
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</tr>
<tr>
<td>DPA</td>
<td>Digital Precipitation Array</td>
</tr>
<tr>
<td>DRP</td>
<td>Daily Reported Precipitation</td>
</tr>
<tr>
<td>E</td>
<td>East (direction)</td>
</tr>
<tr>
<td>ENE</td>
<td>East-Northeast (direction)</td>
</tr>
<tr>
<td>EDAS</td>
<td>Eta Data Assimilation System</td>
</tr>
<tr>
<td>ESE</td>
<td>East-Southeast (direction)</td>
</tr>
<tr>
<td>FL</td>
<td>Florida</td>
</tr>
<tr>
<td>GA</td>
<td>Georgia</td>
</tr>
<tr>
<td>GLOBE</td>
<td>Global Land One-km Base Elevation</td>
</tr>
<tr>
<td>Geos2MAP</td>
<td>Geostatistical and Multivariate Mapping and Analysis of Precipitation</td>
</tr>
<tr>
<td>GIS</td>
<td>Geographic Information Systems</td>
</tr>
<tr>
<td>GRID</td>
<td>A Geos2MAP prediction grid</td>
</tr>
<tr>
<td>HRAP</td>
<td>Hydrologic Rainfall Analysis Project</td>
</tr>
<tr>
<td>HSA</td>
<td>Hydrologic Service Area</td>
</tr>
<tr>
<td>I</td>
<td>Initial number of gauges available as reported by NCDC station lists</td>
</tr>
<tr>
<td>IDW</td>
<td>Inverse Distance Weighting</td>
</tr>
<tr>
<td>IDP</td>
<td>Interpolated Daily Precipitation</td>
</tr>
<tr>
<td>ISIP</td>
<td>Intrinsically Stationary, Isotropic, and Parametric</td>
</tr>
<tr>
<td>KED</td>
<td>Kriging with External Drift</td>
</tr>
<tr>
<td>KY</td>
<td>Kentucky</td>
</tr>
<tr>
<td>LS</td>
<td>Least-Squares</td>
</tr>
<tr>
<td>lnDRP</td>
<td>Logarithmically Transformed DRP Values</td>
</tr>
<tr>
<td>M</td>
<td>Number of Gauges Reporting Missing Data</td>
</tr>
<tr>
<td>ML</td>
<td>Maximum Likelihood</td>
</tr>
<tr>
<td>MLR</td>
<td>Multivariate Linear Regression</td>
</tr>
<tr>
<td>MPE</td>
<td>Multi-sensor Precipitation Estimator</td>
</tr>
<tr>
<td>MSE</td>
<td>Mean Square Error</td>
</tr>
<tr>
<td>MSEError</td>
<td>Mean Standardized Error</td>
</tr>
<tr>
<td>N</td>
<td>North (direction)</td>
</tr>
<tr>
<td>NARR</td>
<td>North American Regional Reanalysis</td>
</tr>
<tr>
<td>NC</td>
<td>North Carolina</td>
</tr>
<tr>
<td>NCDC</td>
<td>National Climatic Data Center</td>
</tr>
<tr>
<td>NCEP</td>
<td>National Centers for Environmental Prediction</td>
</tr>
<tr>
<td>ND</td>
<td>Number of Gauges with No Data Reported</td>
</tr>
<tr>
<td>NE</td>
<td>Northeast (direction)</td>
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<td>NHC</td>
<td>National Hurricane Center</td>
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<tr>
<td>NLS</td>
<td>Non-Linear Least Squares</td>
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<td>NNE</td>
<td>North-Northeast (direction)</td>
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<td>NNW</td>
<td>North-Northwest (direction)</td>
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<td>NW</td>
<td>Northwest (direction)</td>
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<td>NWS</td>
<td>National Weather Service</td>
</tr>
<tr>
<td>OK</td>
<td>Ordinary Kriging</td>
</tr>
<tr>
<td>Abbreviation</td>
<td>Description</td>
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</tr>
<tr>
<td>ONLS</td>
<td>Ordinary Non-Linear Least Squares</td>
</tr>
<tr>
<td>PA</td>
<td>Pennsylvania</td>
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<tr>
<td>PPS</td>
<td>Precipitation Processing System</td>
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<tr>
<td>PRISM</td>
<td>Parameter-elevation Regression on Independent Slopes Model</td>
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<tr>
<td>QC</td>
<td>Quality control</td>
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<tr>
<td>QPE</td>
<td>Quantitative Precipitation Estimate</td>
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<tr>
<td>QQ</td>
<td>Quantile-Quantile</td>
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<td>REML</td>
<td>Restricted Maximum Likelihood</td>
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<tr>
<td>RFC</td>
<td>River Forecast Center</td>
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<tr>
<td>RMKV</td>
<td>Root Mean Kriging Variance</td>
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<tr>
<td>RMSE</td>
<td>Root Mean Square Error</td>
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<tr>
<td>RMSSE</td>
<td>Root Mean Square Standardized Error</td>
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<tr>
<td>RT</td>
<td>Number of Gauges Rejected Due to Poor Reporting Times</td>
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<tr>
<td>S</td>
<td>South (direction)</td>
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<td>SC</td>
<td>South Carolina</td>
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<td>SE</td>
<td>Southeast (direction)</td>
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<tr>
<td>SlopeWind</td>
<td>Vertical Component of 10 m Horizontal Wind Due to DEMSlope</td>
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<td>South-Southeast (direction)</td>
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<td>SSR</td>
<td>Regression Sum of Squares</td>
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<td>SSRE</td>
<td>Sum of Squared Regression Errors</td>
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<td>SSQI</td>
<td>Type I Sum of Squared Errors (Sequential)</td>
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<td>SSQII</td>
<td>Type II Sum of Squared Errors (Partial)</td>
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<td>Standardized Error</td>
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<td>Southwest (direction)</td>
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<td>United States</td>
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<td>UTC</td>
<td>Universal Time, Coordinated</td>
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<tr>
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<td>Tennessee</td>
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<tr>
<td>TD</td>
<td>Tropical Depression</td>
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<td>TS</td>
<td>Tropical Storm</td>
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<td>Virginia</td>
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<td>W</td>
<td>West</td>
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<td>WV</td>
<td>West Virginia</td>
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<tr>
<td>WNLS</td>
<td>Weighted Non-Linear Least Squares</td>
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<td>West-Northwest (direction)</td>
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<td>Weather Service Radar-1988 Doppler</td>
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<td>WSW</td>
<td>West-Southwest (direction)</td>
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<td>Rate of Change of DEM with Distance Along the X Axis</td>
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<td>XWind</td>
<td>X-component of the NARR 10 m Horizontal Wind</td>
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<td>YSlope</td>
<td>Rate of Change of DEM with Distance Along the Y Axis</td>
</tr>
<tr>
<td>YWind</td>
<td>Y-component of the NARR 10 m Horizontal Wind</td>
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1. **MOTIVATION and INTRODUCTION to GEOSTATISTICS**

1.1 **Motivation**

For centuries, humans have sampled meteorological conditions at single points along the surface of the earth, motivated by a desire to gain knowledge of the infinitely complex atmosphere above. Unfortunately, for nearly as long, humans have had to contend with the limitations of observational datasets: their startup and maintenance costs, transmission failures, instrumentation errors, and human errors. Most importantly, while observations are the closest representations of truth available, they are limited by their representation as a single point across an expansive spatial domain; the number of points available at any one time across that domain is unfortunately inversely correlated to the errors listed above.

Consider these limitations along with continued advancements in computer efficiency and decreases in technological costs. Technological improvements have revolutionized the way meteorologists obtain data, process output, and transmit information to the public, yet these changes also proportionally increase the demand for higher-resolution, regularly spaced interpretations of the observational dataset. Applications demanding spatial prediction include gridded operational forecasting and hydrologic modeling; gridded forecast verification schemes; mapping of climatological datasets and new and existing measurement networks; flash flood monitoring and prediction; and newer initiatives like drought and wildfire monitoring and mitigation. Weather’s critical impact in ecology, agriculture, on soil and vegetation, in development and construction, transportation, and energy, for example, requires high-resolution data to perform the increasingly complex modeling and observational studies required in these and many other fields.

Of course, higher resolution not only requires a smaller grid, but each new grid point must provide value to the spatial field. In other words, there must be prior knowledge of the variability in the field in order to understand how data change with location. Unfortunately, point measurements are valid only at a single point in space and while they may contain some information about the surrounding area, the available spatial information for a point measurement is limited by the scales of meteorology surrounding that point. For example,
the spatial influence of a point measurement during an isolated thunderstorm will be far smaller than for a stratiform precipitation shield associated with a synoptic-scale warm front. Geophysical features including terrain and bodies of water also exert large- and small-scale influences on the surrounding meteorology. Depending on the scale of variability and the density of the measurement network, point measurements may or may not be able to capture the associated spatial variability of a meteorological event. In cases where the network is insufficient, certain scales of spatial variability may only be explained by external datasets, which must supplement the prediction technique. Regardless, point observations are not usually spatially independent and the amount of variability that they do explain across a spatial domain may still be significant.

There clearly is a desire and need to assess the spatial variability of the source or primary variable and there must also be an acknowledgement that any gridded field that results from a set of point measurements is merely a prediction. Therefore, without a complete understanding of the variability in the spatial field at scales equal to the desired resolution, there will be uncertainty in that prediction. In order to provide meaningful gridded datasets, there then must be an assessment of that uncertainty. These requirements are why, eventually, spatial prediction must rely on statistical methods. Some methods, like inverse distance weighting, however, rely exclusively on simple empirical relationships to describe the spatial field. Unfortunately, despite their popularity and utility in some applications, these methods assume that the relationship exactly describes the spatial field and cannot, therefore, make any inferences on the spatial variability or the uncertainty/confidence in the prediction. Required, therefore, is a more sophisticated empirical approach that attempts to model the spatial variability of the field, not the observations themselves. If a model can be created that attempts to describe the spatial relationship or dependency between the observations (i.e., the autocorrelation), then each prediction can be assigned a level of confidence. This philosophy describes a special subset of statistical analysis known as geostatistics. As it may be implied from the name, “geo” statistics is often interpreted to mean a specialized set of statistical methods applied to the surface of the earth. Within the discipline are numerous methods that attempt to model a
spatial surface, some significantly more complex than others, but the field continues to gain popularity in response to the growing demand for gridded output where only irregular datasets exist.

Geostatistical techniques have enjoyed much success in many meteorological applications (e.g., see Chapter 2), though to-date the largest application of geostatistical methods have occurred at climatological time scales or time scales greater than one month. A major reason for this is that geostatistical methods are, inherently, still empirical methods that cannot independently replicate the complex spatial variability often attributed to physical processes. Maps of annual precipitation, for example, are often much smoother than maps of hourly precipitation because they represent the average of multiple physical processes accumulated over time. As time-scales are decreased to “subclimatic” levels, on the order of hours or days, the increased complexity of the resultant spatial fields will likely require geostatistical techniques to become more sophisticated, adapting empirical representations of physical processes to better model the various scales of variability in the spatial field. Previous research has already shown this need exists on climatic time scales.

Furthermore, as both the research and operational communities move to increasingly complex, higher-resolution datasets, there will also be an increase in the demand for geostatistical expertise, which will require many meteorologists to learn and understand the discipline and be able to apply it accurately and properly, especially as the resultant fields and measurements of uncertainty are used in decision-making processes (i.e., operational guidance verification). This may be of particular concern in the operational environment, where the demands on time are constantly distributed amongst many tasks often simultaneously, and the ability to develop a sound understanding of geostatistics will be limited. The misapplication of general statistical methods within the field should already be of major concern to the meteorological community; it certainly is a concern amongst the statistical community. The mitigation of similar misinterpretations in geostatistics should be of paramount importance in future applications.

Therefore, this research had two primary objectives. The first was to begin an investigation on the application of basic geostatistics at subclimatic time scales. To
accomplish this objective, this study applied geostatistical predictions to the precipitation observations of three tropical storms: Hurricane Floyd (1999); Hurricane Frances (2004); and Hurricane Ivan (2004). The domain selected was centered on North (NC) and South Carolina (SC) but included much of Georgia (GA) and smaller areas of other surrounding states. This research also incorporated basic geophysical and physical data into the geostatistical model in order to mimic physical processes. The study compared the results of the geostatistical techniques to inverse distance weighted interpolation in order to analyze the impact of spatial variability modeling on the predicted field. All interpolation techniques were also assessed with reference to multi-sensor precipitation estimates in order to analyze the ability of the resultant predictions to mimic both large- and small-scale variability. The main challenges in this research were to assess the impact of highly-variable precipitation data on the assumptions of the geostatistical model and to analyze the sensitivity of different geostatistical techniques to the variability in the spatial field while understanding how this sensitivity impacted the resultant predicted fields.

The second goal developed during the research and writing process due to the personal experiences of the author, who admittedly began this project with zero prior knowledge of geostatistics in any form. One formal class in spatial statistics began the process, but it was only upon proceeding through the research that a truly solid understanding of basic geostatistics occurred. The process is continual, however, and with every new published paper or perusal through preferred texts on the subject, concepts never before seen are discovered or concepts that were once believed to be understood are discovered to be, as it happens, misinterpreted. Therefore, an objective throughout this discussion is to not only conduct a very thorough introduction to basic geostatistics as applied in this research, but provide a very thorough analysis of the behavior of the geostatistical methods; linking the drier, more abstract discussion with beneficial application. The result will hopefully enhance the understanding of the statistical methodology and establish a firm footing for future research without requiring the next researcher to invest the same level of time and effort originally needed to assimilate the required knowledge from various sources. The author is also hopeful that this approach will mitigate future user misinterpretation and misapplication.
Finally, there are several additional objectives that will be discussed in Chapter 2. However, the first objective is to introduce the reader to geostatistics in a way that will, hopefully, serve as a foundation upon which that aspired solid understanding can be built. That discussion follows below. Second, the reader will be introduced to some published research that will illustrate how geostatistics has been previously applied as well as discuss other relevant topics related to this study.

1.2 Inverse Distance Weighting (IDW) Interpolation

Unambiguously in concept and its implementation, inverse distance weighted (IDW) interpolation is a classic means of point estimation. Popularized throughout the years, Lloyd and Atkinson (2002), for example, decided not even to review the IDW technique despite utilizing it in their comparative study and despite its various forms (e.g., see Shepard 1968) “because it is so well known”.

As discernable from its name, the IDW predictor is a distance weighted linear combination of all observations in a specified neighborhood. This neighborhood can be all-inclusive (i.e., all observations contribute to the prediction) or limited to any number of observations. The predictor is inversely weighted in the sense that the reciprocal of the distance is used. Thus, those observations further from the prediction location have proportionally less influence. Shepard (1968) was one of the first to extensively illustrate the various derivations of the IDW concept. His “pure” IDW equation is now known as perhaps the most common (e.g., see Burrough and McDonnell 1998) form:

\[
\hat{Z}(g) = \frac{\sum_{i=1}^{n} \lambda [d_i^{-p} Z(x_i)]}{\sum_{i=1}^{n} d_i^{-p}} = \sum_{i=1}^{n} \{\lambda [Z(x_i)]\}
\]  

(1.2.1)

where \( g \) is the prediction point, \( d_i \) is the distance between \( g \) and the \( n \)th observation point \( x_i \) \{\( Z(x_i) : i = 1, 2, \ldots, n \)\}. The denominator standardizes the weight \( d_i^{-p} \) to allow for a new weight \( \lambda \):
\[ \lambda_i = \frac{d_i^{-p}}{\sum_{i=1}^{n}(d_i^{-p})}, \] (1.2.2)

which carries the convenient property

\[ \sum_{i=1}^{n}\lambda_i = 1 \] (1.2.3)

regardless of the selection of any power \( p \) such that \( p > 0 \). Property 1.2.3 implies each observation contributes a certain percentage of its value to the prediction and it will be shown in later sections that it allows the predictor to be unbiased regardless of \( p \): the expected value of the estimation error is zero for any \( p \). One can conclude the IDW predictor must converge on the observation when \( d = 0 \) because it is otherwise undefined and this property makes it a forced exact interpolator.

The exponent \( p \) serves to either dilute or strengthen the weights such that when \( p \to 0 \), the weights \( \lambda \to 1/n \) and the predictor is merely the simple average or local sample mean (Isaaks and Srivastava 1989) of the observations in the neighborhood. When \( p \to \infty \), \( \lambda \to 0 \) and the prediction is a polygonal estimate (Isaaks and Srivastava 1989): it is equal to the value of the nearest observation. Burrough and McDonnell (1998) provide graphical illustrations on the effect of \( p \); as \( p \) increases, sharp gradients exist (Shepard 1968) and the spatial fields become blotchy in appearance as a reflection of the increased influence of the closest observations. Decreasing values of \( p \) result in smoother spatial fields with “short blips” (Shepard 1968) to signify convergence of the prediction with the observations.

Additionally noted in their text, the spatial appearance of the IDW-produced maps is also largely dependent on the distribution of observations, with the blotchy appearance being magnified by instances of isolated observations. Both Isaaks and Srivastava (1989) and Shepard (1968) remark \( p=2 \) is traditionally used, which originally was largely out of convenience at being computationally inexpensive. Shepard (1968) also concluded an exponent of two produced the most consistent spatial distributions.

IDW cannot account for spatial autocorrelations, in other words, correlations amongst the observations themselves; for example, a cluster of observations in one quadrant
cannot contribute any more to the confidence in the prediction than one observation in another quadrant displaced from the prediction point by the same distance. There is, therefore, clearly no means to evaluate and quantify (i.e., model) the spatial distribution of observations other than the assumption that the relationship between observations and the prediction point is modeled by a $p^{th}$-order algebraic surface. There may be times when this rather arbitrary assumption, which is indirectly investigated in this research, is valid. Limited, nevertheless, are the ways to evaluate the accuracy of the prediction (see Section 1.6) as well as justify it. The heavy reliance on observation quality, high density, and random distribution, as well as the extremely subjective parameter $p$, may make IDW interpolation most useful for quick and qualitative analysis (e.g., contouring) of an irregular spatial grid, as seen in Geographic Information Systems (GIS) applications (e.g., see Burrough and McDonnell 1998), rather than the production of a high-resolution gridded field, which may serve as input into hydrologic and meteorological models.

1.3 The Geostatistical Model

1.3.1 A Spatial Stochastic Process

With no means to model the autocorrelation likely (but not necessarily) present in a spatial field, the IDW approach allows no quantitative evaluation of the confidence in the prediction. Desired is an empirical model that measures the spatial distributions of observational data. The approach is probabilistic (Kitanidis 1997, Cressie 1993), relying on the loose description of the spatial field using averages and the correlation of data as a function of distance. Given the usual coarse spatial density of measurements, any estimation of the primary variable, in this case, precipitation, is not unique, rather a solution from a

---

1 The geostatistical empirical model enjoys broad support and use throughout many disciplines, including the atmospheric sciences. The goal in this lengthy discussion is to provide an overview of the geostatistical model and two interpolation techniques which utilize it in enough detail such that the reader need not reference another source to understand the basic applied geostatistics investigated in this research. Cressie (1993) is one of the most widely-referenced and well-respected texts on spatial statistics and approaches the topic from a more theoretical perspective for those readers interested in further discussion. Kitanidis (1997), meanwhile, is a thorough introduction on applied geostatistics, and too elaborates on the topics contained herein. Of course, the scope of geostatistics is far greater than the scope covered in this research, and thus both texts serve as appropriate reference materials.
given number, or ensemble, of possibilities. Kitanidis (1997) defines these possibilities as realizations or sample functions and notes that the collection of these realizations along with their associated probabilities comprise the spatial stochastic process, where stochastic is synonymous with random.

The spatial stochastic process is quite abstract without an example. In this research, the derivation of a spatial precipitation field to estimate the truth has an infinite number of solutions; one could come up with an infinite number of precipitation patterns to describe the true field. When observations exist to help diagnose the precipitation field, these infinite solutions now have probabilities associated with them. The solutions with the highest probabilities are those that most agree with the observations. The more observations that exist (i.e., the denser the rain-gauge sites), the fewer solutions that can be considered correct. Thus, when a field of precipitation is estimated from observations, a solution is chosen from this ensemble of infinite solutions. A successful empirical model automatically chooses the solution that maximizes the probability of regenerating the observations. This is the objective of the geostatistical model.

1.3.2 The Two Moments of the Geostatistical Model

Recalling there may be an infinite number of realizations of the precipitation field, the motivation behind the geostatistical model is that it would be very difficult to work with each realization and their probabilities across any given spatial domain. The model simplifies this stochastic process or random field by working with its ensemble averages or statistical moments (Cressie 1993, Kitanidis 1997). The first two moments are those that form the foundation of the geostatistical model. The first moment is the mean function, and the second is the covariance function. Consequently, the geostatistical model is defined as the decomposition of data into two principal components: the trend and the residual. Thus, consider a set of $n$ irregularly-spaced rain gauge measurements $\{Z(x_\alpha): \alpha=1,\ldots,n\}$, where $x_\alpha$

---

2 Throughout the literature, the terms “trend” and “drift” are also used to identify the mean component of the original dataset. Hereafter, in order to distinguish between the mean of a spatial dataset and the mean of any other series (though conceptually these means are the same), the terms “trend” and “drift” will replace “mean”.


represents the coordinate vector of rain gauge \( \alpha \). For simplicity, let \( x_\alpha = x \). The resultant
geostatistical model for \( Z(x) \), is then,
\[
Z(x) = m(x) + \varepsilon(x),
\]
where \( m(x) \) represents the trend function or the first moment of the precipitation field and \( \varepsilon(x) \) represents the second moment or covariance function for the field. The trend function
gives the expected value of precipitation, \( Z \), at any point \( x \),
\[
m(x) = \mathbb{E}[Z(x)].
\]
An expected value is defined as the probability-weighted ensemble average (Kitanidis 1997).
In other words, an expected value is the sum of each realization of a spatial stochastic
process (e.g., a spatial precipitation field) multiplied (i.e., weighted) by their associated
probability. The covariance function \( C(x,x') \) (i.e., the function by which the residuals are
described and approximated) consists of the precipitation covariance between any pair of
points \( x \) and \( x' \),
\[
C(x,x') \equiv \text{cov}\{(Z(x)-m(x)), (Z(x')-m(x'))\} \equiv \text{cov}\{\varepsilon(x), \varepsilon(x')\}.
\]

1.3.3 Deterministic Versus Stochastic Functions

It has already been suggested that the residual part of the geostatistical model is
approximated. This is the result of approximating the covariance function via the limited
observational data; precipitation and therefore its covariance are rarely exactly known across
a spatial domain. However, the residuals are a direct effect of the specification of the trend
function. That is, the trend function is determined first, and the residuals that result from
the removal of the trend are approximated by way of a covariance function. Therefore, the trend
is said to be deterministic\(^3\) (i.e., exactly or definitely computed from the observational data),
whereas the residuals are stochastic (i.e., generated or approximated from a random process
based on the spatial variability of the observational data) (Kitanidis 1997). Thus, it is logical
to conclude that the trend portion of the model can be attributed with higher confidence and

\(^3\)The IDW technique can be considered deterministic because it is definitely computed from the observational
data, the distance separating them from the prediction point, and an arbitrary parameter \( p \). The parameter \( p \),
which defines the shape of the function that models the spatial field, is considered truth.
can best explain an a priori understanding of the rain-gauge measurements. It is unlikely residual information can, without understanding of the trend, better justify spatial patterns in the primary variable (i.e., precipitation field). However, poor knowledge of the true spatial field would require additional reliance on the stochastic process. Prior knowledge of the precipitation field, therefore, is a principal factor in the degree to which the trend function describes the spatial structure, since the more powerful the trend function, the less significant the covariance function and vice-versa. The exact power of the trend function is the critical distinction between the ordinary kriging (OK) and kriging with external drift (KED) interpolation techniques.

It is understood that the trend function represents an average around which precipitation values across the spatial domain oscillate. The oscillation is measured by the magnitude of the residual, which then represents the deviation from the trend. Given this relationship, spatial variability can be parsed into a large-scale and small-scale component, where large-scale variability is captured by the rather coarse trend function and the small-scale variability is captured by the finer perturbations around the trend. Describing a stochastic process, it is assumed the residuals are approximately uncorrelated and normally distributed with a zero mean and unit variance. However, when the true trend function is not known, any model of the trend from the available observations may fail to describe the trend completely. Remnant trend characteristics passed onto the residuals may force the residuals to deviate from a true random process. The implications of these characteristics are discussed further in subsection 1.6.2.

1.3.4 Second-Order Stationarity, Isotropy, and Attributes of the Covariance Function

Equations 1.3.2 and 1.3.3 are known as the second-order stationary model (Cressie 1993). At this point in the discussion, therefore, it is assumed that the random function \( Z(x) \) is known as a second-order or weak stationary function, where the trend or drift is known and constant and the covariance function for any two points depends only on their relative position. One can think of a relative position as considering both the distance between \( x \) and \( x' \) and the orientation of the separation (e.g., northeast, southwest, north, etc.).
In perhaps the most common geostatistical model, the second-order stationary covariance function, \( C(\mathbf{x},\mathbf{x}') = C(h) \), where

\[
    h = ||\mathbf{h}|| = ||\mathbf{x} - \mathbf{x}'|| = \sqrt{(x - y)^2 + (x' - y')^2}
\]  

(1.3.4)
is the distance between the points \( \mathbf{x} \) and \( \mathbf{x}' \). Given \( C(\mathbf{x},\mathbf{x}') = C(h) \), the covariance function no longer depends on the direction of the separation [i.e., linear segment (Kitanidis 1997)] between \( \mathbf{x} \) and \( \mathbf{x}' \). As a result, the random function and the covariance function that estimates it are known as isotropic and depend only on the distance \( h \).

Though there are many types of functions that satisfy the second-order stationary model, second-order stationarity relies on a finite variance. Generally, at least one of the following three properties is considered when considering a covariance model:

1. \( C(h) \) decreases as \( h \) increases;
2. \( C(h) \to 0 \) as \( h \) increases;
3. \( C(h) \geq 0 \) for all \( h \).

Given this reliance, for the models utilized in this research, there are two parameters comprising the vector \( \mathbf{\theta} \) that control the covariance function \( C(h) = C(h; \mathbf{\theta}) \) as it applies to the geostatistical model. These parameters are also known as attributes of the covariance function. The sill \( \theta_1 \) of the covariance function occurs when \( h = 0 \), and represents the variance \( \sigma^2 \) of the random field. The range \( \theta_2 \) of the covariance function is also known as the correlation scale parameter and controls the shape of the function or how the covariance changes with \( h \). The range is commonly defined as the finite distance \( h \) where the covariance function \( C(h) \) equals zero. However, this definition is inappropriate for several different covariance models as illustrated in Section 1.3.8 and must be used with caution. It may be better to consider the range as an attribute at which the covariance function “vanishes” (equals zero) or “tends to vanish” (Kitanidis 1997) (asymptotic to zero). Finally, though not one of the two parameters comprising \( \mathbf{\theta} \), the slope of the covariance function is derived from the sill and the range and represents, intuitively, the rate of change of the covariance as distance \( h \) increases. The slope is often interpreted as the rate at which the range is
approached and, since at that distance covariance is zero or approximately zero, the slope also describes how quickly independence within the spatial domain is achieved.

1.3.5 Intrinsic Stationarity and the Semivariogram

Limited observational data, without prior knowledge of the truth, results in inferences on the trend and covariance functions of the entire spatial field that are limited only to the observed occurrences. Any unobserved possible occurrence (i.e., unmeasured areas within the domain) may only have its trend and covariance properties approximated by modeling them (i.e., filling in the gaps) based on the available data. Selecting appropriate covariance models is simplified by making certain assumptions about the data. The assumptions of second-order stationarity and isotropy limit the trend to a constant and the covariance function to a distance-only dependency. However, the trend, though constant, is not known. Therefore, in order to avoid having to define a specific constant for the trend, the intrinsic assumption supplements stationarity and isotropy. In the intrinsically stationary isotropic model, the trend/drift is still a constant but it is undefined and the covariance function is ignored in favor of a function of the mean square difference of the spatial field between \( x \) and \( x' \). Thus,

\[
E[Z(x) - Z(x')] = 0, \quad \text{and} \quad (1.3.7)
\]

\[
\frac{1}{2} E\{[Z(x) - Z(x')]^2\} = \gamma(h), \quad (1.3.8)
\]

where,

\[
\gamma(h) = \frac{1}{2} \text{var}[Z(x) - Z(x')], \quad (1.3.9)
\]

and is known as the semivariogram [a variogram is defined as \( 2\gamma(h) \)].

The relationship between the covariance function in the second-order stationary isotropic model and the semivariogram in the intrinsically stationary isotropic model is defined as:

\[
\gamma(h) = -C(h) + C(0) = -C(h) + \sigma^2, \quad (1.3.10)
\]
and all attributes of the covariance function, including the sill, range, and nugget effect (discussed in Section 1.3.6), can be displayed in a semivariogram plot. However, though a second-order stationary model is intrinsic, an intrinsic stationary model is not necessarily second-order stationary. For example, an intrinsically stationary random function that violated second-order stationarity would have infinite variance, and therefore, have semivariogram functions that approach infinity as \( h \) approaches infinity (e.g., \( \gamma(h) = h \)) (Kitanidis 1997). The consequence of infinite variance is that the covariance function would be undefined because the definition of the covariance function as illustrated in equation 1.3.10 requires both the semivariogram at distances smaller than the range and the variance of the random function or sill. Therefore, while intrinsic stationarity is a weaker form of stationarity, it is also more inclusive and reduces the rigor of assumptions necessary to perform spatial prediction.

1.3.6 The Nugget Effect and Anisotropy

An additional attribute of both the covariance and semivariance (SV) functions is that they can reveal both measurement errors and microvariability in the data. In the presence of these characteristics, the residual function for any measurement site \( \alpha \) becomes

\[
\varepsilon(x_\alpha) = \varepsilon_{ME}(x_\alpha) + \varepsilon_{MV}(x_\alpha) + \varepsilon_R(x_\alpha),
\]

where \( \varepsilon_{ME}(x_\alpha) \) is the measurement error at rain-gauge site \( \alpha \), \( \varepsilon_{MV}(x_\alpha) \) is the microvariability at rain gauge site \( \alpha \), and \( \varepsilon_R(x_\alpha) \) is what remains of the residual after microvariability and measurement error effects are removed. As with most measurements, and as discussed in Chapter 2, rain gauges are associated with an inherent margin of error the result of multiple issues both environmental and man-made. It is very difficult to pinpoint this error consistently across different meteorological regimes and rain-gauge types. However, the presence of \( \varepsilon_{ME}(x_\alpha) \) and \( \varepsilon_{MV}(x_\alpha) \) can be inferred, for example, when the SV between two co-located points (\( h = 0 \)) deviates from zero. Furthermore, if the minimum distance separating any two rain gauges in the domain of study is greater than zero, the covariance/SV between any two points separated by a distance smaller than the minimum distance must be estimated.
from a covariance/SV model. The lack of sampling at these distances may suggest the presence of microvariability, since the data prevent the estimation of covariance/SV at small distances because no such sample is present. The measurement density, therefore, may inhibit the understanding of variability at fine scales, causing a gap in the covariance/SV function between the minimum available distance and \( h = 0 \). The combination of these effects is known as the **nugget effect**, parameterized as \( \theta_0 \), where the covariance function, for example, becomes:

\[
C(h; \theta) = \begin{cases} 
\theta_0 + C_r(h; \theta) & \text{if } h = 0 \\
C_r(h; \theta) & \text{if } h > 0 
\end{cases}
\]  

(1.3.6)

Additionally, while in its basic form the geostatistical model is isotropic, it may be idealistic to assume spatial variability is independent of orientation. When the orientation of the linear segment separating two points is crucial in determining the covariance/SV of the points’ measurements, the spatial field is said to be **anisotropic**. Anisotropy exists in many forms and is subcategorized based on the covariance/SV function attributes. Thus, range anisotropy, sill anisotropy, slope anisotropy, and/or nugget anisotropy is present when the random function is direction-dependent. Range and sill anisotropy are usually the most occurring forms, and the presence of sill anisotropy may indicate that either: (1) second-order stationarity is an appropriate assumption but spatial correlation does not vanish in every direction as \( h \) increases; or (2) second-order stationarity is violated. Correction of anisotropic conditions occurs through the stretching or shrinking and tilting of the SV function along the directional axes where isotropic conditions are violated.

1.3.7 The Estimated/Experimental Semivariogram

The SV function, when plotted, shows the spatial variance between points separated by a given distance \( h \), where every distance is assumed to be unique; that is, no two point pairs are separated by the same distance. The approximation of residual correlations (recall \( \varepsilon(x) = Z(x) \) when \( m(x) = 0 \)) via the semivariogram model occurs only through exploratory analysis of the spatial variability of the current sample. Returning to the idea of a mean
square difference, mapping of the spatial variability for this sample field is accomplished through the experimental or estimated semivariogram,

\[ \hat{\gamma}(L_\beta) = \frac{1}{2N(L_\beta)} \sum_{N(L_\alpha)} \left[ \hat{\epsilon}(\mathbf{x}_\alpha) - \hat{\epsilon}(\mathbf{x}_\alpha') \right]^2, \]

where \( L_\beta \) is lag class \( \beta \) and \( N(L_\beta) \) is the number of rain-gauge (i.e., measurement) pairs separated by distances that fall within the range occupied by the lag class \( L_\beta \). In other words, \( h \), representing the distances between all possible gauge pairs, is divided into bins or lag classes. The estimated spatial variability at lag class \( \beta \) is the average of the squared differences of residuals at two gauges for all gauge pairs separated by distances that fall within the range \( (L_{\beta\text{mid}} - r/2 \leq L_{\beta\text{mid}} < L_{\beta\text{mid}} + r/2) \), where \( L_{\beta\text{mid}} \) is the midpoint of the lag class \( L_\beta \) and \( r \) is the range of the lag classes \( L \). The estimated semivariogram or spatial variance carries the fortunate property of being approximately unbiased so long as the trend function is correctly defined. This property holds when the observations themselves are used (i.e., the trend function is defined by a zero mean). The approximate nature of this property is due to the use of lag classes, which blur or smooth the squared measurement differences.

Additionally, the experimental semivariogram can be polar partitioned into angle and distance classes. The main advantage of this partitioning is to identify discontinuity in spatial variance across different directions, thereby identifying potential sources of anisotropy in the precipitation field. The most common form of partitioning dissects the point pairs into four angle classes in addition to the lag classes. The four angle classes used in this research are oriented such that their midpoints are 0°, 45°, 90°, and 135° with a deviation from the midpoint of ±22.5°. It needs to be clarified that, for example, the angle class centered at 0° or north is symmetric about the east-west axis such that it also includes all directions centered at 180° deviating up to ±22.5°. The angle classes are based on axes, where the 0° angle class is equally understood as the north-south axis class. Thus, the 45° angle class includes a 225° midpoint and is known as the northeast-southwest axis class, the 90° angle class includes a 270° midpoint and is known as the east-west axis class, and the 135° angle class includes a 315° midpoint as the southeast-northwest axis class.
1.3.7.1 Experimental Semivariogram Caveats

The experimental semivariogram is insufficient as a model of spatial variance for a few reasons. First, consider an experimental semivariogram with a linear behavior across the entire domain (e.g., $\gamma(h) = h$), such that a sill does not exist. Conceptually, the linear semivariogram implies infinite variance, therefore suggesting that there is no sill and therefore no range attribute of the covariance function. In this case second-order stationarity is violated. Recall that the proposed geostatistical model in Section 1.3.2 is comprised of a constant, known, large-scale (relative to the domain) trend around which small-scale fluctuations or residuals exist. It is expected that such a model will yield a covariance/SV function that is stable after some distance if the trend is indeed constant and the residuals represent small-scale perturbations (e.g., see Kitanidis 1997). In the case of a linear semivariogram function across the entire domain, it is inferred that while the sites with smaller lags may have similar trend, the sites separated by larger lags may not. This inference is also possible with experimental semivariograms that exhibit negative slopes or unstable behavior after a certain distance. Unlike a linear semivariogram, these behaviors actually suggest intrinsic stationarity is also violated. In either example, local versus global stationarity should be considered. It is possible for a non-constant trend to exist at larger-scales within the domain such that global stationarity is violated while trend remains constant at smaller lags such that local stationarity is not violated. Therefore, caution must be exercised when analyzing experimental semivariograms at sufficiently large lags. During the analysis of results, there will be additional references to stationarity as it pertains to the experimental semivariogram. It should be assumed in future discussion that the author is referring to this above situation of violating second-order stationarity through the lack of finite variance. Recall, a lack of finite variance is not a violation of intrinsic stationarity because the covariance function is not considered. However, given the second-order violation, experimental semivariogram behavior may suggest that the mean is not constant across different scales of the domain, and this is the focus of future stationarity discussions since it implies trend/drift modeling may be necessary.
Additionally, the experimental semivariogram, depending on the size of each lag class, may be considerably noisy, thus making specification of the $\theta$ vector via an analyst’s judgment and experience subjective and difficult. Finally, though the grouping of lags into classes results in the impression that the estimated semivariogram is continuous; the reality remains that the spatial density of rain gauges and most other observing networks prohibits the knowledge of spatial variance at non-represented lags. It is necessary to find a semivariogram that: (1) smoothes the noisy variability patterns in the data; (2) allows for estimation of the spatial variance at lags unrepresented by the original data; and (3) allows for the interpolation of precipitation data from the observations $Z(x)$ without violating the limitations set forth in the geostatistical model. The next step, therefore, in the geostatistical method is the fitting of an intrinsically stationary, isotropic, and parametric (ISIP) (i.e., $\theta$) model to the SV function of the spatial field. The set of models that can be used to represent spatial variability is restricted in that no model within the set can become negative. This is due to the fact that the covariance function or semivariogram explicitly identifies the variance (which is nonnegative) of any linear combination of values of $Z(x)$ (Kitanidis 1997) as shown in equation 1.3.11. Within this research, three of the most common ISIP models (i.e., exponential, spherical, and Gaussian) are discussed.

### 1.3.8 Three Idealized Parametric Spatial Covariance/Semivariance Models

The exponential model defines the covariance and SV functions as

$$
C(h; \theta) = \begin{cases} 
\theta_0 + \theta_1 & \text{for } h = 0 \\
\theta_1 \exp(-\theta_2 h) & \text{for } h > 0
\end{cases}
$$

and

$$
\gamma(h; \theta) = \begin{cases} 
\theta_0 & \text{for } h = 0 \\
\theta_0 + \theta_1 [1 - \exp(-\theta_2 h)] & \text{for } h > 0
\end{cases}
$$

where $\theta_0 \geq 0$, $\theta_1 \geq 0$ and $\theta_2 \geq 0$. Notice that the covariance function approaches zero asymptotically while the SV function approaches the sill $\theta_1$ asymptotically as $h$ increases. Hence, as $h \to \infty$, $C(h) \to 0$, and $\gamma(h) \to \sigma^2$. In other words, the range $\theta_2$ cannot be defined as
the point at which \( C(h) = 0 \), otherwise it would equal infinity. Instead, an effective range \( \theta_2 \) is defined for the exponential model and other models with asymptotic behavior. The effective range identifies the point where the covariance function is approximately 5% of its value at \( h = 0 \) (Duetsch and Journel 1992). The effective range, therefore, can be interpreted as the point at which the covariance function begins to tend towards zero.

The exponential model’s system of equations accounts for the nugget effect, which is parameterized by \( \theta_0 \). Due to the presence of the nugget \( \theta_0 \), the sill \( \theta_1 \) represents the maximum or total variance of the exponential function, but not the total variance of the spatial field. Therefore, when \( \theta_0 > 0 \), \( \theta_1 \) is referred to as the partial sill and represents the remaining variance of the spatial field after measurement error and/or microvariability are removed. Therefore, the total sill is the summation of the variance due to 1) the nugget effect and 2) the spatial field [i.e., Total Sill = \( (\theta_0 + \theta_1) \)]. If the nugget effect is zero, in other words, if there is no measurement error or microvariability in the spatial field, then \( \theta_0 = 0 \) and the partial sill \( \theta_1 \) becomes the total sill. Figure 1.3.1 attempts to illustrate the exponential model by providing a set of exponential covariance (dash-dot curve) and SV (solid curve) models with a nugget \( \theta_0 = 0 \); total sill \( \theta_1 = 1.00 \); and effective range \( \theta_2 = 100 \). In order to illustrate the nugget effect, Figure 1.3.1 includes an additional exponential semivariogram model (dashed curve) with a nugget \( \theta_0 = 0.25 \); partial sill \( \theta_1 = 0.75 \); and effective range \( \theta_2 = 100 \).

For the Gaussian model

\[
C(h; \theta) = \begin{cases} 
\theta_0 + \theta_1 & \text{for } h = 0 \\
\theta_1 \exp\left(-\theta_2 h^2\right) & \text{for } h > 0,
\end{cases}
\]

and

\[
\gamma(h; \theta) = \begin{cases} 
\theta_0 & \text{for } h = 0 \\
\theta_1 \left[1 - \exp\left(-\theta_2 h^2\right)\right] & \text{for } h > 0,
\end{cases}
\]

where \( \theta_0 \geq 0, \theta_1 \geq 0, \text{ and } \theta_2 \geq 0 \). The Gaussian model is illustrated by Figure 1.3.2. The set of Gaussian covariance (dash-dot curve) and SV (solid curve) models have a nugget \( \theta_0 = 0 \); total sill \( \theta_1 = 1.00 \); and effective range \( \theta_2 = 100 \). An additional exponential semivariogram
model (dashed curve) is provided in Figure 1.3.2 with the following parameters: nugget $\theta_0 = 0.25$; partial sill $\theta_1 = 0.75$; and effective range $\theta_2 = 100$. The distinctive feature in the Gaussian shape occurs at distances closest to zero where the function is parabolic [$\gamma(h) \propto h^2$ for small $h$ (Kitanidis 1997)], implying a smoothness to the random field at short lags. The suggestion is that at small distances the correlation between measurement points is very high and this can be unrealistic, depending on the exact parabolic nature (i.e., flatness) of the covariance/SV function.

The covariance and SV functions for the spherical model are defined as

$$C(h; \theta) = \begin{cases} \theta_0 + \theta_1 \left[ 1 - \frac{3}{2} \left( \frac{h}{\theta_2} \right) + \frac{1}{2} \left( \frac{h^2}{\theta_2^3} \right) \right] & \text{for } 0 \leq h \leq \theta_2, \\ 0 & \text{for } h > \theta_2 \end{cases}$$

for $0 \leq h \leq \theta_2$, and

$$\gamma(h; \theta) = \begin{cases} \theta_0 & \text{for } h = 0 \\ \theta_1 \left[ \frac{3}{2} \left( \frac{h}{\theta_2} \right) - \frac{1}{2} \left( \frac{h^3}{\theta_2^3} \right) \right] & \text{for } 0 < h \leq \theta_2, \\ \theta_1 & \text{for } h > \theta_2 \end{cases}$$

(1.3.14)

where $\theta_0 \geq 0$, $\theta_1 \geq 0$, and $\theta_2 \geq 0$. The spherical model is illustrated by Figure 1.3.3. The set of spherical covariance (dash-dot curve) and SV (solid curve) models have a nugget $\theta_0 = 0$; total sill $\theta_1 = 1.00$; and range $\theta_2 = 50$. An additional exponential semivariogram model (dashed curve) is provided in Figure 1.3.3 with the following parameters: nugget $\theta_0 = 0.25$; partial sill $\theta_1 = 0.75$; and range $\theta_2 = 50$. Notice that unlike the exponential and Gaussian models, the spherical model explicitly defines the distance $h$ where $C(h) = 0$.

1.3.9 Semivariance Model Fitting: By Eye

Various approaches to ISIP model fitting (i.e., finding the set of parameters $\theta$ for an ISIP model that most closely reproduce the true SV function of the spatial field) exist. Nevertheless, in applied geostatistics, the end result is generally expected to be consistent
with the measurements and a priori information while adhering to the assumptions imposed on the geostatistical model. A very straightforward and common technique attempts to fit a parametric model to the experimental semivariogram by eye with a variable amount of parameter trial and error. This approach is typically seen when the sample size (i.e., number of measurements) is low and is popular when computational limitations prevent more advanced methods from being used. The use of an ISIP model is an improvement over simply relying on the experimental semivariogram directly; however, the information on the ISIP model parameters is derived directly from the experimental semivariogram, which remains subject to the shortcomings discussed previously.

1.3.10 Semivariance Model Fitting: Non-Linear Least Squares (NLS)

Two popular techniques applied to the experimental semivariogram originate from non-linear least squares regression\(^4\). The ordinary non-linear least squares (ONLS) approach fits a pre-selected ISIP model to the experimental semivariogram by minimizing the error sum of squares between them. However, the ONLS approach cannot consider the spatial variance and correlation structure present in the sample set of observations and thus is inappropriate as part of the geostatistical analysis; the reliance on the experimental semivariogram remains. Further, the ONLS approach is equally influenced by point pairs separated by large distances as it is by point pairs closer to each other. Often at these large lags, the number of point pairs decreases and the reliability of the estimated residual sum of squares dwindles, yet ONLS takes none of this into account. Meanwhile, the weighted non-linear least squares (WNLS) approach incorporates a weighting factor on the error sum of squares and minimizes the product (i.e., the weighted error sum of squares). The weighting factor is the ratio between the number of sample pairs \(N(L_h)\) and the experimental semivariogram squared \(\hat{\gamma}(h)^2\). The consequence is that lags populated by large numbers of point pairs and/or low \(\hat{\gamma}(h)^2\) values receive greater weight. Though it is a significant improvement over the ONLS method, the WNLS approach still avoids explicit interpretation.

\(^4\) Further analysis of the NLS approaches is available in Cressie (1993).
of spatial dependency. Cressie (1993) comments that the appeal to using an NLS approach, especially ONLS, is often visually-based, because the end result seeks to fit a model that resembles the experimental semivariogram, and consequential agreement between the model fit and the estimate may be instinctively sensible.

1.3.11 Semivariance Model Fitting: Maximum Likelihood

Though this research investigated fitted models in each precipitation sample using the NLS approaches first, final ISIP model selection was based on the concept of finding the parameters $\theta$ given a generic ISIP model that maximized the likelihood (i.e., probability) of obtaining the observed spatial SV structure. This concept of maximum likelihood (ML), via the assumption of an intrinsically stationary random field, uses the generic ISIP model (e.g., exponential, Gaussian, spherical) to produce a $n \times n$ (where $n$ is the total number of observation points $Z(x)$) covariance matrix $V(\theta) = \text{cov}(Z(x), Z'(x))$ in order to account for spatial dependency. Here, the $n\times 1$ matrix $Z(x) = (Z(x_1), Z(x_2), \ldots, Z(x_{n-1}), Z(x_n))'$. Furthermore, the likelihood technique estimates the trend function coefficients(s) $\beta$ simultaneously as expressed by the log likelihood function $P(\beta, \theta)$, where

$$P(\beta, \theta) = \left(\frac{n}{2}\right) \log(2\pi) + \left(\frac{1}{2}\right) \log|V(\theta)| + \left(\frac{1}{2}\right)(Z - X\beta)'V(\theta)^{-1}(Z - X\beta), \quad (1.3.15)$$

(Cressie 1993) and represents a probability that the chosen trend function coefficients $\beta$ and ISIP model parameters $\theta$ will produce the SV function of the observed random field. The matrix $X$ is an $n \times q$ matrix where $q$ represents the number of trend function covariates (i.e., copredictors) and the first column is all 1’s to correspond to the constant term $\beta_0$. The similarity of $Z - X\beta$ to the multivariate regression model $Z = X\beta + \epsilon$ in Section 1.5 is not coincidental; if it was assumed $Z(x)$ were an independent random sample, the likelihood method would converge on the ordinary least squares estimate for $\beta$ and

$$\theta = \hat{\sigma}^2 = \frac{\sum_{i=1}^{n} (Z(x_i) - X\hat{\beta})^2}{n}. \quad (Cressie 1993)$$
Numerical optimization methods take an adequate (i.e., stable or reasonable) initial set of parameters and converge on those parameters which yield the largest $P(\beta, \theta)$. Therefore, given prior knowledge of covariate values at the observation points and a pre-specified ISIP SV function with initial parameters, the likelihood function can simultaneously estimate a set of multivariate trend coefficients and SV function parameters by converging on the solution that yields the greatest probability of reproducing the true SV function for the random field. This is a significant result because equation 1.3.15 indicates that the solution of $\beta$ requires knowledge of the spatial variance of the random field (i.e., $V(\theta)$) and therefore assumes that the trend function is spatially dependent. This concept will be revisited and elaborated upon in future sections as it has a critical role in the geostatistical model.

It should also be apparent from equation 1.3.15, however, that the log likelihood function is dependent on the trend function coefficients $\beta$. An additional dependency on the trend exists because the data $Z(x)$ itself are partially constructed from that same trend. These dependencies on $\beta$ are cited by Cressie (1993) as a reason why ML estimators of $\theta$ are often biased and “prohibitively so in small to moderate samples”. One method documented in Cressie (1993) to reduce these biases is restricted maximum likelihood or REML, where the estimators of $\theta$ are based on error contrasts $W$ instead of the data themselves. The log likelihood function to minimize is defined as

$$P_{RE}(\beta, \theta) = \left(\frac{n-q}{2}\right)\log(2\pi) + \frac{1}{2} \log|A'V(\theta)A| + \left(\frac{1}{2}\right) (W - A'X\beta)'(A'V(\theta)A)^{-1}(W - A'X\beta),$$

(1.3.16)

Error contrasts are defined as $W = A'Z$, where $W$ is a $n-q$ list and $A = (a_{ij})$ is an $(n-q) \times n$ matrix where

$$a_{ij} = \begin{cases} 1, & \text{for } i = j, j = 1,\ldots,n-q \\ -1, & \text{for } i = j+1, j = 1,\ldots,n-q \\ 0, & \text{elsewhere.} \end{cases}$$

In simpler terms, an error contrast list is nothing more than a series of differences between any two observations $Z(x)$ and $Z'(x)$ for $n-q$ observations. For example, if it is assumed the
trend function is merely a constant $\beta_0$, then $q = 1$ and the error contrasts $W = (Z(x_1) - Z(x_2), Z(x_2) - Z(x_3), \ldots, Z(x_{n-1}) - Z(x_n))'$. Bound by the assumption of intrinsic stationarity, as always, the error contrasts $W$ have zero mean and thus eliminate the dependency inherent within $Z(x)$. Furthermore, if the contrasts $W$ are linearly independent (i.e., one set of contrasts cannot be obtained from a linear combination of the remaining contrasts) then this implies, by definition of $W$, that the columns of $A$ are also linearly independent and $A'X = 0$. From equation 1.3.16, the $A'X\beta$ term reduces to 0 and the dependency on the trend $\beta$ disappears. It may be helpful to think of this method as residual maximum likelihood.

1.3.12 Caveats for Likelihood and NLS Semivariance Model Fitting

As a caveat and in analysis of previous research, Cressie (1993) stresses that though likelihood approaches do quite well in parameter estimation, their success is dependent on the assumption of a normally distributed random field (see subsection 1.6.2). Cressie (1993) does document studies that show the simpler WNLS procedure is adequate not only for data which are stationary, but also for data that are not and may be a more universal approach to model fitting. The theoretical benefit of likelihood estimation is that it converges on the best parameters for the ISIP model without relying on the experimental semivariogram. Thus, if the ISIP model specification is correct, the parameters derived from likelihood estimation can be considered a better representation of the truth. NLS approaches assume automatically that the experimental semivariogram derived from a sample of the spatial field is the truth or true representation of spatial variability. This may be incorrect if the observations comprising the sample are compromised due to measurement error, nonrandom sampling, or other issues. In using likelihood estimation, the experimental semivariogram serves only as a guide to the user for choosing the ISIP SV model shape (i.e., exponential, Gaussian, spherical, etc.) and initial model parameters. Therefore, the resultant “best” SV function is not necessarily going to be the one that best replicates the experimental semivariogram. Furthermore, it should be stressed that regardless of the technique employed to select a set of SV model parameters, the resultant SV model is simply an estimate of the true SV function for the random field. It is
very unlikely that the ISIP SV function will capture all spatial variability present in the original random field.

1.4 Ordinary Kriging (OK) Interpolation

Though the solution may not be, the problem this research investigates is straightforward: Given \( n \) rain-gauge measurements of precipitation \( Z \) at locations defined by spatial coordinates \( x_1, x_2, \ldots, x_n \), estimate the precipitation \( Z \) at a gridded network of \( p \) points \( g_1, g_2, \ldots, g_p \). As the descriptor of spatial variability, the ISIP model carefully selected through an iteration of the geostatistical model can now be used to find the best estimator of the spatial field. The process which predicts the unknown quantity from known observations using the geostatistical model is called kriging.

There are many forms of kriging and all forms adhere to a fixed set of specifications. Like IDW interpolation, kriging is a linear estimator (i.e., produces an estimate that is a linear combination of the measurements). Thus, at any gridded point \( g \),

\[
\hat{Z}(g) = \sum_{i=1}^{n} \lambda_i Z(x_i).
\]  

1.4.1 The OK System of Equations

From equation 1.4.1, the estimation error

\[
\tilde{Z}(g) - \hat{Z}(g) = \sum_{i=1}^{n} \lambda_i Z(x_i) - Z(g),
\]  

In other words, the predictor model is rather simple; the estimated value \( \hat{Z} \) of the random field (i.e., precipitation) at point \( g \) is the sum of the weighted observations \( Z(x) \). The weights \( \lambda \) are different from the weights of IDW in that they are dependent on the spatial correlation or covariance of the random field. However, as explained in Section 1.3, spatial covariance is itself a function of distance. In any case, the geostatistical ISIP model now can be used to derive a set of weights \( \lambda \) to perform the spatial prediction.
is the difference between the estimated value $\hat{Z}(g)$ and the actual value $Z(g)$. The linear kriging estimator must also be *unbiased*. In other words, the estimator should predict such that, across all possible realizations\(^5\), the average of the estimation errors is zero:

$$E[\hat{Z}(g) - Z(g)] = \left( \sum_{i=1}^{n} \lambda_i d \right) - d = \left( \sum_{i=1}^{n} \lambda_i - 1 \right) d = 0.$$  \hfill (1.4.3)

However, equation 1.4.3 is dependent on the value of the drift $d$. To ensure the kriging estimator is unbiased for all possible values of drift $d$, equation 1.4.3 reduces to:

$$\sum_{i=1}^{n} \lambda_i = 1.$$  \hfill (1.4.4)

In other words, if the weights $\lambda$ sum to one, equation 1.4.3 reduces to zero regardless of the value of the drift $d$.

Finally, this linear and unbiased kriging estimator is only the *best* of all such predictors that are linear and unbiased if it minimizes the variance of the prediction error or the mean square estimation error. Beginning with equation 1.4.2, utilizing the unbiasedness constraint of equation 1.4.3, and after some algebraic manipulation\(^6\) it can be shown:

$$E[\hat{Z}(g) - Z(g)]^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} \lambda_i \lambda_j \gamma(x_i - x_j) + 2 \sum_{i=1}^{n} \lambda_i \gamma(x_i - g(x)) = \sigma^2_{\delta K}(g).$$  \hfill (1.4.5)

To minimize the variance of the estimation error, equation 1.4.5 must be minimized subject to the constraint of equation 1.4.4, and this is accomplished using the optimization method of Lagrange multipliers\(^7\). As a result, the linear kriging system of $n+1$ equations and $n+1$ unknowns is as follows:

---

\(^5\) Any subset of the possible solutions may, in fact, be biased (constant over- or under-prediction), so long as the average of all realizations is not (Kitanidis 1997).

\(^6\) See Section 3.9 of Kitanidis (1997) for a derivation of the mean square estimation error equation 1.4.5.

\(^7\) See Appendix B of Kitanidis (1997) for a partial derivation of the Lagrange multiplier linear kriging system.
where $\nu$ is a Lagrange multiplier. Substituting system 1.4.6 into equation 1.4.5 we can derive a simpler expression for variance of the estimation error or *kriging variance* in terms of the Lagrange multiplier $\nu$ and the sum of the weighted semivariogram between each observation $x_i$ for $i = 1, 2, \ldots, n$ and the gridded prediction point $g$:

$$\sigma_{\text{OK}}^2(g) = E \left[ \tilde{Z}(g) - Z(g) \right]^2 = -\nu + \sum_{i=1}^{n} \lambda_i \gamma(\|x_i - g\|).$$  \hfill (1.4.7)

Knowledge of the kriging variance $\sigma_{\text{OK}}^2$ permits, assuming a normal distribution, the calculation of the 95% confidence interval (CI) of the estimation of precipitation $\tilde{Z}(g)$. In other words, the 95% CI

$$P \left\{ \left[ (\tilde{Z}(g) - 1.96\sigma_{\text{OK}}) \leq Z(g) \leq (\tilde{Z}(g) + 1.96\sigma_{\text{OK}}) \right] \right\} = 0.95$$  \hfill (1.4.8)

should provide, with a probability of 0.95, the actual value of precipitation $Z(g)$.

### 1.4.2 OK in Matrix Notation

Conceptualizing the linear kriging system of equations is notably easier when the system is expressed in matrix notation. At that point, it resembles a system much like what is seen in least squares regression analysis, as shown in Section 1.5. Let $A$ represent the $(n + 1) \times (n + 1)$ matrix of spatial variance or semivariogram values for the distances between each of the $n$ measurement points $x_i (i = 1, 2, \ldots, n)$ and $x_j (j = 1, 2, \ldots, n-1)$ for all point combinations such that $x_i \neq x_j$,

$$A = \begin{bmatrix}
0 & -\gamma(\|x_1 - x_2\|) & \cdots & -\gamma(\|x_1 - x_n\|) & 1 \\
-\gamma(\|x_2 - x_1\|) & 0 & \cdots & -\gamma(\|x_2 - x_n\|) & 1 \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
-\gamma(\|x_n - x_1\|) & -\gamma(\|x_n - x_2\|) & \cdots & 0 & 1 \\
1 & 1 & \cdots & 1 & 0
\end{bmatrix}$$
Next, define the \((n + 1) \times 1\) matrix of unknowns (i.e., \(n\) kriging weights or coefficients \(\lambda\) and the Lagrange multiplier \(\upsilon\)),

\[
X = \begin{bmatrix}
\lambda_1 \\
\lambda_2 \\
\vdots \\
\lambda_n \\
\upsilon
\end{bmatrix}.
\]

Finally, represent the right-hand side of equation 1.4.6 with the \((n + 1) \times 1\) matrix

\[
b = \begin{bmatrix}
-\gamma||x_1 - g|| \\
-\gamma||x_2 - g|| \\
\vdots \\
-\gamma||x_n - g|| \\
1
\end{bmatrix},
\]

where \(b\) contains the semivariogram values for the distances between each measurement point \(x_i\) and the gridded prediction point \(g\). Given \(A_{ij}\) is the element of \(A\) at row \(i\) and column \(j\), \(X_i\) is the \(i\)-th element of \(X\), and \(b_i\) is the \(i\)-th element of \(b\), the linear kriging system is defined as:

\[
\sum_{j=1}^{n+1} A_{ij} X_i = b_i \text{ or } AX = b.
\]

Thus, the solution to the kriging system is obtained by multiplying the inverse of \(A\) by \(b\). It can be readily seen then that the solution to the system can be computationally intense especially as the number \(n\) of measurement sites \(x_i\) increases and the number \(p\) of prediction points increases (one kriging system of equations exists for each prediction point \(g\)).

1.4.3 Kriging Characteristics

The kriging predictor assumes, through the above characteristics, the properties of a best, linear, and unbiased estimator (BLUE). The kriging estimator relies only on the semivariogram (it is not a function of the data itself) and the semivariogram is modeled by an intrinsically stationary, isotropic, and parametric function which measures the spatial
variability of the random field. The weights $\lambda$ are related to the way at which spatial variability and thus the semivariogram increases with distance. This relationship is usually far more complex than simply the inverse of the distance squared but it is an indirect function of distance nonetheless. Interpreted another way, the weights are assigned to measurement locations by the amount or percentage of influence those locations exert on the prediction point. This percentage of influence is directly proportional to the covariance between the measurement location and the prediction point. However, it is inversely proportional to the covariance between that same measurement location and surrounding measurement locations. In other words, if a dense cluster of measurement points in one quadrant is opposed by one measurement point in another quadrant, and all of these points are approximately the same distance from the prediction point, the weight of the single point will be larger than any of the individual weights of the cluster of points.

As an interpolator, kriging is exact. This means that if the prediction point was collocated with the measurement point, the predicted value would equal the measurement value. The kriging variance therefore reduces to zero at the measurement locations. This is not the case, however, when microvariability or a nugget effect exists because in such circumstances the presence of uncertainty at the measurement point is reflected in a discontinuous or inexact prediction. As a result, the kriging variance reduces to the nugget variance. In either case, an enormous advantage of kriging interpolators is the ability to measure a confidence in the prediction. The calculation of the minimized mean square estimation error or kriging variance is only a function of the semivariogram model and the location of the measurements. As a result, it is an excellent indicator of the need for proposed measurement locations and can be a powerful tool in the design of measurement networks.

Finally, the distinction between kriging and ordinary kriging is straightforward. The linear kriging system discussed above is essentially that of the ordinary kriging technique. When the ordinary kriging technique is applied, the drift is unknown; however, it is assumed to be constant. As shown above via equations 1.4.3 and 1.4.4, the drift $d$ is eliminated from the ordinary kriging system and does not factor into the solution of the system. However, it
is likely to be deduced that an underlying constant trend seldom defines spatial random fields, and the likelihood of constant trend should become less the larger the domain of study. This is no less true of meteorological spatial fields. In fact, the assumption of constant trend in a random field where the trend is location dependent violates the assumption of stationarity. Including a variable drift in the residual moment of the geostatistical model will be detrimental to the modeling of spatial variance because an ISIP model will be inappropriate and unrepresentative of the covariance/SV of the random field.

1.5 Kriging with External Drift (KED) Interpolation

1.5.1 Interpreting Variable Drift/Trend

Seeking mitigation of variable drift in the geostatistical model, the concept of kriging with external drift (KED) is introduced. Recall the concept of intrinsic stationarity requires constant drift across the spatial domain; thus, variable drift is synonymous with non-stationarity. Consider the possibility of increasing the power of the drift \( m(x) \) in equation 1.3.1 to the point that the residual \( \varepsilon(x) \) is an intrinsically stationary random field. In other words, let \( m(x) \) be estimated by a function \( d(x) \) such that the residual of the random field has a constant trend across space. At that point, the residuals’ spatial SV could be modeled using the geostatistical model and OK can be used to predict residual values at the gridded network of \( p \) points \( g \). Adding the drift \( d(g) \) to the residual \( \hat{\varepsilon}(g) \) at each prediction point yields the predicted precipitation grid and is the essence of KED. Though the drift function theoretically could resemble many forms, this research proposes using the most common representation of the drift: a multivariate, linear (in \( \beta \)) polynomial function,

\[
d(x) = \beta_0 + \beta_1 f_1(x) + \beta_2 f_2(x) + \ldots + \beta_s f_s(x) = \hat{m}(x)
\]

for \( s \) variables \( f(x) \).

---

8 For the purposes of this research, the polynomial is not fixed to a certain degree. Also, it is more sensible in this research to treat each higher power of a particular unique variable \( f(x) \) as its own “hybrid” variable. The same holds for interactions between two or more unique variable(s) and/or interactions between a unique variable and a “hybrid” variable.
Essentially, the spatial distribution of precipitation is both directly and indirectly associated with specific dynamical principles. Due to the generalization implied by the drift function $d(x)$, and the empirical nature of the geostatistical interpolation models described in this research, the variables $f_\alpha(x)$ ($\alpha = 1, 2, \ldots, s$), may not describe the physical properties associated with atmospheric motions that produce precipitation; however, they most certainly can represent atmospheric and other geophysical variables that correlate with both quantitative precipitation and its spatial distribution.

Another way to interpret this new decomposition of the geostatistical model classifies the multiple datasets that now exist into two groups. First, consider the rain-gauge measurements $Z(x)$ representing the precipitation field as precise (though not always accurate) and known at a limited number of locations. Recall from Section 1.3 that they comprise the primary variable. The field’s spatial trend can be modeled by a surface defined by a linear combination of variables measured densely and across the entire domain, yet they are usually imprecise and best considered estimates of the true field they represent. These variables are known as secondary. (In part from Wackernagel 1998)

1.5.2 Multivariate Linear Regression (MLR)

Let the influence of each secondary variable $f(x)$ then be determined by the non-spatial correlation of $f(x)$ to the precipitation $Z(x)$ and represented by weights $\beta_\alpha$ ($\alpha = 1, 2, \ldots, s$). This problem can be solved employing the multivariate linear regression (MLR) model

$$Z(x) = d(x) + \varepsilon(x). \quad (1.5.2)$$

In fact, equation 1.5.2 resembles a more complex version of the original geostatistical model (equation 1.3.1). Be aware though that the resulting residuals $\varepsilon(x)$ are assumed in the MLR model to have a constant mean equal to zero, be normally distributed, and independent. Though the first two assumptions are desirable for reasons explained in Section 1.3 and subsection 1.6.2, the expectation of the geostatistical model is that the residuals are, in fact,
spatially correlated. Otherwise, the residuals are independent and cannot be modeled, and the MLR model serves as an adequate spatial predictor of precipitation (see subsection 1.6.2).

To fit the “best” MLR model to the data, the sum of squared deviations from the observed precipitation \( Z(x) \)

\[
Q = \sum_{i=1}^{n} \left[ Z_i - \left( \beta_0 + \beta_1 f_1(x) + \beta_2 f_2(x) + \ldots + \beta_s f_s(x) \right) \right]^2
\]  

(1.5.3)

is minimized in what is known as the least squares (LS) fit. Setting the partial derivatives of \( Q \) with respect to the coefficients \( \beta \) equal to zero yields \( s \) equations, which are solved to yield the LS estimates \( \hat{\beta} \) of \( \beta \). This is best illustrated in matrix notation where the LS system of equations

\[
(F'F)\hat{\beta} = F'\hat{Z}
\]  

(1.5.4)

has the solution

\[
\hat{\beta} = (F'F)^{-1} F'\hat{Z}
\]  

(1.5.5)

for the MLR model

\[
Z = F \beta + \varepsilon,
\]  

(1.5.6)

where

\[
Z = \begin{bmatrix} Z(x_1) \\ Z(x_2) \\ \vdots \\ Z(x_n) \end{bmatrix}, \quad \hat{Z} = \begin{bmatrix} \hat{Z}(x_1) \\ \hat{Z}(x_2) \\ \vdots \\ \hat{Z}(x_n) \end{bmatrix}, \quad \text{and} \quad \varepsilon = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix}
\]

are the \( n \times 1 \) matrices of the precipitation measurements \( Z(x) \), the estimated precipitation \( \hat{Z}(x) \), and the residuals or errors \( \varepsilon(x) \),

\[
F = \begin{bmatrix} 1 & f_1(x_1) & f_2(x_1) & \cdots & f_s(x_1) \\ 1 & f_1(x_2) & f_2(x_2) & \cdots & f_s(x_2) \\ 1 & \vdots & \vdots & \ddots & \vdots \\ 1 & f_1(x_n) & f_2(x_n) & \cdots & f_s(x_n) \end{bmatrix},
\]

is the \( n \times (s + 1) \) matrix of secondary variable (i.e., covariate) values, and
are the $s \times 1$ matrices of actual ($\beta$) and estimated ($\hat{\beta}$) coefficients.

### 1.5.3 Interpreting the Drift/Trend Model

Evaluation of the “goodness of fit” of the MLR model estimate $\tilde{Z}(x)$ to the precipitation field $Z(x)$ occurs through the study of numerous parameters or performance metrics [e.g., coefficient of determination $R^2$, the F ratio, Type I and Type II Sum of Squares (SSQI and SSQII, respectively), etc.], scatterplots, and residual normality. Note, however, that it is not the evaluation of the estimate of the drift function $d(x)$ to the true drift that is under investigation; the limited number of observations prohibits understanding of the true drift anyway. All of these performance metrics, plots, and normality tests address the ability of the model estimate to “explain” the variability of the random field, either by evaluating the model’s usefulness in its entirety, or by evaluating the predictive ability of each covariate. Interpretation of the evaluation techniques used will be provided in the case-study analyses; further discussion of the drift/trend model selection methodology is available in Section 3.5; further discussion of MLR assumptions, their relationship to kriging assumptions, and their impact on the current research is available in subsection 1.6.2 and section 3.5; and detailed theory and discussion of the techniques can be found in any intermediate statistical analysis text (e.g., Tamhane and Dunlop 2000; Rao 1998).

The resulting polynomial $d(x)$ models the drift as a surface and the degree of the polynomial determines the surface’s shape. Protruding from the surface are the residuals $\varepsilon(x)$. For example, when the drift was constant, its surface was flat planar. A first-degree polynomial yields a sloped planar surface, a second-degree polynomial yields a quadratic or parabolic surface, and so on. From this visualization it can be seen that the higher the order of the polynomial, the noisier the trend surface and, if the fit improves, the smaller the
residuals. However, the polynomial is derived from the \textit{non-spatial} correlations between precise but limited rain-gauge measurements and imprecise but dense covariates. Areas within the domain where the primary variable was not measured (and thus the correlation between the primary and secondary variables is unknown) may have unrealistic predicted trend values. This problem is amplified as the order of the polynomial increases and/or as the number of secondary variables increases. Finally, as the degree of the drift function increases, the number of secondary variables increases and the power of the polynomial decreases. In other words, the amount of variability explained by each secondary variable becomes an increasingly smaller (and possibly negligible) amount of the total variance. Any increase in the regression sum of squares (SSR; a measurement of variance explained by the regression model) or reduction in the error sum of squares (SSRE; a measurement of residual variance left unexplained by the model) also comes at the expense of maintaining and processing numerous datasets. The balance that must be achieved given the potential sensitivities described above is somewhat subjectively obtained which is why using valuation parameters like $R^2$, SSQI, and SSQII and evaluating scatterplots and residual normality is vital to justifying the chosen model.

1.5.4 The KED System of Equations

Proper application of the MLR model and LS analysis yields intrinsically stationary residuals $\varepsilon(x)$ whose SV can be modeled by an ISIP function and can be interpolated by the ordinary kriging system of equations (1.4.6). Adding the drift $d(g_{\alpha})$ to the residuals $\hat{\varepsilon}(g_{\alpha})$ ($\alpha = 1, 2, \ldots, p$) produces the precipitation grid of $p$ points $\hat{Z}(g_{\alpha})$. In its piecemeal form, this non-stationary approach to geostatistical interpolation is often referred to ordinary (or simple) kriging with local means (e.g., Goovaerts 2000), detrended kriging (e.g., Chua and Bras 1982; Kitanidis 1997), or kriging of the residual (e.g., Rivoirard 2002). KED (e.g., Goovaerts 2000; Wackernagel 1999) assimilates all steps into one system of equations with additional benefits. Consider, at any gridded point $g$, the estimator $\hat{Z}(g)$ is the linear combination of $n$ weighted observations $\{Z(x_i): i = 1, 2, \ldots, n\}$, which are decomposed into
the deterministic trend and stochastic residual components \(d(x_i)\) and \(\varepsilon(x_i)\):
\[
\hat{Z}(g) = d(g) + \hat{\varepsilon}(g) = \sum_{i=1}^{n} \lambda_i Z(x_i) = \sum_{i=1}^{n} \lambda_i \left[ d(x_i) + \varepsilon(x_i) \right].
\]
(1.5.7)

The weights \(\{\lambda(x_i): i = 1, 2, \ldots, n\} = \lambda\) are still subject to the original unbiasedness constraint such that the average of the estimation error,
\[
\hat{Z}(g) - Z(g) = (d(g) + \hat{\varepsilon}(g)) - (d(g) + \varepsilon(g)) = \hat{\varepsilon}(g) - \varepsilon(g)
\]
\[
= \left( \sum_{i=1}^{n} \lambda_i \varepsilon(x_i) \right) - \varepsilon(g),
\]
(1.5.8)
equals zero:
\[
E[\hat{Z}(g) - Z(g)] = \left( \sum_{i=1}^{n} \lambda_i d(x_i) \right) - d(g) = 0.
\]
(1.5.9)

Notice equation 1.5.9 requires
\[
\left( \sum_{i=1}^{n} \lambda_i d(x_i) \right) = d(g).
\]
(1.5.10)

Consequently,
\[
d(g) = \left( \sum_{i=1}^{n} \lambda_i d(x_i) \right) = \left( \sum_{i=1}^{n} \lambda_i \left( \beta_0 + \beta_1 f_1(x_i) + \beta_2 f_2(x_i) + \ldots + \beta_s f_s(x_i) \right) \right)
\]
\[
= \beta_0 \left( \sum_{i=1}^{n} \lambda_i \right) + \beta_1 \left( \sum_{i=1}^{n} \lambda_i f_1(x_i) \right) + \beta_2 \left( \sum_{i=1}^{n} \lambda_i f_2(x_i) \right) + \ldots + \beta_s \left( \sum_{i=1}^{n} \lambda_i f_s(x_i) \right),
\]
(1.5.11)
requiring that:
\[
\left( \sum_{i=1}^{n} \lambda_i f_\alpha(x_i) \right) = f_\alpha(g) \quad \text{for } \alpha = 1, 2, \ldots, s,
\]
(1.5.12)
and
\[
\sum_{i=1}^{n} \lambda_i = 1.
\]
(1.5.13)

In other words, the weights \(\lambda\) are selected such that they allow for the exact interpolation of any secondary variable \(f_\alpha(g)\) as a weighted sum of the secondary variable values \(\{f_\alpha(x_i): i = 1, 2, \ldots, n\}\). Secondly, the weights must sum to one to be applicable for any \(\beta_0\). These
constraints are often referred to as **universality conditions** (Cressie 1993; Kitanidis 1997; Wackernagel 1999) because the weights are universally applicable across all possible regression coefficients \( \{\beta_\alpha; \: \alpha = 0, 1, \ldots, s\} \). This result is significant; it now allows the kriging system to be solved **without knowing the regression coefficients \( \beta_\alpha \) at all**, whereas without condition 1.5.12, the weights would be dependent on the coefficients and the coefficients would need to be solved first before the weights could be computed.

It follows from constraints 1.5.12 and 1.5.13 that the variance of the estimation error is defined as:

\[
E\left[\left(\hat{Z}(g) - Z(g)\right)^2\right] = E\left[\left(\hat{e}(g) - e(g)\right)^2\right] = \sigma^2_{KED}(g)
\]

\[
= -\sum_{i=1}^{n} \sum_{j=1}^{n} \lambda_i \lambda_j \gamma(x_i - x_j) + 2 \sum_{i=1}^{n} \lambda_i \gamma(x_i - g),
\]

where \( \gamma(x_i - x_j) \) is the semivariogram value between the residuals \( e(x_i) \) and \( e(x_j) \).

Minimizing equation 1.5.14 subject to the constraints of equation 1.5.12 and equation 1.5.13 yields the linear KED system of \( n+s \) equations and \( n+s \) unknowns (Goovaerts 2000; Wackernagel 1999):

\[
\begin{cases}
\sum_{j=1}^{n} \lambda_j \gamma(x_i - x_j) - v_0 - \sum_{a=1}^{s} v_a f_a(x_i) = \gamma(x_i - g) & \text{for } i = 1, 2, \ldots, n \\
\sum_{j=1}^{n} \lambda_j = 1,
\end{cases}
\]

\[
\begin{cases}
\sum_{j=1}^{n} \lambda_j f_a(x_j) = f_a(g) & \text{for } \alpha = 1, 2, \ldots, s
\end{cases}
\]

Substituting the system 1.5.15 into equation 1.5.14 yields the mean square estimation error (i.e., the kriging variance) in terms of the Lagrange multipliers \( v_0, v_1, \ldots, v_s \):

\[
\sigma^2_{KED}(g) = E\left[\left(\hat{e}(g) - e(g)\right)^2\right] = -v_0 - \sum_{a=1}^{s} v_a f_a(g) + \sum_{i=1}^{n} \lambda_i \gamma(x_i - g).
\]

The earlier comparison of OK and KED – the latter merely being a detrended form of the former – should be readily apparent from system 1.5.15. In other words, OK assumes a
constant trend and requires the estimator to be unbiased regardless of the value of the trend while KED assumes a variable trend yet still requires the estimator to be unbiased regardless of the value of the trend. In order to accomplish the KED version of the unbiasedness restraint, each covariate at each prediction point must be a function of the covariate values at each of the observation points, multiplied by the weight $\lambda$ at each point such that the summation of all weights equals one, just like they are required to equal one for OK.

1.5.5 KED Characteristics

The incorporation of the drift into the kriging system allows the restriction of observations to pre-defined neighborhoods. As a result, KED can address larger domains where the significance of secondary variables may vary by partitioning the domain into smaller sub-domains. However, the use of neighborhoods complicates the analysis of drift and residuals because for each neighborhood the drift function and thus the resulting residuals may vary substantially. Extraction and evaluation of the drift coefficients for each sub-domain is difficult especially as the number of neighborhoods increases (e.g., see Wackernagel 1999). Analysis of spatial variance is equally challenging because it too is sub-domain dependent. Further, all-encompassing support for this moving-window approach is largely lacking in popular geostatistical software. Though the moving-window KED technique is not used in this research, it is recommended as future research with the proper resources (see Section 6.2).

Caution must be exercised in interpreting the KED variance due to the deterministic trend assumption. Notice in equation 1.5.14 that the kriging variance is a function only of the spatial variance of the residual. As a known quantity, the drift function $d(x)$ and the process through which the secondary variables are selected have no measured variability or error associated with them. It will be shown, however, that KED results are highly sensitive to the secondary variables and the drift they represent. The low density of observations means that drift across the entire domain can only be inferred from limited measurement locations, and the KED approach cannot account for the errors of the chosen drift function in between those measurement locations. Therefore, the KED variance is likely to
underestimate the total variance of the prediction and drift function evaluation is limited to
the conclusions that can be drawn from the MLR modeling and the drift’s effect on the KED
predicted spatial field. Advanced methods do exist to treat the drift as probabilistic and offer
additional insight into the confidence in the prediction (see, e.g., Cressie 1993; Kitanidis
1997; Wackernagel 1999), but they are beyond the scope of this research.

1.6 Cross-Validation and Orthonormality

1.6.1 Assessing Interpolation Accuracy via Cross-Validation

Assessment of the aforementioned interpolation techniques associated with the
geostatistical model is likely going to be both qualitative and quantitative. In either case,
direct comparison of predicted and actual (i.e., true) values is required, yet the only “actual”
dvalues available to most users of geostatistics are the measurements themselves, which of
course are also estimates of the true values. Therefore, consider the elimination of one
measurement value from the sample dataset such that prediction \( \hat{Z}_{p-1} \) of the random variable
can occur at the location of the removed measurement based on the non-deleted measurement
points. Repeat this step for each measurement location. This procedure is otherwise known
as cross-validation; the resultant predictions can be compared to each of the original
measurements (i.e., actual values) they represent in order to generate an error dataset. From
the error dataset, performance statistics can be examined to evaluate interpolation model
performance.

Perhaps the most popular cross-validation performance statistic is the root mean
square error (RMSE):

\[
RMSE = \sqrt{\frac{1}{n} \sum_{a=1}^{p-1} [Z(g_a) - \hat{Z}_{p-1}(g_a)]^2}.
\]

(1.6.1)

The RMSE originates from the mean square error (MSE), which combines both the variance
(i.e., precision or consistency) and the bias (i.e., accuracy) in the prediction (e.g., see
Tamhane and Dunlop 2000). The principle difference between RMSE and MSE is that
RMSE has the same units as the predicted value, and thus represents the combination of the
standard deviation and the bias in the prediction. Thus, an unbiased estimator is one whose MSE is equal to the average prediction variance and RMSE is equal to the average prediction standard error. With or without bias present in either value, the usual goal in interpolation is to minimize the RMSE relative to the interpolation techniques used. In other words, and considering all else being equal, the closer the RMSE is to zero, the lower the variance and bias in the prediction and the better the predictor.

Unfortunately, usage of MSE/RMSE as a sole evaluator of model performance is very dangerous. A primary limitation of MSE/RMSE as a measure of predictor performance is that the single value cannot reveal the magnitude of the components due to bias and variance. Obviously, lower MSE and RMSE values should be preferred, but is the model which has the lowest variance also the least biased? Identifying these components is possible with geostatistical interpolation because of the explicit accounting of prediction variance, the lack of which is a serious limitation of IDW. Division of the prediction errors by the kriging variance, or standardization of the prediction error, can evaluate the adherence of the prediction to the zero-mean and unbiasedness assumptions. For example, the mean standardized error (MSError)

\[
MSError = \frac{1}{n} \sum_{a=1}^{n-1} \left[ \frac{Z(g_a) - \hat{Z}_{p-1}(g_a)}{\hat{\sigma}_{p-1}(g_a)} \right],
\]

where \( \hat{\sigma}_{p-1}(g_a) \) is the standard deviation of the prediction, should be equal to zero in cases of a zero mean for the standardized error (Cressie 1993). Furthermore, the root mean square standardized error (RMSSE)

\[
RMSSE = \sqrt{\frac{1}{n} \sum_{a=1}^{n-1} \left[ \frac{Z(g_a) - \hat{Z}_{p-1}(g_a)}{\hat{\sigma}_{p-1}(g_a)} \right]^2},
\]

should be approximately equal to one in cases of negligible or zero bias, unit variance and, thus, a normal distribution of the errors \([Z(g) - \hat{Z}(g)] \sim N(0, 1)\) (Cressie 1993). Conceptually, the RMSSE is very similar to the ratio of the RMSE and the root mean kriging variance (i.e., RMKV; the square root of the average kriging variances from the cross-validation of each
prediction); the closer the ratio of RMSE to RMKV is to one, the better the kriging technique approximates an unbiased estimator. This implies that the “best” predictor is one that minimizes the MSE/RMSE (i.e., minimizes the variance and the standard deviation of the prediction errors) while having the least bias (i.e., an RMSSE approximately equal to one and the least spread between the RMSE and the RMKV). However, from a predetermined list of interpolation techniques, this ideal scenario may not always occur. Consider, for example, two kriging techniques. Suppose the first kriging technique has a higher RMSE than the second technique, but it also has a lower RMSSE because the spread between RMKV and RMSE is smaller. In other words, the first technique, despite having a higher RMSE and, therefore, a higher variance, is less biased. Compared to the second technique, it is less reliable because each prediction, on average, has a larger deviation from the actual value. However, the set of predictions are more randomly scattered around the actual values such that there is less or no systematic over- or under-estimation. In the second technique, the average deviation of each predictor from the true value is smaller, but a larger number of predictors are systematically higher or lower than the actual values. This is one example which suggests the intercomparison of RMSE, RMKV, and RMSSE values may not always lead to the “best” predictor; in other words, the user will have to determine whether an unbiased predictor is more important than a reliable predictor or vice-versa.

The above concerns require the introduction of another cross-validation statistic which attempts to evaluate overall model calibration. Recall, from equation 1.4.8, that given a normal distribution, the 95% CI can be calculated for the prediction. The containment percentage is simply the percentage of all actual values that fall within the 95% CIs as established by each cross-validation prediction and the associated prediction variance. The higher the containment percentage, the better the model’s calibration; in other words, despite the variance and/or bias present, the higher the containment percentage the more consistent the model is at yielding predictions that are within two standard deviations of the actual values. Therefore, the user can be assured that, all else being equal, the selected model will contain the actual values within the predicted 95% CIs a certain percentage of the time equal
to the containment percentage. The interpretation of the containment percentage will be elaborated upon in Chapters 4 and 5.

Another cross-validation statistical tool is evaluation of the linear relationships between predicted values, measurements, and errors, which is achieved via the *sample correlation coefficient*

$$\hat{\rho} = \frac{\hat{\sigma}_{xy}}{\hat{\sigma}_{x}\hat{\sigma}_{y}}, \quad (1.6.4)$$

where

$$\hat{\sigma}_{xy} = \frac{1}{n-1} \sum_{i=1}^{n} [(x_i - \bar{x})(y_i - \bar{y})] \quad (1.6.5)$$

is the sample covariance between $x$ and $y$ and $\hat{\sigma}_{x}$ and $\hat{\sigma}_{y}$ are the sample standard deviations of $x$ and $y$, respectively (Tamhane and Dunlop 2000). Kyriakidis et al. (2001) analyzed the sample correlation coefficient between predicted values and actual values $\hat{\rho}_{AP}$ as a quantitative tool for assessing the reliability of the prediction and the correlation between actual values and errors $\hat{\rho}_{AE}$ as an indicator of “systematic” bias. For example, values of $\hat{\rho}_{AP}$ close to one indicate near-perfect (one-to-one) linear relationship of cross-validation estimates and actual values. Values of $\hat{\rho}_{AE}$ near zero indicate either there is no bias or that the predictions either universally overestimate or underestimate the actual values. This is a fairly large range of potential interpretations for near-zero $\hat{\rho}_{AE}$ values. It illustrates that, similar to most cross-validation statistics, the use of correlation coefficients independently of other analyses is of limited benefit. Without a scatterplot of the prediction error versus actual values, for example, knowing $\hat{\rho}_{AE}$ is near-zero is largely unhelpful. Unfortunately, such scatterplots are lacking in Kyriakidis et al. (2001). Finally, one sample correlation coefficient not employed by Kyriakidis et al. (2001) is between the predictor value and predicted error, or $\hat{\rho}_{PE}$, which may reveal remnant trends in the errors. The significant of correlated errors is discussed in the next subsection.
It should already be vividly clear that the reliance on any single cross-validation statistic is a precarious way to evaluate model performance. However, it has also been shown that the use of multiple statistics may also not provide a clear, definitive answer to the problem of choosing the “best” model. Additionally, Cressie (1993) clarifies cross-validation cannot prove an interpolation technique and its associated components (e.g., the ISIP model of spatial variability, the drift function, etc.) are correct, it can only provide confidence in model adherence to unbiasedness and minimization of the prediction error. Cross-validation does not, therefore, abate the importance of qualitative assessments like the study of the spatial fields themselves for scientific validity and the comparison of model output to other products. Consequently, cross-validation should be treated as only one of many techniques to assess geostatistical model performance. Additional tests for model validity are rooted in the concept of uncorrelated prediction errors and are discussed in the next subsection.

1.6.2 Implications of Orthonormality

MLR and kriging, as well as other linear estimators that attempt to minimize the variance in the prediction, are statistically successful if the resulting errors are uncorrelated (i.e., independent) with a mean of zero (i.e., unbiased) and a unit variance $\sigma^2$. If the errors are standardized (SError), the unit variance equals one. Kitanidis (1997) refers to these properties as conditions of orthonormality. The primary implication of orthonormality is that no further information can be gathered from the errors. Errors that exhibit this property are often referred to as white noise. If orthonormality is not achieved, the errors’ autocorrelation could be manipulated to predict the value of each error as a function of the remaining errors, thereby further reducing the MSE or the variance in the prediction. In both MLR and kriging, a lack of orthonormality prohibits the predictor from being the “best” because it does not minimize the error in the prediction and may not produce unbiased estimates. The orthonormal requirement is why scatterplots of the kriging or MLR errors versus the prediction should exhibit random scatter about the zero axis. It follows that orthonormal errors should also be normally distributed or at least are approximately normal as the number
of measurements increases (in adherence to the *central limit theorem* of probability). Probability density histograms can provide insight into the normality of the error distribution, identify outliers, and assess potential bias, while quantile-quantile (QQ) plots assess how closely the normal and error/SE error quantiles follow a one-to-one relationship. Deviations from the linear relationship can characterize the strength and behavior of positive and negative tails as well as the inner quantiles relative to the expected normal distribution.

However, the integration of MLR into the geostatistical model is desired when the original spatial field appears to violate the assumptions of stationarity, where the trend is not constant such that the covariance function is dependent on direction as well as distance. In other words, the goal in the use of MLR to derive an estimate of the trend is to produce a residual spatial field that is stationary and isotropic. The use of MLR, therefore, is somewhat precarious from the onset because the technique is being used on a dataset that is spatially autocorrelated. A non-stationary spatial field will also violate the constant variance assumption required for MLR. Of additional, but secondary, concern is the normality of the original dataset. There are many advantages to a normal distribution for both residuals and the primary variable due to its symmetry about the mean, which permits the spread of the distribution to be represented by the standard deviation of the dataset. However, primary variable normality is not as critical as the normality of the residuals when using linear estimation methods such as kriging or MLR because such techniques seek the best predictor by assuming a constant *residual* trend of zero and by minimizing *residual* variance. Nevertheless, since the primary variable’s distribution can easily deviate from normality, even after data transformation, it follows that the use of MLR to model trend may produce, due to the properties of the linear estimator, approximately normal residuals that can be used as input into the kriging interpolator. MLR-derived, normally distributed residuals are beneficial, for example, when using ML/REML in order to estimate the parameters of the covariance function (see Section 1.3.11). Normal data also adhere to second-order stationarity assumptions and allows the BLUE to become the best predictor amongst all predictors, linear and non-linear.
In summary, the role of MLR is to produce stationary and normalized residuals that will improve adherence to the assumptions required for kriging estimation. However, the violation of assumptions required for MLR estimation limit the ability of the user to determine the statistical significance of the trend model. In other words, statistical robustness or accuracy is sacrificed in MLR in order to reinforce the statistical accuracy of the kriging estimator. This is why the supplementary ML/REML estimation of trend coefficients becomes a critical part of the geostatistical model, as explained in Chapter 3. Nevertheless, MLR remains a critical exploratory tool for trend analysis and is used to determine the preferred set of covariates and an initial set of coefficients. Unfortunately, the violation of constant variance and independence render the formulas used to calculate coefficient variance invalid, prohibiting the use of the standard error of the coefficient estimate as well as the CIs, Student’s t-tests, and F-tests used to test model and covariate significance, as these metrics are based on the variance estimate (e.g., see Tamhane and Dunlop 2000). Therefore, this research can only approximate whether a model is significant through the careful examination of the SSR, SSRE, SSQI, SSQII and, perhaps most importantly, the normality of the resultant residuals.
Figure 1.3.1. Example of an exponential covariance and semivariance model with the following model parameters: nugget $\theta_0 = 0$; total sill $\theta_1 = 1.00$; and effective range $\theta_2 = 100$. The covariance model is represented by a dash-dot curve while the semivariance model is illustrated with a solid curve. In addition, a second exponential semivariance function, represented by a dashed curve, is plotted with a nugget $\theta_0 = 0.25$; partial sill $\theta_1 = 0.75$; and effective range $\theta_2 = 100$. 
Figure 1.3.2. Example of a Gaussian covariance and semivariance model with the following model parameters: nugget $\theta_0 = 0$; total sill $\theta_1 = 1.00$; and effective range $\theta_2 = 100$. The covariance model is represented by a dash-dot curve while the semivariance model is illustrated with a solid curve. In addition, a second Gaussian semivariance function, represented by a dashed curve, is plotted with a nugget $\theta_0 = 0.25$; partial sill $\theta_1 = 0.75$; and effective range $\theta_2 = 100$. 

The graph shows the relationship between the lag or distance ($h$) and the semivariance or covariance functions. The total sill, partial sill, and nugget values are indicated on the graph, with the range (effective) represented as a horizontal line. The semivariance function with zero nugget is also shown for comparison.
Figure 1.3.3. Example of a spherical covariance and semivariance model with the following model parameters: nugget $\theta_0 = 0$; total sill $\theta_1 = 1.00$; and range $\theta_2 = 50$. The covariance model is represented by a dash-dot curve while the semivariance model is illustrated with a solid curve. In addition, a second spherical semivariance function, represented by a dashed curve, is plotted with a nugget $\theta_0 = 0.25$; partial sill $\theta_1 = 0.75$; and range $\theta_2 = 50$. 
2.  PREVIOUS RESEARCH and CURRENT OBJECTIVES

2.1  Previous Research

2.1.1  Applied Geostatistics in Meteorology

Geostatistics has enjoyed continually expanding usage across a wide variety of fields for the past two decades. However, the methodology was “born” from a series of publications on mineral geology produced in the early 1950s. There was some additional work in forestry at that time as well, but the term “geo”statistics was primarily meant to define a specialized set of spatial-statistical methods for application in geology. Now, geostatistics has acquired wide acceptance and benefits from continual theoretical research within the statistical community while the application of geostatistics has usage not only in geology and forestry, but in additional disciplines including hydrology, oceanography, ecology, soil science, agriculture, and atmospheric science.

Of course, geostatistical application in meteorology goes beyond its usage in precipitation analysis. Numerous studies have adapted the geostatistical model to variables other than precipitation and offer beneficial conclusions about its application. For example, air temperature is a widely interpolated variable and the well-known relationship between temperature and elevation has yielded viable trend models for temperature mapping. Hudson (1993) performed the KED technique on monthly mean temperature data in Scotland in order to provide data for land-use research. Hudson’s findings showed a strong linear relationship between temperature and elevation such that the resultant linear trend model produced superior predictions compared to constant-trend OK and KED with a coordinate trend model. Ishida and Kawashima (1993)* performed a similar experiment in Japan and also found elevation-derived trend modeling yielded improved accuracy. In both examples the size of the domain permitted the use of a wide range of elevation values. Despite the fact that the

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* References followed by an asterisk indicate studies that compared an additional geostatistical technique known as co-kriging. Co-kriging is a method that attempts to model the spatial variability of the covariates as well as the primary variable. The modeling of the spatial variance of each covariate makes co-kriging considerably more computationally expensive. Since co-kriging is a technique not investigated in this research, it will be ignored in any discussion of research that employs it. References with an appended asterisk therefore include analysis of the co-kriging technique in addition to IDW, OK, and/or KED, but this discussion focuses only on the latter methods.
2.1.2 Applied Geostatistics and Precipitation

A wealth of precipitation mapping projects exist in the literature especially since the mid-1990s [e.g., Armstrong et al. (1993); Daly et al. (1994); Dirks et al. (1998); Drogue et al. (2002); Goovaerts (2000); Grimes et al. (1999); Hevesi et al. (1992a); Hevesi et al. (1992b); Kyriakidis et al. (2001); Pardo-Igúzquiza (2005); Phillips et al. (1992); and Stow and Dirks (1998)]. The primary focus during the past 15 years has been the analysis of climatological precipitation values, in other words, accumulations over periods greater than or equal to one month. Few studies have been found that studied smaller time scales [e.g., Dirks et al. (1998); Grimes et al. (1999)]. In both examples, however, mapping performance was
evaluated against very dense gauge networks atypical of most regions. The modeling of trend in an attempt to remove non-stationarity and improve accuracy has been an objective of many studies, primarily relying on elevation as a covariate and/or attempts to mimic the physical process of orographic enhancement [e.g., Goovaerts (2000); Hevesi et al. (1992a); Hevesi et al. (1992b); and Kyriakidis et al. (2001)]. Throughout these studies, the intercomparison of KED, OK, and IDW is a common methodology, with KED usually offering superior performance. There have been exceptions, however, as shown in the study by Dirks et al. (1998) where it was concluded that IDW was sufficient in areas of dense gauge networking regardless of temporal scale (i.e., daily to annual). Like several other studies, Dirks et al. (1998) also considered the computational expense of more elaborate geostatistical methods when deciding on the superior technique. Meanwhile, studies like Pardo-Igúzquiza (2005), Grimes et al. (1999), and Kyriakidis et al. (2001) documented improved performance from using more sophisticated adaptations of geostatistical models. Pardo-Igúzquiza (2005), for example, incorporated a moving-window approach to modeling monthly precipitation in Africa, while Grimes et al. (1999) incorporated satellite data and rain-gauge data for the mapping of precipitation across a dense gauge network in Sahelian Africa. Armstrong et al. (1993) used average seasonal rainfall as a covariate when using KED to model monthly precipitation in South Africa. There have also been examples of climatological mapping that deviate from the geostatistical framework. Some researchers have developed unique, hybrid modeling approaches based on linear regression analysis [e.g., Daly et al. (1994); Grimes et al. (1999); and Drogue et al. (2002)] and claim superior performance when compared to geostatistical techniques including OK and KED.

2.1.2.1 Review and Critique of Kyriakidis et al. (2001)

Kyriakidis et al. (2001) established an important foundation for the integration of geostatistics and physical covariates by investigating OK, “simple kriging with local means”
(SKLM)$^2$, and KED on a 300 x 360 km$^2$ grid with a cell size of 1 km$^2$ centered near San Jose, California. A seasonal time scale representing the period from November to January during the 1981-1982 cool-season was used for this study, incorporating daily precipitation data from 77 stations. Digital Elevation Model (DEM) data of 30 arc-second (~1 km$^2$) resolution was used as the first regression (trend) model covariate. Their study incorporated two variables from the 2.5° x 2.5° National Centers for Environmental Prediction-National Center for Atmospheric Research reanalysis dataset: specific humidity integrated from 1000 mb to 850 mb; and 700 mb horizontal wind. IDW was used to interpolate the reanalysis variables to the prediction grid; the former variable was used as a second regression (trend) model covariate, while the latter variable was used to calculate a vertical wind component that served as a third trend covariate. From the three covariates of DEM, specific humidity, and vertical wind, four additional, interaction covariates were studied including the interaction of humidity with elevation, the interaction of humidity with vertical wind, and the interaction of elevation with vertical wind. The fourth interaction term combined all three original covariates and was intended to empirically represent the physical process of orographic enhancement.

Kyriakidis et al. (2001) also performed a study of the correlation between DEM and precipitation as a function of resolution, averaging the DEM dataset across continually coarser resolutions while studying the resultant correlation coefficients. Their conclusions suggested that, for the seasonal time-scale, averaged DEM over a 13 x 13 km$^2$ grid yielded the best correlation coefficient (0.36), while resolutions from 8 x 8 km$^2$ to 21 x 21 km$^2$ yielded consistently higher coefficients >0.30 when compared to resolutions greater than 8 x 8 km$^2$. Resolutions higher than 8 x 8 km$^2$ produced correlations from 0.22 (1 x 1 km$^2$) to 0.28 (6 x 6 km$^2$). Unfortunately, while the study exclusively used a 13 x 13 km$^2$-averaged DEM dataset that appeared to maximize the correlation with precipitation, no attempt was made to investigate the impact of the varying correlations on the resultant regression model, vertical wind component, interaction covariates, spatial variances, or kriging techniques.

$^2$ Simple kriging with local means (SKLM) is a term often referred to when describing the piecemeal form of KED as discussed in Chapter 1.
Semivariogram modeling was not performed using a classical ISIP model. The employed model appeared to be a hybrid, nested exponential model which was claimed to have contained a large-scale component and a small-scale component with a set of sill and range parameters for each scale. No reference or further explanation was provided for this model and no discussion was provided on its adherence to ISIP assumptions. Model fitting was completed by eye, employing full cross-validation to optimize the SV model parameters. Furthermore, this study assumed a zero nugget and made no comments about the reliability of the rain-gauge data or the number of point pairs used in the experimental semivariogram at small lags.

Through the cross-validation of precipitation predictions from OK and SKLM/KED using three unique trend models, Kyriakidis et al. (2001) indicated via RMSE that SKLM and KED outperformed OK regardless of trend model. Two cross-validation techniques were performed: a full cross-validation employing all 77 gauges, and a partial, hybrid cross-validation using the 15 highest rain-gauge measurements only. The latter cross-validation procedure was a hybrid approach because it removed all 15 gauges simultaneously and estimated the values at each gauge using the other 62 gauges in the dataset. For the partial cross-validation, the minimum RMSEs ranged from 3.42 mm for SKLM and 4.17 mm for KED to 4.57 mm for OK. For the full cross-validation differences were less impressive; the minimum RMSEs ranged from 1.56 mm for SKLM and 1.52 mm for KED to 1.67 mm for OK. The trend model yielding the lowest RMSE included the vertical wind covariate, the interaction of specific humidity with elevation, and the interaction of all three original covariates. Fortunately, Kyriakidis et al. (2001) also provided resultant maps derived from OK, SKLM, and KED using the three unique trend models. However, they only provided a cursory assessment of the maps in terms of perceived detail; there was no assessment of the spatial distributions in terms of physical realism.

There are additional concerns about the results presented in this research. For example, the authors advertised significant differences between KED and SKLM for the same regression models. The authors presented results showing ~14%-18% improvements in RMSE by using SKLM over KED during the partial, non-random cross-validation of
maximum values and 1-3% improvements using KED over SKLM in the full cross-validation. While this obviously implies SKLM was more accurate with maximum values and KED was more accurate overall, the differences in the partial cross-validation RMSEs are significant considering the fact that SKLM and KED are nearly identical techniques across a global neighborhood (e.g., see Hengel et al. 2003). The partial cross-validation procedure is also suspicious because the gauges removed were not randomly selected, resulting in clusters of data voids across a wide distribution of covariate values. It is unclear how this technique affected the legitimacy of the conclusions drawn from it. These results warrant additional study to investigate if the authors used SKLM and KED properly and if they had, why SKLM and KED behaved differently when multiple neighboring gauges were removed given identical SV model parameters and trend models. Finally, assessment of the BLUE characteristics was also lacking. For example, the discussion of bias was exclusively reliant on the correlation coefficients discussed in Section 1.6 and there is no discussion of zero-mean or error distribution behaviors. Furthermore, the analysis of uncorrelated errors is done by performing a linear regression analysis on the errors using the best trend model as described previously. Obviously, it follows that the KED and SKLM errors based on the best trend model originally would yield the lowest coefficients of determination because the trend model being applied to the errors has already been applied to the dataset. The justification for this approach is therefore very unclear. Applying the best trend model to the errors from KED and SKLM techniques that used different trend models yielded higher percentages of variance explained and Kyriakidis et al. (2001) argued that this showed the superiority of the best trend model, but it failed to illustrate whether or not the final KED or SKLM models were approximate BLUEs.

### 2.1.2.2 Review and Critique of Daly et al. (1994)

One of the, if not the most operationally viable mapping project to appear in the literature was derived after a perceived inadequacy in basic geostatistical techniques. Daly et
al. (1994)* (hereafter referred to as D94) compared OK and “detrended” kriging\(^3\) results from a previous study (Phillips et al. 1992)* while validating their own unique model known as the Parameter-elevation Regressions on Independent Slopes Model (PRISM). D94 found, for mean annual precipitation, that while Phillips et al. (1992) showed KED was superior to OK, PRISM was superior to both.

Phillips et al. (1992) investigated mean annual precipitation predictions of kriging and KED on the Willamette River Basin in Oregon using 52 rain gauges and a 5-minute resolution DEM dataset. Their results showed that detrended kriging offered higher accuracy and improved realism in the resultant spatial patterns when compared against OK. They also briefly examined these techniques across a larger domain occupying the Columbia River Basin in the northwest (NW) United States (US) but failed to derive a statistically significant trend model between precipitation and DEM data across the larger domain, concluding that “piecewise” detrending would be necessary (i.e., either a moving-window or a domain disaggregation approach).

Since D94, PRISM has been enhanced many times in order to increase the model’s intelligence. However, PRISM has always fundamentally relied on the strength in the relationship between climate variability and elevation. As a result, the overall model has always been a simple linear regression of elevation on precipitation. The uniqueness of the model comes from the procedure that precedes the regression equation. In the most basic of terms, PRISM accounts for the orientation of the slope of the terrain in order to eliminate stations from the regression sample prior to model derivation. This orientation is known as a “facet”. In addition, the “facet” concept is attached to a very sophisticated variation of the classical moving-window estimator. PRISM not only adjusts its regression model by focusing first on a specified maximum radius of influence, it can adjust the facet characteristics via one or more of any number of advanced techniques, as necessary, in order to increase the sample size when it is originally insufficient. As documented in Daly et al.

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\(^3\) Detrended kriging is a term often referred to when describing the piecemeal form of KED as discussed in Chapter 1. Unlike Kyriakidis et al. (2001), Daly et al. (1994) and Phillips et al. (1992) do not compare piecemeal non-stationary kriging with KED. Therefore, for the purposes of this discussion, detrended kriging will be referred to as KED.
(2000) for example, PRISM now incorporates weights for each station based not only on elevation and distance to the prediction point, but the proximity to nearby stations; the vertical layer of the atmosphere the station exists within (i.e., boundary or free); the facet; the distance to the coastline; and the “effective” terrain at the station, or the residual terrain that exists after a mean areal terrain is removed.

PRISM is a very complex, multi-faceted system that has been continually investigated across numerous applications for over 15 years. The project resulted in the formation of a dedicated department at Oregon State University devoted to the continued research, development, and operational application of PRISM across a wide consortium consisting of US state and federal agencies (including state climate agencies; the National Weather Service (NWS); the US Department of Agriculture; the National Aeronautics and Space Administration; etc.), the private sector, and several international governments and agencies. In addition to producing monthly and annual precipitation maps, the PRISM Group has applied its methodology to temperature, dewpoint, and other climate variable mapping projects across the entire continental US and abroad in Canada, the European Alps, China, and even Mongolia [see e.g., Daly et al. (2000) for a list of accomplishments]. The group has also worked with the National Climatic Data Center (NCDC) to develop a new official climate atlas for the US; works with the USDA to map fog frequency along the Oregon coastline; and benefited from an expansive peer-review project involving representatives from many state and federal agencies and disciplines to review the quality of PRISM mean monthly and annual precipitation for a 30-year period of record across all 50 states (e.g., see Daly et al. 2000 for additional detail, but no published results from this study appear to be available in the literature).

The primary shortcoming in the PRISM technique is that while it provides meaningful small-scale detail to many mountainous regions, it provides much less detail at locations outside of regions where effective terrain is significantly greater than zero. This area includes over half of the US, including all of the Eastern Unites States with the exception of the Ozarks and Ouachita Mountains in west (W) Arkansas, the Cumberland Plateau in Tennessee (TN) and north (N) Alabama (AL), and the Appalachian Mountains
from the Blue Ridge into much of the interior Northeast US (e.g., see Figure 1 in Daly 2002). Outside of the effective terrain areas, the PRISM model reduces to a linear model of weighted station values whose weights are a function of distance and the proximity to coastal regions. While Daly (2002) reasonably explains that performance in the non-mountainous regions is restrictive due to limited observational data and a lack of scientific understanding regarding the role of small terrain variations, these conclusions are partially due to the fact that the PRISM model is restricted itself to elevation only and does not incorporate other covariates into its regression model. Therefore, it appears that the best opportunities to improve upon the PRISM technique lie outside of mountainous regions, not within them.

There are concerns as well about the robustness of the intercomparison project presented in D94. From D94, at least within the confines of the Willamette River Basin and the cross-validation of the 52 gauges, KED was found to have

1) a significantly larger error in the minimum value (-42 cm versus -6 cm);
2) significantly underestimated the maximum estimate (error = -34 cm) while PRISM overestimated by a larger absolute value (error = 51 cm);
3) overestimated the mean estimate by 6 cm while PRISM underestimated by 7 cm;
4) a mean bias of -1.4 cm versus a bias of 0.1 cm for PRISM; and
5) a mean absolute error of 19 cm versus 17 cm for PRISM.

A personal analysis of side-by-side KED and PRISM maps presented in D94 showed that the most striking differences between the two spatial fields occurred across the lowest elevations and smallest gradients, for example, within the river valley, where PRISM’s advantages are more unclear. Across the greater elevations and gradients, KED output often represented a smoothed version of the PRISM output. It is the viewpoint of this author that KED offered significant promise in the application studied; the comparison against PRISM during cross-validation suggested the most significant improvements yielded by PRISM data were with the accuracy of the minimum estimate and the overall bias. Mean absolute error of the mean annual precipitation differed by only 2 cm. However, from the results of a cursory analysis
of one watershed and the very preliminary, yet unfavorable conclusion of Phillips et al. (1992) on the use of KED across a larger domain, D94 concluded that the geostatistical model was inapplicable without a disaggregation of the domain.

Unfortunately, D94 offered no justification for why the use of a moving-window approach in geostatistics was inferior to the use of moving-windows on a simple linear regression model, but the conclusions drawn from the cursory study may permanently impact the future role of geostatistics in climate mapping. No attempt has ever been made to intensively investigate the spatial differences between KED and PRISM output in the Willamette Basin or any other geographical region. Now that PRISM has become such a fundamental part of climate variability studies, and rightfully so, it is hypothesized that it will be very difficult for scientists or statisticians to acquire the funding necessary to investigate the performance of an alternative, robust geostatistical approach to climate mapping.

Finally, while it is inarguable that PRISM enjoys a scientific validation process unparalleled in other mapping studies, PRISM may require a more rigorous test of its statistical assumptions. D94 legitimately challenges the lack of trend model variability in the calculations of kriging error, while arguing that their approach does account for this source of variability by using the standard estimate of linear regression variance [e.g., see Tamhane and Dunlop (2000)]. However, since the resultant model is a simple linear regression model, the calculation of variance only assesses the variance of a single coefficient: elevation. The application of numerous weights to each station is performed empirically with no assessment of the prediction variance of the weights. Furthermore, PRISM, as it is not a geostatistical model, does not account for the spatial variance between predictions, thereby assuming that the calculation of regression variance, which requires primary variable and residual independence, is sufficient. It also does not explicitly account for measurement error or microvariability as described by a nugget effect. D94 justified the lack of knowledge of spatial variance by hypothesizing that the use of facets and the additional restrictions on domain creates such a focused dataset that the spatial dependence of the variables is irrelevant because the regression relationship is equally applicable to all prediction points. The implication from this is that the simple regression model is so accurate that the resultant
residuals are spatially independent and orthonormal. However, to the author’s knowledge, no research has been done to test this theory by analyzing the spatial variance of the PRISM residuals, nor has any research been performed to investigate the residuals in any other capacity, for example to test the statistical robustness of the variance estimate or the adherence of the regression model to its statistical assumptions, including orthonormality.

Therefore, in consideration of statistical robustness and the results from D94, it is the opinion of this author that the PRISM group hastily and prematurely rejected geostatistics based on the results of Phillips et al. (1992) and that a version of PRISM incorporating geostatistics may have yielded improved performance and more accurate uncertainty estimates. It is believed that any future assessment of geostatistics in climate mapping must attempt to either integrate the PRISM algorithm into a geostatistical framework or prove an independent geostatistical approach is superior to PRISM in order to optimize climate mapping statistically and reintroduce geostatistics as a viable methodology. It is also believed that the incorporation of physical covariates as shown by Kyriakidis et al. (2001) and this research is an important step towards improving PRISM, especially outside of the effective terrain regions.

2.1.3 Rain-Gauge Measurement Accuracy

Rain-gauge measurements are often treated as ground-truth as a means to calibrate other precipitation estimators including radar, satellite, numerical models, data assimilation techniques, and, of course, empirical models. Rain gauges are also intercompared in order to analyze and calibrate different gauge instrumentation. Unfortunately, both automated and manual [i.e., non-recording NWS (1989)] rain gauges are inherently prone to error. Brock and Richardson (2001), for example, identify the most common error sources as exposure and “representativeness”. Representativeness simply refers to the fact that rain-gauge measurements are point, not areal measurements. This is of obvious concern in any spatial mapping project that relies primarily on rain-gauge spatial density in order to produce realistic spatial predictions. For example, Brock and Richardson (2001) (hereafter referred to as B&R01) observe that when there is one gauge for an area of ~750 km² (i.e., a resolution of
~25-30 km), the proportional area covered by that gauge is on the order of $10^{-6}$. This issue is of significant concern in hydrologic modeling, for example, when the precipitation is areally averaged by basin prior to the simulation. Consider an environment supportive of isolated, “pulse-type” convection. If a thunderstorm passes directly over a gauge, and there is only one gauge representing that river basin, the precipitation across the entire basin will be overrepresented. Conversely, if an intense thunderstorm misses the gauge, the basin-average precipitation will be underrepresented.

Exposure is a source of error that encompasses errors in station siting as well as errors due to natural variability. Wind is a major source of exposure error. B&R01 document experiments which reveal the error may be -20% for winds of 5-10 m s$^{-1}$, and over -80% for winds >10 m s$^{-1}$. Obviously, wind error is a substantial concern during tropical cyclone events, especially in the time period surrounding landfall, when the cyclone is its most intense. Natural or man-made obstructions, such as trees or buildings, are also principal sources of exposure error, and can cause either over- or under-estimation depending on the prevailing winds and precipitation characteristics. For example, B&R01 identify large drops as more prone to deflection by wind than small drops. Large drops also are a source of negative error known as “splash out” (e.g., B&R01). Contrastingly, heavy dew formation may cause false reports of precipitation when none is occurring and may also produce small overestimates when precipitation occurred previously during the period.

Other natural errors include various sources of clogging or “plugging” from, for example, ice and snow; grass clippings; dirt and dust; insects, nests, and webs; and even small animals and animal waste [e.g., see B&R01 and Steiner et al. (1999)]. Animals may also obstruct or damage the mechanisms inside recording gauges. In 2007, the NWS Weather Forecast Office in Peachtree City, GA reported a frog had established a habitat inside a tipping-bucket gauge and was responsible for numerous false tips.

Rain-gauge errors may also be due to instrumentation limitations. Weighing gauges, for example, are subject to errors proportional to rain rate during the emptying of the collection cylinder, as the gauge does not record precipitation during the emptying process. Both voltage-based and rotating-drum weighing gauges may be sensitive to ambient
temperature, wind, and other environmental factors; for example, environmental factors can induce sudden changes in voltage [i.e., transients (B&R01)] that are interpreted as precipitation. A well-known source of error with tipping-bucket rain gauges is the underestimation in heavy rain events when the tipping bucket does not empty quickly enough and rain is deflected off the bucket. Conversely, the tipping-bucket is also subject to “double-tipping”, where the bucket tips twice as often as it should during the emptying of the funnel, leading to overestimation (e.g., see B&R01). This can occur in instances of poor, uneven, and/or unstable siting (e.g., placement on a heavily traveled bridge) and it can also occur when the gauge is receiving volume from the funnel at a rate that is greater than the volume of the tipping bucket [e.g., see Maksimović et al. (1991)]. Maksimović et al. identify that double-tipping can distort the temporal distribution of rainfall as well which may require an empirical adjustment to the raw data. Furthermore, their research suggests that the tipping-bucket gauge produces a non-linear relationship between the rainfall intensity and the number of tips per minute, requiring a non-linear equation adjustment to the raw data in order to avoid an approximate 10% estimation error for a rainfall intensity of 5 mm min⁻¹. While B&R01 identify calibration errors as small when the instrument is properly maintained and when compared to exposure and representativeness errors, studies like Steiner et al. (1999) and Daly et al. (2007) (i.e., with respect to non-recording gauges), and personal experience gathered from the operational environment, suggest proper maintenance and operation is far from guaranteed.

Lack of proper maintenance, poor operation, and/or other man-made errors, frequently affects both recording and non-recording rain gauges. Steiner et al. (1999) for example, observed one site whose data transmission cable was accidentally cut when the grass around the site was being trimmed. Personal observations in the operational environment indicate gauge errors may go unnoticed for a period of several days or longer and, due to a lack of man-power, malfunctioning gauges may not receive proper maintenance for weeks after identification. The slow rate of repair suggests routine maintenance of similar gauge networks may not occur as frequently as required to minimize imprecision and bias. Unfortunately, it has also been shown as recently as Daly et al. (2007) that non-
recording gauges, often characterized by a dual-cylinder rain gauge with an accompanying measurement stick for manual observations, are subject to significant and widespread observer bias. Daly et al. (2007) observed two main biases, one they referred to as an “underreporting bias” and another was classified as a “5/10 bias”. The underreporting bias occurred most often when the amounts were less than 0.05 in. (1.27 mm); Daly et al. (2007) suggest a possible reason for this is that the human observer subjectively determines when precipitation is “significant” enough to report. Meanwhile, the 5/10 bias represents the tendency for an observer to round observations up or down to the nearest 0.05 and/or 0.10 in. The 5/10 bias can be attributed to many factors, including the difficulty of reading the measuring sticks which rely on the adhesion of water to the surface of the stick; the use of different measuring sticks across the network; the psychological impact of seeing certain measurements with large marks or labels; and the tendency of observers to manually disaggregate accumulations with rounded values when they failed to take observations at the proper interval. These and other sources of human error can have significant spatial and temporal impacts. Spatially, for example, the bias of certain observers may artificially smooth or enhance the spatial distribution and gradient of precipitation. Daly et al. (2007) show that across the entire NWS Cooperative Observer Program (COOP) network, only 6% of the gauges passed all quality control tests they devised at any one time during the period of record. The removal of failing stations from the spatial analysis of percent of wet days for a case study in Oklahoma, for example, revealed dramatic changes to the spatial field and indicated that the inclusion of failing gauges introduced inaccurate or phantom spatial patterns.

Clearly, the impact from various error sources can be significant and easily challenges any assertion that rain-gauge data represent “truth”. Many studies have shown the impact poor measurements can have on other estimators during calibration and in the derivation of multi-sensor approaches to estimation. Steiner et al. (1999), for example, analyzed the impact poor gauge data can have on the calibration of radar estimates and found, in a dense network of gauges across a small watershed, that inclusion of all gauges regardless of quality resulted in a 25% underestimation of radar-estimated precipitation
compared to using only high-quality gauges. None of the 30+ gauges in their study operated correctly 100% of the time during the two-year study. For 80% of the 30 storms they investigated, only 70% of the gauges functioned adequately for use. Steiner et al. (1999), Seo et al. (1999), Seo (1998a), Seo (1998b), among other studies, illustrate the importance of rain-gauge quality when performing bias adjustment on radar estimates as well as the challenges inherent in automating procedures to account for erroneous observations, especially in an operational, real-time environment. Mitigating gauge errors requires redundancy; for example Steiner et al. (1999) suggest setting up a cluster of three or more gauges separated only by a few hundred meters throughout any network in order to methodically assess bias and identify malfunctions. Unfortunately, this is an expensive proposition that is seldom realized in operational networks.

2.1.4 Relationships between Precipitation, Tropical Cyclones, and Terrain

Many past studies have focused on the relationships between precipitation patterns and intensities as a function of tropical cyclone intensity and scale. Some researchers have focused on a small set of cyclones, while others have made generalized conclusions based on climatological datasets. In order to study precipitation across a larger scale, Cerveny and Newman (2000), for example, utilized daily precipitation estimates derived from microwave radiometers in order to assess climatological relationships between tropical cyclone attributes and precipitation distribution. Employing a 25-year period from 1979-1994, the analysis included both the North Pacific and Atlantic Ocean basins. Two satellite precipitation-estimate datasets were created based on 2.5° x 2.5° grid cells: the first was based on a ~24,000 km² (~155 km resolution) grid cell containing the average center of the cyclone for the day of observation; and the second distribution was based on the surrounding nine grid cells, occupying a total area of ~220,000 km². On these large scales, Cerveny and Newman (2000) were able to identify a linear regression model based on 10 kt daily mean wind classes that explained 94% of the total variance in the precipitation, confirming similar relationships derived from earlier studies for smaller datasets.
Cerveny and Newman (2000) were also able to identify a strong linear relationship between the precipitation totals in the outer 9-cell domain and the inner-cell precipitation, with approximately 70% of the variance explained, suggesting a significant correlation between inner-core strength and the outer rain-band accumulations. They used these results to imply an empirical relationship between the dynamics of the inner core, the outward energy distribution of the tropical cyclone, and the resultant impact on feeder band formation and intensity. Furthermore, a parabolic relationship was identified between wind speed and inner-core precipitation such that both the strongest storms (>120 kt average central wind speeds) and the weakest storms (<30 kt average central wind speeds) had the greatest percentage of total precipitation located within the inner core. In between these intensity extremes, the inner-core precipitation maintained a steady average precipitation while the outer-cell precipitation accumulations exhibited a linear relationship with surface winds, implying important differences between inner-core and outer-core dynamics as it pertains to precipitation. Cerveny and Newman (2000) also identified a strong relationship between the time of season and heavy precipitation, highlighting September as the month in the Atlantic basin most likely to produce storms with intense precipitation. Geographically, they identify a spike in Atlantic basin precipitation intensities between 40-45°N, suggesting interactions with mid-latitude systems and geophysical features may be important even at a large scales.

Konrad et al. (2002) significantly improved upon the specificity of the Cerveny and Newman (2000) work by investigating two-day tropical cyclone-induced precipitation totals from the NWS COOP network across the eastern half of the US; the study used four geographical subsections and ten different radial scales ranging from 2500 km² (50 km resolution) to 500,000 km² (~700 km resolution). Konrad et al. (2002) compared tropical cyclone precipitation extremes against precipitation extremes from an all-event climatology in order to measure the impact of tropical cyclones on the entire precipitation distribution across the eastern US at different spatial scales. Interestingly, their work revealed that both the Northeast US [including southeast (SE) Kentucky (KY), south (S) West Virginia (WV), S Virginia (VA), N NC] and the Southeast US [including S NC, SC, GA, east (E) TN] received 35-46% of their extreme events at scales >50,000 km² from tropical cyclones, while
only 10-15% of the extreme events at 2500 km\(^2\) were due to tropical cyclones. The investigation of 101 different landfalling storms from 1950-1993 revealed that precipitation extremes at the smallest scale (2500 km\(^2\)) occurred near the coast with no extreme events at that scale occurring over the Appalachians, suggesting that orographic enhancement was never more important than eyewall convection at that scale. At the circular area of 300,000 km\(^2\), the majority of precipitation extremes in the SE US occurred along the Piedmont, with no events occurring across the Appalachians. Investigation of tropical cyclone attributes in Konrad et al. (2002) indicated that the size of the cyclone was more important than the strength of the cyclone at both large- and small-scales, while at small-scales there was a moderate, indirect relationship between storm speed and precipitation intensity.

While many empirical studies have investigated the relationships between precipitation and terrain across the globe, none are perhaps as locally relevant as the study performed by Konrad (1996). Konrad (1996) investigated the significance of southern Appalachian topography on precipitation events of light (2.54-6.30 mm), moderate (6.40-25.30 mm), and heavy (>25.40 mm) intensity. Using the NCDC hourly precipitation dataset for 44 stations across the southern Appalachians of TN, NC, and GA, Konrad (1996) illustrated the need to investigate the (non-spatial) distribution of the precipitation event, the magnitude of orographic enhancement relative to the orientation of terrain exposure, and the importance of considering cool-season versus warm-season meteorology when assessing relationships between topography and precipitation.

Konrad (1996) defined a precipitation event as any period in which zero precipitation did not occur over intervals greater than one hour. Topographic sampling within the gauge dataset was said to have been adequate, and the stations had reasonably complete records with >85% temporal coverage. While many stations had records >20 years, unfortunately, Konrad (1996) identified that the gauges at the highest elevations has the smallest periods of record, usually ~8 years, suggesting that a complete climatology was not possible at those locations. Nevertheless, Konrad (1996) evaluated several variables as part of a regression analysis for cool-season (October-March) and warm-season (April-September) cases at both
the event scale and the annual scale. Defining six “vector directions”, a total of ten covariates were studied:

1) elevation;
2) the mean elevation at a resolution of 10 km;
3) the difference in degrees between each vector direction and the orientation of the valley containing the gauge;
4) slope for each vector direction;
5) exposure (defined as “the distance to an upwind mountain barrier that is 150 m higher than the gauge”) for each vector direction;
6) an interaction term of elevation and exposure for each vector direction;
7) the distance between the gauge and the Gulf of Mexico;
8) the distance between the gauge and the Atlantic Ocean;
9) the distance of the Blue Ridge to the Gulf of Mexico; and
10) the distance between the Blue Ridge and the Atlantic Ocean.

Warm-season results showed that, light precipitation events exhibited the greatest average correlation with elevation at 0.80, followed by moderate events with 0.65, and, an insignificant, weak correlation of 0.17 with heavy events. Konrad’s analysis showed that mean elevation produced very similar correlations, and appeared to, across a climatological period, have no advantage over local elevation. Other covariates produced mixed results; for example, the distances to the Gulf of Mexico and Atlantic Oceans and the valley orientation covariates produced weak correlations of ≤0.30. Interestingly, NW exposure was moderately correlated (~0.40-0.54) to light- and moderate-events while S and southwest (SW) exposure was best correlated to heavy-precipitation events. Slope was moderately correlated (~0.35-0.54) at all vector directions in light- and moderate-precipitation events, but exhibited no correlation to heavy events. Finally, when exposure was combined with elevation, the resultant interaction term was moderately correlated (~0.43-0.63) to light- and moderate-events across most vector directions, and produced weak correlations (~0.33) to heavy events.
for the S and SW directions. The regression analysis for all warm-season events suggested that slope and elevation were the most beneficial covariates and that exposure was only significant when considered with elevation. No analysis was performed to investigate the significance of the elevation covariate when combined with the interaction term.

The regression analysis suggested that heavy events were least benefited by topographic covariates on average throughout the climatology, but unfortunately, an analysis isolated to tropical events was not provided by Konrad (1996). Despite a smaller sample, such an analysis would have been beneficial since the attendant tropical atmosphere has a structure dominated by a deep-layer warm and moist-adiabatic profile, contrasting the drier and cooler middle-tropospheric profiles typically seen with warm-season continental airmasses.

2.2 Current Objectives

The first objective in Section 1.1 – “begin an investigation on the application of basic geostatistics at subclimatic time scales” – is admittedly very vague. The choice of the word “begin” was an exercise in humility: given the breadth of previous research across larger time scales and the novice responsible for this study, it was rather quickly realized that this work would be most beneficial if it was approached from the perspective of foundation building, not with the intention that it would address all issues related to subclimatic spatial mapping. PRISM, for example, is a 20-year project in the making with the support of numerous individuals and organizations, yet it still has important limitations. Still other, complex and multi-facteted research has been presented in the literature via 10-20 page journal articles that fail to adequately describe the impact employed techniques have on the resultant predictions. Unfortunately, many in the intended audience are not statisticians and likely do not possess the required background to adequately interpret or apply the methods discussed. This supplements the concern for user misapplication and error and inspires the second principal objective in Section 1.1 that stresses a thorough introduction to and application of the geostatistical methods within this discussion.
The two primary objectives logically progress to a third objective from which all other objectives are based. This objective is to evaluate the robustness of the geostatistical model. It is why precipitation is such an excellent variable for analysis. Robustness also justifies the selection of the domain and the use of three unique tropical storms; validates the extensive evaluation of cross-validation and other model performance metrics; requires the various sensitivity tests conducted throughout the evaluation of OK, MLR, and KED; assesses the feasibility of future automation or semi-automation; and permits justifiable recommendations for future study. Robustness is also imperative in the discussion of user misapplication: is the geostatistical model sensitive to user error or can it withstand poor decision-making? If the model is relatively desensitized to user error, then the primary concern becomes user misinterpretation.

Domain size is one of the best metrics for model robustness because of its direct relationship on sample size and the magnitude of both large- and small-scale variability. Domain size was, for example, responsible for the rejection of geostatistics by D94, because it eliminated the relationship between trend model covariates and precipitation. Several other studies focus on small domains because they are restrictive and increase the likelihood of good model performance. While attempts to empirically represent orographic enhancement are important, as previously shown additional work is required on establishing empirical relationships outside the mountainous regions. Left unresolved is the analysis of the trend model across multiple regimes and the advantages and disadvantages associated with increasing sample size due to the increase in domain size. Domain size also challenges the stability of the selected trend models; however, this is also a function of the model itself and the variability of the covariates across any domain, regardless of size.

The investigation of robustness is partially responsible for the focus on tropical cyclone precipitation in this study; however, this focus was also due to a lack of study of tropical events in previous geostatistical analyses. While the reasoning for this deficiency is partially due to the focus on climatic time scales, it is also due to the fact that many of the geostatistical studies occurred in mountainous regions or in other regions typically unaffected by tropical cyclones directly. Additionally, tropical cyclones typically offer good
representation of heavy and lighter precipitation values, as well as varying zero and near-zero precipitation fields across a moderately-sized domain, providing several different challenges for the geostatistical model. Furthermore, the specific events chosen allow for the comparison of two storms with similar storm tracks over the domain as well as the comparison of these systems with a third cyclone which had minimal mountain region impact. It is important, therefore, to investigate the impact of basic tropical cyclone attributes including storm size, storm track, and storm strength as well as the resultant precipitation distribution on the consistency of the geostatistical model across all cases. It is hypothesized that the dramatic variations in spatial distribution typically seen over subclimatic time scales require a unique set of covariates for each precipitation distribution.

Of course, any discussion of model robustness is incomplete without sensitivity tests on the geostatistical model itself. The main objective in the intercomparison of IDW, OK, and KED is to first test the necessity of the geostatistical model, followed by the necessity of the trend model, all while considering the marked increase in computational cost and man-hours. Given the input datasets and the size of the domain, it is expected that attempts to model the SV of the original field will be hampered by non-stationarity and anisotropy. Therefore, superiority of KED over OK and IDW is expected during this analysis, at least in the context of adherence to geostatistical assumptions. Performance quality must then be based on the assumptions of a BLUE, and thus the presence of orthonormality. Meanwhile, sensitivity of both OK and KED to SV model parameterization will also be examined, especially since the literature has often ignored more complex estimation techniques like ML/REML in favor of NLS or even eye fitting of the exponential semivariogram. It is therefore crucial for this research to assess the significance of likelihood estimation on all subsequent levels of the geostatistical model. Furthermore, of interest is the role of anisotropic correction on the resultant spatial fields. Overall, not only does each sensitivity test impact the study of user error, but if model insensitivity can be shown it can reduce the complexity of the geostatistical methodology, saving computational and human capital.

The performance of KED is also expected to be a function of trend model significance. Recall that the objective of the trend model in the geostatistical framework is to
remove non-stationarity and isotropy present in the original spatial field, resulting, ideally, in a BLUE. This research investigates the sensitivity of multiple elements in the geostatistical model to variations in the trend model. The significance of the physical and geophysical covariate trend model is also investigated through its comparison to a Cartesian coordinate trend model, and each trend model is involved in the sensitivity analysis on KED. Furthermore, of interest is the role of the trend on large- and small-scale variability; therefore, the sensitivity of SV modeling on the trend model residuals is also of concern. It will also be important to investigate the significance of trend model covariates after spatial autocorrelation is accounted for (i.e., ML/REML) in order to assess the impact of assuming variable independence on covariate selection and coefficient estimation. If the analysis can show that trend model selection is largely unaffected by erroneous MLR assumptions, it reinforces the legitimacy of the trend model selection methodology. Finally, the spatial analysis of trend model residuals is expected to be important in order to investigate trend model behavior across the domain and assess trend model performance as a function of precipitation.

In much of the literature, there is a tendency to focus on cross-validation statistics at the expense of the predicted spatial fields when analyzing model performance. Often, this is due to the prioritization of creating mass-produced gridded fields across large time scales encompassing numerous meteorological and/or geophysical regimes versus the detailed analysis of a smaller subset of cases. In the former case, the use of cross-validation statistics may be the only practical way to assess model performance across the period of analysis. In the latter case, while an assessment of long-term stability is not possible, greater emphasis can be placed on variations in model behavior and the implications of those variations on the resultant field. Therefore, an objective of this research is to evaluate the conclusions derived from cross-validation against those derived from visually based spatial analyses in order to assess the consistency of the numerous performance metrics available to the end user and the quality of such metrics compared to the scientific interpretation of the resultant field. This study will allow the reader to understand the dangers of focusing on one or even a small set of metrics when evaluating model performance. To accomplish this goal, output from
quality-controlled multi-sensor precipitation estimates were used to compare the differences in spatial variability and both spatial and non-spatial distributions. Admittedly, the availability of high-quality, remotely sensed estimates of any variable is a luxury, but it affords the opportunity to perform knowledge-based analyses of the predicted spatial fields in a manner not typically seen in the literature.

Finally, the study of model robustness is obviously critical in any discussion of automation. The demands for automation are high simply because the demands for long-term, consistent, reliable, and readily accessible information are staples of human nature. However, as Chapter 1 indicates, there are many potential sources of study within the geostatistical model and many of the steps are not trivial. It follows that model sensitivity to each step within the analysis of spatial variability is inversely proportional to the feasibility of automation. It also suggests that automation requires sophistication; in other words, automation of a process with little consistency from day-to-day or event-to-event will require numerous internal consistency checks and the intelligence to adapt to changing spatial distributions and model behavior. Consideration of the time invested in a project like PRISM should reveal the magnitude of this challenge. Nevertheless, a very initial aspiration of this study was such automation. While that quickly grew well beyond the scope of logic, what resulted from these initial goals was the development of an organized methodology to the progression through the modeling process, accompanied by thoughtfully-written scripts, programs, that were supplemented with thorough documentation (e.g., see Appendix A). This accomplishment also significantly contributed to the fulfillment of the second principal objective (Section 1.1)

However, the automation process is not solely dependent on the geostatistical model. Like the geostatistical model, the automation process is also sensitive to the primary variable. Unfortunately, many past studies (e.g., Daly et al. 1994, Konrad 1996, Goovaerts 2000, Kyriakidis et al. 2001, Konrad et al. 2002, etc.) spend little time discussing measurement quality, at least partially because the automation of quality control is a formidable hurdle long before model automation is considered. Therefore, this research also assesses the state of one of the most widely-used, long-term precipitation datasets available. Furthermore,
through the analysis of and associated impact on the geostatistical model, observations are made on the quality of the daily precipitation dataset. The aforementioned methodology to the modeling process also accounts for some of the most common issues associated with the precipitation dataset (see Section 4.1).
3. DATA and METHODOLOGY (The Geos2MAP MODEL)

3.1 Introduction to the Geos2MAP Model

3.1.1 Model Purpose and Overview

A wealth of proprietary and open-source software is available to address multiple levels of geostatistical modeling and subsequent spatial prediction. It was discovered early, albeit not surprisingly, that the main challenge in meeting and testing, respectively, the objectives and hypotheses discussed in Section 2.2 was the assimilation of numerous sources of data and output into preexisting software. Usual complications arising from format, spatial, and temporal incompatibilities needed to be resolved, not to mention various quality-control issues. Therefore, evolving from the piecemeal development of over 40 scripts and programs was the Geostatistical and Multivariate Mapping and Analysis of Precipitation (Geos2MAP) model. A primitive methodology, the Geos2MAP model accomplishes the following eight general objectives:

1. Extensive data manipulation and organization, including quality control;
2. Development, manipulation, and organization of new datasets;
3. Exploratory data analysis;
4. Assimilation of all data onto one grid for prediction;
5. Extensive analysis of the trend and residual components of precipitation;
6. Creation of multi-resolution gridded precipitation estimates via three distinct interpolation techniques;
7. Customizable and high-quality graphical representation of all datasets.
8. Basic quantitative and qualitative comparisons of multiple-sensor precipitation estimates to the multivariate-geostatistical gauge-based estimates.

Thorough operational documentation\(^1\) is available from the author and Appendix A offers an abbreviated “descriptions-only” version of that document detailing the role of each script and program.

To accomplish the above goals, the Geos2MAP model employs two programming languages: Perl and FORTRAN. The Perl scripts primarily perform dataset and grid

\(^1\) In some respects, this thesis and especially Chapter 1 serves as technical documentation for the Geos2MAP model; this purpose is another reason extensive detail was provided in the explanation of basic geostatistics.
manipulation and organization tasks and Perl is also used for dataset development. FORTRAN is used almost exclusively to accumulate raw rain-gauge data, monitor its quality, and perform some gauge quality-control tasks. Cartesian coordinates used to map multiple-sensor precipitation estimates are converted to geometric coordinates using FORTRAN code provided by Stackpole and Jones (1990). Scripts written to perform analysis of the trend component of precipitation and subsequent modeling via multivariate linear regression were completed using SAS/STAT® software. All remaining statistical analyses – most notably the geostatistical analyses – were performed using the R language and environment (R Development Core Team 2005). The R environment also provides the graphical support for the Geos2MAP model and generates the prediction grids. Gridded binary (GRIB) datasets (i.e., the multiple-sensor QPEs and the numerical model reanalysis output) were decoded and converted to flat files (i.e., ASCII text) using the wgrib software developed by Ebisuzaki (2004). All other datasets used in the Geos2MAP model are in flat file format as required by the R environment.

Outside development of R function sets are completed as packages, and four specific packages were implemented as part of the Geos2MAP model. The fields package (Fields Development Team 2004) features a wealth of geostatistical functions; however, in this research it was exclusively used for graphical support. The maps package (Brownrigg et al. 2005) provided state and county outlines on all maps of the primary, secondary, and predicted variables. Support for IDW interpolation is provided by the gstat package (Pebesma and Wesseling 1998). Foremost, geostatistical support – including the spatial analysis and geostatistical modeling of precipitation data, its interpolation via OK and KED, and cross-validation – was provided by the geoR package (Ribeiro and Diggle 2004).

The following (sub)sections detail: the prediction grid and resultant domain of study (subsection 3.1.2); the primary variable and secondary variables used in this study (Sections 3.2-3.3); the dataset of multi-sensor precipitation estimates (Section 3.4); and additional

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2 Data analysis of and related graphics for the trend component of precipitation were generated using SAS/STAT software, Version 9 of the SAS System for Microsoft Windows®. Copyright © 2004 SAS Institute Inc. SAS and all other SAS Institute Inc. product or service names are registered trademarks or trademarks of SAS Institute Inc., Cary, NC, USA.
methodologies for the geostatistical model not previously discussed (Section 3.5). Abbreviations assigned to each dataset within the Geos2MAP model will be consistently assigned in upcoming subsections for use throughout the remainder of this thesis.

3.1.2 The Domain of Study and Prediction Grids

With the majority of research in geostatistical mapping focusing on the mountainous regions of the western United States and Europe, there is a need to investigate the performance of geostatistics over alternative terrains. Hence, the domain of study in this research is centered on the Carolinas: a topographically heterogeneous area ranging from coastal plains to aged mountains. Specifically, the domain extends from 85°W to 75°W longitude and from 37.5°N to 31.5°N latitude. It encompasses seven states, including all of NC and SC, a majority of GA, and portions of TN, KY, WV, and VA. Of special interest are the various regimes responsible for the climatological distribution of precipitation across this domain and the challenges of this variability on the stability of the geostatistical model.

The datasets utilized in the Geos2MAP model are compiled with geometric coordinates (i.e., latitude and longitude). However, the visualization of spatial dependency is complicated by thinking in terms of degrees; thus, all coordinates are converted to Cartesian coordinates prior to analysis and prediction. The Geos2MAP model does this conversion simply by assuming a spherical earth and calculating the great circle distance of the mean domain-bounding latitude and longitude coordinate pairs. Obviously, the result is a prediction grid with points separated by equal distance only on a spherical model of Earth and for domain areas where the variance in the distance separating lines of equal latitude is “negligible”. It is important to note then that in future references to the prediction grids, distance (km) is inherently assumed to be approximate.

Currently, the Geos2MAP model accommodates eight different prediction grids with the express purpose of examining “resolving power” or the power of a resolution to capture the “true” precipitation field. The eight prediction grids have “idealized” grid spacings of (4 km)$^2$, (8 km)$^2$, (12 km)$^2$, (16 km)$^2$, (20 km)$^2$, (24 km)$^2$, (28 km)$^2$, and (32 km)$^2$, respectively. However, to simplify the process of collocating multiple sources of data and output the
prediction grids are subsampled from the grid space for the Digital Elevation Model (DEM) output (detailed in subsection 3.3.1). An artifact of this approach is the fact that the “idealized” resolutions and grid spacings differ from the actual resolutions and grid spacings on the order of approximately 0.1 to 0.5 km (Table 3.1.1).

### 3.2 Daily Reported Precipitation (DRP)

Representing the primary variable are daily (i.e., 24-hr accumulation) precipitation observations obtained from the NCDC’s “Data Set 3200” (DSI-3200) database (NCDC 2005). The DSI-3200 database consists of several parameters, including maximum and minimum temperatures; daily snowfall; the temperature and snow depth at observation time; and, of course, daily precipitation for 24 hours ending at the observation time. The dataset consists of over 23,000 stations across the United States, ~8,000 of which are active, with some stations having periods of record greater than 150 years. However, most stations began recording observations in the mid- to late-1940s, providing a climatological dataset that spans ~60 years. (NCDC 2006)

Obviously, the DSI-3200’s long period of record and large station set should be of particular appeal to many individuals, agencies, and organizations: the list includes not only those interested in meteorological and climatological studies, but those involved in agriculture, hydrology, environmental monitoring, flood and other hazard insurance, construction and public works, and many other fields. Of course, past and future climate mapping initiatives will require robust and lengthy datasets, which is why this dataset was used exclusively for this research. Other precipitation datasets from smaller networks, whether operated by universities, private industry, state governments, or other agencies, were not collected for this study in order to investigate empirical model performance with sample sizes that would be more consistent with sample sizes likely to be seen across the climatological period. However, it should be assumed that given additional, reliable datasets, the sampling of the spatial variability would improve, especially at smaller lags, leading to more accurate empirical models.
The majority of stations in the DSI-3200 database are part of the NWS COOP network. The COOP largely consists of sites operated by unpaid private citizens, but the network also includes the NWS “principal climatological stations” (NCDC 2006) which are usually automated, including stations part of the Automated Surface Observing System (ASOS) network. The ASOS network is the combined effort of the NWS, the Federal Aviation Administration, and the Department of Defense. All sites in the COOP network are maintained by the NWS; however, the DSI-3200 database also includes station data outside of the COOP network from other federal agencies (NCDC 2006). The majority of “principal climatological stations”, including those in the ASOS, record precipitation using tipping-bucket rain gauges. As documented in NWS (1989), volunteer observers in the COOP use either non-recording cylindrical (4- or 8-inch diameter) gauges, where precipitation is measured manually using a calibrated measuring stick, or weighing rain gauges that measure precipitation in a collector mounted on a scale (i.e., a Fischer & Porter rain gauge or a Universal Recording rain gauge). According to Daly et al. (2007), the majority of volunteer observers use the 8-inch diameter non-recording gauge.

The DSI-3200 dataset is subjected to multiple quality control (QC) processes at the NCDC, as briefly discussed in NCDC (2006). These processes include both automatic and manual edits via internal consistency checks, areal (i.e., station-to-station) consistency checks (beginning October 1992), and climatological checks. QC flags are assigned to each observation which document the type of QC error that occurred and the action taken, if any.

The Geos2MAP model itself incorporates extensive processing after extracting the precipitation data from the DSI-3200 dataset (i.e., DRP dataset). A byproduct of this research was the creation of an in-house precipitation database derived from the DSI-3200 for NCSU’s Department of MEAS. The NCSU MEAS DRP database ingests, reformats, and archives all 24-hour precipitation accumulations (i.e., entire period of record) from seven states (KY, WV, VA, TN, NC, GA, and SC) in three formats: ASCII text, comma-delimited text, and Microsoft® Access™ database. The Geos2MAP model includes software that will accumulate DRP data at different time scales, tracking quality-control flags, computing additional statistics, and outputting other analysis files. Additional scripts and manual
processing allows for the fusion of precipitation accumulations with coordinate information in order to append the point measurements to a spatial surface. Appendix A provides additional details for each step taken during DRP processing.

The Geos2MAP model offers automatic instrumentation QC, but does not provide automatic measurement or value QC (outside of the QC performed by NCDC). Instrumentation QC includes the accounting of sites that report either missing values, do not report any data, or fail a reporting time consistency check (see Chapter 4). Measurement QC includes the QC of specific non-missing measurements for spatial and/or temporal consistency. The motivation to not consider measurement errors is threefold: 1) NCDC QC is described as a “stringent” and multi-layered process (NCDC 2006), and while no automatic QC process is perfect, NCDC should provide superior, validated, and thoroughly-researched QC methods that would eliminate the most severe issues in the DRP dataset; 2) the existence of outliers in the DRP dataset, if any, is desired in order to test the impact of these outliers on trend modeling and spatial prediction; and 3) most importantly, manual “QC” of a relatively sparse set of point measurements is dangerous and very subjective without robust and validated consistency checks and the cross-reference of a high-resolution, high-quality, and spatially continuous dataset available across the period of record (see Section 3.4. Additionally, over the entire period of record, the movement of gauge sites is a common occurrence. Due to the time scales studied in this research, the Geos2MAP model does not currently account for the spatial shift of gauge sites. For the cases studied in this research, no gauge sites were relocated during the period of analysis. Further information on the instrumentation QC process and the DRP dataset, including analyses of spatial density, is reserved for Chapter 4. The impact of potential gauge outliers is discussed in Chapters 5 and 6.

3.2.1 Logarithmic Transformation of DRP

Two issues are presented by a variable-like precipitation: (1) precipitation is nonnegative; and (2) precipitation is often non-normal in its distribution. Nonnegativity issues become apparent when studying kriging predictions or confidence intervals; the
prediction of a negative number or the possibility of confidence intervals extending below zero is obviously unrealistic with any non-negative variable. Second, as discussed in previous sections, normal distributions of the primary variable are less than critical but nevertheless beneficial for both MLR and kriging processes. For example, precipitation distributions are commonly exponential in nature, with the smallest values receiving the highest probability of occurrence and the maximum values occurring at a limited number of locations. Therefore, this is not an unusual problem, and one of the most common transformations, especially when the distribution is positively skewed, is logarithmic:

$$Y(x) = \ln(Z(x)),$$

where the distribution of the transformed dataset, $Y(x)$, often becomes approximately normal through the shrinking of the positive tail and the extension of the negative tail. The back transformation:

$$\hat{Z}(g) = \exp(\hat{y}(g)), $$

provides the estimates of the original primary variable $Z$ at the prediction points $g$. Since the logarithmic function is asymptotic to the original value of zero ($\ln(0) = \infty$) and undefined for negative original values, the transformation addresses the non-negativity issue but requires the redefinition of zero values to a value slightly greater than zero in order to complete the transformation for the dataset. Additional discussion of the impact of this redefinition will occur in Chapter 4, prior to analysis of IDW and OK. DRP data that have undergone a logarithmic transformation are abbreviated in this research as lnDRP data.

Caution must be taken, however, because the back transformation of $\hat{y}(x)$ results in a biased predictor for $Z(g)$. To avoid this bias, cross-validation and model evaluation should only be done using the transformed variable and under no circumstances should the kriging variance and associated confidence intervals be presented by following a simple back transformation as in 3.2.2. Cressie (1993) provides bias-corrected back-transformed predictors and kriging variance equations, and while beyond the scope of the current research, they must be implemented before inferring any confidence in the prediction as it applies to the original primary variable. However, failure to address the non-normal and
non-negative properties of precipitation data can have major consequences on the validity of the geostatistical model, thus the logarithmic transformation remains an important step.

3.3 Geos2MAP Model Covariates

3.3.1 Covariate DEM: Digital Elevation Model Output

Studies that apply multivariate geostatistics to precipitation often incorporate terrain as a secondary variable or covariate. Many studies (e.g., Daly et al. 1994, Kyriakidis et al. 2001, Goovaerts 2000, Chua and Bras 1981) attempt to capture orographically enhanced precipitation by correlating elevation to precipitation. The works of these authors and others successfully related these two parameters empirically across climatic time scales usually as a linear relationship in areas dominated by mountainous terrain. Here, the inclusion of elevation as a covariate tests the strength of this correlation not only across different meteorological regimes and in a heterogeneous domain, but also at the subclimatic time scale. In other words, while the physical processes responsible for precipitation maxima along windward slopes are often present during events with considerable low-level moisture advection, the variability of the precipitation field on such a small time scale and across a highly-variable terrain pose significant challenges to resolving orographic lift empirically.

To investigate these challenges, terrain is represented in the Geos2MAP model using the National Geophysical Data Center’s Global Land One-km Base Elevation (GLOBE) DEM (GLOBE Task Team et al. 1999). The GLOBE DEM is developed by a worldwide consortium whose members contribute regional DEMs for assimilation into a global product. The resulting DEM is independently peer-reviewed and quality controlled. Documentation on the product is available from Hastings and Dunbar (1999). The DEM has a constant 30 arc-second (0°0’30") grid spacing, which equates to slightly more than 1 km at the Equator and, approximately, a 0.76 km x 0.93 km resolution in the center of the domain of study (34.5°N). Within the domain of study, the GLOBE DEM output (Figure 3.3.1) resolves a maximum elevation of 1967 m, a minimum elevation of 0 m, a mean elevation of 236 m, and a median elevation of 150 m. The discrepancies between the mean and median elevations reveal a non-normal distribution of values skewed towards lower terrain.
3.3.2 Covariate NARR: North American Regional Reanalysis Output

It is hypothesized that the trend function sought in the KED approach can better represent the precipitation field by incorporating basic atmospheric conditions into the mapping process without severely diluting the power of the trend function through “over-representation”. The inclusion of meteorological variables into the Geos2MAP model is accomplished using the National Center for Environmental Prediction’s (NCEP) North American Regional Reanalysis (NARR) dataset. The NARR dataset uses the NCEP regional Eta Model and its Data Assimilation System (EDAS) to provide 3-hourly output of analysis fields and forecasts (out to 72 hours). Its output relies on several additional components, most notably:

1. NCEP/Department of Energy Global Reanalysis to establish the lateral boundary conditions
2. Noah land-surface model
3. Rawinsonde, dropsonde, aircraft, satellite, and surface station observations
4. Climatological data [e.g., PRISM data (see Chapter 2)]
5. Observed precipitation assimilation

The NARR dataset provides a 32-km horizontal resolution (Figure 3.3.2) and 45 vertical layers. The dataset spans a 25-year period from 1979 to 2003 and is also being run in “near real-time” (Mesinger et al. 2005). The period of record is important to future work in this precipitation-mapping project; as emphasized in Chapter 1, climatological gridding of meteorological variables using multivariate geostatistics relies on a consistent, high-resolution, and long-term covariate dataset, which the NARR dataset provides. Consequently, the NARR dataset lends itself well to the ability of the Geos2MAP model to account for the regional atmospheric conditions that influence precipitation; the dataset provides the flexibility necessary for further model improvements in future studies.

The Geos2MAP model extracts multiple variables from the NARR output in preparation for future work, but it currently uses only the \( x \)- and \( y \)-components of the 10 m horizontal wind as covariates (XWind and YWind in the Geos2MAP model) for KED

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3 Information on the NARR dataset was adapted from Mesinger et al. (2005).
interpolation. The covariates are also incorporated into a third covariate as described in subsection 2.6.7.

Of course, the 3-hourly analysis fields are incompatible\(^4\) with the Geos2MAP daily and event-based mapping. To produce a daily and event-based representation of NARR covariates, the Geos2MAP model averages 3-hourly NARR analysis fields over the time resolution specified by the user (i.e., daily or event-based averaging). It is true that the smoothing of 3-hourly values could be detrimental in measuring a significant statistical correlation between covariates and precipitation. Geos2MAP model support for analyzing maximum, minimum, variance and standard deviation derivations of the 3-hourly fields, as well as directly applying one 3-hourly field (perhaps representative of the time frame when the largest proportion of precipitation occurred) is available; however, sensitivity tests resulting from these features are reserved for future research into model performance. In the interim, the current research investigates both average and maximum 10 m horizontal wind during analysis of the KED adaptation of the geostatistical model.

3.3.3 Covariate DEMSlope: Rate of Change of DEM with Horizontal Distance

Orographic lift, or terrain-induced vertical motion, is, of course, not merely a function of elevation. The vertical tilting of horizontal wind is directly proportional to the gradient of elevation as well as the velocity of the horizontal wind. In other words, the process of orographic lift and any resulting precipitation enhancement relies of a convergence of horizontal wind along a slope whose magnitude partially determines the magnitude of vertical forcing. This process is why mountainous regions are defined by upslope and downslope conditions. Climatologically-favored regions of precipitation along mountain slopes benefit from the majority of converging winds, while the opposing slopes induce rain “shadows”: the same winds travel down and away from the slope, inducing negative vertical motion, compressional heating, and drying within the air column.

\(^4\) This is, of course, as long as the daily precipitation field is aggregated from more than 3-hours worth of precipitation, which is the case in the events investigated herein.
Thus, as with elevation, of interest is the role of terrain gradients or slope in the ability to empirically model regional precipitation trends. Chapter 2 reviewed the works of others who implemented slope with some success in the mountainous west [e.g., D94, Kyriakidis et al. (2001)]. The Geos2MAP model also incorporates slope as a covariate for analysis (DEMSlope), and this covariate is subjected to the same challenges posed to the DEM covariate.

To remain consistent with the NARR covariate, the DEMSlope covariate is calculated as an east-west (x-component: XSlope) and a north-south (y-component: YSlope) pair of values. The DEMSlope covariates are calculated at each GLOBE DEM grid point by taking the difference of the two immediately neighboring points and dividing by the total distance spanned between the three grid points (1 arc-minute). In other words, XSlope and YSlope are estimates of the partial derivatives ∂h/∂x and ∂h/∂y, respectively. Figure 3.3.2 illustrates well the effect this calculation has; the resulting dataset nicely captures the terrain of the domain by providing the illusion of a three-dimensional relief map.

3.3.4 Covariate SlopeWind: Vertical Component of Wind Due to DEMSlope

Representing orographic lift in the Geos2MAP model requires a final puzzle piece: the resultant vertical motion itself. The final covariate, referred to in the Geos2MAP model as SlopeWind, is adapted from the lower boundary condition for vertical velocity. The lower boundary condition, usually defined from the surface to the top of the terrain, requires the conservation of mass and can be expressed using an approximate form of the continuity equation [e.g., Smith (1979), Alpert (1986), and Lin et al. (2001)]:

\[ \omega_t = \mathbf{u} \cdot \nabla h = \left[ u \frac{\partial h}{\partial x} + v \frac{\partial h}{\partial y} \right], \]  

where vertical motion \( \omega_t \) is the dot product of the horizontal wind velocity \( \mathbf{u} \) and the gradient of elevation \( \nabla h \). Essentially, \( \omega_t \) is one component of large-scale vertical motion \( \omega \) – the other being the environmental component due to atmospheric forcing (e.g., upper-

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5 The effect of evaluating slope across three grid points in effect reduces the resolution of the dataset by approximately half (~ 1 arc-second) while maintaining the same 30 arc-second grid spacing.
tropospheric divergence-induced vertical motion) – and represents the net horizontal convergence due to topography.

Clearly, horizontal wind velocity is provided by the NARR covariates, while DEMSlope approximates the gradient of elevation. SlopeWind values are calculated at each DEM/DEMSlope grid point yet, like DEMSlope, have approximately half the resolution of the DEM covariate. The grid spacing of the SlopeWind covariate (30 arc-seconds or ~0.85 km) conflicts with the grid spacing of the NARR covariates (32 km), and this is one reason the NARR covariates are downscaled to the DEM grid space (see subsection 3.5.3). SlopeWind acquires the challenges experienced by its components due to the domain of study, hence the intrigue in its consistent or inconsistent viability in precipitation mapping.

3.4 **Multisensor Precipitation Estimator (MPE) Output**

Chapter 2 discusses the inherent limitations of rain-gauge or point precipitation measurements and the spatially sparse networks they comprise. As previously explained, geostatistics is one way to quantify and visualize the spatial variability the rain-gauge networks reveal. In addition, continuing advancements in the integration of remote sensors and point measurements from rain gauges result in high-resolution QPEs that reveal spatial variability between the gauges with improving accuracy. Therefore, it is sensible to compare the output from empirical interpolation techniques to output from multiple-sensor technology to gain an understanding of the deficiencies and strengths in the single-sensor, multivariate, and geostatistical approach to high-resolution QPEs.

As a first step to such a comparison, the current Geos2MAP model incorporates output from the Multi-sensor Precipitation Estimator (MPE): an NWS algorithm that relies on rain gauges to mitigate bias in the radar QPEs. Run operationally by the 13 NWS river forecast centers (RFCs), the MPE produces seven⁶ quantitative precipitation estimate (QPE)

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⁶ The MPE creates the following seven products (references to additional information are provided): (1) Radar Mosaic (Breidenbach and Bradberry 2001; Quina 2003); (2) Field Bias Mosaic (Seo et al. 1999); (3) Local Bias Mosaic (Quina 2003; Seo 1999b); (4) Gauge-Only Analysis Mosaic (Seo 1999a; Seo 1999b); (5) Satellite Analysis Mosaic (Fortune et al. 2002); (6) Local Bias Satellite Mosaic (Fortune et al. 2002); and (7) Multisensor Mosaic (Seo 1998b).
products or mosaics on a polar stereographic grid known as the Hydrologic Rainfall Analysis Project (HRAP) grid. The HRAP grid resolution is approximately \((4 \text{ km})^2\) at mid-latitudes. Hydrometeorologists at the RFCs integrate all seven products as necessary and perform additional manual quality control to produce “best-estimate” hourly QPEs. The resulting “best-estimate” MPE QPEs are fed into River Forecast Center (RFC) hydrologic models, disseminated to NWS weather forecast offices for, among other uses, flash flood monitoring and prediction, and archived at the NCEP for many purposes including assimilation in the EDAS, precipitation verification, and disaggregation of daily gauge values (Lin and Mitchell 2004).

Input into the MPE is an HRAP-gridded precipitation product known as the Digital Precipitation Array (DPA): an hourly estimate of precipitation extending 240 km from a Weather Surveillance Radar-1998 Doppler (WSR-88D) and produced by the Precipitation Processing System (PPS). In addition to integrating the reflectivity/rain-rate relationship over time, the PPS attempts to account for beam blockage, radar bias, bright banding, anomalous propagation, ground clutter, and other consistency and quality issues (Fulton et al. 1998). Nationwide RFC launch of the MPE occurred on 1 October 2002, replacing QPEs produced by the four-level Stage methodology: the legacy NWS multi-sensor precipitation estimator (e.g., see NWS OH 2002). The MPE features improvements in mosaicking and manual quality-control methodologies, gauge-only analyses, and mean-field bias adjustments. It also introduces satellite-derived QPE, offers a local bias adjustment, and, as discussed in Chapter 1, abandons IDW averaging of gauge measurements and radar estimates in favor of a geostatistical “optimal estimation procedure” to merge the two sources (Seo 1998a). The Stage nomenclature is still used, albeit inconsistently, in NWS documentation (e.g., NWS NCEP 2006; Lin and Mitchell 2004). For example, the NCEP has borrowed the Stage terminology for its national mosaic archival project: NCEP Stage IV output is the manually quality-controlled RFC MPE QPEs (2002 to present) and NCEP Stage II output (1996 to 2002) is produced at the NCEP and absent of human quality control.
Specifically, the Geos2MAP model utilizes the NCEP Stage IV product. Generation of this product began 1 January 2000. Prior to 2000 and since 1996, the NCEP Stage II product was the only archived national mosaic of multi-sensor precipitation estimates. However, the current Geos2MAP model does not incorporate the NCEP Stage II product considering the following challenges: (1) the Stage legacy algorithms underwent multiple and significant changes throughout the period of their use; and (2) while the gauges are subject to minor and automated quality control, the multi-sensor mosaics undergo no quality-control other than those steps taken in the PPS. Therefore, only the events occurring after 1 January 2000 will include comparisons to MPE QPEs.

Each RFC mosaic is largely comprised by the DPAs of those WSR-88Ds whose coverage pattern at least partially extends into the RFC hydrologic service area (HSA). Each RFC is only responsible for those HRAP grid cells that lie within its HSA, but it may edit parts of its MPE mosaic that lie outside the HSA. However, the area outside the HSA is often a low priority during significant precipitation events and may lack complete gauge and radar information; thus, the quality-control process is inconsistent or nonexistent in these areas. Since the entire mosaic is sent to the NCEP, this presents a challenge when mosaicking all the RFC mosaics to create a national product. The NCEP mosaicking approach simply (but ideally) assigns each HRAP cell the value assigned to it by the RFC with primary responsibility for that cell. If no RFC is responsible for a HRAP cell, but one or more RFC mosaics have definitions for that cell, the average of the values is assigned to the cell (Lin and Mitchell 2004).

Integration of MPE output into the current Geos2MAP model is threefold. First, the Geos2MAP model maps the output for visual comparison of the precipitation patterns resolved by the multiple-sensor and the multivariate-geostatistical gauge-only techniques. Second, the raw output is used to produce probabilistic distribution graphs (i.e., histograms) and box-and-whisker plots in order to study the non-spatial precipitation distributions and variability between the two sets of QPEs. Finally, as was done for each sample of rain gauges, MPE raw output is used to compute an estimated semivariogram and the resulting
guidance is used to converge on an ISIP model semivariogram in order to describe the spatial covariance of the MPE QPEs and compare the spatial variability of the two QPE datasets.

3.5 Additional Methodology

One of the research objectives stated in Section 2.2 is to evaluate the feasibility of applying one methodology to the geostatistical model and the interpolation process under varying spatial patterns of precipitation that logically then have varying spatial covariance functions. A cursory glance at the Geos2MAP model documentation, the documentation of various geostatistical software, or the theory of geostatistics illustrates that the development of one methodology is quite a challenge. This is why the Geos2MAP model is more of a methodology than a piece of software; its purpose is to investigate various avenues available in basic geostatistics and evaluate the results of choosing one avenue over another. It is not yet intended as an automated tool. Given that disclaimer, the following five subsections summarize important decisions made in this current process of modeling spatial covariance and mapping precipitation not yet discussed.

3.5.1 IDW

In applying equation 1.2.1, a power of \( p = 2 \) is used. The selection of the power is consistent with Isaaks and Srivastava (1989) and Shepard (1968): both stated \( p = 2 \) often serves as a default power. This research does not investigate the effects of varying the power; however, adjusting the power in the Geos2MAP model is simple if future users decide to change it. Additional information on the effect of power adjustment can be found in Section 1.2. The explicit determination of weights based on the spatial variability of the data itself as opposed to an arbitrary and implicit parameter like \( p \) is one major advantage of geostatistical approaches in general.

Recall from Section 1.6 that IDW cross-validation statistics are limited due to the inability of IDW to measure spatial variance, and thus, provide error variances of the prediction. Therefore, the use of standardized statistics and confidence intervals to evaluate IDW performance is not available.
3.5.2 Experimental Semivariograms

As discussed in subsection 1.3.7., the estimated semivariogram is a function of the number of rain-gauge measurement pairs $N(L\beta)$ within a particular lag class $L\beta$. The magnitude of $N(L\beta)$ and the total number of lag classes is dependent on the range $r$ of distances occupied by each lag class $L\beta$. If the number of point pairs in $L\beta$ is too small, the estimated semivariance at $L\beta$ will be heavily dependent on a small number of samples and may poorly represent the population semivariance at the distances contained within $L\beta$. The resultant experimental semivariogram may be excessively noisy. Conversely, if the number of point pairs is too large, point pairs are being squandered to contribute to semivariance estimations that represent a wide range of distances. The result would be an experimental semivariogram that is excessively smoothed over large distances, sacrificing detail necessary to fitting an ISIP covariance model. Obviously then, the user is required to partition the largest separation between any two point pairs (~1000 km in the current domain of study) in such a way that a balance between the above two scenarios is reached. SAS Institute, Inc. (1996), for example, suggests that users plot the frequency of point pairs given a selected lag class range $r$ for each lag class $L\beta$ and choose $r$ such that no fewer than 30 point pairs exist within the first few lags. Given the usually approximate normal distribution of randomly dispersed measurement sites, this will guarantee the most important, first several lags (where the semivariance rate of change with distance is greatest) have adequate sampling while additionally ensuring that subsequent lag classes will have more than adequate sampling.

Stationarity of a covariance function implies that the experimental semivariogram will steady at a distance of $\theta_2$ (i.e., the range) and a semivariance of $\theta_1$ (i.e., the sill). Therefore, at distances larger than $\theta_2$, the correlation of point pairs is near zero and the use of these point pairs or the lag classes they exist within contribute little to the estimated semivariogram or to the fitting of an ISIP model. Additionally, $N(L\beta)$ begins to decrease detrimentally to the semivariance estimate, often introducing significant noise and instability at the higher lag classes. Therefore, when representing the sample semivariogram and especially when utilizing fitting techniques that rely on the estimated semivariogram directly (e.g., the “by-eye” and NLS techniques), maximum distances are usually specified to ignore
lag classes that lie well beyond $\theta_2$. SAS Institute, Inc. (1996) suggests when the true range is unknown, the maximum distance should be no more than 50 to 75% of the largest distance of separation.

Within the Geos2MAP model both the maximum distance and range $r$ are manipulated to investigate various estimated semivariograms. The model outputs experimental semivariograms at the eight ranges $r$, which equal the eight resolutions of the predicted precipitation grids. Maximum distances of 450 km, 650 km, and 1000 km are used and frequency histograms are produced to study the availability of point pairs at all lag classes for each $r$. Favored semivariograms best balance the considerations discussed above.

To reiterate, recall that all of the above experimental semivariogram manipulations are only beneficial when fitting an ISIP covariance model to a semivariogram (e.g., by-eye, ONLS, and WNLS), they are not influential on ML/REML techniques.

3.5.3 Implications of Multivariate Trend Modeling on the Grid Space

Recall that the introduction of several secondary variables into the model, detailed in Section 3.3, occurs when MLR is used to model the spatial trend of the precipitation field or primary variable. Correlating the secondary variables to the primary variable can only occur using MLR if the variables are collocated on the same grid space. In addition, the secondary variables must have values at the prediction locations since the drift function is added to the predicted residuals at each grid point to yield the predicted precipitation. This double requirement on each secondary variable is not possible without interpolating the secondary variables onto both the irregular grid of the precipitation observations as well as the prediction grid. The workloads these requirements present are reduced in two ways. First, utilizing the DEM grid space as the prediction grid space eliminates the need to interpolate DEM and DEM-derived (e.g., DEMSlope and SlopeWind) covariates. Second, considering the high resolution of the DEM grid and the proximity of DEM grid points to gauge locations, gauge measurements are transposed to the nearest DEM grid point instead of interpolating covariates to the gauge locations. The result is that all data are now collocated on the same grid space.
Conceivably, OK, KED, or other geostatistical methods could be used to accomplish these interpolations; however, given the purpose of the secondary variables as approximate representations of the precipitation trend and considering the reasonably higher resolution (~32 km) of the NARR covariates, instead of doubling the efforts of this research, IDW is used to provide straightforward estimates of the covariate values on the prediction grid spaces. At this time, the Geos2MAP model does not attempt to analyze the shortcomings of the IDW approach as it applies to the interpolation of these secondary variables; however, IDW can provide reasonable downscaled predictions of fairly dense gridded datasets. At least in this research, more advanced methods may not provide enough of a performance versus cost benefit.

3.5.4 Trend Model Selection Methodology

This research incorporates both geophysical covariates (i.e., DEM and DEMSlope) and physical covariates (i.e., XWind and YWind and SlopeWind) into the analysis of non-constant trend. However, this research also investigates the role the coordinates themselves may have in explaining trend; in other words, the trend may be successfully defined as simply as a function of location, which would require a less rigorous trend model. As a result, there are generally two⁷ sets of covariates being investigated in this research. Therefore, in order to methodically address the large number of covariates, associated interaction terms, and possible covariate combinations during the development of linear trend models for each precipitation field, the following procedure was developed. First, the analysis of Cartesian coordinates was largely isolated from the analysis of physical covariates with the exception of the first-order coordinates X and Y. This was because the evaluation of physical covariates was restricted to the first-order terms and associated interaction terms. The comparison between Cartesian polynomial trend models and the physical models occurred after optimal trend equations were selected from within each set. As the ultimate

⁷ Throughout this research, the term “physical” will be used to incorporate both physical and geophysical covariates into one group such that there will be two sets of covariates: 1) the physical covariates which include the geophysical covariates; and 2) the Cartesian coordinate covariates.
goal is to produce a residual field whose distribution is approximately normal, the most important metrics for model success are the residual probability density histograms and normal QQ plots. However, the analysis of normality only occurred after increases in SSR (decreases in SSRE) from subsequent trend models became too small to arbitrarily determine whether the decrease in power was worth the increase in explained variability (i.e., cost of power reduction).

To improve organization, a naming convention was developed for the various trend models. The Cartesian polynomial trend models are classified first by order, then by transformation, and finally by model type. Thus, the first-order polynomial is classified as “1”, the second-order polynomial as “2”, etc.; the use of logarithmically transformed data is classified by an “L”; and the model type is “Cartesian”, which is classified as “XY”. The first-order Cartesian polynomial based on logarithmically transformed DRP data is therefore identified as “1LXY”; the second-order Cartesian polynomial is identified as “2LXY”; and the third-order polynomial is “3LXY”. For the physical covariate models, the identifiers are somewhat less self-explanatory, but the definitions remain consistent for each case. As before, the models are classified first by order and second by transformation. However, since this research only investigated the first-order physical covariates, all physical trend model identifiers begin with “1”. The third classifier “I” is included for those models that contain interaction terms, otherwise it is omitted. Model identifiers using only the first two or three classifiers served as parent models from which higher-power “child” models could be derived. The lowercase letters of the alphabet were used as a fourth classifier to represent each child model (i.e., a model derived from the parent model containing only the most significant terms from that parent). Clarification of the naming convention will occur as the models are discussed below.

Within the group of Cartesian polynomials, the first-order (i.e., highest-power) model was evaluated first, followed by the higher-order (i.e., lower-power) polynomials. Each subsequent polynomial was analyzed against the previous polynomials to evaluate the necessity of additional terms. However, the cost of power reduction was not evaluated based on individual covariates, rather the entire polynomial itself. Therefore, the objective was to
significantly reduce the SSRE (increase the SSR) in higher-order models while considering
the reduction in degrees of freedom. However, due to the large sample size of the lnDRP
dataset, the impact of the associated reduction in degrees of freedom through the addition of
second or third-order covariates was relatively inconsequential. Nevertheless, if an
arbitrarily small reduction in SSRE came at the expense of several additional terms, the
lower-order model was preferred. Once a model was selected that optimized the above
cost/benefit ratio, it was compared to the preceding lower-order polynomial to investigate
residual normality. If the inclusion of additional terms increased the percent of variance
explained but the lower-order model produced residuals whose distribution significantly
better approximated normality, the lower-order model was selected. If neither model yielded
residuals that approximated normality, the lower-order model(s) were evaluated for
normality regardless of the reduction in variance explained.

An alternative methodology was generated for the first-order physical and Cartesian
covariate trend models; instead of comparing each model against preceding higher-power
models, analysis focused on the significance of each individual covariate. Therefore, the
order of evaluation was reversed such that the first model evaluated (1LALL) included all
first-order Cartesian and physical terms (8 covariates), as well as all interaction terms
between them with (28 covariates). The objective during the analysis of 1LALL was to
examine, regardless of power, the total amount of variance explained by all covariates,
thereby using the $R^2$, SSR, and SSRE values as ceilings from which to examine higher-power
models. In other words, the goal was to derive the highest-power model (i.e., fewest
covariates) that yielded an explanation of variance as close to the lowest-power model
(1LALL) as possible, while producing an approximately normal distribution of residuals.
However, the significance of a covariate can change simply through rearranging the order of
the covariates in the model or by including or excluding certain covariates when the
interaction between the covariates significantly explains some variance in the data.
Considering the number of permutations possible from up to 36 different covariates and
instead of increasing the power of 1LALL by eliminating non-significant covariates directly,
model selection began with the first-order model of Cartesian and physical covariates (1L),
where the terms were ordered X, Y, XWind, YWind, SlopeWind, DEM, XSlope, and YSlope. Each covariate was primarily evaluated using SSQII, since SSQI is dependent on order of the covariates, while SSQII explains how important a term is once all other covariates are considered. Covariates were eliminated by evaluating the differences in SSQII between the least-significant covariates (i.e., the covariates with the smallest SSQII). As variables were eliminated, the new model’s SSR, SSRE, and $R^2$ were compared to the previous model’s values in order to evaluate if there was detrimental decrease in the percent of variance explained. The covariates remaining immediately prior to an important reduction in variance explained (i.e., the “best” model of first-order physical and Cartesian-coordinate covariates) created the model “1La”. The next model evaluated was “1LIa”, which included all interaction terms derived from the covariates in 1La. In other words, only the interaction terms of significant first-order predictors were evaluated during this process. The process of eliminating covariates was repeated for the interaction terms until the final model was derived, known as “1LIai”, which represents the first-order coordinate- and physical-covariate trend model with significant predictors from 1LIa. The entire evaluation process was performed for both averaged NARR covariates and maximum NARR covariates, yielding two models: 1LIai “Avg” (average NARR) and 1LIai “Max” (maximum NARR). One 1LIai model was chosen from the pair based, once again, on the premise that the chosen model either significantly improved upon the normality of the residuals, decreased/increased the SSRE/SSR, or both. The selected 1LIai model was compared to the selected LXY model throughout the analysis of residuals and the final KED analysis in order to investigate the importance and influence of each set of covariates on the geostatistical model.

Finally, it was discovered during the interpolation of the lnDRP field using KED that the 3LXY covariate values were too large and prevented the inversion of matrices within the KED system of equations. To correct this problem the first-order covariate values (X and Y) in the 3LXY model were scaled down by two orders of magnitude ($10^{-2}$) in order to successfully process the data. All higher-order polynomial terms were calculated using the scaled first-order Cartesian coordinates. Note that scaling the values has no impact on the MLR model’s performance; it only changes the order of magnitude of the coefficients.
Nevertheless, to distinguish between models with the same covariates but different scales, the scaled version’s identifier is appended with an “s” such that 3LXY becomes 3LXYs.

3.5.5 Reassessing the MLR Trend Model Coefficients using ML/REML

Recall that the presence of spatial autocorrelation amongst both the DRP dataset (primary or response variable) and the trend model residuals violates the critical MLR assumption of independence. Fortunately, ML/REML covariance model parameter estimation allows for the simultaneous estimation of the trend model coefficients, which as shown by the log-likelihood functions for ML and REML (equations 1.3.15 and 1.3.16, respectively), are assumed to be spatially dependent through the specification of a covariance matrix for the primary data (or their error contrasts). Therefore, the Geos2MAP model treats MLR as the “exploratory” or “experimental” approach to estimating variable trend, while the final KED analysis is performed using a trend model whose coefficients are estimated by ML/REML, in order to account for the spatial variability in the trend. In other words, MLR is used much in the same way the experimental semivariogram was used. This methodology for trend model derivation still requires the use of MLR to derive the preferred set of covariates from the multi-faceted assessment of the percent of variance explained; it is from this set of covariates that the covariate matrix is defined for the log-likelihood function and new coefficients are generated. Of course, this approach stills requires the violation of MLR assumptions in order to generate that preferred covariate matrix, but the impact of the spatial autocorrelation on the MLR-derived covariate matrix and the associated covariate coefficients can now be assessed due to the ML/REML procedure. The assumption of a spatially dependent trend and the presence of a covariance matrix for the DRP dataset allows the log-likelihood function to derive a covariance matrix for the ML/REML-derived trend model coefficients. While MLR estimates of coefficient standard error were unusable due to the violation of assumptions required for the MLR estimates of variance, the presence of the coefficient covariance matrix from ML/REML now allows coefficient standard deviations to be calculated. From the standard deviations and, once again, assuming a normal distribution, 95% CIs can also be calculated for the ML/REML-derived coefficients.
From the standard deviations and 95% CIs for the ML/REML-derived coefficients, the quality of the MLR-derived coefficients can be assessed. First of all, standard deviations that are near or exceed the actual coefficient values obviously signal coefficients that may not be statistically significant, allowing the user to assess the relevancy of the associated covariates and therefore assess the legitimacy of the MLR-derived covariate matrix. Furthermore, while a simple comparison of the MLR-derived coefficient to the ML/REML-derived coefficient for the same covariate may reveal MLR coefficient values that are hampered by the presence of spatial variance, the 95% CI for the ML/REML-derived coefficient can be used to assess whether the differences in coefficient estimates are statistically significant. MLR-derived coefficient estimates that fall outside the CI can be considered unreliable, once again allowing the user to assess the validity of the experimental trend model.

Finally, assuming the ML/REML-derived trend models provides legitimacy to the respective experimental MLR trend models, the MLR trend models are still used for exploratory purposes in order to analyze all trend model properties, including the percent of variance explained, the behavior of the predicted values versus residual and actual values, and the spatial and non-spatial behavior of the trend model residuals. Again, ML/REML-derived coefficients are treated as the final coefficients and the simultaneously-derived ML/REML covariance model parameter estimates characterize the covariance model submitted to KED.
Table 3.1.1. The approximate true resolution (km x km), grid points along the x-axis, grid points along the y-axis, total grid points, and approximate total area (km²) of each GRID available in the Geos2MAP model.

<table>
<thead>
<tr>
<th>Grid Spacing</th>
<th>Approximate Resolution</th>
<th>Grid Points (x)</th>
<th>Grid Points (y)</th>
<th>Total Grid Points</th>
<th>Approximate Total Area</th>
</tr>
</thead>
<tbody>
<tr>
<td>4 km</td>
<td>03.82 x 03.71</td>
<td>241</td>
<td>181</td>
<td>43621</td>
<td>618205</td>
</tr>
<tr>
<td>8 km</td>
<td>07.64 x 08.18</td>
<td>121</td>
<td>81</td>
<td>9801</td>
<td>612515</td>
</tr>
<tr>
<td>12 km</td>
<td>12.23 x 12.06</td>
<td>76</td>
<td>56</td>
<td>4256</td>
<td>627733</td>
</tr>
<tr>
<td>16 km</td>
<td>16.05 x 15.77</td>
<td>58</td>
<td>43</td>
<td>2494</td>
<td>631252</td>
</tr>
<tr>
<td>20 km</td>
<td>19.87 x 20.41</td>
<td>47</td>
<td>33</td>
<td>1551</td>
<td>629003</td>
</tr>
<tr>
<td>24 km</td>
<td>24.12 x 23.69</td>
<td>39</td>
<td>28</td>
<td>1092</td>
<td>623972</td>
</tr>
<tr>
<td>28 km</td>
<td>28.28 x 27.83</td>
<td>33</td>
<td>25</td>
<td>825</td>
<td>649302</td>
</tr>
<tr>
<td>32 km</td>
<td>32.10 x 32.47</td>
<td>29</td>
<td>21</td>
<td>609</td>
<td>634753</td>
</tr>
</tbody>
</table>
Figure 3.3.1. DEM output for the domain of study from the NDGC GLOBE Project. Available DRP data (rain gauge) locations from the Hurricane Ivan event case are provided as a reference.
Figure 3.3.2. DEMSLOPE output for the domain of study in a) along the E-W or X axis and b) along the N-S or Y axis.
4. CASE SUMMARIES, PRECIPITATION ANALYSES, and IDW and OK PERFORMANCE

4.1 Case Summaries and Precipitation Analyses

4.1.1 14-17 September 1999: Hurricane Floyd

Hurricane Floyd originated as a tropical wave off the coast of Africa in early September 1999. The wave traveled across the Atlantic uneventfully until it became a tropical depression (TD #8) on 7 September 1999, approximately 1850 km east of the Lesser Antilles. On 8 September, TD #8 was upgraded to a tropical storm (TS) and on 10 September, approximately 370 km northeast (NE) of the Leeward Islands, Floyd was upgraded to hurricane status. Floyd’s motion turned to the west on 11 September in response to building heights in the mid-troposphere and shortly after the shift in track Floyd underwent rapid strengthening, reaching maximum strength on 13 September 1999, with a central minimum pressure of 921 mb and maximum sustained winds of 135 kt, making the storm a Category 4 on the Saffir-Simpson Scale. The best track positions for Floyd are available from the National Hurricane Center (NHC) as shown in Figure 4.1.1. Additional information on the synoptic history of Hurricane Floyd is available from Pasch et al. (1999).

As Floyd struck the Bahamas on 14 September 1999, the storm began to turn right in response to a large mid- and upper-tropospheric trough centered over the Ontario Province, N of Lake Superior. The mid-latitude trough was weakening a western Atlantic Ocean subtropical ridge centered to the N of Floyd. In response, Floyd’s storm motion became NW and eventually N as the storm paralleled the Atlantic Coast of Florida (FL) and GA on 15 September 1999, centered ~175-200 km offshore. During this time, the storm was experiencing increasing south-southwest (SSW) shear as it interacted with the mid-latitude trough; 250mb winds exceeded 200 kt across an area spanning much of the Mid-Atlantic and NE United States on 15 September 1999 (e.g., see Figure 4.1.2). Despite the strong shear in place, E NC was under a region of large-scale ascent due to the favorable dynamics associated with the right entrance region of the upper-tropospheric jet streak. Meanwhile, downstream of Floyd, a stationary coastal front developed along much of the Eastern Seaboard as easterly flow from the Atlantic interacted with N to NW flow across Appalachia.
that was associated with a surface high pressure system located over the Midwest. In fact, as documented in studies such as Atallah and Bosart (2003) and Colle (2003), this baroclinic zone extended deep into the troposphere due to the favorable interaction of the potential vorticity anomalies of the warm-core and cold-core systems. The resultant low-level convergence zone is clearly illustrated at both 850 and 925 mb by 16 September 1999 at 0000 UTC (Figure 4.1.3). Furthermore, easterly moisture flux across the Eastern Seaboard combined with both the topographic barrier of the Appalachians and dry air affiliated with the Midwest high created an impressive dewpoint gradient extending from the western Piedmont and Blue Ridge into New England as evidenced by 925, 850, and 700mb analyses valid for 0000 UTC on 16 September 1999 (Figure 4.1.3). Therefore, precipitation intensity quickly decreased to the W across the Piedmont as total moisture content decreased in response to the competing continental-air advection to the NW.

Continually assaulted by SSW shear, by 16 September 1999 at 0000 UTC Floyd weakened into a strong Category 2 hurricane as it was being absorbed into the positively-tilted mid-latitude trough centered over the Great Lakes and Upper Midwest (Figure 4.1.3). The SSW shear was accompanied by significant dry- and cold-air advection associated with 30+ kt NW to north-northwest (NNW) winds from the mid- to low-levels of the atmosphere (Figure 4.1.3). Nevertheless, as discussed in Atallah and Bosart (2003) and Colle (2003), the unfavorable conditions for tropical cyclone maintenance were overshadowed by the favorable interaction of Floyd’s circulation with the intensifying baroclinicity downstream of the circulation center across E NC and VA, where warm-air advection combined with intense, tropical moisture flux and isotropic ascent to support efficient, warm rain processes ahead of the asymmetric storm and to the left of its eventual storm track as it approached the Atlantic coast. Both studies also note that the latent heat release ongoing with the downstream precipitation enhanced not only the baroclinic zone but the ridging taking place in the middle- and upper-troposphere along the East Coast, acting to change the tilt of the mid-latitude trough from positive to negative. Furthermore, favorable coupling of the upper-level jet streak with the divergent outflow above Floyd’s low-level center acted to enhance the jet dynamics already in place, aiding precipitation processes. With much of the deep
convection eroded by the dry-air intrusion in the SW quadrant of the storm, by the time Floyd made landfall near Cape Fear, NC at 0630 UTC on 16 September, Floyd was a rapidly weakening Category 2 hurricane with maximum sustained winds of 90 kt and a minimum central pressure of approximately 956 mb. As identified by Pasch et al. (1999), Floyd was quickly losing its eyewall characteristics at landfall and was beginning to accelerate to the NE as it became caught in the impressive SSW mean flow. Nevertheless, due to the pre-existing environment in the interim prior to landfall from 0000 UTC 15 September 1999 through 0630 UTC on 16 September, the Atlantic Coastal Plain of NE SC and E NC already experienced a prolonged period of tropically enhanced precipitation such that by the time Floyd made landfall, precipitation associated with and located just north of the northern eyewall simply contributed to already impressive accumulations. Floyd continued off to the north-northeast (NNE) across the swamplands of E NC, located near Washington, NC at 1200 UTC on 16 September as a moderate Category 1 hurricane with maximum sustained winds of 70 kt, a minimum central pressure of 967 mb and a storm speed of 22 kt. Later on 16 September, Floyd passed over Norfolk, VA and was downgraded to a TS, reaching the coast of Maine by 1200 UTC 17 September as an extratropical low completely absorbed into mid-latitude trough.

4.1.1.1 Rain-Gauge (DRP) Data Analysis

As with all cases studied, the Hurricane Floyd event was investigated on two time scales: a) “daily”, specifically 1200 UTC from 15 September to 1200 UTC on 16 September, which represents the single “day”\(^1\) with the greatest rain accumulations; and b) “event”, which consists of the period from 1200 UTC on 13 September to 1200 UTC on 17 September or a four-day accumulation of DRP data beginning with the 24-hr accumulation for 14

\(^1\) In this research a “day” is defined as the period from 1200 UTC to 1200 UTC in order to correspond to the period during which COOP observers collect 24-hr rainfall data. Hereafter, all 1200 UTC to 1200 UTC 24-hr periods will be referenced by the date upon which the 24-hr period ends. Thus, the 24-hr accumulation for 1200 UTC on 15 September 1999 to 1200 UTC on 16 September 1999 will be simply known as the 24-hr accumulation for 16 September 1999.
September. Basic distribution statistics for the DRP data on both time scales are displayed in Table 4.1.1.

Plots of the point DRP values for both the daily and event scales, shown in Figure 4.1.4, reveal a fairly simple precipitation pattern highlighted by a linear, NNE-SSW axis of maximum accumulations beginning across Horry County, SC towards Cape Fear then NNE through the NC coastal plain and into the Chesapeake Bay. The highest accumulation measured for Floyd, 464.82 mm for 16 September 1999 and 611.12 mm for the four-day period ending on 17 September 1999, occurred within the eyewall approximately 8 km N of Southport, NC and 15 km N of the outlet of the Cape Fear River. Intense precipitation within the eyewall also produced day/event accumulations of 356.62/489.20 mm at Wilmington. A total of three gauges in extreme NE SC, 15 gauges across eastern NC, and three gauges in SE VA reported accumulations greater than 250 mm during the four-day event period. Unfortunately, the nature of the precipitation distribution relative to the rain-gauge locations indicates that the maximum accumulation axis fell across an area with poor site density. The center of the storm itself passed across the swamplands of extreme eastern NC, where less than one gauge per county was available for analysis. Perhaps partially due to this gauge sampling bias, the maximum precipitation axis was measured to be immediately west of the storm track where gauge density slightly improves. This axis was highlighted by day/event accumulations of 386.59/409.45 mm at Snow Hill, NC. Other notable day/event observations within the Coastal Plain axis include 299.72/335.28 mm at Kinston, 273.05/361.70 mm Greenville, and 278.13/413.51 mm at Williamston.

Unlike the cases of Hurricanes Frances and Ivan, both of which made landfall along the eastern Gulf Coast, Hurricane Floyd’s Atlantic Coast landfall, resultant storm track, and interaction with the frontal boundary already in place across central NC, yielded very little rain for the western Carolina mountains and an impressive E-W accumulation gradient across the Piedmont. For example, 16 September 1999 (14-17 September 1999) accumulations decreased from 237.49 mm (237.49 mm) ~5 km SW of Zebulon, NC to 85.85 mm (86.11 mm) at Siler City, NC, located ~100 km to the W. Approximately 110 km further W, near Barber, NC, only 19.05 mm (19.05 mm) of rain fell, while the gauge at Lookout Shoals Lake,
located ~45 km W of Barber and ~300 km W of Zebulon, reported zero precipitation for the entire event.

Analysis of the non-spatial distribution of the DRP data reveals the magnitude of the issues inherent in the spatial distribution of sites and values. From the data summary in Table 4.1.1, the area occupied by zero and near-zero accumulations results in a 25\textsuperscript{th} percentile value of zero at the event and daily scales. At the daily scale, the median value is also zero (0.25 mm at the event scale), while, despite maximum accumulations exceeding 450 mm, the upper quartile value equals 29.21 mm (36.45 mm at the event scale). The significance of the positive skewness in this distribution can be further illustrated with a probability density histogram which removes all zero values (Figure 4.1.5). Nearly 35\% (22\%) of all DRP data values fall below 10mm for the event (daily) scale, and this number increases to over 65\% (70\%) when all zero values are included. Less than 15\% (10\%) of the non-zero values exceed 200 mm. Coupling the spatial distribution of both the site locations and their respective measurements with the non-spatial distribution of the DRP dataset reveals considerable challenges for the geostatistical model under the restriction of a fixed domain, most notably in drift and spatial variance analysis and modeling. Hurricane Floyd’s rain pattern, therefore, permits a good test of robustness in the interpolation techniques studied.

4.1.2 05-10 September 2004: Hurricane Frances

Hurricane Frances originated as an impressive tropical wave off the coast of Africa on 21 August 2004. Four days later, on 25 August, the wave developed into the sixth TD of the 2004 season, located ~1200 km SSW of the Cape Verde Islands. The TD quickly became TS Frances later on the 25\textsuperscript{th} and intensified into a hurricane only 24 hours later. During this time, Frances was propagating west-northwest (WNW) around the base of an Azores high, but began to turn right as it intensified into a Category 4 hurricane on 28 August, eventually sparing the Lesser Antilles. The storm weakened and then regained Category 4 intensity for a final time as it passed N of Puerto Rico and the Virgin Islands on 1 September when the minimum central pressure reached 935 mb. During 2 through 5 September, Frances
weakened in response to westerly shear as it passed over the Bahamas, and made its first landfall at ~0430 UTC on 5 September along the east coast of FL as a moderate Category 2 hurricane. Frances emerged off the west coast of FL, ~30 km N of Tampa, as a strong TS on 6 September, but it did not intensify while over the NE Gulf of Mexico. The best track positions for Frances are available from the NHC as shown in Figure 4.1.6. Additional information on the synoptic history of Hurricane Frances is available from Bevin (2004).

Meanwhile, while Frances was impacting the western Bahamas and the FL peninsula, the 500mb pattern was highlighted by a closed low centered over the Province of Newfoundland and Labrador and an upstream ridge across the Hudson Bay (Figure 4.1.7a). The ridge axis extended S through the Upper Great Lakes and into the Lower Mississippi (MS) River Valley while to the west a vigorous low centered over Utah ejected a surface low into Nebraska. Flow at 500 mb across the SE US veered from NW to NE in response to Frances as it made its first landfall on 5 September. Across the lower troposphere, winds continued to veer northeasterly and easterly with decreasing height as shown by the 700, 850, and 925 mb maps valid on 0000 UTC 5 September 2004 (Figure 4.1.7b-d). An area of confluence at 500 mb located between the Canadian ridge/trough complex provided additional subsidence to SE Canada and the NE US during this time, slowing and strengthening a surface high pressure system centered over New York (NY) and Pennsylvania (PA). Near the surface, the high pressure system allowed slightly cooler but moist NE flow to traverse the Eastern Seaboard into the Carolinas and the Deep South, as the gradient wind started to increase in response to Frances (Figure 4.1.8a). Just above the surface in the lower troposphere, the airmass associated with the ridge was warm, but drier with temperatures/dewpoints from the Mid-Atlantic to the N GA of 14-18°C/8-11°C at 850 mb and 20-22°C/12-15°C at 925 mb.

As Frances propagated across the FL peninsula and into the NE Gulf of Mexico, the Canadian ridge propagated in the opposite direction into Quebec and the NE US, merging with a large lower- and middle-tropospheric high pressure system over the western Atlantic developing in Frances’s wake. Frances’s steering currents were being enhanced by the Rocky Mountain 500 mb trough which lifted into northern Ontario. Moving NW, Frances
made its second landfall in the FL Panhandle near the mouth of the Aucilla River at ~1800 UTC on 6 September as a moderate TS with maximum sustained winds near 50 kt and a minimum central pressure of 982 mb. Meanwhile, the progressive nature of the mid-latitude trough across southern Canada allowed for quick propagation of the deep-layer ridge downstream as the associated NE US surface high slid E into the Gulf of Maine. Therefore, SE flow upstream of the surface high ended near-surface cold-air advection across the Mid-Atlantic by 0000 UTC on 7 September as shown in the Figure 4.1.8b. By 1200 UTC on 7 September (Figure 4.1.8c), TD Frances was beginning to phase with the Canadian trough as its storm motion changed from NW to NE along the Alabama/GA border near Columbus. At this time, the thermal/moisture gradient across the Piedmont remained impressive with Charleston, SC reporting a surface temperature/dewpoint of 27°C/25°C and Greer, SC reporting saturated conditions at 21.6°C. Winds veered from east-northeast (ENE) at Florence, SC to east-southeast (ESE) at Charleston, SC identifying a convergence zone that separated the cooler maritime near-surface airmass associated with the high pressure system from the deep-layer tropical airmass associated with Frances. This boundary persisted into the first half of 8 September 2008 and was responsible for several tornadic convective feeder bands across the Carolinas, enhancing rainfall in several locations from NE GA into NC.

By 0000 UTC on 8 September, TD Frances was nearly absorbed into the middle-tropospheric trough as shown from the 500 mb analysis (Figure 4.1.9a). After several hours of favorable moisture flux within the lower troposphere in advance of Frances, an impressive, nearly saturated tropical airmass was fully established across the Carolinas and southern VA, replacing the warm, but drier airmass previously in place. The deep, moist layer was characterized by a large area across the southern Appalachians and Piedmont with 6-10°C dewpoints at 700 mb, 14-17°C dewpoints at 850 mb, and 19-22°C dewpoints at 925 mb (Figure 4.1.9b-d). The deep-layer tropical environment was especially impressive for early September and obviously conducive to warm-rain processes. In the NE quadrant of the TD, SE flow dominated at 925, 850, and 700 mb enhancing moisture flux and upslope flow along an axis orthogonal to the Blue Ridge of the southern Appalachians. The advection of tropical air against favorable exposures along the Blue Ridge yielded important orographic
enhancement of precipitation as Frances propagated to the NE across the NC/TN border into NE TN by 1200 UTC on 8 September.

As Frances lifted N into VA and WV during the second half of 8 September, continental air was starting to infiltrate the storm in the middle troposphere. Dewpoints at 500 mb near the center of circulation decreased substantially from the negative single digits less than 12 hours earlier to as low as -40 °C while significant dry-air advection was taking place at 700 mb further S across the southern Appalachians. The loss of warm-rain processes at these levels; the advection of cooler, more stable air from the N and NW in the lower troposphere; and the earlier interception of moisture upstream along the eastern Appalachians and Blue Ridge contributed to an overall minimum of precipitation across parts of E TN, SW VA, and SE KY. The overall environment at these levels signaled Frances was losing its tropical characteristics and the storm was downgraded to an extratropical low by 0000 UTC on 9 September, accelerating NE into W PA and W NY by 1200 UTC 9 September.

4.1.2.1 Rain-Gauge (DRP) Data Analysis

During Hurricane Frances, maximum 24-hr rain accumulations within the domain of study occurred on 8 September, which subsequently represents the daily scale. The event period for this storm occurs from 5 September to 10 September. Basic distribution statistics for the DRP data on both time scales are displayed in Table 4.1.2.

Hurricane Frances’s secondary landfall, which occurs along FL’s Gulf Coast, yielded a markedly different precipitation distribution compared to Floyd across the western Carolinas, as illustrated by the polka-dot plots of DRP data for both the event and daily scales (Figure 4.1.10). Maximum observed accumulations of 602.70 mm and 419.10 mm for both the event and daily scales, respectively, occurred at Mount Mitchell, which, at 2037 m, represents the highest point in the domain of study. Clearly, an additional axis of maximum values exists along the extreme northwest border of SC along and E of the Nantahala National Forest, including Sassafras (elevation 1085 m) and Hogback Mountains (elevation 979 m) within the front range of the Blue Ridge. This region is especially vulnerable to a strong low-level southeasterly flow and moisture transport such as seen downstream of
Hurricane Frances, as it transitioned from a TS to a TD. However, it is not the only upslope region that felt the impact of the NE quadrant of Frances; the windward-facing slopes of the Blue Ridge into NC and VA constitute a secondary rain axis extending from Grandfather Mountain (293.88 mm on 8 September and 337.06 mm for the event; elevation 1818 m) in Avery County, NC NNE along the Blue Ridge Parkway into southern VA. There, the highest amounts are confined to a narrow axis that correlates well to the significant elevation gradient (see Figure 3.3.1) denoting the sharp transition from the Piedmont to the Blue Ridge. While the influence of small-scale topography on rain accumulations is evident in this case, the large-scale topographic changes from the Coastal Plain to the Piedmont may partially explain the widespread 100-180 mm accumulations across the border of NC and SC from Rockingham and Cheraw W to the Charlotte metro and into the highlands from Spartanburg north to Casar, NC [located ~15 km south-southeast (SSE) of High Peak (elevation 908 m)], where another secondary maximum occurred of 254.00 mm on 8 September (289.81 mm for the event).

Despite the contributions of topography, however, even in the coarse resolution offered by rain gauges the impact of hurricane rain bands can be noted. Consider the axis of 150-225 mm of rain along the Savannah River Basin between GA and SC from Russell Lake N towards Lake Keowee. While harder to discern, yet another rain band may have been responsible for a potential axis from Lake Robinson, SC to Lake Tillery, NC across the central border between the two states. A third rain band persisted from Fairfield County, SC to Cleveland County, NC likely enhancing rain near High Peak at Casar.

The largest discrepancies between the daily and event timescales appear to be across much of GA and southeast SC, where the majority of rain fell prior to 8 September, and across central and eastern NC and SE VA where the rain fell after 8 September. The difference is most significant across southern and eastern GA, where an additional 100-200 mm of rain fell prior to 8 September as Frances regained some strength across the NE Gulf of Mexico before her second landfall in FL, creating a second maximum of accumulations GA’s coastal plain. The net effect of the additional accumulations can be readily seen in the both in the spatial and non-spatial distributions of rain. Frances’s precipitation distribution was
large enough to cover the whole domain of study over the event time scale, with a minimum accumulation of 13.46 mm; however during 8 September, several near-zero accumulations were recorded with over 18% of the measurements having values between and including zero to 10 mm (see Figure 4.1.11). As typically observed, the non-spatial distribution during the daily scale was approximately exponential with the discrepancies between the mean (61.63 mm) and median (41.53 mm; see Table 4.1.2) indicative of a distribution skewed towards lower values. Fewer than 10% of all values exceeded 150 mm. However, the event distribution had the largest percentage of amounts between 50 and 100 mm with nearly 10% of the data measuring between 80 and 90 mm of rain, and resembled not an exponential distribution but an F distribution. The basic statistics for both time scales (Table 4.1.2) provide yet another indicator of the significance of the event scale on total accumulations; while <25% of all values exceeded 90 mm during 8 September, over 50% of all values exceeded 90 mm during the entire event. Unlike Hurricane Floyd, the precipitation pattern of Hurricane Frances largely eliminates the influence of zero values in the geostatistical analysis.

4.1.2.2 MPE Analysis and Comparison to DRP

Adjustments in spatial density or resolution can be thought of much like bringing an image in and out of focus. A principal advantage of integrating high-resolution radar precipitation estimates with the rain gauge measurements previously discussed (i.e., MPE output) is the clarification of the spatial distribution of rain as shown in Figure 4.1.12. Confirmed is the impact of the tropical cyclone’s typical banding structures on the precipitation pattern, even in the comparatively lighter accumulations across E NC and SE VA. Storm motion can be derived from the precipitation field as well. For example, banding signatures across southern GA are oriented SSW to NNE as the center of Frances crosses the Atlanta metro early on 8 September. Meanwhile, across northern GA, NW SC, and adjacent areas of NC convection is oriented from SE to NW ahead of the center in the NE quadrant. Rain bands across central SC and the NC Piedmont have a S-to-N orientation as the weakening TD traversed the Great Smokey Mountains and NE TN. Finally, within the SE
quadrant across eastern NC and SW VA, the precipitation pattern is aligned SSW to NNE as the remnant storm lifted out of the domain into WV and PA.

Inferior resolution in the rain gauge dataset is visually evident from Figure 4.1.12 and it should be of no surprise that this places any empirical interpolation scheme at a marked disadvantage. However, if it is assumed that the distribution of the MPE dataset is approximately representative of the true rain distribution for Frances (i.e., within the domain of study), then the quality of sampling in the rain gauge dataset can be analyzed. From Figure 4.1.12, gauge density in the western Piedmont and Blue Ridge suggests good coverage where the largest rain accumulations occur. Conversely, sampling over the coastal plain is poorer, and since radar coverage extends over the Atlantic Ocean, where Frances’s rain impact was minimal, it can be expected gauge sampling favors the higher accumulations\(^2\). Frances also reveals the danger in assuming MPE is representative of the true rain distribution, since, despite poorer spatial density, point measurements from gauges tend to do a better job capturing the maximum rain totals if the sites are favorably located. An inherent limitation of MPE is its 16 km\(^2\) grid cell size as it averages out accumulations over the cell area. During the convective banding events typically seen in landfalling hurricanes the precipitation gradient is often tighter than MPE can resolve and small-scale, intense rainfall rates are likely to be averaged with lesser rates. This is evident for Frances, as the Mount Mitchell accumulation was underestimated by over 150 mm in MPE (maximum value of 467.90 mm as indicated in Table 4.1.3).

Despite the limitations of the MPE algorithm, its total coverage and high resolution result in a large sample size and a high confidence in its role as an estimate of the true distribution. Comparison of the full-scale histograms for MPE (Figure 4.1.13) and DRP data indicate the siting bias across the western Carolinas resulted in a positively skewed sampling

\(^2\) The presence of MPE values over the ocean clearly introduces a bias in the distribution when comparing the output to the Interpolated Daily Precipitation (IDP) and DRP datasets, which are restricted to land. The strength and sign of this bias is dependent on the magnitude and frequency of the ocean MPE values compared to those values over land. To eliminate this bias, the MPE data was filtered exactly the same way IDP values were filtered to remove the portion of the grid that lay over the ocean. This procedure consisted of setting all grid cell values to missing where the corresponding DEM = -500. All comparisons in this research between MPE and the other datasets are completed after removal of these “ocean values”.

of rain for the DRP data [~17 mm (~20 mm) spread between the median and mean for gauge data during the event (daily) scale vs. ~11 mm (~15 mm) spread for the MPE output]. Nevertheless, MPE output confirms exponential and positively skewed normal distributions of the daily and event scales, respectively. While it is clear that a greater percentage of the distribution is attributed to values greater than 250 mm in the gauge distribution, the intermittent sampling of these values is undoubtedly an artifact of poor spatial density. Averaging limitations of MPE aside, the comparisons do suggest the DRP dataset oversamples the extreme rain amounts. Furthermore, the poor spatial coverage across the Coastal Plain results in an undersampling of minimum values during the event. The lack of zero accumulations in the DRP dataset for the event is likely not representative of truth; however, the DRP dataset appears to adequately capture 0-10 mm accumulations for the daily scale while undersampling amounts between 10 and 20 mm.

4.1.3 16-20 September 2004: Hurricane Ivan

Hurricane Ivan originated as a large tropical wave that emerged off the coast of Africa on 31 August 2004, only ten days after Frances. The principal difference between the two systems at this point was the lower latitude development (~10°N latitude) of Ivan as it became TD #9 on 2 September and a TS only 12 hours later at 0600 UTC on 3 September. Ivan maintained a westward track and continued to intensify, becoming a hurricane on 5 September and on 6 September, after a period of rapid intensification, becoming the “southernmost major hurricane on record” Stewart (2004). Ivan entered the Caribbean Sea on 8 September and while on a WNW to NW motion across the Caribbean reached Category 5 strength three times (and a minimum central pressure of 910 mb twice), passing just south of Jamaica and Grand Cayman before emerging from the Yucatan Channel as a Category 5 storm in the Gulf of Mexico on 14 September. At this time, Ivan was responding to a weakness in the subtropical ridge over the Gulf of Mexico and continued to turn right from NW to NNW to N. Meanwhile, a large trough in the middle and upper troposphere across the Great Plains induced shear across Ivan as the storm weakened upon its approach to the Gulf Coast. The best track positions for Ivan are available from the NHC as shown in
Figure 4.1.14. Additional information on the synoptic history of Hurricane Ivan is available from Stewart (2004).

As Ivan neared landfall on 0000 UTC 16 September, it was encountering middle-tropospheric cool- and dry-air advection from the west; 500 mb dewpoint depressions of 10°C at Jackson, MS; 15°C at Lake Charles, Louisiana (LA); 18°C at Shreveport, LA; and 23°C at Little Rock, AR were being advected into the storm due to NW flow across the SW to NE moisture and thermal gradient over the Lower MS River Valley (Figure 4.1.15a). The closed low associated with the negatively tilted Great Plains trough continued to lift into northern Minnesota and SW Ontario. Across the eastern US, a middle-tropospheric ridge axis was oriented across the eastern OH River Valley to the southern Appalachians and coastal SC with very dry air in place across the Carolinas, TN, VA, WV, and KY (500 mb dewpoint depressions of 27°C at Greensboro, NC; 28°C at Blacksburg, VA; and 30°C at Morehead City, NC, respectively). Due to the mean southerly flow across much of the eastern third of the US, the lower troposphere was dominated by preexisting warm and moist conditions, with dewpoints generally 10-15°C at 850 mb and 12-20°C at 925 mb. At the surface, (Figure 4.1.15b) high pressure centered over the western Atlantic and an attendant ridge axis through S VA and into the TN River Valley kept flow NE to E across the Carolinas and GA, advecting a slightly cool but moist near-surface airmass into the region.

Landfall occurred on 16 September at 0650 UTC near Orange Beach, AL. Ivan had maximum sustained winds of 105 kt (Category 3) with a minimum central pressure of ~943 mb. Ivan continued a rapid weakening process as it entered S AL, being downgraded to a TS at 1800 UTC on 16 September with maximum sustained winds of 50 kt. However, Ivan’s favorable landfall location, impressive lower-tropospheric shear, and intense cross-isobaric flow enhanced convergence across much of the FL Panhandle, AL, and W GA (Figure 4.1.16a-b), barraging the area with several severe and tornadic convective feeder bands. As Ivan propagated across interior AL, it began to experience greater influence from the Canadian trough lifting into NE Ontario, and, as a weakness in the Atlantic ridge started to develop near the Delmarva coast, Ivan began to take a NNE turn by 0000 UTC on 17 September 2004. At this time, the near-surface easterly flow previously in place across much
of N GA and NW SC began to veer to the SE and S in response to Ivan (Figure 4.1.17b). Deep-layer 30-50 kt southerly flow from S GA into the Blue Ridge of GA and NC advected the tropical airmass into the region, creating a large dewpoint field exceeding 17°C at 850 mb and 20°C at 925 mb. In addition, a modest moisture gradient was in place across the southern Appalachians as dewpoints in the lower levels decreased 3-5°C into TN (Figure 4.1.17c-d), suggesting important moisture flux convergence. Moisture advection was ongoing aloft as well and much of the previously noted dry air in place across the TN River Valley and Carolinas was replaced by an airmass with dewpoints of -9°C above Blacksburg and Greensboro and near-zero dewpoint depressions (Figure 4.1.17a). While Ivan retained many of its tropical characteristics its absorption into the mid-latitude westerlies was being delayed by the remnants of the ridging in place across the Mid-Atlantic, as the center of the deep-layer ridge propagated further east into the Atlantic.

During the first half of 17 September, TD Ivan turned NE across Huntsville, AL and along the Great Smokey Mountains, intersecting a similar path taken by Frances approximately nine days earlier and traversing a region with previously saturated soils and swollen rivers. Like Frances, SE flow throughout Ivan’s eastern quadrants arrived nearly perpendicular to the Blue Ridge across NC and VA and intense moisture flux across the mountains once again resulted in damaging orographic enhancement to the precipitation. However, the westward shift in storm track prior to 1200 UTC on 17 September also subjected the south-facing slopes of the Blue Ridge across N GA to a longer period of orthogonal flow while the SE flow around the center of Ivan as it propagated into N AL led to critical orographic enhancement across the Cumberland Plateau of NE AL and SE TN. Nevertheless, by 1200 UTC on 17 September, (Figure 4.1.16c), Ivan was ingesting drier and cooler air near the surface from a continental high pressure system across the Upper Midwest as the Canadian trough and westerlies began to absorb the storm. In the middle troposphere, Ivan was ingesting very dry air from the MS River Valley where dewpoint depressions were in excess of 35-40°C. However, in the tropical environment to the east of the circulation, Ivan was still inducing important precipitation across the Blue Ridge of VA and maintained TD classification (Figure 4.1.16d) until 1800 UTC on 18 September when it was declared
extratropical. Phasing with the Canadian trough never fully materialized and Ivan was
captured in the Delmarva region with a building ridge of high pressure to its N. As a result,
Ivan turned E, then SE, and finally S, reemerging over the Atlantic Ocean as an extratropical
low late on 18 September.

4.1.3.1 Rain-Gauge (DRP) Data Analysis

During Hurricane Ivan, maximum 24-hr rain accumulations within the domain of
study occurred on 17 September, which subsequently represents the daily scale. The event
period for this storm occurs from 16 September to 20 September. Basic distribution statistics
for the DRP data on both time scales are displayed in Table 4.1.4.

Primarily as a result of Hurricane Ivan’s landfall near Orange Beach, AL, which was
over 300 km west of Frances’s landfall near St. Marks, FL, Ivan’s precipitation distribution
was largely characterized by a westward shift in the axis of heaviest precipitation when
compared to Frances; this axis is shown in truncated form in Figure 4.1.18 with widespread
80-200 mm rains evident across central and W GA and most significantly across parts of TN.
Southerly flow on the E and NE side of Ivan favored the typical windward slopes of the
southern Appalachians and Blue Ridge similar to Frances. However, a greater orographic
enhancement is noted in Ivan over the mountains of N GA, with the highest accumulation
recorded at Clayton, GA, located ~20 km from Rabun Bald (elevation 1431 m) with 346.71
mm for the event and 323.85 mm for the day. The prominent orographic axis has origins at
the southern base of the Blue Ridge near Mount Oglethorpe (elevation 1003 m) where nearby
gauges located to the west and south in the towns of Jasper and Ball Ground recorded 190.25
and 160.02 mm, respectively. The axis extends N and E along the eastern mountains of the
Blue Ridge and is oriented slightly further west than the axis defined with Frances. Notable
event (daily) accumulations in NC include the following: Lake Toxaway located ~15 km NW
of Sassafras Mountain with 283.21 mm (254.51 mm); Enka, located ~10 km SW of Asheville
with 287.53 mm (280.16 mm); Mount Mitchell with 276.35 mm (174.24 mm); and Banner
Elk with 257.05 mm (188.72 mm). The latter two accumulations indicate that more than one
day of significant precipitation occurred while Ivan traversed the TN/NC border as a TD
from 1200 UTC on 17 September to 0000 UTC on 18 September. NW of the Blue Ridge into the Ridge and Valley Province of TN and VA a significant decrease in accumulations is noted with much of the tropical moisture intercepted upstream. Despite upslope flow behind the Ivan’s passage, the region was caught in the SW quadrant of the storm where significant amounts of continental air infiltrated the storm. It is likely the further decay of Ivan into VA explains the weakening of the Blue Ridge precipitation axis as it traveled towards Roanoke.

Clearly, the daily scale captures most of the significant rain associated with Ivan in the domain of study. However, also prevalent is a large zero and near-zero (<10 mm) field across much of SE GA, the Carolina coastal plain, and the eastern Carolina Piedmont into VA. Analysis of the full-range histogram in Figure 4.1.19 indicates more than 35% of the DRP dataset consists of measurements <10 mm with 10% equaling 0.00 mm. The unusual eastward track of Ivan across VA and then S into the Atlantic Ocean brought additional rains to the same area that initially received very little, resulting in an event scale pattern with 20-80 mm widespread across NC, VA and parts of SC. Consequently, the presence of zero and non-zero values is confined to the coastal plain of GA and SC with a dramatic decrease of the near-zero (zero) values to only 6% (2%). Of interest in this event is the impact of the transition from widespread zero values to a widespread, comparatively light field of precipitation on the geostatistical analysis dominated by moderate to heavy rain in the western domain.

4.1.3.2 MPE Analysis and Comparison to DRP

Unlike Frances, the DRP data collected during Hurricane Ivan resolved very little storm structure. Once again MPE output, as shown in Figure 4.1.20, resolves lighter convective banding features generally oriented SSW to NNE across much of the Piedmont. Heavier S to N banding is evident in N GA and Upstate SC. In both cases, the accumulation gradients occur on such small scales that the gauge density is much too low to resolve these features. Also unlike Frances, gauge sampling issues exist as illustrated from the five number summaries in Table 4.1.5; MPE estimated an event (daily) maximum 409.40 mm (347.00 mm) in an axis along the NC Blue Ridge Parkway from Hawksbill Mountain
(elevation 1222 m) to Grandfather Mountain versus the DRP data’s 346.40 mm (323.90 mm) in NE GA. Unfortunately, the precipitation data at Grandfather Mountain were missing on 18 September and the event accumulation had to be ignored. Nevertheless, even on 17 September, notice gauge sampling was poor and the discrepancies between MPE and DRP in that area are large. The significance of small-scale precipitation gradients left unresolved in the DRP dataset pose substantial challenges for basic empirical methods.

Analysis of the full-range event histograms for MPE output (Figure 4.1.21) suggest two peaks in the samples (i.e., a bimodal distribution): the first of lighter accumulations from about 10-40 mm and a secondary peak between 70-100 mm. With a dominant number of near-zero values in the daily histograms the bimodal distribution is less pronounced. However, from these distributions it is implied that outside the heaviest axes of rain, the mean precipitation across much of western third of the domain was approximately 70-100 mm for both time scales. While both datasets are positively skewed (median to mean spreads of ~15-20 mm for MPE and ~20-25 mm for DRP), the effect of higher gauge sampling in the western Carolinas and N GA is evident in the spread between DRP and MPE percentile values; at the 25th percentile less than 4 mm separates the datasets at both timescales while the median is ~7-10 mm higher in the DRP datasets, the mean ~12-15 mm higher, and the 75th percentile ~17-21 mm higher. The proportions of ≥100 mm values in the DRP datasets are about 5-10% higher than the MPE output, despite MPE having larger maximum accumulations. Therefore, basic interpolation schemes are likely to overestimate the spatial coverage of significant rain thereby introducing large errors where strong gradients are excessively smoothed or omitted entirely3. However, it must also be noted that MPE, as a derivation of radar precipitation estimates, suffers from similar shortcomings in areas of mountainous terrain. While the incorporation of gauge data should improve MPE estimates not only at the gauge locations but across the field through bias adjustments, without ample, high-density gauge coverage in these regions, MPE still underestimates precipitation across the interior Appalachians of the SE US. With the nearest radars at Morristown, TN and

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3 Realistically, the smoothing effect and skewed sampling of a low-density dataset is always going to be a concern when interpolating via empirical methods.
Greer, SC, the interior mountainous region must contend with beam blockage, attenuation and radar bin size, among other issues. Attenuation is of particular concern during systems like Ivan and Frances; for example, the Greer radar first sampled the most intense energy across the Blue Ridge before sampling hydrometeors closer to the NC/TN/GA borders. Therefore, both Ivan and Frances highlight the importance of treating MPE as another valuable tool for estimating the precipitation spatial field, but MPE should not be interpreted as the true spatial field.

4.1.4 Basic DRP Quality Control and Transformation Analysis

Prior to the covariate analysis and the derivation of trend models, extensive preprocessing is performed on the DRP dataset. Several quality control (QC) statistics retrieved from preprocessing output produced by Geos2MAP are shown in Table 4.1.6. Table 4.1.6 familiarizes the user with the sample size from which the trend is modeled and underscores the impact of the QC process on that sample size. For each case, the individual state statistics are provided along with domain totals.

Considering the small amount of time separating the two cases, Frances and Ivan post very similar QC statistics with an identical number of total original and total available gauges of 613 and 398, respectively, or 65.4% of the original set of gauges available within the domain as provided by the NCDC station lists. For Floyd, the numbers are worse despite a larger initial dataset of 620 gauges, as 37.9% of the gauges were removed from the final list leaving 380 available for analysis. In all three cases, the number of gauges reporting missing data (M); the number of gauges with no data reported (ND); and the number of gauges rejected due to poor reporting times (RT) are similar. Nevertheless, several issues were discovered during the analysis of the NCDC dataset. First, approximately 16% of the sites removed from each case actually had no data available (i.e., no entry in the database) for the period of study, despite being listed as active stations. Several reasons for the lack of data are likely, including failure to report observations, errors in transmitting, receiving, or processing observations, or accounting errors in the station lists themselves. Fortunately, of the sites that did have entries for the period of study, a very small percentage of sites had data
set to missing in the original dataset (<2% in Floyd and <1% in Frances and Ivan). However, perhaps the largest disappointment came from sites whose reporting times were excessively\(^4\) different from the COOP network’s standard reporting time of 0700 local time [as defined in NWS (1989)]. The issue of observer reporting time is significant within the operational environment as it has tremendous impact on many services that rely on timely measurements, including gauge reporting; gauge mapping; data assimilation; flash-flood guidance products; precipitation estimation products such as MPE and river basin-averaged estimates; hydrologic modeling and calibration; and verification of both meteorological and hydrological forecasts.

Consider a gauge in Wake County, NC whose 24-hr measurements are taken by an observer at 1500 UTC each day. Precipitation from a landfalling hurricane arrives at this gauge beginning on 1300 UTC, August 10, and 25 mm accumulates by 1500 UTC. Though precipitation starts accumulating beyond the end of the 1200 UTC – 1200 UTC period ending on August 10, it begins within the 1500 UTC – 1500 UTC period. While the true precipitation for August 10 is 0.00 mm, this gauge reports 25.00 mm. From 1500 UTC to 1200 UTC on August 11, another 75.00 mm falls at this gauge, while 0.00 mm falls between 1200 UTC and 1500 UTC on August 11. For the 24-hr period ending at 1200 UTC on August 11, the true precipitation accumulation is 100.00 mm. However, the 24-hr measurement at the gauge, taken at 1500 UTC on August 11, will be 75.00 mm. From this example, it should be clear that as the deviation of the actual reporting time from the observed reporting time increases, microvariability increases. Shifting the period of study to accommodate such sites is often done at the expense of excluding precipitation at some point within the original period of study. Selection of a sample therefore requires a compromise of accepting some microvariability in order to increase sample size.

\(^4\) The user has the ability to control the size of the window of acceptable times as a feature within Geos2MAP. For this research, an excessively unacceptable reporting time was arbitrarily defined as earlier than 0500 or later than 1000 local time. The window size of five hours was determined from studying the reporting times used by observers in each case. It was determined that usually, reporting times were within one to three hours of 1200 UTC or greater than five hours from 1200 UTC.
For Hurricanes Ivan and Frances, approximately 17% of gauges were rejected due to poor reporting times and this rejection rate increases to 20% for Floyd. Furthermore, approximately 10% of the gauges removed from the original dataset have reporting times of “24” (i.e., midnight). Unfortunately, the generally well-maintained ASOS gauges are archived in the DSI-3200 database with 24-hour accumulations ending at midnight local time. This is a most unfortunate statistic since ASOS gauges also report 24-hour accumulations ending at 1200 UTC (~0700 local time). However, these accumulations are not included in the DSI-3200 database despite the fact that the majority of the gauges in the database are derived from the COOP network (e.g., even NCDC (2006) acknowledges that the majority of observation times are at 0700 or 1900 local time). The rationale behind favoring midnight accumulations is therefore quite unclear. Nevertheless, for this research, ASOS sites must be ignored in the sample (see Section 6.2) in order to avoid introducing significant temporal autocorrelation.

As discussed in subsection 3.2.1, a logarithmic transformation was performed on the dataset (lnDRP) prior to geostatistical and MLR analyses in order to address non-negativity and non-normality in the sample distribution. Of course, the datasets purposely included measurements of 0.00 mm as part of the investigation into geostatistical modeling (see Section 2.2), yet zero values cannot be logarithmically transformed without removing the reference to infinity. As a compromise in this research, zero values in the DRP dataset were first changed to 0.01 mm prior to transformation and subsequent analysis. The decision to use “0.01” was rather arbitrary. The problem lies with the significant digits of the millimeter measurement, since the raw measurements are in inches (0.01in = 0.254 mm) The true resolution of the gauge data is 0.254 mm, not 0.001 mm, 0.01mm, or even 0.10 mm. Therefore, the selection of a substitute for a zero value was kept to the nearest hundredth as a compromise. In any case, due to the measurement resolution, a non-continuous distribution exists. Unfortunately, the substitution amplifies the gaps in the sample after the logarithmic transformation occurs as shown from the lnDRP histograms in Figure 4.1.22, where values

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5 The NCDC dataset defines “24” as the midnight of the following day.
between 0.01 mm [-4.61 \ ln(\text{mm})] and 0.254 mm [-1.37 \ ln(\text{mm})], while occurring in nature, are too small to be measurable. Regardless, the quantity of zero values compared to near-zero values is quite large for Ivan and Floyd, as previously discussed, such that even after a logarithmic transformation the likelihood of achieving approximate normality is low. Further analysis of Figure 4.1.22 shows that while the resulting distributions are no longer exponential, the zero values, when significant in quantity, induce a bimodal distribution. Analyzing the non-zero values independently from the zero values (i.e., isolating the first and second modes in the distribution), however, reveals that regardless of the zero value field the \ln\text{DRP} dataset would still be negatively skewed.

Certainly there are additional ways to handle the existence of zero data while performing a logarithmic transformation. For example, once could perform the transformation after universally adding an arbitrary value to each observation [i.e., \ln(1+Z(x))], such that any alteration of the data would be consistent across all observations. In this example, while the method is somewhat less subjective than the elementary and exclusive shift of zero values, the method does not eliminate the underlying bimodal and non-continuous characteristics of the distribution, nor would it correct the lack of normality in the distribution of non-zero observations. These and other issues discussed throughout this research suggest more advanced approaches are still required if one seeks to normalize the original precipitation dataset prior to analysis.

The logarithmic transformation is arguably the most common transformation; it is preferred in situations where the original dataset is positively skewed as the logarithmic curve tends to shrink larger values inward. This type of distribution is common among precipitation datasets, and, based on the original DRP distributions, it appears to be appropriate here. The results above suggest that, zero values aside, the logarithmic transformation overcompensates by truncating the positive tail too severely while excessively elongating the negative tail. Additional transformations could be tried on the original DRP dataset. For example, the square-root transformation is documented to have a weaker shrinking effect (Tamhane and Dunlop 2000) and may be more effective. However, the square-root transformation would not correct the non-negativity issue. Furthermore, the
success of any transformation will be dependent not only on the size of the sample and thus the domain, but also on the precipitation event itself, such that no single DRP distribution can be anticipated across all regimes nor can any one transformation technique be expected to successfully modify the distribution every time. This is why, regardless of the original distribution or the transformation technique, the principal objective is to produce a set of kriging and trend model residuals whose distributions are approximately normal.

4.2 IDW Performance

4.2.1 Non-Spatial Distribution Analysis

Substantial distribution differences exist between the IDW interpolated daily precipitation (IDP) grids, the DRP datasets upon which they are derived, and the MPE gridded output for the daily scale. From the basic statistics in Table 4.2.1, IDWIDP has a significant negative shift in the distributions of Frances and Ivan with ~-15 to -30 mm differences in the mean and 75th percentiles and ~-7 to -15 mm shifts in the median. In contrast, IDWIDP for Floyd actually records a positive shift of approximately 43 mm in the 75th percentile with a very minor positive adjustment in the median and a 13 mm shift in the mean. Prediction performance for the maximum amounts was somewhat more erratic since the ability to capture these extreme values is largely dependent on gauge location relative to the nearest grid cell. Not surprisingly, where the distance was negligible, as in Floyd, the sampling of extreme values was good and where the separation was larger, as in Frances and Ivan, the maximum DRP value was underestimated by ~20-30 mm. With respect to MPE, IDW underestimated the overall field by ~7-15 mm in Frances and Ivan.

Similar conclusions can be drawn by examining the non-zero histogram for Floyd and the full-range histograms for Frances and Ivan as shown in Figure 4.2.1. While the overall shape of the distributions do not change from DRP to IDWIDP in any daily case, for Frances and Ivan near-zero (<10 mm) values increase by 12% and 15%, respectively, while overall percentages for each histogram bin decrease slightly compared to DRP. Recalling the density of observations over the precipitation axis across the Coastal Plain, gauge sampling is of particular issue for Floyd as evidenced by the presence of several histogram bins with few
or zero samples. The IDWIDP histogram for Floyd reveals the interpolator smoothes the inconsistent DRP distribution especially when values exceed 100 mm, resulting in the large positive shift previously noted. It is unfortunate MPE output is not available for 1999; it is hypothesized that the DRP dataset underestimates the overall field due to this sampling bias.

4.2.2 Spatial Distribution Analysis

Perhaps most notable in the examination of the spatial distribution is the unrealistically blotchy appearance to the spatial field typical of IDW (Figure. 4.2.2). As previously discussed, the realism of the estimated spatial field is primarily a function of gauge density and measurement accuracy, as the only assumption made between grid points is that the influence of surrounding gauges is a function of distance to an arbitrary power \( p \). Despite improved sampling in the western third of the domain, several precipitation maxima evident in MPE output escape the gauge network and are therefore nonexistent in the IDWIDP field, regardless of the resolution of the prediction grid. Additionally, the dependency on the gauge network tends to shift the axes of heaviest precipitation in the Frances and Ivan cases. All of these limitations indicate that there is little advantage to projecting IDW on high-density prediction grids.

Analysis of the spatial distribution in the coastal plains during Hurricanes Frances and Ivan reveals near-zero gauge measurements were overrepresented in the IDWIDP field due to the large radius of influence many of the measurements were given in an area with low site density. It is proposed that a decrease in the power of IDW would mitigate the underestimation in this region. Reducing the power \( p \) is not a consistent solution, however. For example, it would be a detriment to large maximum precipitation axes while beneficially decreasing the influence of gauges that lie in narrow convective bands. Lower resolution prediction grids would effectively reduce the radius of influence as well by reducing the probability that any gauge is close enough to the nearest grid cell to be exactly interpolated; however, results show that lower resolution grids average out the entire field, diluting the influence of significant accumulations and further underestimating the spatial field.
4.2.3 Cross-Validation Analysis

Without the ability to measure spatial variance, cross-validation statistics are provided with caution. Nevertheless, RMSE values range from 1.63 ln(mm) for Floyd to 2.03 ln(mm) for Ivan, suggesting large scatter and significant mean standard deviation or variance (RMSE$^2$) in the prediction (Table 4.2.2). Scatterplots of actual versus predicted precipitation as shown in Figure 4.2.3 indicate a significant increase in scatter for lighter values of precipitation as errors grow quite large for actual values <4 ln(mm). Also evident is the minimal skill in the prediction of zero values, as nearly the entire range of predicted values is used. It will be shown from scatterplots produced during cross-validation of the OK output that there are significant similarities between OK and IDW when assessing the relationships between error and actual/predicted values. Plots of error versus predicted values as shown in Figure 4.2.4 confirm the inverse relationship between the scatter of errors and the value of the prediction as well as the overestimation bias in the zero fields. Clearly, two clusters of data exist for these fields separating the predictions of the zero and non-zero fields. In all cases a clear negative linear trend exists for both clusters, yet if the clusters are combined it appears overall bias in the predictor would be minimal. As a result, the significance of the zero field makes drawing conclusions about the unbiasedness of the predictor difficult without first isolating these signals. This is an issue which will reappear in both OK and KED output.

4.3 OK Performance

4.3.1 Semivariogram Analysis

Experimental semivariograms of the single-day lnDRP datasets for Floyd and Ivan challenge the assumptions required as part of the OK geostatistical model. Non-stationarity is inferred from the linear semivariograms shown in Figures 4.3.1a and 4.3.1c, though it may be argued that subtle Gaussian behavior exists at short and large lags. Nevertheless, semivariance is exceptionally large in these cases, exceeding 20 [ln(mm)]$^2$ at 500 km in Ivan and 30 [ln(mm)]$^2$ in Floyd, indicative of the banding nature of the precipitation pattern and the wide distribution of rain totals across the domain. Frances was the clear outlier, as shown
by Figure 4.3.1b, for despite the assumption of a constant mean the associated dataset was able to produce an experimental semivariogram that resembled a spherical or perhaps an exponential function through 700 km with a sample sill of \( \sim 5 \ln(\text{mm})^2 \).

In all three cases, point pair analysis (using lag classes with 4 km range) indicates <30 point pairs exist at distances less than \( \sim 8-12 \) km and greater than \( \sim 800 \) km. While WNLS model fitting adjusts weights based on the number of point pairs in each lag class, and ML/REML approaches are independent of the experimental semivariogram, the point pair analysis reveals the following: 1) experimental analysis at these very short and very long distances will likely be unstable due to insufficient sampling; and more importantly, 2) very few gauges are separated by distances that rival the resolution of MPE. In other words, there is very little DRP data available to assess the variability of precipitation at distances of \( \sim 10 \) km and less. As a result, the user is left to rely on more abundant point pairs at lags of considerably lower resolution to derive a continuous ISIP SV function at small distances, regardless of the fitting method used to determine SV function parameters.

As discussed in Chapter 1, the lack of point pairs at high resolutions results in microvariability, or variability that cannot be estimated from the sample. In addition, measurement errors inherent in the instrumentation are anticipated, though their exact significance is unknown (i.e., a sufficient sample of collocated gauges is required). The combination of these factors implies the user should expect to see non-zero nuggets in all spatial analyses of gauge data. The dangers in ignoring the effects of microvariability are evident in each of the three cases, for the estimated semivariograms suggest either little or no nugget effect is present at the 0-4 km lag while the overall trend of the estimated spatial variance suggests the 0-4 km semivariogram estimates are outliers. In fact, the resultant SV model parameters provided in Table 4.3.1 confirm, regardless of technique, the estimated nugget effect is large and significant. For example, the nugget effect for Hurricane Frances on the daily scale represents \( \sim 40\% \) of the total spatial variability as estimated by the REML technique. While the proportions of nugget effect on the total variability are smaller for all techniques used in Floyd and Ivan, partial sills are considerably higher due to the suggested non-stationarity of the spatial fields. There also appears to be an inverse relationship
between the nugget effect and the slope of the function regardless of stationarity. For example, the WNLS-fitted model in Frances produces a relatively small nugget yet a large and positive spatial variance slope to result in a partial sill much larger than estimated using REML.

Not surprisingly, analysis\(^6\) of directional experimental semivariograms (Figure 4.3.2) for all storms suggests severe sill and potential range anisotropy, though these conditions are most evident in Floyd and Ivan. Directional semivariograms for Frances suggest nearly isotropic conditions through ~250 km despite the presence of sill anisotropy approximately maximized along the 70\(^o\)-250\(^o\) [ENE – west-southwest (WSW)] axis. Variability is minimized along the N-S axis during Floyd while maximized along the E-W axis, which is consistent with the orientation of the precipitation axis; however, Floyd had little favorable interaction with the terrain further west. The same variability trends were also true for Ivan while the opposite was subtly observed for Frances, despite the fact that the storm path for Ivan had a greater E-W component. It is believed the westward shift in Ivan’s track, which resulted in a consistent axis of rain along the domain’s western boundary and a fairly consistent lack of rain across much of the eastern half of the domain, reduced N-S variability while maximizing E-W variability. The localized shadow effect in NE TN further amplifies these dependencies. However, the focus of maximum precipitation along the Blue Ridge and western Piedmont in Frances flanked by lighter accumulations to the east and west explains the minimized E-W gradient despite similar initial storm motion. Therefore, isotropic assumptions cannot be correlated to storm motion; in these cases it is clear longitudinal shifts and the resultant changes in orographic interaction are more responsible for deviations from isotropy. How much these physical features contribute to a problem that is also a function of domain size (i.e., spatial scale) is unclear. Nevertheless, anisotropic correction factors obtained from ML/REML estimation (Table 4.3.1) largely confirm what can already be observed from the sample dataset. In both Floyd and Ivan the anisotropic ratios are substantial with the axis being stretched from ~215% to ~250%.

\(^6\) This research will not attempt to make inferences about the presence of nugget anisotropy due to the limitations of the DRP dataset at small lags.
While multiple SV models and fitting techniques were analyzed during the course of the research, the final analysis attempts to address the significance of performing ML/REML assuming isotropy versus adjusting for anisotropy and the performance of the ML/REML techniques compared to the performance of isotropic WNLS (WNLS fits to the experimental semivariograms are shown in Figure 4.3.1). Figures 4.3.3, 4.3.4, and 4.3.5 show both the ML/REML models derived assuming isotropy and those derived after anisotropic correction for Floyd, Frances, and Ivan respectively. Overall, few general conclusions can be made based on all three storms. While REML is the preferred estimation technique as discussed in subsection 1.3.11, for both Floyd and Ivan the resultant REML parameters were unrealistic and unstable, suggesting point pair dependencies at distances several times larger than the domain of study as well as the domain of the storms themselves. The instability exhibited by REML is likely due to its greater dependency on intrinsic stationarity (subsection 1.3.11), an assumption which is clearly violated for both Floyd and Ivan. In contrast, REML parameter estimates are more stable in Frances where the estimated semivariogram infers stationarity. Furthermore, the lack of a normally distributed random field in both Floyd and Ivan, largely due to the large area of near-zero values, questions the validity of using ML/REML to derive SV parameters from the InDRP dataset. Regardless, little variation exists between anisotropic and isotropic ML/REML parameter estimates in any of the cases. This is especially true for the nugget and beta parameters, though these estimates are less dependent on anisotropic characteristics present at larger lags. The largest discrepancies occurred in range and partial sill estimates for Ivan. In most circumstances, however, near independent conditions were estimated to be beyond 800 km for the non-stationary fields and beyond 600 km for Frances using the ML/REML techniques.

Table 4.3.1 exhibits, for the most part, that the sensitivity between ML/REML and WNLS estimation is greater than the sensitivity between ML/REML anisotropic and isotropic estimation. The use of WNLS in all cases results in higher partial sills and steeper slopes resulting in smaller ranges on the order of ~450-575 km, though these results are not surprising considering in all cases the experimental semivariogram suggests greater spatial variance than estimated by ML/REML. However, due to the inability of the user to make
direct comparisons between the estimated semivariogram and SV models derived from the
ML/REML technique, it is unclear exactly how detrimental flawed assumptions are in
converging upon an accurate SV model. It is also unclear how those same SV models impact
the final prediction. Therefore, in the following subsections the significance of parameter
differences and model selection will be analyzed through the study of the predicted fields and
cross-validation statistics.

4.3.2 Non-Spatial Distribution Analysis

Despite dramatic differences between the three approaches to SV model parameter
estimation, the non-spatial distribution of the OKIDP datasets suggest very little sensitivity
of the OKIDP model to the ML, REML, and WNLS techniques or the adjustments made to
account for anisotropy. Studying the data presented in Table 4.3.2, OK underestimates
accumulations in the majority of quartiles from all cases regardless of the parameter
estimation technique. The ML/REML techniques perform the most consistently across
different cases and adjustments for significant anisotropy do very little to produce more
realistic non-spatial distributions. Meanwhile, performance from the WNLS approach is
erratic, especially in the upper quartile. The approach outperformed the ML/REML
techniques by a significant margin during Floyd, made slight improvements to the
distribution during Frances, but performed poorly during Ivan.

Ordinary kriging provides no improvement to the non-spatial distributions produced
using IDW. Through the 50th percentile, the OK-predicted precipitation distributions are
nearly identical to IDW distributions with differences of <2 mm. OK-predicted mean values
average ~2-6 mm less than IDW predictions. However, by the 75th percentile, differences
between the two interpolation schemes become more significant. OK behavior is most
inconsistent for Hurricane Floyd where differences with IDW range from ~1 mm for ML to
~23 mm for the WNLS fit. OK performance continues to deteriorate across the fourth
quartile such that, with only one exception, maximum value performance across all cases and
SV models is very poor. In Floyd, the maximum OKIDP value predicted using a WNLS-
fitted SV model differs from the maximum IDWIDP and DRP values by only ~18 mm.
However, for the ML techniques in Floyd and all cases in both Frances and Ivan, the discrepancies between IDWIDP, DRP, and MPE values (when available) increased to ~150-240 mm. From these results, it should be clear that the significant nugget effects estimated for each case act to generalize or smooth the small-scale variability and effectively filter out the areas of heaviest precipitation. In these circumstances, the inability of IDW to account for spatial variance requires it to have a greater dependency on precipitation measurements and allows it to outperform OK within the positive tail of the distribution.

The underestimation bias in the OKIDP output can be easily seen from the non-zero (Floyd) and full-range histograms (Frances and Ivan) shown in Figure 4.3.6. Analysis of the shape of the non-spatial distribution reveals OK performs inconsistently across different cases with no one approach yielding generally better results. For example, near-zero prediction performance was equally inconsistent between cases. However, performance was generally consistent within each case with good performance in Floyd and Frances (compared to MPE) and poorer performance in Ivan, where significant overestimation of 0-10 mm values (>55% of total distribution versus 45% for MPE) and underestimation of 10-20 mm values (5% versus 12%) occurred. Histograms also reveal previously discussed OK characteristics. The distributions are often abruptly terminated in the upper percentiles, most notably by the WNLS variation of OK for Ivan. While the IDW histograms tend to be more sensitive to smaller variations in DRP, OK histograms resemble the smoother generalization of the expected field. Nevertheless, the non-spatial distributions from OK offer no notable improvement beyond IDW and cannot better replicate the distribution provided by MPE.

4.3.3 Spatial Distribution Analysis

4.3.3.1 Mapping Analysis

Regardless of the various SV models used, OK does not fare much better upon analysis of its resultant spatial fields. Each case reports a unique set of results. The worst predictions came from WNLS-fitted SV models which were applied to non-stationary

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7 Spatial field performance is evaluated using MPE output as the standard or closest estimate of truth.
experimental semivariograms. The Gaussian WNLS-fitted model used for Floyd may have yielded the most realistic maximum amount, but it displaced the location ~150 km inland to the Johnston-Sampson County border, netting the most unrealistic spatial distribution and exhibiting nearly zero skill (Figure 4.3.7c). Meanwhile, the WNLS-fitted Gaussian model used for Ivan (Figure 4.3.9c) places its precipitation axis across E TN over a region experiencing a downslope component to the low-level flow and consequently minimized precipitation accumulations. In Frances, however, where the experimental semivariogram suggested a stationary sample field, the WNLS fit provides the best resolution of both light and heavy precipitation features with the highest spatial accuracy (Figure 4.3.8c). In both unsuccessful cases the conclusion is two-fold. First, the Gaussian ISIP SV function is not a realistic model of the DRP spatial field, much less the true spatial field. Second, the failure of the Gaussian function combined with the fact that both exponential and spherical model WNLS fits were essentially linear functions within the domain of study confirm the non-stationarity of the sample fields and the violation of the assumptions required to make OK a BLUE.

Where anisotropy is the most significant (i.e., in Floyd and Ivan) the most notable differences between the two ML/REML SV functions were 1) the clear stretching of the precipitation pattern along the axis of least variance, exactly 0° for Floyd (Figure 4.3.7b) and 19° for Ivan (Figure 4.3.9b); and 2) the shifts in the placement of maximum predictions. Not surprisingly in Frances, where directional semivariograms suggested less direction dependency, the field differences were insignificant, allowing the conclusion that anisotropy at sufficiently large lags (i.e., especially lags beyond the estimated range) yields little impact on the derived SV model parameters or the predicted precipitation distribution. Within both Floyd and Ivan, corrections for anisotropy unrealistically displaced maximum amounts approximately 30-40 km to the N and NE, respectively. Overall, no improvement of the predicted field occurred with anisotropic correction even when experimental analysis suggested significant anisotropy at relatively short lags.

OK predictions yield very smooth representations of the true field with little resolving of the precipitation patterns or storm structure evident in MPE output. At best, the
suggestion of precipitation banding during Frances is subtle. Close inspection of the Frances and Ivan fields reveals the difficulty in placing the axes of maximum precipitation in the correct locations, with errors on the order of 10s of kilometers. Ivan OK fields accurately predict the presence of the Blue Ridge precipitation axis and Frances OK fields generally target the area of maximum accumulations. However, in neither case can OK resolve the small-scale maxima and minima present as each storm interacted with the local terrain. In other words, the spatial fields clearly illustrate a failure of OK to provide the detail necessary to classify its grids as high-resolution. Despite predictions to 4 km, the overall resolution is much coarser, perhaps as low as 30-50 km. If anything, OK predictions may only be suitable for the same quick or rough estimate of the field originally attributed to IDW predictions. However, IDW is more sensitive to individual gauge locations and produces better non-spatial distributions at higher percentiles, all while requiring a significantly smaller workload.

4.3.3.2 Spatial Analysis of Standard Deviation

Figures 4.3.10, 4.3.11, and 4.3.12 are plots of the OK standard deviation fields derived from the various SV models used in Floyd, Frances, and Ivan, respectively. From all plots it is clear that standard deviation is a function of gauge density, as the largest kriging weights are applied to the gauges with the shortest lags. With all exponential and spherical models it is a useful tool for identifying dense and sparse gauge placement, contrasting the dense coverage within several urban areas, the western Piedmont, and Appalachian Mountains with the pockets of very poor coverage in the coastal plains and parts of the central Piedmont. Around the domain boundary in all cases the standard deviation increases sharply to reflect the ignoring of gauges outside the domain and the obvious lack of gauges over the ocean. Furthermore, downward spikes in the standard deviation field indicate the proximity of a gauge to a prediction grid point. In other words, the shorter the lag, the smaller the SV function such that collocated gauges and prediction points will have a standard deviation equal to the square-root of the nugget effect. Overall, however, total variability in the standard deviation is small, significant to the tenth of a ln(mm).
Anisotropic correction stretches the standard deviation field along the axis of least variance and also tends to produce slightly lower values compared to the uncorrected model. Additionally, the SV models themselves leave imprints on the standard deviation fields. The asymptotic nature of the Gaussian function at small lags appears to have strong influence on the standard deviation plots for Floyd (Fig. 4.3.10c) and Ivan (Fig. 4.3.12c). The results are smooth, nearly constant standard deviations whose values are generally smaller than those resulting from the exponential and spherical models, both of which have much steeper slopes over the same short lags.

4.3.4 Cross-Validation and Analysis of Orthonormality

Recall from the above spatial analysis that the determined “best” SV models, in other words, those models producing the most realistic spatial fields, were the ML-derived SV models uncorrected for anisotropy in Floyd and Ivan and the WNLS-fitted exponential model for Frances. Also recall that one of the many objectives in this research is to investigate the level of consistency between cross-validation statistics and the predicted spatial fields. Therefore, as a result of performing cross-validation on the OK technique, numerous performance metrics are available in Tables 4.3.3 and 4.3.4 in order to investigate the ability of OK to produce minimized, normal, and unbiased prediction errors. The metrics suggest that the OK technique is not completely successful at yielding unbiased predictions and thus normally distributed, orthonormal (i.e., uncorrelated) errors. RMSSE, which resembles the ratio of RMSE to the RMKV (see Section 1.6), suggests that the ML/REML techniques whose SV models are uncorrected for anisotropy produce the least bias and yield OK error distributions that best approximate normality regardless of case. However, despite having higher RMSSEs, anisotropically corrected ML/REML-derived SV models actually yield the lowest RMSEs. Therefore, of the studied OK techniques, they are the “best” in that they minimize the error of the prediction, but they are not the most unbiased predictors. It will be shown that these inconsistencies between the various SV models are evident across a wide array of cross-validation statistics and graphics.
4.3.4.1 SError Distribution Analysis

Regardless of the SV model used, Table 4.3.4 indicates that the mean of the SError distribution is near zero while the median is greater than zero, suggesting an underestimation bias in the prediction. This signal is strongest in Frances, where there is a significant negative tail, and weakest in Floyd. The negative tail indicates there is a tendency to make larger over-predictions compared to under-predictions, despite the fact that overall, the models make more under-predictions of a smaller magnitude. The largest over-predictions occur in Frances which may suggest a correlation to the level of performance of OK when the actual accumulation is zero. For example, in Frances, where there are the fewest zero reports, the small sample is interpreted as a set of outliers and OK exhibits little skill. In Floyd and Ivan, however, despite a larger number of zero values and the fact that the minimum errors are of similar magnitude to Frances’s minimum errors, the fact that the median and mean spreads are smaller than those observed in Frances suggest a smaller proportion of zero values are treated as outliers. This may make sense if it is assumed that, overall, the large areas of zero values in both Floyd and Ivan are actually not as unstable as the zero values embedded within or located near non-zero values. This concept will become clearer during the discussion of KED.

Nevertheless, within each case, as suggested by the statistics in Table 4.3.2, the bias in the prediction is indeed heavily dependent on the SV model used. Indeed, when compared to the ML/REML derived models in each case, the WNLS-fitted Gaussian model for Floyd is the most unstable with the longest positive and negative tails, followed by the WNLS-fitted exponential model for Frances, and finally the WNLS-fitted Gaussian model for Ivan. Concurrently, the WNLS-fitted fields also have the largest RMSSE values and the largest RMSEs within each case compared to the ML/REML-derived SV models. Analysis of the 25th and 75th percentiles reinforce the high RMSE values, indicating that the WNLS approach may have heavier distributions away from the median, suggesting fewer errors are located near zero. Interestingly however, in both Floyd and Frances, the WNLS-fitted SV models yield the lowest RMKVVs by a significant margin. The wide spread between RMSE and RMKV in each WNLS approach suggests that OK in these circumstances may have the
greatest precision, but it is also the most unreliable or least accurate technique of those investigated. While these performance conclusions reinforce the spatial analysis of WNLS OK fields in Floyd and Ivan, they contradict favorable performance observed qualitatively in Frances. Meanwhile, between the corrected and uncorrected ML/REML approaches in each case, differences in the distribution statistics are fairly small in most circumstances. The greatest discrepancies occur with the minimum SError for Floyd and in Ivan’s first quartile error and SError distributions. In both cases the anisotropically corrected SV model yields longer negative tails, suggesting the uncorrected SV models yield slightly more normal distributions.

SError distributions for the uncorrected ML/REML-derived SV model and the WNLS-fitted SV model in each case are visually represented by probability density histograms and normal QQ plots in Figures 4.3.13, 4.3.14, and 4.3.15 for Floyd, Frances, and Ivan, respectively. All histograms indicate a greater percentage of SError values are positive in all three cases, though the majority of these values are less than 1 ln(mm). Adjacent to each corresponding histogram in Figures 4.3.13-15, normal QQ plots of selected SErrors confirm the light-tailed distributions evident for all three cases. In contrast, the centers of the distributions are heavy, especially for the ML/REML-derived SError distributions, as indicated by the shallow slopes within the QQ plots. While the exceedingly high percentages of near-zero SError values deviate the distributions from normality, it also indicates that a majority of estimates are within 1 ln(mm) of the measured value, which can be considered a favorable metric for OK when considering overall reliability. Furthermore, the QQ plots confirm the inconsistent behavior of the distributions, making selection of a distribution that best approximates normality difficult. For example, the WNLS derivations of the field produce SError distributions that best approximate normality for all three cases primarily via improved distributions in the middle two quartiles, yet have longer tails than the ML/REML-derived SError distributions. Notice how the original concern, from Table 4.3.4 was accurate: the WNLS SError distribution had a larger number of values that were not near zero. However, the resultant distribution has a more normal shape near zero, showing, once again, the value of a thorough analysis of multiple performance metrics. Additionally,
despite the presence of a large near-zero and zero field, Ivan’s SError distribution, especially for ML/REML-derived SV models, best approximate normality regardless of case.

4.3.4.2 Containment Percentages

In order to investigate the cross-validation results, the Geos2MAP model produces several scatterplots comparing error, SError, and actual and predicted precipitation values. Scatterplots of actual versus predicted values for the three SV models used in each case are provided in Figures 4.3.16-18. Included in those plots are the 95% CIs. With large nugget effects in place even the closest gauges to the prediction points will produce high kriging variances. Immediately, the general tendency of the geostatistical model will be to produce smoothed representations of the actual field. Nevertheless, as discussed in Section 1.6, if the estimated SV function is an approximation of the true SV in the spatial field, the actual value should lie within the CI established by the kriging variance\(^8\). Therefore, despite inherent limitations in the kriging technique, a well-calibrated model should have the truth embedded in its CIs. In all events, cross-validation of ML/REML-derived SV models yielded a greater percentage of actual values within the 95% CI (i.e., containment percentage) when compared to the WNLS approach. This observation holds for Frances where the sample data suggest stationarity and WNLS produced a superior spatial field. In Frances the improvement was about 2.5% from 93.2% to 95.7%, for Ivan it was 3.0% from 90.5% to 93.5%, and in Floyd the improvement was most significant, as containment increased 6.0% from 85.6% to 91.6%. With >90% containment of the actual values within the 95% CIs for Floyd and Ivan, the SV models have good calibration while calibration is very good in Frances with >95% containment. SV models accounting for anisotropy yielded nearly identical scatterplots with very similar CIs and therefore provided identical containment percentages (significant to 0.1%). Nevertheless, it is clear from all cases that the minimal skill in the prediction of zero

\(^8\) CIs are calculated assuming a normally distributed predicted field. In the cases presented herein, approximate normality is not obtained even after a logarithmic transformation, so the calculated CIs must be used with caution, and only as approximations.
values negatively contributed to the containment percentages. In Frances, for example, none of the zero values in the actual DRP dataset were predicted within the 95% CIs.

4.3.4.3 Relationship between SError and Predicted Values

Scatterplots of SError versus predicted values for isotropic ML SV models in Floyd and Ivan and for the WNLS-derived SV model in Frances are provided in Figure 4.3.19. Many of the same conclusions drawn from the IDW scatterplots are applicable here. For the largest values, generally greater than 4 ln(mm), SError is comparatively minimal in all cases. However, as with IDW, the presence of the zero field in each case negatively impacts the validity of assumptions made for OK. For example, in Floyd and Ivan, almost all predictions of zero values are overestimates, balancing the notable underestimation bias in the prediction of non-zero values. Considering each cluster of predictions independently suggests the use of RMSSE to assess the unbiased properties of OK may not be entirely appropriate when a bimodal distribution is evident. Evident in all cases, there is also an obvious inverse relationship between the predicted precipitation and the scatter of SErrors. The presence of a negative linear trend in the relationship between SError and predicted precipitation values suggests a strong non-random signal in the residuals and thus, a non-constant trend and correlated errors (i.e., non-orthonormality). Interestingly, if one isolates the highest predictions little trend is evident. Furthermore, where stationarity was implied (i.e., Frances), this trend is significantly weaker, which should be an obvious relationship if conclusions drawn from the experimental semivariograms are accepted.

4.3.4.4 Relationship between OKIDP Performance and Cross-Validation Metrics (Final Conclusions)

All variations of the OK prediction for each case demarcated the zero accumulation line reasonably well. However, similar to the maximum amounts, isolated non-zero gauge reports embedded in the zero field were poorly predicted if represented at all. The lack of predictability of small-scale patterns indicative of showers, such as those associated with convective cells, is part of a circular problem in that the smoothed predicted field is due to
the presence of a large nugget effect which, in turn, exists due to large quantities of small-scale variability. The same phenomenon is responsible for the lack of upper-percentile accuracy. In other words, natural variability is its own worst enemy in terms of empirical mapping, and it is important to remember that OK is performing exactly as designed; these examples only highlight the many shortcomings inherent in the approach. For example, the various OK approaches in each case show good to very good calibration from cross-validation statistics but still poorly reproduce the spatial field due to high kriging variance. Furthermore, note all OK models improve on the RMSE calculated for IDW. It is clear, however, that RMSE serves as a poor and inconsistent metric of the overall quality of the predicted field. The anisotropically corrected SV models produce the lowest RMSEs but also produce inferior spatial fields, identical containment percentages, and higher RMSSEs compared to the uncorrected ML/REML models.

At this point, considering the poor adhesion to geostatistical assumptions in addition to the cross-validation statistics, it is likely that the IDW fields would be preferred across a wide variety of applications, especially where computationally inexpensive modeling is required. However, based on the plethora of performance metrics, if using OK, which model should be chosen in each case? The comparison of predicted fields to cross-validation results suggest that sacrificing precision for reduced bias generally results in a more attractive spatial field, favoring the uncorrected ML-derived exponential models in Floyd and Ivan. In Frances, despite a higher RMSE (i.e., lower precision), higher RMSSE (i.e., higher bias), and a lower containment percentage (i.e., worse calibration), the resultant spatial field better captures spatial patterns and maximum values present in the original DRP dataset. Thus, while the uncorrected spherical model derived from REML is the “best” model in that it is more statistically sound, the WNLS-fitted exponential model may produce a more realistic spatial field. Comparison of the models’ parameters suggest that the significantly lower nugget effect predicted from the WNLS-fit may be responsible for the improved spatial patterns in the final field as DRP values exert a greater influence on the prediction. However, overall cross-validation performance may be due to the significantly higher total sill and shorter range, which creates a large slope such that spatial variance increases much
more quickly than via the REML OK approaches, decreasing the likelihood that OK will predict accurately during cross-validation. These and other inconsistencies emphasize the importance of thoroughly evaluating and cross-referencing the performance metrics and statistics with the spatial and non-spatial distributions. Certainly, no matter what the metric, based on this analysis, OK is not a BLUE and the presence of correlated errors suggest regardless of the “best” OK approach, a better interpolation technique must exist.
Table 4.1.1. Basic distribution statistics for DRP data collected during Hurricane Floyd. Represented are two time intervals: 1) 1200 UTC on 15 September 1999 to 1200 UTC on 16 September 1999; and 2) 1200 UTC on 13 September 1999 to 1200 UTC on 17 September 1999. Information is presented with accepted gauge data only. From left to right the basic statistics are comprised of the minimum (mm); the 1st quartile or 25th percentile (mm); the 2nd quartile, 50th percentile, or median (mm); the mean; the 3rd quartile or 75th percentile (mm); and the maximum (mm).

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Table 4.1.2. Basic distribution statistics for DRP data collected during Hurricane Frances. Represented are two time intervals: 1) 1200 UTC on 7 September 2004 to 1200 UTC on 8 September 2004; and 2) 1200 UTC on 4 September 2004 to 1200 UTC on 10 September 2004. Information is presented with accepted gauge data only. From left to right the basic statistics are comprised of the minimum (mm); the 1st quartile or 25th percentile (mm); the 2nd quartile, 50th percentile, or median (mm); the mean; the 3rd quartile or 75th percentile (mm); and the maximum (mm).

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Table 4.1.3. Basic distribution statistics for MPE output collected during Hurricane Frances. Represented are two time intervals: 1) 1200 UTC on 7 September 2004 to 1200 UTC on 8 September 2004; and 2) 1200 UTC on 4 September 2004 to 1200 UTC on 10 September 2004. Summaries including and excluding MPE grid points over the ocean are provided. From left to right the basic statistics are comprised of the minimum (mm); the 1st quartile or 25th percentile (mm); the 2nd quartile, 50th percentile, or median (mm); the mean (mm); the 3rd quartile or 75th percentile (mm); and the maximum (mm).

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Table 4.1.4. Basic distribution statistics for DRP data collected during Hurricane Ivan. Represented are two time intervals: 1) 1200 UTC on 16 September 2004 to 1200 UTC on 17 September 2004; and 2) 1200 UTC on 15 September 2004 to 1200 UTC on 20 September 2004. Information is presented with accepted gauge data only. From left to right the basic statistics are comprised of the minimum (mm); the 1st quartile or 25th percentile (mm); the 2nd quartile, 50th percentile, or median (mm); the mean (mm); the 3rd quartile or 75th percentile (mm); and the maximum (mm).

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Table 4.1.5. Basic distribution statistics for MPE output collected during Hurricane Ivan. Represented are two time intervals: 1) 1200 UTC on 16 September 2004 to 1200 UTC on 17 September 2004; and 2) 1200 UTC on 15 September 2004 to 1200 UTC on 20 September 2004. Summaries including and excluding MPE grid points over the ocean are provided. From left to right the basic statistics are comprised of the minimum (mm); the 1st quartile or 25th percentile (mm); the 2nd quartile, 50th percentile, or median (mm); the mean (mm); the 3rd quartile or 75th percentile (mm); and the maximum (mm).

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Table 4.1.6. DRP quality-control statistics for (a) 16 September 1999, (b) 8 September 2004, and (c) 17 September 2004. Individual state statistics are provided followed by domain totals. From left to right the provided statistics are the initial number of gauges available as reported by the NCDC station lists (I); the number of gauges reporting missing data (M); the number of gauges with no data reported (ND); the number of gauges rejected due to poor reporting times (RT); the total number of gauges available after removal of M, ND, and RT data (AQC); the percent of accepted gauges (%A); the percent of rejected gauges (%R); and the number of gauges with reporting times of 2400 local time (ASOS?), representing likely ASOS gauges rejected due to poor reporting times. Poor reporting times are defined as reporting hours that are earlier than 0500 local time or later than 1000 local time.

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Unaccounted Gauges: 4
Sites w/ Missing Covariates: 1
Co-Located Gauges: 0
Gauges Available for Analysis: 380
| State | IM | ND | RT | AQC | %A | %R | ASOS?
|------|----|----|----|-----|----|----|-----
| GA   | 130| 3  | 24 | 12  | 91 | 70 | 30  | 8   |
| KY   | 35 | 0  | 15 | 2   | 18 | 51.4| 48.6| 1   |
| NC   | 195| 1  | 27 | 42  | 125| 64.1| 35.9| 24  |
| SC   | 113| 1  | 21 | 22  | 69 | 61.1| 38.9| 11  |
| TN   | 44 | 0  | 5  | 10  | 29 | 65.9| 34.1| 6   |
| VA   | 89 | 1  | 9  | 15  | 64 | 71.9| 28.1| 10  |
| WV   | 7  | 0  | 1  | 1   | 5  | 71.4| 28.6| 1   |
| TOTAL| 613| 6  | 102| 104 | 401| 65.4| 34.6| 61  |

Unaccounted Gauges: 2
Sites w/ Missing Covariates: 0
Co-Located Gauges: 2
Gauges Available for Analysis: 398

| State | IM | ND | RT | AQC | %A | %R | ASOS?
|------|----|----|----|-----|----|----|-----
| GA   | 130| 0  | 24 | 12  | 94 | 72.3| 27.7| 8   |
| KY   | 35 | 0  | 15 | 2   | 18 | 51.4| 48.6| 1   |
| NC   | 195| 5  | 27 | 40  | 123| 63.1| 36.9| 24  |
| SC   | 113| 2  | 21 | 22  | 68 | 60.2| 39.8| 11  |
| TN   | 44 | 0  | 5  | 10  | 29 | 65.9| 34.1| 6   |
| VA   | 89 | 1  | 9  | 15  | 64 | 71.9| 28.1| 10  |
| WV   | 7  | 0  | 1  | 1   | 5  | 71.4| 28.6| 1   |
| TOTAL| 613| 8  | 102| 102 | 401| 65.4| 34.6| 61  |

Unaccounted Gauges: 2
Sites w/ Missing Covariates: 0
Co-Located Gauges: 2
Gauges Available for Analysis: 398
Table 4.2.1. Basic distribution statistics for IDWIDP output for (a) 16 September 1999, (b) 8 September 2004, and (c) 17 September 2004. From left to right the basic statistics are comprised of the minimum (mm); the 1st quartile or 25\textsuperscript{th} percentile (mm); the 2\textsuperscript{nd} quartile, 50\textsuperscript{th} percentile, or median (mm); the mean (mm); the 3\textsuperscript{rd} quartile or 75\textsuperscript{th} percentile (mm); and the maximum (mm).

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<td>20040917-17</td>
<td>0.010</td>
<td>0.255</td>
<td>7.485</td>
<td>30.340</td>
<td>46.990</td>
<td>310.200</td>
</tr>
</tbody>
</table>

Table 4.2.2. Cross-validation statistics for IDWIDP output for (a) 16 September 1999, (b) 8 September 2004, and (c) 17 September 2004. From left to right the provided statistics are the correlation between predicted and actual values (corPA, unitless); the correlation between actual values and the associated error (corEA, unitless); and the root mean square error [RMSE, ln(mm)].

<table>
<thead>
<tr>
<th></th>
<th>CorPA</th>
<th>CorEA</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>19990916-16</td>
<td>0.920</td>
<td>0.340</td>
<td>1.630</td>
</tr>
<tr>
<td>20040908-08</td>
<td>0.490</td>
<td>0.710</td>
<td>1.780</td>
</tr>
<tr>
<td>20040917-17</td>
<td>0.800</td>
<td>0.460</td>
<td>2.030</td>
</tr>
</tbody>
</table>
Table 4.3.1. SV model parameters resulting from ML/REML estimation without anisotropic correction, ML/REML estimation with anisotropic correction (denoted with “Aniso”), and WNLS estimation without anisotropic correction for (a) 16 September 1999, (b) 8 September 2004, and (c) 17 September 2004. From left to right the provided parameters are the estimated constant mean \([\ln(\text{mm})]\); the estimated nugget effect \([\ln(\text{mm})]^2\); the partial sill \([\ln(\text{mm})]^2\); the range (km); the angle of minimum variance for anisotropic correction (radians); and the stretching ratio for anisotropic correction.

### 19990916-16

<table>
<thead>
<tr>
<th>Technique</th>
<th>Model</th>
<th>Mean [ln(mm)]</th>
<th>Nugget [ln(mm)]^2</th>
<th>Partial Sill [ln(mm)]^2</th>
<th>Range km</th>
<th>Angle (radians)</th>
<th>Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>ML</td>
<td>Exp.</td>
<td>0.364</td>
<td>1.565</td>
<td>19.730</td>
<td>830.90</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ML Aniso</td>
<td>Exp.</td>
<td>0.368</td>
<td>1.676</td>
<td>17.160</td>
<td>833.30</td>
<td>6.283 (360°)</td>
<td>2.158</td>
</tr>
<tr>
<td>WNLS</td>
<td>Gau.</td>
<td>N/A</td>
<td>1.454</td>
<td>38.150</td>
<td>433.78</td>
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</table>

### 20040908-08

<table>
<thead>
<tr>
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<th>Model</th>
<th>Mean [ln(mm)]</th>
<th>Nugget [ln(mm)]^2</th>
<th>Partial Sill [ln(mm)]^2</th>
<th>Range km</th>
<th>Angle (radians)</th>
<th>Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>REML</td>
<td>Sph.</td>
<td>4.737</td>
<td>2.195</td>
<td>2.693</td>
<td>639.00</td>
<td></td>
<td>1.725</td>
</tr>
<tr>
<td>REML Aniso</td>
<td>Sph.</td>
<td>4.736</td>
<td>2.154</td>
<td>2.975</td>
<td>625.90</td>
<td>1.725 (99°)</td>
<td>1.347</td>
</tr>
<tr>
<td>WNLS 650^1</td>
<td>Exp.</td>
<td>N/A</td>
<td>1.199</td>
<td>6.318</td>
<td>577.38</td>
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<td></td>
</tr>
</tbody>
</table>

### 20040917-17

<table>
<thead>
<tr>
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<th>Model</th>
<th>Mean [ln(mm)]</th>
<th>Nugget [ln(mm)]^2</th>
<th>Partial Sill [ln(mm)]^2</th>
<th>Range km</th>
<th>Angle (radians)</th>
<th>Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>ML</td>
<td>Exp.</td>
<td>1.281</td>
<td>2.538</td>
<td>14.150</td>
<td>877.30</td>
<td>0.3307 (19°)</td>
<td>2.509</td>
</tr>
<tr>
<td>ML Aniso</td>
<td>Exp.</td>
<td>1.449</td>
<td>2.351</td>
<td>10.470</td>
<td>485.10</td>
<td>0.3307 (19°)</td>
<td>2.509</td>
</tr>
<tr>
<td>WNLS</td>
<td>Gau.</td>
<td>N/A</td>
<td>2.885</td>
<td>28.470</td>
<td>572.06</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

^1 650 refers to the maximum lag distance (650 km) used for the WNLS fit due to the instability of the experimental semivariogram at larger distances.
Table 4.3.2. Basic distribution statistics from OKIDP output for (a) 16 September 1999, (b) 8 September 2004, and (c) 17 September 2004. From left to right the basic statistics are comprised of the minimum (mm); the 1st quartile or 25th percentile (mm); the 2nd quartile, 50th percentile, or median (mm); the mean (mm); the 3rd quartile or 75th percentile (mm); and the maximum (mm).

<table>
<thead>
<tr>
<th>19990916-16</th>
<th>Technique</th>
<th>Model</th>
<th>Minimum mm</th>
<th>25% (50%) mm</th>
<th>Median (50%) mm</th>
<th>Mean mm</th>
<th>75% mm</th>
<th>Maximum mm</th>
</tr>
</thead>
<tbody>
<tr>
<td>DRP</td>
<td></td>
<td></td>
<td>0.010</td>
<td>0.010</td>
<td>0.010</td>
<td>37.770</td>
<td>29.210</td>
<td>464.800</td>
</tr>
<tr>
<td>MPE (N/A)</td>
<td></td>
<td></td>
<td>0.010</td>
<td>0.010</td>
<td>0.148</td>
<td>50.800</td>
<td>72.670</td>
<td>464.400</td>
</tr>
<tr>
<td>IDW</td>
<td></td>
<td></td>
<td>0.009</td>
<td>0.010</td>
<td>0.187</td>
<td>46.660</td>
<td>71.410</td>
<td>360.700</td>
</tr>
<tr>
<td>ML</td>
<td>Exp.</td>
<td></td>
<td>0.009</td>
<td>0.010</td>
<td>0.178</td>
<td>45.100</td>
<td>63.130</td>
<td>341.400</td>
</tr>
<tr>
<td>WNLS</td>
<td>Gau.</td>
<td></td>
<td>0.005</td>
<td>0.011</td>
<td>0.196</td>
<td>47.670</td>
<td>49.980</td>
<td>446.700</td>
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<table>
<thead>
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<th>20040908-08</th>
<th>Technique</th>
<th>Model</th>
<th>Minimum mm</th>
<th>25% (50%) mm</th>
<th>Median (50%) mm</th>
<th>Mean mm</th>
<th>75% mm</th>
<th>Maximum mm</th>
</tr>
</thead>
<tbody>
<tr>
<td>DRP</td>
<td></td>
<td></td>
<td>0.010</td>
<td>18.670</td>
<td>41.530</td>
<td>61.630</td>
<td>86.360</td>
<td>419.100</td>
</tr>
<tr>
<td>MPE</td>
<td></td>
<td></td>
<td>0.000</td>
<td>15.570</td>
<td>35.600</td>
<td>50.650</td>
<td>70.490</td>
<td>338.600</td>
</tr>
<tr>
<td>IDW</td>
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<td></td>
<td>0.010</td>
<td>7.779</td>
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<td>40.570</td>
<td>54.170</td>
<td>400.500</td>
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<tr>
<td>REML</td>
<td>Sph.</td>
<td></td>
<td>0.010</td>
<td>7.309</td>
<td>26.430</td>
<td>34.520</td>
<td>45.390</td>
<td>180.700</td>
</tr>
<tr>
<td>REML Aniso</td>
<td>Sph.</td>
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<td>0.010</td>
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<td>26.780</td>
<td>34.740</td>
<td>45.540</td>
<td>179.700</td>
</tr>
<tr>
<td>WNLS 650</td>
<td>Exp.</td>
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<td>27.600</td>
<td>36.380</td>
<td>47.050</td>
<td>214.900</td>
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<table>
<thead>
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<th>Technique</th>
<th>Model</th>
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<th>25% (50%) mm</th>
<th>Median (50%) mm</th>
<th>Mean mm</th>
<th>75% mm</th>
<th>Maximum mm</th>
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<tbody>
<tr>
<td>DRP</td>
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<td></td>
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<td>82.110</td>
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<tr>
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<td></td>
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<td>0.519</td>
<td>14.020</td>
<td>35.330</td>
<td>61.230</td>
<td>347.000</td>
</tr>
<tr>
<td>IDW</td>
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<td></td>
<td>0.010</td>
<td>0.255</td>
<td>7.485</td>
<td>30.340</td>
<td>46.990</td>
<td>310.200</td>
</tr>
<tr>
<td>ML</td>
<td>Exp.</td>
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<td>0.010</td>
<td>0.246</td>
<td>6.057</td>
<td>27.010</td>
<td>43.550</td>
<td>168.300</td>
</tr>
<tr>
<td>ML Aniso</td>
<td>Exp.</td>
<td></td>
<td>0.010</td>
<td>0.216</td>
<td>6.199</td>
<td>26.840</td>
<td>45.660</td>
<td>164.400</td>
</tr>
<tr>
<td>WNLS</td>
<td>Gau.</td>
<td></td>
<td>0.009</td>
<td>0.360</td>
<td>4.453</td>
<td>28.380</td>
<td>50.260</td>
<td>141.200</td>
</tr>
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</table>
Table 4.3.3. Cross-validation statistics for OKIDP output for (a) 16 September 1999, (b) 8 September 2004, and (c) 17 September 2004. From left to right the provided statistics are the correlation between predicted and actual values (corPA); the correlation between actual values and the associated error (corEA); the correlation between the actual values and the associated standardized error (corSEA); the root mean square error [RMSE, ln(mm)]; the root mean kriging variance [RMKV, ln(mm)]; the root mean square standardized error (RMSSE, unitless); and the percent of actual values that lie within the 95% confidence interval (%CI, %).

<table>
<thead>
<tr>
<th>19990916-16</th>
<th>Technique</th>
<th>Model</th>
<th>CorPA</th>
<th>CorEA</th>
<th>CorSEA</th>
<th>RMSE</th>
<th>RMKV</th>
<th>RMSSE</th>
<th>%CI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>ln(mm)</td>
<td>ln(mm)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ML</td>
<td>Exp.</td>
<td></td>
<td>0.925</td>
<td>0.367</td>
<td>0.369</td>
<td>1.592</td>
<td>1.548</td>
<td>1.014</td>
<td>91.6</td>
</tr>
<tr>
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<td>Exp.</td>
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<td>0.371</td>
<td>1.583</td>
<td>1.499</td>
<td>1.048</td>
<td>91.6</td>
</tr>
<tr>
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<td>Gau.</td>
<td></td>
<td>0.913</td>
<td>0.403</td>
<td>0.401</td>
<td>1.700</td>
<td>1.234</td>
<td>1.378</td>
<td>85.6</td>
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</table>

<table>
<thead>
<tr>
<th>20040908-08</th>
<th>Technique</th>
<th>Model</th>
<th>CorPA</th>
<th>CorEA</th>
<th>CorSEA</th>
<th>RMSE</th>
<th>RMKV</th>
<th>RMSSE</th>
<th>%CI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td>ln(mm)</td>
<td>ln(mm)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>REML</td>
<td>Sph.</td>
<td></td>
<td>0.564</td>
<td>0.812</td>
<td>0.811</td>
<td>1.623</td>
<td>1.593</td>
<td>1.009</td>
<td>95.7</td>
</tr>
<tr>
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<td>Sph.</td>
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<td>0.566</td>
<td>0.811</td>
<td>0.810</td>
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<tr>
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<td>Exp.</td>
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<td>0.778</td>
<td>0.776</td>
<td>1.651</td>
<td>1.274</td>
<td>1.281</td>
<td>93.2</td>
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<table>
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<th>Technique</th>
<th>Model</th>
<th>CorPA</th>
<th>CorEA</th>
<th>CorSEA</th>
<th>RMSE</th>
<th>RMKV</th>
<th>RMSSE</th>
<th>%CI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
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<td></td>
<td>ln(mm)</td>
<td>ln(mm)</td>
<td></td>
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<td>Exp.</td>
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<td>Exp.</td>
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<td>1.719</td>
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<td>93.5</td>
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<td>1.722</td>
<td>1.110</td>
<td>90.5</td>
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</table>
Table 4.3.4. Basic distribution statistics for both error and standardized error resulting from the cross-validation of OK output for (a) 16 September 1999, (b) 8 September 2004, and (c) 17 September 2004. From left to right the basic statistics are comprised of the minimum [ln(mm)]; the 1st quartile or 25\textsuperscript{th} percentile [ln(mm)]; the 2\textsuperscript{nd} quartile, 50\textsuperscript{th} percentile, or median [ln(mm)]; the mean [ln(mm)]; the 3\textsuperscript{rd} quartile or 75\textsuperscript{th} percentile [ln(mm)]; and the maximum [ln(mm)].

<table>
<thead>
<tr>
<th>Technique</th>
<th>Model</th>
<th>Minimum</th>
<th>25%</th>
<th>Median (50%)</th>
<th>Mean</th>
<th>75%</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Error</td>
<td></td>
<td>ln(mm)</td>
<td>ln(mm)</td>
<td>ln(mm)</td>
<td>ln(mm)</td>
<td>ln(mm)</td>
<td>ln(mm)</td>
</tr>
<tr>
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<td>Exp.</td>
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<td>0.092</td>
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<td>Exp.</td>
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<td>-0.082</td>
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<td>0.0005</td>
<td>0.099</td>
<td>4.942</td>
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<tr>
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<td>0.003</td>
<td>0.476</td>
<td>5.191</td>
</tr>
<tr>
<td>SError</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
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<td>-0.054</td>
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<td>0.0004</td>
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<td>Exp.</td>
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<td>4.265</td>
</tr>
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</table>

<table>
<thead>
<tr>
<th>Technique</th>
<th>Model</th>
<th>Minimum</th>
<th>25%</th>
<th>Median (50%)</th>
<th>Mean</th>
<th>75%</th>
<th>Maximum</th>
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</thead>
<tbody>
<tr>
<td>Error</td>
<td></td>
<td>ln(mm)</td>
<td>ln(mm)</td>
<td>ln(mm)</td>
<td>ln(mm)</td>
<td>ln(mm)</td>
<td>ln(mm)</td>
</tr>
<tr>
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<td>-0.004</td>
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<td>Exp.</td>
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</tr>
<tr>
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<td>-0.001</td>
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</tr>
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<td>-0.001</td>
<td>0.418</td>
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<td>Exp.</td>
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<td>0.124</td>
<td>-0.001</td>
<td>0.492</td>
<td>3.318</td>
</tr>
<tr>
<td>Technique</td>
<td>Model</td>
<td>Minimum</td>
<td>25%</td>
<td>Median (50%)</td>
<td>Mean</td>
<td>75%</td>
<td>Maximum</td>
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<td>--------------</td>
<td>------</td>
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<td>---------</td>
</tr>
<tr>
<td>Error</td>
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<td>ln(mm)</td>
<td>ln(mm)</td>
<td>ln(mm)</td>
<td>ln(mm)</td>
<td>ln(mm)</td>
<td>ln(mm)</td>
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<td>0.101</td>
<td>-0.001</td>
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Figure 4.1.1. NHC Best Track summary for Hurricane Floyd during the period 7 September to 17 September 1999. Each point represents an adjusted storm location as part of a post-storm data analysis. Best Track locations occur in 6-hour intervals at 0000 UTC and 1200 UTC, respectively. The various line types indicate the storm classification. [Image courtesy Pasch et al. (1999)]
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a.

b.
C.
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a.

b.
c.
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C.
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a.

b.
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C.
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a. 

b.
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a. 

b.
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a.

b.
C.
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C.
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a.

b.
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a.

b.
5. TREND MODEL, RESIDUAL, and KED PERFORMANCE

5.1 Trend Model Performance

5.1.1 Covariate Analysis

Principally, the use of MLR to derive trend surfaces is rooted in the desire to keep the resultant trend models simple and straightforward, as such an approach, if successful, will achieve more universal appeal beyond the academic environment. Therefore, the selection of model covariates was based on the desire to investigate the statistical significance of basic physical principles. In order to visualize these potential relationships, the Geos2MAP model plots the physical covariates for each of the three cases as shown in Figures 5.1.1-5.1.6, representing average XWind (ms\(^{-1}\); Figure 5.1.1), maximum XWind (ms\(^{-1}\); Figure 5.1.2), average YWind (ms\(^{-1}\); Figure 5.1.3), maximum YWind (ms\(^{-1}\); Figure 5.1.4), SlopeWind based on the average 10 m horizontal wind (ms\(^{-1}\); Figure 5.1.5), and SlopeWind based on the maximum 10 m horizontal wind (ms\(^{-1}\); Figure 5.1.6). The geophysical covariates DEM and DEMSlope were previously shown in Figures 3.3.1 and 3.3.2, while study of the relationship between the coordinate covariates X and Y can be directly assessed from the plots of DRP data or MPE output.

5.1.1.1 Cartesian Coordinates

Given the anticipated inverse relationship between mean areal precipitation maxima and the distance from the center of the hurricane, storm motion and the resultant track were most influential on the relationship between DRP and Cartesian coordinates. The general northward storm motion from all three storms during the period of study left a precipitation distribution whose variation along the E-W axis was significantly larger than that seen along the N-S axis. Of course, for such northward tracks, hurricanes making landfall along the Atlantic coastline (e.g., Floyd) would produce direct relationships between DRP and X while landfalling Gulf Coast hurricanes yield inverse relationships (e.g., Frances and Ivan). Additionally, storm motion and the resultant counterclockwise circulation around the centers of Frances and Ivan combined with the SSW-NNE orientation of the Blue Ridge amplified the distribution of similar rain totals across a wide range of Y values.
5.1.1.2 DEM and DEMSlope

Even independent of the atmospheric covariates, the geophysical covariate DEM is clearly correlated to the precipitation distribution for Frances and Ivan. The presence of precipitation over the mountainous western domain is not a requirement for a relationship between DEM and DRP, as shown by Floyd. With the assistance of a preexisting frontal boundary, its storm track enhanced the downslope, subsident flow off the Blue Ridge, confining the entire precipitation field to the eastern Piedmont and Coastal Plain. This resulted in an inverse DEM to DRP relationship. However, for Ivan the strength of the DEM to DRP signal is slightly diminished by the axis of moderate accumulations across western GA, an area closer to the landfall and initial inland track of the storm. It further suggests that the area selected for analysis has major implications on the strength of linear relationships as it modifies the sample from which the analysis is conducted. There are concerns about the relevance of DEMSlope as well, which carry forward to the analysis of SlopeWind. Immediately evident is the size of the domain occupied by near zero DEMSlope values compared to the area occupied by significant values. Second, the very high resolution of the DEMSlope field may imply that the relationship between precipitation and upslope flow is significant only on the smallest scales. Regardless, while it is clear some relationship exists from DEMSlope to DRP, it may only be significant for a small percentage of the total DRP sample.

5.1.1.3 XWind

XWind appears to be the most successful physical covariate of those employed in this research, as the domain location combined with overall storm motion suggests easterly flow has a far greater impact on precipitation amounts than southerly flow. Being much of the important precipitation occurs while the domain is under the NE storm quadrant, average XWind appears to produce far stronger relationships with DRP than maximum XWind for all three cases, suggesting minimum XWind would have produced even stronger relationships. Evident in all three cases, Floyd especially, for example, is the strength of the easterly moisture flux originating from the Atlantic. Clearly, the orientation of the Blue Ridge
influences the relationships seen in the horizontal wind components, as it impacts the orientation of the exposure. Overall, this favors using E-W wind components in future covariate analyses. Perhaps the best exception to this is along the extreme southern Blue Ridge across N GA, as the orientation becomes E-W, resulting in a southern exposure. Unfortunately, as can be seen from the SlopeWind plots, this relationship is confined to a very small area relative to the domain size, making the likelihood of resolving this relationship very small. The XWind covariate also reveals the problems associated with time scale on the strength of correlation. For example, during the 24-hour period sampled from Ivan, Ivan’s storm motion takes the center from extreme southern AL into SW NC. Weak easterly flow to strong westerly flow in the average and maximum fields across SW GA contradict the association of westerly flow with continental air intrusion or entrainment as seen with Floyd and Frances and diminish some of the easterly flow correlation. Across SW GA, however, much of the precipitation occurred early in the period in the SE quadrant of the storm as cellular convection from the outer feeder bands propagated within the southerly low-level flow. It was only a few hours later in the period as the storm center passed to the NW, N, and NNE that westerly flow dominated the western domain. As with domain, changes to the selected time interval may have a significant impact on the sample characteristics.

5.1.1.4 YWind

Visual analysis of the YWind for all three cases suggests little to no correlation overall with the precipitation fields. The most impressive field is the maximum YWind sample from Ivan which captures the strongest winds associated with the center of circulation as the storm traversed the Appalachians (the signal is similar but weaker for the average YWind field). Despite this, notice how similar winds occurred throughout SC, E GA, and points offshore where precipitation totals are minimal. With Frances there exists a clear axis of strong southerly flow into the western Piedmont and Blue Ridge within the heart of the precipitation distribution, while on the moisture-starved, northward-facing slopes of the Appalachians across E TN, northerly flow dominates and amplifies the relationship. Yet
again, however, this is noteworthy only if confined to the mountainous part of the domain as
the strongest southerly flow exists where minimal precipitation occurs. The high scatter of
DRP for similar values of YWind is observed with Floyd as well: despite the fact that the
maximum totals are clearly associated with the intense eyewall convection and the average of
near-zero winds along the precipitation axis, similar winds are evident across the western part
of the domain, negating much of the signal.

5.1.1.5 SlopeWind

As a storm with little direct interaction with the mountainous terrain within the
domain, it should be of no surprise to see very little visual evidence suggesting a relationship
between SlopeWind and DRP for Floyd. Yet, even for Frances and Ivan, where it is clear
that orographic forcing influenced precipitation distribution, the impact of strong vertical
motion in areas of heavy rain may be minimal. The dilution of the signal once again appears
to be a significant concern as it is clear a large percentage of the sample has comparatively
weak or statistically insignificant small-scale orographic forcing. Nevertheless, across the
mountainous terrain visually significant, yet small-scale differences do exist in the
SlopeWind field when using average versus maximum 10 m horizontal wind. For example,
Ivan’s southerly flow, which clearly impacted precipitation amounts along the southern
slopes of the Blue Ridge across N GA, best enhances the vertical component to the flow
when the maximum YWind field is used. Recall, however, that the easterly component of
the upslope flow, which dominates orographic forcing further north into NC and VA, is best
represented by the average 10 m wind. Similar issues are seen with Frances, where
maximum wind fields tend to negate the impact of strong easterly (“negative”) flow as the
center of the storm passes through the region. As a result, the SlopeWind fields vary in their
magnitude and significance across the western domain for both storms depending on the
method of representing the 3 hr output from the NARR. Without varying the SlopeWind to
maximize the vertical motion regardless of the direction of exposure, which requires varying
the method of representing NARR wind within the domain of a single case for any fixed
temporal scale, it appears achieving statistically significant correlations may be difficult or at
least not fully realized even if the domain size is reduced to only cover the southern Appalachian region.

5.1.1.6 DRP Correlation Coefficients and Comparison to Visual Analyses

Table 5.1.1 provides sample correlation coefficients, $\rho$, between DRP data and the first, second, and third-order Cartesian coordinates (i.e., Cartesian or coordinate covariates) as well as the first order physical covariates DEM, XWind, YWind, XSlope, YSlope, and SlopeWind for all three cases. Upon initial inspection of these values it might be concluded that very little relationship exists between most of these covariates and DRP. Obviously, however, precipitation is not a simple linear process; in fact, its noisy behavior at these subclimatic time scales renders the likelihood very low that strong correlations exist with coordinates and physical parameters. Therefore, weak to moderate correlation coefficients ranging from 0.20-0.80 may be important in the derivation of a simple model of trend. It follows that significantly high correlations would suggest that the spatial behavior of precipitation could be explained by a linear model, yielding independent residuals that exhibit no autocorrelation and rendering any of the geostatistical models irrelevant.

In any case, many of the quantitative sample correlations confirm qualitative conclusions derived from the visual analysis above. For example, the Cartesian coordinate X and the physical coordinates DEM and XWind almost always yield the highest correlations with DRP, ranging from $\rho = -0.421$ (DEM vs. DRP for Floyd) to $\rho = 0.710$ (X vs. DRP for Floyd). Cartesian coordinates perform worst in Frances (e.g., $\rho = -0.209$ between X and DRP), where the upper percentiles of the sample extended further east into the Piedmont than observed for Ivan. Regardless of the hurricane or the associated storm path, YWind has a weaker linear relationship with DRP. However, the strength and spatial distribution of the maximum southerly flow in Ivan produces moderate correlation with DRP ($\rho = 0.431$), representative of 1) the southerly moisture flux from the Gulf of Mexico on the eastern two quadrants of the storm; and 2) the impact of southern exposure across the N GA mountains. Nevertheless, initial concerns about the detrimental impact of averaging 3-hr wind values
across a single day appear to be unfounded, though it is possible that the strong Atlantic flow would be even better represented by the minimum field.

Unfortunately, the impact of slope, in its current representation, is not a statistically significant contributor to the trend analysis, with very weak correlations and high p-values indicative of the lack of skill and high amount of scatter in the DRP field across the slope covariates. In all cases and as expected, the relationship with SlopeWind is direct, though such a conclusion is only statistically significant in Frances. Yet even for Frances, $\rho \approx 0.14$ which likely will have little statistical meaning in the analysis of trend. However, these results also allow the working hypothesis that a statistically significant relationship appears to be masked by controllable but challenging factors such as the domain size, temporal resolution, and perhaps the resolution of slope covariates relative to the DRP sample.

It is also important to note the moderate correlations that exist amongst higher-order Cartesian covariates. For example, the second-order Y coordinate and the XY interaction term yield higher correlations than the first-order coordinate covariates in Frances, while the second- and third-order X coordinates in Ivan and Floyd suggest significant contributions to the trend analysis as well. Enough of a signal is evident across both the second and third order coordinates and interaction terms to suggest polynomial surfaces may model meaningful portions of the sample precipitation field.

5.1.1.7 Impact of lnDRP Correlation Coefficients on Analysis

Finally, note Table 5.1.1 also provides the sample correlation coefficients between the covariates and lnDRP values. As these transformed DRP values represent the spatial field during trend analysis, it is important to note how the transformation affects previous conclusions about the relationship between precipitation and the covariates. While in no case does the transformation change the sign of the relationship when correlations are “significant”, it does, in some circumstances, dramatically enhance or diminish coefficient values. For example, the log transformation enhances the linear relationship between DRP and X in all cases, most notably in Floyd (0.710 to 0.849) and Ivan (-0.615 to -0.755), while
weakening the correlation between DRP and DEM (0.534 to 0.386) and DRP and average XWind (-0.562 to -0.435) for Frances.

5.1.2 Evaluation of Trend Model Equations

Any evidence of trend model consistency amongst the various hurricanes would have aided justification for semi-automating future versions of the Geos2MAP model. Table 5.1.2 reveals that covariate success varied widely across the different events and even between the different representations of the NARR variables. Based on Table 5.1.2, there appears to be little consistency across the three storms. In fact, Frances and Ivan yielded remarkably different trend models upon analysis despite having similar storm tracks and despite both enduring constructive and destructive interaction with terrain. Obviously, Ivan and Frances, while sharing similar storm tracks, did not share identical ambient environments or storm dynamics, nor did they produce similar precipitation fields. These differences are clearly reflected in the trend analysis. Ironically, however, Ivan and Floyd shared several covariates. The principal characteristic shared between these storms is the comparatively localized areas of moderate to heavy precipitation and, as previously discussed, this localization was due, in part, to the geophysical and physical covariates that dominated the respective trend models.

Further assessment of the individual covariates in Table 5.1.2 confirms some expectations resulting from the covariate analysis of Section 5.1.1, but not all. For example, both X and average XWind were important covariates for all three storms. However, maximum YWind played a significant role in the physical trend models for Floyd, despite ρ<0.19. In addition, DEM proved insignificant in Frances despite ρ>0.50 between DRP and DEM (the relationship between lnDRP and DEM was weaker with ρ<0.39). It is believed that the more widespread spatial distribution of rain experienced in Frances was only partially responsible. As feared, in no circumstance was the slope or the derived SlopeWind field beneficial, suggesting further study is needed to uncover their statistical significance. Interestingly however, the interaction between XWind and DEM was significant in both Floyd and Ivan; in fact, interaction terms were significant in most models.
DEM covariate performance in Frances also highlights the influence other covariates may have on the success of any single predictor. As the first covariate in all of the initial models, X is usually successful at removing a large amount of variance in the trend. This is especially true for Ivan and Frances, where, despite some of its success being attributed to its order in the models, the SSQII values for X remain the highest of any of the covariates. In Frances, however, X and Y share significance depending on whether average or maximum NARR variables are employed. Average 10m horizontal wind explains variance previously explained by X as X is non-significant when XWind and YWind are introduced. Both average and maximum XWind are largely responsible for making DEM an insignificant covariate in Frances as well. In other words, XWind is able to not only explain the same variance as DEM, but it is able to explain a significant amount of additional variance, rendering DEM insignificant.

The consequences of including or excluding certain covariates is illustrated in Table 5.1.3, which provides basic regression statistics for all of the trend models investigated. In terms of the percent of variance explained, the selected Cartesian and physical models perform similarly within each case, especially in Ivan (3LXYs $R^2 = 0.683$ vs. 1L1ai Avg. $R^2 = 0.691$). Within the Cartesian polynomials, there were notable improvements in Floyd and Ivan when going from a second-order to third-order model despite the reduction in power. However, the improvement in Frances was marginal in terms of the sum of square metrics, and no improvement was made in the residual distribution, suggesting the 2LXY model was sufficient. For the physical models, a majority of the total possible variance explained (see 1LALL) could be realized with fewer than 8 of the 36 possible covariates, indicating high power models with important explanation of variance are possible from a relatively simple set of predictors.

It has already been observed that RMSE is not the best indicator of model success, and in Table 5.1.3, while the best models generally have lower RMSEs, the best models still have high RMSEs overall, which is indicative of the degree of scatter present in the dataset. Even for Frances, where the original sample dataset was closest to the ideal assumptions of the geostatistical model, the RMSE may be the lowest of any of the storms yet it is still
substantial. Again, there was little expectation that the complex physical process responsible for precipitation were going to be simplified into a linear model using basic covariates; RMSE values simply validate this hypothesis.

Not surprisingly, there is a strong relationship between the inherent stationarity of the original sample precipitation field and the percent of variance explained by the regression models. While recalling the experimental semivariograms of the lnDRP field, note in Table 5.1.3 that the storm whose precipitation field was the most non-stationary, Hurricane Floyd, benefited the most by the use of MLR. Approximately 80% of the variance present in the original field was removed via MLR. For Hurricane Ivan, where non-stationarity was slightly less intense, both Cartesian and physical trend models were able to model nearly 70% of the variance present in the original field. In both cases, less than 10 of the original 36 covariates were required. With Hurricane Frances, however, only ~30% of the variance could be explained by the trend models and only 5 (2LXY) and 4 (1Llai Avg.) covariates were significant. However, it was suggested by Frances’s experimental semivariogram that the trend had a large constant. Therefore, it would be logical that the intercept of the selected models would be the most significant “covariate” yielding high SSQI and SSQII values and therefore a larger coefficient relative to the other covariates. This is exactly what is observed in Table 5.1.4, which provides covariate statistics for the selected Cartesian and physical trend models in all cases. Note that the intercept is one to six orders of magnitude larger than the covariate coefficients for both selected models in the Frances case.

Finally, scatterplots of actual versus predicted lnDRP for the selected Cartesian and covariate models are shown in Figures 5.1.7, 5.1.8, and 5.1.9 for Floyd, Frances, and Ivan, respectively. These scatterplots closely resemble actual versus predicted value scatterplots resulting from OK cross-validation. It is clear now how variable trend influences kriging interpolation as it had an overwhelming presence in the OK analysis. Many of the same comments about over- and under-prediction, the failure of the model to handle zero observations, and the overall influence of the zero observations on the SV models and OK can now be applied to the trend models of the three cases.
Between the Cartesian and covariate models in Floyd and Ivan there are no substantial differences in the overall distribution of actual versus predicted values. In other words, there is no reason to justify one model over another based on the comparison of actual and predicted values alone. For Frances, a few outlier predictions in the 2LXY model increases scatter around the one-to-one line in the lower precipitation values when compared to the 1LIai model. Nevertheless, better metrics for choosing one model over the other are discussed in the following sections.

5.1.3 Trend Model Residual Analysis

Residuals derived from the selected trend models are used to investigate the model characteristics with respect to the assumptions supporting MLR. First, as previously discussed, the DRP/lnDRP datasets exhibit autocorrelation (i.e., are not spatially independent). MLR assumes no spatial relationship is present (i.e., only accounts for non-spatial variance); therefore it is not assumed that the response variable, lnDRP, or the residuals are independent.

5.1.3.1 Constant Variance and the Impact of Zero DRP Values

Examination of the trend model residuals versus the predicted values for the selected models (Figures 5.1.10, 5.1.11, and 5.1.12) reveals an obvious lack of constant variance in Floyd and Ivan for both 3LXYs (Figures 5.1.10a and 5.1.12a) and 1LIai (Figures 5.1.10b and 5.1.12b). However, the residuals are not randomly scattered about the zero axis in Frances either (Figure 5.1.11), albeit the function of variance versus predicted value clearly evident in Floyd and Ivan is less significant here. These results obviously support the expectation of non-constant variance in the original DRP/lnDRP datasets. Recalling the histograms of the logarithmically transformed datasets, also evident is the bimodal nature of the distribution of residuals across the predicted values. Therefore, the failure of the MLR models to integrate zero values of DRP into the trend (i.e., the lack of skill) is evident from these scatterplots, much in the same way SV models of the lnDRP dataset lacked the same skill. Notice how the residuals at locations where DRP equals zero follow a straight line whose slope is
proportional to the linear correlation of the MLR model to the response variable, lnDRP (i.e., $R^2$). The zero values influence the increase in variance for smaller predicted values, as MLR attempts to produce unbiased residuals with zero mean (i.e., the expected value of the residuals equals zero in an MLR model). As the predicted values increase, the residuals associated with zero DRP decrease in frequency yet increase in magnitude. Overall, the inference is that these models become unstable as the DRP values decrease and approach zero; and the fewer zero reports, the less unstable the trend model, as evidenced by Frances’s scatterplots in Figure 5.1.11. These characteristics appear largely independent of the type of MLR model employed, meaning the selection of the physical model over the Cartesian model will not significantly mitigate or amplify these limitations. In other words, it is hypothesized that if the zero values were eliminated from the dataset, the resultant residuals from similar MLR models would exhibit better scatter about the zero axis with near constant variance. Many of the residuals would likely be less significant as well, suggesting the models would be less unstable and more reliable. The MLR models would no longer have to compensate for a lack of predictive ability and straddle the two modes within the distribution as predicted values approach zero. The elimination of this mode in the distribution would remove a significant source of non-stationarity in the spatial field, as suggested by Frances where, with significantly fewer zero values reported, the original DRP field is approximately stationary.

5.1.3.2 Residuals versus Individual Covariates

The selected models’ residuals were also plotted against each of their first order physical and Cartesian covariates (Figures 5.1.13, 5.1.14, and 5.1.15, for Floyd, Frances, and Ivan, respectively) in order to investigate any additional trend that may not have been successfully removed. Scatterplots for the first-order covariates not included in the selected models, including the slope covariates, were also provided as derived from the 1L model. From these scatterplots, there are very few significant remnant trends that suggest a higher-order analysis of any of the covariates is necessary. The important exception is with X in Hurricane Floyd for both 3LXYs and 1L1a Max. For 3LXYs (Figure 5.1.13a), the scatterplot of residuals versus X indicate a higher-order trend may exist. An initial glance at the same
scatterplot for 1LIa Max (Figure 5.1.13c) suggests a linear trend remains, but in reality a higher-order term may be required to explain the slight curve in the residuals. A minor exception is also noted from the scatterplots of residuals versus X for the 3LXYs (Figure 5.1.15a) and 1LIai Avg (Figure 5.1.15c) models from Hurricane Ivan; however, the remnant Gaussian-like trend noted here is attributable to the zero DRP values.

Another advantage of the residual versus covariate scatterplots is the ability to further show how the zero values are impacting the magnitude of the residuals and thus their variance across covariate values. The scatterplots for the covariates X and Y are especially important because they visualize the distribution of residuals across the spatial domain. From the scatterplots of residuals versus X for Floyd, as X becomes negative in the western domain, note how the trend model performs well in predicting the zero field. However, progressing east towards the Piedmont, where the outer bands of Floyd provided light to moderate precipitation, the model is unstable overall, either seriously underestimating the non-zero precipitation values or seriously overestimating the zero values. Finally, across the Coastal Plain, the trend model once again performs well, with relatively small residuals in the areas of heavy precipitation. The stronger non-linear distribution of residual values from the 3LXYs model suggests this model is more volatile. Similar observations can be identified in Ivan, and to some extent in Frances. The distribution of residuals along the north-south axis (Y) from all cases is more random.

For the slope covariates, appreciable spread is observed along and near the zero slope and zero SlopeWind axes. In Frances and Ivan, however, on either end of the zero axes, relatively small residual values for these few points suggest that where the slope covariates deviate from zero (i.e., in places of significant upslope or downslope) the model is capturing some trend in the data. Similar performance is seen with the DEM covariate from the selected models in Frances and Ivan, where, aside from a few outliers, residual variance decreases with increasing DEM. For the remaining covariates from all storms and models, the residuals were more randomly scattered with less significant variance trends. However, the irregularity in the sampling of covariate values is evident in many of these scatterplots as several clusters of data exist.
5.1.3.3 Residual Distribution Analysis

Of course, achieving approximate residual normality is a critical goal of MLR modeling and, overall, the modeling of the lnDRP datasets is successful. Figures 5.1.16, 5.1.17, and 5.1.18 display probability density histograms and QQ plots from the residuals in each of the selected models for Floyd, Frances, and Ivan, respectively. Normality appears to be proportional to the percent of variance explained, as Hurricane Floyd’s lnDRP dataset is best served by the MLR models, while the lnDRP dataset for Frances is least improved. Only for Hurricane Floyd did the Cartesian and physical models yield substantially different residual distributions; the distribution produced from the 3LXYs model has a significantly heavier negative tail and a truncated positive tail whereas the 1L1a Max model produces an approximately normal positive tail and only a slightly heavy negative tail. In terms of residual normality, the 1L1a Max model is obviously preferred.

Across all cases, the principal issue in the residual distribution is the severity of the negative tail. Analysis of the QQ plots for Frances’s selected models (Figure 5.1.17b for 2LXY and Figure 5.1.17d for 1L1ai Avg, respectively) reveal an obvious and exceptionally heavy negative tail from an otherwise straight, one-to-one relationship between residual and normal quantiles. On the positive tail, a slight deviation from the linear relationship (i.e., a positive inflection for the 2LXY model and a negative inflection for the 1L1ai model) in the QQ plot is indicative of a truncated right end to the distribution. The flawed negative tail is clearly attributable to the zero values which are substantially overpredicted in nearly all cases. The magnitude of the negative residuals in these cases suggests that a relatively small number of zero values may be more destructive to a residual distribution than a large number of zero values because of a lack of sampling. This is consistent with observations made during OK analysis. Since Ivan had the median number of zero values, it would be expected from the preceding hypothesis that the negative tails from its model residuals would, in terms of severity, lie between Floyd and Frances. Analysis of Figure 5.1.18 substantiates this hypothesis as the QQ plot’s negative inflection on the left tail and weaker positive inflection on the right tail are the result of a heavily tailed distribution more significant than seen with Floyd, but lighter than observed with Frances.
Again, the overall conclusion is that the resultant residual distributions are a marked improvement over the original lnDRP distributions, being approximately normal but marred by the presence of poorly predicted zero values. However, for two of the three hurricanes, there was no substantial difference between Cartesian and physical models in terms of residual normality. The analysis must now investigate whether there will be appreciable difference in the SV models and resultant gridded precipitation fields derived from each model.

5.2 Residual Performance

5.2.1 Impact of Spatial Autocorrelation on MLR Covariates and Coefficients

Recall from subsection 1.3.11 that a principle advantage of ML/REML over ONLS and WNLS is that the trend model coefficients are estimated simultaneously with the SV model parameters such that neither the gauge measurements nor the trend model residuals are assumed to be independent. With an estimate of the true covariance matrix for the data, the trend model can account for spatial autocorrelation and a covariance matrix can be produced for its coefficients. Furthermore, standard deviations derived from the coefficient covariance matrix can be used to produce CIs for each coefficient. As demonstrated in Table 5.2.1, this research uses both the standard deviation for each coefficient and the associated CIs as approximate metrics in order to investigate the success of the MLR trend models. It is for these reasons that WNLS is omitted from the following analysis. Finally, REML is preferred over ML in this analysis due to the tendency for REML to be less biased than ML, also as discussed in subsection 1.3.11.

To simplify the study of Table 5.2.1, highlighted covariate rows indicate where MLR coefficients do not fall within the CIs specified by REML. Here, the original MLR coefficient value is spurious, because it is not significant when spatial autocorrelation is considered. However, the covariate itself may still be significant. Additionally, bold text is used to indicate where the standard deviation exceeds the REML estimate of the coefficient. In this circumstance, the confidence in the REML coefficient value and the associated statistical significance of the covariate are in question; for example, not even the sign of the
relationship with lnDRP is known with high confidence. If the covariate cannot provide value when an estimate of spatial dependency is incorporated, the original MLR coefficient is likely insignificant as well.

From the analysis of Table 5.2.1 one can conclude that the methodology used in this research to derive trend models is successful at producing significant covariates despite ignoring the spatial variance in the precipitation field. In the three cases studied, the transition from MLR to REML shows the original trend models retain most of their significance. In the case of the LXY models, where the full form of the polynomials was maintained, it is not surprising that some of the covariates within the polynomials are insignificant; this is consistent with the analysis of the correlation coefficients. For the 1LIa(i) models, performance was generally very good, in fact only the 1LIa Max model for Floyd had difficulty validating a first-order covariate (DEM). This model was also the only model where any of the MLR coefficients failed to fall within the REML-derived CIs (DEM and XU). Nevertheless, the CIs, reflective of the intense variability in the precipitation field, are admittedly wide at times. Elsewhere, 1LIa(i) performance was excellent in Ivan with the caveat that standard deviations were the same order of magnitude as the coefficients for 7 out of 8 covariates. In Frances, as in Floyd, excessive standard deviations occurred only once, but for both storms they were associated with an interaction term whose elements were already represented. Of course, in order for the coefficient to be significant the sign must stay consistent from MLR to REML as is the case for the studied hurricanes; however, in many cases the CI was wide enough to span both signs. Nevertheless, even in Ivan the two sets of coefficients were remarkably similar. The most significant differences between REML and MLR coefficient estimates were with the intercept in the 1LIa Max model of Floyd and the 1LIai Avg model of Ivan, yet both estimates were still within the 95% CI.

5.2.2 Semivariogram Analysis

Dramatic improvements in the experimental semivariograms and SV model parameters are observed after the removal of trend. Included in Table 5.2.2 are the parameters for exponential and spherical models derived using REML for both the selected
LXY and 1LIa(i) models in each case. Highlighted parameter rows indicate the selected models used in the analysis of KED. Figures 5.2.1, 5.2.2, and 5.2.3 allow comparison of the selected SV model with the experimental semivariograms derived from the selected trend model residuals in Floyd, Frances, and Ivan, respectively.

5.2.2.1 Experimental Semivariogram Characteristics

From the experimental semivariograms in all cases, the trend models significantly reduce non-stationarity beyond 100-200 km, while altering the small-scale variability very little. Clearly, the effect is to dramatically reduce the partial sill and range, even in Frances where large-scale non-stationarity was exhibited, while contributing very little to the mitigation of the nugget. In both Floyd and Ivan the linear SV function is largely eliminated, though in Ivan the new trend remains somewhat linear through 400 km and may conform poorly to a WLNS fit using a classic ISIP model. In Floyd, the SV function quickly grows unstable beyond 400 km, decreasing with distance. Nevertheless, at this point the radius of the precipitation axis is exceeded and the SV is largely influenced by the expansive zero field present in the western domain. In fact, a similar behavior is present in Ivan, albeit at a greater distance due to the somewhat smaller zero field and fewer available point pairs. Frances’s trend model residuals exhibit a classical ISIP structure, but, as confirmed in Table 5.2.2, the significant reduction in partial sill leaves a spatial variance field dominated by the nugget effect and relatively little slope. The significance of the nugget is also noted when a fixed zero nugget is attempted while performing REML, producing unstable and unrealistic results. Examination of the semivariograms suggests the reduction in large-scale non-stationarity in Frances actually increased the estimated nugget effect by pivoting the SV function and altering its slope at the shortest lags.

5.2.2.2 REML-Derived Semivariance Model Behavior

Overall, the conclusions drawn from the visual analysis of the experimental semivariograms are confirmed after performing REML. In Frances especially, the 2LXY and 1LIa Avg models appear to be interchangeable when using a spherical SV model. Note,
however, that REML becomes unstable when using the exponential model and 1LLIai Avg residuals. Even for the 2LXY model the range increases nearly 100 km and the partial sill increases by nearly 1 \([ \ln(\text{mm})]^2\) when switching from the spherical to the exponential model. With the selected spherical models, the estimated distance of independence is near 250 km while for the exponential models the range spans from 340 km to an unimaginable 28278 km. These results suggest the exponential model is far from ideal; Frances represents the only case where the proper selection of the classical ISIP SV model is essential. Therefore, it is also the only case that produces very high confidence in one classical model (spherical) over the alternative (exponential). Here, the incorrect choice means choosing the proper trend model becomes essential for yielding stable parameter estimates; otherwise, trend model selection is of negligible importance.

Compared to the spherical model estimates in Frances, for Ivan and Floyd, the trend models produce more substantial differences. The estimated range in Floyd varies from \(~35-65\) km to nearly 200 km with the nugget increasing similarly from \(~0.8\) to \(~1.5\) \([ \ln(\text{mm})]^2\) while transitioning from the 3LXYs model residuals to the 1LLa Max model residuals. Partial sills do not decrease to maintain similar total sills, instead increasing proportionally with the other parameters. Therefore, the estimated total sills in Floyd are substantially lower when using 3LXYs residuals \(\{\sim 3.3\ \text{versus} \sim 5.3 \ [\ln(\text{mm})]^2\}\). Of course, the major concern is that while the 3LXYs residuals are far more attractive, without cross-validation and spatial analysis, there is no certainty that they produce the better approach. Knowledge-based evaluation of the 3LXYs range values, however, suggests that independence at only 35-60 km may be too aggressive. The range value associated with 1LLa Max is consistent with estimates obtained for Frances and Ivan. Meanwhile, differences between the exponential and spherical models (i.e., when the trend model is fixed) are less significant but not negligible. For example, the partial (and total) sill increases by \(~1.6\) \([ \ln(\text{mm})]^2\) when transitioning from the spherical to the exponential model for 1LLa Max model residuals. Therefore, for Floyd, the highlighted models in Table 5.2.2 sample the extremes in nugget and range estimates while maintaining similar partial sills. These models will offer excellent evaluation of nugget, range, and slope significance.
In Ivan, the overall discrepancies are less significant, but there remain important differences between the partial sill and range estimates. In contrast, estimated nuggets are similar regardless of the trend or SV model at \( \sim 2.6 \, [\ln(\text{mm})]^2 \). When fixing the SV model shape, it appears the exponential model produces somewhat more volatility; the 3LXYs model residuals lead to an increase of \( \sim 1 \, [\ln(\text{mm})]^2 \) in the partial sill and a \( \sim 50 \, \text{km} \) increase in the range compared to the 1LIai Avg residuals. When fixing the trend model, the transition from a spherical to an exponential model yields higher partial sills while the ranges decrease \( \sim 50-100 \, \text{km} \). This indicates the REML-derived exponential parameters produce steeper slopes which may impact the kriging variance in areas of sparser gauge coverage. Nevertheless, selecting a SV model from these inconsistent parameters would be extremely challenging independent of other performance metrics. The highlighted models were chosen due to the stable estimates of the nugget and partial sill. However, differences in range values of \( \sim 100 \, \text{km} \) capture the previously observed variations in slope, allowing evaluation of slope on cross-validation performance and KEDIDP.

In conclusion, the use of REML with a spherical SV model consistently produces less volatile results and suggests that the spherical model is more appropriate regardless of case or trend model. However, the above analysis is important because not only does it suggest proper selection of the ISIP SV model is critical to achieving realistic parameters, it also reveals that, when the original precipitation field is highly non-stationary, the selected trend covariates are also very influential, making progression through the geostatistical model a challenge across varying meteorological regimes and complicating automation.

5.2.2.3 Impact of Trend Modeling on Anisotropy

Another objective in the removal of trend was the mitigation of anisotropic conditions, and, as indicated by the directional semivariograms in Figures 5.2.1-5.2.3, this objective was largely met, regardless of the selected trend model. Perhaps the most impressive example is Ivan, as shown in Figures 5.2.3b and 5.2.3d where approximate isotropy is achieved through 550 km. In Frances, however, the presence of approximate stationarity in the original precipitation field (and, thus, a weaker trend model) means almost
no improvement in anisotropy beyond 300 km, though this is beyond the range of the estimated SV models anyway (recall the OK analysis). Similar to Ivan, anisotropy in Floyd’s original field was noted over distances as short as 50-75 km. After trend removal, three out of the four directional axes now show similar SV structures through ~250 km. Unfortunately, the trend models were not successful at eliminating anisotropy along the N-S axis as shown in Figures 5.2.1b and 5.2.1d. In fact, the SV structure along that axis still poorly resembles any classic SV model. However, stretching the N-S axis to correct for these anisotropic conditions yielded nearly no change in the SV model parameters for each set of trend model residuals, similar to what was observed in the OK analysis.

5.2.2.4 Brief Statement on WNLS Feasibility

Given the relative success of MLR in selecting a trend model despite ignoring spatial autocorrelation, the approximate stationarity and isotropy present in the trend model residuals, and the similarities between the experimental semivariogram and ML/REML, it can be concluded that the use of WNLS to produce a SV model for KED interpolation would yield approximately similar results given a properly selected trend model. Caution would be needed with Ivan, as previously mentioned. Remember, however, that the final trend model coefficients would be estimated by MLR, not REML, and the overall precipitation field predicted by KED would vary due to the resultant differences in the trend estimate.

5.2.3 Spatial Distribution Analysis

Illustrating the spatial performance of the trend models, Figures 5.2.4, 5.2.5, and 5.2.6 display OK-interpolated gridded residual fields (at 4 km resolution) from the selected LXY and 1L1a(i) trend models for Floyd, Frances, and Ivan, respectively. Each interpolated residual field is derived from the preferred SV model for each trend model. Immediately evident is the irrelevancy of the model selection on the overall spatial pattern or shape of the residual field. In all three cases, however, there are variations in the magnitude of the field’s peaks and troughs. The differences between the trend model fields are perhaps most evident
in Ivan over the Appalachians and extreme eastern domain where instability associated with the cubic polynomial is causing an oscillation of over- and underestimates.

5.2.3.1 Residual Performance, Localized MLR, and Smaller Domains

The residual spatial fields can also provide insight into the success of the trend models in different sectors of the precipitation field, allowing some generalizations about the role smaller domains and/or localized MLR could play in future analyses. Nevertheless, in Floyd, for example, both trend models handle the axis of heaviest rain across the Coastal Plain quite well with a widespread, but small overestimation [usually <1 ln(mm)]. From the geophysical boundary between the eastern Piedmont and Atlantic Coastal Plain and points west or for accumulations <~150 mm, the models increasingly underpredict the lnDRP field. Behavior of the trend model along the boundary separating near-zero from zero values across SW VA, W NC, and central SC is most interesting as the trend field predicts the transition itself with near-zero residuals. Since the trend underestimates the precipitation immediately to the east of this transition, it follows that it would overshoot the zero field just beyond the transition to the west, resulting in the axis of strongly negative residuals. This residual analysis suggests three to four smaller domains, oriented N-S, could isolate the axes within the residual field by isolating the axis of >150 mm precipitation, followed by a domain for precipitation >0 mm and <150 mm, with a third domain for zero values. The third domain may need to be split between those zero values near the transition zone and those values greater than ~150 km from the transition boundary.

Analysis of trend model performance is comparatively more difficult for Frances and Ivan given the added complexity of the respective precipitation patterns. Frances’s trend model behavior is generally similar to Floyd’s along the axis of lightest precipitation (<20 mm) from S GA NE through the Atlantic Coastal Plain. Here the trend models generally

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1 This part of the residual discussion must only be considered in a generalized context because the use of a smaller sample size will undoubtedly change the relationships (and thus the coefficients) between each covariate and DRP/lnDRP. Additionally, some covariates may become insignificant while others that were originally excluded may become significant; therefore, the conclusions drawn from this discussion must only be considered in terms of the current trend models.
overestimate amounts less than 20 mm while underestimating amounts immediately to the NW of the 20 mm boundary. This region is highlighted by three distinct regions of strong underestimation from S central GA to the central Piedmont along the NC/SC border and into the Blue Ridge of VA along the northern domain boundary. In between each underestimation cluster are regions of overestimation, especially across S central SC where 1) an axis of light precipitation is flanked by two areas influenced by convective banding; and 2) immediately adjacent to the SE to NW swath of heavier precipitation along the NC/SC border across N central NC. Further west, the oscillation continues but dampens with weaker overestimates across N GA and Upstate SC, centered along either side of the Savannah River Basin where persistent rain bands were previously noted. From the heaviest axis of precipitation to points NW the trend model differences increase. Overall, however, amounts are slightly underestimated in both models along the windward Blue Ridge with no severe gradients in the field. 2LXY model performance appears to be slightly worse in the maximum precipitation axis, yet it appears to be slightly more stable in the lighter precipitation regions further E. Within the 2LXY model there is a pronounced transition from the maximum axis to the leeward side of the Appalachians where the smaller accumulations are generally overestimated. However, yet another oscillation occurs further NW such that the extreme NW region of the domain (i.e., SE KY) is underestimated. This SE to NW signal becomes a weaker SW to NE signal when switching to the 1LIai Avg model. Overall, however, the recommendation would be similar to Floyd, creating smaller domains based on the following: 1) the light precipitation field, representing in Frances values <~75 mm; 2) a moderate precipitation field with values >75 mm and <150 mm; and 3) the maximum precipitation axis of values >150 mm. It is unclear if a fourth domain on the leeward side of the Appalachians would be necessary, while a fifth domain for zero values is likely unnecessary given the dataset distribution.

Ivan’s residual fields incorporate many of the same characteristics seen in Frances and Floyd. As in Floyd, the strongest residuals lie on either side immediately surrounding the transition from zero to measurable precipitation. Like Floyd, the light precipitation (<20 mm) is severely underestimated while the zero field is strongly overestimated. On the
eastern side of the strongly negative residuals across central NC, an axis of scattered to
isolated light precipitation stretching from Wilmington N to SE VA creates a secondary
transition to positive residuals that are, for the ILIai Avg model, stronger than those observed
across N central SC. As in Frances the largest discrepancies between the two trend models
occur over the Appalachians where, once again, the LXY model is more unstable. Generally
the areas of precipitation >75 mm are underestimated in both models, though the
performance is weaker in the LXY model.

The major difference between Frances or Ivan and Floyd is that the precipitation
domains would be far more irregularly shaped for the former, though this should be the more
frequent occurrence across precipitation events. It is why localized regression techniques
would be favored over the dissection of the precipitation field into smaller domains;
however, as illustrated from these analyses, neither approach would adequately address the
trend model performance along precipitation domain boundaries. In these regions, the
smaller sample from which to perform localized MLR would span across a wide distribution
of values possibly diluting covariate significance. Additionally, the mosaicking of
neighboring domains would likely create significant boundary discrepancies. A final caveat
in the use of precipitation-derived domains is that the size of the domain must not be smaller
than the range of the SV function in order to ensure an ISIP SV model would be appropriate
for the spatial variance within the smaller domain. Of course, the estimated range may be
dependent of the trend model structure itself, as previously demonstrated. Therefore, it is the
interdependency of the various steps within the geostatistical model that makes additional
sophistication in the mapping technique exponentially more complex and computationally
expensive.

5.2.3.2 Residual Performance and Rain Gauge Measurement Quality

To this point in the research the role of questionable gauge measurements in the field
has been ignored. While additional discussion of DRP value quality control (as opposed to
the instrumentation quality control previously discussed) will be reserved for Chapter 6, the
residual datasets may serve as a good metric for identifying erroneous measurements within
the DRP dataset, especially since automation will be critical for climatological mapping projects. In each case analyzed, a small percentage of the sample contains potential outliers that excessively deviate from the surrounding field. Some outliers correlate to suspicious gauges identified at each step of the research (e.g., DRP, IDWIDP, OKIDP, etc.), but the available residual fields are inconsistent in their guidance from case to case. For example, Ivan appears to have one questionable measurement in NW SC and two in N central GA highlighted by strong outliers in the 3LXYs residual field. However, the signal from the 1L1ai Avg residuals is much weaker. Contrasting Ivan with Frances, the residual fields are less revealing, despite the IDWIDP field suggesting several unusual observations. Furthermore, there is a danger in assuming outlier residuals correlate to bad gauges, as shown in Floyd. While one suspicious gauge in NE NC correlates to an outlier in both residual fields, the strength of the outlier is very weak compared to the instability of the field across the western Piedmont and Blue Ridge, which is largely the result of a legitimate but poorly modeled transition from near-zero to zero values. Additionally, the presence of light precipitation in the midst of a zero field can be legitimate in any situation where isolated to widely scattered showers persist. Similarly, broken light precipitation coverage can generate a precipitation field where light values dominate but isolated zero values exist. The impact of these observations on the residual field, however, is significant, as shown in all three cases. Finally, deviations from the standard reporting time can yield outliers in the residual field, especially when a strong temporal gradient in precipitation exists during the hours surrounding the reporting time. Examples of this source of inconsistency are evident across the SC coastal plain in Floyd and in S GA during Frances.

5.2.3.3 Spatial Analysis of Standard Deviation

Analysis of the standard deviation fields, as shown in Figures 5.2.4-5.2.6, reveals similar behaviors as those seen with the OK standard deviation fields derived from the original lnDRP dataset. As before, the magnitude of kriging standard deviation is directly proportional to the lag between the gauge locations with the largest weights and the prediction point, as expected from the kriging variance equations. The shape or pattern of
the standard deviation fields is identical between the LXY and 1LIA(i) models within each case, varying primarily by magnitude. Trend model residuals that had both the lowest associated RMSE and smallest SV model parameters had the lowest standard deviations overall. The largest standard deviation discrepancies between trend models occurred in Floyd where the SV models had the most divergent parameters. In Floyd, the dominant parameter was range, as shown with the plot of standard deviation from the OK of 3LXYs residuals (Figure 5.24b). Despite a significantly smaller nugget which resulted in smaller standard deviations in the areas immediately surrounding gauge locations, the shorter range required a steeper slope in the SV model, resulting in rapid increases in standard deviation over small lags. Contrast this behavior with the 1LIA Max model and all models from the Frances and Ivan cases, where the nugget effects and ranges were larger while the partial sills decreased, requiring shallow slopes and resulting in smoother standard deviation fields. Therefore, while smaller nugget effects would undoubtedly improve the confidence in the prediction at the shortest lags, widespread improvement in model accuracy, especially in the sparser areas of the gauge network, would require a SV structure that reduced the nugget effect while simultaneously reducing the partial sill and/or increasing the range of the prediction, in order to generate overall reductions in RMSE. Meeting these objectives, based on the current analysis, will require far more sophisticated trend modeling.

5.2.4 Cross-Validation and Analysis of Orthonormality

Though there were significant discrepancies in REML-estimated SV model parameters due to varying trend and ISIP SV models, similarities in the standard deviation fields, especially for Frances and Ivan, suggested what cross-validation confirms: these variations had very little influence on the statistical performance of residual OK as illustrated in Table 5.2.3. More importantly, the removal of the trend prior to OK, regardless of method, contributes very little to the mitigation of the overall errors in the prediction, yielding RMSEs that are either just above or just below the RMSEs obtained by lnDRP OK. In other words, cross-validation statistics do not suggest the removal of trend substantially improves the accuracy of the geostatistical model.
5.2.4.1 Impact of Semivariance Model Parameters on Cross-Validation

Reductions in the partial sill indicate reduced spatial variance over moderate to large lags while coinciding reductions in the nugget contribute to the reduced variance at shorter lags. This type of joint improvement between the nugget and partial sills is most beneficial to reductions in the kriging variance since the kriging weights will be highest for those data points with the shortest lags to the prediction point (recall equation 1.4.5). Only in Floyd, however, did the removal of trend result in a smaller estimated nugget effect and a coinciding reduction in partial sill. However, the 3LXYs model, whose residuals were estimated to have the smallest nugget effect, performed somewhat worse than the 1Lla Max model during cross-validation, yielding a higher RMSE [1.590 ln(mm) vs. 1.564 ln(mm)], RMKV [1.534 ln(mm) vs. 1.531 ln(mm)], and RMSSE (1.019 vs. 1.014) with less linear correlation between the predicted and actual values (0.387 vs. 0.586). As seen from the analysis of the standard deviation fields, it is clear the very short estimated range (<40 km) had a major role in the cross-validation performance, especially in areas where gauge density was low and the nearest gauges were displaced by distances >10 km. In choosing the optimal configuration, therefore, one clearly cannot simply choose those models which have the most appealing SV model parameters. Nevertheless, in Frances and Ivan, where nugget effects increased slightly from those estimated during lnDRP analysis despite significant reductions in the partial sills, the trend model residuals yielding the lower SV model parameter estimates generally outperformed the alternative residuals largely because range values were similar. In these cases, the slope of the SV function was better related to nugget and partial sill exclusively. However, the differences in these cases were subtle and the statistics inconsistent as performance metrics, making final judgment based solely on cross-validation especially dubious.

5.2.4.2 Containment Percentages

As a measurement of model calibration, containment percentages only increased for the Floyd case (from 91.6% for the best lnDRP OK results to 92.7% for the OK of 3LXYs model residuals). In Frances, containment percentages were either the same (1Lla Avg...
residuals) or slightly decreased (from 95.7% to 95.2% for the 2LXY residuals) when compared to the best lnDRP OK results, while in Ivan no change occurred. Containment percentages are a function of the size of the confidence interval, which is based on the kriging standard deviation and the assumption of a normally-distributed field. The lnDRP OK-predicted fields were not normally distributed, so making final conclusions based on the containment percentages is not recommended. However, these percentages do confirm what has been shown throughout this section: the tendency for trend modeling to be beneficial on the larger-scale at removing variance in the spatial field, but largely unsuccessful at addressing the shape of the SV function at distances less than the estimated range (<100-200 km). Since the nearest neighboring gauges (gauges with the highest kriging weights) are often located at distances less than 100 km even where gauge density is comparatively poor, trend modeling is unable to remove the primary source of variance in the residual field. Therefore, these cross-validation results should be of little surprise. Of course, there are exceptions, as shown with the Floyd cases. The improvement in containment percentage for the 1LLa Max residuals (92.7%) over OK results can be explained through the combination of the lowest RMSE and lowest RMSSE, signaling lower bias and higher precision or reliability, which should lead to an improved calibration. However, despite poorer cross-validation statistics from the 3LXYs residuals, the containment percentage (92.7%) is the highest of all examples. In this circumstance, precision and bias are worse than measured for 1LLa Max, yet the nugget value and partial sill are the lowest of all OK and KED techniques. The significantly lower small-scale spatial variance (despite a higher slope in the SV function) is at least partially responsible for the high containment percentage and compensates for the poorer cross-validation statistics. This example suggests, once again, that the intercomparison of all available performance metrics is necessary to properly analyze an interpolation technique. As illustrated between this paragraph and the previous paragraph, it is very easy to contradict conclusions if isolating performance metrics from each other.
5.2.4.3 SError Distribution Analysis

As in the lnDRP OK analysis, several sets of scatterplots are presented in order to investigate the SError field produced by cross-validation. Figures 5.2.7, 5.2.8, and 5.2.9 plot the actual versus predicted residuals from the selected LXY and 1LIA(i) models along with the associated 95% CIs for Floyd, Frances, and Ivan, respectively. In addition, plots of SError versus predicted and actual values are shown in Figures 5.2.10, 5.2.11, and 5.2.12 for each case. From these scatterplots, it is clear that, due to removal of the deterministic portion of the geostatistical model, the residual OK technique largely corrects the issues of trend and non-constant variance in the SError field previously found by using OK on the original lnDRP field. Nevertheless, the non-spatial distribution of the SError field is essentially identical to the distribution of the SError field derived from lnDRP OK cross-validation, and both of these distributions are very similar to the trend model residual distributions. The unchanged SError distributions are illustrated in Figures 5.2.13, 5.2.14, and 5.2.15 which provide probability density histograms and normal QQ plots for the SError fields from the selected LXY and 1LIA(i) models for each hurricane. These plots indicate, aside from the fact that trend modeling has no impact on the distribution, that the slight underestimation bias is still present in the new error field and that the removal of this bias must come from a change in the sampling of the original dataset. These observations are largely confirmed by relatively little change in the RMSSE from lnDRP OK to trend model residual OK, especially for Floyd and the 3LXY’s model in Ivan. However, for a few of the trend models, namely those used for Frances and 1LIAi Avg in Ivan, there is a very slight reduction in the RMSSE as the ratio between RMSE and RMKV improves, suggesting that the error field’s underestimation bias may be negligible and the distribution of the errors is approximately normal.

Despite the nearly identical graphical interpretations of the SError distributions, inspection of the SError basic distribution statistics in Table 5.2.4 does reveal that there are subtle differences between the KED and OK approaches during cross-validation. Generally, basic distribution statistics can provide meaningful insight into the minimization of outlier predictions, the adherence to the zero-mean assumption, and basic bias tendencies by
comparing the mean and median against the minimum and maximum values. However, the inconsistency of the differences between KED techniques and the competing OK techniques makes it nearly impossible to base model performance and selection on SError distribution. For example, the zero-mean assumption actually has a slightly better compliance from the OK SErrors in Floyd than the KED SErrors. Overall, however, the differences are very minor [on the order of 0.01 or 0.001 ln(mm)]. In Frances, the 2LXY KED SError values yield a mean of -0.00035 ln(mm) versus -0.001 ln(mm) for each of the OK techniques while the 1LIai Avg KED approach mean is worse at -0.00137. Meanwhile, for Ivan, both KED techniques yield means closer to zero, but 1LIai Avg KED produces the most substantial improvement from -0.001 ln(mm) for ML OK to 6.2 x 10⁻⁶ ln(mm). Analysis of the outliers in each of the KED and OK predictions (i.e., analysis of the maximum and minimum SError values) also suggests inconsistent performance from all adaptations of KED regardless of case. Oftentimes, reductions in minima compared to OK are countered by increases in maxima or vice-versa, as shown in Floyd. Overall, SError extremes in Frances are most reduced using KED, but again the differences are fairly minor [e.g., SError maximum of 2.239 ln(mm) from REML Aniso OK versus 2.062 ln(mm) from 2LXY KED]. The most consistent approach is once again 1LIai Avg KED for Ivan, which yields slightly smaller maximum and minimum outliers compared to all of Ivan’s OK techniques. The comparisons of mean and median values produce many of the same conclusions. Even where KED mean SError is improved, median values either increase slightly or are nearly unchanged implying little improvement in the overall bias of the prediction or even a slight increase in the bias. These interpretations are consistent with analysis of RMSSE where values were nearly unchanged. As with OK, the observation points are, on average, overestimated slightly with median values exceeding mean values. KED SError values in Ivan and Floyd exhibit slightly greater deviations from zero at the 25th and 75th percentiles suggesting a slightly less heavy distribution in the middle two quartiles compared to OK SError distributions. Again, the largest improvements were in Ivan with 1LIai Avg KED where even though the median value was unchanged from ML Aniso OK and worse than ML OK, the combination of a significantly improved mean and smaller extremes led to the best reduction in bias with an
RMSSE of 1.005 versus 1.009 and 1.042 for ML and ML Aniso OK, respectively. Once again, the user should compare all of these conclusions with other cross-validation metrics which show that in some instances (e.g., Floyd KED) slightly poorer distribution performance was countered by improved RMSE, RMKV, RMSSE and/or containment percentage values. As always, the most important conclusion from these cross-validation statistics is that the spatial analysis of the KEDIDP field will be absolutely critical to performance analysis and model selection. Consider the importance of the MPE output now, with its relatively short period of record, and the reader should quickly realize how precarious using cross-validation statistics to evaluate geostatistical performance may be during the investigation of meteorological fields that lack access to high-resolution, high-quality estimates.

5.2.4.4 Relationship between Error/SError and Predicted and Actual Values

The correlation coefficient between predicted and actual values (CorPA), which originally ranged from ~0.55 in Frances to ~0.92 in Floyd, decreased substantially to ~0.45 in Floyd and ~0.10 in Frances upon removal of the trend. This is illustrated qualitatively in Figures 5.2.7-5.2.9 by the large variance in predicted versus actual values, especially for residual predictions within ~1 ln(mm) of zero. CorPA remains directly proportional to the amount of variance explained by MLR (R²) and the slope of the SV function. Furthermore, scatterplots of SError versus actual values reveal a substantial linear relationship present in all trend models for all cases. Table 5.2.3 reveals that the correlation coefficient between standardized error and actual values (CorSEA) increased substantially from ~0.38 to ~0.82 in Floyd, from ~0.80 to a strong ~0.92 in Ivan, and from ~0.80 to a very strong ~0.97 in Frances. Nearly identical behavior is seen from the correlation coefficient between error and actual values (CorEA). Clearly, the worst predictions occur for the residual outliers that reside primarily within the transition zone from light to zero precipitation values, not for the residuals associated with zero values that lie beyond these zones. The fact that this relationship is strongest for Frances and weakest for Floyd implies that it is directly proportional to the percentage of light precipitation values in the distribution compared to
moderate, heavy, and zero precipitation values (i.e., the approximate normality of the lnDRP dataset). The normality of the dataset has already been shown to correlate to the stationarity of the spatial field, which is inversely proportional to the ability of the trend model to remove a significant amount of variance from that field. Consequently, a better-behaved original field should lead to larger residuals or at least a less precise residual behavior when using trend models because there is less variance to explain via a deterministic, non-constant trend. In other words, the use of trend modeling should explain the high correlation between error and actual values as kriging predicts a smoothed representation of the residual field that overestimates small residual values and underestimates large residual values much in the same way the deterministic trend overestimated zero precipitation values and underestimated light precipitation values near the transition zones in each case.

5.2.4.5 KED and the BLUE Characterization (Final Conclusions)

Nevertheless, KED has proven that when given a well-behaved estimate of a spatial field and/or a statistically significant trend model, it can further minimize the variance of the prediction error and improve the orthonormality of the error field. Therefore, this implies that CorPA should be minimal when there is not much more spatial variability the SV model can explain. In other words, in Frances, with CorEA/CorSEA near one and CorPA near 0.10, the implication is that, given all of the restrictions of the current study (i.e., domain size, trend model derivation and structure, original dataset distribution and sampling, nugget effect, etc.) there is not much more that can be done to explain the variability in the precipitation field. This would therefore imply that KED is an approximate BLUE in Frances regardless of the trend model used. It has also been shown that trend model selection may be a significant factor in the minimization of the prediction error as suggested by Ivan where the first-order Cartesian coordinate and physical covariate trend model produced better KED performance statistics when compared to the third-order Cartesian-coordinate polynomial. While KED may be an approximate BLUE for Ivan when the 1LIai Avg trend model is used, the poorer 3LXYs performance suggests that an improved trend model may further reduce the variance in the prediction error and may improve the overall
accuracy of the model. Similar conclusions may be drawn for Floyd, where again the 1LIa model outperformed the 3LXYs model in overall accuracy, but here the results are the least consistent and of all the cases is the one that best suggests additional investigation is needed. In the Floyd case, the declaration of either KED technique being a BLUE would be especially dubious. However, even here either KED technique could be declared the “best” technique compared to all OK and IDW interpolations; whether due to the superior calibration for the 3LXYs KED or the highest accuracy and lowest bias for the 1LIa Max KED.

5.3  KED Performance

5.3.1  Non-Spatial Distribution Analysis

Basic distribution statistics provided in Table 5.3.1 show that both KEDIDP techniques have similar behavior through the third quartile, yielding differences no greater than 3 mm, regardless of case. Similar to the behavior seen with OKIDP, results between the two selected trend models in each case differ more substantially in the final quartile. In each case, the 1LIa(i) model yields significantly higher maximum accumulations. Differences between the LXY and 1LIa(i) KEDIDP maximum values exceed 200 mm in Floyd and 100 mm for Frances and Ivan.

5.3.1.1 Comparison to OK

Comparisons to the OKIDP output reveal the two sets of interpolation techniques yield very similar non-spatial distributions. The most significant discrepancies between OKIDP and KEDIDP techniques occur at the 100th percentile. In Ivan, KEDIDP maximum values exceed OKIDP values by ~40-190 mm while in Floyd they exceed OKIDP maximums by ~45 to as much as ~270 mm. In Frances, the 2LXY KED approach actually yields a smaller maximum value on the order of ~13-50 mm, yet 1LIai Avg KED produces a maximum value that exceeds OKIDP values by ~55-90 mm. The significance of these observations is that the KEDIDP fields are able to better replicate the maximum values estimated from the DRP dataset and MPE output, overcoming an important limitation of OK.
However, the nugget effect and small-scale spatial variance do not appear to be principal contributing factors. It has already been shown that overall, the SV functions at the shortest lags are only marginally improved by the use of KED, and in Frances and Ivan, nugget values are either unchanged or increased upon the removal of trend. Nevertheless, despite slightly less favorable SV model parameters when compared to the LXY trend models, the 1LIa trend models for Frances and Ivan produce more accurate maximum amounts. Therefore, the modeling of the deterministic component of each spatial field is primarily responsible for improvements in the prediction of the upper quartile. These benefits are best exhibited by the use of physical covariates.

5.3.1.2 Assessing Trend-Model Stability and Distribution Shape

As always, the goal in presenting the probability density histograms of the IDP fields is to examine the shape of the non-spatial distribution relative to estimates of truth provided by DRP and MPE. KEDIDP introduces additional uncertainty because this research uses trend surfaces based on a diverse set of covariates across a large domain. Trend analysis indicates a large amount of scatter in the MLR predictions and residual spatial fields. Fortunately, despite the potential instability in the trend models, the histograms of the KEDIDP fields provided in Figures 5.3.1, 5.3.2, and 5.3.3 indicate relatively stable distributions, mimicking the smoothness of the distributions resulting from OK.

Regarding trend model stability, the only significant concern is with the 1LIa Max model in Floyd, where the accuracy of the maximum amount is questioned. Confidence in the upper quartile of the distribution is low not only because of the >220 mm increase over the 3LXYs estimate. The technique’s predicted maximum domain value of 608.30 mm is also over 140 mm larger than the precipitation measured at Southport, NC on 16 September 1999. Nevertheless, it is very similar to the four-day event accumulation of 611.12 mm recorded by the Southport gauge (the actual event accumulation at that gauge occurred across 15 and 16 September 1999; zero precipitation was recorded on 14 and 17 September 1999). Comparisons between the 3LXYs KED histogram and the 1LIa Max KED histogram reveal that significant differences in the distributions begin at values greater than 250 mm despite
the percentage of values beyond 250 mm being similar for the two predictions. Values are
distributed fairly evenly (between 0.25 and 0.50% of the total distribution per 10 mm bin)
across the 1LIai Max KED prediction through ~500 mm while the 3LXYs distribution
abruptly ends at ~390 mm (values are distributed evenly from 250-390 mm at approximately
1–1.25% of the total distribution per 10 mm bin). Clearly, physical covariate values near the
region of maximum accumulations are influencing the shape of the KED 1LIai Max
distribution. Additional analysis occurs with the study of the spatial distribution in the
following section.

Otherwise, the smooth non-spatial distributions previously noted are observed
regardless of the trend model selected. Despite having the simplest spatial distribution, the
most complex distribution shapes produced by KED are observed for the Floyd output from
both selected trend models. However, it is doubtful this behavior can be attributed solely to
the selected covariates. The presence of localized maxima and minima (i.e., secondary
modes) can be traced back to the DRP distribution where gaps in the distribution bins are
clearly the result of the poor gauge sampling across the eastern domain. The repercussions of
this sampling deficiency can be traced through the IDW and OK IDP output as well.
Meanwhile, MPE distributions for Frances and Ivan are far less noisy despite more volatile
precipitation patterns, suggesting the DRP distribution for Floyd is spurious and the influence
of the original DRP dataset greatly exceeds the influence of the trend model covariates.
Nevertheless, the two secondary maxima in distribution percentage first predicted by
IDWIDP for Floyd are modeled differently by the two KED techniques indicating the trend
model covariates exhibit some influence. However, the interpretations of these secondary
modes are inconsistent, suggesting neither model outperforms the other, especially without
MPE data available to provide a cross-reference.

5.3.1.3 Inter-Quartile Performance

Middle-quartile performance in Frances and Ivan is nearly identical between the two
trend model techniques. Unfortunately, KEDIDP continues to under-represent values in the
second and third quartile while over-representing the lowest quartile (especially in the 0-10
This is consistent with behavior noted in Table 5.3.1, which suggests that trend modeling in its current form does not improve upon the general OK underestimation of the precipitation field in any of the first three quartiles. As OKIDP performance is nearly identical, there is also no suggestion from the analysis that the addition of trend modeling improves upon the ability of OK in regions of lighter precipitation. The analysis of trend model residual spatial patterns foreshadowed this conclusion.

Upper-percentile behavior in Frances between the two trend model techniques is similar to that observed in Floyd. As with Floyd, the principal characteristic separating the 2LXY KED technique from the 1LIai Avg KED technique is the truncation of precipitation at the 160-170 mm bin, compared to the smooth, diminishing tail evident in the 1LIai KEDIDP output. The behavior of the polynomial trend models is consistent with ML/REML OKIDP output from both Frances and Floyd, and contradicts the observed distributions from DRP and MPE. Meanwhile, regardless of the precipitation value, differences between the distributions for Ivan are minimal, especially through 150 mm. Between 150 mm and the maximum values, the KED 1LIai distribution is slightly wider (longer positive tail) with only a fractional percentage of the total values in the KED 1LIai distribution exceeding the KED 3LXY's maximum of ~207 mm.

5.3.1.4 Near-Zero Performance

Near-zero performance in Ivan is independent of interpolation technique as the 0-10 mm predictions are continually excessive with bin percentages of ~57% for both the OKIDP and KEDIDP output. These percentages exceed MPE estimates of 45% and DRP estimates of ~38%. Similar performance is observed in Frances, though there are small differences between IDP outputs on the order of 1-2 percentage points. Regardless, average near-zero (0-10 mm) distributions from the IDP output of ~31% greatly exceed estimates from DRP and MPE of ~19%. Near-zero performance for Floyd is somewhat improved with differences between KED and DRP/MPE of only 4-6 percentage points, but again, there is little difference between the two trend model techniques.
5.3.2 Spatial Distribution Analysis

From the analysis of drift, it is clear that in several circumstances, performance between the best Cartesian and physical covariate models is similar in terms of standard metrics like SSR, SSRE, $R^2$, and RMSE. However, the application of these trend surfaces to the prediction grid as noted in Figures 5.3.4, 5.3.5, and 5.3.6 for Floyd, Frances, and Ivan, respectively, reveals that the inclusion of physical covariates introduces a vastly different interpretation of the spatial field than previously achieved with OK or with LXY KED. In the following analysis, the comparisons between KED and OK that take place neglect analysis of the OKIDP fields resulting from anisotropically corrected Gaussian SV models as it has already been shown that these results are inferior. Furthermore, the following analysis seeks to investigate the merits of the predicted field independent of its assigned variances; calibration percentages previously discussed already incorporate the standard deviation of the field into the analysis of model accuracy. In other words, this analysis investigates whether KED chooses the solution from the spatial stochastic process discussed in Section 1.3.1 that maximizes the probability of recreating the original DRP measurements. Finally, recall as well that the KEDIDP fields under investigation are those as highlighted in Table 5.2.2.

5.3.2.1 KEDIDP Performance Using the 1L1a(i) Trend Model

5.3.2.1a Hurricane Floyd (1L1a Max):

Assessing the Limitations of Point-Based DRP/Covariate Relationships

In the analysis of the non-spatial distribution, confidence in the accuracy of the maximum amount for Hurricane Floyd’s 1L1a Max model was low. Analysis of the spatial field shows predictions greater than 500 mm occupying a small area near the landfall of Floyd just to the west of the Cape Fear River in eastern Brunswick County and then north of the Cape Fear River into southwestern Pender County. Immediately to the NW of these maxima, a swath of 400-500 mm values extend into western Pender, southern Sampson, SE Bladen, and NE Columbus Counties, with dramatic departures of 100-150 mm from output provided by 3LXYs KED, OK, or IDW. Along the coast an axis of 400-500 mm precipitation extends into Carteret and southern Pamlico Counties, where a secondary
maximum of 550-600 mm is predicted. This coastal swath of high predictions correlates well to the maximum XWind field and the XU interaction term used in the 1LIa trend model for Floyd.

While it is difficult to ascertain the realism of the Floyd fields without MPE, the resultant pattern produced by 1LIai Max KED is inconsistent with the guidance from the DRP dataset and predictions produced by IDWIDP, which best spatially emulate the DRP point measurements. Combined with the apparent overestimation of precipitation values in the upper quartile, the physical covariate approach does not appear to be successful in this case. Ironically, if the spatial field of residual values is recalled, the most questionable performance is within the maximum precipitation axis where the residual values were actually very consistent and slightly below zero. Closer inspection of the 1LIa Max KEDIDP field reveals very sharp gradients of precipitation in what, at first, appears to be random patterns. However, comparison to the DEM field reveals that these patterns are highly correlated to the terrain of the western Atlantic Coastal Plain and eastern Piedmont. Recall that DEM is determined to be a significant covariate, as well as the interaction terms XDEM and UDEM within the 1LIa Max model. Observe that, for example, a thin axis of 300-350 mm values extending from the Carteret/Pamlico County secondary maximum NW into Lenoir, Greene, and Wayne Counties correlates well to the Neuse River and Contentnea Creek Basins. A similar gradient is observed along the Tar River Basin in eastern Edgecombe County. In addition, the combination of high maximum winds near the center of the storm and near-zero elevations along the coast likely contributes to the maximum amounts near the shore due to the contributions of the UDEM interaction term. Yet, in none of these cases do the resultant precipitation predictions make physical sense; there is no indication that Floyd’s precipitation pattern was severely sensitive to relatively minor elevation changes. Instead, these observations support the conclusion that MLR is observing a broader, lower resolution relationship between DRP and DEM that, when interpreted at the high resolution of the DEM field, becomes overstated. Furthermore, much of the DEM/DRP relationship was generated due to the domain of the DRP sample. On one hand the argument from these results is that a smoother DEM field should be investigated. On the other hand,
previous suggestions for localized regression or smaller, precipitation-based domains would likely eliminate much of the signal and change the structure of the trend model. Therefore, the avenue of approach in future work will greatly influence the role of these and other covariates.

The somewhat odd performance from the 1LIa Max trend model in Floyd reveals some limitations in the KED approach due to the assumption of deterministic or known trend. In some locations within and around the periphery of the maximum precipitation axis (>200mm) across E NC, the trend model covariates take strong precedence over many DRP values. This is a sensible observation if it is understood that the trend has no assigned prediction variance when used concurrently with KED because it is assumed that the trend model represents truth. Furthermore, the residual dataset, while it successfully eliminates much of the spatial uncertainty in the original field, still possesses significant short-lag uncertainty due to the nugget effect and large slope in the estimated SV function. This concurrently handicaps residual OK and prevents any significant explanation of small-scale spatial variability necessary for high-resolution prediction. In other words, much of the 1LIa Max model is based on a trend model whose spatial surface is derived not from analysis of spatial SV between rain-gauge observations, rather from a sample dataset assumed to be spatially independent. The resultant KEDIDP field in Floyd highlights the problems associated with assuming the trend model will produce a reliable trend surface especially when the spatial variability of the residual field is large enough to desensitize the predicted residual field to the DRP observations. This observation is not exclusive to Floyd, though it is most prevalent there. Frances and, to a much lesser extent, Ivan both exhibit these characteristics; however, the gauge sampling in Floyd’s maximum precipitation axis is much worse meaning the MLR’s insensitivities to spatial autocorrelation are even more important.

5.3.2.1b Hurricane Frances (1LIai Avg):

Assessing the Advantages of Physical Covariates

Overall, the 1LIai Avg KEDIDP field in Frances maintains a similar precipitation pattern to those achieved via 2LXY KED or OK, but it tends to enhance precipitation across
the entire region of maximum values (values >100 mm) by selectively enhancing precipitation relative to the average 10 m horizontal wind field. In several locations, most notably in extreme NW SC, NE GA, and near the highest totals across McDowell and Rutherford Counties in NC, the 1L1ai Avg KED approach dramatically outperforms the 2LXY KEDIDP with average field improvements in some locations reaching 100 mm. These improvements are also noteworthy when compared against the WNLS OK technique. The added detail provided by the 1L1ai Avg KED technique also enhances the predicted field just north of the NC/SC border west of Charlotte. Close inspection of the field in this region indicates that the 1L1ai Avg trend model contributes to a higher-resolution interpretation of the DRP field; capturing precipitation banding structures in Cleveland, Rutherford, and Henderson Counties, for example. Of course, the predicted values themselves in many of these areas still fall well short of values predicted by MPE and even IDWIDP, but this remains an anticipated byproduct of the smoothed representation characteristic of kriging. Performance from all OK and KED interpolation techniques is especially poor across E GA and SC, where MPE indicates intense convective banding occurred largely unbeknownst to the gauge network. In these locations, the exact interpolation of the IDWIDP field can be beneficial by predicting heavier amounts and even resolving, albeit weakly, better sampled banding structures, as observed along the Savannah River Basin, and portions of northern SC. It may also be suggested that despite the low statistical significance, the inclusion of the DEM covariate may prove beneficial in some areas, especially across the SW VA Blue Ridge, where unfavorable gauge sampling and excessive smoothing play large roles in the underprediction of rain along the Blue Ridge Parkway SW of Roanoke for all OK and KED techniques. In this area, IDW and WNLS OK produce the most realistic fields. As with the other cases, there are locations where the trend model appears to excessively influence the field. For example, the eastern portion of the maximum precipitation field in the 1L1ai Avg KEDIDP output appears to be somewhat overdone, perhaps on the order of 25-75 mm, especially across Iredell, Alexander, and Wilkes Counties. A respectable gauge density in this region and a close correlation to the average XWind field substantiates this
interpretation. Exact comparisons to MPE must be avoided, however, due to poor radar coverage.

5.3.2.1c Hurricane Ivan (ILI\text{ai Avg}):

Assessing the Accuracy of Added Detail as a Function of Location

Upon study of the ILI\text{ai} KEDIDP field for Ivan, it is clear the inclusion of geophysical covariates and interaction terms, combined with a favorable relationship with average 10 m horizontal wind, creates a very detailed and visually appealing precipitation field. Closer inspection suggests that, while in many locations the added detail may have some realism, the trend model does not appear to discriminate enough between the highest elevations. For example, comparisons between the ILI\text{ai} Avg KEDIDP, MPE, and IDWIDP suggests that the KEDIDP field overestimates precipitation along the highest elevations near and along the NC/TN border and the Appalachian Trail. This region, located downwind (NW) of the Blue Ridge near the GA/NC/SC borders, likely experienced reduced moisture advection and reduced quantities of precipitable water as suggested by all precipitation fields, but to what magnitude is unclear because of the limitations of MPE within this area. Furthermore, gauge density is good, but in proportion to the small-scale terrain variability, it is not sufficient enough to either confirm or deny the KEDIDP field. A few gauges in this area may even be legitimate outliers, but without detailed analysis of the surrounding location and terrain and a thorough understanding of the gauge sitings, assessing measurement quality is very difficult.

DEM-induced precipitation maxima are also noted along the Cumberland Plateau, along the western domain boundary in TN through extreme SE KY, including KY’s Black Mountain (KY’s highest point at 1262 m), and into the Ridge and Valley Province of SW VA. In isolated locations, across the highest elevations, ILI\text{ai} Avg KEDIDP reaches ~150 mm. While MPE suggests some isolated amounts in similar locations across SE KY and SW VA as high as 90 mm, gauge data do not resolve these features. Meanwhile, across the Cumberland Plateau in TN, a larger area of values >175 mm is predicted to the NW of similar MPE estimates that lie off the Plateau in the Ridge and Valley Province, where
average DEM values are lower. Differences between MPE and KEDIDP on and near the Plateau exceed 100 mm in some locations. Across this area the suggestion is that the geophysical relationship which appears to work better along the Blue Ridge is not appropriate across the Plateau which was located in the western quadrants of Ivan during much of the event. Regardless, it is unclear whether any of these values are accurate. Analysis of similar predictions in earlier datasets, where MPE is unavailable, would prove to be even more challenging, thus suggesting the use of geophysical variables, even those accounting for slope, must be used with caution and only when uncertainty in the prediction can be quantitatively expressed. In these circumstances, the general smoothing behavior exhibited by KED and OK is a favorable property and the overall argument for usage of smoothed geophysical variables is supported.

Despite these criticisms, there are favorable results as well within the 1LIai Avg field for Ivan. The best performance is along the maximum precipitation axis across the N GA and W NC Blue Ridge. Comparisons with the DEM field reveal the trend model is not simply mimicking the terrain, as there are clear influences between both DEM and the average 10 m horizontal wind which work to improve the accuracy of the model. Nevertheless, where DEM and wind covariates interact best, especially along the GA Blue Ridge, the correlation between local precipitation maxima and DEM is strong. However, domain maximum precipitation amounts approaching 350 mm are not predicted in NE GA where DRP data are highest, rather in Murray and Fannin Counties in extreme N central GA and in NC near Mount Mitchell. Comparisons to MPE reveal maxima in these locations, albeit at smaller magnitudes. Neither KED approach nor any other interpolation technique predicts the large accumulations evident in MPE estimates across extreme NW SC and to the NE of Mount Mitchell near Hawksbill Mountain, where gauge data are lacking. Furthermore, the 1LIai Avg KED approach still averages or smoothes the maximum axis and cannot replicate the heaviest totals in MPE and IDWIDP. Overall, however, it is clear that the 1LIai Avg KEDIDP improves upon the 3LXYs KEDIDP in this region. Nevertheless, the KEDIDP fields from all three cases highlight the need to understand both the non-spatial and spatial distributions; regardless of the accuracy of the maximum value itself, there may be
important spatial discrepancies between the predicted fields, the point measurements, and/or MPE output that influence interpretation of model performance.

5.3.2.2 KEDIDP Performance in Light, Near-Zero, and Zero Precipitation

Zero, near-zero, and “light” (<75 mm) precipitation performances amongst all cases and all models are fairly consistent, suggesting little advantage to trend modeling. This is consistent with analysis of the residual spatial fields, which suggested the selected trend models were most unstable in these transition zones. In Frances, for example, the best resolution of subtle precipitation patterns in these lighter amounts is not achieved via KED but through the WNLS OK technique. Between the two KED techniques, however, the 1LIai Avg KED approach slightly outperforms 2LXY KED along the NC/TN border with better resolution of small variations in the field when compared against MPE output, yet otherwise the two fields are nearly identical in these precipitation regions. In Floyd, geophysical covariates and interaction terms in the 1LIa Max trend model create differences in the field especially for light and moderate (~100-200 mm) precipitation amounts similar to the way they influence heavier amounts in the Coastal Plain. Unfortunately, many of these performance differences occur in between gauge observations and cannot be validated. It is assumed, therefore, that the erratic behavior from the 1LIa Max trend model across the Coastal Plain translates to these lighter amounts. Interestingly, the 3LXY's trend model was somewhat more sensitive to the lightest amounts along the transition zone, identifying some of the zero reports and comparatively larger reports in southern SC as well as the isolated non-zero report in western NC. The 3LXY's KED approach also predicts precipitation across extreme NE SC in Horry County better than any other OK or KED technique, while producing predictions in central NC similar to the ML OK approach.

Meanwhile, the largest light/near-zero/zero discrepancies in Hurricane Ivan occur across the Ridge and Valley Province of eastern TN. Across this region, the DEM and NARR 10 m horizontal wind covariates interact to strongly influence the 1LIai Avg KEDIDP output. Notice, for example, centered near the intersection of Knox, Loudon, Roane, and Anderson Counties, the strong correlation between the KEDIDP and DEM, YWind, and
XWind fields. The 1LIai Avg KED values differ from nearby MPE and 3LXYs KED values by 50 to as much as 200 mm. However, to the NE of this region, comparisons between MPE and the 1LIai Avg KED field are significantly improved, as the additional detail provided by the physical covariates produces areal precipitation averages lower than the overestimates produced by 3LXYs KED. Caveats about MPE performance in the Appalachians aside, the increased detail in these lighter precipitation regions is obviously inconsistent and, like in the heavier regions of the KEDIDP fields for Ivan, it is unclear whether the visual appeal of the field correlates to increased accuracy. Recall that cross-validation results suggest, though the differences are small, 1LIai Avg KED appears to reduce the errors in the prediction, suggesting there is some skill in using this approach. Thus, while the field is heavily influenced by high-resolution DEM output, and overall there may be a need to smooth the DEM output in order to generalize the KEDIDP field, the 1LIai Avg KED approach is successful when compared against the other techniques. Elsewhere, light/near-zero/zero value performance for Ivan is nearly identical across all interpolation techniques. KED offers no improvement in the analysis of near-zero precipitation across SE GA, SC, and W central NC, nor is either KED approach able to identify isolated reports of light precipitation across the Atlantic Coastal Plain.

5.3.2.3 Assessing the Impact of Questionable Gauge Measurements

For Hurricane Ivan, comparisons of all interpolated fields to the MPE field do highlight the significant influence of two suspicious gauges across central GA. These gauges, located SE of Atlanta in Newton and Gwinnett Counties, measure near-zero to zero values. According to MPE, however, the Gwinnett County gauge lies within a 150 mm precipitation axis extending from Metro Atlanta north to Mount Oglethorpe. Meanwhile, the Newton County gauge lies within an axis of relative minima averaging 50-75 mm of precipitation. In both cases, MPE strongly suggests that the measurements from these gauges are erroneous. Additionally, the variability in the spatial pattern across central and N GA highlights the general concern of using empirical mapping during convective precipitation patterns, especially where gauge sampling is particularly poor. These convective events can
easily “miss” gauge networks such that one gauge representing one or more counties samples near-zero precipitation while MPE indicates significant precipitation occurred nearby. Therefore, the IDW/OK/KED fields will also “miss” these high-resolution patterns while concurrently overstating the spatial influence of the near-zero gauge. This is seen frequently in Frances and Ivan where MPE indicates definitive banding features that the point measurements cannot resolve. Assessing the legitimacy of gauges in these environments is very difficult, yet this situation is frequently seen in operational meteorology.

Much of the discussion has focused on the hindrance of large prediction variances in the analysis of small-scale features, most notably with the maximum amounts and non-continuous light precipitation fields. However, the incorporation of questionable measurements, whether due to measurement error, reporting times, transmission issues, or other flaws in the dataset, impacts spatial variance estimates as well. Therefore, in OK and KED the presence of uncertainty in the prediction tends to smooth out potential outliers as well as legitimate extremes. This is exhibited, for example, in Floyd with the 1LIa Max KED technique in NE NC; with both OK and KED techniques in Frances across central and NW SC and central NC among other locations; and in Ivan across central GA, and central and NW SC. In other words, the use of the geostatistical model and its tendency to average out the entire field will, at times, be advantageous in the mapping of large climatological datasets with imperfect quality control techniques, especially since at least some of the uncertainty in the prediction can be communicated quantitatively to the user.

5.3.2.4 Downscaling Physical Covariates and Spatial Pattern Impacts

Each 1LIa(i) KEDIDP field is easily identified by the presence of noise in the field. Analysis of lower-resolution predictions reveals similar behavior, albeit it does become progressively smoother as the grid cell size increases. Nevertheless, the wavy pattern is persistent across most contours and usually is noted along the entire length of each contour. The behavior is best observed in Frances, least observed in Ivan, and is not likely due to one specific variable as no case contains a unique physical variable that mitigates or enhances the pattern. However, the lack of geophysical variables in Frances suggests that the issue is
linked to the physical covariates, whether individually or through the interaction with each other or with the first-order Cartesian coordinates. Analysis of the NARR fields suggests the downscaling of the 1024 km² grid cell from the NARR output to a 16 km² cell for interpolation may be responsible for the introduction of noise into the KEDIDP field. However, investigation of lower-resolution NARR grids, even to the original 32 km x 32 km scale, reveals similar patterns in the covariates’ fields, albeit the intensity of the noise present in these fields is certainly proportional to the resolution of the covariate grid. In any case, these observations, as well as observations noted with the geophysical covariates, argue for the use of lower-resolution covariate grids in order to address the dangers of assuming a deterministic trend with no prediction variance.

5.3.2.5 KEDIDP Performance Using the LXY Trend Model

Unfortunately, a potential consequence of using lower-resolution covariate grids may be the smoothing of the overall fields to the point where they mimic the results produced by the Cartesian coordinate polynomial trend models. Analysis of the LXY KEDIDP from all cases reveals these predicted fields closely resemble OKIDP output. The predicted spatial fields generally duplicate observations made in the non-spatial analysis. The performance is best in Floyd, where maximum amounts are enhanced and better replicate the implied precipitation distribution from the DRP dataset. In Ivan, performance is slightly improved over the OKIDP output along the maximum precipitation axis extending from extreme NE GA along the Blue Ridge into SW NC. However, the perceived improvement in maximum precipitation values from the non-spatial analysis is incorrect. Values across the southern Appalachians are only slightly higher compared to OKIDP, while there appears to be an erroneous maximum along the southern AL/GA border at the domain boundary. Meanwhile, in Frances, spatial analysis confirms what was observed from the non-spatial distribution. The 2LXY model actually is the worst predictor of all available predictors, further smoothing maximum values across W NC and diluting precipitation patterns along the Savannah River Basin, VA Blue Ridge, and along the SC/NC border. The use of the LXY models reinforce the impression that KED serves primarily to enhance the robustness of the assumptions made
for the geostatistical model, and only in limited circumstances does KED actually improve the quality or accuracy of the final predicted field. Where the original DRP field best approximated stationarity, as in Frances, the use of OK with a WNLS-fitted SV model best replicates the subtle precipitation patterns evident in the original field. However, where the original field has an unstable estimated SV structure, as in Ivan and Floyd, the use of the third-order coordinate polynomial allows adherence to geostatistical model principals while providing a smoothed but stable representation of the precipitation field.

5.3.2.6 Actual Versus Predicted Values (Final Conclusions)

Finally, scatterplots of actual versus predicted values (Figures 5.3.7, 5.3.8, and 5.3.9 for Floyd, Frances, and Ivan, respectively) do not suggest significant changes between either KED technique for any of the cases, nor do they indicate any important, widespread accuracy improvement over OK and IDW techniques. These results are consistent with the conclusions derived from the trend model residual analysis, as they should be. Remember, KED assumes the presence of non-constant trend, but it does not account for the uncertainty in the prediction of trend; it assumes that the trend is known (i.e., the modeled trend represents truth). The removal of trend and the analysis of residuals via OK based on this assumption implies that the presence of prediction error exists only in the residual field. Clearly, the trend models are successful at removing variability originally assigned to the stochastic portion of the field, but by the very definition of trend the models could not replicate the extreme scatter present in the DRP dataset. The nature of OK may be to minimize error, as KED appears to do, but it will not eliminate error. Given previous analyses of residual OK prediction errors, and as evidenced by the 95% CIs for KED, overall confidence or accuracy in the prediction does not change, regardless of the obvious improvements to the adherence of statistical assumptions that form the foundation of the geostatistical model. This analysis suggests the geostatistical model is very robust despite instances of user misinterpretation or error. However, it is clear that trend model selection is critical for the resultant KEDIDP spatial fields; therefore, it is equally critical that the user
thoroughly evaluate the impact of any trend model on the final prediction regardless of the cross-validation metrics.
Table 5.1.1a. Sample correlation coefficients between DRP values and the first-, second-, and third-order Cartesian coordinates for 16 September 1999, 8 September 2004, and 17 September 2004. Below each row of correlation coefficients are p-values for the null hypothesis that the correlation coefficient equals zero. Note however, these p-values require a normal distribution and are to only be treated as guidance.

### 19990916-16

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<th>Y^2</th>
<th>XY</th>
<th>X^3</th>
<th>Y^3</th>
<th>X^2Y</th>
<th>Y^2X</th>
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<tr>
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<td>0.033</td>
<td>-0.299</td>
<td>-0.181</td>
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<td>0.405</td>
<td>-0.023</td>
<td>0.021</td>
<td>0.388</td>
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<td>&lt;0.001</td>
<td>0.526</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>0.661</td>
<td>0.685</td>
<td>&lt;0.001</td>
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<td>ln(DRP)</td>
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<td>-0.573</td>
<td>-0.095</td>
<td>0.259</td>
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<td>0.058</td>
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<td>0.523</td>
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<tr>
<td>p-value</td>
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<td>&lt;0.001</td>
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<td>&lt;0.001</td>
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### 20040908-08

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<th>Y^3</th>
<th>X^2Y</th>
<th>Y^2X</th>
</tr>
</thead>
<tbody>
<tr>
<td>DRP</td>
<td>-0.209</td>
<td>0.079</td>
<td>-0.120</td>
<td>-0.306</td>
<td>-0.276</td>
<td>0.035</td>
<td>-0.038</td>
<td>0.077</td>
<td>0.052</td>
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<tr>
<td>p-value</td>
<td>&lt;0.001</td>
<td>0.113</td>
<td>0.017</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>0.492</td>
<td>0.455</td>
<td>0.125</td>
<td>0.305</td>
</tr>
<tr>
<td>ln(DRP)</td>
<td>-0.270</td>
<td>0.147</td>
<td>-0.023</td>
<td>-0.254</td>
<td>-0.350</td>
<td>-0.127</td>
<td>0.091</td>
<td>0.099</td>
<td>-0.009</td>
</tr>
<tr>
<td>p-value</td>
<td>&lt;0.001</td>
<td>0.003</td>
<td>0.646</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>0.011</td>
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<td>0.844</td>
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### 20040917-17

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<th>Y^3</th>
<th>X^2Y</th>
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<tbody>
<tr>
<td>DRP</td>
<td>-0.615</td>
<td>-0.043</td>
<td>0.547</td>
<td>-0.259</td>
<td>-0.242</td>
<td>-0.564</td>
<td>-0.112</td>
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<td>p-value</td>
<td>&lt;0.001</td>
<td>0.393</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
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<td>0.228</td>
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<tr>
<td>ln(DRP)</td>
<td>-0.755</td>
<td>-0.098</td>
<td>0.430</td>
<td>-0.108</td>
<td>-0.339</td>
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<td>p-value</td>
<td>&lt;0.001</td>
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<td>&lt;0.001</td>
<td>0.031</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
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<td>0.559</td>
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Table 5.1.1b. Sample correlation coefficients between DRP values and the first-order physical coordinates for 16 September 1999, 8 September 2004, and 17 September 2004. Below each row of correlation coefficients are p-values for the null hypothesis that the correlation coefficient equals zero. Note however, these p-values require a normal distribution and are to only be treated as guidance. Values in parenthesis are derived from the NARR maximum 10m horizontal wind taken for the 1200 UTC-1200 UTC day.

<table>
<thead>
<tr>
<th>19990916-16</th>
<th>DEM</th>
<th>XWind</th>
<th>YWind</th>
<th>XSlope</th>
<th>YSlope</th>
<th>SLOPEWIND</th>
</tr>
</thead>
<tbody>
<tr>
<td>DRP</td>
<td>-0.421</td>
<td>-0.625 (0.132)</td>
<td>-0.215(-0.067)</td>
<td>-0.010</td>
<td>-0.015</td>
<td>0.034 (0.005)</td>
</tr>
<tr>
<td>p-value</td>
<td>&lt;0.001</td>
<td>0.001 (&lt;0.001)</td>
<td>0.193 (&lt;0.001)</td>
<td>0.846</td>
<td>0.772</td>
<td>0.513 (0.928)</td>
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<tr>
<td>ln(DRP)</td>
<td>-0.412</td>
<td>-0.483 (0.153)</td>
<td>-0.499(-0.185)</td>
<td>-0.037</td>
<td>0.043</td>
<td>-0.023(-0.053)</td>
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<tr>
<td>p-value</td>
<td>&lt;0.001</td>
<td>&lt;0.001 (0.003)</td>
<td>&lt;0.001 (&lt;0.001)</td>
<td>0.475</td>
<td>0.402</td>
<td>0.650 (0.300)</td>
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<th>20040908-08</th>
<th>DEM</th>
<th>XWind</th>
<th>YWind</th>
<th>XSlope</th>
<th>YSlope</th>
<th>SLOPEWIND</th>
</tr>
</thead>
<tbody>
<tr>
<td>DRP</td>
<td>0.534</td>
<td>-0.562(-0.276)</td>
<td>-0.096 (-0.115)</td>
<td>-0.128</td>
<td>-0.106</td>
<td>0.143 (0.144)</td>
</tr>
<tr>
<td>p-value</td>
<td>&lt;0.001</td>
<td>&lt;0.001 (&lt;0.001)</td>
<td>0.055 (0.021)</td>
<td>0.010</td>
<td>0.035</td>
<td>0.004 (0.004)</td>
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<tr>
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<td>&lt;0.001 (&lt;0.001)</td>
<td>&lt;0.001 (0.043)</td>
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<td>0.603</td>
<td>0.089 (0.136)</td>
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<table>
<thead>
<tr>
<th>20040917-17</th>
<th>DEM</th>
<th>XWind</th>
<th>YWind</th>
<th>XSlope</th>
<th>YSlope</th>
<th>SLOPEWIND</th>
</tr>
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<tbody>
<tr>
<td>DRP</td>
<td>0.556</td>
<td>-0.674(-0.141)</td>
<td>0.074 (0.431)</td>
<td>-0.086</td>
<td>-0.023</td>
<td>0.085 (0.023)</td>
</tr>
<tr>
<td>p-value</td>
<td>&lt;0.001</td>
<td>&lt;0.001 (0.005)</td>
<td>0.143 (&lt;0.001)</td>
<td>0.087</td>
<td>0.645</td>
<td>0.091 (0.651)</td>
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<tr>
<td>ln(DRP)</td>
<td>0.525</td>
<td>-0.631(-0.288)</td>
<td>0.158 (0.478)</td>
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<td>&lt;0.001 (0.566)</td>
<td>0.002 (&lt;0.001)</td>
<td>0.613</td>
<td>0.457</td>
<td>0.275 (0.293)</td>
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</table>
Table 5.1.2. Covariates included for each of the trend models investigated. All models use the logarithmically transformed DRP dataset as the response variable. The LXY models are polynomials based only on the Cartesian coordinates X and Y and are applicable for all three cases studied. The 1LALL model includes all first-order Cartesian and physical coordinates studied, as well as the all interaction terms between them. The 1L model investigates only the first-order Cartesian and physical coordinates. Both 1LALL and 1L are applicable for all cases. Thereafter, the 1La, 1LiA, and 1LiAi models using either the average (“Avg”) or the maximum (“Max”) XWind and YWind NARR variables are provided for each case. The 1La model consists of only the significant first-order predictors from 1L. The 1LiA model includes all of the interaction terms from the covariates in 1La. Finally, the 1LiAi model incorporates only the significant predictors from the 1LiA model. When 1LiA is the final model, all covariates are significant and a 1LiAi model is unnecessary. The highlighted models represent the “best” models as determined from the MLR methodology discussed in Section 3.5.

<table>
<thead>
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<tr>
<td>3LXYs</td>
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<tr>
<td>1LALL</td>
</tr>
<tr>
<td>1L</td>
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<tr>
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<tr>
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<tr>
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<th>1Li  Avg</th>
<th>1Li  Max</th>
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<td>X + XWind</td>
<td>Y + XWind + YWind + YU + YV + UV</td>
<td>X + XWind + XU</td>
<td>Y + XWind + YWind + YU</td>
<td>1Li a is the final model</td>
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<tr>
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<td>X + Y + XWind + YWind + DEM</td>
<td>X + Y + XWind + YWind + DEM + XY + XU + XV + XDEM + YU + YV + YDEM + UV + UDE + VDEM</td>
<td>X + Y + XWind + YWind + DEM + XV</td>
<td>X + Y + XWind + YWind + DEM + UV + UDE + VDEM</td>
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Table 5.1.3. Regression statistics for the trend models provided in Table 5.1.2. Included from left to right are the model degrees of freedom (DFM); the error degrees of freedom (DFE); the regression sum of squares \{SSR, [\ln(mm)]^2\}; the error sum of squares \{SSE, [\ln(mm)]^2\}; the coefficient of determination \(R^2\); and the root mean square error \[RMSE, \ln(mm)\]. The selected Cartesian coordinate-only polynomial and the selected first-order physical and Cartesian coordinate model are highlighted.

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1LLa is the final model
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Table 5.1.4. Covariate statistics for the selected trend models used in each case, where $\beta_0$ is the model intercept (i.e., component of constant trend). Ordered from left to right are the coefficient value ($\beta$); the standard error [$\sigma$, ln(mm)]; the sequential or Type I sum of squares {SSQI, [ln(mm)]$^2$}; and the partial or Type II sum of squares {SSQII, [ln(mm)]$^2$}. It is important to note that the formulas upon which $\sigma$ is based require valid MLR assumptions, which are not valid for the precipitation fields studied herein. $\sigma$ is shown for guidance only.

<table>
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Table 5.1.4 Continued

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Table 5.2.1. Covariate statistics derived from REML for the selected trend models used in each case, where $\beta_0$ is the model intercept (i.e., component of constant trend). Ordered from left to right are the coefficient value derived from REML ($\beta_{\text{REML}}$); the standard deviation [$\sigma$, $\ln(\text{mm})$]; the 95% confidence interval for the REML-derived trend coefficients [95% CI, $\ln(\text{mm})$]; and the coefficient value derived from OLS ($\beta_{\text{OLS}}$). Each highlighted row indicates where $\beta_{\text{OLS}}$ lies outside the 95% CI. Standard deviations that exceed the value of the coefficient appear in bold font. It is important to note that because REML accounts for the spatial variance in the dataset, estimates of $\sigma$ derived from the covariates’ covariance matrix are valid, allowing the calculation of each coefficients’ 95% CI.

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<td>$\ln(\text{mm})$</td>
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<tr>
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<td>0.448</td>
<td>[2.261, 4.017]</td>
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<tr>
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<td>0.086</td>
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<th>$\sigma$</th>
<th>95% CI</th>
<th>$\beta^{OLS}$</th>
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<td>$\ln(\text{mm})$</td>
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<td>$Y$</td>
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<td>0.0017</td>
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<th>$\sigma$</th>
<th>95% CI</th>
<th>$\beta^{OLS}$</th>
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<td>$\ln(\text{mm})$</td>
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<tr>
<td>$Y\text{Wind}$</td>
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<td>0.083</td>
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<td>-0.296</td>
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<tr>
<td>$YU$</td>
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Table 5.2.1 Continued

<table>
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<th>( \beta^{\text{REML}} )</th>
<th>( \sigma )</th>
<th>95% CI</th>
<th>( \beta^{\text{OLS}} )</th>
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</thead>
<tbody>
<tr>
<td>ln(mm)</td>
<td>ln(mm)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| \( \beta_0 \) | -0.506 | \textbf{0.675} | [-1.830, 0.818] | -0.633 |
| X           | -1.419 | 0.333         | [-2.072, -0.766] | -1.580 |
| Y           | 0.320  | \textbf{0.416} | [-0.495, 1.135]  | 0.311  |
| X^2         | 0.225  | 0.108         | [0.0125, 0.437]  | 0.279  |
| Y^2         | 0.0021 | \textbf{0.179} | [-0.349, 0.352]  | 0.052  |
| XY          | -0.373 | 0.22          | [-0.803, 0.058]  | -0.478 |
| X^3         | 0.054  | 0.025         | [0.0055, 0.103]  | 0.080  |
| Y^3         | 0.0019 | \textbf{0.047} | [-0.091, 0.094]  | -0.0062|
| X^2Y        | -0.115 | 0.044         | [-0.201, -0.029] | -0.134 |
| Y^2X        | 0.055  | \textbf{0.059} | [-0.061, 0.171]  | 0.066  |

<table>
<thead>
<tr>
<th>1LIai Avg</th>
<th>( \beta^{\text{REML}} )</th>
<th>( \sigma )</th>
<th>95% CI</th>
<th>( \beta^{\text{OLS}} )</th>
</tr>
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<tbody>
<tr>
<td>ln(mm)</td>
<td>ln(mm)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| \( \beta_0 \) | -5.671 | 2.122        | [-9.830, -1.512] | -7.593 |
| X            | -0.0067| 0.0022       | [-0.011, -0.0024] | -0.006 |
| Y            | 0.0048 | 0.0034       | [-0.0020, 0.012]  | 0.0062 |
| XWind        | -0.954 | 0.394        | [-1.725, -0.182]  | -1.303 |
| YWind        | 0.855  | 0.438        | [-0.0039, 1.714]  | 1.119  |
| DEM          | 0.0044 | 0.0022       | [0.000021, 0.0088] | 0.0052 |
| UV           | 0.112  | 0.069        | [-0.023, 0.248]   | 0.149  |
| UDEM         | 0.00049| 0.00031      | [-0.00012, 0.0011] | 0.00063 |
Table 5.2.2. SV model parameters derived using REML and after removing the trend using the selected Cartesian and physical trend models for (a) 16 September 1999, (b) 8 September 2004, and (c) 17 September 2004. From left to right the provided parameters are the estimated constant mean $[\ln(\text{mm})]$; the estimated nugget effect $[\ln(\text{mm})]^2$; the partial sill $[\ln(\text{mm})]^2$; and the range (km).

### 19990916-16

<table>
<thead>
<tr>
<th>Technique</th>
<th>Model</th>
<th>Mean $[\ln(\text{mm})]$</th>
<th>Nugget $[\ln(\text{mm})]^2$</th>
<th>Partial Sill $[\ln(\text{mm})]^2$</th>
<th>Range (km)</th>
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<tbody>
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<tr>
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### 20040908-08

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<th>Partial Sill $[\ln(\text{mm})]^2$</th>
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<th>Partial Sill</th>
<th>Range</th>
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<td>[ln(mm)]^2</td>
<td>km</td>
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Table 5.2.3. Cross-validation statistics for the OK interpolation of trend model residuals for (a) 16 September 1999, (b) 8 September 2004, and (c) 17 September 2004. From left to right the provided statistics are the correlation between predicted and actual values (corPA); the correlation between actual values and the associated error (corEA); the correlation between the actual values and the associated standardized error (corSEA); the root mean square error [RMSE, ln(mm)]; the root mean kriging variance [RMKV, ln(mm)]; the root mean square standardized error (RMSSE, unitless); and the percent of actual values that lie within the 95% confidence interval (%CI, %).

<table>
<thead>
<tr>
<th>Technique</th>
<th>Model</th>
<th>CorPA</th>
<th>CorEA</th>
<th>CorSEA</th>
<th>RMSE</th>
<th>RMKV</th>
<th>RMSSE</th>
<th>%CI</th>
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<td>0.772</td>
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<tr>
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<td>0.369</td>
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<td>0.371</td>
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<table>
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<tr>
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<th>CorPA</th>
<th>CorEA</th>
<th>CorSEA</th>
<th>RMSE</th>
<th>RMKV</th>
<th>RMSSE</th>
<th>%CI</th>
</tr>
</thead>
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<tr>
<td>Residual OK – REML</td>
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<td>0.971</td>
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<td>1.601</td>
<td>1.008</td>
<td>95.7</td>
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<tr>
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<tr>
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<td>0.564</td>
<td>0.812</td>
<td>0.811</td>
<td>1.623</td>
<td>1.593</td>
<td>1.009</td>
<td>95.7</td>
</tr>
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<td>1.620</td>
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<td>WNLS 650</td>
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<th>RMKV</th>
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</tr>
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<td>0.915</td>
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<td>1LIai Avg</td>
<td>Exp.</td>
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<td>0.939</td>
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Table 5.2.4. Basic distribution statistics for both error and SError resulting from the cross-validation of OK on trend model residuals for (a) 16 September 1999, (b) 8 September 2004, and (c) 17 September 2004. From left to right the basic statistics are comprised of the minimum [ln(mm)]; the 1st quartile or 25th percentile [ln(mm)]; the 2nd quartile, 50th percentile, or median [ln(mm)]; the mean [ln(mm)]; the 3rd quartile or 75th percentile [ln(mm)]; and the maximum [ln(mm)].

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<th>Model</th>
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<th>Median (50%)</th>
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**Error**

**Residual OK – REML**

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**SError**

**Residual OK – REML**

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Table 5.2.4 Continued
Table 5.3.1. Basic distribution statistics from KEDIDP output for (a) 16 September 1999, (b) 8 September 2004, and (c) 17 September 2004. From left to right the basic statistics are comprised of the minimum (mm); the 1st quartile or 25th percentile (mm); the 2nd quartile, 50th percentile, or median (mm); the mean (mm); the 3rd quartile or 75th percentile (mm); and the maximum (mm). Included in this table are the basic statistics from the original DRP dataset, the MPE dataset (available for 2004 cases only), IDWIDP output, and OKIDP output. These basic statistics are identical to those shown in previous tables yet are included here for comparison purposes.

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Figure 5.1.1. Average NARR E-W component of the 10m horizontal wind (XWind, m s\(^{-1}\)) for (a) 16 September 1999, (b) 8 September 2004, and (c) 17 September 2004.
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6. CONCLUSIONS and FUTURE RESEARCH

6.1 General Conclusions

Geostatistical methods have enjoyed successful implementation across climatic timescales (i.e., greater than or equal to one month), but very little research has been done to investigate the viability of these methods on subclimatic time scales, where the spatial variability of many meteorological variables increases substantially. To address the rising demand for high-resolution, gridded meteorological data at shorter time scales, this research investigates the use of two geostatistical methods, OK and KED, on daily tropical cyclone-induced precipitation data obtained across the Carolina region of the SE US. Compared to the simple, but popular, IDW interpolation technique, both methods generally improve upon the overall accuracy of the predicted spatial field in each tropical cyclone. Additionally, both OK and KED provide estimates of the uncertainty in the prediction which are essential to many applications yet cannot be produced from IDW interpolation. However, the use of a multivariate linear trend model to first remove the non-stationarity present in the original dataset dramatically increases the validity of important assumptions that comprise the geostatistical model by normalizing the primary variable; removing non-stationarity in the original DRP field; reducing or eliminating anisotropy; producing more stable estimates of SV model parameters; and minimizing the bias and variance of the prediction error.

Comparison of Cartesian coordinate polynomials of the first through third order and a first-order trend model comprised of significant Cartesian, geophysical, and physical covariates suggests that the latter models produce better spatial accuracy and more realistic spatial fields when the maximum precipitation axes occur in the western Carolinas. However, this research also concludes that the third-order Cartesian coordinate polynomial is more reliable when tropical cyclones make landfall along the Atlantic coast and the heaviest precipitation is confined to the Atlantic Coastal Plain.

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1 It is important that the reader review Section 1.1 (Motivation) and Section 2.2 (Current Objectives) in order to evaluate the final conclusions presented here properly.
6.2 Trend Modeling Conclusions and Recommendations

The preferred KED techniques as a result of this research are based on the 3LXYs trend model for Hurricane Floyd (1999); the 1LIIai Avg trend model for Hurricane Frances (2004); and the 1LIIai Avg trend model for Hurricane Ivan (2004). Review of Table 5.1.2 shows that for Frances and Ivan, both components of the 10 m horizontal wind from the NARR dataset are significant covariates, as well as the N-S Cartesian coordinate. For Ivan, DEM was also a significant covariate, and the inclusion of the interaction between XWind and DEM suggests that orographic enhancement resulting from the strong ESE flow across the Blue Ridge was statistically significant within the DRP dataset.

In regions of strong orographic enhancement, the use of a physical covariate model appears to provide some enhanced value; predicting higher-resolution spatial patterns in the precipitation fields that obviously mimic the high-resolution covariates on which they are based. Comparison with MPE confirms improved interpretation of the spatial field at smaller scales, especially within and near the maximum precipitation axes. However, the performance is inconsistent across the domain, suggesting that the trend model is not valid across the entire domain. Clearly, more study is needed to better calibrate the trend models and their significant covariates.

For example, domain size likely impacted the relevancy of the DEMSlope and SlopeWind parameters, which were largely ineffective with very low and statistically insignificant correlations to DRP values. Nevertheless, a small percentage of the total DRP sample was sensitive to these covariates, and the immediate suggestion is that a smaller sample isolating these gauges would have improved the relationship. However, the poor relationships observed overall are also due to the high resolution of the geophysical covariates, suggesting that orographic enhancement is more sensitive across coarser resolutions. These observations are consistent with previous research into empirical modeling of orographic enhancement on seasonal time scales. Future research would likely benefit from assessing the relationship of related covariates at multiple resolutions in order to recommend a preferred degree of spatial averaging prior to trend modeling. However, these recommendations may be dependent on different meteorological events and regimes as well
as variations in terrain such that it may not be an easy problem to overcome. This research also suggests additional investigation into the utility of interaction terms to empirically represent orographic enhancement considering the success of the UDEM covariate in emphasizing elevations with stronger easterly forcing.

While this research was restricted to average and maximum 10 m horizontal wind, clearly in the instance of tropical cyclones across the SE US, the research would have benefitted from the use of minimum 10 m horizontal wind, which may have better represented the strength of the easterly flow and related moisture flux from the Atlantic Ocean. It is anticipated that the relationships between XWind and DRP may have been even stronger as a result. However, the use of maximum YWind has shown to be important when modeling orographic enhancement off the extreme southern Blue Ridge in N GA. Therefore, temporal smoothing of wind should be a function of the predominant direction of exposure across smaller domains. This research also suggests that concerns about averaging three-hour winds across the 24-hour period are largely unsubstantiated and that the average winds are very important during the derivation of a trend equation, regardless of case.

At this time, the use of third-order coordinate polynomials is recommended in regions where the orographic effects are minimized. In these regions, the use of physical or geophysical covariates at high resolutions produces trend models that are excessively noisy and dominate the geostatistical model, resulting in unrealistic interpretations of small-scale variability. These limitations appear to affect model stability as well, as shown by the 1LLa Max KED in Floyd. The marginal improvement of the 3LXYs KED over the best OK technique for Floyd suggests that additional investigation into other potential covariates is required in order to improve performance outside of regions of orographic uplift. Proposed, for example, are physical variables that represent the moisture content of the atmosphere and the atmosphere’s overall precipitation efficiency. Unfortunately, the 32 km resolution of the NARR dataset has already implied in this research (e.g., see the 1LLai KED results for Frances) that any trend model based on this dataset will likely be largely unsuccessful at explaining a significant portion of small-scale variability.
6.3 Cross-Validation versus Distribution Analysis

This research successfully addresses the reliance on cross-validation metrics in the previous literature by incorporating high-resolution (~4 km) MPE output into the analysis of the spatial and non-spatial distributions of the predicted fields. The research shows that there is no single performance metric that can choose the best interpolation technique, best SV model, best trend model, or best SV model parameter estimation technique at these small temporal scales. It is important to remember that cross-validation only assesses the accuracy of the model at the measurement locations, which is why access to a high-resolution estimate is valuable during calibration. In reality, RMSE is a relatively poor metric for model performance and minimizing RMSE did not always result in the selection of the best model. Instead, containment percentages and RMSSE combined to be far superior estimates of model performance. In the end, the use of multiple cross-validation metrics, combined with an extensive knowledge-based approach to SV model and predicted field interpretation is recommended whenever possible.

Analysis of the cross-validation metrics in tandem with the assessment of SV model parameters and experimental semivariograms suggests that trend modeling is best at removing large-scale variability while contributing little to the explanation of small-scale variability. While the final KED field is certainly influenced by deterministic trend at small-scales, the resultant trend residuals contain similar SV structures at small lags to the original DRP field. Without mitigation of the nugget effect and observed small-scale variability at subclimatic temporal scales, the presence of large CIs and high prediction variances will remain a challenge in future research.

Finally, in order to improve operational implementation, additional work will be required to create CIs and prediction variances that are based on the original units of measurement. This may require further investigation into the logarithmic transformation or the use of an alternative transformation that satisfies the requirement of non-negativity while normalizing the dataset. At a minimum, the Geos2MAP model will need to account for the bias otherwise present in a standard back-transformation (e.g., see Chapter 3 and Cressie 1993).
6.4 Localized Domains: Advantages and Limitations

Despite generally improved performance of KED over OK and IDW techniques, this research certainly suggests that the domain size may have considerable implications on the significance of covariate values in relationship to DRP. Though computationally expensive, future research would likely incorporate a moving-window approach in an attempt to improve trend model performance and reduce the dilution of important relationships due to a large sample size across a diverse domain. There are various ways to incorporate such an approach. For example, within each window the algorithm could fix covariates while recalculating coefficients, or it could reassess covariate significance and generate entirely new trend models for each window. There are many potential ways to define the window as well. The basic approach would tend to partition the domain into equal-area windows. Of course, this approach is independent of the precipitation field. Since the window size must be large enough to capture an adequate sample from which to perform least-squares regression, some windows would cover areas where the precipitation gradient was high, replicating the problems of the larger domain without enjoying the larger sample size. It is likely that more robust methods would be required. For example, the PRISM analysis relied on high-resolution DEM data to create irregular windows based on elevation and slope. In order to improve mapping performance across all terrain, analysis of trend model residuals suggests that localized domains may be best generated by precipitation values, not geophysical features. Ideally, the precipitation distribution could be divided into multiple sections, for example, in terms of zero, transition-zone, light, moderate, and extreme values. Regression equations could be devised from all measurement locations that fall within each precipitation window. Unfortunately, the primary limitation of such an approach is that the window definition creates a circular problem since each prediction point would require a precipitation value prior to assigning the point a trend model. Instead, the algorithm would have to be far more sophisticated, for example, by assessing the nearest measurement points and performing a best-guess of the likely precipitation domain prior to trend modeling.

Clearly, the moving window concept introduces substantial challenges including in the analysis of performance (it would no longer be feasible to produce detailed analyses of
the geostatistical model especially across multiple gridded fields) and in the analysis of statistical assumptions. Of course, any window definition would have to be large enough to generate a sufficient sample size from which to perform the analysis. In other words, it is unclear how changes in the sample size and the limited density of the gauge dataset will impact MLR. Furthermore, there is no certainty that the localization of regression modeling alone will be sufficient enough to improve the accuracy of the geostatistical model. The main objective would be to reduce the small-scale variability in the residuals by tailoring the trend model to small-scale domains. While it is unclear how different window definitions would impact the SV model at short lags, it is also unclear how the nugget effect inherent in the dataset would be mitigated. Remember, the use of point measurements as a foundation for spatial mapping will always have associated limitations due to the nature of the measurements and the density of the network used.

6.5 Improving the In-House Precipitation Database

This research and its design, combined with the creation of an in-house precipitation database and the development of the Geos2MAP model, supports many areas of future research with the overarching objective of improving model performance. However, it is first recommended that prior to any future work, the DRP database is supplemented with hourly precipitation data archived at NCDC as Data Set 3240 (DS-3240) in order to reintroduce ASOS measurements into the analysis. Approximately 10% of the gauge locations removed from the analysis were flagged with inappropriate reporting times of midnight. However, the accumulation of hourly precipitation reports would allow for the computation of 24-hour accumulations based on the 1200 UTC – 1200 UTC reporting interval adopted by the COOP Network. Fortunately, preliminary work on the Geos2MAP model included the development of an accumulation program for DS-3240 data. Additional development will be required to properly pre-process and merge the hourly-reported precipitation and the DRP into one seamless dataset while accounting for the redundancy in data as well as the variations in formatting and included quality-control flags. However, the
increase in station density may significantly improve geostatistical model performance even prior to implementing additional improvements to the model itself.

6.6 Assessing the Demand for Future Research

It is important to consider that future development will run in parallel to work being done at Oregon State University, which is leading the climate mapping project worldwide. The principal challenge for future work will be the justification of continuing research independent of the PRISM Group, which will require large technological and human expenses. There is no guarantee that the investment in time and resources would prove fruitful nor be able to yield results that have garnered such universal appeal amongst state climate agencies, the NWS and other federal agencies, and international government and private entities.

It remains the opinion of the author that the PRISM Group should have not abandoned the geostatistical model so quickly. These results on the daily scale show enough promise, despite the challenges placed upon the geostatistical techniques, that the investigation of a specialized or unique trend model and moving window algorithm within the geostatistical framework would have been worth pursuing. Any resultant model would have possessed the physical robustness required for climate mapping while guaranteeing the statistical robustness needed to support its claims. Unfortunately, the inertia associated with the PRISM project means it would take a significant parallel effort using a highly-sophisticated geostatistical model in order to assess the viability of such an approach on climate mapping. To quote the familiar adage: “The train may have already left the station.”


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Appendix
Appendix A
Geos2MAP Operational Manual (Descriptions Only)
Primary Step I

*Creating DEM, DEMSLOPE, NARR, GAUGE, and SLOPEWIND (Primary and Secondary Variables) Datasets*

**A. DEM**

*DESCRIPTION*
National Geophysical Data Center (NGDC) Global Land One-km Base Elevation (GLOBE) Digital Elevation Model (DEM) Output. The grid resolution is actually a constant 30 arcseconds or approximately 0.00833333 degrees.

1. **Download output**

2. **Execute:** DEMMatrixGen.pl
   *Description*
   This code inputs raw DEM data in matrix form and outputs a matrix form with coordinate headers.

3. **Execute:** DEMLineGen.pl
   *Description*
   This code inputs raw DEM data in matrix form and outputs a list form, with one point per line. It also creates a new list of coordinates whose associated values are -500, indicating ocean grid points.

**B. DEMSLOPE**

*DESCRIPTION*
This data set is derived from the DEM output and is calculated as the rise in $m$ meters for every kilometer of distance in two components: one along the $x$- or longitudinal axis and the other along the $y$- or latitudinal axis.

1. **Execute:** DEMSLOPEGen.pl
   *Description*
   This code computes the slope at all DEM grid points in two components. SLOPEX is the slope along the $x$-axis or across a line of constant latitude. SLOPEY is the slope along the $y$-axis or across a line of constant longitude. The slopes are calculated as rise over run in meters of rise per 1 km (m/km) from the west or north adjacent grid point to the east or south adjacent grid point. The distance from north to south ($d_{isty}$) is constant across all lines of longitude and is approximated by 1.8554166667 km, which is the distance of 60 arcseconds or 1 arcminute, since each DEM grid point is separated by 30 arcseconds. The distance from east to west varies depending on latitude and is calculated assuming a spherical earth using the
following formula: \(((\cos(\text{latitude(in radians)}) \times 111.325\text{km})/3600)\times 60\).

### C. NARR

**DESCRIPTION**

National Centers for Environmental Prediction (NCEP) North American Regional Reanalysis (NARR) Data. Model consists of over 400 variables most of which could, conceivably, be studied for model significance.

1. **Download Data**
   - [http://nomads.ncdc.noaa.gov/#narr_datasets](http://nomads.ncdc.noaa.gov/#narr_datasets)

2. **Execute NARRProcessor.pl**
   **Description**
   This code performs a series of tasks needed to convert GRIB-formatted NARR output into a ASCII text file with associated coordinates broken down by the variables and domain desired. First the script condenses the filenames of the raw data. Next, the scripts invokes `wgrib`, a software that decodes GRIB data and has the capability of providing the data in text form. Next, the script merges the text data with the geometric coordinate grid file after adjusting the geometric coordinates (the original grid file references all coordinates in the western hemisphere and treats all western hemisphere values as positive). The geometric coordinates are obtained from NCEP; at the onset of this dataset, no specific information about coordinates had been provided. However, NCEP allows download of geometric coordinates based on ETA grids, in this case, the Eta-211 32km grid.

3. **Organize output files from NARRProcessor.pl**
   **NOTE**
   All new data should be filed in the main NARR directory, sorted as they have been sorted in past case folders. It is recommended that you compress (e.g., WinRAR) the non-“Domain Only” files to conserve space as has been done for other cases.

4. **Execute NARRAccumulator_v130.pl**
   **Description**
   This script accumulates 3-hourly NARR output files on daily and event timescales, specified by the user. It also relies on the Statistics::Descriptive library to produce simple statistics (average, max, absolute maximum, min, variance, standard deviation) on both daily and event data at each NARR grid point. The script addresses both standard (0000 UTC - 0000 UTC) and 1200 UTC - 1200 UTC days without additional input from the user. It is therefore necessary to have NARR output from the days immediately preceding the user-specified days to process non-standard days.

The program treats missing NARR output ("9.999e+20") as terminal. The current variables supported are 289, 292, 293, 294, and 380. Accumulations are
limited to variable 380 as it would be nonsensical to accumulate the remaining, currently supported variables.

5. Organize output files from NARRAccumulator_v130.pl following convention used in previous studies.

D. DRP

DESCRIPTION

Daily Reported Precipitation (DRP) from rain-gauge data taken from the ASOS/COOP Observing Network. An in-house database was originally developed for North and South Carolina in 2002 containing all hourly and daily data available from NCDC for the period of record. That database has been updated once each year since to reflect new data and changes to the original data. These changes occur when NCDC evaluates the validity of measurements and/or entire sites. Thus, it is not possible to simply add new years to the pre-existing database and ensure the entire database is up-to-date. The best and most complete method involves obtaining the entire period of record each year, updating the previous year in May or June of the current year (to allow NCDC to quality control the data). For the Geos2MAP model, only daily data (DRP) is used; thus, the hourly data (HRP) instructions have not been written, but largely follow the steps below.

DOWNLOAD DRP DATA

UPDATE STATE STATION LISTS – COOP/ASOS

UPDATE STATE STATION LISTS – MILITARY

UPDATE INFORMATION WORKBOOK

Update C-A-M Station List

Update C-A-M (COOP-ASOS-MILITARY) Precip Station Database

CROSS-CHECK MILITARY SITES

CREATE COOPID LIST

UPDATE ALL DRP GAUGE DATABASES
SCRIPT EXECUTION

1. **Execute** GAUGEInfoFilter.pl (First command line prompt = 2; Second prompt = 1)
   
   **Description**
   This code extracts the gauge information entries that match the user's specified search (time) and restriction criteria and creates new information lists both of complete and abbreviated lengths. The user can also restrict whole state data to just the data within a specified domain. The code can do multiple states in one full run. Though it has other uses and intentions, the main intention of this code is to produce coordinates for use in the Geos2MAP model.

2. **Execute** accumulator_DRPevent_121.exe *(Fortran 95)*
   
   **Description**
   Given a state NCDC DRP dataset, state COOPID list, and a user-specific reporting time window, the program will accumulate NCDC/NWS/ASOS/COOP daily-reported precipitation (DRP) and output event-reported accumulation (ERP), the DRP for each day in the event, a list of COOPIDs with missing data, a list of COOPIDs with no data, a list of COOPIDs rejected due to bad reporting times, and a list of statistics detailing the effects of the QC process.

3. **Sort** YYYYMMBD-ED - DRP - ST - Domain Available Gauges – Short.txt by decreasing latitude followed by increasing longitude. 
   - Complete by executing SortMachine.pl *(See Universal Scripts section of documentation)*.

4. **Execute** GAUGESiteCleaner.pl
   
   **Description**
   This code analyzes the information files from GAUGEFileFilter.pl by removing sites that either are non-operational or contain missing data. Non-operational sites are defined here as sites that are operational, but are not measuring precipitation. It creates "cleaned" versions of the input files for further analysis by Geos2MAP model.

5. **Sort** YYYYMMBD-ED - DRP - ST - Domain Available Gauges – Short - Cleaned.csv by decreasing latitude followed by increasing longitude. 
   - Complete by executing SortMachine.pl *(See Universal Scripts section of documentation)*.

   - Complete by executing CSVMachine.pl *(See Universal Scripts section of documentation)*.
E. SLOPEWIND

**DESCRIPTION** The SLOPEWIND variable is simply the component of the horizontal wind due to slope. It is the horizontal wind in the x-direction multiplied by the change in elevation in the x-direction ($m/m$) added to the horizontal wind in the y-direction multiplied by the change in the elevation in the y-direction ($m/m$).

**NOTE** Dataset created in Primary Step IV.

F. MPE

**DESCRIPTION** This data is output from the Multi-sensor Precipitation Estimator (MPE): an algorithm developed by the National Oceanic and Atmospheric Administration’s National Weather Service. The MPE computes precipitation estimates at a resolution of $(4 \text{ km})^2$ by optimally combining rain-gauge, satellite, and radar data. Rain-gauge measurements and, to a much lesser extent, satellite precipitation estimates, reduce the bias of the raw radar estimates, while manual, human quality control adds much-needed improvements to the final output. The final output is archived at the National Centers for Environmental Prediction (NCEP) and is available for public access as a national mosaic beginning in 2002. The MPE output’s purpose in the latest version of Geos2MAP is to serve as comparison to the gauge-only precipitation estimates. MPE output mapping and spatial and non-spatial distribution analysis are the features currently supported by Geos2MAP.

**NOTE** Additional information on the NCEP MPE dataset is available at: http://www.emc.ncep.noaa.gov/mmb/ylin/pcpanl/QandA/

1. **Download Data**
   - [http://www.joss.ucar.edu/cgi-bin/codiag/fgr_form/id=21.093](http://www.joss.ucar.edu/cgi-bin/codiag/fgr_form/id=21.093)

2. **Execute MPEProcessor.pl**
   **Description** This script accomplishes several tasks in order to develop a MPE dataset in flat file format. First the NCEP Stage IV MPE output files are renamed. Second, the files are uncompressed and **wgrib** decodes the GRIB files to create data only flat files. Third, the geometric coordinates from the HRAP grid are created using an algorithm developed by Stackpole and Jones (1990). Fourth, the geometric coordinates are combined with the Cartesian HRAP coordinates and the MPE output to create the final form MPE output flat file. Fifth, the data is clipped to a user-specified domain and the results create new output files and coordinate file. The program currently works with NCEP Stage IV MPE output and all available time resolutions (1hr, 6hr, and 24hr).

3. **Execute MPEAccumulator.pl**
   **Description** This script accumulates MPE data processed using **MPEProcessor.pl**. It is based on the NCEP MPE archive, which contains three periods of raw accumulation (1hr, 6hr, 24hr). It produces daily and event-based accumulations.
for each of the raw accumulation periods and produces three types of files for each raw period: (1) accumulation files; (2) summary files; and (3) statistics files. The user has the ability to specify the ending hour of the accumulation and ignore or account for missing values. Missing periods and missing accumulated values are tracked and the statistics output to the accumulation files and the statistics file, respectively. The statistics file is envisioned to contain additional information in future versions as the user desires.
Primary Step II

Creating GRID Dataset and Cartesian Coordinate System

1. **Execute** DEMDRPNARRCoordConcat.pl
   
   **Description**
   This script extracts the geometric coordinates for the DEM/DEMSLOPE, NARR, and DRP databases, concatenating them into one list with a third column to distinguish data type and a fourth column for the COOPID if the data is DRP.

2. **Execute** 01_GRID_Creator.R
   
   **Description**
   Creates prediction grids, imports and merges all geometric coordinates from all data sources, creates a Cartesian grid based on all coordinates, and writes out a combined coordinate file including all prediction grid points.

3. **Execute** DEMDRPNARRGRIDDataGen.pl
   
   **Description**
   This code takes the Cartesian and geometric coordinates from the final output of the R code 01_GRID_Creator.R and parses the long data set with all data sources into individual data source files with all coordinates AND data values. This algorithm also verifies all data being concatenated corresponds to the same grid point.

4. **Convert** YYYYYMMBD-ED - DRP.txt to a comma-delimited file.
   
   - Complete by executing CSVMachine.pl (See *Universal Scripts* section of documentation).

5. **Sort** DRP data file: YYYYYMMBD-ED - DRP.txt by decreasing latitude followed by increasing longitude.
   
   - Complete by executing SortMachine.pl (See *Universal Scripts* section of documentation).

6. **Execute** GAUGEClosestPointGen.pl
   
   **Description**
   This program compares two datasets on two different grid spaces and finds the points on one grid space nearest each point on the other grid space. To do this it assumes that one grid space is regular and the other irregular, OR a regular grid of less resolution/density. The algorithm visualizes a box within which an irregular grid point is located and at each corner of the box lies a regular grid point. The program is intelligent enough to account for irregular grid points that lie on the
box or co-exist with a regular grid point at a corner. The program outputs a file with all nearest points as well as a file that reports only the closest of the nearest points. Other output files are variations on the above two file types.

7. **Convert** YYYYMMBD-ED - DRPtoDEM Coordinates - Short.txt to a comma-delimited file.
   - Complete by executing CSVMachine.pl (See *Universal Scripts* section of documentation).

8. **Sort** DRPtoDEM data file: YYYYMMBD-ED - DRPtoDEM Coordinates - Short.csv by decreasing closest latitude followed by increasing closest longitude.
   - Complete by executing SortMachine.pl (See *Universal Scripts* section of documentation).

9. **Execute** DEMSLOPEtoGRID.pl
    
    **Description**
    
    This code takes the DEM and SLOPE data sets with both geometric and Cartesian coordinates and finds data points that are co-located with prediction grid points creating DEM and SLOPE data sets with only those points corresponding to the respective prediction grid.
Primary Step III

Interpolation of NARR Datasets to GRID and DRPtoDEM Coordinate Spaces

**NOTES**

The DRPtoDEM Coordinate Space consists of those DEM grid points that are closest to the DRP gauge locations and are outputted after executing `GAUGEClosestCoordGen.pl`.

At this time, the NARR variables are interpolated using the Inverse Distance Weighting technique. Though several hours were devoted to attempting to analyze the spatial variability for more advanced interpolation (i.e., OK), it has yet to be an important priority and this research was stopped to focus on completing the Geos2MAP model. Again, it is not imperative we create a highly accurate NARR prediction; however, we are trying to capture the overall pattern inherent in the NARR dataset. If time is present before the first phase of research is complete (Joshua Palmer’s thesis) more effort will be put into a geostatistical interpolation. Otherwise, it is future work.

1. **Execute** [02_NARR293_to_GRID.R]
   **Description** Takes the original NARR 293 dataset (XWind) and interpolates data to all prediction grids specified using Inverse Distance Weighting. The code also produces image and contour maps in both PNG and EPS format for each resolution of the resultant predictions.

2. **Execute** [03_NARR294_to_GRID.R]
   **Description** Takes the original NARR 294 dataset (YWind) and interpolates data to all prediction grids specified using Inverse Distance Weighting. The code also produces image and contour maps in both PNG and EPS format for each resolution of the resultant predictions.
Primary Step IV

Calculation of SLOPEWIND

1. **Execute** SLOPEWINDGen.pl

   **Description**
   This program computes the component of horizontal wind due to slope (m/m). The SLOPEWIND variable is simply the component of the horizontal wind due to slope. It is the horizontal wind in the x-direction multiplied by the change in elevation in the x-direction (m/m) added to the horizontal wind in the y-direction multiplied by the change in the elevation in the y-direction (m/m). The code operates on all available grid spaces and can be easily modified to run on additional spaces as determined by the user.
### Primary Step V

**Mapping Covariate Datasets**

<table>
<thead>
<tr>
<th>Step</th>
<th>Execute</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td><strong>04_DEM_Mapping_v110.R</strong></td>
<td>Takes original DEM datasets at all GRID resolutions and maps data.</td>
</tr>
<tr>
<td>2.</td>
<td><strong>05_DEMSLOPE_Mapping_v110.R</strong></td>
<td>Takes original DEMSLOPE datasets at all GRID resolutions and maps XSLOPE and YSLOPE data.</td>
</tr>
<tr>
<td>3.</td>
<td><strong>06_SLOPEWIND_Mapping.R</strong></td>
<td>Takes original SLOPEWIND datasets at GRID coordinates and maps data by creating image and filled contour plots. Completely overhauled the mapping section including a revision of all map types, dramatically improved quality and labeling, PNG AND EPS output for unlimited image manipulation options, and a new algorithm that eliminates the need for the same commands to be reissued for each grid resolution, saving enormous amounts of editing time in the future if plots are changed and dramatically improving efficiency.</td>
</tr>
</tbody>
</table>
Primary Step VI

Creation and Analysis of Trend (DRIFT) Through Multivariate Linear Regression Modeling

1. **Execute** DRIFTDataConcat_v101.pl

   **Description**

   This script culminates all previous work by matching DRP and covariate data to DRPtoDEM coordinates in order to create a comprehensive dataset with which DRIFT can be studied. It also:

   1) Ignores sites with missing DRP or covariate data
   2) Converts DRP values from inches to millimeters and permits the logarithmic transformation of the DRP data in SAS by setting all zero values of precipitation to 0.01 mm. The metric conversion can be avoided by changing the logical `$metric` from `true` to `false`, while the zero transformation can be avoided by changing the logical `$zeroconv` from `true` to `false`.
   3) Sets a dummy variable to distinguish sites with non-zero precipitation from sites with zero precipitation in case the user wishes to analyze this dummy variable in SAS.
   4) Analyzes the DRPtoDEM coordinates to ensure nearby sites do not have the same DRPtoDEM coordinates (co-located).
   5) Tracks the loss of data due to missing values and co-location.

   To accomplish its objectives, the code is divided into four sections: 1) Setup; 2) Data Acquisition; 3) Co-Location; and 4) Printing. The co-location section is interactive, requiring the user to choose how the code should handle multiple DRP values for the same DEM grid point.

2. **Execute** 07_DRP_to_DRIFT.sas

   **Description**

   Previous scripts and steps in Geos2MAP model perform a wealth of data creation and manipulation so that it can be fed into this **SAS** code for the analysis of drift in the dataset. In depth details of the methodology behind the Geos2MAP model can be found in the appropriate documentation, but in short, this code is the hub of all multivariate regression analysis and output. It is highly dynamic in that it requires interpretation and tweaking as determined by the user, so the user must have a clear understanding of the statistics and **SAS** language within. Essentially, the code performs five main steps:

   1) Creates higher-order terms from the original variables, including interaction terms.
   2) Partitions the data into zero and non-zero data for optional analysis.
   3) Produces scatterplots of DRP/logarithmic DRP vs. covariates.
   4) Performs DRP/logarithmic DRP regression analysis, including normality, residual, and predicted value analyses through tests and plots.
5) Exports chosen DRIFT datasets for interpolation.
Primary Step VII

Creation, Mapping, and Cross-Validation of IDWIDP Data
(Interpolating Precipitation via Inverse Distance Weighting)

1. **Execute** 08_DRP_to_IDWIDP_v101.R
   
   **Description**
   - Takes original DRP dataset and, using Inverse Distance Weighting, projects the data onto a regular grid. The resultant maps are meant to be for evaluating an initial field, however, this program can also accomplish studies evaluating IDW as an interpolator. This script also performs cross-validation, calculates RMSE, and other related validation tools.

2. **Execute** IDWIDPNOOCEANDataGen.pl
   
   **Description**
   - This script compares each grid point of all IDWIDP gridded datasets to each DEM grid point that falls over the ocean (defined by DEM=−500) and changes available precipitation values to NA if and when matches are found. Thus, all values of precipitation over the ocean are set to NA. IDWIDP gridded datasets are used to create initial fields of the GAUGE data for analysis and also in investigations of IDW (Inverse Distance Weighting) as an interpolation technique. The code 08_DRP_to_IDWIDP.R produces the gridded datasets and maps of the datasets are produced in 09_IDWIDP_Mapping.R. Interpolation over the ocean grows increasingly unreliable because coastal GAUGE data becomes less of an accurate representation of precipitation with distance. This script just assists in creating "cleaner" maps and is optional in the Geos2MAP model.

3. **Execute** 09_IDWIDP_Mapping.R - **LEGACY ALGORITHM - DISCONTINUED**
   
   BEGINNING WITH Geos2MAP VERSION 1.6.0
Primary Step VIII

*Analysis, Mapping, and Cross-Validation of RESID Data*
*(Interpolating Regression Residual Precipitation via Ordinary Kriging)*

1. **Execute** 10 Explore_RESID_v231.R  
   **Description**  
   A dynamic script that provides analysis and modeling of RESID data and associated spatial variability.

   The following steps consist of the current exploratory analysis:

   1) DRIFT/RESID import; creation of RESID geodata objects  
   2) Exploratory summaries and plots of RESID and/or DRIFT data  
   3) Point Pairs Plots  
   4) Exploratory semivariogram analysis - Omnidirectional  
   5) Exploratory semivariogram analysis - Unidirectional  
   6) Model semivariogram analysis - Ordinary Least Squares approach  
   7) Model semivariogram analysis - Weighted Least Squares approach  
   8) Model semivariogram analysis - Maximum Likelihood (ML) approach  
   9) Model semivariogram analysis - Restricted ML (REML) approach

   Case-specific regression models are imported into the script once the user defines the model to import and the formatting of the DRIFT output file.

   Exploratory semivariograms are produced for all 8 Geos2MAP resolutions and both full domain and limited domain maximum point pair separation distances. A least-squares exponential and spherical model fit to the exploratory semivariograms is performed for the two highest resolution datasets (04km and 08km) and for each of four maximum distance thresholds (450km, 650km, 850km, 1000km).

   ML/REML analyses default to the exponential model, however the user may select other models as necessary. ML/REML analyses are independent of the resolution of the datasets as well as any maximum distance limitation placed on the exploratory semivariogram as it relies on the raw data to produce a fit. All ML analyses are completed with both `fix.nugget=TRUE` (nugget=0) and `fix.nugget=FALSE`. For reference purposes, the ML/REML fits are plotted against the three highest-resolution exploratory semivariograms for analysis.

   The script currently outputs R objects for each model produced as well as an extensive set of graphics for both model fits and exploratory semivariograms. Model parameters are output as simple dumps of the `summary()` functions of geoR.

2. **Execute** 11 RESID_to_GRID.R  
   **Description**  
   A dynamic script that performs Ordinary Kriging (OK) interpolation
on RESID data (regression residual precipitation) using model
semivariograms produced in 10_Explore_RESID.R.

Its main steps include:
1) Import of the DRIFT Dataset;
   Establishing the Covariate Names;
   Creation of REGRESS geodata Object.
2) GRID Import;
   Extraction of GRID Cartesian Coordinates
3) Import of Model Semivariogram
4) Ordinary Kriging of RESID data (at all GRID resolutions)
5) Cross-Validation - Including various plots and statistics:
   - Error vs. Predicted Values
   - Error vs. Actual Values
   - Correlation Between Error and the Actual Values
   - Correlation Between the Predicted and Actual Values
   - Standardized Error vs. Predicted Value
   - Standardized Error vs. Actual Value
   - Correlation Between Standardized Error and the Actual Values
   - Root Mean Square Error (RMSE)
   - Root Mean Square Standardized Error (RMSSE)

3. **Execute** RESIDNOOCEANDataGen.pl

   **Description**
   This script compares each grid point of all RESID OK interpolated datasets to each DEM grid point that falls over the ocean (defined by DEM=-500) and changes available precipitation values to NA if and when matches are found. Thus, all values of precipitation over the ocean are set to NA. The resulting RESID datasets are primarily for mapping predictions that become unstable over the ocean. Predictions over the oceans have low confidence by the very fact GAUGE data is limited to land; however, the Geos2MAP model permits prediction of RESID values anyway and the option of not plotting them at a later step. The Geos2MAP model also allows prediction over land ONLY if the user specifies the correct datasets, and in those circumstances this code is unnecessary.

4. **Execute** 12_RESID_Mapping_v110.R

   **Description**
   This script produces maps for both the interpolated RESID grids and the associated standard error grids. It also performs an IDW interpolation of the RESID dataset produced from 07_DRP_to_DRIFT.sas. The IDW interpolation, completed only at 32km, is intended to provide a visual comparison to the OK interpolated RESID grids.

   The script produces three graphic types in two formats (PNG and EPS): 1) Images Plots; 2) Contour Plots; and 3) Filled Contour Plots. The script incorporates hacked versions of `image.plot()` from the fields library and `filled.contour()` from the standard R graphics package. These hacked
versions produce cleaner legends and color scales by separating the lowest and highest 0.1 percentile from the legend and adding those values separately without causing the color scale to adjust to the outliers.
Primary Step IX

Creation, Mapping, and Cross-Validation of KEDIDP Data
(Interpolating Precipitation via Kriging with External Drift)

1. **Execute 13_DRP_to_KEDIDP.R**
   
   **Description**
   A dynamic script that performs KED interpolation on raw DRP data based on results from previous scripts and the compilation of data that took place in initial Primary Steps.

   Its main steps include:
   1) Import of the REGRESS dataset;
      Extracting the RESID dataset from the REGRESS dataset;
      Establishing the covariate names;
      Creating REGRESS and RESID geodata objects.
   2) GRID Import;
      Extraction of GRID Cartesian coordinates
   3) Covariate Import
   4) Observational trend.spatial Object Import
   5) Semivariogram Model Import
   6) Creation of GRID geodata objects;
      Creation of GRID covariate datasets, including any desired interaction terms
   7) Create GRID trend.spatial objects - Store the covariate information at GRID coordinates
   8) Kriging with External Drift
   9) Manual Cross-Validation - Including the following plots and statistics:
      - Error vs. Predicted Values
      - Error vs. Actual Values
      - Correlation Between Error and the Actual Values
      - Correlation Between Predicted and Actual Values
      - Standardized Error vs. Predicted Values
      - Standardized Error vs. Actual Values
      - Correlation Between Standardized Error and the Actual Values
      - Root Mean Square Error (RMSE)
      - Root Mean Square Standardized Error (RMSSE)

2. **Execute KEDIDPNOOCEANDataGen.pl**
   
   **Description**
   This script compares each grid point of all KEDIDP (KED Interpolated Daily Precipitation) datasets to each DEM grid point that falls over the ocean (defined by DEM=-500) and changes available precipitation values to NA if and when matches are found.
   Thus, all values of precipitation over the ocean are set to NA. The resulting KEDIDP datasets are primarily for mapping predictions that become unstable over the ocean. Predictions
over the oceans have low confidence by the very fact GAUGE data is limited to land; however, the Geos2MAP model permits prediction of KEDIP values anyway and the option of not plotting them at a later step. The Geos2MAP model also allows prediction over land ONLY if the user specifies the correct datasets, and in those circumstances this code is unnecessary.

3. **Execute** `14 KEDIP Mapping.R - LEGACY ALGORITHM - DISCONTINUED BEGINNING WITH Geos2MAP VERSION 1.6.0`
Primary Step X

**Creation, Mapping, and Cross-Validation of OKIDP Data**
*(Interpolating Precipitation via Ordinary Kriging)*

1. **Execute** 15Explore_DRP_v110.R
   
   **Description**
   
   A dynamic script that provides analysis and modeling of DRP data and associated spatial variability.

   Its main steps include:
   
   1) DRP import;
      creation of DRP geodata objects
   2) Exploratory summaries and plots of DRP data
   3) Exploratory semivariogram analysis - Omnidirectional
   4) Exploratory semivariogram analysis - Unidirectional
   5) Model semivariogram analysis - Ordinary Least Squares approach
   6) Model semivariogram analysis - Weighted Least Squares approach
   7) Model semivariogram analysis - Maximum Likelihood (ML) approach
   8) Model semivariogram analysis - Restricted ML (REML) approach

   The script imports DRP data from the Source Dataset comma-delimited file, which is stored in all NARR directories under the DRP case directories. Selection of any Source Dataset file from these directories will yield the same results for each case since DRP data is independent of NARR output. A log transformation of the data is performed automatically within the script but this data is only used at the request of the user via the LOG input variable.

   Omnidirectional and unidirectional (via the N-S, NE-SW, E-W, and SE-NW axes) exploratory semivariograms are produced for all 8 Geos2MAP resolutions and both full domain (1000km) and limited domain (650km) maximum point pair separation distances. Ordinary and weighted least-squares exponential, spherical, and Gaussian model fits to the exploratory, omnidirectional semivariograms are performed for the two highest resolution datasets (04km and 08km) and for three maximum distance thresholds (450km, 650km, and 1000km).

   ML and REML analysis are independent of the resolution of the datasets as well as any maximum distance limitation placed on the exploratory semivariogram as it relies on the raw data to produce a fit. All ML analyses are completed with both `fix.nugget=TRUE (nugget=0)` and `fix.nugget=FALSE`. In addition, the user may allow for anisotropic correction when performing ML/REML analyses. For reference and analysis, the ML/REML fits are plotted against the three highest-resolution exploratory semivariograms for analysis.

   The script currently outputs R objects for each model produced as well as an extensive set of graphics for both model fits and exploratory semivariograms.
The user may control the size of the graphics using input variables. Model parameters are output as simple dumps of the summary() functions of geoR.

2. **Execute** 16\_DRP\_to\_OKIDP\_v110\_R

*Description*

A dynamic script that performs the OK technique on the raw DRP data and cross-validates the results.

Its main steps include:

1) Import of the DRP dataset;  
   Create logarithmic DRP column;  
   Create DRP geodata object based either on logarithmic or original DRP.

2) GRID Import;  
   Extraction of GRID Cartesian coordinates

3) Semivariogram Model Import

4) Ordinary Kriging of DRP data (at all GRID resolutions)

5) Cross-Validation - Including the following plots and statistics:
   - Error vs. Predicted Values
   - Error vs. Actual Values
   - Correlation Between Error and the Actual Values
   - Correlation Between Predicted and Actual Values
   - Standardized Error vs. Predicted Values
   - Standardized Error vs. Actual Values
   - Correlation Between Standardized Error and the Actual Values
   - Root Mean Square Error (RMSE)
   - Root Mean Square Standardized Error (RMSSE)

3. **Execute** OKIDP\_NO\_OCEAN\_DataGen.pl

*Description*

This script compares each grid point of all OKIDP (OK Interpolated Daily Precipitation) datasets to each DEM grid point that falls over the ocean (defined by DEM=-500) and changes available precipitation values to NA if and when matches are found. Thus, all values of precipitation over the ocean are set to NA. The resulting OKIDP datasets are primarily for mapping predictions that become unstable over the ocean. Predictions over the oceans have low confidence by the very fact GAUGE data is limited to land; however, the Geos2MAP model permits prediction of OKIDP values anyway and the option of not plotting them at a later step. The Geos2MAP model also allows prediction over land ONLY if the user specifies the correct datasets, and in those circumstances this code is unnecessary.

4. **Execute** 17\_OKIDP\_Mapping.R - **LEGACY ALGORITHM - DISCONTINUED BEGINNING WITH Geos2MAP VERSION 1.6.0**
Primary Step XI

Comparison of IDP Techniques
(Various Scripts Designed to Facilitate Comparison of Different Interpolation Schemes)

1. Execute 18_CompareIDP_v13.1.R
   
   Description
   A dynamic script that compares statistical output of the three IDP techniques (IDW, OK, KED) to gauge data and MPE output through an ever-increasing number of plots. This source code is not intended to house scripts comparing precipitation maps, that should be performed in a separate source code/step. The list of tasks is listed below and should be expanded upon as new tasks are created.

   1)  IDP vs. DRP/MPE Boxplots - Boxplots of each IDP distribution for each available resolution alongside the DRP and MPE boxplots.
   2)  IDP vs. DRP/MPE Boxplots [(Precip > 0.25 mm) ONLY] - Same as 1) but the datasets have been revised to omit all precipitation predictions less than 0.01 in. Standard errors of OK/KED predictions are ignored in this revision.
   3)  IDP, DRP, and MPE PD Histograms - Probability Density Histograms of each IDP distribution and the DRP and MPE distributions.
   4)  IDP, DRP, and MPE PD Histograms [(Precip > 0.25 mm) ONLY] - Same as 3) but the datasets have been revised to omit all precipitation predictions less than 0.01 in. Standard errors of OK/KED predictions are ignored in this revision.

2. Execute 19_MPE_to_IDW_MPE.R
   
   Description
   Takes original MPE dataset and, using Inverse Distance Weighting, projects the data onto a regular grid. The resultant maps are meant to be for evaluating an initial field, however, this program can also accomplish studies evaluating IDW as an interpolator. This script also performs cross-validation, calculates RMSE, and other related validation tools.

3. Execute IDWMPENOOCEANDataGen.pl
   
   Description
   This script compares each grid point of all IDWMPED gridded datasets to each DEM grid point that falls over the ocean (defined by DEM=-500) and changes available precipitation values to "NA" if and when matches are found. Thus, all values of precipitation over the ocean are set to "NA". While MPE data over the ocean have value, because the DRP dataset has no sites beyond the coastline and the interpolation techniques therefore have minimal skill over the ocean, the removal of MPE values over the ocean improves intercomparison of the various datasets.
4. **Execute** 20_IDPMPE_Mapping_v111.R

**Description**

This script replaces the following legacy IDP mapping scripts:

- 09_IDWIDP_Mapping.R
- 14_KEDIDP_Mapping.R
- 17_OKIDP_Mapping.R

It additionally allows the plotting of IDW Multisensor Precipitation Estimator (MPE) output (~(4km)² native resolution, interpolated to Geos2MAP prediction grids) using files produced by

MPEAccumulator.pl and 19_MPE_to_IDWMPE.R.

The script's important features include:

1) **UNIVERSAL INTERVAL**: By condensing the plotting of all four datasets into one script, it can plot all data using one universal interval and color list.

   The universal lists are created by finding the absolute maximum and minimum of all datasets. If the user wishes to use the QUANTILE functionality featured in the legacy scripts, the script will also utilize the maximum 99.9% value and the minimum 0.1% value of all datasets (as necessary). The universal functionality applies to OKIDP and KEDIDP plots of standard deviation as well.

2) **IDP/MPE-SPECIFIC INTERVAL**: The user may opt to avoid universal interval and color lists, in which the script creates interval and color lists unique to each IDP and MPE grid type (e.g., IDWIDP, OKIDP, KEDIDP, IDWMPE, etc.).

3) **IMPROVED PLOTTING FUNCTIONS**: The script features the `image.plot.Geos2MAP` and `filled.contour.Geos2MAP` R functions modified for Geos2MAP which create significantly more polished plots given the unique QUANTILE functionality featured in Geos2MAP.
Universal Scripts

Scripts Designed to Service Multiple Sections and Steps within the Geos2MAP Model

- **CSVMachine.pl**
  
  **Description**
  
  This program is meant to transform Geos2MAP DRP space-delimited files into comma-delimited files. However, the program will transform any space-delimited file into a comma-delimited file (see Special Notes and Warnings). The user can supply a list of an unlimited number of files that have the same column widths and the program will transform all files automatically. To accomplish this, the program requires a list of column widths as described below.

- **SortMachine.pl**
  
  **Description**
  
  This program is meant to sort comma-delimited files containing Geometric coordinates. However, the program will sort any comma-delimited file that has two "sortable" columns. As of Version 1.0.0 the program only sorts by DECREASING ORDER for the first sort-by column, then INCREASING ORDER for the second sort-by column to support Geos2MAP functions. Conceivably, the program could support other sorting preferences using an additional command-line preference code. The program can adapt to different column quantities within the run as long as the $incolumn and $deccolumn command-line variables remain constant within the run.