ABSTRACT

WOOTTEN, ADRIENNE. Uncertainty in Climate Projections: An Investigation of the Contribution from Downscaling. (Under the direction of Dr. Fredrick Semazzi and Dr. Adam Terando).

In recent years, there has been an increasing emphasis on the need to support local climate adaptation decisions. These decisions may require information about the future at a finer resolution than what is available from global climate model (GCM) projections. Downscaling is used to translate the coarse scale GCM output to finer scales. Downscaling methods include using both regional climate models (RCMs) and statistical techniques. This additional layer of modeling presents new sources of uncertainty. This dissertation explores sources of uncertainty in regional climate modeling and characterizes downscaling as a source of uncertainty in projections of anthropogenic climate change. It consists of three components.

First, the range of model errors from different parameterizations and nudging approaches is explored. We find evidence that changing the cumulus parameterization (CP) within a single RCM influences the accuracy. The interaction between the analysis nudging approach and cumulus parameterization also influences the accuracy of the RCM. Changing the CP scheme from the Tiedtke to the modified Kain-Fritsch scheme and having more strict analysis nudging decreases the error for historical precipitation. Although other parameterizations and GCM used in the RCM remain the same for each sensitivity test, the projected change of precipitation is sensitive to the CP scheme used.

Second, the structural errors between RCMs and the differences in how GCM output is incorporated (forcing approach) are explored. The different structural errors between RCMs lead to differences in the accuracy but also in the spread of the ensemble. In
situations where the RCMs are both indirectly forced by the same GCM, the difference in error and spread is stable in ensembles with more than 12 members. In situations where the RCMs have different forcing approaches the difference in accuracy and spread is not stable. This suggests that the forcing approaches are an added source of uncertainty unique to RCMs. The finer resolution RCMs offer more improvement in error both in individual simulations and when included in ensembles of GCMs.

Finally, downscaling itself is characterized as a source of uncertainty in climate projections. While not dominant (> 50% of the total uncertainty), the uncertainty attributable to downscaling reaches ~20% for large areas of the Southeast U.S. for precipitation variables and ~30% for the Appalachians for projections of the number of days with maximum temperatures > 95°F. The incomplete sample and time slicing of the projections reflects the fragmentation in downscaling and this reduces the information available during some periods in the future. This suggests that the fragmentation of downscaling limits the representation of possible futures available for impact assessments and adaptation decisions.

Future regional climate modeling efforts should consider carefully the interaction between parameterization and nudging approach as it can influence both accuracy and projected change. In addition, future efforts in regional climate model comparisons should go beyond current efforts, including experiments to characterize errors associated with forcing approach. These future efforts should consider high resolution, as it remains unclear if structural uncertainty (structural error differences between RCMs) remains consistent at all resolutions. Finally, while downscaling as a whole is not the dominant source of uncertainty, it still provides a significant contribution. Impact assessments considering the use of projections should use more than one downscaling technique where possible to minimize
overconfidence. The climate modeling community should consider a framework for the creation of future projections to address the fragmentation of projections which results in limiting the representation of uncertainty provided to users.
Uncertainty in Climate Projections: An Investigation of the Contribution from Downscaling

by
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DEDICATION

To my parents – you’ve been the greatest blessing in my life. You taught me never to give up and gave me a lot of the lessons that formed the base of who I am. You stuck by me through a lot, and while I don’t say it as often as I should I’m so thankful for that. I love you both!
BIOGRAPHY

Adrienne Wootten was born near New York, NY and raised outside of Baltimore, MD. She is the daughter of two supportive parents, Peter and Liidia, and has an exceptional sister, Jennifer and brother-in-law, Ian. She enjoys being an aunt to her niece and nephew, Abigail and Michael. During her undergraduate education, she was actively involved with the NCSU Women in Science and Engineering (WISE) program, where she served on the student council and received the Lifesaver Award for service to program in 2005. In addition, she became involved in the Environmental Statistics Practicum program under the direction of William F. Hunt Jr. from Spring 2007 through Spring 2008. Under this program, Adrienne was involved in consulting projects with various agencies including the North Carolina Department of Environment and Natural Resources, the New Jersey Department of Environmental Protection, and the Maryland Department of the Environment. Her involvement in AMS also led to her involvement in research with Dr. Sethu Raman and the State Climate Office of North Carolina during the summer of 2007. Adrienne graduated in May 2008 from NCSU with a Bachelor of Science Degree in Meteorology and a minor in Statistics. Following graduation, she was hired by the U.S. Environmental Protection Agency Atmospheric Modeling and Analysis Division (U.S. EPA-AMAD) as a student contractor while continuing her work at the North Carolina State Climate Office. In fall of 2009, Adrienne was accepted into the Master of Science in Atmospheric Science program at NCSU as a graduate research assistant under the guidance of Dr. Ryan Boyles. She received her Master of Science degree in Fall 2011, and was accepted in the Ph.D. program at NCSU in Fall 2012. During her Ph.D. program, she was a Global Change Research Fellow for the
Department of Interior Southeast Climate Science Center and remained involved with outreach and education activities at the North Carolina State Climate Office. In addition, Adrienne is one of the co-founders and editors of the Early Career Climate Forum which works to promote cross-discipline communication and collaboration among early career scientists in climate research. She remains actively involved and interested in collaborative research and engagement in climatology, particularly with regards to the use of climate projections in decision making and impact assessments.
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CHAPTER 1. Introduction

1.1. Global Climate Models, Downscaling, and Decision Making

In a warming world, global climate models (GCMs) have been used in decision making related to emissions abatement for at least the past 20-30 years. Recent examples of such decisions are those made for the Paris agreement during the United Nations Conference on Climate Change in 2015. For these abatement decisions, GCMs have provided information for the third link in the chain of mitigation decision making (Smith and Stern, 2011).

In recent years, climate modeling has begun to be used for adaptation decisions in addition to mitigation decisions. For these adaptation decisions and associated impact assessments, projections of climate variables of interest to the decision maker are required at resolutions where the physical processes which influence those variables are better represented (Cholette et al. 2015; Tabari et al. 2016; Rummukainen 2016). Although the GCMs have progressed to finer resolution with newer generations, many GCMs currently provide a grid-spacing of 100 km or coarser. GCMs are unable, to capture local physical processes such the interaction with complex topography and nearby oceans, which effect key variables of interest for impact assessments important to decision making (Rummukainen 2010).

In time, GCMs may be operated at a resolution fine enough to capture the physical processes effecting local adaptation decisions and impact assessments. However, impact
assessments that could inform adaptation decisions have already begun to use high resolution projections (< 10 km grid spacing, e.g. Argüeso et al. 2015; San José et al. 2016). Therefore, to bridge this gap over the past few decades’ climate scientists have engaged in climate model ‘downscaling’. Downscaling is defined as “the process of translating the state of some variable in the large space to the state of some variable in a much smaller space” (Benestad 2008). There are two types of techniques:

- **Dynamic Downscaling**: the use of regional climate models (RCMs) which, like GCMs, are numerical models that use the same fundamental physical equations to simulate climatic processes. A RCM is initialized for smaller areas at finer resolutions and a GCM provides the boundary conditions at each model time step.

- **Statistical Downscaling**: based on a statistical relationship built between the historical baseline period of each GCM and observed data. This relationship is then applied to the future projection of the same GCM to predict what the future projection would be at local scales.

Each type of downscaling technique has its strengths and weaknesses and the details of such techniques are available in Wootten et al. (2014). Downscaling can provide the resolution that is assumed to be needed for decision making, while RCMs can provide projections in regions with sparse observations.
1.2. Uncertainty in Projections

At this point, numerous GCMs exist, and many downscaling techniques (both dynamic and statistical) have been developed. However, where the process of producing projections begins is with the GCM forcing scenarios that depict differing trajectories of human emissions of greenhouse gases. With the Coupled Model Intercomparison Project Phases 3 and 5 (CMIP3 and CMIP5 respectively), there are two generations of emissions scenarios. The radiative forcing prescribed by the emissions scenarios are used with each GCM, which in turn can then be downscaled using either type of technique. Considering only the GCM based projections there are three sources of uncertainty (Hawkins and Sutton, 2009; Gettelman and Rood, 2016), which are classified as:

- Scenario Uncertainty – uncertainty associated with different societal actions such as the amount and rate of emissions of greenhouse gases into the atmosphere.
- GCM Model Uncertainty (also referred to as model uncertainty) – uncertainty associated with the differences between GCMs and the differences in scientific understanding as a result.
- Natural Variability – uncertainty associated with forced and unforced variability not associated with human activity. Examples include the El Nino Southern Oscillation, the North Atlantic Oscillation, and volcanic activity.

The uncertainty coming from GCMs can be split into two further sources including the different structural errors (structural uncertainty) that cannot be reduced regardless of the parameterizations used and the parametric uncertainty that arises from the different parameterization schemes to account for processes which must be approximated and in some
cases are not well constrained to observations (Knutti 2008). Knutti (2008) described parametric and structural errors for GCMs, and since RCMS are constructed in a similar way, these types of errors are present in RCMs also.

Regardless of the technique applied, downscaling is a modeling process which adds another level of uncertainty to downscaled climate projections on top of those coming from GCM based projections. There is disagreement in the literature on the strength of the influence of downscaling as a source compared to other sources of uncertainty. Chen et al. (2011) concluded that the downscaling technique is a significant contributor to the uncertainty related to projected changes in river discharge in Canada. Pourmokhtarian et al. (2016) concluded that the statistical downscaling technique along with the observed dataset used to train them is an important source of uncertainty to ecological assessments. Mandal et al. (2016) concluded that the downscaling technique provides the largest source of uncertainty in downscaled projections. In contrast, Dobler et al. (2012) concluded that RCMs provide a comparable source of uncertainty to GCMs, while others have concluded that the differences between GCMs are the dominant source of uncertainty (Kay et al. 2012). Much of the literature on this topic has focused on small regions, one type of downscaling, or on impact variables (streamflow, discharge, etc.) rather than climate variables (temperature, precipitation, etc.).
1.3. Science Questions and Objectives

This dissertation focuses on three primary hypotheses related to our current ability to characterize uncertainty associated with downscaling in general and dynamic downscaling in particular. The hypotheses which are the focus of this dissertation are that:

- The differences between CP schemes and analysis nudging approach will have an influence on the historical accuracy of an RCM, and that the CP schemes also have an influence on the projected change of precipitation in a RCM.
- There are differences in historical accuracy between RCMs given the prior literature and the differences in dynamic cores between RCMs.
- While downscaling adds a level of uncertainty as an additional modeling process it is not a dominant source of uncertainty in downscaled climate projections, because downscaling is meant to translate large scale change to local scales.

There are numerous questions associated with each of these hypotheses. They include:

- How do differences between cumulus parameterization schemes and analysis nudging approaches affect the historical accuracy and spread of projections of precipitation within a single RCM?
- Do regional climate models increase the spread of the ensemble beyond the range of GCMs when they are included in an ensemble? Is the response to the presence of an RCM in an ensemble different for each RCM? Is the approach to forcing a RCM important to the error of an RCM and its ensemble?
• How does downscaling contribute to the spread of future projections? Does the
collection from different sources of uncertainty change in space and time? Is the
collection consistent across multiple climate variables?

Based on these hypotheses and questions these are the following objectives of this study:

• Characterize the parametric uncertainty associated with performing dynamic downscaling
  using a single RCM with respect to the simulation of precipitation (Chapter 2).

• Characterize the structural uncertainty using multiple RCMs and test whether the
  resulting ensemble range expands beyond the bounds of a GCM-only ensemble (Chapter
  3).

• Develop a method to characterize the contribution of downscaling to the total uncertainty
  in climate change projections. Assess if the uncertainty associated with downscaling is a
  dominant source of uncertainty in downscaled climate projections and if this uncertainty
  is sensitive to the region of analysis (Chapter 4).

The analysis in this dissertation uses multiple available datasets and two separate regions to
address these hypotheses and questions. The appendices detail those datasets and regions
used in Chapters 2-4.

1.4. Dissertation Structure

Chapter 2 discusses the parametric errors associated with a single RCM. How does
changing a parameterization scheme affect the accuracy and spread of the projections? Does
the interaction between analysis nudging and parameterization schemes influence the
accuracy? Chapter 3 discusses the structural errors between RCMs and the impact when
included in an ensemble of GCMs. How do RCMs influence the error and spread of an ensemble and are there differences with resolution? Chapter 4 describes the contribution methodology developed in this study and the contribution of each source of uncertainty for multiple variables. Regardless of the individual sources within different downscaling techniques, how much does downscaling contribute to the total uncertainty of climate projections? Is there a difference in the contribution in space and time? Finally, Chapter 5 discusses the broad conclusions from this study, recommendations, and suggestions for future work.
CHAPTER 2. The Sensitivity of WRF downscaled precipitation in Puerto Rico to Cumulus Parameterization and Interior Grid Nudging1

2.1. Introduction

A significant reduction in precipitation from anthropogenic climate change is predicted in sub-tropical regions (Chou et al. 2009), which makes these areas vulnerable to significant impacts to multiple sectors including agriculture, infrastructure, and wildlife. This drying is suggested both by the “rich-get-richer” mechanism (the tendency of rainfall to increase in convergence zones with large climatological precipitation and decrease in subsidence regions) and the GCMs used in the Coupled Model Intercomparison Project Phase 5 (CMIP5, Scheff and Frierson, 2012). However, the “rich-get-richer” mechanism is considered in the absence of additional local topographic factors and forcing, which could mitigate the predicted drying. Efforts are underway to dynamically downscale select CMIP5 GCMs under different greenhouse gas emission scenarios to aid in the development of adaptation strategies that respond to anthropogenic climate change for the island of Puerto Rico, located on the boundary between the Caribbean Sea and Atlantic Ocean. Credible simulation of rainfall is critical in this effort, including consideration of how climate change could affect rainfall intensity, distribution, frequency and totals. Puerto Rico has complex topography which forces spatial variability in precipitation patterns across the island (Jury

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2009). However, the current generation of GCMs is unable to resolve this and other precipitation generating processes. Dynamical downscaling using regional climate models, such as the Weather Research and Forecasting model (WRF), has the potential to resolve convective scale processes required to simulate the precipitation across the island. While the potential exists for WRF to capture the processes in this region, it remains unclear which configuration of WRF is the most appropriate to dynamically downscale to a high horizontal grid spacing over the island. Here we test eight WRF configurations in a hindcast mode to select a WRF configuration that provides the most accurate simulation of precipitation from one-year WRF simulations down to 2 km horizontal grid spacing. The configurations reflect combinations of two cumulus parameterizations (CP) scheme and three interior grid nudging approaches along activation of the CP schemes at convective permitting scales (grid spacing of a few km). Interior grid nudging is an approach used to constrain the RCM simulation to the driving fields (Bowden et al. 2012). Select WRF configurations are also tested in a climate change context by downscaling the CCSM4 climate model for two 3-year time slices (1985-1987 and 2040-2042). The goal is to aid climate change adaptation planning by systematically evaluating the internal structural uncertainty associated with the WRF configuration differences between the CP scheme and interior grid nudging approach. It is essential to characterizing the uncertainty for dynamically downscaled precipitation over the island.

Studies have shown that in areas with deep convection, such as Puerto Rico, precipitation is a large source of uncertainty for climate modeling, even at grid spacing of a few kilometers (Sherwood et al. 2014; Brisson et al. 2015; Prein et al. 2015). The use of CP
schemes at grid spacing between 1 km to 5 km is sometimes referred to as a “gray-zone” because not all convective processes are resolved at these scales (Niemelä and Fortelius, 2005; Craig and Dörnbrack, 2008, Hong and Dudhia, 2012). Therefore, the “gray-zone” is convective permitting (not necessarily convective resolving) and some locations may still warrant the use of a CP scheme to represent the sub-grid scale convective processes in a high-resolution simulation (Deng and Stauffer, 2006). Lee et al. (2011), and Sun and Barros (2014) demonstrated that activating the CP scheme in the high-resolution inner domain improves the representation of precipitation beyond the ability of explicit microphysics alone. Specifically, Lee et al. (2011) demonstrated that activating the CP scheme at high resolutions improved the representation of heavy rain events. CP schemes applied in the “gray-zone” also have important implications for the thermodynamic and dynamic environment of tropical cyclones, by influencing both model convergence and the strength of convection in the eyewall (Sun et al. 2013). Finally, CP schemes impact the marine boundary layer structure (by influencing boundary layer depth, temperature, moisture, and winds), and the geographic placement of clouds (Zhang et al. 2011), which is important for simulating impacts in areas where clouds are an important source of moisture in addition to rainfall (e.g. Comarazamy and Gonzalez, 2011).

However, CP schemes are known to contribute to rainfall errors including the diurnal cycle, frequency, and intensity (Prein et al. 2015) and not all CP schemes are scale aware (assumptions in the parameterization scheme changes as one increases the model’s horizontal resolution) and suitable for grid spacing of a few kilometers. At “gray scales” many assumptions that are made in the CP schemes are no longer valid, such as convection being
self-contained within one grid column (Arakawa et al. 2011; Grell and Freitas et al. 2014). An alternative approach to using a CP scheme is to increase the horizontal grid spacing to begin explicitly resolving the convection (Grell et al. 2000; Chan et al. 2013). A convective permitting simulation (turning off the CP scheme) can be particularly advantageous for Puerto Rico, which has a heterogeneous land surface and mountainous terrain in the tropics. Explicitly resolving the convection has been shown to improve precipitation errors such as diurnal cycle, extreme precipitation on hourly time scales, wet-day frequency, and small-scale processes in tropical cyclones and other convective systems (e.g. Done et al. 2004; Prein et al. 2015). Grell et al. (2000) shows that convective permitting simulations produce precipitation away from the top of mountains as the convection moves with the upper level flow. Convective permitting simulations may also provide a different sample of projected change for precipitation, especially for high precipitation events (Kendon et al. 2012). An additional consideration for convective permitting simulations is that the choice of the CP scheme used in the outermost domains can impact the convective permitting simulations in the innermost domain. For example, Perez et al. (2014) simulated precipitation over the Canary Islands with WRF and found that the largest model errors in precipitation for the innermost domain with explicitly resolved convection occurred when changing the CP scheme in the outer domains. They attributed the precipitation changes to the amount of water available in the innermost domain with different CP scheme choice. In this study, we apply two different CP schemes and assess the impact on simulated precipitation over Puerto Rico. This includes an assessment of differences that result from activating different CP schemes at convective resolving scales.
Studies have also discussed the importance of interior grid nudging, such as spectral and analysis nudging, for simulating regional climate (von Storch et al. 2000; Bowden et al. 2012 and 2013; Otte et al. 2012; Feser and Barcikowska 2012; Cha et al. 2015). In the WRF model used in this study, analysis nudging adds an artificial tendency term to the prognostic equations that is proportional to the difference between the model state and a value that is interpolated in time and space to a grid point from the reference analysis (Stauffer and Seaman 1994; Otte et al. 2012). Spectral nudging is similar, but the non-physical term is based on the difference between the spectral decompositions of the driving fields and the model state (Otte et al, 2012). Otte et al. (2012) and Bowden et al. (2012 and 2013) demonstrated using analysis nudging in WRF improved the overall accuracy of the simulated climate over the Contiguous United States at 36 km and does not squelch extremes in temperature and precipitation. Bullock et al. (2014) showed additional accuracy in precipitation and temperature when applying analysis and spectral grid nudging in WRF at a 12 km horizontal grid spacing. Using nudging in the interior of the domain has also been shown to improve formation of typhoons and their tracks (Feser and Barikowska, 2012) and synoptic flow and precipitation associated with the East Asian summer monsoon (Cha et al. 2015). All of these improvements ranging from extreme near surface meteorological fields to the representation of weather regimes and large-scale atmospheric processes point toward the need for interior grid nudging. However, few studies have analyzed the importance of interior grid nudging for small tropical islands at high horizontal “gray-zone” resolutions. In this study, we apply three different nudging strategies (from no nudging to applying nudging on the middle and outer domains) to determine the impact on the accuracy of simulated
precipitation across the island. Given that high resolution projections will ultimately be provided to decision makers in Puerto Rico, it is likely that this high resolution information will be used for adaptation decision making and vulnerability assessments, and so such evaluation is critical to drive future projections being produced for this region.

The rest of the chapter is organized as follows. In section 2, the model setup and sensitivity simulations unique to this chapter. Section 3 describes the validation data and verification of the sensitivity simulations. We conclude with a summary and discussion of the results and future directions for research.

2.2. Model Setup and Simulations

Prior studies have used WRF over Puerto Rico at a 1-km horizontal grid spacing (Jury and Chiao, 2013; Villamil-Otero et al. 2015) to understand the atmospheric circulation across the island. Villamil-Otero et al (2015) applied the WRF model to understand the topographic-thermal circulations in western Puerto Rico, while Jury and Chiao (2013) used WRF to understand the leeside boundary layer confluence and afternoon thunderstorms in western Puerto Rico. Both of these studies illustrated that WRF simulates atmospheric processes that are important for local precipitation across Puerto Rico; therefore, WRF is hypothesized to provide significant value for downscaling climate change projections because GCMs cannot resolve these local scale processes. WRF is used to downscale NCEP-DOE AMIP-II reanalysis version 2 (R-2, Kanamitsu et al. 2002) over Puerto Rico to a 2 km horizontal grid spacing. R-2 (which has a horizontal grid spacing of T62, 1.875° ×
1.875° at the equator) is used here to mimic the coarser grid spacing of the GCMs used in CMIP5 to help establish a dynamic downscaling method for future climate change downscaling efforts. For this study, WRF version 3.6.1 was used to downscale R-2. WRF was initialized at 0000 UTC 1 December 2009 and run for a 1-month spin up time, then run continuously through 0000 UTC 1 January 2011. To provide a WRF configuration for the downscaled climate change projections, precipitation from eight one-year WRF simulations (Table 2.1) are compared with observations for validation. The analysis in this study focuses on rainfall statistics as a result of changes in the application of the CP scheme and interior grid nudging. The remaining model setup for WRF remains consistent to what is described in Chapter 1, and the CP scheme and nudging are used here to focus on differences in unique ways to apply parameterization schemes using WRF as the example RCM.

The simulations use two different CP schemes: the Tiedtke scheme and the Kain-Fritsch (KF) scheme. The Tiedtke scheme (Tiedtke 1989; Zhang et al. 2011) is used to match the similar research efforts done for Hawaii (Lauer et al. 2013). The Tiedtke scheme is a mass flux-type scheme and represents various types of convection that occur around the globe including deep, shallow, and mid-level convection (Tiedtke 1989). In WRF, the Tiedtke scheme has been shown to improve the geographical distribution of marine boundary layer clouds (Zhang et al. 2011). Simulations using Kain-Fritsch implement a modified version of the original scheme (Alapaty et al. 2012; Herwehe et al. 2014). The Kain-Fritsch scheme is also a mass flux scheme that considers shallow and deep convection. This modified CP scheme (as in Alapaty et al. 2012; Herwehe et al. 2014), KFMODS, considers cumulus cloud feedbacks to the radiation and has been shown to improve precipitation
biases, especially for a humid climate such as the Southeast US. While the Kain-Fritsch and Tiedtke schemes are both mass flux schemes which use CAPE closure, they have differences in the trigger mechanism (Suhas and Zhang, 2014). The Kain-Fritsch scheme uses a temperature perturbation to determine the vertical velocity for potential updraft source layers, while the Tiedtke scheme uses both temperature and moisture perturbations. In addition, the Kain-Fritsch scheme activates convection if the vertical velocity of the potential updraft source layer has a minimum depth of 3 km, while the Tiedtke scheme uses a depth of 200 hPa. Finally, the Kain-Fritsch scheme searches the lowest 300 hPa for updraft source layers, and the Tiedtke scheme searches the lowest 350 hPa. All simulations use a CP scheme in the two outermost domains (30 km and 10 km). Most the simulations (6 of 8) are convective permitting, CP scheme not active in the inner (2 km) domain. For two simulations (KFMODS_INNER and TIEDTKE_INNER) the CP scheme is active in the innermost domain of WRF.

In addition, the simulations also reflect three different analysis nudging approaches. As in prior regional climate modeling studies, such as Bowden et al. (2012) and Otte et al. (2012), analysis nudging is applied toward horizontal winds, potential temperature, and water vapor mixing ratio above the PBL. Nudging above the PBL is advantageous because it allows WRF freedom to develop and respond to mesoscale forcing while simultaneously being constrained to the large-scale atmospheric circulation in the free atmosphere. The analysis nudging coefficients are provided in Table 1.1 and represent the nudging strength, which is the e-folding time that would be required to adjust the model to the observed state in the absence of other (physical) forcing (Bowden et al. 2012). Similar
analysis nudging coefficients have been shown to improve the representation of errors in near surface fields including precipitation extremes at similar grid spacing to those used here (Bowden et al. 2012 & 2013; Otte et al. 2012; Bullock et al. 2014). However, the focus of these studies has been on areas outside of the tropics. As precipitation can have more influence than temperature in tropical regions (for example on tropical forests as in Schuur 2003), exploring the impact of nudging on precipitation simulation is important to improving the simulation of precipitation in tropical regions for use in adaptive management. In this study, we test different CP schemes with different analysis nudging strategies using annual simulations at a high-resolution (2 km grid spacing). The first approach uses analysis nudging on the outer two domains (TIEDTKE, KFMODS, TIEDTKE_INNER, KFMODS_INNER). The second approach applies analysis nudging only to the outermost domain (TIEDTKE_ON and KFMODS_ON). The final approach does not use analysis nudging (TIEDTKE_NN and KFMODS_NN).

2.3. Validation Procedure

For validating each of the WRF simulations, the Multi-Sensor Precipitation Estimates (MPE) provided by National Weather Service is used for comparison (Seo and Breidenbach, 2002). This dataset used rain gauge calibrated radar estimates of rainfall to produce a gridded estimate of rainfall at ~4.765 km grid spacing. For this analysis, we use the daily MPE product aggregated to a monthly sum for each month in 2010 for comparison with the WRF simulations. It is important to note MPE is created with modeled processes and has known errors related to these processes. The MPE are created using similar algorithms to the
Stage IV Precipitation Estimates produced by the National Centers for Environmental Prediction. The accuracy of the Stage IV estimates is well documented for the continental United States, most recently by Wootten and Boyles (2014). The Stage IV estimates demonstrate a tendency to over-estimate light rain events and underestimate heavy rain events on a daily timescale. We expect that the MPE in Puerto Rico shares similar errors to the MPE and Stage IV estimates in the continental United States. This should be considered here as limiting factors for this study.

For this study, the focus is primarily on precipitation since it is one of the primary variables that determine the location of the ecology within Puerto Rico. Specifically, the focus is on the precipitation in the inner (2 km) and middle (10 km) domains of the WRF simulation for the following:

- Seasonal cycle of precipitation totals for 2010
- Monthly total precipitation
- Number of days of rain > 25.4 mm (1 inch) in a month

In addition to the qualitative comparisons of the inner domain precipitation to MPE, the root mean square error (RMSE), correlation, and percent bias are used to provide quantitative comparisons of the accuracy between each simulation. Percent bias is calculated as the following:

$$\% Bias = 100 \frac{\sum_{i=1}^{n}(y_i - x_i)}{\sum_{i=1}^{n} x_i}$$
where $x$ is the value of MPE, $y$ is the value of the WRF simulation, for each time $i$. Each simulation in the 2 km domain is aggregated via grid averaging to the MPE grid over Puerto Rico, and these metrics are calculated for each grid cell where data are available for both the WRF simulations and MPE grid. The grid cell values are then averaged over the island to provide values of RMSE, correlation, and percent bias, and included in the appropriate figures. In this study, for the statistical metrics described above, much of the focus is on the simulated precipitation within the inner (2 km) grid spacing domain. However, given the influence of outer two domains on the inner domain precipitation totals, we will discuss the results in these domains as needed.

2.4. Results

For this section, we focus on the differences related to CP scheme and interior grid nudging separately. The first subsection focuses on the differences between WRF simulations with differing CP schemes. The second subsection focuses on the influence of analysis nudging on precipitation in the inner domain of WRF. The third subsection here focuses on the statistical metrics for the inner domain across all the WRF simulations included in this study. The final subsection presents additional analysis which discusses the implications of differences between CP schemes in future projections.
2.4.1. CP Scheme Sensitivity

The focus in this subsection is on the differences in precipitation across CP schemes. This includes a comparison of convective and non-convective permitting simulations in the 2-km inner domain. For each of the four simulations discussed here, analysis nudging is applied to the winds, moisture, and temperature in the middle and outer domains. January is the middle of the dry season for Puerto Rico, and all simulations have some general agreement on the spatial distribution of the precipitation (Figure 2.1). TIEDTKE_INNER is drier than TIEDTKE and does not improve the simulation of drier conditions along much of the southern coast. The differences are small when activating the CP scheme for KFMODS (with KFMODS_INNER slightly wetter than KFMODS), and both have a dry bias compared to MPE. In general during the dry season, we do not see large improvements when activating the CP scheme in the inner domain, which agrees with Sun and Barros (2014). This may be expected because the atmosphere is generally more stable and drier. There are also larger differences between CP schemes relative to the CP scheme being active in the 2 km domain during the dry season.

A similar comparison is made during the middle of the wet season. The magnitude of simulated precipitation is larger during the wet season in all versions (Figure 2.2). Each simulation remains drier compared to MPE, but WRF simulates the rainfall patterns with driest conditions in the central part of the island and wettest conditions in the convergence zone on the west side of the island. The TIEDTKE_INNER and TIEDTKE simulations have little difference in terms of precipitation totals, but the TIEDTKE_INNER simulation does
provide a better representation of rainfall on the east side than the TIEDTKE simulation. For KFMODS_INNER, activating the CP scheme in the inner domain improves the simulation of precipitation totals by increasing the precipitation amount across the island. In particular, activating the CP scheme restores the precipitation on the northeast side of the island in the KFMODS_INNER simulation. Activating the KFMODS scheme in the inner domain more accurately represents the precipitation amounts across the island during the wet season. There is little to no improvement to activating the TIEDTKE scheme in the inner domain in WRF.

Simulating heavy rainfall events is critical for precipitation totals, as having light precipitation occur frequently may lead to the correct rainfall totals but with a skewed distribution. The frequency of heavy rain events (> 25.4 mm, 1 inch) is also under-represented in the wet season. Each WRF simulation underestimates the number of heavy rainfall events, with some locations having 7+ fewer heavy rain days in July than observed by MPE (Figure 2.3). Activating the CP scheme in the 2 km inner domain tends to improve and concentrate the rainfall for the far eastern side of the island for both CP schemes. In particular, places like the northeast corner show large improvements in the number of heavy rainfall events when using a CP scheme in the innermost domain. However, there is more sensitivity between CP schemes in the 2 km innermost domain for the western half of the island. Turning on the CP scheme in the TIEDTKE comparison shows a reduction in the number of heavy rainfall days in general but particularly on the west side. Turning on the CP scheme in the KFMODS comparison shows smaller response to the change in the number of heavy rainfall days on the west side. This demonstrates that activating the CP scheme at
“gray-zone” resolutions can provide a different regional response for different CP schemes for extreme rainfall. Overall, the KFMODS_INNER simulation restores heavy rain events across much of the island, while the TIEDTKE_INNER contributes to more heavy rain events on the east side than the west side of the island.

For each of the above four simulations, we compare the inner domain monthly precipitation totals (2 km) to that available from the middle domain (10-km) averaged over all land points within Puerto Rico (Figure 2.4), to assess the consistency between the middle and inner domains. For each CP scheme, the middle domain precipitation (red-dashed line) is closer to the MPE observations (black line) on average for the year with a smaller percent bias (value KFMOD – value TIEDTKE), unlike the dry bias in the 2 km domain for both CP schemes (blue and green-dashed lines). Specifically, KFMODS and KFMODS_INNER simulations, there is a significant dry bias in the inner 2-km domain compared to the middle domain, 52% and 23% respectively. However, activating the CP scheme in the inner 2 km domain (KFMODS_INNER, Figure 2.4 top, green-dashed line) increased the simulated monthly precipitation totals compared to the KFMODS simulation (Figure 2.4 top, blue-dashed line). However, we do not find the same response as we see in the KFMOD case between the TIEDTKE and TIEDTKE_INNER for the inner 2 km domain. The TIEDTKE_INNER simulation (Figure 2.4 bottom, green-dashed line) reduced the average total precipitation, which actually result in a more accurate representation of precipitation totals in December, February-April and August. However, during the majority of the rainy season, the reduced rainfall total creates a larger dry bias. Overall, the results illustrate an important point that at “gray-zone” resolutions, the island average precipitation is
underestimated in the innermost 2 km domain with two different CP schemes and was better represented on average at the coarser (10 km grid spacing) resolution with both CP schemes. Note CP schemes used here are not scale aware (that is, they do not relax the typical assumptions, such as the scale separation assumption which considers all convection to be contained within one column, associated with CP schemes as the grid-spacing decreases). The scale-aware limitation may help to explain why the simulated rainfall totals on average for the island agree better with observations for the 10 km domain. However, the sharp rainfall gradient is not well resolved in the 10 km middle domain while it is apparent in the 2 km inner domain with the Kain-Fritsch scheme active (KFMODS_INNER). In our study, it is imperative to model the rainfall gradient for terrestrial ecosystems and thus more emphasis is placed on the rainfall placement. Therefore, efforts were placed on improving the rainfall amounts at the “gray-zone” grid spacing of 2 km. We find that turning on the CP schemes in the inner 2 km domain typically improves the rainfall statistics in the 2 km inner domain for Puerto Rico (see Table 2.2 for RMSE, correlation, percent bias).

2.4.2. Nudging Sensitivity

This second subsection focuses on the distinct differences in precipitation with regards to how (and if) analysis nudging is applied. All nudging sensitivity simulations are convective permitting, that is the CP scheme is active in the middle and outer domains only. Here we only focus on July when the precipitation bias is large, as previously shown. During July 2010, there are distinct differences in total precipitation when comparing between model domains, inner 2 km and middle 10 km, for the KFMODS simulations
compared to MPE (Figure 2.5). The number of domains to which nudging is applied decreases from the top panel (outer and middle domain), to the middle panel (outer domain only), to the bottom panel (no nudging) in Figure 2.5 and following similar figures. A striking contrast is that the inner domain in all three simulations is much dryer (~150-200 mm) overall than the middle domain (which agrees with the time series shown in Figure 2.4), especially for the eastern side of the island. However, the dry bias is independent of the use of analysis nudging for the KFMODS simulations. Comparing the July precipitation totals in Figure 2.5 to KFMODS_INNER in Figure 2.2, we see that using the CP scheme in the inner domain had a larger impact on the monthly precipitation totals, increase of 50-75 mm, than changes to analysis nudging, difference of < 50 mm between them. However, the changes in island precipitation between the nudging techniques are more noticeable at 10 km. For instance, KFMODS in the middle domain is wetter (> 200 mm) than the KFMODS_ON for the eastern half of the island. Although the dry bias exists transitioning from the middle to the inner domain, the KFMODS simulation in the middle domain most closely matches the MPE. In contrast, reducing the number of domains where nudging is applied causes a dry bias to appear in the middle domain on the east side of the island. So, reducing the number of domains where nudging is applied degraded the representation of precipitation in the middle domain for the KFMODS simulations.

When altering the choice of CP scheme from KFMODS to TIEDTKE, analysis nudging shows larger sensitivity (Figure 2.6). In particular, there are larger differences in the middle domain between the analysis nudging approaches for the TIEDTKE simulations in Figure 2.6 when compared to the KFMODS simulations in Figure 2.6. The large differences
in the TIEDTKE simulations for the middle domain clearly impact the inner domain precipitation. For instance TIEDTKE_NN in the middle domain is wetter than TIEDTKE_ON (> 300 mm on average over the island). The TIEDTKE_NN also has a large rainfall totals in the inner domain. In general the simulation without nudging, TIEDTKE_NN, is an outlier and much wetter than the analysis nudging simulations. Even though rainfall is sensitive to CP scheme choice, the choice to use nudging can also have a significant impact on the precipitation climatology over Puerto Rico. The changes and discrepancies between domains are also reflected in the heavy rain events in WRF (not shown).

2.4.3. Overall Accuracy for Precipitation

The nudging and CP scheme both have an impact on the precipitation produced in the inner domain of WRF for Puerto Rico. However, up to this point we have considered this qualitatively. This sub-section focuses on quantitative measures of accuracy for the precipitation simulated by WRF compared to the MPE for the inner domain only. Figure 2.7 shows the root mean square error (RMSE) for the monthly total precipitation for each of the eight WRF simulations compared to the MPE. For both CP schemes, applying the grid nudging in the outer domain only, KFMODS_ON and TIEDTKE_ON, increases the RMSE for precipitation in the inner domain. However, the CP schemes respond very differently when no nudging is applied. The RMSE for the inner domain precipitation is far larger in the TIEDTKE_NN simulation compared to the TIEDTKE and TIEDTKE_ON simulations. In contrast, the RMSE for the KFMODS_NN simulation is similar to both the KFMODS and
KFMODS_ON simulations. Therefore, the nudging does have an influence on the RMSE for precipitation in the inner domain, but each CP scheme reacts differently to the influence of nudging. The TIEDTKE and KFMODS simulations are comparable both in the magnitude, but activating the CP scheme in the inner domain of each improves the RMSE. The reduction in the RMSE is largest for the KFMODS_INNER simulation. The convective permitting simulations have a RMSE of around 150 mm or more on average for Puerto Rico. The KFMODS_INNER simulation decreased the RMSE to be less than 150 mm on average. This suggests that activating the CP scheme in the inner domain improves the magnitude of precipitation in Puerto Rico, more so for the Kain-Fritsch scheme than the Tiedtke scheme.

The simulations also have differing representations of the annual cycle of rainfall in the simulation. Each of the eight simulations is well correlated to MPE on the southwest side of Puerto Rico (Figure 2.8). However, in six of the simulations there are many locations with a near zero correlation or strongly negative correlation to the MPE. For the TIEDTKE simulations, applying nudging degraded the correlation of simulated rainfall with the MPE in the inner domain on the northwest side. In contrast, applying nudging to the KFMODS simulations improved the correlation between the simulations and MPE across much of the island as a whole. In both cases, activating the CP scheme in the inner domain also improved the correlation across Puerto Rico (more so for KFMODS_INNER). This indicates that the annual cycle and magnitude of precipitation is improved with the CP scheme activated in the 2 km inner domain of WRF for this region. So the choice of nudging and CP scheme together can improve the representation of the annual cycle of precipitation.
Each simulation also has a distinct tendency to over or underestimate precipitation totals in Puerto Rico depending on CP scheme and nudging approach. Figure 2.9 shows the percent bias for the monthly total precipitation for each of the WRF simulations compared to the MPE. Figures 2.4-2.5 indicated the tendency for the WRF simulations to underestimate wet season rainfall in Puerto Rico. However, considering the entire year shows a slightly different pattern. The KFMODS simulations underestimate precipitation along the coasts of Puerto Rico. KFMODS simulation, which incorporates nudging in the 10 km and 30 km domains, underestimates precipitation over a larger area along the coastline compared to the other KFMODS simulations. Although the KFMODS simulation underestimates precipitation over a larger area, it improves the correlation of precipitation over the same area. However, activating the CP scheme in the inner domain (KFMODS_INNER) reduces this tendency to underestimate precipitation. Using the KFMODS scheme in the inner domain does reduce the underestimation, but also seems to cause precipitation to remain over the mountains which provide topographic forcing on the island. For the Tiedtke simulations, applying nudging to multiple domains dampens the tendency to overestimate rainfall. In addition, activating the CP scheme in the inner domain further dampened the tendency of the Tiedtke simulations to overestimate rainfall, actually causing a stronger tendency to underestimate rainfall. Of the eight simulations, using the KFMODS CP scheme (active in all 3 domains, KFMODS_INNER) with nudging applied to the middle and outer domains provides the lowest RMSE, improves the annual cycle while reducing the tendency to underestimate rainfall, and captures much of the gradients of rainfall over the island. In general, activating the CP scheme can improve the representation of precipitation in a high
resolution WRF domain. However, it is important to note the interaction between nudging and CP scheme has a significant influence on precipitation. As such, the choice of both should be considered carefully for high resolution WRF simulations.

2.4.4. Climate Change Context

Distinct differences in the representation of historical precipitation exist with changes to CP schemes and nudging approach. However, while this is well documented by many studies (including this one for Puerto Rico), there is little discussion regarding the implications of changing CP schemes or nudging approach on the spread of projected change from WRF as a regional climate model. For this supplemental experiment, three of the eight WRF simulations are used with the CCSM4 to downscale a historical and future 3-year time-slice for Puerto Rico. These three simulations of WRF used here are the KFMODES, KFMODES_INNER, and TIEDETTKE simulations. For this supplemental experiment the focus is on differences between CP schemes to focus on the possible spread of projections from a common RCM (in this case WRF) and GCM with variations to the CP scheme in the RCM. For this analysis, each WRF simulation is initialized with the CCSM4 simulation data for two three-year periods with one-month spin up for each period. The past period used in 1985-1987 (initialized 0000 UTC 1 December 1984), and the future period used from the CCSM4 RCP8.5 output is 2040-2042 (initialized 0000 UTC 1 December 2039). The three WRF simulations are run using the same domains, nesting, and grid spacing as in the previous sensitivity runs initialized with R-2. The two periods are used to determine for each
simulation the change in average summer (JJA) total precipitation over Puerto Rico in the high resolution inner domain of WRF.

Although the only difference between the WRF simulations is the choice of CP scheme and if the CP scheme is active in the inner domain, there are still obvious differences for the projected change in average summer precipitation over Puerto Rico (Figure 2.9). In some locations the projected change ranges from wetter to drier by mid-century. While there is some agreement between the KFMODS_INNER and TIEDTKE simulations for the western half of the island, the magnitude of the drying is much larger in the KFMODS_INNER for much of the island. In addition, the projected changes are not just different visually, but have statistical significance (Figure 2.10). Colored areas in Figure 2.10 show statistical significance at 90% or greater confidence (p-values ≤ 0.1) from an Analysis of Variance (ANOVA) test run with all three simulations for each grid cell. At the 90% confidence level, 50% of the island shows a statistically significant difference between the WRF simulations for the projected change in summer precipitation. That is, for half of Puerto Rico, the projected change in precipitation is significantly different despite the use of the same period, GCM, and RCP for the WRF simulations.

The potential differences between these simulations, though the driving factors (GCM, RCP, domains, grid spacing, nudging approach) remained constant, highlights an important source of uncertainty in WRF. Not only do changes in CP scheme influence the accuracy of historical precipitation, but there is also an influence on the projected changes for precipitation. Given the prior results for nudging approach and CP scheme it follows that
these results could extend also to projected changes in precipitation and other critical variables of interest for decision making and impact assessments. Therefore, the choice of CP scheme and use at “gray-zone” resolution when using WRF for climate change studies is an important aspect for consideration. The differences between CP schemes represent a source of uncertainty not fully represented by the current suite of available regional climate model output. The computational expense limits most studies using regional climate models to focusing on one set of parameterization schemes or nudging approaches. It should be noted that the periods used for comparison here are short (3 years past and future) and therefore should not be used to the climate change signal itself for this region. However, these three years are the start of a longer period that is being downscaled (1985-2005 vs. 2040-2060). Overall, this is a short time period but the example analysis highlights that the differences between CP schemes could expand the uncertainty associated with high resolution projections for a region. Therefore, careful consideration should be given to the choice of parameterization schemes in WRF with regards to both the historical accuracy and potential differences for projected change. In addition, the potential expansion of the envelope of uncertainty is a concern for using projections from WRF in decision making or impact assessment. Therefore, this merits consideration of how this source of uncertainty could influence regional projections of climate change and if it is significant in the face of other sources of uncertainty. Such work was far beyond the scope of this study, but is suggested as an avenue of future study.
2.5. Summary and Conclusions

In this study we have used several variations of CP scheme and interior grid nudging, to assess the uncertainty associated with both for precipitation simulated by WRF. This included activating the CP scheme in the 2 km inner domain. With the exception of one simulation (the TIEDTKE_NN), WRF displayed a tendency to underestimate rainfall in Puerto Rico, particularly during the wet season. The lack of nudging in the TIEDTKE_NN simulation in combination with the TIEDTKE CP scheme illustrated the only overestimation of simulated precipitation at the “gray-zone” 2 km grid spacing. This included all the simulations where nudging was applied in either the outer (30 km) domain only or the middle (10-km) and outer domains. This is interesting given that all these simulations downscale R2, which has been shown to overestimate precipitation climatology in the Caribbean (Wang et al, 2011). The dry tendency, especially for the 2 km domain, is not solely from the lack of days with rain, but from the lack of days with heavy rain represented in each simulation. Regardless of the CP scheme used, activating the CP scheme in the inner domain improved the representation of precipitation. This is similar to other studies using WRF including Lee et al. (2011), and Sun and Barros (2014).

Precipitable water was considered here, but did not explain why the WRF simulations in general are dryer than observations (not shown). While not explicitly discussed by Lee et al. (2011), that study did demonstrate that the explicit microphysics in high resolution domains can be suppressed as the Kain-Fritsch scheme dries and warms much of the troposphere in the driving domain in convective permitting simulations. Although the
modified Kain-Fritsch scheme was used in this study, the improvement in accuracy by activating this CP scheme in the inner (2 km) domain is similar to the results presented by Lee et al. (2011) during the wet season (which has frequent rain events) and for the frequency of intense events. The improvement with the active cumulus physics is more marginal in the dry season (with lighter rain events), which is similar to the result shown by Sun and Barros (2014) for light rain events. We speculate that the mechanism behind this difference in the Kain-Fritsch scheme is similar to those described by Lee et al. (2011). What Lee et al (2011) describe is that activating the Kain Fritsch scheme in the inner domain (as in KFMODS_INNER) increases the vertical motion and lower troposphere moisture during heavy rain events compared to relying on the explicit microphysics (as in KFMODS) improving the representation of rainfall totals for those events. Activating the KFMODS scheme does improve precipitation in the inner (2 km) domain. The middle (10 km) domain provides a better representation of the island average rainfall but does not have the grid spacing needed to resolve the sharp precipitation gradient observed over the island. However, the Tiedtke CP scheme was also used and better represented the gradient of dry season precipitation in Puerto Rico when activated in the inner domain and little to no difference during the wet season. While such case studies of individual events as in Lee et al. (2011) or Sun and Barros (2014) were not the focus of this study, such case studies are recommended for future research as the interaction between microphysics and CP schemes that Lee et al. (2011) demonstrated for the Kain-Fritsch CP scheme is not reflected by the Tiedtke CP scheme in this region. The differing responses may be associated with differences in scale separation assumptions between the Tiedtke and Kain-Fritsch schemes.
In addition to the CP scheme, the choice of nudging approach also influences the representation of precipitation in the high resolution domain. In most cases, applying the analysis nudging in both the middle and outer domains improved the representation in the inner domain. This is consistent with Bowden et al. (2012 and 2013) and Otte et al. (2012) and is reflected in the quantitative analysis of total monthly precipitation. What has not been highlighted in previous high-resolution climate modeling studies is the sensitivity of WRF precipitation to the interaction of both nudging and CP scheme for a tropical location at “gray-zone” resolutions. Since applying nudging at different levels (no nudging, or having nudging active in one or more domains) with different CP schemes does not have the same effect on simulated precipitation, the interaction between the nudging approach and CP scheme can have a strong influence on the simulated precipitation. Care should be taken in future efforts to consider this interaction when using WRF for high resolution climate modeling.

The distinct differences between CP schemes and the interaction with analysis nudging could have implications for using WRF for very high-resolution climate change simulations (< 5 km grid spacing). The differences between these simulations imply that the projected change with regards to precipitation can vary widely given choices of parameterization scheme and nudging approach. This was shown in small experiment here with WRF and different CP schemes. However, this aspect of uncertainty in regional climate modeling is not well represented in current regional climate modeling efforts as the focus remains on differences between regional and global climate models rather than the structural differences that can exist between individual simulations of a single regional climate
model. Therefore, the potential influence on the uncertainty for climate change projections from a regional model is worth exploring given the differences found here in both a historical and climate change context.

As mentioned previously, this study focused solely on the influence of analysis nudging and CP scheme. This study did not change any other parameterization schemes in WRF or use spectral nudging in this region. Given the potential influence on precipitation in this region it is recommended as an avenue of future work to consider the influence of other parameterization schemes and spectral nudging on the WRF simulated climate in Puerto Rico. In addition, MPE and R-2 are created using modeling or algorithms combining radar and station gauge precipitation. They are subject to their own errors which likely had some influence in this study. Given that the focus here was on the eventual application of WRF for use in climate change simulations the analysis here focused on monthly and annual timescales. We acknowledge that there are challenges representing the diurnal cycle of convection (e.g. Hohenegger et al. 2015). Therefore, this is also suggested as an avenue of future research for tropical regions. Finally, the focus of this study was on 2010. Therefore, there is no evaluation of the inter-annual variability of WRF simulated precipitation. While this study did evaluate the frequency of heavy rain events in 2010, an avenue of future study includes an analysis of the frequency of heavy rain events over multiple years. As mentioned previously this would be recommended given the discrepancy present between CP schemes shown in this study. While there are several avenues of future study based on the results of this study, for Puerto Rico it is recommended to use the modified Kain-Fritsch CP scheme,
active at convective permitting scales, with analysis nudging applied on the middle and outer domains.

2.6. Acknowledgements

The study presented here was funded by the Department of the Interior Southeast Climate Science Center (USGS Cooperative Agreement G13AC00408). We thank the Renaissance Computing Institute for providing the super-computing for the WRF simulations. Finally we thank the anonymous reviewers for their feedback and suggested improvements. Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government.
Table 2.1. WRF simulations used in this study. Differences are specifically on the CP, grid nudging used, and if the CP is also active in the inner domain.

<table>
<thead>
<tr>
<th>WRF Simulation Name</th>
<th>CP scheme</th>
<th>Nudging</th>
<th>Inner Domain CP scheme active</th>
</tr>
</thead>
<tbody>
<tr>
<td>TIEDTKE</td>
<td>Tiedtke</td>
<td>Analysis nudging middle and outer domains</td>
<td>No</td>
</tr>
<tr>
<td>KFMODS</td>
<td>Modified Kain-Fritsch</td>
<td>Analysis nudging middle and outer domains</td>
<td>No</td>
</tr>
<tr>
<td>TIEDTKE_INNER</td>
<td>Tiedtke</td>
<td>Analysis nudging middle and outer domains</td>
<td>Yes</td>
</tr>
<tr>
<td>KFMODS_INNER</td>
<td>Modified Kain-Fritsch</td>
<td>Analysis nudging middle and outer domains</td>
<td>Yes</td>
</tr>
<tr>
<td>TIEDTKE_ON</td>
<td>Tiedtke</td>
<td>Analysis nudging outer domain only</td>
<td>No</td>
</tr>
<tr>
<td>KFMODS_ON</td>
<td>Modified Kain-Fritsch</td>
<td>Analysis nudging outer domain only</td>
<td>No</td>
</tr>
<tr>
<td>TIEDTKE_NN</td>
<td>Tiedtke</td>
<td>No nudging applied</td>
<td>No</td>
</tr>
<tr>
<td>KFMODS_NN</td>
<td>Modified Kain-Fritsch</td>
<td>No nudging applied</td>
<td>No</td>
</tr>
</tbody>
</table>

Table 2.2. Island Average monthly RMSE, Correlation, and Percent Bias for the KFMODS, KFMODS_INNER, TIEDTKE, and TIEDTKE_INNER simulations for the inner domain.

<table>
<thead>
<tr>
<th>Simulation</th>
<th>Average RMSE (mm)</th>
<th>Avg. Correlation</th>
<th>Avg. Percent Bias (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>KFMODS</td>
<td>154</td>
<td>0.108</td>
<td>-52.4</td>
</tr>
<tr>
<td>KFMODS_INNER</td>
<td>117</td>
<td>0.303</td>
<td>-23.0</td>
</tr>
<tr>
<td>TIEDTKE</td>
<td>144</td>
<td>0.034</td>
<td>-8.21</td>
</tr>
<tr>
<td>TIEDTKE_INNER</td>
<td>143</td>
<td>0.118</td>
<td>-28.3</td>
</tr>
</tbody>
</table>
Figure 2.1. January 2010 total precipitation (mm), WRF inner domain vs. MPE. Island averages shown in the top right corner of each panel.
Figure 2.2. July 2010 total precipitation (mm), WRF inner domain vs. MPE. Island averages shown in the top right corner of each panel.
Figure 2.3. July 2010 number of days with rainfall over 25.4 mm, WRF inner domain vs. MPE. Island averages shown in the top right corner of each panel.
Figure 2.4. Annual cycle for WRF and MPE, for KFMODS and TIEDTKE simulations for inner and middle domain precipitation for the explicit and active CP scheme in the inner domain. Time series average total precipitation over Puerto Rico for January to December 2010.
Figure 2.5. July 2010 total precipitation (mm), WRF inner and middle domains vs. MPE. Left is the inner domain (2 km), right is the middle domain (10 km). From top to bottom, KFMODS, KFMODS_ON, KFMODS_NN. Island averages shown in the top right corner of each panel.
Figure 2.6. July 2010 total precipitation (mm), WRF inner and middle domains vs. MPE. Left is the inner domain (2 km), right is the middle domain (10 km). From top to bottom, TIEDTKE, TIEDTKE_ON, TIEDTKE_NN. Island averages shown in the top right corner of each panel.
Figure 2.7. RMSE (mm) for total precipitation for all WRF simulations across Puerto Rico for 2010. Numbers included for each are the average values for the island.
Figure 2.8. Correlation of total precipitation for all WRF simulations across Puerto Rico for 2010. Numbers included for each are the average values for the island.
Figure 2.9. Percent Bias (%) for total precipitation for all simulations across Puerto Rico for 2010. Numbers included for each are the average values for the island.
Figure 2.10. CCSM-WRF Projected change in summer (JJA) total precipitation from 1985-1987 to 2040-2042 for three configurations of WRF. Numbers included are the average projected change across Puerto Rico.
Figure 2.11. Analysis of Variance P-values for the Projected change in summer total precipitation. Colored areas indicate p-values of 0.1 or less, or a statistically significant difference between the three CCSM-WRF simulations.
CHAPTER 3. Uncertainty in Regional Climate Models: Are We Only Scratching the Surface?

3.1. Introduction

With the increasing attention being given to local and regional-scale adaptation decisions related to anthropogenic climate change, climate models are being repurposed to meet the needs of such activities. This is a significant shift from the original decision context that gave rise to the current generation of, and continuing investment in global climate models (GCMs) and the associated large coordinated experiments. Such experiments, like the Coupled Model Intercomparison Projects (CMIP, Taylor et al. 2012), help frame and inform international policies and agreements that address global greenhouse gas emissions. But in a new era with committed warming of at least 1.5°C above the conditions of the 20th century (IPCC 2014), the desire to use climate model output to adapt to local and regional manifestations of global warming is likely to be both inexorable and permanent. As such, it is important to consider the reliability and uncertainty of all types of climate models (including downscaled climate models) which will be used to inform decision making in this adaptation context. Downscaling, the translation of coarse scale climate model output to a finer resolution through the use of regional climate models (RCMs) or statistical modeling, is currently the dominant method for providing climate change information to decision makers for use in an adaptation context. Statistical downscaling techniques rely on the construction of an empirical model of the relationship between observations and GCMs. Concerns about the utility of this method in data sparse regions and the potentially difficult to justify
stationarity assumption (Dixon et al. 2016) have led to calls for an emphasis on the use of alternative modeling approaches to inform climate change adaptation decisions (e.g. Hazeleger et al. 2015). Alternatively, while the use of RCMs, particularly at very high spatial resolutions (< 10 km grid spacing), poses its own set of challenges (e.g. large computational expense and smaller attendant model ensembles), the perceived advantages over statistical downscaling show potential for use in impact assessments and decision making (Wootten et al. 2014; Di Luca et al. 2015).

By its nature, downscaling is meant to translate information between the coarser resolution (> 100 km grid spacing) of the GCMs in a global domain to a finer resolution in a smaller region. RCMs operate at resolutions finer than the GCMs for smaller regions, which allow them to explicitly represent some processes and features (like topography) which are not present or parameterized in a GCM. However, there are still processes which are parameterized in a RCM and the RCMs have similar construction to GCMs. Knutti (2008) described parametric and structural errors for GCMs, and since RCMs are constructed in a similar way, these types of errors will be present in RCMs. For example, individual RCMs have differing dynamic cores and computational resource demands, and can use differing approaches to forcing the RCM. One climate modeler may nest together domains with multiple resolutions in a RCM simulation to produce output at a desired resolution to circumvent computational resource demands (Rummakainen 2010). Another modeler may gather the computational resources to overcome those demands (e.g. Lucas-Picher et al. 2016). This represents two different approaches to forcing the RCM with GCM output. Therefore each RCM has their own structural error, but there is also added uncertainty
stemming from choices about how the output fields from the GCM are used to force the RCM integration (forcing approach). The errors from the forcing approach are unique to RCMs and the associated uncertainty has yet to be characterized in a projection ensemble. Both the structural and forcing errors are sources of uncertainty in high resolution RCMs and would affect the accuracy and spread of an ensemble of climate projections. This is important because the physical processes which influence local climates and could affect adaptive decisions (and the associated impact assessments) are better captured at higher resolutions (Di Luca et al. 2015; Lucas-Picher et al. 2016). The ability to capture these physical processes has led to the use of high resolution projections for impact assessments in multiple sectors including (but not limited too) urban development (Argüeso et al. 2015), water resources (Koutroulis et al. 2015), and air quality (San José et al. 2016). Others have also highlighted the improved representation of physical processes using high resolution simulations compared to coarser resolutions like the ~25 and ~50 km grid spacing used in CORDEX (Tabari et al. 2016; Rummukainen 2016; e.g. Endris et al. 2013). Knowing that the RCMs have a structural uncertainty component similar to GCMs as well as forcing errors, what then is the effect of these when a high resolution RCM is used in an ensemble, given prior work suggesting less error at high resolution (Cholette et al. 2015; Tabari et al. 2016; Rummukainen 2016)?

Several regional climate model intercomparison projects (RCMIPs) exist, such as PRUDENCE (e.g. Jacob et al. 2007) and CORDEX, but no systematic comparisons of RCMs at high resolution (< 10 km grid spacing) exist as of this writing. Many of the studies exploring differences between RCMs at high resolution have focused on one to two RCMs in
small regions (e.g. Iizumi et al. 2011; Inatsu et al. 2015). Typically, the computational expense of regional climate modeling (Rummukainen 2010) precludes a comprehensive intercomparison of high resolution RCMs. Compounding the issue, this computational expense may be most prohibitive in regions with a high vulnerability to climate change (Mahlstein et al. 2011). While we recognize the importance of initial conditions (Deser et al. 2012) and emissions scenarios (Monier et al. 2015) to GCM prediction uncertainty, the focus of this study is on the uncertainty that arises in high resolution RCMs due to differences in model structure and GCM-to-RCM forcing approach. Our goal is to characterize the differences in accuracy between RCMs and the effect of forcing errors at different resolutions and the effect they have on ensemble accuracy and spread when included in an ensemble of GCMs. By examining the influence of RCM inclusion into a GCM ensemble, we are also able to examine the potential overconfidence and stability of ensemble climate predictions at local scales.

3.2. Study Area and Methodology

We extend the approach developed by Sanderson et al. (2015) to include high resolution RCMs in a domain centered over the island of Puerto Rico in the eastern Caribbean. Sanderson et al. (2015) used singular value decomposition on observed and GCM-simulated anomalies of multiple climate variables to create a distance metric that represents the similarity of GCM ensemble members both to each other and to the observations at the global scale. We created a similar anomaly matrix, but only for the local
domain covering Puerto Rico using the surface air temperature and precipitation climatology from the GCM and RCM output rather than the global domain used in Sanderson et al. (2015). For this local domain, we used the WorldClim dataset to represent observations (Hijmans et al. 2005) which is available at ~1 km grid spacing. We limit the analysis to temperature and precipitation since these are currently the only observed variables that are available at high resolution consistent with the RCM output.

The composition of each of the five ensembles includes 20 GCMs from the CMIP5 archive (Taylor et al. 2012, Table B.2). In four of the ensembles we replace one of the GCMs, CCSM4, with output from two RCM configurations forced by CCSM4. The first configuration is a triple nested domain configuration of the Weather Research and Forecasting (WRF) model (Skamarock et al. 2008). The WRF model was run with a triple nested domain at 30, 10, and 2 km resolutions, respectively (Figure B.1). The WRF (10 km grid spacing) simulations are forced by the results from the 30 km outer domain of WRF which was forced with CCSM4, and the WRF (2 km grid spacing) simulations are forced by the WRF (10 km) simulations. The second RCM used in the analysis is a dual configuration of the Regional Spectral Model (RSM, Juang and Kanamitsu 1994; Kanamitsu et al. 2010) with 10 km grid spacing forced by CCSM4, and the Non-Hydrostatic Model (NHM, Saito et al. 2006) with 2 km grid spacing forced by the RSM. For this analysis, five ensembles of climate model projections are considered. Four of these ensembles replace CCSM4 with the 2 and 10 km WRF simulations, the 2 km NHM simulations, and the 10 km RSM simulations (Table 3.1) forced by CCSM4. The configurations represent both different RCM structures, and different approaches to RCM forcing at high resolutions since the RSM boundary
conditions are directly forced by CCSM4 and the WRF boundary conditions are indirectly forced.

Using the distance metric from the Sanderson et al. (2015) methodology and the five ensembles of climate projections, this analysis focuses on the error reduction using an individual RCM simulation and the ensemble error reduction when RCMs are used with GCMs. This distance metric can be calculated for each ensemble member to the observations and to all the other members. This multivariate distance metric can also be used to show the spread each ensemble, allowing this analysis to estimate the variance of the ensemble uncertainty with different RCMs included compared to a GCM only ensemble.

3.3. Results: Structure, Forcing and Resolution

Encouragingly, we find that in most cases the use of a high resolution RCM reduces the multivariate distance to the observed climatology relative to the forcing GCM (Figure 3.1). However, incorporating the RCM also causes the spread of the ensemble to increase beyond the GCMs alone. There is little difference in the spread or error between the WRF and NHM ensembles at 2 km. However, the distance to the observations (error) from RSM is nearly double that of the 10 km WRF (1.31 and 0.77 respectively), while NHM has a similar distance to the 2 km WRF (0.66 and 0.65 respectively) and the 10 km WRF.

Incorporating a single RCM in the ensemble decreases the similarity between the now downscaled GCM and the other members (Figure 3.2). The tight cluster away from the observations for the GCM-only ensemble confirms that the GCMs alone are biased and likely overconfident when used for adaptive decisions and impact assessments at local scales. In
addition, the difference between the 2 km RCM simulations is less than the difference between the 10 km RCM simulations. The distance from WRF (2 km) to the observations and the average distance to other ensemble members is 0.65 and 0.91, while the distance from NHM to observations and the average distance to other ensemble members is 0.66 and 0.87. In contrast, while the 10 km WRF output is closer to the observations than the RSM, both ensembles also increase the dissimilarity in the ensemble. NHM is also more alike to both WRF simulations than it is to RSM.

The difference between the WRF (both 2 and 10 km) and NHM ensembles and the RSM ensemble is evident regardless of the size of the ensemble. To show this, the size of the ensemble is varied from 4-20 members but the CCSM4 (or the RCM driven by CCSM4) is retained. The RCMs reduce the bias of their respective ensembles beyond GCMs alone, and this effect is more pronounced with increasing ensemble size (Figure 3.3a). In addition, at around 12 members the difference between the WRF (2 km) ensemble and the NHM ensemble plateaus. In contrast the difference between the WRF (10 km) ensemble and the RSM ensemble plateaus at 19 members (Figure 3.3b). More interestingly, for ensemble sizes larger than 8 members the NHM ensemble has error more alike to the WRF ensembles than to the RSM ensemble. This difference between the NHM and RSM ensembles are not limited to the error; the spread also shows a similar difference. For ensemble sizes larger than 8 members the NHM ensemble spread (0.43 average) and error (0.96 average) is different from the RSM ensemble spread (0.53 average) and error (1.08 average). At around 10 members, the difference for both error and spread between the WRF (2 km) ensemble and
the NHM ensemble plateaus (Figure 3.4). The same plateau is never reached between the
WRF (10 km) ensemble and the RSM ensemble.

Both the individual NHM and RSM simulations have different errors from each other
(Figure 3.2) as do their respective ensembles (Figure 3.3a and Figure 3.4). The RSM
simulation and ensemble also have different error and spread from the WRF (10 km)
simulation and ensemble. The difference between the RSM and WRF simulations is more
than structural. The WRF (10 km) simulation has an indirect forcing approach while RSM
(10 km) has a direct forcing approach. This stands in contrast to the 2 km simulations where
both NHM and WRF are indirectly forced. Therefore, at 10 km, the difference between
WRF and RSM for the error of the individual simulations, the error of the ensemble, and the
spread of the ensemble is not solely from differences in structure, but also from differences in
forcing approach.

What is the best way to incorporate the information provided by a GCM into RCMs?
There is no clear answer to this question, and so we have errors in RCMs associated with the
approach to incorporating GCM output into an RCM. In a simple way, these forcing errors
might occur if a RCM at a given resolution is directly or indirectly forced by a GCM.
However, if a RCM is directly forced by a GCM how then is it forced? There are different
approaches to applying the forcing from a GCM to a RCM. These forcing errors represent
another source of uncertainty in RCM projections.

Although there are forcing errors in RCM simulations, the 2 km RCMs are both
indirectly forced by CCSM4. Since the forcing approach is similar in these situations, the
differences here are likely more related to the structure of the models. These two RCMs
have different dynamic cores, but at the same time the difference between them in both spread and error is small compared to the combined structural and forcing differences between the 10 km RCMs. This implies that the forcing error is larger than the structural errors of RCMs.

The WRF ensembles demonstrate the effect of RCM resolution on an ensemble of GCMs. The individual WRF simulation at 2 km outperforms the WRF simulation at 10 km (distance to the observations 0.65 and 0.77 respectively). However, we can also see that the ensemble error for the 2 km ensemble is less than 10 km ensemble, while the spread is nearly identical (Figure 3.4). In this case, there are no structural differences as both are WRF simulations and both are indirectly forced. Given that the other members of the ensemble in both cases are the other GCMs the error of these other members does not change. Therefore the result of adding a finer resolution RCM which has less error reduces the ensemble error. Incorporating any RCM likely lessens the chance for overconfidence beyond an ensemble of GCMs alone. However, the only difference between the two WRF simulations and their ensembles is the resolution of the WRF simulations. The result is that the interdependence relationship between WRF and the other ensemble members does not change with the increase in resolution (Figure 3.2). Therefore, adding a RCM to an ensemble of GCMs would likely lessen the chance for overconfidence, but increasing the RCM resolution likely does not lessen that chance further. Though it should be noted that this analysis was performed with temperature and precipitation climatology, and the result may change if the remaining variables like those in Sanderson et al. (2015) are included.
3.4. Connections to RCMIPs

Several RCMIPs now exist, which include but are not limited to CORDEX (e.g. Endris et al. 2013). The simulations being produced for CORDEX have the potential to address many questions on the structural uncertainty associated with regional climate modeling. However, the current CORDEX experiments do not reach the high resolution which makes RCMs potentially useful for adaptation decisions. For example, the current arrangement of North America CORDEX (NA-CORDEX) focuses on RCM simulations with ~50 km and ~25 km grid spacing, but includes no simulations with grid spacing ≤ 10 km. We find in our multivariate analysis that there is a decrease in the error of the individual WRF simulations with increasing resolution. This agrees with the conclusions of Luca-Picher et al. (2016) that there was less error in the CRCM5 simulations when the resolution was increased from 0.44° to 0.11° for multi-year means of temperature and precipitation in the NA-CORDEX domain.

The major difference between this study and Luca-Picher et al. (2016) is that this analysis incorporates the nested grid modeling common to the production of high resolution projections (e.g. Iizumi et al. 2011; Wootten et al. 2016). The nested grid modeling configurations used in this analysis reflect different forcing approaches. However, the RCM simulations used for CORDEX do not include nested grid modeling approaches and thus do not address the potential errors associated with the forcing approaches of RCMs.

Aside from the forcing approaches used in RCM configurations the structural errors of RCMs are also an important component to the uncertainty of RCMs. Each RCM decreases the bias and overconfidence compared to an ensemble of GCMs alone, but the
degree of improvement varies between RCMs. The CORDEX simulations provide more RCMs than those used here, which allows a more thorough comparison though not at the high resolutions of interest to adaptive decisions. Therefore, future RCMIPs should use simulations at higher resolution particularly if the current coarse resolution experiments determine that the structural uncertainty is sensitive to RCM resolution.

The structure between RCMs is not the same, leading to differences in the effect on an ensemble, which can be captured by the numerous RCMs in CORDEX. However, these structural error differences have not been shown to be same between the same RCMs at different resolutions as of this writing. The differences in forcing approach connected to nested grid configurations used for high resolution projections is a source of error that has not been considered in RCMIP efforts. Both structural errors and forcing approach differences have not been considered with respect to resolution. Without considering both sources of uncertainty current efforts have only begun to scratch the surface regarding sources of uncertainty RCMs. An ensemble of high resolution climate projections for a given region are likely to be overconfident if they include only one or two RCMs because of the sensitivity of the projections to the structure of the RCMs and forcing approaches. Smaller efforts with resource constraints to produce these projections will often be limited to one to two RCMs and one forcing approaches, and thus the projections made for regions most vulnerable to anthropogenic climate change are likely overconfident. RCMIP efforts have the potential to assist in adequately characterizing these sources and providing guidance for smaller efforts for these regions. Therefore, efforts using RCMIPs should continue and
expand to characterize these sources of uncertainty in RCMs and their potential impact to adaptive decision making and impact assessments.

3.4. Acknowledgements

The study presented here was funded by the Department of the Interior Southeast Climate Science Center (USGS Cooperative Agreement G13AC00408). We thank the Renaissance Computing Institute for providing the super-computing for the WRF simulations. All NHM/RSM model integrations for this paper were done on the computational resources provided by the Extreme Science and Engineering Discovery Environment (XSEDE) under TG-ATM120010. Finally, we thank the anonymous reviewers for their feedback and suggested improvements. Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government.
Table 3.1 Descriptions of the differences between the ensembles used in the analysis.

<table>
<thead>
<tr>
<th>Ensemble Name</th>
<th>GCMs / RCMs included</th>
<th>RCM used</th>
</tr>
</thead>
<tbody>
<tr>
<td>GCMs</td>
<td>GCMs alone</td>
<td>NA</td>
</tr>
<tr>
<td>WRF2</td>
<td>GCMs with 2km RCM</td>
<td>Weather Research and Forecasting Model (WRF)</td>
</tr>
<tr>
<td>WRF10</td>
<td>GCMs with 10km RCM</td>
<td>Weather Research and Forecasting Model (WRF)</td>
</tr>
<tr>
<td>NHM2</td>
<td>GCMs with 2km RCM</td>
<td>Non-Hydrostatic Model (NHM)</td>
</tr>
<tr>
<td>RSM10</td>
<td>GCMs with 10km RCM</td>
<td>Regional Spectral Model (RSM)</td>
</tr>
</tbody>
</table>
Figure 3.1. Euclidean distances to observations from each ensemble. Black diamonds are the observations (WorldClim), red diamonds are the location of the member using CCSM4, black circles represent the location of all other ensemble members relative to the observations.
Figure 3.2. Euclidean distance from ensemble members to observations versus the average Euclidean distance from each ensemble member to the other members in the ensemble. The circles are the location of CCSM4 in each ensemble, while the polygons are the extents of the entire ensemble. An ensemble, or any single member, is more(less) alike to the observations (other members) if they are in the upper left corner. An ensemble, or any single member, is less (more) alike to the observations (other members) if they are in the lower right corner.
Figure 3.3. Average Euclidean Distance of each ensemble to the observations by ensemble size (a) and the distance difference by ensemble size between the ensembles with a 10 km RCM and a 2 km RCM (b).
Figure 3.4. Ensemble Error and Spread by the Size.
CHAPTER 4. Characterizing the Sources of Uncertainty from GCMs and Downscaling Techniques

4.1. Introduction

In the past, ensembles of global climate models (GCMs) have been used to predict the response of earth’s climate to different trajectories of anthropogenic greenhouse gas emissions to help inform climate change mitigation strategies. The agreement made at the United Nations Conference on Climate Change in 2015 is a recent example of such policy decisions where GCMs are implemented. There are three sources of uncertainty from these ensembles of GCMs (Hawkins and Sutton, 2009; Gettelman and Rood, 2016); scenario uncertainty, model uncertainty, and natural variability.

Climate modeling has been drafted into service to provide guidance for adaptation decisions in recent years. Decisions for adaptation require finer resolution information because there are physical processes and features which can affect the impacts of climate change (and therefore effect these decisions) that are either parameterized or non-existent in GCMs. This has led to the use of downscaling to capture the key local and regional-scale processes which cannot be represented by a GCM. Downscaling is another layer of modelling applied on top of GCM output, and represents an added source of uncertainty. This is important because impact assessment studies are beginning to use downscaled climate projections, but are focusing on using projections consisting of dynamic downscaling (e.g. Argüeso et al. 2015; Koutroulis et al. 2015) or statistical downscaling (e.g. Basso et al. 2015; Parmesan et al. 2015; Werth and Chen, 2014). By using one set of projections are these
impact assessments overconfident because they are ignoring downscaling as a source of uncertainty? How critical is downscaling as a source of uncertainty compared to those from GCMs?

Studies addressing downscaling as a dominant source of uncertainty have led to mixed conclusions. Chen et al. (2011) used six downscaling techniques and 28 combinations of GCM and emissions scenarios to produce river discharges for the Manicouagan river basin (45,800 km²) in Canada. Using these experiments, Chen et al. (2011) determined that the uncertainty from downscaling was comparable to the uncertainty from GCMs and emissions scenarios. This study focused on a single river basin and on an impact variable (discharge) instead of climate variables. Likewise, Mandal et al. (2016) used six statistical downscaling techniques with four GCMs and four emissions scenarios to determine uncertainty related to precipitation projections in the Campbell River basin (1,856 km²) in Canada. Using a calculated uncertainty metric, Mandal et al. (2016) concluded that downscaling was the largest source of uncertainty. While this study did consider uncertainty with regards to precipitation, Mandal et al. (2016) based results on a single river basin, few GCMs, focused solely on statistical downscaling techniques, with no distinction made between downscaling and natural variability. Pourmokhtarian et al. (2016) used three statistical downscaling techniques, four GCMs, and two emissions scenarios to generate output for a forest biogeochemical model applied in the Hubbard Brook Experimental Forest (0.13 km²). The investigators concluded that the statistical downscaling technique was an important source of uncertainty for variables from the biogeochemical model but that the observations used to train the statistical downscaling is also important. Pourmokhtarian et al. (2016) focused on
one small region, on statistical techniques, and focused primarily on variables produced by the biogeochemical model used. Minville et al. (2008) again focused discharge for the Chute-du-Diable watershed (9,700 km$^2$), finding that the GCMs are the largest source of uncertainty but performed downscaling and gave minimal attention to the uncertainty associated with downscaling. Like Chen et al (2011), Dobler et al. (2008) focused on parameters from hydrological modeling with GCMs, regional climate models (RCMs), bias-corrections, and the hydrological models themselves in the Lech watershed (1,000 km$^2$) in the North Limestone Alps. While this is again a small domain not focused on climate variables, Dobler et al. (2008) determined that the uncertainty from GCMs and RCMs were comparable to each other. Kay et al. (2012) focused on sources of uncertainty from climate projections related to flood frequency for catchments in England (point locations), but while this was one of the few studies to focus on multiple types of downscaling, they still concluded that the difference between GCMs provide the largest source of uncertainty related to flood frequency rather climate variables.

These studies reveal several common threads which limit their ability to answer the question of how critical downscaling is as a source of uncertainty. First there is a tendency to focus on impact variables (in hydrology or ecology) rather than on the climate variables themselves. The relationships between climate variables and impact variables are often non-linear (e.g. Jin et al. 2005), therefore, prior results that hold for impact variables may not hold for projections of the climate variables themselves. Second, prior literature tends to focus on small regions (such as river basins) rather than larger regions (such as the Southeast or continental U.S.). While some statistical downscaling techniques may work well in areas
with complex topography, other techniques may be designed to more accurately model coastal interaction processes (Wootten et al. 2014). And in contrast, dynamic downscaling approaches use different numerical modeling (such as finite differencing, finite volume, or a spectral representation) to capture the same physical processes. This implies that the uncertainty from downscaling is likely not the same everywhere and as such the results of these studies in their respective small regions may not be transferable to other regions. Finally, the focus tends to be on one type of downscaling technique be it statistical or dynamic. Statistical and dynamic downscaling techniques are constructed differently (Wootten et al. 2014), not incorporating both types of techniques implies that the uncertainty from downscaling is underrepresented. This study characterizes and quantifies uncertainty that results from downscaling global climate models using an extension of a prior methodology first developed by Hawkins and Sutton (2009) for use with GCM ensembles. This extension is applied to downscaled projections representing multiple types of downscaling techniques for a domain covering the Southeast U.S. (~3,484,800 km²).

To characterize the contribution of sources of uncertainty from GCM based projections, Hawkins and Sutton (2009, hereafter called HS09) introduced a variance decomposition approach to characterize the individual contribution from natural variability, model uncertainty, and scenario uncertainty. The HS09 approach decomposes variance by partitioning the residuals from a polynomial model fit to the projected anomalies for each combination of GCM and emissions scenario. The original HS09 approach was developed specifically for use with GCM projections and was implemented to characterize the uncertainty contribution in the 5th Assessment Report of the Intergovernmental Panel on
Climate Change (IPCC, Kirtman et al, 2013). The HS09 approach provides a simplistic way to characterize the contribution of different sources of uncertainty from GCMs, but it does not provide the ability to characterize the contribution of downscaling as a source of uncertainty. The main goal of this study is to characterize the contribution of downscaling as a source of uncertainty compared to the sources of uncertainty from GCMs. To achieve this, this study extends the HS09 approach to include downscaling by adjusting the variance decomposition to incorporate the influence of downscaling as a source of uncertainty. This extension is then applied using multiple publicly available downscaled projections (both dynamic and statistical) to characterize the contribution from four sources of uncertainty across the Southeast United States.

In section 4.2, the HS09 approach is reviewed and the changes to HS09 to incorporate downscaling are described. In section 4.3, the datasets, experiments and variables used for this analysis are discussed. In section 4.4, the results of the extended approach as applied to two experiments for the Southeast U.S. is presented. Finally, in section 4.5 the conclusions from the study and possible improvements to the approach are discussed.

4.2. Methods

HS09 was originally developed to characterize the contribution of three sources of uncertainty from GCM projections from the Coupled Model Intercomparison Project Phase 3 (CMIP3), and was also implemented with CMIP5 GCMs. In HS09, a fourth order polynomial is fit to the time series of absolute anomalies of temperature for each combination of GCM and emissions scenario from 1950-2099. Hawkins and Sutton (2011) extended
HS09 for use with precipitation projections by using a percent anomaly instead of the absolute anomaly. The fitted values and residuals from this polynomial fit are used to perform a variance decomposition to capture the following sources of uncertainty:

- **Natural Variability** – year to year changes not influenced directly by human activities (e.g. El Nino Southern Oscillation, Volcanic activity)
- **Scenario Uncertainty** – uncertainty associated with human actions including decisions on policy and emissions.
- **GCM Model Uncertainty (called model uncertainty in HS09)** – differences between global climate model (GCM) construction, different representation of scientific knowledge at large scales.

The decomposition equation for natural variability ($V$) is then:

$$ V = \sum_m W_m Var_{s,t}(\varepsilon_{m,s,t}) $$

where $W_m$ is the weight given to each GCM by the ability to estimate the anomaly for the year 2000 from the baseline period as given by observations and $\varepsilon$ is the residuals from the polynomial fit for each GCM $m$, scenario $s$, and time $t$. The decomposition equations for the scenario uncertainty ($S$) and GCM model uncertainty ($M$) are:

$$ S(t) = Var_s \left( \sum_m W_m x_{m,s,t} \right) $$

and
\[ M(t) = \frac{1}{N_s} \sum_s \text{Var}_m^W (x_{m,s,t}) \]

where \( x \) is the fitted values from the polynomial fit for each combination of GCM and emissions scenario in time, and \( N_s \) is the number of emissions scenarios. The variance is used to calculate the values of \( V \) and \( S \), while the weighted variance is used to calculate the value of \( M \). The sources are assumed to be independent, and the total uncertainty is the sum of the sources. The value of \( V \) is also assumed to be constant in time, which was shown in HS09 to be an acceptable assumption given that prior studies indicated the contribution of natural variability did not change significantly in time.

For projections from GCMs, HS09 provides a reasonable approach to characterizing the three sources of prediction uncertainty. To extend this approach for use with downscaled projections there are two important considerations. First, the extension must consider multiple different downscaling techniques including dynamic and statistical techniques. That is, it must include a decomposition equation for a source of uncertainty unique to downscaled projections:

- **Downscaling Uncertainty** – differences between downscaling techniques, including differences between regional climate models, differences between statistical downscaling techniques, and differences between regional climate models and statistical downscaling techniques.

Second, the extension must account for the fragmented nature of downscaling as much as possible. This fragmented nature results from the fact that the downscaled projections do not share all the same common GCMs and emissions scenarios. Each of set of
publicly available downscaled projections used in this study (Table B.3) incorporates different GCMs and emissions scenarios. The original intent for creating a set of projections results in the fragmented nature of downscaled projections. An individual modeler involved in downscaling has their own set of questions and requirements. As a result an individual modeler will choose GCMs and emissions scenarios (and perhaps even time periods or temporal resolution) to satisfy their own needs, and the output is then provided for public use. The result is that the collection of publically available downscaled projections is an incomplete and fragmented sample of the available combinations of downscaling techniques, GCMs, and emissions scenarios (Figure 4.1). Incomplete in that the downscaled projections do not use all the GCMs or emission scenarios available in the CMIP archive. Fragmented in that the downscaled projections do not share all the same common GCMs and emissions scenarios. This fragmentation is further exacerbated because some downscaled projections, or GCMs within a set of downscaled projections, are only available for time slices rather than a continuous period. This fragmented sample causes the sum of the weights in HS09 to be less than one in situations where not all combinations exist, causing the variance estimates to be biased. So to extend the HS09 approach to include downscaling this must be addressed.

To address these limitations differences between downscaling techniques are directly incorporated into the base equation used for the fourth order polynomial fit.

\[ X_{m,d,s,t} - i_{m,d,s} = x_{m,d,s,t} - \epsilon_{m,d,s,t} \]

The left hand side of this equation reflects the anomalies of a variable in time where \( X \) is the value of the variable of interest in time for each combination of GCM \( m \), downscaling
technique $d$, and emissions scenario $s$, and $i$ is the average of the variable of interest over 1981-2000. The right-hand side contains the fitted values ($x$) and residuals ($\varepsilon$) from a fourth order polynomial fit in time ($t$) for each combination of $m$, $d$, and $s$. The fourth order polynomial fit is chosen to represent the slowly varying signal of anthropogenic climate change (Benestad, 2003), while the residuals of that fit represent the remaining fluctuations.

In this way downscaling is incorporated at the outset, which enables the variance decomposition method to include this source of uncertainty. The full period used for each fit is 1950-2099 and variance decomposition is applied to the fitted values and residuals.

We also include a weighting scheme to account for the accuracy of the GCMs and downscaling techniques for the historical anomaly:

\[
    w_m = \frac{1}{x_{obs} + \left| \frac{1}{N_d} \sum x_{m,d,1999} - x_{obs} \right|}
\]

\[
    w_d = \frac{1}{x_{obs} + \left| \frac{1}{N_m} \sum x_{m,d,1999} - x_{obs} \right|}
\]

In these weighting schemes, $x$ is the anomaly from the fourth order polynomial fit of the variable in 1999 taken from the Parameter Regression Independent Slopes Model dataset (PRISM, designated as $obs$, Daly et al, 2008) and each combination of downscaling technique $d$, and GCM $m$. The year 1999 is used as the reference year as it is a year in common between all the downscaled projections. The anomaly from the fourth order polynomial in 1999 is used to assess the ability to simulate the recent change of a variable of interest to allow the best performing GCMs and downscaling techniques in recent history to
retain the highest weights in the variance decomposition equations. In order to focus on the historical accuracy of each individual GCM or downscaling technique, the mean of the values across downscaling techniques or GCMs is used. The weights for GCMs and downscaling techniques calculated this way do not sum to one. So to adjust for this the weights used are:

\[
W_m = \frac{w_m}{\sum_{i=1}^{N_m} w_m}
\]

\[
W_d = \frac{w_d}{\sum_{i=1}^{N_d} w_d}
\]

Where \(W\) is the rescaled weights for the GCMs and downscaling techniques, and \(N_m\) and \(N_d\) are the number of GCMs and downscaling techniques. At this point, the weighting is similar to HS09. As in HS09, this weighting is used to down-weight GCMs and downscaling techniques for which the recent anomaly is too large or small. The weighting is kept simple as in HS09 because the choice of weighting does not affect the results greatly. However, the usual limitations associated with model weighting apply in that the available sample of models and downscaling techniques represents an ensemble of opportunity, and cannot be considered an unbiased sample (Sanderson and Knutti, 2012). Finally, an additional rescaling is also applied to account for situations where the full complement of GCM and downscaling combinations is not available for variance decomposition.

\[
\omega_m(\text{exists}) = \frac{W_m(\text{exists})}{\sum W_m(\text{exists})}
\]
\[ \omega_{d(exists)} = \frac{W_{d(exists)}}{\sum W_{d(exists)}} \]

This calculation is iterative in connection with the different components. The values of \( \omega \) depend on which GCMs or downscaling techniques exist in the sample at the particular point of the calculation. Therefore, the values of \( \omega \) do not remain constant, while the values of \( W \) do remain constant regardless of the calculation. More importantly, as the sample becomes more complete the values of \( \omega \) approach \( W \) as more combinations become available. In addition, the calculation of \( \omega \) forces the weights used in future combinations sum to one, ensuring that the estimates of mean and variance in the equations are unbiased.

The calculation for each component of uncertainty uses the fitted values, residuals, and weights and is described separately here:

1. Natural Variability:

\[ V = \sum_{m} \omega_{m} \sum_{d} \omega_{d} \text{Var}(\varepsilon) \]

Where \( V \) is the natural variability. The values of \( \omega \) are the rescaled weights described previously. The variance of the residuals of the polynomial fit \( \varepsilon \) is used here. The value of \( V \) is assumed constant in time.

2. GCM Model Uncertainty:
\[ M(t) = \frac{1}{N_s N_d} \sum_s \sum_d \text{Var}_{m}^{\omega} (x_{m,d,s,t}) \]

Where \( M \) is the GCM Model Uncertainty for each time \( t \). In this case, rather than taking the variance across the GCMs of the fitted values, the weighted variance is taken using the value of \( \omega_m \) for the weights. \( N_s \) and \( N_d \) represent the total number of emissions scenarios and downscaling techniques available.

3. Downscaling Uncertainty:

\[ D(t) = \frac{1}{N_s N_m} \sum_s \sum_m \text{Var}_{d}^{\omega} (x_{s,d,m,t}) \]

Where \( D \) is the Downscaling Uncertainty for each time \( t \). Similarly to the calculation of \( M \), the weighted variance is taken using the value of \( \omega_d \) for the weights. \( N_m \) represents the total number of GCMs available.

4. Scenario Uncertainty:

\[ S(t) = \text{Var}_{s} \left( \sum_m \omega_m \sum_d \omega_d x_{m,d,s,t} \right) \]
Where $S$ is the scenario uncertainty each time $t$. The values of $\omega$ are the rescaled weights described previously. The fitted values of regression are used, and the variance is taken across the emissions scenarios.

The total variance is then defined as:

$$ T(t) = V + M(t) + D(t) + S(t) $$

Where $T$ is the total variance from the projections. Note that using this equation to define the total variance requires an assumption that each source of uncertainty is independent. The mean change relative to the baseline period (1981-2000) from all the projections is defined as:

$$ G(t) = \frac{1}{N_s} \sum_{m,s} \omega_m \sum_d \omega_d x_{m,d,s,t} $$

Where $G$ is the mean change relative to the baseline period for the projections. This is calculated from the fitted values of the regression and weights.

4.3. Downscaled Projections, Experiments, and Variables

The downscaled projections used in this analysis were chosen for several reasons. They are commonly used and publicly available, provide representation of multiple
downscaling techniques, and reflect the fragmented nature with which downscaling is currently done (Table B.3). The downscaled projections used here represent four different statistical techniques and one dynamic downscaling approach. SERAP (16 GCMs, 4 emissions scenarios, Stoner et al. 2012) and CCR (13 GCMs, 3 emissions scenarios, Lorenz 2014) represent two statistical downscaling techniques which are considered transfer functions. MACA (20 GCMs, 2 emissions scenarios, Abatzoglou et al. 2012) and BCCA (21 GCMs, 4 emissions scenarios, US Bureau of Reclamation 2013) represent two statistical techniques which are considered weather typing approaches. Finally, the Hostetler dataset (3 GCMs, 1 emissions scenario, Hostetler et al. 2011) is created using dynamic downscaling with RegCM3 regional climate model. These sets of projections used here show a lack of overlap between GCMs and downscaling technique (Figure 4.1a). In addition, the different generations of GCMs and emissions scenarios also clearly affect which emissions scenarios overlap between downscaled projections (Figure 4.1b). With these five datasets the available combinations of GCM, downscaling technique, and emissions scenario are far less than all the possible combinations. In addition, not all the downscaled projections are continuous; several only have output available for one or more GCM time slices, which do not always overlap (Table B.3).

The differences between downscaled projections provide an incomplete sample for this analysis as well as for use in impact assessments and decision making. To assess how this incomplete sample can affect the representation of uncertainty, and the contribution of downscaling to the overall uncertainty, two experiments are considered.
1. IDEAL – a subset of the five downscaled projections reflects an ideal complete sample. This subset has 16 common GCMs and two common emissions scenarios from MACA and BCCA. These two sets of downscaled projections are also continuous in time, which also allows the issue of time slices to be removed.

2. ALLDATA – the entire collection of five downscaled datasets, including all eight emissions scenarios and 46 GCMs in addition to time slices.

The downscaled projections represent a range of statistical techniques and one example of regional climate modeling (Hostetler) (cf. Wootten et al. (2014) for an extended description of the differences between these downscaling techniques).

The domain in this analysis is the Southeast U.S. (Figure A.2), which covers a much larger geography (~3,484,800 km²) compared to the analysis area in prior studies (< 46,000 km²). This large region incorporates complex topography and coastlines, as well as climate change adaptation planning where downscaled projections are actively being considered for use in water and conservation planning. For this analysis there will be both time series analyses and gridded analyses. For the gridded analyses all the downscaled datasets are aggregated to a 15 km resolution grid, which is the coarsest resolution of the available downscaled projections used. For the time series analysis, the three subdomains shown in Figure A.2 are used.

The analysis is performed for the following variables:

- Decadal mean of the annual average high temperature (TMAX)
- Decadal mean of the annual number of days the high temperature > 95°F (35°C, TMAX95)
• Decadal mean of the annual average low temperature (TMIN)
• Decadal mean of the annual number of days the low temperature < 32°F (0°C, TMIN32)
• Decadal mean of the annual total precipitation (PR)
• Decadal mean of the annual number of days with precipitation > 1 inch (25.4 mm, PR25)

The variables TMAX, TMIN, and PR are chosen as similar to those variables characterized in HS09 and Hawkins and Sutton (2011). The variables TMAX95, TMIN32, and PR25 are chosen as they reflect extremes of concerns in the Third National Climate Assessment (Carter et al, 2014). In addition to decadal means of these variables the annual values from each were also analyzed. Finally, a random effects model is also used to compare to the sample variance calculated by the extended methodology. The HS09 and this extension could be described as an ad-hoc statistical approach. The random effects model (Diggle et al. 2002) is a more robust and well known statistical modelling approach, and provides a point of comparison to assess the validity of the sample variances calculated by this ad-hoc technique. However, the results from the random effects model and the annual values analysis are only discussed as needed.

It is important to note that the typical idea of a variance estimate based on a sample drawn from a population can be quite problematic when applied to climate model ensembles. In this case, the ‘sample’ of GCMs and downscaled GCMs that form an ensemble can either be interpreted as being drawn from a distribution that represents “truth plus error” (random samples from a distribution of plausible models centered around the true future realized climate), or it can be interpreted as being drawn from an “indistinguishable” distribution (where the truth and all models are thought to be drawn from the same distribution with equal
probability, Sanderson and Knutti, 2012). Weighting the variance estimates according to model performance is particularly problematic if the ensemble is actually derived from an indistinguishable population. Given the weighting scheme used by HS09 and as followed in this study, the “truth plus error” interpretation is followed (implicitly in HS09, explicitly here). An alternative interpretation could yield different variance estimates.

4.4. Results

For each experiment and variable the percent of the total variance contribution from each source to the total is calculated. To visualize this contribution in space and time, three time periods are shown; early century (2016-2025), mid-century (2051-2060), and late-century (2086-2095). In the IDEAL experiment, the analysis with the extended methodology shows that GCM model uncertainty is the dominant source of uncertainty (> 50% of the total uncertainty) followed by natural variability early in the century for TMAX (Figure 4.2). Scenario uncertainty becomes the dominant source by the end of the century across the domain, which agrees with prior literature for GCMs (e.g. HS09). The downscaling uncertainty in Florida is greater than 30% of the total uncertainty in the IDEAL experiment for TMAX in the early and mid-century. The mid-century and late-century pattern for TMAX remains consistent with the IDEAL experiment in the ALLDATA experiment for the dominant sources (Figure 4.3). In the ALLDATA experiment, the downscaling uncertainty is less than 30% of the total in the early and mid-century in Florida, which is different from
the IDEAL experiment. This suggests that adding more downscaling techniques increased the consistency (decreased the variability) in Central Florida.

For TMAX95, the downscaling uncertainty becomes larger than 30% for much of the domain in the early century in the IDEAL experiment (Figure 4.4). Downscaling becomes the dominant source of uncertainty for areas of Florida and the Appalachians in the early century. In addition, downscaling uncertainty is dominant in the mid-century for areas of the Appalachians for TMAX95 and remains significant (> 30%) through the end of the century in this area in the IDEAL experiment. While the contribution from downscaling uncertainty is diminished in the ALLDATA experiment for TMAX95 (Figure 4.5), it remains greater than 30% for parts of the Appalachians through the end of the century. As with TMAX, the scenario uncertainty becomes the dominant source of uncertainty across much of the domain in the ALLDATA experiment by the end of the century.

For precipitation (PR) in the IDEAL experiment, the natural variability and GCM model uncertainty together are dominant sources through the future period (Figure 4.6). However, the downscaling uncertainty reaches 20% of the total uncertainty across parts of the domain. In parts of south Florida the downscaling uncertainty is greater than 30% of the total uncertainty. The ALLDATA experiment shows that at the end of the century much of the uncertainty is split between the three sources from GCM projections for PR (natural variability, GCM uncertainty, scenario uncertainty, Figure 4.7). While the signal from downscaling is diminished, there are areas of the domain where downscaling reaches 20% of the total uncertainty for projections of PR.
For projections of PR25 there are similar, but not identical, patterns to the projections of PR. For the IDEAL experiment, the primary sources of uncertainty for projections of PR25 transitions from natural variability in the early century (2016-2025) to GCM model uncertainty in the late century (2086-2095, Figure 4.8). While not the dominant source, the contribution from downscaling uncertainty is more than 30% in portions of the domain for all three future periods. As with PR, the three sources from GCMs are equally dominant by the end of the century for PR25 in the ALLDATA experiment (Figure 4.9) and downscaling uncertainty still reaches ~20% of the total uncertainty for areas of the domain by the end of the century.

A possible concern with the HS09 methodology, and the extended version with the downscaling component, is that the variability captured may not be meaningful given the background variance in the ensemble spread. It is expected that HS09, this extended HS09, and the random effects model will overestimate the total variance from this ensemble because they rely on the assumption of independence between sources (Pennel and Reichler, 2011). The extended methodology captures the mean change in very different areas of the Southeast U.S. but overestimates the variance compared to the ensemble itself (Figure 4.10). This overestimation is present for all tested climate variables and decadal means (not shown). In addition, a random effects model produced the same result as the extended methodology, overestimating the variance with the same magnitude and capturing the mean change. This demonstrates the expected overestimation of the total variance connected to the assumption of independence between the sources in the extended methodology.
There is a difference in the gridded percent contributions between the ALLDATA and IDEAL experiments in the early century (2016-2025). The percent contribution in time is visualized with the filled blocks for each source encompassing the space from zero to one hundred percent of the total contribution. The time series of the percent contributions in the subdomains reveal the reason for the difference between experiments in the early century.

First, for projections of TMAX95 in the IDEAL experiment, the contribution from downscaling uncertainty reaches 50% for the Appalachians subdomain at 2030, but is much less in the Central Florida subdomain (Figure 4.11). The pattern is much less clear in the ALLDATA experiment, primarily because the contribution from GCM model uncertainty and downscaling uncertainty spikes for two periods in the future time. The overall pattern is different between variables, but the spiked pattern remains consistent in the ALLDATA experiment for PR25 (Figure 4.12).

This analysis is performed with publicly available downscaled climate projections and three of these datasets (Hostetler, CCR, and SERAP) do not provide continuous projections in time. These downscaled datasets instead provide time slices of future which satisfied the original intents of the creators of those datasets. In the ALLDATA experiment, these three datasets do not provide projection data for the early period used in the gridded analysis, which causes the difference in the contribution between experiments. The time slicing approach used in these downscaled datasets also causes this spiked pattern in the representation of sources of uncertainty in time.
4.5. Discussion

Impact studies are beginning to use downscaled projections in decision making, but prior studies focusing on the uncertainty from downscaling are mixed in conclusions and limited in scope by factors including region size, variables used, and the type of downscaling techniques. In this study, a methodology is developed to assess the contribution of the four major sources of uncertainty to the total uncertainty in downscaled climate projections, which also enables characterizing these sources of uncertainty with a much larger region and multiple climate variables. For the temperature variables (TMAX, TMAX95, TMIN, and TMIN32), the dominant source transitions from natural variability and GCM model uncertainty in the early and mid-century to scenario uncertainty by late century. For both precipitation variables (PR and PR25), the dominant source in the early century is natural variability, but becomes split between natural variability, GCM model uncertainty, and scenario uncertainty by the end of the century. The uncertainty contribution due to the use of downscaling is never dominant (> 50% of the total), but nevertheless can be significant. The contribution from downscaling uncertainty is greater than 10% of the total uncertainty for projections of PR25 for 39% of the Southeast domain in the late century and 30% for the projections of TMAX95 in the Appalachians.

The IDEAL experiment focused on two sets of downscaled climate projections with the 16 common GCMs and two common emissions scenarios between them. In this experiment the contribution of downscaling uncertainty becomes most visible particularly for projections of TMAX95. The two statistical downscaling techniques in the IDEAL experiment are both weather typing approaches. The primary difference is that the MACA is
a multivariate approach originally tested and implemented in the Pacific-Northwest United States, which has more complex topography similar to the Appalachians. The BCCA was not created for complex topography or multivariate analysis. These differences drive the downscaling uncertainty to be a dominant source in the IDEAL experiment.

In recent years, while individual downscaling efforts may have originally been intended for specific uses or to inform specific decisions, the resulting information are typically still made available to the public regardless of the intended use. So while the availability of multiple downscaled datasets presents a significant opportunity to develop ensemble climate projections that potentially are more robust and less likely to be underdispersed, it remains a significant challenge to rigorously and consistently quantify and partition the uncertainty from all relevant sources. For the future time periods where all five sets of downscaled data provide guidance, the contributions from downscaling and GCMs are amplified in the percent contribution time series for the ALLDATA experiment. The contributions from these sources during these periods more accurately reflect the contribution from all four sources compared to other periods in the ALLDATA experiment, because all five sets of projections provide guidance during these periods. So the contributions in these periods reflect the full range of information possible in the collection of projections used in the ALLDATA experiment. While these projections (SERAP, CCR, Hostetler) provide guidance for these time slices only; this may not be the time horizon of interest for a decision maker. For instance, a decision maker in the Appalachians subdomain may have a 30-year time horizon for planning purposes. In this situation, the projections used in the IDEAL experiment suggest that using multiple downscaling techniques (i.e. downscaling
uncertainty) is an important consideration. The results of the ALLDATA experiment indicate otherwise for this region and that time period, but the sample in the ALLDATA experiment for that period is incomplete. This in turn illustrates that the non-standardization among downscaling experiments artificially limits the expected uncertainty contribution. The combinations of downscaling, emissions scenario, and GCM available reflect different ways that a future climate would unfold. Under the current fragmented style of downscaling, many of these possible futures are unavailable in this sample for time horizons of interest. This in turn complicates the representation of uncertainty, but also suggests that the full range of possible future climates is not being provided for decision making except for during common periods in the downscaled projections. This raises a critical concern for impact assessments and adaptation planning activities using downscaled projections. Since the full range of possible climates is potentially not available for a time horizon of interest for impact assessments because that period is outside those common periods, the results of such assessments (as in the earlier Appalachians example) may be overconfident.

The two experiments used here characterize the uncertainty in an idealized experiment versus a subsample of what is available from the publicly released downscaled projections. During the time periods for which all the datasets provide data, the contribution from downscaling, GCMs, and emissions scenarios tend to be less in the ALLDATA experiment than in the IDEAL experiment. This actually suggests that during these periods there is more consistency between the downscaled projections when these additional datasets are included. During the time periods where all the projections exist in the mid-century and late-century both experiments indicate that downscaling is not a dominant source. The
ALLDATA experiment during these periods can provide guidance on the contribution of uncertainty during these periods, but not outside them. The IDEAL experiment can provide guidance during the other periods, but it should be taken with caution as it reflects only two statistical downscaling approaches.

All these sets of downscaled projections are created by different modeling groups for impact assessments and decision making. While not the dominant source, downscaling should not be ignored when used in impact assessments or decision making as it can reach 20-30% of the total uncertainty for temperature and precipitation. Therefore, it is recommended to use more than one set of projections to fully capture and propagate this source of uncertainty to the impact assessments. The modeling community involved in doing downscaling has long done their work independently from each other with little consideration of the potential influence to other studies or impact assessments. The result of this is a fragmentation which was shown in this analysis to effect the representation of uncertainty provided to impact assessments and decision making. Time periods common to all the sets of projections produced independently can be used to characterize the uncertainty, but these common periods are not always the time horizons of interest for decision making and impact assessments. As such, the unintended fragmentation of downscaled projections has made these projections overconfident for use in impact assessments.

4.6. Conclusions

This analysis used an extension of the methodology presented in HS09 to characterize contribution from downscaling to the total uncertainty in downscaled climate projections.
compared to sources from the GCMs. Using the Southeast U.S. domain for this analysis extends the literature on this question across a region with complex features and conservation management decisions. In addition, the extended methodology allows for the incorporation of projections created with dynamic and statistical downscaling by using those projections publicly available to all users. While this allowed more focus on how critical downscaling is as a source of uncertainty, it also allowed for a focus on the influence that the fragmented style of downscaling may have on impact assessments and adaptation planning.

While downscaling is not the dominant source of uncertainty in downscaled projections, it should not be ignored. For complex terrain and extreme variables the choice of downscaling technique contributes between 30%-50% of the uncertainty for future projections. The results from this study suggest that the uncertainty associated with downscaling does vary across the Southeast U.S. domain. In most of the domain the uncertainty associated with downscaling is not the dominant source for projections of average temperature and average precipitation change, though it can be nearly a fifth of the total uncertainty. However, for projections of temperature extremes and precipitation extremes particularly in the southern Appalachians downscaling can be significant or dominant. Therefore, studies using a single set of downscaled projections (i.e. one downscaling technique) should be treated cautiously because they are likely not incorporating the full range of uncertainty (particularly in complex topography such as the Appalachians) and are potentially overconfident.

This approach assumes that the sources are independent and that natural variability is constant in time. The assumption of independence has been shown to cause an overestimate
of the variance. Both assumptions should be addressed in future work with this methodology. The second important caveat is that only one set of downscaled projections used regional climate modeling (dynamic downscaling). Therefore, additional future work with this methodology should include more projections created with regional climate modeling. It is also important to acknowledge that the sample used was based upon what was provided in publicly available projections, and does not reflect all the emissions scenarios and GCMs provided in the CMIP3 or CMIP5 archives, nor do they reflect all the possible downscaling techniques which exist in the literature. However, while this methodology can be applied to the full CMIP archive with many more downscaling techniques the calculated variances and contributions would still represent a sample from the population of GCMs, downscaling techniques, and emissions scenarios.

The results from the analyses of climate variables (temperatures and precipitation) agree with prior studies where downscaling was shown to not be a dominant source of uncertainty (Dobler et al. 2012; Kay et al. 2012). Much of the literature discussing downscaling as a source of uncertainty has considered this with respect to impact relevant variables in hydrology (e.g. streamflow) or ecology (e.g. species distribution) instead of climate variables. The relationships between climate variables and impact variables are often non-linear (e.g. Jin et al., 2005). This implies that while downscaling uncertainty is not a dominant source of uncertainty for all climate variables, downscaling uncertainty may be a larger source for impact variables. Therefore, future work should characterize the contribution of different sources of uncertainty from the downscaled climate projections for impact variables. In addition to improving the methodology to address potential dependence
between individual sources of uncertainty, there are additional future efforts applicable to this research. This analysis characterized sources of uncertainty on subdomains for specific regions and the gridded analysis used on a 15 km grid. Given that downscaling may become a more critical source of uncertainty with smaller regions or decreased grid-spacing, a future extension of this analysis to explore both would be warranted.

The fragmented nature of the application of downscaling in recent years complicates the ability to provide the most realistic representation of uncertainty for decision makers and impacts assessment. This also implies that the range of possible futures for the future climate may be limited for time horizons of interest to decision makers because some downscaled projection data are unavailable for these time horizons. The result is to make impact assessments using downscaled projections for these time horizons potentially overconfident because of the lack of downscaling techniques represented. To increase the salience of downscaled projections in decision making, the downscaling community as a whole should consider a framework to capture similar periods (if not be continuous) using common GCMs and emissions scenarios. This framework should be designed with potential users involved to improve the usefulness of projections for decision making and impact assessments.

4.6. Acknowledgements

This project was completed as part of the Defense Coastal Estuarine Research Program (DCERP) funded by the Strategic Environmental Research and Development Program (SERDP). In addition, we thank David Blodgett (USGS Center for Integrated Data...
Analytics) for providing assistance to access some of the publicly available downscaled projections via the USGS GeoData Portal.
Figure 4.1. Available sample vs. the possible sample from the five sets of downscaled climate projections used in this analysis. GCM and downscaling technique (a) and emissions scenario and downscaling technique (b). Every yellow block is a combination which exists in the five downscaled datasets. White blocks are possible combinations but do not exist in the five downscaled datasets used.
Figure 4.2. Percent contribution from each source of uncertainty in the downscaled climate projections for the decadal mean annual average high temperature from the IDEAL experiment.
Figure 4.3. Percent contribution from each source of uncertainty in the downscaled climate projections for the decadal mean annual average high temperature from the ALLDATA experiment.
Figure 4.4. Percent contribution from each source of uncertainty in the downscaled climate projections for the decadal mean annual number of days the high temperature is greater than 95°F from the IDEAL experiment.
Figure 4.5. Percent Contribution from each source of uncertainty in the downscaled climate projections for the decadal mean annual number of days the high temperature is greater than 95°F from the ALLDATA experiment.
Figure 4.6. Percent contribution from each source of uncertainty in the downscaled climate projections for the decadal mean annual total precipitation from the IDEAL experiment.
Figure 4.7. Percent contribution from each source of uncertainty in the downscaled climate projections for the decadal mean of annual total precipitation from the ALLDATA experiment.
Figure 4.8. Percent contribution from each source of uncertainty in the downscaled climate projections for the decadal mean annual number of days with precipitation > 1 inch from the IDEAL experiment.
Figure 4.9. Percent contribution from each source of uncertainty in the downscaled climate projections for the decadal mean annual number of days with precipitation > 1 inch from the ALLDATA experiment.
Figure 4.10. Spaghetti plot of from Idealized experiment members for annual average high temperature for Southern Appalachians (left) and Central Florida (right) domains. Mean and bounds derived from the methodology overlaid with mean and bounds calculated from the ensemble from the IDEAL experiment. Bounds are two standard deviations above and below the mean in each subdomain.
Figure 4.11. Percent contribution from each source of uncertainty in time for decadal mean annual number of days the high temperature > 95°F for the Appalachians (top) and Central Florida (bottom) for the IDEAL experiment (left) and the ALLDATA experiment (right).
Figure 4.12. Percent Contribution from each source of uncertainty in time for decadal mean annual number of days with precipitation > 1 inch for the Appalachians (top) and Central Florida (bottom) for the IDEAL experiment (left) and the ALLDATA experiment (right).
CHAPTER 5. Conclusions and Recommendations

5.1. Conclusions

The uncertainty associated with downscaled projections is not limited to the sources from global climate models (GCMs). If one were to map out the numerous sources of uncertainty projections mentioned in this work, we see the depth of the challenges associated with uncertainty more clearly (Figure 5.1). Of those shown several sources are discussed in this dissertation which come from GCMs and downscaling. Natural variability (referred to by initial conditions or internal variability) is one major source of uncertainty in the GCM projections (Hawkins and Sutton, 2009; Deser et al, 2012). The emissions scenarios represent the scenario uncertainty (Hawkins and Sutton, 2009; Monier et al. 2015), which is the second source in GCM projections. The GCMs themselves represent a source of uncertainty as different GCMs reflect the representation of scientific knowledge at large scales (Hawkins and Sutton, 2009; Gettelman and Rood, 2016). Within GCMs there is structural uncertainty (the structural errors which differ between GCMs) and parametric uncertainty (Knutti 2008).

With the rise of downscaling to translate the GCM output to scales relevant to adaptation decision making, new sources of uncertainty have arisen from the downscaled projections, but as with the GCMs, downscaling uncertainty can be broken into other sources of uncertainty. In dynamic downscaling with regional climate models (RCMs) there are multiple sources of uncertainty. Knutti (2008) described the parametric and structural errors for GCMs and since RCMs have a similar construction the same types of errors exist in RCMs. However, as was pointed out in Chapter 3, the GCM-RCM forcing approach is
another source of uncertainty. This includes differences related to direct or indirect GCM-RCM forcing, along with differences between direct forcing approaches.

While not analyzed in depth in this dissertation, statistical downscaling has its own sources of uncertainty. Each technique has error which is irreducible regardless of the observations used to train them or improvements in the GCMs used to drive them. This error is not the same between statistical downscaling techniques and this is the structural uncertainty of statistical downscaling. Statistically downscaled projections use observed data to train the statistical relationship. Observed data could be interpolated observed data, such as the Parameter-elevation Relationships for Independent Slopes Model (PRISM, Daly et al. 2008) dataset or the Livneh CONUS near-surface gridded data (Livneh et al. 2013). Station data (with known measurement errors) are also used to train statistical downscaling techniques. This reveals a source of uncertainty in the projections from errors in the training data used with statistical downscaling techniques. This was not explicitly named as such by Pourmokhtarian et al (2016), but it was highlighted as a critical component of uncertainty for statistically downscaled projections in addition to the differences between techniques.

All these described sources from Figure 5.1 come from downscaled climate model projections alone, prior to their use in impact assessment modeling (such as the hydrology modeling done by Chen et al. 2011). This list of sources is likely not all inclusive. For instance, there is no standard approach to bias correction of projections (Wantanabe et al. 2012) and this could be considered another source of uncertainty as bias correction is another process which could be applied to either GCM output or downscaled output. This dissertation was not meant to investigate all these sources of uncertainty, but rather to focus
on those that result specifically from current dynamic downscaling practices and to evaluate whether the totality of downscaling approaches act as a significant contributor to uncertainty in climate projections.

In Chapter 2, the importance of parametric uncertainty in RCMs was examined with respect to the effect on high resolution simulations of precipitation. The differences between cumulus parameterizations were shown to have an influence on the historical accuracy for precipitation. In addition to changing a single parameterization scheme, this study shows that the interaction between the cumulus parameterization and analysis nudging also has an influence on the historical accuracy. Adjusting only a single parameterization scheme influences the projected change from a single RCM. The effect of parameterization change on historical accuracy is well known in the literature, but the potential effect on future spread of the projections is documented here. Given the influence of a single parameterization on projected change the interaction of parameterization and nudging may also have an influence on the range of projected change from a single RCM.

In Chapter 3, the importance of structural uncertainty, forcing approach, and resolution in RCMs was examined with respect to high resolution projections using a multivariate distance metric. Regardless of the size, when an RCM was incorporated into an ensemble reduced the error and overconfidence of the ensemble beyond an ensemble of GCMs alone. There was also an increase in the spread of each ensemble when an RCM is incorporated. However, for a given resolution, the structural uncertainty is not as large as the forcing errors used. For two of the RCMs used at 10 km there was a difference in how the GCM was used to force the RCM. The forcing approach is a source of uncertainty unique to
RCMs. The difference in forcing approach contributes to significant differences in error between these RCMs at 10 km. The difference between the potential influences of structural errors versus forcing approach is an important consideration, particularly since forcing approach may be a larger source of error than the structural differences between models. The results show that the error of WRF also improved with increasing resolution, which agrees with prior studies such as Luca-Picher et al. (2016). While the introduction of forcing approach and the characterization of the associated uncertainty compared to structural uncertainty is an important finding, a caveat in this analysis is that only 3 RCMs (NHM, RSM, and WRF) were used.

In Chapter 4, the contribution of downscaling to the total expected uncertainty in climate change projections was characterized using a variance decomposition method and applied to a domain covering the Southeast U.S. Downscaling is not the dominant source of uncertainty in downscaled projections. This was expected given that the primary purpose of downscaling is to translate the state of a variable from global to regional / local scales (Benestad, 2008). While not the dominant source of uncertainty (where ‘dominant’ is defined as contributing greater than 50% of the total estimated uncertainty) for all locations and variables, it can be a significant source (> 20% of total uncertainty), particularly in complex topography and coastal plains for extremes of temperature and rainfall. Downscaling is a consistent and significant source of uncertainty (~20 %) across much of the domain for the number of days with precipitation greater than 1 inch. Furthermore, downscaling is a dominant source of uncertainty for the number of days > 95°F in the Appalachians, particularly in the mid-century. While downscaling is not a dominant source
of uncertainty in downscaled projections for all variables and regions, the analysis revealed
the challenges associated with attempting to combine independent downscaling efforts into a
common climate change projection.

Downscaling as a whole is useful because of the ability to translate from GCM
resolution to resolutions where local physical processes which could affect adaptation
decisions are captured. However, current independent efforts results in fragmented guidance
provided for decision making and impact assessments. One reason for this fragmentation is
the computational expense of regional climate modeling. The expense involved with regional
climate modeling efforts (Rummakainen, 2010) has led to the use of time slices and nested
domains to achieve projections at a desired output resolution. The expense of regional
climate modeling has also led to situations where few of the emissions scenarios and GCMs
available are used. In the case of statistical downscaling, it is cheaper to create projections
with multiple emissions scenarios and GCMs with continuous time periods. However, the
original intent for some statistically downscaled products can also result in providing time
slices even though a continuous output is feasible. All of this results in an incomplete sample
for comparison between downscaled projections. The analysis in Chapter 4 revealed that the
uncertainty from each source in downscaled projections is affected by the fragmented style of
downscaling. If the time horizon of interest falls outside those time slices where multiple
sets of projections exist, the range of future climates projected by the models will be limited.
Thus, for climate adaptation planning and decision making, the potential value of
downscaling is likely to be higher than what is currently possible due to the wide variety of
experimental designs that limit our ability to fully sample differences in model structure, approach, error, and bias.

5.2. Recommendations and Future Work

Downscaling is currently being used to provide regional and local scale climate projections that can be used in impact assessments and decision making. With the results from this analysis, there are numerous recommendations related to future efforts in regional climate modeling and characterizing uncertainty in the downscaling projections. The interaction between cumulus parameterization scheme and nudging approach is shown to have an impact on the accuracy of WRF, and switching a single parameterization scheme also had an influence on the projected change produced by WRF. Future high resolution modeling efforts should carefully consider the parameterization schemes and their interaction with the nudging approach prior to initializing long term simulations.

Much of the regional climate model intercomparisons (RCMIP), such as CORDEX, focus on grid spacing of 25 km or coarser, and do not include different forcing approaches. From the analysis presented here, the error and spread of RCMs is not identical at differing resolutions. This is in part because the approaches to forcing each RCM is different, including nested grid modeling which results in an indirect GCM-RCM forcing. Given that a large proportion of the total simulation error may be due to the forcing approach, a recommendation from this analysis is a RCMIP (or multiple RCMIPs) in which the experimental design accounts for different forcing approaches, structural differences, and
reaches high resolution (< 10 km grid spacing). Establishing a RCMIP using all possible combinations of forcing approach and RCM structure would be a large and potentially prohibitive resource cost. Therefore, rather than considering all possible combinations a balanced experimental design (such as in NARCCAP [Mearns et al. 2009]) should be used to sample uncertainty associated with forcing approach and structural differences.

Although this dissertation has shown that downscaling is not likely to be a dominant source of uncertainty in climate projections, several caveats apply to this finding that suggest future avenues for further research. First, the analysis in Chapter 4 has been limited by using only one set of dynamically downscaled projections, which limits the representation of uncertainty in RCMs (as described in Figure 5.1). Repeating this analysis with additional RCMs, particularly those using the CMIP5 generation of GCMs, is warranted. Second, the analysis highlighted that downscaling is not a dominant source of uncertainty for climate variables. This would seem contradictory to some recent studies (e.g. Chen et al, 2011), but these studies have focused on the impact variables while this study focused on climate variables. The non-linear relationship between climate variable and impact variables of interest (e.g. Jin et al. 2005) may mean that the dominant source of uncertainty in ensemble climate model projections could be due to downscaling. Therefore, a recommendation for future research is to repeat this analysis with impact variables of interest in hydrology and ecology applications. In addition, while downscaling is not a dominant source of uncertainty, it is still 20-30% of the total uncertainty. Therefore, impact assessments should consider using more than one set of downscaled projections where possible to avoid making results overconfident with respect to downscaling technique.
The fragmented style of downscaled climate projections is an issue for their effective incorporation into impact assessments and decision making. During a time period of interest to a decision maker many combinations of GCM, downscaling technique, and emissions scenario are unavailable in the current suite of projections. The fragmentation of the sample of GCMs, downscaling techniques, and emissions scenarios causes an unintended overconfidence with respect to the individual sources of uncertainty applied to impact assessments using downscaled projections. To make downscaled projections more applicable for impact assessments, the climate modeling community should consider a guidance framework for future individual projects to reduce this fragmentation. This does not mean that the downscaling techniques themselves should be restricted, but rather that the output produced should be continuous in time and have common GCMs and emission scenarios wherever possible. This will aid future impact assessments by allowing for a more complete consideration of the future possible responses of the earth’s climate system to the current anthropogenic perturbation.

The current guidelines for the International CORDEX Flagship program recommend more process-based assessments of RCMs forced by GCM super ensembles which considers regional factors such as large lakes and air-sea coupling in greater detail in those super ensembles. Under that recommendation the implicit assumption is that the sources of uncertainty from RCMs (parametric, structural, and forcing approach) is negligible. This assumption contradicts these results with respect to the uncertainty that can be solely attributed to parameterization choice and forcing approach in RCMs. While emphasizing the incorporation of regional processes into the CORDEX program would likely increase the
historical accuracy of the projections it is unknown if the uncertainty in RCMs would be reduced to negligible levels (as is assumed in the CORDEX Flagship program guidelines).

This is of particular concern considering that the same guidelines also recommend increasing the number of convective permitting simulations in participating experiments. Therefore, coordinated regional climate modeling experiments such CORDEX exercise extreme caution in assuming that the uncertainty in regional climate modeling is negligible, as the results of projections created under that assumption, and as shown in this dissertation, may be overconfident.
Figure 5.1. Schematic of the sources of uncertainty in downscaled climate projections mentioned in this study.
REFERENCES


APPENDICES
Appendix A. Study Regions

For Chapters 2 and 3, the analyses with single and multiple RCMs use Puerto Rico as an example domain. Puerto Rico is a small island (9,104 km$^2$) with a very complex topography that cannot be adequately represented by the 25 km or coarser grid spacing being considered for CORDEX, let alone the vast majority of GCMs. The complex topography of this region causes a precipitation gradient which is evident in the precipitation climatology of the island (Figure A.1). On this island, the central mountain range interacts with the easterly background flow, influencing the precipitation gradient on the island (Jury 2009; Jury and Chiao, 2013). Recent efforts have produced high resolution regional climate modeling output for this region. The RCMs used to produce the output are also used for the analyses related to structural uncertainty and forcing approaches in RCMs.

In Chapter 4, the Southeast U.S. region is the focus of the downscaling uncertainty contribution analysis (Figure A.2). While Puerto Rico could be used as a domain for this, there is a limited amount of observations, and few downscaled datasets aside from the recently produced high resolution regional climate modeling output. This limits the representation of GCMs, emissions scenarios, and downscaling techniques for this analysis. In addition, Puerto Rico represents only a sub-tropical climate, and current literature considering the influence of downscaling covers small regions in multiple different climates. The Southeast U.S. domain stretches from the eastern Texas to the Atlantic Coast and from southern Florida to Maryland. This domain covers a wide range of climates within the Southeast. This allows for the assessment of the contribution differences across space for a wide variety of topographic and climatic regimes. There are also many sets of downscaled
climate projections available for the Southeast U.S. allowing a more complete representation of GCMs, downscaling techniques, and emissions scenarios than can be represented for Puerto Rico.
Figure A.1. Precipitation climatology for Puerto Rico and the U.S. Virgin Islands. El Yunque National Rainforest is circled in red as a point of reference. Courtesy of the San Juan, PR Office of the National Weather Service.
Figure A.2. Domain for the Uncertainty Contribution Analysis in Chapter 4. Subdomains shown in red. Total domain area is \( \sim 3,484,800 \) km\(^2\).
Appendix B. Models and Datasets

B.1. RCM and GCM output

For the analyses focusing on RCMs alone, there are two RCMs which are used in the analyses in this study. The first RCM is the Weather Research and Forecasting (WRF) model version 3.6.1 (Skamarock et al. 2008), which was run with a triple nested domain centered over Puerto Rico (Figure B.1). The three domains have a grid spacing of 30 km, 10 km, and 2 km. The WRF model is run with a 35 sigma layer configuration extending up to 50 hPa with 16 layers in the lowest 1.5 km of the atmosphere. WRF is relaxed toward the driving model with a five point sponge zone. Analysis nudging is applied for some of the simulations in either the 30 or 10 km domains, with the nudging coefficients shown in Table B.1. While the CP scheme is varied in some of the analyses, there are several common parameterization schemes used.

- Radiation – RRTMG (Iacano et al. 2008)
- Microphysics - WSM6 (Hong and Lim, 2006)
- PBL – YSU (Hong et al. 2006)
- Land Surface – Noah (Chen and Dudhia, 2001)

The variations in the CP scheme used in the analysis related to the parametric uncertainty with RCMs is described in Chapter 2.

The second RCM configuration is a dual configuration of the Regional Spectral Model (RSM, Juang and Kanamitsu, 1994; Kanamitsu et al. 2010; DiNapoli and Misra, 2012) and the Non-Hydrostatic Model (NHM, Saito et al. 2006; Iizumi et al. 2011; Inatsu et
This dual configuration is run to match the domain the 10 and 2 km domains of WRF (Figure B.2). RSM is run with boundaries from the driving model and produces output at 10 km directly using scale selective bias correction. The following parameterizations are used for the RSM model:

- **PBL** – Hong and Pan, 1996
- **Radiation** – Chou and Suarez, 1994; Chou and Lee, 1996
- **Shallow convection** – Tiedtke, 1983
- **Deep Convection** – Simplified Arakawa Schubert (Pan and Wu, 1995)
- **Land Surface** – Noah 4 soil layers (Ek et al, 2003)

The RSM output is used to force the NHM simulations which produce output at 2 km grid spacing. The NHM uses the following parameterization schemes:

- **PBL** – Mellor Yamada Level 3 (Nakanishi and Niino, 2006)
- **Microphysics** – Three ice bulk microphysics (Ikawa and Saito, 1991)
- **Land Surface** – Beljaars and Holstag, 1991
- **Convective permitting at 2 km**

The RCMs used for this analysis are forced with the CCSM4 GCM from the CMIP5 archive (Taylor et al. 2012). The GCM was chosen to provide the forcing for both RCM configurations as it was one of the CMIP5 GCMs shown to best replicate the climatology of precipitation by Ryu and Hayhoe (2013). For the structural uncertainty analysis, 20 of the GCMs in the CMIP5 archive are used including CCSM4 (Table B.2). Some simulations are also forced with NCEP-DOE AMIP-II Reanalysis Version 2 (R-2), which has a resolution of 1.875° x 1.875° at the equator (Kanamitsu et al, 2002).
B.2. Observed Data

For the analysis of RCMs two sets of observed data are used. First, the National Weather Service Multi-Sensor precipitation estimates (MPE, Seo and Breidenbach, 2002). MPE is created similarly to the Stage IV precipitation estimates created by the National Centers for Environmental Prediction. The Stage IV estimates have been evaluated by Wootten and Boyles (2014) and MPE is assumed to have similar errors given that the algorithms are similar and the use of only one available radar for estimation in Puerto Rico.

The second observed dataset used is the WorldClim Global Climate Data temperature and precipitation climatology version 1.4. WorldClim is created by interpolating station data, so there are errors associated with the interpolation described by Hijmans et al. (2005). The grid spacing of WorldClim is approximately 1 km, and is currently the only gridded observation dataset known for Puerto Rico with a grid spacing finer that 10 km.

B.3. Publicly Available Downscaled Climate Projections

With the large number of downscaling techniques used for in continental U.S. there are multiple publicly available sets of downscaled climate projections (hereafter downscaled datasets). Five of these downscaled datasets are used in the analysis to determine the contribution of downscaling as a source of uncertainty (Table B.3). These downscaled datasets are chosen because they are publicly available, which allows the focus on the development of the methodology and scientific questions. The chosen downscaled datasets
also provide representation of the fragmented style with which downscaling in current performed in the United States. Finally, this collection of downscaled datasets is used as it represents multiple generations of GCMs and emissions scenarios, and a range of downscaling techniques (both dynamic and statistical).
Table B.1. Analysis nudging coefficients (s⁻¹) used for the 30-km and 10-km domains. Time scales (h) that correspond to the nudging coefficients are in parentheses.

<table>
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<tr>
<th>Nudging</th>
<th>Wind</th>
<th>Potential temperature</th>
<th>Water Vapor Mixing Ratio</th>
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<td>5.0 x 10⁻¹ (0.6)</td>
<td>1.0 x 10⁻¹ (27.8)</td>
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<tr>
<td>Analysis Nudging (10 km)</td>
<td>3.0 x 10⁻⁴</td>
<td>3.0 x 10⁻¹ (0.9)</td>
<td>1.0 x 10⁻¹ (27.8)</td>
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Table B.2. CMIP5 GCMs used for the ensemble analysis.

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<th>Institution (Country)</th>
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<td>Wu et al. (2014)</td>
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<td>BCC-CSM1.1(m)</td>
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<td>BNU-ESM</td>
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<td>CanESM2</td>
<td>Canadian Centre for Climate Modeling and Analysis (Canada)</td>
<td>Yang and Saenko (2012)</td>
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<td>CCSM4</td>
<td>National Center for Atmospheric Research (USA)</td>
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<td>Marsh et al. (2013)</td>
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<td>CSIRO Mk3.6.0</td>
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<td>Jeffrey et al. (2013)</td>
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Table B.2. Continued.

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<td>IPSL-CM5B-LR</td>
<td>Institut Pierre-Simon Laplace (France)</td>
<td><a href="http://icmc.ipsl.fr/index.php/icmc-models/icmc-ipsl-cm5">http://icmc.ipsl.fr/index.php/icmc-models/icmc-ipsl-cm5</a></td>
</tr>
</tbody>
</table>
Table B.3. Comparison of metadata for downscaled climate projections used in uncertainty source contribution analysis.

<table>
<thead>
<tr>
<th>Name (Reference)</th>
<th>Provider</th>
<th>GCM Source – Downscaling Technique Type</th>
<th>Spatial Resolution</th>
<th>Time Period covered</th>
</tr>
</thead>
<tbody>
<tr>
<td>BCCAv2-CMIP5 (Reclamation 2013)</td>
<td>Bureau of Reclamation</td>
<td>CMIP5 - Statistical</td>
<td>1/8 degree (~12 km)</td>
<td>1950-2100</td>
</tr>
<tr>
<td>MACA (Abatzoglou et al. 2012)</td>
<td>University of Idaho, Northwest Knowledge Network</td>
<td>CMIP5 - Statistical</td>
<td>4 km</td>
<td>1950-2100</td>
</tr>
<tr>
<td>Hostetler (Hostetler et al. 2011)</td>
<td>USGS</td>
<td>CMIP3 - Dynamic</td>
<td>15 km</td>
<td>1968-1999, 2010-2099</td>
</tr>
<tr>
<td>CCR (Lorenz 2014)</td>
<td>Center for Climatic Research, Wisconsin Initiative on Climate Change Impacts</td>
<td>CMIP3 - Statistical</td>
<td>11 km</td>
<td>1961-2000, 2046-2065, 2081-2100</td>
</tr>
<tr>
<td>SERAP (Stoner et al. 2012)</td>
<td>Texas Tech University</td>
<td>CMIP3 - Statistical</td>
<td>12 km</td>
<td>1960-2099</td>
</tr>
</tbody>
</table>
Figure B.1 Domain configuration for the WRF simulations used.
Figure B.2. Domain configuration for the dual NHM-RSM simulations used.
Appendix C. Review of the Sanderson Distance Metric Calculation

This appendix reviews the methodology of Sanderson et al. (2015) with respect to its use in Chapter 3. This method is used to characterize the similarity of each member of a multi-model ensemble to all other members, and to a set of verifying observations. The reader may refer to Sanderson et al. (2015) for a complete description of the method as originally applied to the CMIP5 archive of GCMs.

The Sanderson et al. (2015) methodology uses a singular value decomposition (SVD) to characterize the differences between ensemble members. First, for each model used from CMIP5 ensembles, monthly climatologies are obtained for the surface temperature and total rainfall by averaging the monthly mean fields for the time period January 1986 to December 2005. This period of 1986-2005 was chosen to match the time period of the high resolution RCM simulations produced for Puerto Rico. To prepare the data for the singular value decomposition (SVD) used, the data are first regridded to the 2 km grid used by the WRF simulations. The WorldClim dataset, used as the observations, are also regridded to match the 2 km WRF grid. To concatenate the two variables for the multivariate analysis, the variables are normalized for each to represent a similar amount of variance in the multi-model ensemble. The normalization factors are the average grid cell variances for each variable. The corresponding output from each model (including the observations) and variable is divided by the normalization factor.

Second, to prepare the data for the SVD analysis, the elements of each variable are reformed into a one-dimensional vector. Each model (including the observations) and variable reflects one vector, and if any elements from a single vector the corresponding
element is removed from all models. Each of the temperature vectors are concatenated with the precipitation vectors to form a single vector. Thus, one concatenated temperature and precipitation vector is created for each model and the observations. The resulting $m$ vectors are combined to form a matrix $X$ with size $m$ by $n$ (where $m$ is the number of models plus the observations, and $n$ is the number of grid cells in the domain times the number of variables times 12 monthly climatology values). The ensemble mean is calculated by averaging across the $m$ rows of this matrix. The ensemble mean is then subtracted from each row to yield the anomaly matrix $\Delta X$.

The third step in the distance metric calculation is to perform a singular variance decomposition on the anomaly matrix $\Delta X$. The SVD results are truncated to $t$ modes to obtain the dominant modes of multivariate ensemble variability such that

$$\Delta X = U \lambda V^T$$

Where $U$ is the matrix of model loadings (size $m$ by $t$), whose columns are the eigenvectors of the model covariance matrix, $\lambda$ (size $t$ by $t$) are the eigenvalues, and $V$ (size $n$ by $t$) are the eigenvectors of the field covariance matrix. The dimensions are sorted by decreasing eigenvalue, so that they can be truncated to a smaller number of $t$ dominant modes ($m$ modes defines a complete basis to reconstruct $\Delta X$, so for a truncated case $t < m$).

The final step is the distance metric calculation. The model loadings $U$ define a $t$-dimensional space in which the distances between each model and from each model to the observations can be calculated. The distance $\delta_{ij}$ between two models $i$ and $j$ can be expressed as
\[ \delta_{ij} = \left( \sum_{l=1}^{t} [U(i, l) - U(j, l)]^2 \right)^{1/2} \]

This is calculated using the \( t \) dominant modes in \( U \), and \( i \) and \( j \) reflect the different models. When \( i=j \) the value of \( \delta_{ij} = 0 \). In addition, recall that the final row of \( \Delta X \) is always the observations. Through this calculation, the final row \( (m) \) of \( U \) is also the observations. The result is that \( \delta_{i,m} \) is the distance from each model \( i \) to the observations. The distance matrix \( \delta \) is a symmetric matrix, therefore \( \delta_{m,j} \) is also the distance from each model to the observations. It is this distance matrix, \( \delta \), that is used for the analysis with multiple ensembles in Chapter 3.
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