ABSTRACT

VILLEGAS ORTIZ, LAURA. Integrating Econometric Models of Land Use Change with Models of Ecosystem Services and Landscape Simulations to Guide Coastal Management and Planning for Flood Control. (Under the direction of Laura Taylor).

In the natural resources and environmental sciences literature, little research analyzes the dynamic implications of land use policy for land development and conservation in the face of changing climatic conditions. Moreover, few studies have put forward methods to systematically connect policy impacts on land use decisions and the resulting changes in ecosystem services provision. With this project, I contribute to a growing area of research in the land use and environmental economics by evaluating the relative effectiveness of alternative land use policies that target the management of natural coastal resources in preparation for increased risks of flooding.

Floods can cause significant natural, human, and economic damage. According to the National Oceanic and Atmospheric Administration, flooding is the costliest and fastest growing climatic threat in the United States. Every year between 1980 and 2017, flooding and tropical cyclones caused an average of $26.16 billion in damages and 184 fatalities. Hurricanes Harvey, Irma, and Maria made 2017 the costliest year on record for weather and climate disasters. Total costs of flooding and tropical cyclones were approximately $273.6 billion and there were 3,193 associated deaths (NOAA, 2018).

Across US coasts, the number of inland floods has increased between 300 and 925 percent in the last 50 years, and American households residing in coastal counties (about 39 percent of the nation's population) are increasingly vulnerable to flood risks as the combination of urbanization, climate change, and the resulting loss of natural barriers like wetlands, leads to more floods, more economic damages, and more natural and human

losses (NOAA, 2017).[1] The National Flood Insurance Program, which provides necessary flood coverage to more than 5 million property owners nationwide, already costs taxpayers up to $30 billion per year (Congressional Research Service, 2018). Yet, the current program does little to encourage mitigation and instead subsidizes development in environmentally sensitive areas. A 2017 report by the National Institute of Building Sciences found that every dollar invested in flood mitigation saves the Federal government $6 in flood insurance payouts (Multihazard Mitigation Council, 2017). Thus, local mitigation efforts and policy interventions are of increasing vitality to relieve the Federal government and taxpayers nationwide of flood related expenses.

In this study, I design different land use regulations that protect natural resources and alter current trends of urbanization in three fast-growing coastal counties of South Carolina that encompass the Charleston metropolitan area. I evaluate the relative performance of these policies in terms of avoiding future property damages from flooding, limiting economic losses from restricted development, raising tax revenue, and equalizing the spatial configurations of damage. Specifically, I pose three questions: (1) which policy is more cost-effective at reducing future damages; (2) are there differences across policy scenarios in the spatial distribution of damages; and (3) do these answers differ when considering different time horizons.

To conduct this comparative analysis, I use an iterative approach that integrates spatially explicit dynamic econometric models of land use change with statistical analysis of land markets to generate predictive models of urban growth. Then, using a Monte Carlo procedure, I use the generated models of land use change to simulate alternative versions

[1] At the time this dissertation was written, the Intergovernmental Panel on Climate Change launched its 2018 report. According to the report, at the current pace of emissions, by 2040, temperatures will be 1.5° higher than preindustrial levels, and the impact on risk of flooding is projected to be high, particularly for coastal locations (Intergovernmental Panel on Climate Change, 2018).

of the physical landscape 5 and 25 years into the future, each alternative scenario corresponding to a different land use policy. After that, I couple these future urban scenarios with an ecosystem services model of flood protection to associate each simulated landscape with some ability to prevent property damages from a major future hypothetical storm resembling the 2017 Hurricane Irma.

In this study, I consider three types of potential land use policies: (1) a development tax proportional to the property's value that applies to each parcel that is developed; (2) a heterogeneous impact fee meant to discourage development in areas that are relatively more densely urbanized; and (3) a subsidy for owners of agricultural land that encourages the conservation of wetlands, which are critical for flood prevention.

The results of this study indicate that price instruments based on land value and varying on landscape composition are mostly not cost–effective strategies. However, when examining various outcomes that policy makers may be interested in, these instruments can be modestly effective at altering urban development patterns, enabling the region to make economic savings on property repairs, raising tax revenues, or delivering a marginally more equal spatial distribution of damages. The findings from this work also provide supportive evidence to research illustrating how natural infrastructure, such as coastal wetlands, is beneficial to coastal communities in terms of flood damage reduction.[2]

More specifically, the findings presented here imply that policy makers face interesting trade–offs in designing forward–looking land use policy aimed at mitigating flood damages, and that they can take better advantage of the economic benefits different policies offer by differentiating between fiscal, environmental, and social objectives, and between short term and long term objectives. In general, no policy dominates across all criteria, thus, this work cannot alone determined the preferred route of action. However,

[2]See Loerzel et al. (2017), Walls et al. (2017), Narayan et al. (2016), Boutwell and Westra (2015).

the framework and analysis established here serve as a strong starting ground for research trying to answer the questions of how planners can choose among policies, and what is the optimal policy for meeting local environmental, social, and fiscal goals—given a level of creativity and assertiveness that is both socially and legally feasible.

Among the three policies, a tax on development that reduces the value of developable land by 10% is the most cost–effective approach to reducing flood damages from a storm while limiting the amount of forgone benefits of development. Such a policy is associated with lower costs in terms of lost development value, moderate savings in terms of flood damages, and it delivers positive tax revenues (which can be tied to specific investments on infrastructure that mitigates risks of flooding). In addition, it protects wetland covers in the short run. However, such a tax is not the most effective policy for reducing damages, deterring urban growth, or equalizing damages across the region. Alternatively, a heterogeneous tax based on developed cover surfaces discourages development, delivers a more equal spatial distribution of damages, and is the most effective at reducing damages. Yet, it is associated with high costs in terms of losses in development value. Finally, a subsidy on wetland covers delivers outcomes that are generally between those associated with the tax on development that reduces the value of developable land by 10%, and the heterogenous tax based on developed surfaces cover, with the main difference being its high cost to local governments.

Integrating Econometric Models of Land Use Change with Models of Ecosystem Services and Landscape Simulations to Guide Coastal Management and Planning for Flood Control

by
Laura Villegas Ortiz

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APPROVED BY:

Erin Sills	Zachary Brown
Walter Thurman	Laura Taylor Chair of Advisory Committee

DEDICATION

"Servir es reinar," *Lumen Gentium* 36

To Mario and Charito. The OD's.

BIOGRAPHY

Laura was born in a rural neighborhood of Bogotá, back in a time when it was not a densely developed and impoverished ghetto. It was an accelerating Saturday night at a small and remote university hospital where Laura's father, Mario, assisted an emergency C–section for Charito, Mario's wife. Those where stressful times for Mario and Charito. Violence in Colombia was at its peak, and their first born had arrived with some *manufacturing errors*. A grim outlook.

Nevertheless, against the odds and unlike most people of her generation, Laura grew up fearless and healthy in an idyllic environment. Mario and Charito were part of the counter–culture of their time, raised under the "Theory of Liberation"as taught by progressive Jesuits of Latin America in the 60's. They moved to a small agricultural town out of the city limits, Cota. In Cota, the problems facing the country and the distinctive chaos of Latin American urban centers did not exist. There were no fences and no paved roads. The *cerros* were at walking distance from the house. There was only one bus a day running to Bogotá. In a way, Cota was a perfect bubble of innocence.

The young family, Mario, Charito, Laura and the forever precious Gabi—Laura's little sister who grew up to be an outstanding woman full of virtues and with a heart as warm as her temper—lived in a neighborhood with some signs of social division and a rather diverse population, for a little corner in the end of the world. To the West side of her house, lived the very wealthy Europeans looking to escape the city: the Swiss and their restaurant, the Italians with their cheese factory, and the industrious Germans. To the East, lived very poor mestizo peasants, people who had been born in their homes and where going to die there in the same manner their elders had. Somewhat miraculously, there was no clear spatial segregation, and, strangely enough, no notion of "class."

Laura's parents are doctors, and their doors are always open to those looking for help—free of charge, of course. People come to them looking for answers to similar problems: diarrhea, strong coughing, vomiting, skin rashes, broken bones, bleeding parts, etc. People come to find relief to their pain and suffering. People come looking for a way to live better lives. Laura's parents are humble, generous, compassionate, merciful, and all loving. More than hippies, they are missionaries: they are true disciples of their professional training and their moral beliefs. The medical oath says "Do no harm."Laura's parents live by these words, together with "Love one another, as I have loved you."

Everyone met in Laura's house: the poor, the rich, the foreign, and the native. The only other place she saw these people share space was at a small parish nearby during Catholic mass on Sunday. Colombia is not a noticeably racist society, but there is tangible classism, and economic inequality is a persistent malaise. Yet, Laura's family was able to keep this social disease from contaminating her set of believes and ethical norms.

Throughout the years, Laura got to observe and participate in multiple spontaneous medical visits at the doctors' house, that little red–roofed wooden house guarded by three majestic German Shepherds and surrounded by the large orchard with oaks and feijoa trees and tamarillos and black berries and astromelias and that especial guayacán growing over the ashes of abuelo James. The first thing Laura learned watching her parents work at home was that everyone gets sick. Everyone is fragile and everyone needs help to live better and to die in peace. Laura understood that people came together around their mortality, and she learned to see this as a very positive sign: it meant people don't want to die without having tried to get better first. It showed people were optimistic and that they believed they could improve before the time was out. Big and small, rich and poor, white or brown, people were just people. Everyone hoped they could do better, that they could live well and be loved, and that they could die without much pain.

At some point, magic gave way to conflict and confusion. The second thing Laura learned was that while everyone gets sick, only some get better. Eventually, Laura realized that many of the pains people endured were unfair and absurdly persistent: even though at their bodily and spiritual core people were the same, some people seemed more prone to be repeatedly and disproportionately shocked by misfortune and sickness.

Laura grew frustrated watching her parents fix people one problem at the time, only to see the same problem come up again a few weeks later. There was something systemic about these health problems: the majority had remedy and were preventable, yet, they persisted and reached fatal points, particularly among those who already seemed to have been suffering the most. The world was not equal nor fair, and the vulnerable usually got the short end of stick. They seemed to have a magnet for misfortune. Here is when Laura understood that poverty, culture, and history were big reasons behind people's bodily ills. The pains of the body were merely a symptom of the afflictions of society. Economic context became a thing in her life and she understood she was not going to be a doctor like her parents. To fix the problems of the poor, the system had to change.

Laura did not join a revolution or become a poet, as she once thought she might. Instead, she traveled, she studied, got exposed to other problems and other solutions. She met different people and went to different places with institutional environments that showed her new ways to think about poverty, injustice, health, and what helps people feel they live with dignity. Years later, she was getting a PhD in development and environmental economics and getting ready to start a job as a researcher for the New Climate Economy, an international initiative that examines how countries can achieve economic growth while dealing with the risks posed by climate change. She still wants to change the system and continue her parents' work of making the most out of hope. She still wants to help people live *better* lives.

ACKNOWLEDGEMENTS

"In this world, there are two kinds of people, my friend: those with loaded guns and those who dig."

The Good, The Bad, and The Ugly

I dig. I dig hard. But in the last five years, I found things that no amount of digging could have accomplished without the support, guidance, inspiration, funding, and care provided by many. Also, the digging could not have been nearly as fun without the company of great people. Here, I want to acknowledge those who made this title attainable and enjoyable, although not desirable enough to be repeated.

The people that made this possible are a colorful set. First and foremost, I want to thank my family, all of it. Those who stayed back home, those who also left, and those who I adopted as family along the way. I thank my mother, father, and sister for their eternal and unconditional love and trust. I also want to thank my grandmothers, aunts, uncles, cousins, and my new brother, Marshall. Of my adopted family, I want to thank my friends from Montana State University, Rebecca Mondics and Heidi Schwizer; my good friend and classmate, the super talented, modest, and incredibly sharp and funny, the next macro-economist: Tiezheng Song; and my Durham/Motorco gang for their active support. May everyone's dating life improve after this reference.

Of course, I want to give special thanks my committee members for their contribution to this project, and for their patience, trust, and support. First, I want to thank my advisor, Laura Taylor, who spent a lot of time looking over this work and monitoring the quality of this research. I want to further recognize Erin Sills for having set up and directed the Lowcountry study group: the conversations we had during those sessions

helped me put things in perspective and become completely fascinated by the historical, social, and natural intricacies of this region of the country. I am also deeply thankful to Wally Thurman, his always difficult questions were key to encourage me to never be completely satisfied with how much rigor I was putting into the work. Also, all his high–level comments were always timely and necessary for me to keep the economics at the forefront of this research. Finally, I want to acknowledge Zack Brown, who despite being extremely busy since I recruited him into this fellowship, managed to dedicate honest and thoughtful time to help me navigate the labyrinth of econometric theory.

I am very proud of the research that we conducted. I think with this study we came up with a new way of thinking about problems in environmental economics and we designed a new methodology and applied a novel assortment of techniques in a way I had not seen before. We took many risks. I once heard a story about economists (if I remember correctly, I heard it from the Wally during my first year as a PhD student) in which one night a policeman sees an economist looking for something by a light pole. The policeman asks the economist if he has lost something there. The economist says he lost his key over in the alley. The policeman asks him why he is looking by the light pole and not in the alley. The economist responds that it is because it is a lot easier to look over by the light pole. I think this is very telling. I haven't been an economist for too long but I think I can recognize some truth in this story. I can say with complete confidence that in the last couple of years we have not exactly been looking under the light pole. During this process, there were a lot of decision points where we couldn't use much guidance on how to proceed because there just aren't many studies like this. That was scary but it was also exciting. In retrospect, it is easy to see the weak links and fall on the temptation of being too harsh on ourselves and of judging our choices as suboptimal or even poor. But the truth is that although this work is not perfect, what we did here was authentic

science and it was ground–breaking: we followed the scientific method to make decisions in the dark and we found and prepared new ground over which new questions can be asked and new research can be built. I am honored for having been part of a brave team.

If there are still any doubts about the value of this work, one has only to open the news. The week of my defense, the Intergovernmental Panel on Climate Change launched its 2018 report. The world is going to be difficult for us and our children and action needs to be taken now, at a global scale. Currently, the world is 1°C warmer than preindustrial levels, and in the last decade we have seen astonishing and devastating impacts on the environment. At the current pace of emissions, by 2040, temperatures will be 1.5° higher than preindustrial levels, and the impact on risk of flooding alone is going to be high, and particularly so for coastal locations. In addition, just a week before the launching of the IPCC report, the Royal Swedish Academy of Sciences awarded the 2018 Nobel Prize in economics to William Nordhaus and Paul Romer. Nordhaus got selected because he was able to translate climate science into economics, and explicitly incorporate climate change into macroeconomic modeling. The Prize was awarded to both economists because, when combined, their macroeconomic models propose a balanced approach to growth that involves both, sticks and carrots: taxes to correct actions that generate negative externalities in the case of Nordhaus, and subsidies to activities that generate positive externalities, in the case of Romer. This model of growth that considers regulation in a very uncertain environment, is very much in line with what was proposed in this study. If we are looking for validation, take the IPCC report recommendations and the Nobel Prize as indications that society and academia thinks our work is not just important but, in fact, vital.

Before moving on to a different sentiment and a different group of people, I want to extend my gratitude and recognize the important role of my professors at NC State in

firmly and gently looking over my progress and guiding me through the whole process. In particular, I want to thank Roger von Haefen, Mitch Renkow, and Paul Fackler for their always kind, respectful, and encouraging feedback. I consider myself privileged and lucky to have had them as my mentors throughout this program, I admire and respect them, and I truly appreciate their guidance and support. I also want to give a shout out to the professors at Montana State who touched my career, particularly, Vince Smith, Christiana Stoddard, Nick Parker, Linda Young, and Dave Sands—all of them outstanding scientists and humans, truthful to the scientific method, devoted to teaching, and passionate about their work. Their input and criticism motivated me to become a better researcher and fueled my passion for learning, and I hope to follow their example.

For more practical matters, I want to thank the team of scientists at the South East Climate Adaptation Science Center, especially, Mitch Eaton. Their continuous interest, input, encouragement, and financial support were essential in this project.

At a more personal level, I want to thank the BGEES, the Busy Graduate Environmental Economics Students who are always trying to stay alive, particularly... well, each one of them: Yu, Sasha, Nino, Lee, Serkan, Tugba, Ali, Mike, Bruno, Kelly, and those not listed. I also want to thank my friends from the Latin American Student Association for their constant optimism, generosity, and rigorous help. Also, I am grateful to Bogdan Nikiforov, Jane Casteline, Robin Carpenter, Tamah Morant, and the sweet Liza Sagor for their help, patience, compassion, and their support during my stay in North Carolina.

To end this note, I want to thank Ios. This experience would not have been nearly as enriching, accelerating, fulfilling, and fantastic without his company. He is my favorite partner and life coach, my best friend and confidant, and the one I wisely chose to love. Thanks to Ios, I was able to find, everyday, my desire to persevere, improve, enjoy, and kick ass with style and determination.

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"The first principle of conservation is development, the use of the natural resources now existing on this continent for the benefit of the people who live here now... natural resources must be developed and preserved for the benefit of the many, and not merely for the profit of the few... Conservation means the greatest good for the greatest number for the longest time."

Gifford Pinchot, *The Fight for Conservation*

"Nature has given recurrent and poignant warnings through dust storms, floods and droughts that we must act while there is yet time if we would preserve for ourselves and our posterity the natural sources of a virile national life... Prudent management requires not merely works which will guard against these calamities, but carefully formulated plans to prevent their occurrence... A comprehensive program of flood control must embrace not only downstream levees and reservoirs on major tributaries, but also smaller dams and reservoirs on the lesser tributaries, and measures of applied conservation throughout an entire drainage area, such as restoration of forest and grasses on inferior lands, and encouragement of farm practices which diminish runoff and prevent erosion on arable lands."

Franklin D. Roosevelt, *Message to Congress*, 1937

1 INTRODUCTION

In the natural resources and environmental sciences literature, there are few examples of research analyzing the dynamic behavioral implications of land use policy for land development and conservation, particularly in the face of changing climatic pressures.[1] Moreover, few studies have developed methods to connect policy impacts on land use decisions and the resulting changes in ecosystem services provision.[2] With this dissertation, I contribute to a growing area of research in the fields of land use and environmental economics by evaluating the relative effectiveness of various land use policies targeting the management of natural coastal resources in preparation for increased risks of flooding.

In this application, I use an iterative procedure to develop a spatially explicit econometric model of land use change that directly integrates ecosystem services and feedback mechanisms between land use, ecosystem services, and land values in a dynamic framework. More specifically, using landscape simulations, I study how spatial patterns of urbanization and alternative coastal development policies affect land use decisions, and how these decisions affect the conservation of critical wetland habitat in the physical landscape and the landscape's general capacity to mitigate risks from future flooding.

Coastal flooding is an imminent climatic and economic threat in the United States.

[1] Many of the analyses evaluating growth management policies options come from the urban economics literature and they tend to focus on the management of urban sprawl. The growing body of literature on the economics of urban sprawl is surveyed in Glaeser and Kahn (2004) and Nechyba and Walsh (2004). Recent studies in the natural resources area have examined the effects of incentive policies on carbon sequestration, biodiversity conservation, pollination services, habitat fragmentation, agricultural land prices, economic returns from different land use patterns, and provision of spatially dependent ecosystem services. See for example the works of Lawler et al. (2014), Wu (2014), Wrenn and Irwin (2012), Lewis (2010), Polasky and Segerson (2009), Lewis, Plantinga, and Wu (2009), Nelson et al. (2008), and Lewis and Plantinga (2007). Other economics works have studied urban growth policies in light of concerns over environmental justice, generational equity, gentrification and even gerrymandering of political districts, for example Bento, Franco, and Kaffine (2006, 2011).

[2] Irwin (2010) and the chapters by Irwin and Wrenn, Klaiber and Kuminoff, and Plantinga and Lewis in The Handbook of Land Economics (Wu, 2014) provide a comprehensive review of the land use modeling literature and its current deficiencies.

Since 1960, the number of inland floods has increased between 300 and 925% along coastal areas and climate scientists warn that sea level rise and changes in storm frequency will make coastal systems even more vulnerable to the dynamic forces of wind, waves, tides, currents, and storms. In some regions, biophysical changes have already been shown to impair the capacity of municipal storm water drainage systems to empty into the ocean. For instance, in places like Norfolk, VA, Charleston, SC, and Miami, FL, minor floods now occur as frequently as high tides (NOAA, 2018).

Flooding risks and costs are exacerbated by rapid urbanization trends in coastal areas and the subsequent loss of natural barriers. Land development near the coast or in flood plains creates areas that are impermeable to precipitation, which leads to increased runoff and makes coastal areas more prone to flooding. Additionally, land development destroys, displaces, or inhibits the formation of naturally occurring ecosystems that decrease the landscape's vulnerability to floods—like wetlands, which for instance, reduce flooding risks by promoting infiltration or absorption, reducing runoff, attenuating wave setup, and facilitating sediment accretion (which reduces water depth and wave height).[3] Finally, high density growth increases the magnitude of economic damages and human costs as more people move towards vulnerable areas and become exposed to climatic threats.

Floods can cause significant natural, human, and economic damage. According to the National Oceanic and Atmospheric Administration, flooding is the costliest and fastest growing climatic threat in the United States. Every year between 1980 and 2017, flooding and tropical cyclones caused an average of $26.16 billion in damages and 184 fatalities. In that time series, the costliest years were 2005, 2012, and 2017—the years of the five costli-

[3]Land development and new impervious surfaces prevents water, sediments, organic matter and nutrients from percolating into the soil, therefore inhibiting the formation of wetlands. Additionally, the constructions of physical structures like bulkheads, sea walls, jetties and sandbags pose a physical impediment for wetlands and marshes to migrate inland—which is their response to sea level rise—and further impair the landscape's capacity to prevent flooding.

est events in the history of natural disasters in the United States: Hurricanes Katrina, Sandy, and Harvey, Irma, and Maria. In 2005, the monetary cost of flooding and tropical cyclones was $217.8 billion and there were 2,002 associated deaths. In 2012, damages of Hurricane Sandy added to $75.3 billion and 168 deaths. Finally, Harvey, Irma, and Maria made 2017 the costliest year on record for weather and climate disasters. Total costs of flooding and tropical cyclones were approximately $273.6 billion and there were 3,193 associated deaths (this estimate takes into account the update on Puerto Rico deaths).

American households residing in coastal counties (about 39 percent of the nation's population as of 2010) are increasingly vulnerable to flood risks as the combination of urbanization, climate change, and the resulting loss of natural barriers like wetlands, leads to more floods, more economic damages, and more natural and human losses.[4] The National Flood Insurance Program, which provides flood coverage to more than 5 million property owners nationwide, already costs taxpayers up to $30 billion per year (Congressional Research Service, 2018). Yet, the current program does little to encourage mitigation and instead subsidizes development in environmentally sensitive areas. A 2017 report by the National Institute of Building Sciences found that every dollar invested in flood mitigation saves the Federal government $6 in flood insurance payouts (Multihazard Mitigation Council, 2017). Thus, local mitigation efforts and policy interventions are of vital to relieve the Federal government and taxpayers of flood related expenses.

Urban planners have traditionally dealt with flooding using engineering solutions, for example by building water storage and infiltration structures like dams, pumps, and spillways. To a lesser extent, they have also used prescriptive regulation on land use to

[4]The US has over 12,000 miles of coastline, along which 39% of American households reside. That number is expected to increase by 8% in 2010. Additionally, the 2010 shoreline coastal population density was 446 persons/mi^2, over 4 times the national average (US Census, 2010).

limit the damages to private properties from flooding events.[5] There is a third alternative that is largely unexplored. Policy makers could consider enacting land use policies that promote certain patterns of development (e.g., limiting the level, density, and distribution of development) or favor a desired composition of the natural landscape (e.g., encouraging the conservation of coastal wetlands or other natural barriers that provide beneficial flood protection service) to actively reduce stormwater runoff from impervious surfaces.

It is well established that natural systems that act as coastal barriers, such as wetlands and marshes, protect against floods. According to the Environmental Protection Agency, one acre of wetland can absorb and store up to 1.5 million gallons of flood water.[6] Moreover, recent analyses place the per hectare annual value of flood prevention services from wetlands between $225 and $1,700 (Loerzel et al., 2017; Costanza et al., 2008). However, it remains unclear how much can land use policies aimed at protecting coastal natural resources reduce flood damages. This study is a step to quantify that.

This research provides an initial evaluation of the relative effectiveness of three coastal management strategies that can be deployed to mitigate risks and damages from floods in rapidly growing coastal areas in South Carolina. Specifically, the focal area of study are the three coastal counties that encompass the Charleston metropolitan area, which is a region subject to rapid urbanization and rising flooding threats.

In this study, I pose three questions: (1) which policy is more cost effective at reducing future damages; (2) are there differences across policy scenarios in the spatial distribution of damages; and (3) do these answers differ when considering different time horizons (i.e., are there different policy implications for short–term and long–term planning and management of urban growth and natural coastal resources).

[5] For instance, in South Carolina, the Beachfront Management Act of 1988 establishes a zone adjacent to the shoreline within which structures cannot be built or reconstructed.

[6] According to Ducks Unlimited, the value is 330,000 gallons (Ducks Unlimited, 2018).

To answer these questions, I build upon a framework originally laid out by Bockstael (1996) and later developed and implemented by Newburn et al. (2004, 2006), Irwin (2003), Wrenn and Irwin (2012), Bigelow (2015), and Bigelow et al. (2017). Under this scheme, parameter estimates from an econometric model of land use choice are used to iteratively simulate alternative future physical landscapes that would arise under certain land use policies: specifically, policies designed to ameliorate future expected economic damages from flooding events, and intended to affect land use decisions by altering, through different mechanisms, the value of land under residential or agricultural uses.

After the simulation exercise, each generated alternative scenario is compared to a baseline scenario (one where there is no change in land use policies), and the comparison is based on the benefits and costs associated with each policy, where benefits are defined as expected economic savings in insurance payments after a 100–year flood, and costs are foregone capital gains on land from the restriction on development. To create a confidence interval around estimated effects, I generate 200 landscapes under each policy rule.

There are five main components in the conceptual model that guides this research: (1) a land use change model that results in estimated transition probabilities for each parcel in the landscape; (2) a first–stage hedonic analysis of land value that results in the predicted land values used as inputs in the aforementioned land use change model; (3) an ecosystem service model of flood prevention that depends on the land cover composition of the landscape and that influences flood risks, economic damages from flood events, and how landowners develop expectations over the value of their parcels; (4) a set of land use policies designed to reduce flood risks by altering landowners' relative valuation of their land under developed uses; and (5) an iterative simulation procedure built on a standard Monte Carlo process that allows a dynamic feedback between the other four components of the system, and results in various alternative future physical landscapes.

Figure 1.1 shows the components of the system and how they are related. Presumably, different land use policies have different effects on how landowners develop expectations and make decisions over the use of their land. In turn, decision processes over land use that are systematically different are likely to have different aggregate effects on the physical landscape, and landscapes that exhibit different spatial features are also likely to be associated with variations in the ability that local environments have to prevent floods. Concretely, I evaluate the following policies:

1. a 10% tax on development,
2. a heterogeneous tax discouraging growth in relatively densely developed areas, and
3. a subsidy on natural infrastructure that encourages conservation of wetland covers.

My application of this general framework brings novelty into the literature on multiple accounts. First, it offers an improvement over previous works as it uses parcel–level transactions data to predict land values under alternative uses instead of relying on assessed values or values of land rents estimated using county–level data. Second, by incorporating spatially econometric methods and a comprehensive set of geospatial variables that characterize the composition of the landscape at the parcel level, the analysis captures the effect of spatial spillovers that are typical of environmental processes. Thirdly, using the aforementioned comprehensive set of spatial data, I provide an original attempt to characterize land use choices at the intensive margin by allowing intensity of development to change endogenously in the models of land use change. Lastly, this study is the first to look at alternative regulatory instruments for mitigating flood risk through the coupling of spatially explicit econometric models, a model of ecosystem services, and landscape simulations that allow the incorporation of feedback mechanisms between land use, ecosystem services, and land values.

This dissertation is organized as follows: in chapter 2, I present the analytical framework that guides this work and describe the methods used in the empirical analysis. Chapter 3 provides a thorough description of the study area and the different types of data used in the empirical work together with their limitations. In chapter 4, I present and discuss results from estimating the relevant predictive models. Chapter 5 contains the comparative policy analysis. Here, I describe in detail the policies considered and provide and interpret the results from a single–period and a multi–period simulation of land conversion under each policy regime. The discussion also includes a definition of costs and benefits used to finalize the economic analysis and a presentation of the results. I conclude chapter 5 with a discussion on policy implications. Chapter 6 finalizes this work with a summary of findings, a reminder of the limitations of this research, and an outline of future work. The appendix presents information on data sources, supporting evidence for model selection decisions, complementary documentation on the econometric packages used for estimation and simulation, and background information on the policy context facing coastal managers in South Carolina and the United States.

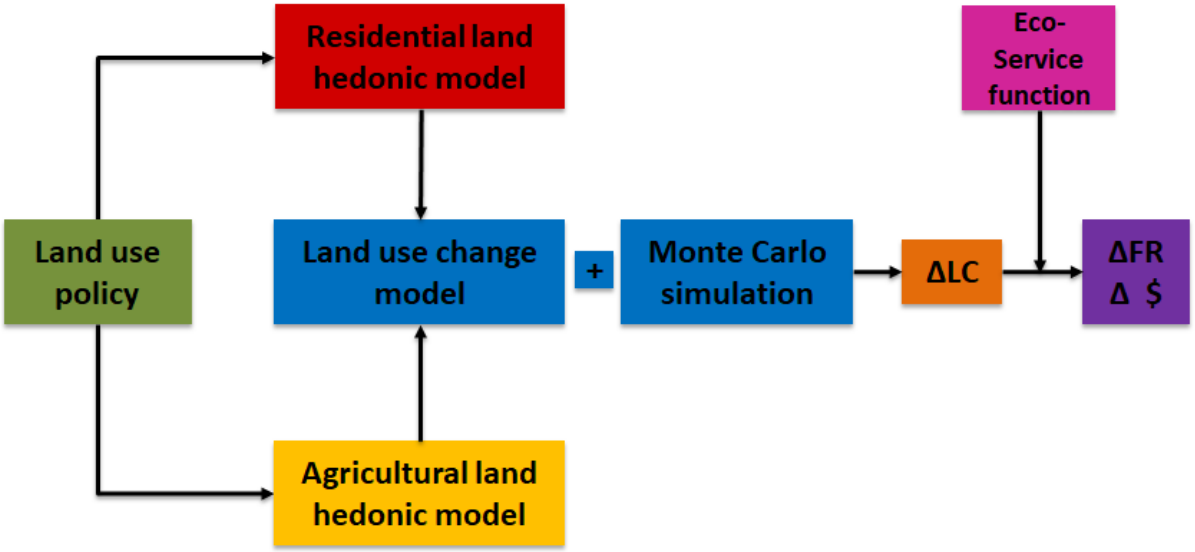

Figure 1.1: Analytical framework. The results from separate hedonic models of land value inform a model of land use change that is used in Monte Carlo simulation to generate future landscapes. Future landscapes may exhibit changes in land cover composition (ΔLC) which in turn influence land values and flood risk indicators (Δ FR) and economic damages from flood events (Δ$). Changes in flood risk indicators are determined using an ecological function that takes as inputs ΔLC. Land use decisions by landowners are influenced by land use policies through their effect on land values.

2 ECONOMIC THEORY AND EMPIRICAL METHODS

2.1 ECONOMIC THEORY

The centerpiece of the analysis is an econometric decision model of land conversion.[1] The decision–makers are risk–neutral, forward–looking owners of private land. Landowners in the model respond to changes in land markets and land attributes that include the capacity of the surrounding landscape to provide protective ecosystem services, such as flood mitigation. Specifically, landowners are responsive to changes in flood risks, which are directly affected by the natural composition of the surrounding landscape. In this model, landowners also develop expectations and make decisions over land use based on existing and potential land use policies.

As put forward by microeconomic theory, rational forward–looking landowners in a deterministic environment decide to convert an undeveloped parcel (e.g., a parcel under agricultural use) to urban uses if the net present value of land when developed is greater than its net present value under current use, net of conversion costs. Here, the net present value of a parcel is defined as the discounted sum of future benefits derived from it.

This study of land use change is primarily concerned with land that is currently undeveloped and which may be converted to residential uses. Thus, in the empirical analysis only two types of land uses are considered: agricultural uses and single–family residential uses.[2] Furthermore, it is assumed that land development is irreversible.

[1] Typically, models of land use change found in the natural resources literature treat urbanization as a phenomenon that naturally occurs in space and depends solely on the distribution of land uses in a given physical space (Irwin, 2010). In contrast, econometric models of conversion link physical changes in the landscape to behavioral motives. In other words, the latter treat urbanization as the aggregation of individual decisions rather than the simple result of a dispersion process. Therefore, they are preferred for economic analyses.

[2] Commercial development is not considered in this study as suburbanization is generally thought to be lead by residential development (Benson, 2009). In addition, by keeping this restriction, the analysis is not subject to inconsistencies between zoning codes and *actual* uses of the land.

More formally, define V_{it}^D and V_{it}^U as the net present value of parcel i under developed and undeveloped uses at time t. Further define the net benefit of developing parcel i in time t, d_{it}^*, to be a latent variable reflecting the difference between these two values, or:

$$d_{it}^* = V_{it}^D - V_{it}^U. \tag{2.1}$$

The latent variable, d_{it}^*, is unobserved by researchers but is assumed to be known by the owner of parcel i. Instead, researchers only observe d_{it}, a binary signal of development that is equal to one if parcel i is developed in time t and equal to zero otherwise, or:

$$d_{it} = \begin{cases} 1 & \text{if } V_{it}^D - V_{it}^U > 0, \\ 0 & \text{otherwise.} \end{cases} \tag{2.2}$$

Under the Random Utility Maximization (RUM) framework, values V_{it}^D and V_{it}^U can be approximated using market prices (which reflect landowners' valuation of property) by decomposing values into an observable deterministic component and a random component that is unobserved by researchers, or:

$$V_{it}^j = \pi_{it}^j(X_{it}; \beta_{it}) + \epsilon_{it}^j, \tag{2.3}$$

where V_{it}^j is the land value under use j (and $j \in \{D, U\}$) and equals a systematic observable component, π_{it}^j, that is assumed to be a linear function of a vector of land attributes and market conditions that drive land value, X_{it}, and an unobservable component, ϵ_{it}^j. The vector of coefficients associated with the factors in X_{it} is β_{it}.

2.2 EMPIRICAL IMPLEMENTATION

Land markets are complex systems that cannot be subject to controlled experimentation. However, combining mechanistic simulation models with statistics to create out–of–sample predictions offers an appealing opportunity to create counterfactuals and gain understanding of land market behavior.[3] In this study, I use market data to estimate separate predictive hedonic models of land value and generate proxies for π_{it}^{D} and π_{it}^{U}. In what remains of this chapter, I present the theoretical and econometric foundations for the empirical analysis that is presented in chapter 4. The discussion on prediction is expanded in chapter 4, where I present the validation technique used to assess the predictive power of the models used to estimate proxies of land value.

2.2.1 PREDICTIVE HEDONIC MODELS OF PROPERTY VALUE

In the econometrics literature, there are two common empirical approaches to specify the inputs in a model of land use choice at the parcel level (i.e., π_{it}^{D} and π_{it}^{U}). First, a land use decision model can be specified directly as a function of parcel characteristics, which serve as proxies for the underlying returns to different uses (Lubowski et al., 2008). Alternatively, when certain parcel–level data are not available, researchers can model the land use change process as an explicit function of the average economic returns to different uses in the county where each parcel is located (Lewis and Plantinga, 2007; Lewis, 2011).

I follow a third modeling strategy: a two–stage approach where proxies for land values are estimated using hedonic price models in a first–stage, and then the resulting predicted

[3]This is an increasingly popular approach to model behavior when experimental methods of science cannot be used to generate a control group against which to test a hypothesis, or when there is missing data that impedes meeting the common support condition for hypothesis testing. Recent research has been shown that it is not only to be valid but also preferable, under certain conditions, than alternative methods such as the use of randomized control trials (Antle, 2018).

values, $\hat{\pi_{it}}^D$ and $\hat{\pi_{it}}^U$, are used in a second–stage as the inputs for a model of land use change. This two–stage strategy was first proposed by Bockstael (1996) and later implemented by Newburn et al. (2005, 2006), Wrenn and Irwin (2012), Bigelow (2015), and Bigelow et al. (2017).

This modeling strategy is chosen for several reasons. First, the two–stage approach incorporates strengths of the other two: it accommodates fine–scale heterogeneity in land characteristics, as does the method used by Lubowski et al. (2008), while also providing an explicit measure of economic returns to land, as accomplished by the use of county–level data on land productivity. Second, to examine benefits and costs of different land use policies in monetary terms, a measure of land value for each parcel is required and provided with this approach. Third, the two–stage approach facilitates the analysis of simulated scenarios that incorporate price instruments designated to affect land use decisions. Finally, because sales prices are observed at higher frequencies than land use changes, there are efficiency gains in using prices as proxies of land values instead of reduced–form estimates of land rents in the land use change model (Bigelow, 2015).[4]

While the two–stage approach has many benefits, it creates a problem: that of unobserved counterfactuals. When using price data, a parcel's value is only observed when a market transaction occurs. Moreover, sales prices are only observed at the time of sale and only for one type of land use. For instance, if an agricultural parcel sells and is converted to an urban use, the price reflects the value of that parcel in development, or π_{it}^D. In this case, π_{it}^D is observed but the value of the land if it had remained undeveloped is not observed (i.e., π_{it}^U is not observed). Conversely, if an undeveloped parcel sells and is not converted to an urban use, the π_{it}^U can be inferred from the observed sales price but the value of the land if it had developed, π_{it}^D, is not observed.

[4]Bigelow (2015) also finds that the efficiency gap widens as the likelihood of development is reduced.

Because only one state of the world is realized, for every parcel that sells, one of the two values, π_{it}^D or π_{it}^U, must be estimated and the estimation is made more or less complex depending on the land uses prior and after an observed sale. Only two types of sales are observed in transaction data:

1. An undeveloped parcel j can be sold and remain undeveloped after the sale. In this case, the sales price of the parcel is not actually equal to the value of the land in undeveloped uses at the time of the sale, π_{jt}^U. Instead, the observed sales price, P_{jt}^U, represents the undeveloped value of the parcel's land plus the net present value of future rents derived from the parcel if it were to be developed in the future (i.e., the parcel's option value). The decomposition of the sales price for parcel j is:

$$P_{jt}^U = \int_0^{t^*} R_{jt}^U \, dt + \int_{t^*}^{\infty} R_{jt}^D \, dt, \tag{2.4}$$

   where R_{jt}^U and R_{jt}^D are the net expected economic returns to undeveloped and developed uses of parcel j in time period t, and t^* is the optimal time for development.

2. A developed parcel k can be sold and remain developed after the sale. In this case, the observed sales price reflects the value of the parcel in a developed use plus the value of the buildings or other structures in the parcel at the time of sale. The decomposition of the sales price can be shown as:

$$P_{kt}^D = \int_{t^*}^{\infty} R_{kt}^D + B_{kt} \, dt, \tag{2.5}$$

   where R_{kt}^D are economic returns to developed uses of parcel k in time period t, t^* is the optimal time for development, and B_{kt} is the value of buildings in the parcel.

While a third case exists, the case of an undeveloped parcel that is developed immediately after being sold, it is not easily obtained from observed transactions. In this case, the observed sales price of undeveloped parcel i, P_{it}^{U}, represents the value of the undeveloped parcel under developed uses, or π_{it}^{D}. To retrieve π_{it}^{D} from these type of transactions, it is required to obtain historical layers of parcel boundaries and determine whether each parcel can be tracked back in time in order to collect information about its original sale before any subdivision or consolidation. The process of matching parcels is cumbersome and typical recording methods may make potential estimation problematic.[5] Thus, while a third case is in theory observable, in practice, it is too costly to pin down. Fortunately, this study is not concerned with the subdivision of parcels. Thus, attending to case three is outside the scope of this research.

To understand how π_{it}^{U} and π_{it}^{D} are inferred from sales prices using the hedonic method, consider the first of the two cases introduced in this section: the case of undeveloped parcels that remain undeveloped after being sold. Under the hedonic framework, land values can be decomposed into attributes that explain the variation in land prices.[6] These attributes can be classified as structural characteristics of improvements on the

[5]It is a protocol of GIS offices to assign a new unique parcel identification number whenever a parcel is established by means of consolidation. In turn, the standard way in which GIS offices keep record of parcels that originate from the subdivision of a parent parcel is slightly more complicated. For example, if parcel A got subdivided into two parcels in 2011, a 2012 parcel layer registers one of the new parcels as B and the other one will maintain the original identifying code, A. The 2012 records will contain updated parcel properties such as size and assessed value in spite of having *recycled* the parcel identification code. Therefore, parcel A in 2011 may be completely different from parcel A in 2012. The fact that two parcels that are fundamentally different are recorded as the "same"observation may be a problem for estimation.

[6]The hedonic method is a revealed preference approach for recovering the implied value of the individual attributes that compose a heterogenous or differentiated good (Taylor, 2003). The founding idea of this modeling approach is that consumers purchase the bundle of attributes that make up such good and not the good itself. Thus, it is the variation in the product what gives rise to variations in product prices. Sherwin Rosen (1974) consolidated the economic foundations of the hedonic method by showing how regressing product prices on their attributed could reveal consumers' willingness–to–pay for a marginal change in a continuous attribute of a differentiated product. Today, the hedonics method is the workhorse of modern empirical revealed preference research, and applications in the environmental and resource economics field are abundant.

land (e.g., houses and barns and their area); land characteristics (e.g., quality of soils, slope, and elevation); and geospatial characteristics (e.g., distance to major cities or to a particular environmental amenity, and spatial features of surrounding land, such as flood prevention capacity of the landscape). Hence, the sales price of an undeveloped (or agricultural) parcel can be expressed as:

$$P_{jt}^{U} = P^{U}(S_{jt}^{U}, L_{jt}^{U}, G_{jt}^{U}, \nu_{jt}^{U}),$$

where P_{jt}^{U}, the sales price of an undeveloped parcel, is a function of structural and building characteristics, S_{jt}^{U}, land characteristics, L_{jt}^{U}, and geospatial attributes, G_{jt}^{U}. The term ν_{jt}^{U} represents uncertainty over how the price of agricultural parcels is developed.

Intuitively, the price schedule for undeveloped parcels is likely to depend mostly on biophysical and location characteristics of the land. Land characteristics that are expected to affect the value of agricultural land include slope, elevation, and size of the parcel. In turn, geospatial characteristics that generally impact agricultural land values include distance to processing facilities (i.e., paper mill facilities), distance to major road networks, percentage of surrounding land that is developed, percentage of surrounding area devoted to conservation, and whether or not parcels are inside the 100–year inundation plain. These characteristics may or may not vary over time.

Under a linear specification, the price equation for undeveloped parcel j at time t is:

$$P_{jt}^{U} = \alpha^{U} + \varphi_{j}^{U} + \tau_{t}^{U} + \beta_{S}^{U} S_{jt}^{U} + \beta_{L}^{U} L_{jt}^{U} + \beta_{G}^{U} G_{jt}^{U} + \nu_{jt}^{U}, \tag{2.6}$$

where α^{U} is an intercept term, φ_{j}^{U} captures fixed effects specific to the census tract where parcel j is located, τ_{t}^{U} is a vector of time dummies that captures year–specific

fixed effects. Vector S_{jt}^U contains building characteristics of barns or farm equipment, vector L_{jt}^U includes land features, and vector G_{jt}^U includes geospatial attributes such as proximity to markets. In addition, since a portion of agricultural land sales prices is attributable to expected future returns to land development, G_{jt}^U may encompass factors that also impact the value of parcels in developed uses, such as density of development in the parcel's surrounding area. Finally, ν_{jt}^U represents the error term.

The estimation of the hedonic function (2.6) may be used to predict the agricultural land values for all parcels in the landscape. First, predicted values, $\hat{P}_{jt}^U$, directly serve as the proxy of agricultural value of land for parcels that are currently undeveloped, or $\widehat{\pi_{jt}^U}$. In addition, the estimated coefficients, $\hat{\beta}^U$, can be used together with complementary information on parcels that are currently developed to construct $\tilde{P}_{kt}^U$, a proxy of the agricultural value of residential parcels, or $\widehat{\pi_{kt}^U}$. Formally, the proxies for π_{it}^U are:

1. For parcels that are currently undeveloped, $\widehat{\pi_{jt}}^U$ is the predicted land price that results from estimating of (2.6), or:

$$\widehat{P_{jt}^U} = \widehat{\alpha^U} + \widehat{\varphi_j^U} + \widehat{\tau_t^U} + \widehat{\beta_S^U} S_{jt}^U + \widehat{\beta_L^U} L_{jt}^U + \widehat{\beta_G^U} G_{jt}^U. \tag{2.7}$$

2. For residential parcels, $\widehat{\pi_{kt}^U}$ is constructed by interacting information on the characteristics of residential land that are related the land's agricultural value with coefficient estimates $\widehat{\beta_S^U}$, $\widehat{\beta_L^U}$, and $\widehat{\beta_G^U}$, or:

$$\widetilde{P_{kt}^U} = \widehat{\alpha^U} + \widehat{\varphi_k^U} + \widehat{\tau_t^U} + \widehat{\beta_S^U} S_{kt}^D + \widehat{\beta_L^U} L_{kt}^D + \widehat{\beta_G^U} G_{kt}^D, \tag{2.8}$$

   where S_{kt}^D, L_{kt}^D, and G_{kt}^D are the covariate matrices with information from residential parcels and $\widehat{\beta_S^U}$, $\widehat{\beta_L^U}$, and $\widehat{\beta_G^U}$ are coefficients that correspond to those in (2.7).

It is worth noting that the predicted agricultural land values generated from estimating hedonic price models are not equivalent to predicted agricultural land rents.[7] Predicted land values are greater than predicted agricultural rents by the amount equivalent to the option value of developing agricultural parcels. Thus, studies that are concerned with estimation of agricultural land rents generally take additional corrective measures to back up from estimated sales prices the portion of agricultural land values that is attributable to potential land development in the future (i.e., the option value component), for instance by manually altering variable related to the land's option value (e.g., setting distance to an employment center or an urban are equal to infinity). However, my study is not concerned with agricultural rents but with agricultural land values in a setting where landowners' expectations about costs and future returns to development are dynamic. Thus, deflating predicted agricultural land prices by the option value would result in over–predicting the probability that agricultural land is developed in the next period rather than later in the future (given that its value in undeveloped uses is lower by the option value amount). Essentially, setting option values equal to zero means that landowners have no reason for waiting to develop their lands. In my research, this is an important consideration because a biased probability value would lead to the generation of future urban scenarios that are not consistent with current market expectations.

To finalize the first–stage analysis of the two–step land use change model, it is required to construct proxy measures of residential land value, π_{it}^{D}, for all developed parcels and all agricultural parcels in the sample. This is done using sales prices of developed parcels through a natural extension of the process described above. To dissect the generation of proxy measures of π_{it}^{D}, examine case (2): the case of developed parcels that remain developed after the sale. Here, sales prices reflect the developed value of land.

[7]Note that (2.7) is also applied out–of–sample to undeveloped parcels which have not sold.

A linear specification of the price function, P^D_{kt}, shows:

$$\begin{aligned} P^D_{kt} &= P^D(S^D_{kt}, L^D_{kt}, G^D_{kt}) \\ &= \alpha^D + \varphi^D_k + \tau^D_t + \beta^D_S S^D_{kt} + \beta^D_L L^D_{kt} + \beta^D_G G^D_{kt} + \nu^D_{kt}, \end{aligned} \tag{2.9}$$

where S^D_{kt} is a vector with structural or building characteristics of developed parcels, such as residential square footage, number of bedrooms, and number of bathrooms; L^D_{kt} contains land characteristics, such as parcel size and elevation; and G^D_{kt} represents geospatial characteristics, such as proximity to major cities and environmental amenities, or urbanization density in the surrounding neighborhood. Similarly to (2.6), α^D is an intercept term; φ^D_k captures block group fixed effects; β^D_S, β^D_L, and β^D_G are vectors of coefficients corresponding to the covariate matrices S^D_{kt}, L^D_{kt} and G^D_{kt}; and ν^D_{kt} is the error term.

To retrieve $\widehat{\pi_{kt}}^D$, the hedonic price function in (2.9) is estimated using data from developed parcels and the component $\int_{t^*}^{\infty} B_{kt}\ dt$ in (2.5) is netted out from the fitted values by manually setting the value of the corresponding coefficients equal to zero. The resulting estimate, $\widehat{P_{kt}}^D$, is used as a proxy of π^D_{kt}. In turn, to construct proxies of π^D_{jt} for parcels that are in agricultural use, their information about factors in the covariate matrices S^D_{kt}, L^D_{kt}, and G^D_{kt} is used together with the coefficients derived from estimating equation (2.9), or $\widehat{\beta^D_S}$, $\widehat{\beta^D_L}$, and $\widehat{\beta^D_G}$.

The constructed proxies for π^D_{it} are:

1. For parcels that are currently in residential uses, $\widehat{\pi_{kt}}^D$ is the predicted value estimated by (2.9), or:

$$\widehat{P^D_{kt}} = \widehat{\alpha^D} + \widehat{\varphi^D_k} + \widehat{\tau^D_t} + \widehat{\beta^D_S} S^D_{kt} + \widehat{\beta^D_L} L^D_{kt} + \widehat{\beta^D_G} G^D_{kt}. \tag{2.10}$$

2. For parcels that are currently in agricultural uses, $\widehat{\pi_{jt}}^D$ is constructed using coefficient estimates $\widehat{\beta_S}^D$, $\widehat{\beta_L}^D$, and $\widehat{\beta_G}^D$ together with information on characteristics that determine the developed value of land, or:

$$\widetilde{P_{jt}^D} = \widehat{\alpha^D} + \widehat{\varphi_j^D} + \widehat{\tau_t^D} + \widehat{\beta_S^D} S_{jt}^U + \widehat{\beta_L^D} L_{jt}^U + \widehat{\beta_G^D} G_{jt}^U, \tag{2.11}$$

where S_{jt}^U, L_{jt}^U, and G_{jt}^U are covariates corresponding to $\widehat{\beta_S^D}$, $\widehat{\beta_L^D}$, and $\widehat{\beta_G^D}$. Again, coefficients from (2.10) are combined with characteristics of agricultural land to determine the land's value in residential uses. Naturally, some components of the coefficient vector in (2.10) are not used as they are unavailable for the sample of undeveloped parcels (e.g., size of residential building).[8]

2.2.2 CHOICE MODELS OF LAND USE

The prediction of alternative land values for each parcel in the sample concludes the first–stage of the land use analysis. In a second stage, these predictions are directly used as inputs of a discrete binary decision model of land use to approximate π_{it}^U and π_{it}^D.

As shown in equation (2.1), landowners in the model convert an agricultural parcel to residential uses if development yields the greater net present value of the land, or:

$$d_{it} = \mathbf{1}[V_{it}^D > V_{it}^U],$$

where V_{it}^D is the expected net present value of parcel i under developed uses, net of conversion costs, and V_{it}^U is the expected value of parcel i under agricultural uses.

[8]Recall that in estimating the developed land value of residential parcels, factors related to structural characteristics were netted out so that the predicted value would reflect the value of land rather than the value of land plus improvements.

For estimation of the land conversion decision model, I rely on the RUM framework as it accommodates incomplete information about private returns (Lewis, 2010). As in equation (2.3), values of a parcel under use j (where $j \in \{D, U\}$) can be decomposed as:

$$V_{it}^{j} = \pi_{it}^{j}(X_{it}^{j}; \beta_{t}^{j}) + \epsilon_{it}^{j}.$$

The covariates vector X_{it}^{j} contains variables determining the value of land in use j. Some characteristics in X_{it}^{j} will influence a parcel's value in both undeveloped and developed states, such as elevation, slope, lot size, and proximity to a major road. Other covariates will pertain only to undeveloped parcels, such as proximity to agricultural markets and processing facilities. Conversely, some covariates will only be relevant for residential parcels, like number of buildings in the lot and their characteristics, or proximity to employment centers and to recreational amenities.

Given a functional form for $\pi_{it}^{j}(\cdot)$ and an assumed distribution for ϵ_{it}^{j}, a probabilistic model of parcel development can be formulated as follows:

$$\begin{aligned} Pr(d_{it} = 1) &= Pr(V_{it}^{D} > V_{it}^{U}) \\ &= Pr(\pi_{it}^{D}(\cdot) + \epsilon_{it}^{D} > \pi_{it}^{U}(\cdot) + \epsilon_{it}^{U}). \end{aligned} \tag{2.12}$$

Rearranging terms and gathering the random components, equation (2.12) becomes:

$$Pr(d_{it} = 1) = Pr(\pi_{it}^{D}(\cdot) - \pi_{it}^{U}(\cdot) > \mu_{it}). \tag{2.13}$$

Equation (2.13) formalizes the land use choice problem and its estimation results in a 2×2 matrix with transition probabilities at time t for each parcel i, m_{it}. The elements in m_{it}, correspond to the probability that a parcel remains undeveloped if its current use

is agricultural $(1-\delta)$; the probability that it develops if originally undeveloped (δ); the probability that it becomes agricultural if currently developed (γ); and the probability that it remains in residential uses if currently developed $(1-\gamma)$. Since development is assumed to be irreversible, γ is assumed to be 0, and thus, $1-\gamma$ is equal to 1.

The resulting transition probability matrix for parcel i and time t, m_{it}, is:

$$m_{it} = \begin{bmatrix} 1-\delta & 0 \\ \delta & 1 \end{bmatrix}$$

The key for parameterizing the landscape simulations that will be used to compare potential future policy scenarios is δ, and its econometric estimation is done using familiar binary or multinomial discrete choice procedures where a categorical variable representing land use is a latent dependent variable hypothesized to depend on the expected net returns from current and alternative land uses. Depending on how the model is specified and the assumptions about the distribution of the error term, the model can be estimated using poisson, probit, logit, conditional logit, random parameters logit, and proportional hazard procedures. These models can be specified to represent decisions at the intensive margin in addition to land use decisions at the extensive margin, and to accommodate spatial and temporal autocorrelation in the data. Ultimately, the choice of estimator largely depends on the structure of the data and to the advantages of different estimators.

There are two estimators found in the recent literature that seem well suited for the problem at hand: the proportional hazards or duration model (also referred to as Cox's regression estimator), and the conditional logit estimator.[9] In a proportional hazards

[9]Other estimators found in the literature include the fixed effects linear probability estimator (Bigelow et al., 2017), the pooled logit (Bigelow, 2015), the random parameters or mixed logit (Lewis et al., 2011), a convolution of probit and poisson estimators (Lewis, 2010), the nested logit (Lubowski et al., 2008), the conditional or fixed effects logit (Lewis and Plantinga, 2007), the multinomial logit

model, the duration for which a parcel has been in an undeveloped state influences the estimated probability of development. Thus, unlike the conditional logit, it allows to directly incorporate temporal considerations into the model of land conversion.

In this research, I use the results from a proportional hazard estimation to build the scenario comparison analysis that will be presented in chapter 5. However, given the prevalent use of the conditional logit in the land use literature, as a robustness check, I estimate the land use model using the more familiar conditional logit. The results of that model are presented in the appendix.[10]

The proportional hazards model

The proportional hazard model is part of a wider branch of statistics called survival analysis, which predicts the amount of time until a certain event event occurs, such as death or land use conversion. In a hazard modeling framework, the distribution of the duration of a parcel in an undeveloped state is described in terms of hazard function. In the land use change context, a hazard function shows the conditional probability that a parcel gets developed between time t and time $t+\Delta t$, given that it has not been developed prior to t. The hazard function is defined at every point in time (t) and is interpreted as the rate at which development occurs (h_t), or:

$$h_t = \lim_{\Delta t \to 0} \frac{Pr(T < t + \Delta t | T \geq t)}{\Delta t}, \tag{2.14}$$

where T denotes the random variable representing the time spent in a given state. In this case, is refers to how long a parcel has remained undeveloped.

(Newburn et al., 2006), the proportional hazard or Cox regression estimator (Irwin et al., 2003; Towe et al., 2008), and the probit estimator (Bockstael, 1996).

[10]Bigelow (2015) offers a comprehensive review of the literature on land use change using logit models.

A hazard function is also the derivative of a survivor function S_t. A survivor function is the probability that an event (e.g., development of a parcel) does not occur until after period t, and it is equivalent to $1 - Pr(T \leq t)$, or $Pr(T > t)$, where $Pr(T \leq t)$ is the probability that the duration is less than t, or the cumulative distribution function of T, or of how long a parcel remains undeveloped.[11]

The survival function is also related to the cumulative hazard or integrated hazard function, Λ_t, which shows the expected number of events (in this case developments) for a given set of covariates at a particular time and is equal to $-\ln S_t$, or equivalently, $S_t = \exp(-\Lambda_t)$. With discrete data, $S_t^d = \prod_{j|\leq t}(1 - h_j)$, and the discrete probability development occurs at t_j (or that the time spent undeveloped is t_j) is $h_j S_{t_j}^d$.

Various assumptions can be made about the distribution of the impact that factors affecting S_t have on h_t. In a proportional model, which is perhaps the most widely used formulation in regression analysis of durations, only the effects of covariates are parameterized, and the hazard function is left unspecified. The most common assumptions are for the covariates to be associated exponentially related to h_t and for the change in risk associated with a change in a particular covariate to be constant for all time durations T. This model is called the Cox proportional hazards model. Cameron and Trivedi (2005) provide a thorough derivation and discussion of this model.

Assuming that changes in risk are constant across T, implies that the length of the duration between events of development does not make a difference in calculating the likelihood that a given parcel develops. In other words, if a parcel has a risk of development at some initial time point is twice as high as that of another parcel, then at all later times the risk of development remains twice as high.

[11] The survivor function is monotonically declining from one to zero (since the cdf $Pr(T \leq t)$ is monotonically increasing from zero) so that if all undeveloped parcels at risk of being developed eventually do so, then $S_\infty = 0$. Otherwise, $S_\infty > 0$ and the duration distribution is called defective.

When the proportional hazard assumptions are imposed, (2.14) can be written as:

$$h_t = h_{0t} \cdot \exp(X^{'}\beta), \tag{2.15}$$

where h_t is the hazard function (or rate) determined by a set of covariates X; h_{0t} is a baseline hazard rate (an intercept–like term that describes the risk for parcels with covariates X equal to zero); and β is a vector of coefficients that measure the impact of covariates. The survival function accompanying the rate expressed in (2.15) is:

$$\begin{aligned} S_t &= \exp\Big(-\int_0^t h_t dt\Big) \\ &= \exp\Big(-\int_0^t h_{0t}\exp(X^{'}\beta)dt\Big). \end{aligned} \tag{2.16}$$

The proportional hazards assumptions are particularly advantageous because they allow a semi–parametric estimation of (2.15) without requiring to specify a form for h_{0t} or having to impose any assumptions about the distribution of T (Irwin et al., 2003). However, to conduct counterfactual simulations of development probabilities, it is necessary to recover a baseline hazard estimate suitable for projecting future development likelihood under baseline conditions. Appendix G discusses baseline hazard estimation.

To estimate the parameters in (2.15), the partial likelihood function of the proportional hazard rate function, or L_p, is minimized. In this study, L_p is the joint product of the probability that an undeveloped parcel develops at time t_j over k time periods:

$$\begin{aligned} L_p &= \prod_{j=1}^{k} \Pr[T_j = t_j \mid j \in R_{t_j}] \\ &= \prod_{j=1}^{k} \frac{\prod_{m \in D_{t_j}} \exp(X^{'}\beta)}{\Big[\sum_{l \in R_{t_j}} \exp(X^{'}\beta)\Big]^{d_j}}, \end{aligned} \tag{2.17}$$

where t_j=$\{t_1, t_2, ..., t_k\}$ denote observed discrete times where development occurred; D_{t_j} is the set of parcels that develop at time t_j, R_{t_j} is the set of parcels at risk of developing at time t_j; and d_j is the number of parcels that develop at time t_j.

The partial log–likelihood corresponding to (2.17) is defined by:

$$\begin{aligned} \ln(L_p) &= \sum_{j=1}^{k} \Bigg[\sum_{m \in D_{t_j}} \ln(\exp(X'\beta)) - d_j \ln \Big(\sum_{l \in R_{t_j}} \exp(X'\beta) \Big) \Bigg] \\ &= \sum_{j=1}^{k} \Bigg[\sum_{m \in D_{t_j}} (X'\beta)) - d_j \ln \Big(\sum_{l \in R_{t_j}} \exp(X'\beta) \Big) \Bigg]. \end{aligned} \tag{2.18}$$

The results from minimizing (2.18) are the estimates of the β coefficients in (2.15).[12] These coefficients are interpreted similarly to how coefficients are interpreted in conventional logistic models, with the difference that in a logit model coefficients refer to some odds ratio while here they refer to the ratio of hazard rates, or the hazard ratio.[13]

Specifically, a hazard ratio is quantity $\exp(\beta_k)$, and it indicates the relative risk of development associated with a unit change in characteristic X_k. A value of β_k greater than zero, or equivalently a value of $\exp(\beta_k)$ greater than one, indicates that the event hazard increases as the value of the kth covariate increases. Put another way, a value of $\exp(\beta_k)$ above one indicates a covariate that is positively associated with the event probability (i.e., the probability of development), and thus negatively associated with the length of time a parcel remains in an undeveloped state.[14] It follows that $\exp(\beta_k) = 1$

[12]This partial-log likelihood stems from a standard approximation of $\Pr[T_j = t_j | j \in R_{t_j}]$ that allows for the specification of a tractable likelihood (Cameron and Trivedi, 2005).

[13]Hazard ratios differ from relative risks and odds ratios in that the latter are cumulative over an entire study, using a defined endpoint, while hazard ratios represent instantaneous risk over the study time period, or some subset thereof. Generally, it is thought that hazard ratios suffer somewhat less from selection bias with respect to the endpoints chosen and can indicate risks that happen before the endpoint (Hernan, 2010).

[14]For example, in a drug study, the treated population may die at twice the rate per unit time as the control population. The hazard ratio would be 2, indicating higher hazard of death from the treatment.

means the covariate has no effect on the probability of development, and that $\exp(\beta_k) < 1$ means the covariate is associated with a reduction in the hazard.

The hazard rate shown in (2.15) is not a density or a probability, but rather the marginal percentage change in risk per unit time. However, output from the estimation of a proportional hazard model can be manipulated to derive probabilities of development. In the appendix, I include a brief explanation on the methods used to obtain the development probabilities from the hazard model estimates.

Modified for the context of this dissertation, $\exp(X'\beta)$ becomes $\exp(\beta_D \pi_{it}^D + \beta_U \pi_{it}^U)$, where π_{it}^D and π_{it}^U are the alternative values of parcel i, and β_D and β_U are the associated coefficients. In this case, $\exp(\beta_D)$ is expected to be greater than one, and $\exp(\beta_U)$ is anticipated to be less than one. The exponentiated coefficients are interpreted as follows:

- $\exp(\beta_D) = \frac{h_t(t|\pi^D+1)}{h_t(t|\pi^D)} = 1 + \alpha$, implying that a one unit increase in the developed value of a parcel increases the hazard ratio by a factor of $1 + \alpha$, therefore leading to an $\alpha \times 100\%$ increase in the relative hazard rate of development, holding π^U constant; and

- $\exp(\beta_U) = \frac{h_t(t|\pi^U+1)}{h_t(t|\pi^U)} = 1 - \alpha$, which implies that a one unit increase in the undeveloped value of a parcel increases the hazard ratio by a factor of $1 - \alpha$. In other words, a unit change in π^U leads to an $\alpha \times 100\%$ decrease in the relative risk of development, holding π^D constant.

Or in another study, men receiving the same treatment may suffer a certain complication ten times more frequently per unit time than women, giving a hazard ratio of 10.

3 DATA

To estimate the land use change models that are a core component of this research, I use the predictions of land values generated in a first stage analysis as explanatory variables in a second stage probabilistic model of land development. The value of undeveloped land in development is estimated using statistical property–value models (i.e. hedonic models) that incorporate information from multiple sources on parcel characteristics such as land market characteristics, characteristics of buildings on the land, and geospatial features of the parcel and its surrounding area. The area of focus of this study are three coastal counties of South Carolina that encompass the Charleston metropolitan area—a region naturally endowed with ecosystems that have the capacity to deliver flood prevention services, and that is also subject to rapid urbanization and rising threats from flooding.

This chapter is organized as follows: first, I describe the study area and give an overview of recent local trends of urban and climatic forces. Next, I describe the procedure used to arrive at the final parcel samples used to estimate the predictive hedonics models and the subsequent models of land conversion. Third, I present and discuss features of the data used to conduct each of the two components of the empirical analysis: the predictive hedonic models and the landscape simulations procedure. The description of the data used to estimate the hedonic models is separated into land market characteristics of residential parcels, and drivers of value in agricultural lands. This discussion is complemented with corresponding tables of summary statistics. In a fourth section of the data chapter, I include a supplementary discussion on the data and methodology used to develop a measure flood risk at the parcel level, a key variable required for the landscape simulations procedure. A full list of the sources of data is presented in the appendix table A.1.

3.1 STUDY AREA

For the empirical analysis, I use data from three coastal counties in South Carolina that surround the Charleston metropolitan area: Charleston, Berkeley, and Georgetown. These counties are part of what is known as "the Lowcountry,"a region along the coast of South Carolina that is well known for its historic legacy, cultural importance, natural environment, and fast–growing economies. Figure 3.1 shows the study area, including county boundaries, major streams and rivers, and county seats.

The major forces driving increased flooding and increased damages from floods in the study area are urban and climatic pressures. In this section of the data chapter, I provide a brief description of general socioeconomic trends in South Carolina followed by some observations on the economic outlook for each county in the study area. I also give a synthesis of historical flood and storm data for South Carolina, and describe recent trends in flooding pressures in the study area and how they compare to the occurrence of flooding events in South Carolina.

3.1.1 LOCAL URBANIZATION TRENDS

The US Census identifies urban areas along coastal watershed counties in the Southeastern US to be among the fastest–growing areas in the country (US Census, 2015). Like other coastal areas in South Carolina, two of the counties being analyzed, have seen a rapid increase in urbanization in the last decade. Between 2010 and 2016, the urban population increased by 12.9% in Charleston and 17.8% in Berkeley, outpacing the nation's overall growth rate of 9.7 percent for the same period. However, in Georgetown, urban population growth was much slower, at 2.1%.[1]

[1]For reference, the nation's urban population increased by 12.1 percent from 2000 to 2010.

Domestic migration and the influx of seasonal residents are important factors behind this large population growth. As such, changes in local property markets closely reflect the preferences of retirees, tourists, and visitors (NOAA, 2016). In recent years, there has been a rapid increase in development of infrastructure to support tourism and retirement communities, and much of that new development has occurred near or on the coast. In fact, according to the latest Census, coastal counties in South Carolina lead the national statistics on both absolute and relative increases in seasonal housing units among coastal counties. In 2010, South Carolina had the third largest share of seasonal housing units in the nation (12%), an important change since the 2000 Census when SC was not even among the top six states in regards to seasonal housing (NOAA, 2013).

Figure 3.2 shows a map of housing unit growth from 1990 to 2016 by census track in the three counties that conform study area. Panel (a) in figure 3.2 shows the number of structures built after 1990 recorded in the 2016 American Community Survey (ACS), and panel (b) shows the percentage growth in housing stock from 1990 to 2016. As shown by the figure, new development is concentrated around urban centers and near the coast, which is consistent with national trends of urban growth.[2]

Figure 3.3 compares the growth in development among counties by examining the total annual number of building permits issued each year by county.[3] The figure makes apparent that Charleston county issues the most number of building permits, followed by Berkeley county.[4] The differences in construction activity shown in figure 3.3 reflect

[2]NOAA identifies 672 coastal counties in the US, and although these counties make up more or less 25 percent of the country's area, they account for almost 46 percent of development. Recent data shows that between 2000 and 2010, around 1,880 building permits were issued per day in coastal counties while the total building permits issued in inland counties was around 2,160 (NOAA, 2013).

[3]Total permits include single family, all multifamily, 2–unit multifamily, 3– and 4–unit multifamily, and 5+ unit multifamily buildings. The data on issuance of building permits are from the State Of the Cities Data Systems Building Permits Database.

[4]In 2015, there were 175,607 total housing units in Charleston, and the county issued 3,936 new building permits (which constitute around 12.3% of all new permits issued in the state of SC that year).

fundamental differences in local demographic and socioeconomic conditions among the three counties. Charleston county is the largest in area and population, has the largest density of housing and average household income, while Georgetown is the most rural, has the lowest population and housing density, and lowest income.

An examination of the most recent national land cover data indicates that much of the new development is dominated by medium and high intensity type of growth, although it is accompanied by growth that is more suburban in nature. Figure 3.4 shows the most recent land cover survey of the study area.[5] Respectively, open space–, low–, medium–, and high–intensity development cover 3.2%, 2.4%, 1%, and 1.15% of the land in the study area.[6] Figure 3.4 also shows that the predominant land cover classes in the study area are woody wetlands, evergreen forests, and emergent herbaceous wetlands, which respectively cover 36%, 31%, and 13% of the study area. Pastures, herbaceous, and cultivated crops lands are concentrated towards the northwest edge of the studied region, and together constitute 6% of the area of interest. The remaining 6% is covered by open water.[7]

Table 3.1 presents change in land cover composition in the three counties between 2001 and 2011 and makes clear that decreases in forest covers, pasture lands, and woody wetlands are likely giving way to the observed increase in medium– and high–intensity

That year, there were 76,503 housing units in Berkeley and 33,930 in Georgetown. Respectively, these counties issued 1,960 and 299 new building permits.

[5]The data used to generate figure 3.4 comes from the National Land Cover Database (NLCD), a land cover database containing 30m resolution normalized imagery for the years 2001, 2006, and 2011. The land cover data are divided into 21 classes.

[6]Areas with mostly vegetation in the form of lawn grasses such as as local parks, golf courses, or large–lot single family parcels, are considered open space development. In these areas, less than 20% of the total cover is accounted for by impervious surfaces. Low intensity development areas are those most commonly used in single–family housing units, where impervious surfaces generally account for 20% to 47% of total cover. Medium intensity development areas, are most commonly single–family units where impervious surfaces account for 50% to 79% of the total cover. In turn, high intensity development areas are where people reside or work in high numbers and where impervious surfaces account for more than 70% of the total cover (e.g., apartment complexes).

[7]The main inland water bodies are Lake Marion and Lake Moultrie, covering over 170,000 acres.

development land uses. Table 3.1 also shows that forest lands were consistently developed at larger rates than agricultural lands, and changes from agricultural land (pastures, hay, and crops) to forest were also important. In Charleston county, increases in area covered by developed surfaces are offset by decreases in forest and pasture covers. Interestingly, shifts from low–intensity to high–intensity development between 2006 and 2011 are also observed, as would be expected in exurban development. In Berkeley county, the large increase in medium– and high–intensity development (52% and 48%, respectively) is accompanied by a substantial reduction in forest (8.21%) and woody wetlands covers (1.45%). Finally, in Georgetown, there is an increase in all types of development but there are important changes in agricultural and commercial agricultural covers (pastures, hay, and crops), reflecting the rural character of the county.

3.1.2 HISTORY OF FLOODS IN THE STUDY AREA

In South Carolina, over 320,000 residents live in flood risk areas, which are defined by the Federal Emergency Management Agency (FEMA) as locations that have a 1% or greater chance of being flooded in any given year (these areas are also referred to as being subject to 100–year floods). Flooding is the second most common natural hazard in the state and it affects every county (NOAA, 2013).

In the past 20 years, floods in South Carolina and the study area have increased in frequency, and the costs associated with flood events have also increased.[8] Between 1996 and 2016 there were 1,628 flooding events in South Carolina (i.e., one every 26 hours).[9]

[8]The National Oceanic and Atmospheric Administration (NOAA) National Weather Service (NWS) division keeps a comprehensive database with records on flooding events from 1996 to present.

[9]NOAA defines a flooding event as a smaller geographic area that together aggregate to a specific storm or flood episode (i.e., one flooding episode can impact multiple locations, each of which would be a flooding event). In turn, a flooding episode is defined as any occurrence of storms and other significant weather phenomena having sufficient intensity to cause loss of life, injuries, significant property damage, and/or disruption to commerce. Between 1996 and 2016, there were 677 unique "flooding episodes"(i.e.,

Figures 3.5 to 3.6 show trends in number floods and property damages from floods in South Carolina and the study area, and table 3.2 presents summary statistics from flood events for the three counties in the study area and South Carolina as a whole.[10]

As shown by figure 3.6, the number of flooding events with economic consequences consistently increased over time. In the study area, there were 436 flooding events between 1996 and 2016, which together summed up to almost $28 million in damages—representing 43% of overall property damages from all types of storms in the study area and over 15% of overall property damages from floods in South Carolina since 1996.[11] The storms data does not yet include information from damages caused by the 2017 Hurricane Irma. Noting that, the costliest year for flooding in the dataset was 2015 (see figure 3.6) when a large storm resulted in catastrophic flooding in South Carolina.[12] That year, damages in summed up to $24.75 million—around a fifth of the state's flooding costs.

Figure 3.7 shows the location of flooding events in the study area since 1996 in relation to the parcels available for analysis. It is apparent from this map that there is heterogeneity across parcels in their exposure to flooding risks. Most flooding events occurred in Charleston county (over 75%). Also, damages caused by the average flooding event in Charleston were $4 to $5.25 million higher than in Berkeley and Georgetown.[13]

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one every 10.8 days) in South Carolina.

[10]Flooding events in NWS database include flash floods, floods, and coastal floods. Other types of storms recorded in the database include storm surges or tides, thunderstorms, hurricanes, "heavy rain"and tropical storms. The discussion below focuses only on flash floods, floods and coastal floods.

[11]The 1,628 flooding events experienced in South Carolina since 1996 caused almost $171 million losses in property damages, which is almost 25% of the overall cost from damages caused by all types of storms in the state. In the last 20 years, the state saw 5,898 storms. Of those, 5,815 caused property damages summing up to $687.5 million in damages. The average flood event caused $16.65 million in property damages and the average damage per affecting event was $248,300.

[12]It is worth mentioning that South Carolina has not been directly impacted by a hurricane since Hurricane Hugo in 1989. However, it is not uncommon for large storm systems over the southeaster states to draw moisture from hurricanes and subsequently result in flooding. In fact, South Carolina experienced property damages from floods every year since 1996.

[13]Analyses by NOAA show that regions within the study area that are the most vulnerable to changes in sea level rise are those around the Santee River (on the border between Berkeley and Charleston

3.2 DESCRIPTION OF DATA USED IN ESTIMATION

In the empirical analysis I use data for two different types of analysis: for the hedonic models of land value and for the landscape simulations procedure. In the following sections, I first describe the process used to arrive at the final parcel sample used in estimation of the hedonic models of property value. Then, I present and summarize the data used in the hedonics analysis. Third, I introduce the data used to simulate alternative landscapes and derive measures of relative economic effectiveness for alternative policies. In that section, I focus the discussion on the data used to generate of a flood risk variable (which is used to simulate alternative landscapes) and describe the methodology followed to derive such measure of vulnerability. I also provide summary statistics of the generated flood risk variable and discuss its features. Finally, I include an additional discussion on the types of data that were explored but not necessarily used to derive an estimate of the costs that floods impose on property owners in the study area.

3.2.1 SAMPLE SELECTION PROCEDURE

For the empirical analysis, I construct a dataset with geographical, biophysical, climatic, and socioeconomic data for a subset of all properties in tax assessor databases. Considerable effort was devoted to arrive at the final parcel sample used in estimation as each dataset had to be carefully pre–processed to accurately characterize the use given to each parcel in the study area.

The first step in constructing the final sample of parcels, was to process the 2016 databases provided by each county's tax assessor office. Specifically, duplicated observations, observations with missing parcel identification numbers, and observations with

counties) and the Wadmalaw River (which has its delta 24 miles South of the City of Charleston).

recording errors were removed. Also, when necessary, separate available datasets provided by tax assessor offices were cleaned and merged to the basic dataset with transactions data to create a complete database with zoning information, building characteristics, year of development, and price information. To verify the accuracy of the information in these datasets, complementary GIS parcel layers were used to estimate parcel size for each parcel in the tax assessor data. When appropriate, the area recorded in the tax assessor data was replaced by a more accurate measure of parcel size generated in GIS.

In a second stage, using zoning codes or property class codes, I grouped parcels into four classes: (1) undeveloped, (2) developed residential, (3) developed industrial, commercial, or mixed uses (which include residential properties under apartment complexes, condominiums, row houses, town houses, et.), and (4) public property. Parcels in the latter two groups were not used for analysis.[14]

Figure 3.8 shows the location of parcels in the sample relative to parcels that were not included and are categorized by land use. Figure 3.9 provides supplementary location information. Specifically, panel (a) of figure 3.9 presents the location of only the parcels included in the final sample and indicates whether they were considered developed or undeveloped, and panel (b) shows the location of parcels in the sample relative to land cover classes in the study area. As shown by the figure, the landscape pf parcels left out from the analysis is dominated by public lands, wetlands and marshes, and open water.

Several property class codes were grouped together to represent each of the land uses considered in the empirical analysis: residential uses and agricultural uses.[15] The

[14]Residential development is generally considered the leading edge of development (Benson, 2009). Thus, industrial, commercial and mixed use properties are removed from the data. In addition, by keeping this restriction, the analysis is not subject to inconsistencies between zoning codes and *actual* uses of the land. These inconsistencies are rather common as shown by the tables in Appendix A that present zoning codes from the three counties.

[15]Zoning and property class codes represent the primary land use upon which the tax assessor bases its assessment of the property's value. In general, zoning and land use codes were difficult to organize and

sample of parcels in Charleston county that were selected as developed was restricted to parcels zoned as single family residential and residential development lots. In turn, parcels included in the undeveloped sample were those in vacant residential zones (as long as the parcel's reported building square footage was zero, otherwise, the parcel was considered developed), agricultural districts, and lots occupied by mobile homes. The reason why lots occupied by mobile homes were considered undeveloped is that these are easily removable structures, and are therefore seen as perfect substitutes for vacant lots. Also, to avoid grouping rural homes with undeveloped parcels, I used data on square footage of residential buildings to sort farms from rural homes. Hence, properties in agricultural zones but with residential buildings were considered developed.

To classify data from Berkeley county, an analogous procedure was followed to define the sample of developed residential and undeveloped parcels. Similar to Charleston county, only parcels zoned as single family residential, rural residential, agricultural districts, or lots occupied by mobile homes were considered for the study. To make sure no parcels zoned as commercial, industrial, mixed uses or having multifamily residential structures were included in this sample, the sample of developed parcels included properties with no assessed commercial value and no square footage of commercial buildings. An analogous filter was applied to data from Georgetown county: vacant lots, lots occupied by mobile homes, and agricultural properties with no residential buildings were grouped into the sample of undeveloped parcels. In turn, occupied single family residential properties, resort lots, and villas were considered developed. Publicly owned properties and properties with industrial, commercial, or mixed uses were excluded from both samples.

interpret. In addition, there were several inconsistencies within and across counties making it necessary to recur to some arbitrary selection rule to judge whether parcels were developed or undeveloped. To arrive at a satisfactory decision rule, I studied county land use codes, zoning classifications, and parcel characteristics. At certain points, I used Google Earth to verify the accuracy of these codes.

The third step in constructing the data for this study, was to drop observations from the developed sample with no information on key variables for the analysis, namely information regarding year of construction and basic information on building characteristics. The fourth step was to merge the parcel data with the spatial variables collected from other public sources and the proximity and buffering measures generated in ArcGIS.

The final step was to restrict the sample of parcels used in the predictive hedonics models according to the suggestions derived from a careful model selection process. Figures 3.10 to 3.12 show flow charts with the steps taken in constructing the datasets used in the land use change models and in the first–stage predictive hedonics analysis. The information shown in the flow charts is summarized in table 3.3, which shows the number of parcels in each county that are kept after each of the restrictions in the construction of the dataset is imposed. The final selection for the land use change model had 53,228 undeveloped parcels and 129,634 developed parcels. In turn, the sample for the residential and agricultural hedonic models, which is composed by parcels which sold in recent years and had complete information, had 33,364 and 6,725 parcels, respectively.

Word of caution

Before moving on, it is important to address concerns over making errors in the process of separating developed from undeveloped parcels. A first concern is that of falsely classifying an undeveloped parcel in the sample as developed (i.e., a type I error).[16]

In this analysis, type II errors (i.e., falsely labeling a developed parcel as undeveloped) are not problematic. If type II errors occur systematically, information about residential parcels will contaminate the sample of undeveloped parcels and result in biased predicted

[16] A type I error is to falsely infer the existence of something that is not there, while a type II error is to falsely infer the absence of something that is.

undeveloped values of developed parcels. Since development is assumed to be irreversible in this study, residential parcels are always predicted to develop, regardless of the corresponding predicted values. However, if undeveloped parcels are systematically falsely labeled as developed, the land use change model may mis predict development patterns in the study area. With type I errors, information of agricultural parcels would bias the hedonic analysis of residential parcels and make the resulting predicted developed values of undeveloped parcels more likely to reflect characteristics of undeveloped parcels than of developed parcels. If developed parcels are generally more valuable than undeveloped parcels, the prevalence of type I errors would cause the predicted developed values of undeveloped parcels to be biased downwards, making the predicted probabilities of development artificially smaller. Alternatively, if undeveloped parcels are generally more valuable than developed parcels, the predicted probabilities of development will be biased upwards and the land use change model will over predict development.

Another source of concern is the effect of not including relevant parcels in the sample. Table 3.4 shows vacant lands left out of the estimation sample by zoning or land use code. The table suggests that the majority of vacant lands not considered in this analysis are public lands, parcels that are undevelopable, parcels without a current classification, or parcels that are classified as agricultural but may also serve as residential dwelling. Parcels for which particular spatial data was not available were also left out from the sample. An important number of those are found in the Northeast of Charleston, where data on soil quality was unsuitable for the analysis.

3.2.2 DATA USED IN HEDONICS MODELS

The data used in the statistical property–value models, can be organized in to three general categories: (1) historical sales price data of parcels in the study area; (2) data on

physical structures on land such as number of buildings and their size; and (3) spatially explicit data on parcel characteristics including physical features of the landscape (e.g., type of land cover) and proximity measures (e.g., distance to the shoreline).

Land market data for the hedonic analyses was obtained from county tax assessor databases and county GIS offices (see Appendix table A.1). The data in these databases contain information for every parcel in each county, including lot size, zoning designation, historical transactions data on property sales, and information on multiple characteristics of the physical structures on the lot, like square footage of the house/building, number of rooms, number of bedrooms, and number of bathrooms. Tax assessor data also contain separate assessed values of land and structures for each parcel.

To complement the data contained in tax assessor databases, county GIS offices from Charleston, Berkeley, and Georgetown were contacted to provide snapshots of the counties' most recent parcel layer and for each time period matching the years of the National Land Cover Database products.[17] These GIS and NLCD layers were used in ArcGIS to create multiple time–invariant variables, as well as time–varying proxies representing different physical properties of each parcel. Among the time invariant variables are various measures of distance, such as distance to flood hazard boundaries, distance to water bodies offering recreational opportunities (i.e., big lakes), distance to the nearest public beach access point, distance to downtown Charleston, distance to the shoreline, and distance to the nearest primary or secondary road. Other variables are percentage cover in the parcel and around it of various habitats, such as crops, forests, and wetlands. Finally, all price data in the tax assessor datasets (i.e., sales prices and assessed values) were adjusted for inflation and expressed in 2016 USD using the Housing Price Index for the Charleston market available from the Federal Reserve Bank.

[17]For Charleston County, the 2003 GIS parcel layer is used instead of the 2001 parcel layer.

Summary of data used in the hedonic model of residential land value

There are 33,364 residential parcels available for the hedonic analysis: 16,300 from Charleston, 12,315 from Berkeley, and 3,627 from Georgetown. This is a subset of all the properties listed in the tax assessor databases. I chose a restricted sample of properties that met certain selection criteria set to minimize potential errors in prediction (see section 3.2.1).

There is considerable variability across counties in terms of what data are kept in record by the different tax assessor's offices. Georgetown has the most comprehensive data available on building characteristics (for instance, it contained information on number of fireplaces, kitchen condition, and type of roof cover), while Berkeley only records basic parcel information, such as number of buildings on the parcel. Importantly for the empirical analysis, improvement data is not available in the tax assessor data Berkeley county. This was problematic to the extent that differences in selling prices could be dictated by the quality of the house or building structure on the property. Given that building characteristics could not be included in the model for Berkeley county, assessed values used for taxation purposes were used to approximate the total value of buildings.[18]

Table 3.5 shows descriptive statistics of variables used in the hedonic analysis of residential properties. As shown by table 3.5, there are important differences among residential properties across counties but these differences do not seem to reflect county differences in terms of their level urbanization. Given that urban pressures are large in Charleston, it is not surprising to find average sales prices to be almost twice as high in Charleston than in Berkeley and substantially larger than Georgetown prices. However,

[18]Tax assessor estimates can be inaccurate and may bias estimated coefficients. However, evidence shows that the difference between using sales price and assessed values in hedonic equations is negligible and that the use of assessed values is likely to be affected by few variables, such as whether the building has a central air, a basement, or 5 or more rooms (Ihlanfeldt and Matinez-Vazquez, 1985). Therefore, I will proceed using building assessed values as proxies for improvement characteristics.

given that population growth is much faster in Berkeley, it is odd to find average sales prices to be evidently lower in the faster growing county, although parcels in this county tend to be smaller in acreage and more uniformly distributed (the average residential parcel in Berkeley has an area of 0.3 acres, compared to 0.61 and 0.43 acres in Georgetown and Charleston, respectively). Assessed building values and building size follow a similar tendency to that of prices but it is important to note that the difference between median values in the three counties is much less pronounced for sales prices and assessed values.

In terms of land and geospatial characteristics, Charleston county is the flattest of all counties and has the largest share of parcels within the 100–year flood boundary. However, the distribution of elevation reveals why this region is referred to as "Lowcountry,"as the maximum recorded elevation is 30 meters and an important share of parcels in all counties is inside the flood plain. Although there are no substantial differences across counties in parcels' proximity to roads or rivers, transacted residential parcels in Berkeley county are much further from the coastline, access points to public beaches, and hurricane evacuation boundaries than parcels in Georgetown and Charleston.

In terms of landscape composition, the share of developed cover for the average transacted residential parcel is the lowest in Georgetown county, which also exhibits the largest share of open–space type of developed covers. Low intensity development has a similar presence in all three counties, but medium– and high– intensity development is more prevalent in Charleston and Berkeley counties. Finally, and interestingly for the ecosystem services discussion, there is no difference across counties in average wetland cover.

Summary of data used in the hedonic model of agricultural land value

Agricultural land is the second land use of focus in this study as it is a major land class that is typically converted to residential uses. There are 6,366 agricultural parcels avail-

able for hedonic analysis: 2,041 from Charleston county, 2,366 from Berkeley county, and 1,959 from Georgetown county. Overall, agricultural land characteristics in the sample do not differ greatly throughout time, and even during the recession years, sales prices for undeveloped parcels show much lower levels of variation than sales prices of developed properties. The general trend across the three counties is for prices to increase. Yet, there are some differences between agricultural parcels in these counties.

Table 3.6 presents summary statistics for variables used in the hedonic model of agricultural parcels.[19] As shown by table 3.6, tendencies in sales prices among agricultural parcels do seem to reflect county levels of urbanization. Sales prices in Charleston are the highest, followed by prices in Berkeley and Georgetown. However, in terms of size, transacted agricultural parcels exhibit trends that resemble those those of transacted residential parcels, where there is no clear relationship with the county's level of urbanization. The average parcel in Georgetown county is larger than the average parcel in Charleston and Berkeley counties, and this difference is partly driven by large observations. Similarly to developed parcels, the spread in area among parcels in Berkeley is much smaller than the spread in area among parcels in Charleston and Georgetown.

Like residential parcels, agricultural parcels in all three counties are located in low elevation areas and a substantial share are located within the 100–year flood boundary. In terms of proximity to particular points of interest, agricultural parcels in Berkeley

[19]Statistics presented in table 3.6 pertain to parcels that sold between 2000 and 2016 but not between 2006 and 2009. Information from properties transacted in these years is not used to avoid misleading representations of the underlying forces in the local land market (refer to discussion on model selection in chapter 4). The impacts of the financial crisis are noticeable in transaction data from all counties. For instance, in Charleston county, when crisis years are considered, the share of undeveloped parcels that sold at prices below $5,000 was 47%, which is much higher than in the pre– and post– crisis periods (9%). In Berkley county, 12% of all transactions occurring after 2000, were recorded at prices below $5,000, but less than 0.5% sold at these price ranges before or after the crisis. Finally, in Georgetown county, 42% of transactions occurred below $5,000 in the 2000–and–after period, but before and after the crisis, these percentage was 9% and 13.5%.

and Georgetown do not seem to be much different from residential parcels. However, in Charleston county there are important distinctions between residential and agricultural parcels. For instance, agricultural parcels in Charleston county are almost twice as far from the city center than residential parcels (undeveloped parcels are, on average, 12 miles away from Charleston's city center, while developed parcels are 7 miles away, on average). Similarly, agricultural parcels in Charleston county are much further away from primary or secondary roads than parcels residential parcels (the average distance from an undeveloped parcel to a primary or secondary road in is 1.9 miles, while that distance from residential parcels is 0.86 miles). Agricultural parcels in Charleston county are also further away from paper mills than parcels in the other two counties but this is not striking as Berkeley's and Georgetown's economies have larger lumber sectors.

In terms of landscape composition, there are no substantial differences across counties. Agricultural parcels exhibit larger shares of wetland covers than residential parcels, particularly in Charleston where over a fifth of the area of the average agricultural parcel is covered in wetlands and a mere sixth of the area of the average residential parcels has this land cover. Finally, agricultural parcels have substantially lower shares of developed covers than residential parcels (between 33 and 51 percent instead of 62 to 66 percent).

3.3 DATA USED IN THE LANDSCAPE SIMULATIONS

Three types of data are required to complete the landscape simulations and assign an economic value to potential flood mitigation services that could arise under alternative policy regimes: (1) coefficient estimates derived from second–stage probabilistic models of land development that take as inputs alternative predicted values of agricultural land; (2) a measure of the cost of flooding in terms of property damages; and (3) and measure

of flood risk at the parcel level. In this section, I first include a short description of the data used to estimate average property damages from floods, and then describe the data and methodology used to obtain the parcel–specific measure of flood risk.

3.3.1 DATA ON PROPERTY DAMAGE FROM MAJOR FLOODS

For the average property damage (i.e., $\overline{\text{Damage}}$), I explore three different estimates of average property damage to develop an idea of confidence around existing measures but only one is used in the final calculation of costs and benefits (the role of this measure in the simulations analysis is further discussed in chapters 4 and 5). The explored estimates come from three sources: data from HAZUS®–MH Flood Module, a recent estimate of average flood damages from Hurricane Sandy to residential properties in three coastal counties of New Jersey, and the 2016 average National Flood Insurance Program (NFIP) payment per claim in South Carolina. In 2016 dollars, the three different values used to calibrate the average residential property damage from a major flood are: $273, $22,672, and $24,776. Because in the simulations procedure I use data from the National Flood Insurance Program (NFIP) to approximate flood damages, I will only discuss this data in the main text. However, a thorough description of the data used by the HAZUS–MH Flood model and Loerzel et al. (2017) to derive their estimates of average flood damage to residential properties is included in Appendix B.

South Carolina ranks among the top states in the country in terms of FEMA payments made for insured losses through the NFIP. In 2016 alone, South Carolina was the third state with the largest NFIP claim payments, just behind Louisiana and Texas (payments in 2016 were $139.8 million in SC, $696 million in TX, and $805 million in LA), and as of July 2017, South Carolina was the sixth state with most NFIP policies in force. Between July 2016 and July 2017 (before Hurricanes Harvey, Irma, and Maria), nationally, the

average payment per claim was $31,593, but in SC it was much higher at $38,217.[20] In 2016, there were 5,643 NFIP claims in SC and the amount of claim payments was $139.81 million. Thus, the average NFIP payment per claim in SC was $24,776.[21] In calculating the benefits of implementing land use policies, I use this measure to approximate property costs from flooding.[22]

3.3.2 FLOOD RISK DATA

For the parcel–specific measure of flood vulnerability, I use predicted probabilities of flooding derived from an inundation model that I develop and estimate using data from the most recent large storm events in South Carolina: Hurricane Irma in 2017 and Hurricane Joaquin in 2015.[23] This aspect of my research was developed in partnership with scientists at the South East Climate Adaptation Science Center.[24]

To develop the flood risk variable for each parcel in the sample, I combine information on actual flooding following two severe storm events. Specifically, I use flood inundation maps created by the US Geological Survey (USGS) to model the incidence of Hurricane Joaquin in 2015, and real time simulation models produced by the Coastal Emergency

[20]Between 1978 and June 2017, FEMA payments in SC were over $748 million. Approximately $192 million were sent to Charleston county (roughly 25% of the state's losses). In turn, FEMA paid more than $105 million to Berkeley (14% of the state's claims) and $113 thousand to Georgetown (III, 2017).

[21]For reference, consider that the average NFIP payment nationwide in 2016 was 62,247. However, in the last decade, average claim payouts vary widely from year to year. From $25,133 in 2009 to $83,198 in 2005 (the year of Hurricane Katrina).

[22]NFIP statistics on total claim payments for the 2017 fiscal year at the state level (when Hurricane Irma occurred) are not yet publicly available as some payouts are still being processed. Thus, data on 2016 claim payments are used. For reference, in 2017, the year of Hurricanes Harvey, Irma, and Maria, the average claim payment nationwide was $91,735. That year there were 83,779 NFIP policies in the three–county study area (67,829 in Charleston, 7,493 in Berkeley, and 8,457 in Georgetown) covering a total of $23,305,207,700 (Insurance Information Institute, 2018).

[23]Data from 2018 Hurricane Florence are not available and prior to 2015, the only other large storm affecting the region was Hurricane Hugo in 1989.

[24]The scientists that informed the development of this FRI are Mitchell Eaton, a research ecologist at the SECASC and the US DOI, and Simeon Yurek, a wetland ecologist at the SECASC, USGS Wetland and Aquatic Research Center and the South Atlantic Landscape Conservation Cooperative.

Risks Assessment (CERA) group to reproduce the effects or Hurricane Irma in 2017. All these data are publicly available and can be viewed and managed using GIS software.

In the paragraphs that follow, I describe the data used to develop a flood risk index (FRI) and then present the methodology followed to derived said measure but before doing so, it is worth noting that the derived measure of flood risk is not directly included in the hedonic models. This is due to theoretical and econometric considerations. From the economic theory standpoint, the FRI variable would be included as determinant of the price function if landowners and investors followed it to develop expectations over land price. However, evidence from literature in psychology and behavioral economics does not always support the existence of this response, and yet it is well established that flood risk plays a significant role in determining insurance premiums and other costs that landowners incur.[25] Thus, instead of explicitly including the flood risk as a explanatory variable, a binary variable showing when a parcel is within the flood plain is included in the price equations. Additionally, land cover characteristics that are included as regressors in the flood risk equation are also included in the hedonic price function. Thus, to the extent that these land cover features reflect changes in flood risk, the hedonic equations do take into consideration landowners' preferences for changes in flood risk. The econometric reason that further justifies excluding the derived flood risk measure from the hedonic estimation is that the FRI variable is generated and not obtained from an external sources, which poses questions of measurement error.[26]

[25] See Tversky and Kahneman (1974), and Kunreuther and Pauly (2006).

[26] As econometric theory indicates, measurement error in the explanatory variable biases the estimates towards zero and can correlation between explanatory variables and the error term can arise, posing problems of endogeneity (Hayashi, 2000).

USGS inundation maps

During October 1 to 5, 2015, heavy rainfall related to Hurricane Joaquin occurred across South Carolina. The storm caused major flooding in the central and coastal parts of the State. The maximum recorded rainfall was almost 27 inches in Charleston county, 22 in Berkeley, and 20.75 in Georgetown (USGS, 2016). Using high–water marks and streamflow measurements, USGS personnel created 20 inundation maps of 12 urban communities. The maps modeled boundary and water depth of the inundations. The digital maps include four inundation zones in coastal Charleston and Georgetown counties: Coastal Charleston, Coastal Georgetown, Black River community, and the Ashley River community. According to these digital images, a total of 4,472 parcels in Charleston and Georgetown counties are shown to have flooded with Joaquin, and the average rainfall was 2.2 inches. Figure 3.13 displays the location of these four inundation maps.

CERA simulations of storm path

The Coastal Emergency Risks Assessment (CERA) group develops real–time forecasting of storm models to provide guidance about storm surge and waves for the Atlantic Coast. The information produced by CERA is based on two models: the Advanced Circulation and Storm Surge model (ADCIRC) for surge and Simulating Waves Nearshore (SWAN) for waves. The CERA team provides all layers in shapefile format, which include comprehensive information of particular storm events. In this study, I use CERA's simulations of Hurricane Irma to measure inundation in the study area.

Figure 3.14 shows CERA's map of maximum water height in feet above mean sea level (MSL) of Hurricane Irma in the three counties of the study area.[27] Of the 237,754

[27]Height above mean sea level is the elevation (on the ground) or altitude (in the air) of an object, relative to the average sea level. A common measure of average sea level is the midpoint between a mean

parcels in the three counties, 7 percent flooded with Irma and the average water depth was 6.9 feet above MSL, which is just higher than the typical high tide in the region.[28]

3.3.3 DEVELOPMENT OF THE FLOOD RISK INDEX

A central interest of this project, is to examine how changes in impervious and wetland covers influence a parcel's vulnerability to flood events. The general understanding in the natural resources literature is that urbanization changes a basin's response to precipitation, therefore changing flood frequency characteristics of urban streams. The most common effects of urbanization on stream characteristics are reduced infiltration of precipitation into the soils and more rapid runoff (or decreased lag time), which substantially increase runoff volume and flood frequency (Feaster, Gotvald, and Weaver, 2011).

Factors that affect the average capacity of a parcel to provide flood preventive services include elevation, proximity to water bodies, as well as how impervious surfaces, wetland habitats, and tree cover are spatially distributed in and around the parcel. Therefore, in this study, I use a measure of flood risk that is a function of landscape characteristics to calculate the economic benefits of imposing different land use policies in the Lowcountry.[29]

Currently, there are no available flood maps or flood risk products that can be used for the purpose of this dissertation. As of 2018, digital flood risk maps only exist for three counties in South Carolina, and only one of them is in my study area (Berkeley). FEMA manages flood maps for about 22,000 communities across the U.S. Almost two–

low and mean high tide at a particular location. A typical high tide at the Cooper River station (ID 8665530) is 6.76 ft above MSL.

[28]As a point of reference, consider that a recent study by Loerzel et al. (2017) calculates that approximately 7.6 percent of the parcels in their study area flooded during Hurricane Sandy, and the mean flood depth in feet above MSL among flooded parcels was 3.5. This information seems to give support to the inferences from inspecting Irma's data.

[29]Recall that benefits are defined as the sum of property damages from major floods that are avoided because of a particular land use policy, such as a policy discouraging land owners from adding hard surfaces to their land or a policy encouraging them to conserve wetlands that are present in their lots.

thirds were officially updated more than five years ago. Some maps have been in place for more than 40 years. In addition, even updated maps may not be suitable for analysis at the parcel level.[30] South Carolina has not been hit by a major hurricane storm since Hurricane Hugo in 1989. Thus, recent mapping techniques have not been applied to this study area to determine inundation after a storm. In addition, because of the cloud cover that accompanies storms, satellite images are difficult to use for measuring inundation and flooding during and immediately after a storm. Hence, due to the lack of appropriate measures, I construct a flood risk index based on the foundations of existing inundation models using data from recent large storm events in South Carolina.

The flood risk index is developed to reflect the dynamics in the natural composition of the landscape so that a parcel that is 5% covered by wetland habitat and 95% covered by impervious surfaces shows a different risk of flooding than a parcel that is 5% wetland, 25% forest, and 75% by impervious surfaces or a parcel that is 25% wetland, 25% forest, and 50% impervious surfaces. Specifically, separate probabilistic models are developed using the data on Hurricanes Joaquin (2015) and Irma (2017) as the dependent variable, and the probabilistic measure of propensity to flooding is modeled as a function of topographic characteristics, like elevation and proximity to water bodies, and the land cover composition of a parcel and its surroundings.[31]

[30]The most recent recent flood model being used by FEMA, the HAZUS–MH flood model. The model defines annual probability of coastal inundation using topographic elevation data. Other inputs include dune erosion, wave effects, and regional riverine water discharge. There are available tools, other than FEMA's flood plain maps, to model inundation, including NOAA's SLAMM and SLOSH models, which project future scenarios under sea level rise and changing storm surge conditions, respectively. However, these models appear to be better suited for analysis at a scale larger than the parcel–level. These models are also criticized for lacking structural strength, i.e., they are mostly statistical extrapolations rather than fundamental models of underlying natural process driving observed events.

[31]For these measures, I define a buffer zone that has a 0.25 miles radius from the parcel's centroid (an area equivalent to 0.2 squared miles).

The model is defined as:

$$Pr(\text{Flood}_{iht}) = f(\text{elevation, proximity to a river, proximity to the coastline,} \\ \text{parcel land cover, land cover in surrounding area}), \tag{3.1}$$

where $\text{Pr}(\text{Flood}_{iht})$ is the probability that parcel i gets inundated during Hurricane h at time t. Variables characterizing parcel land cover are share of the parcel's area under high–intensity development covers, forest covers, and wetland covers. In turn, variables representing land cover in the area surrounding the parcel, are shares of high–intensity developed covers, a mix of developed and vegetation covers, forest covers, and wetland covers. The model is estimated using a probit method on two separate datasets, one corresponding to Hurricane Joaquin and one corresponding to Hurricane Irma.

Estimation results

An additional step was taken before setting up the probabilistic model using the maps created by the USGS to identify inundated areas during Joaquin. Because these maps do not constitute exhaustive maps of inundated areas (i.e., there are zones in the study area that flooded and were not mapped), a 0.25 mile radius buffer zone around the four inundation maps was defined. Only parcels within the buffered zone were considered in estimating the probabilistic model. Thus, parcels within the buffered area and inside the inundation map are recorded as flooded while parcels in the buffered area but outside the inundation map are considered as not flooded. Figures 3.15 and 3.16 illustrate the process of designating parcels as flooded or not during each event.

Results from the probit estimations are presented in table 3.7. As expected, factors that increase probability of flooding are lower elevation, proximity to water bodies, and

prevalence of impervious surfaces in the area surrounding a parcel. Alternatively, the factors that decrease probability of flooding are forest cover and wetland cover in the area surrounding a parcel. The significance of the interaction terms indicate that absolute area of impervious surfaces, and not just relative prevalence, matter in determining the probability of flood, and also that surrounding hard covers increase the probability of flooding slightly more heavily for parcels that are closer to a river.

These results are consistent with findings in the literature. In a study of streamflow and urbanization, Feaster, Gotvald and Weaver (2011) find that a one percent increase in impervious surface cover increases streamflow during a 100–year flood by 0.3 to 3.9%. In turn, ecosystem service valuation studies generally find that wetland covers reduce hurricane damages by attenuating the effect of flooding.[32]

Interestingly, the relative presence of impervious surface in the parcel does not significantly affect the likelihood of it flooding during a hurricane. Only the composition of the area surrounding the parcel seems to matter in this regard. According to the estimation, a one percent increase in total surrounding area covered by impervious surfaces increases the likelihood of flooding from 7.14 to 26.5%. Finally, it is surprising to find that prevalence of general developed covers (i.e., a mix of construction materials and vegetation) *negatively* influences the probability of flood when the model is estimated using data for Hurricane Irma. This suggests that urbanization around a parcel can decrease its chances of flooding, which can occur is impervious surfaces speed up the removal of flood flows from upper parts of stream (Feaster, Gotvald, and Weaver, 2011).

[32]Estimates of economic value of wetland ecosystem services for flood prevention range from 18 to 7,399 2017 $US per hectare per year (Sharma et al. 2015; Ming et al., 2007; Watson et al., 2016; Zhang et al., 2017). Their value for hurricane protection services varies from 225 to 1700 2017 $US per hectare (Loerzel et al., 2017 ; Constanza et al., 2008). The consensus among natural resource scientists is that flood control is a localized benefit, and therefore harder to do a benefits transfer without first having primary data on the flood control at a particular site of interest.

Calculating a parcel–specific FRI

The predicted probabilities of flooding derived from the estimated models, are used to develop a parcel–specific flood risk index. For each parcel in the data, the FRI at t_0 is the predicted probability from the probit estimation using data from Hurricane Irma. However, the FRI at t_1 needs to be adjusted to reflect changes in impervious surface cover resulting from land development decisions in t_0. The FRI for parcel i in t_1 is:

$$Pr(\text{Flood}_{it_1}) = Pr(\widehat{\text{Flood}}_{it_0}) + \hat{\gamma}\Delta\text{Impervious surface cover}, \tag{3.2}$$

where parameter $\hat{\gamma}$ is the average estimated marginal effect of a percentage increase in impervious surface cover on the probability that a parcel floods,[33]and the change in impervious surface cover (ΔImpervious surface cover) is calculated as the difference between the original and the updated share of impervious surfaces in the area surrounding a newly developed parcel.[34] According to the estimations, $\hat{\gamma}$ is 16.8, so that a one percent increase in high intensity development covers leads to an 16.8 percent average increase in the probability of that a parcel floods during a storm.

Summary statistics and description of the generated FRI

In table 3.8, I present summary statistics for the FRI variable at two different points in time. These estimations assume there are not changes to current patterns of land use (i.e., the correspond to predictions following a "business as usual"trajectory). As shown

[33]Taking an average of the available forecasts rather than relying on just one has been found to reduce forecast error (typically measured by the root–mean squared error), often by about 15 to 20 percent (Silver, 2012). Thus, I aggregate output from the two separate models to derive an average effect.

[34]The updated share of surrounding impervious surface cover corresponds to the average percentage impervious surface cover for parcels that developed in the most recent 5 years (i.e., from 2011 to 2016).

by descriptive statistics there is little difference across time periods.

In general, the majority of parcels in the sample are associated with low values of FRI and a few parcels have high values. This observation is also shown in figure 3.17, which is a heat map showing the spatial variation of the FRI_0 variable. As shown in figure, parcels with the highest FRI are neighboring rivers and estuaries, namely, the Wadmalaw and Stono Rivers in Charleston, the Ashley and Cooper Rivers in Berkeley, and the Winyah Bay in Georgetown.[35] Interestingly very few of the parcels with high FRI are near the coast, suggesting that much of the flood risk in the region is that of fluvial flooding rather than coastal flooding.[36]

[35]Winyah Bay is a coastal estuary that is the confluence of the Waccamaw River, the Pee Dee River, the Black River, and the Sampit River in Georgetown county.

[36]The most common kinds of floods are coastal, fluvial, and pluvial floods. Coastal floods are the result of extreme tidal conditions caused by severe weather (e.g., surges). Fluvial floods occur when excessive rainfall over an extended period of time causes a river to exceed its capacity. They are the most common type. Finally, pluvial floods are caused by heavy rainfall and are independent of a water body.

Table 3.1: Land cover by selected habitat and year.

Charleston				
Land Cover	2001	2006	2011	%Δ
Developed, Open Space	4.77	5.19	4.85	1.63
Developed, Low Intensity	3.91	4.60	4.11	5.24
Developed, Medium Int.	1.39	1.83	1.80	29.49
Developed, High Int.	0.60	0.68	0.78	29.34
Forest	17.91	19.33	16.97	-5.24
Shrub/Scrub	6.18	6.99	6.53	5.65
Pasture/Hay/Crops	5.04	5.74	5.05	0.35
Woody Wetlands	22.46	23.37	22.50	0.19
Emergent Wetlands	22.47	23.37	22.51	0.19

Berkeley				
Land Cover	2001	2006	2011	% Δ
Developed, Open Space	3.06	3.15	3.22	5.35
Developed, Low Intensity	1.81	2.06	2.11	16.59
Developed, Medium Int.	0.49	0.68	0.74	52.39
Developed, High Int.	0.18	0.22	0.27	47.38
Forest	30.41	29.10	27.91	-8.21
Shrub/Scrub	7.45	7.91	8.97	20.50
Pasture/Hay/Crops	7.23	7.77	7.39	2.20
Woody Wetlands	34.44	34.45	33.95	-1.45
Emergent Wetlands	4.40	4.37	4.48	1.66

Continued on next page

Table 3.1 (continued).

Georgetown				
Land Cover	2001	2006	2011	% Δ
Developed, Open Space	2.70	2.97	2.79	3.13
Developed, Low Intensity	1.00	1.08	1.12	11.84
Developed, Medium Int.	0.25	0.35	0.35	41.52
Developed, High Int.	0.07	0.09	0.10	44.54
Forest	29.29	28.51	27.10	-7.48
Shrub/Scrub	8.75	11.15	10.70	22.28
Pasture/Hay/Crops	6.09	7.43	5.95	-2.30
Woody Wetlands	30.17	32.11	29.72	-1.50
Emergent Wetlands	12.10	11.99	12.47	3.10

Notes: Table 3.1 shows percent coverage per county per year.

Table 3.2: Summary of flood data (1996–2006).

Region	Episodes	Events	Damages (M$)	Number of events causing damages	Average damage per affecting event (K$)	Average damage per flood (M$)
South Carolina	677	1,628	170.90	669	255.46	25.24
Study area (SA)	167	436	27.81	112	248.30	16.65
% of SC	24.7	26.8	16.3	16.7	97.2	66
Charleston	126	331	20.33	75	271.07	16.13
% of SA	75.4	75.9	73.1	67.0	109.2	96.9
Berkeley	42	64	4.72	17	277.65	11.24
% of SA	25.1	14.7	17.0	15.2	111.8	67.5
Georgetown	22	41	2.75	20	137.50	12.50
% of SA	13.2	9.4	9.9	17.9	55.4	75.1

Notes: Includes flash floods, floods, and coastal floods.
In SC, 71% of all flooding events are classified as flash floods, 20% as floods, and 9% as coastal floods.

Table 3.3: Selection of sample for estimation.

	Charleston	Berkeley	Georgetown	All	Model in which data is used
Number of parcels in Tax Assessor database	181,729	90,684	43,517	315,930	
Parcels in zones considered for analysis	133,461	84,284	42,634		
Residential parcels with GIS variables	77,729	68,515	19,560		
Residential parcels transacted since 2010	27,079	18,700	4,792		
Transacted since 2010 with building data	4,049	6,510	1,341	11,900	Land use change
Transacted since 2010 (preferred price range)	16,300	12,315	3,627	32,239	Hedonic developed
Undeveloped parcels with GIS variables	15,680	20,648	16,891	53,219	Land use change
Undeveloped parcels transacted since 2000*	7,313	8,680	7,566		
Transacted since 2000* (preferred price range)	2,041	2,366	1,959	6,366	Hedonic undeveloped

* Excludes transactions that occurred in 2006, 2007, 2008 and 2009.

Table 3.4: Zones of vacant lots in and out of the sample.

Land class	Vacant lots not in sample	Vacant lots in sample
Charleston county		
140 - MH-PARKS		151
110 - RESID-MBH		1,085
905 - VAC-RES-LOT	5,131	17,293
101 - RESID-SFR		84,013
800 - AGRICULTURAL	684	1,814
999 - Not Currently Classified	40	
910 - COM-DEV-ACRS	135	
952 - VAC-COMM-LOT	2,610	
990 - UNDEVELOPABLE	3,825	
Berkeley county		
Goose Creek - PD-MH (Planned Development Mobile Home Park)		2
Moncks Corner - MH-1 (Mobile home park)		5
Berkeley County - R3 (Mobile home park)		63
Berkeley County - R2-R(F) (Mobile home rural residential district)		661
Moncks Corner - R-3 (Mobile home park)		673
Goose Creek - R-3 (Mobile home park)		1,387
Public/Other (NA)	15,751	104
Georgetown county		
Mobile Home (Q650)		1
Mobile Home on as R/E for Homestead (Q652)		1
MH on as storage (Q659)		1
Lumber Yard (N340)		11
Mobile Home on as Real Estate (N651)		55
Mobile Home Park (N370)	29	59
No infrastructure (N001)	36	167
Rural (Less Than 5 AC with AG use) (Q202)	33	237
Mobile Home On as Real estate (Q165)	12	257
Vacant Commercial Property (N003)	30	556
Rural (More Than 5 AC) (N300)	2,043	998
More Than 5 AC with AG Use (Q302)	3,579	1,890
Mobile Home On Property (N065)	202	2,003
Rural (Less Than 5 AC) (Q200)	612	4,505
Vacant Residential Lot (Q000)	423	7,035

Table 3.5: Summary statistics: data used for hedonic price model of residential land.+

		Charleston	**Berkeley**	**Georgetown**
# obs		16,300	12,315	3,627
Price and structural characteristics				
Sales price	Recorded sales price (in 2016 dollars)	394,095/261,323 [4,457/18,555,786]	192,020/152,503 [7,884/21,618,412]	282,856/222,395 [5,572/3,929,196]
Age	Age of the building in years	36/28 [1/307]	13/9 [0/301]	24/18 [0/279]
SQFT	Building size (sq ft)	21,148/1,959 [300/12,630]	2,062/1,914 [480/9,430]	2,236/2,050 [250/40,320]
Assessed building value	Value assessed by tax office (in 2016 dollars)	247,874/179,510 [-7,761/5,676,500]	147,548/118,728 [1,025/11,648,387]	178,625/152,718 [198/2,096,923]
Land characteristics				
Acreage	Size of lot in acres	0.43/0.24 [0.004/221]	0.3/0.2 [0.01/9.9]	0.61/0.32 [0.01/197.7]
Elevation (m)	Elevation of the parcel (meters above sea level)	3.2/2.7 [1.06/13.7]	12.3/10.4 [0.5/28.6]	5.05/5.1 [0/18.6]
Geospatial characteristics				
Within 100–year flood plain (=1)	If within the 100–year flood plain	0.53/1 [0/1]	0.14/0 [0/1]	0.3/0 [0/1]

Continued on next page

Table 3.5 (continued).

		Charleston	Berkeley	Georgetown
# obs		16,300	12,315	3,627
Geospatial characteristics (continued)				
River (=1)	If a river pases through or by the parcel	0.03/0 [0/1]	0.03/0 [0/1]	0.04/0 [0/1]
Distance to Charleston (mi)	Euclidean distance to Charleston city center	6.9/6.1 [0.05/30.1]	18.73/19.329 [4.54/38.6]	65/66 [42.7/76.7]
Dist. to road (mi)	Euclidean dist. to nearest primary or secondary road	0.86/0.46 [0.002/7.2]	1/0.9 [0.005/4.6]	0.77/0.56 [0.002/4.02]
Dist. to beach access point (mi)	Eucl. dist. to nearest beach public access point	6.5/5.9 [0.0002/18.8]	21.1/22.2 [5.9/41.9]	4.4/2.2 [0.0004/29.8]
Distance to evacuation route (mi)	Eucl. dist. to nearest hurricane evacuation route	0.00008/0 [0/0.06]	4.2/2.73 [0/21.1]	0.45/0 [0/10.37]
Dist. to coastline (mi)	Euclidean distance to coastline	3.1/2.4 [0/12.9]	12.1/12.9 [0/32.5]	2.4/1.6 [0/22.5]
Dist. to river (mi)	Euclidean distance to nearest river	0.16/0.1 [0/1.32]	0.19/0.17 [0/1.34]	0.17/0.13 [0/1.06]
Dist. to lake (mi)	Eucl. dist. to nearest recreational lake	[8.9/10.1]	25.7/25 [2.2/32.2]	8.5/6.1
Wetland cover	% Area w/in 0.25 mi. in wetlands (2011)	11.7/0 [0/100]	12.2/0 [0/100]	11.8/3 [0/100]

Continued on next page

Table 3.5 (continued).

		Charleston	Berkeley	Georgetown
# obs		16,300	12,315	3,627
Geospatial characteristics (continued)				
Developed cover*	% Area w/in 0.25 mi. developed (2011)	66.4/78.8 [0/100]	64.3/78.5 [0/100]	62.3/68 [0/100]
–open space	mean/med	22/1	23/10	35/26
–low intensity	mean/med	32/12	35/2	27/8
–medium intensity	mean/med	8/0	9/0	3/0
–high intensity	mean/med	1/0	0.4/0	0.1/0
Pasture/crop cover	% Area w/in 0.25 mi. in pasture/crop (2011)	1.5/0 [0/100]	1.4/0 [0/100]	0.9/0 [0/83]
Forest cover	% Area w/in 0.25 mi. in forest (2011)	11.7/1.4 [0/100]	10.6/0 [0/100]	16.4/10 [0/100]

Statistics outside brackets represent mean/median; and inside brackets [min/max].
+ Only properties in the hedonic analysis.
* Includes, open space, low–, medium–, and high–intensity development.

Table 3.6: Summary statistics: data used for hedonic price model of agricultural land.+

		Charleston	**Berkeley**	**Georgetown**
# obs		2,401	2,366	1,959
Price and structural characteristics				
Sales price	Recorded sales price (in 2016 dollars)	251,881/100,797 [92/18,631,992]	114,961/58,954 [253/17,850,267]	79,329/40,000 [309/3,610,360]
Assessed building value	Value assessed by tax office (in 2016 dollars)	7,799 /0 [0/2,034,337]	39,296/0 [0/6,364,654]	2,277/0 [0/183,359]
Land characteristics				
Parcel size (acres)	Size of lot in acres	2.6/0.5 [0.01/1,808.7]	0.9/0.3 [0.01/9.9]	3.1/0.5 [0.009/1,500]
LCC1 (=1)	Land capability class 1: Good soil	0.003/0 [0/0.94]	0.05/0 [0/1]	0.003/0 [0/1]
LCC2 (=1)	Land capability class 2: Good soil	0.14 /0 [0/1]	0.6/0.9 [0/1]	0.3/0 [0/1]
LCC3 (=1)	Land capability class 3: Poor soil	0.43/0.2 [0/1]	0.1/0 [0/1]	0.2/0 [0/1]
LCC4 (=1)	Land capability class 4: Poor soil	0.08/0 [0/1]	0.2/0 [0/1]	0.3/0 [0/1]

Continued on next page

Table 3.6 (continued).

		Charleston	Berkeley	Georgetown
# obs		2,401	2,366	1,959
Geospatial characteristics				
Elevation (m)	Elevation of the parcel (meters above sea level)	3.2/2.7 [1.06/13.7]	12.3/10.4 [0.5/28.6]	5.05/5.1 [0/18.6]
Within 100–year flood plain (=1)	If within the 100–year flood plain	0.7/1 [0/1]	0.2/0 [0/1]	0.4/0 [0/1]
River (=1)	If a river pases through or by the parcel	0.08/0 [0/1]	0.08/0 [0/1]	0.05/0 [0/1]
Dist. to river (mi)	Euclidean distance to nearest river	0.16/0.1 [0/1.32]	0.19/0.17 [0/1.34]	0.17/0.13 [0/1.06]
Distance to paper mill (mi)	Euclidean distance to the nearest paper mill	15.9/16.4 [3.33/26.7]	7.9/7.2 [0.18/16.6]	10.8/10.9 [0.1/19.9]
Distance to Charleston (mi)	Euclidean distance to Charleston city center	11.8/12.1 [0.12/25]	20.7/19.4 [4.6/38.5]	62.3/63.1 [42.2/76.7]
Dist. to road (mi)	Euclidean distance to nearest primary or secondary road	1.9/1.1 [0.004/5.09]	0.94/0.7 [0.005/5.2]	0.95/0.65 [0.004/4.3]
Dist. to beach public access point (mi)	Euclidean distance to nearest beach public access point	6.4/5 [0.001/18.8]	22.5/22.4 [5.9/41.6]	7.8/3.3 [0.008/28.9]
Dist. to coastline (mi)	Euclidean distance to coastline	3.45/2.2 [0/12.9]	13.4/12.9 [0/32.3]	4.6/1.9 [0/22.9]

Continued on next page

Table 3.6 (continued).

		Charleston	Berkeley	Georgetown
# obs		2,401	2,366	1,959
Geospatial characteristics (continued)				
Wetland cover	Share of area w/in 0.25 mi. covered by wetlands in 2011	22.9/15.9 [0/100]	15.9/4.6 [0/100]	18.4/10 [0/100]
Developed cover*	Share of area w/in 0.25 mi. in developed surfaces in 2011	33.4/19.66 [0/100]	51.1/58.9 [0/100]	44/41.8 [0/100]
Pasture/crop cover	Share of area w/in 0.25 mi. in crops or pasture in 2011	6.55/0 [0/100]	3.7/0 [0/96.6]	3.8/0 [0/89.4]

Statistics outside brackets represent mean/median; and inside brackets [min/max].
+ Only properties in the hedonic analysis.
* Includes, open space, low–, medium–, and high–intensity development.

Table 3.7: Probit estimation of parcels flooding during Hurricanes Irma and Joaquin.

Dependent variable:	Inundated by Irma		Inundated by Joaquin^{+}	
	Marginal effect		Marginal effect	
Intercept	2.32	***	-12.7	***
Acres	0.005	*	-0.001	
Elevation (m)	-2.37	***	-0.59	***
Dist. River (mi)	-12.3	***	4.6	***
Dist. River^2 (mi)	7.31	***	-6.49	***
Dist. Road (mi)	0.1		0.49	***
Dist. Road^2 (mi)	-0.08		-0.19	***
Dist. Coastline (mi)	0.15	***	-0.77	***
Dist. Coastline^2 (mi)	-0.03	***	-0.017	***
Dist. Charleston (mi)	-0.07	***	0.03	***
Parcel LC24^{++}	-0.59		-0.22	
Parcel Forest Cover	-0.18		0.58	**
Parcel Wetland Cover	0.24		8.55	***
Share of area w/in 0.25 mi. that is LC24^{++}	7.14	*	26.5	**
Share of area w/in 0.25 mi. that is LC21-LC24^{+++}	-0.04	***	0.01	***
Share of area w/in 0.25 mi. in Forest	-0.01	***	-0.05	***
Share of area w/in 0.25 mi. in Wetlands	0.05	***	-0.03	*

Continued on next page

Table 3.7 (continued).

	Inundated by Irma		Inundated by Joaquin^{+}	
	Marginal effect		Marginal effect	
Buffer LC24×Acres	5.03	***	-0.05	
Buffer LC24×Dist.River	-20.2	*	48.2	***
Buffer LC24×Dist.Charl	-1.89	***	0.6	***
Data	CERA		USGS + buffer	
N Parcels	174,687		106,214	
N Flooded parcels (obs=1)	6,999 (7%)		2,871 (24.5%)	
Average water height	6.3 feet above MSL		3.45 inches	
Average predicted probability	0.04		0.03	

Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 1.
Signif. codes correspond to robust standard errors.
$^{++}$ LC24 is the code in the NLCD for high intensity development cover.
$^{+++}$LC21-LC24 are open space, low-, medium-, and high- intensity.

Table 3.8: Summary statistics: parcel–specific predicted flood risk index (FRI).

	FRI_{2016}	FRI_{2021}	FRI_{2041}
Min	0	0	0
Mean	0.101452	0.14461	0.103084
Median	0.039775	0.08627	0.043034
Max	0.973027	0.94812	0.94812
# obs		53,219	

$FRI_t = FRI_0 + \hat{\gamma}\Delta_t$(Impervious surface cover).
$\hat{\gamma} = 16.8$.

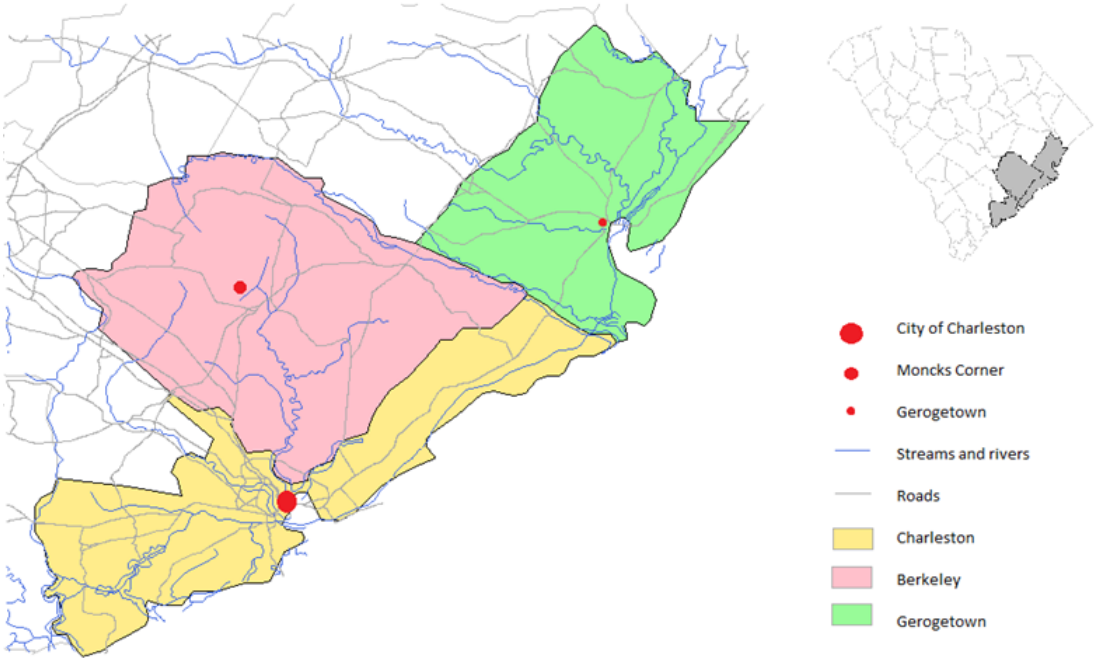
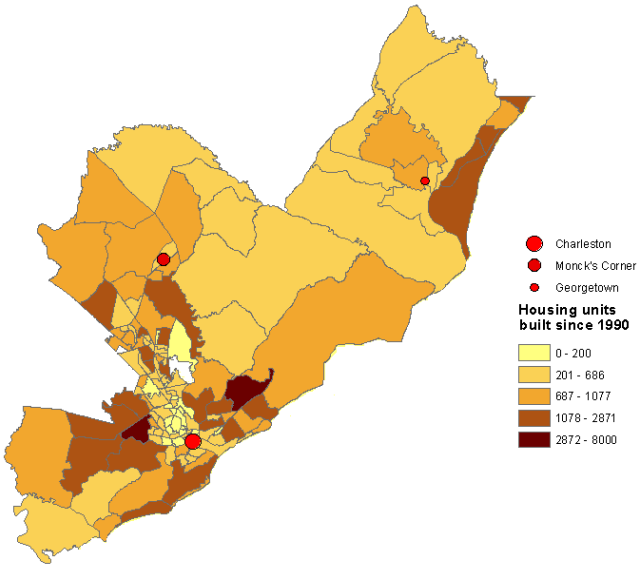


Figure 3.1: The study area.

(a) New housing stock (1990–2016).



(b) Growth in housing stock (1990–2016).

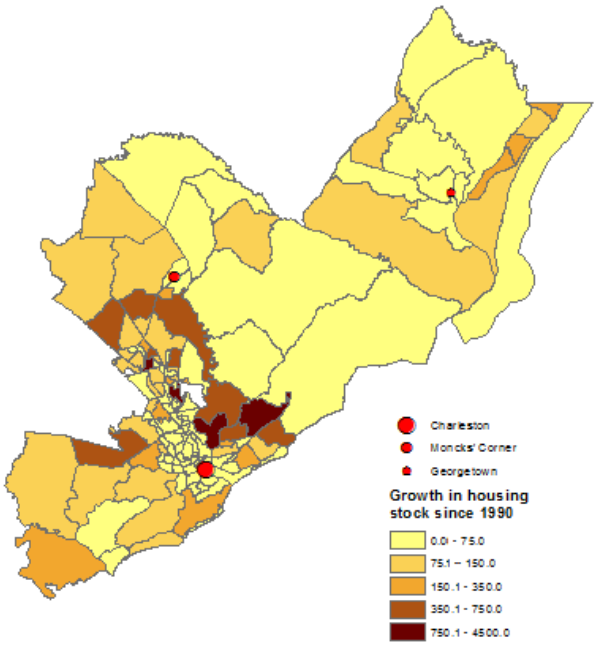


Figure 3.2: Change in housing stock in the study area (1990–2016).

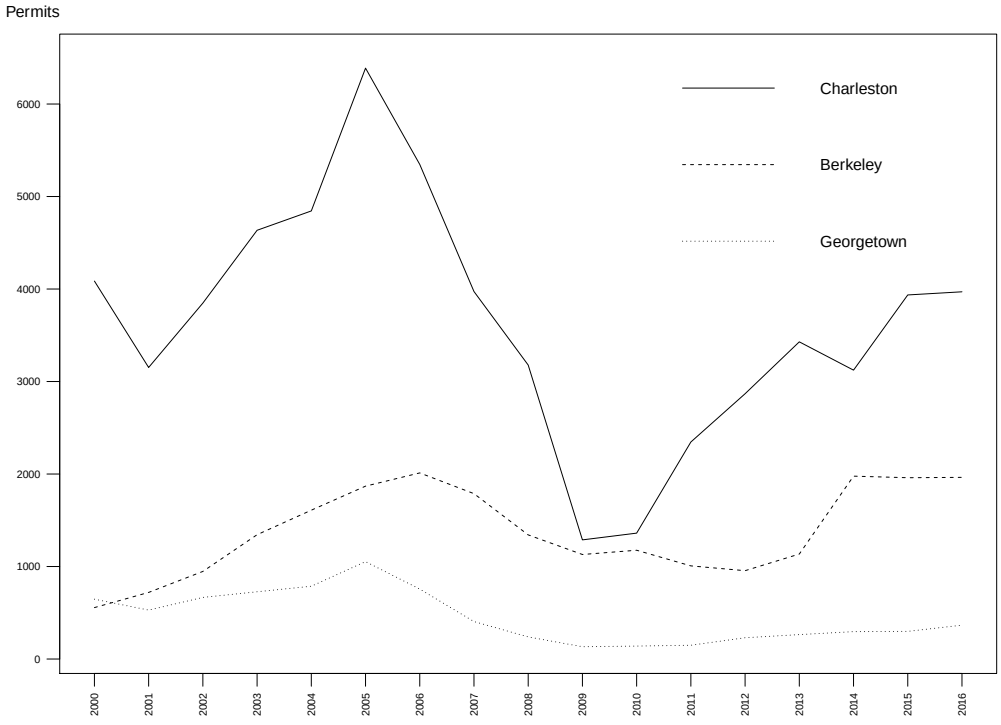


Figure 3.3: Building permits issued in the study area (2000–2016).

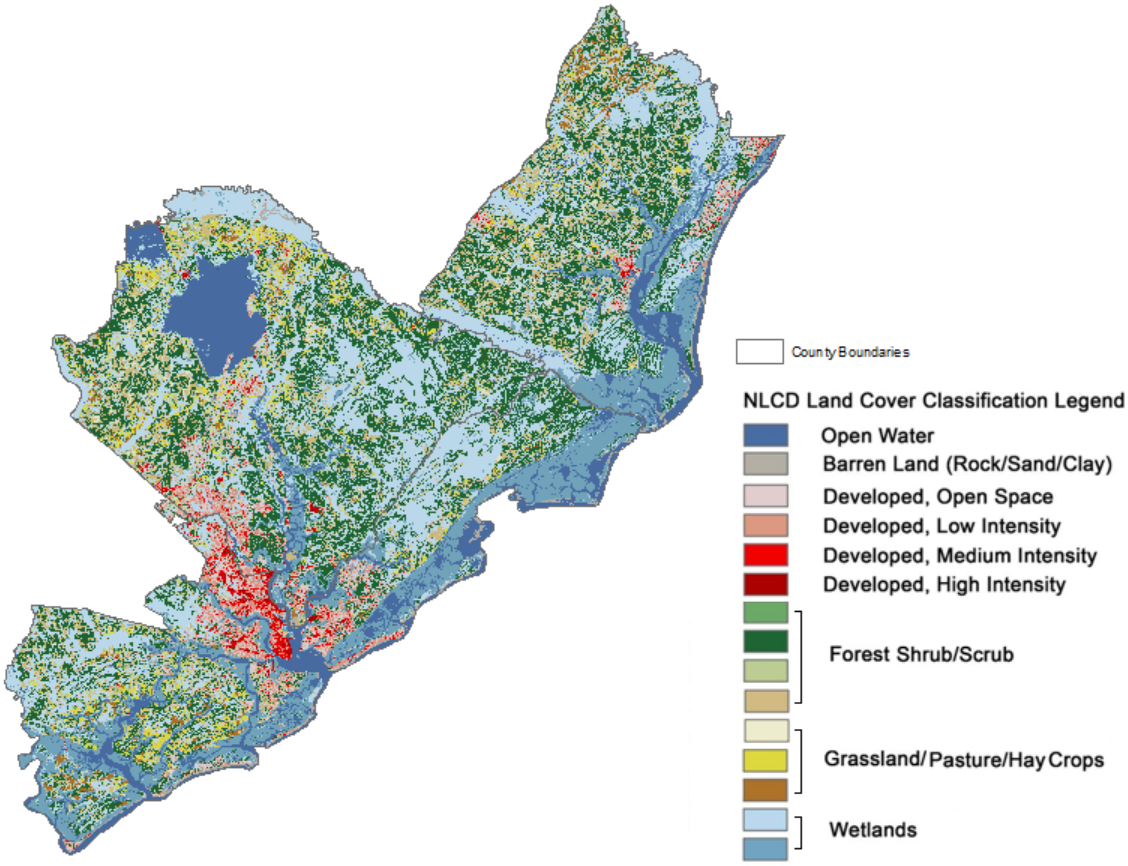


Figure 3.4: Land cover in study area (2011).

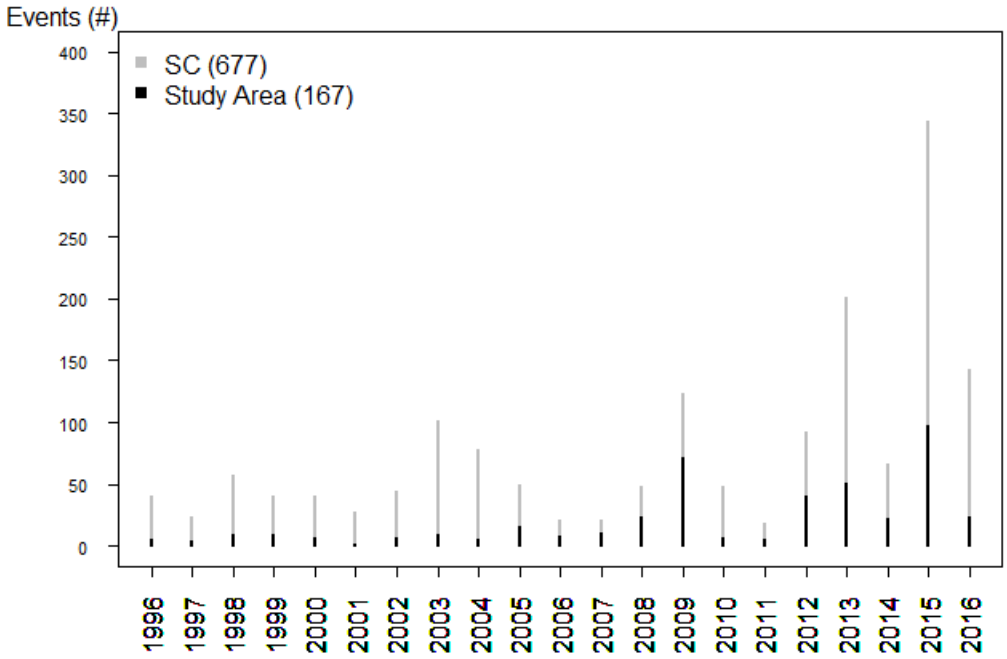
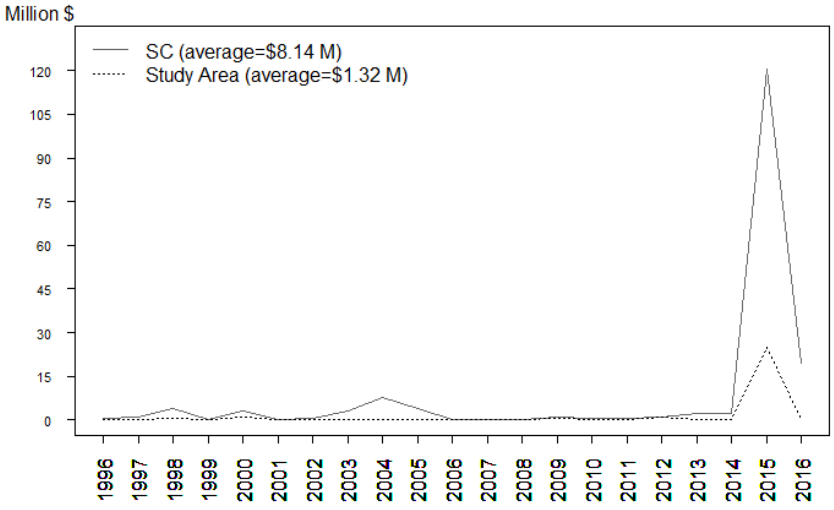


Figure 3.5: Flood records in the study area (1996–2016).

(a) Property damages in SC and study area (1996–2016).



(b) Property damages in the study area (1996–2016).

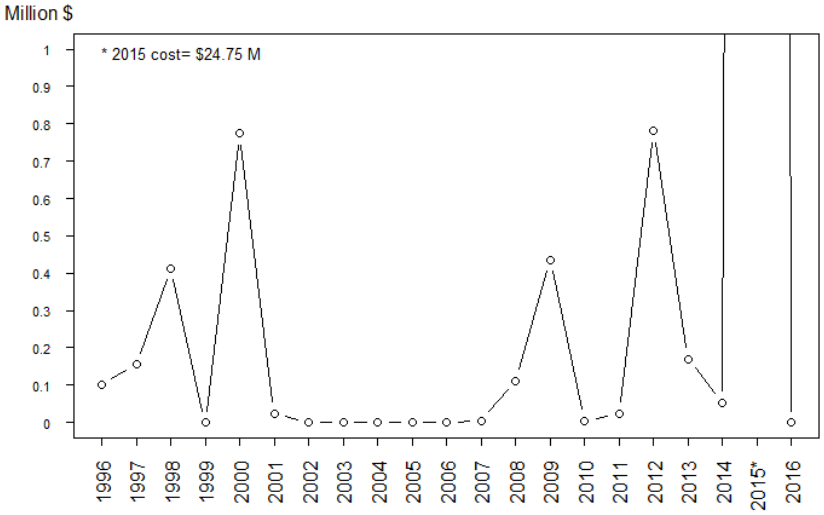


Figure 3.6: Property damages from floods in SC and the study area.

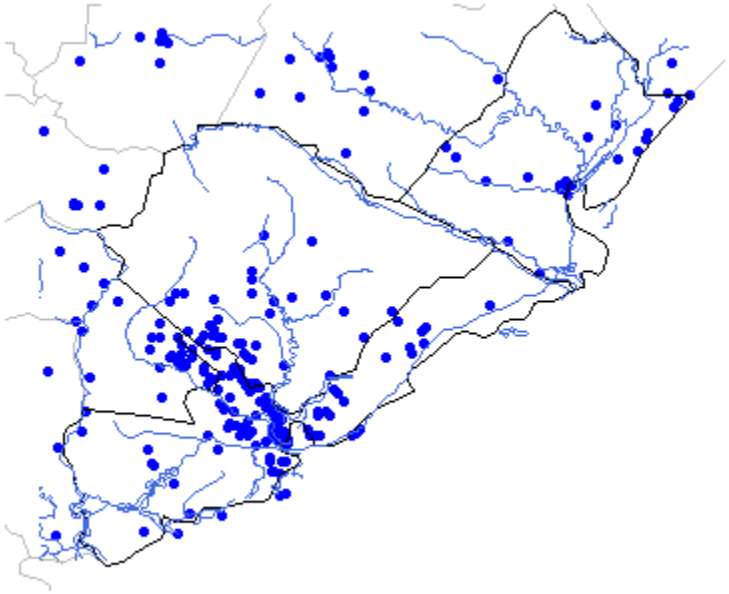


Figure 3.7: Location of flash floods, floods, and coastal flooding incidents (1996–2016).

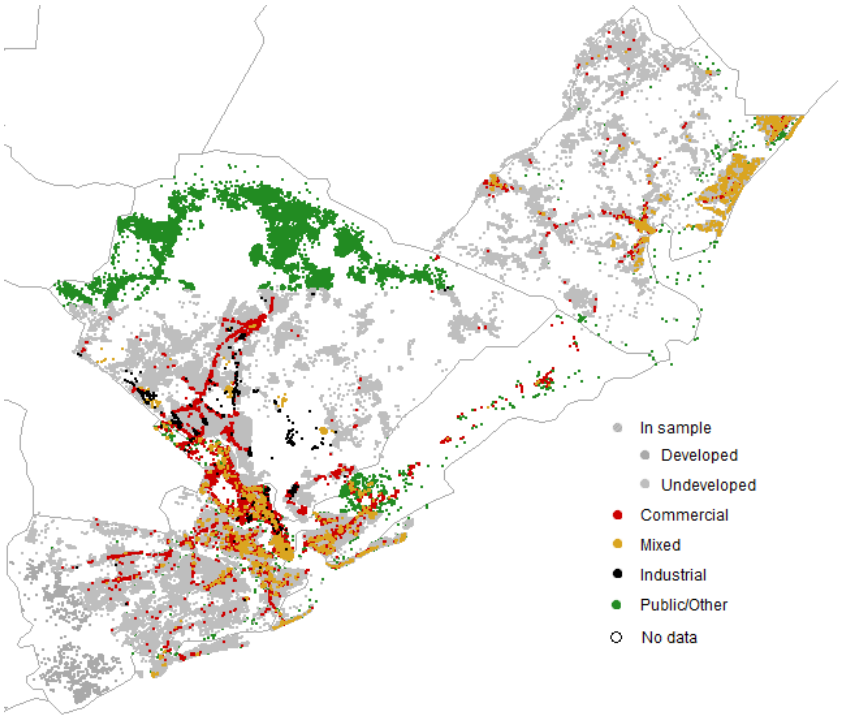
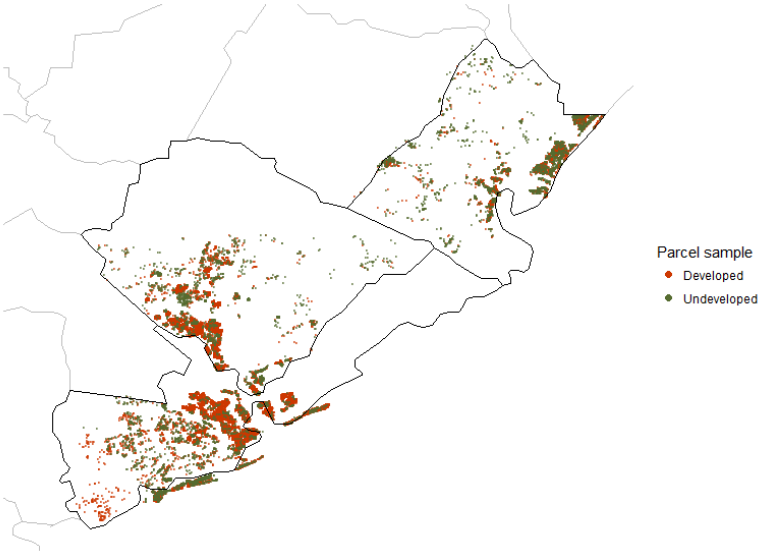


Figure 3.8: Location of selected parcels that are included in the final sample relative to parcels not included in the sample. Parcels that were excluded were zoned commercial, industrial, public, or were in mixed uses.

(a) Location of selected parcels that are included in the final sample. Parcels in orange represent residential parcels, parcels in green are agricultural. White regions are composed by public lands, parcels under commercial, industrial, or mixed uses, or parcels dedicated to conservation.



(b) Selected parcels by land use type relative to land cover.

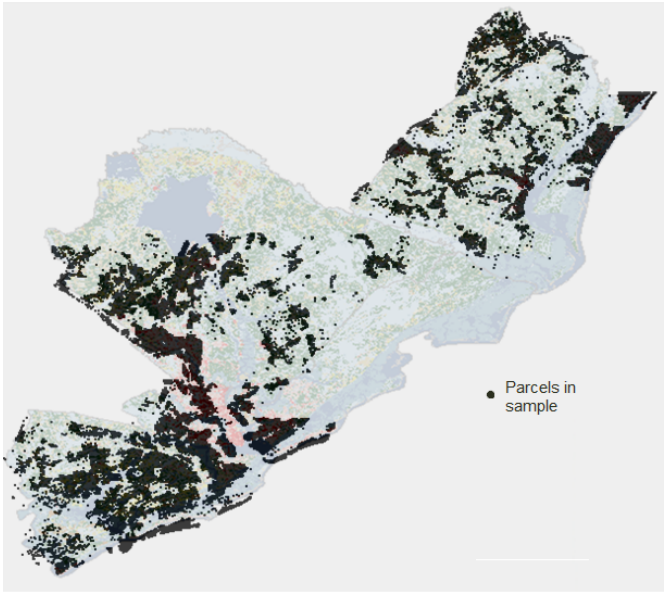


Figure 3.9: Parcel selection, land uses, and land covers.

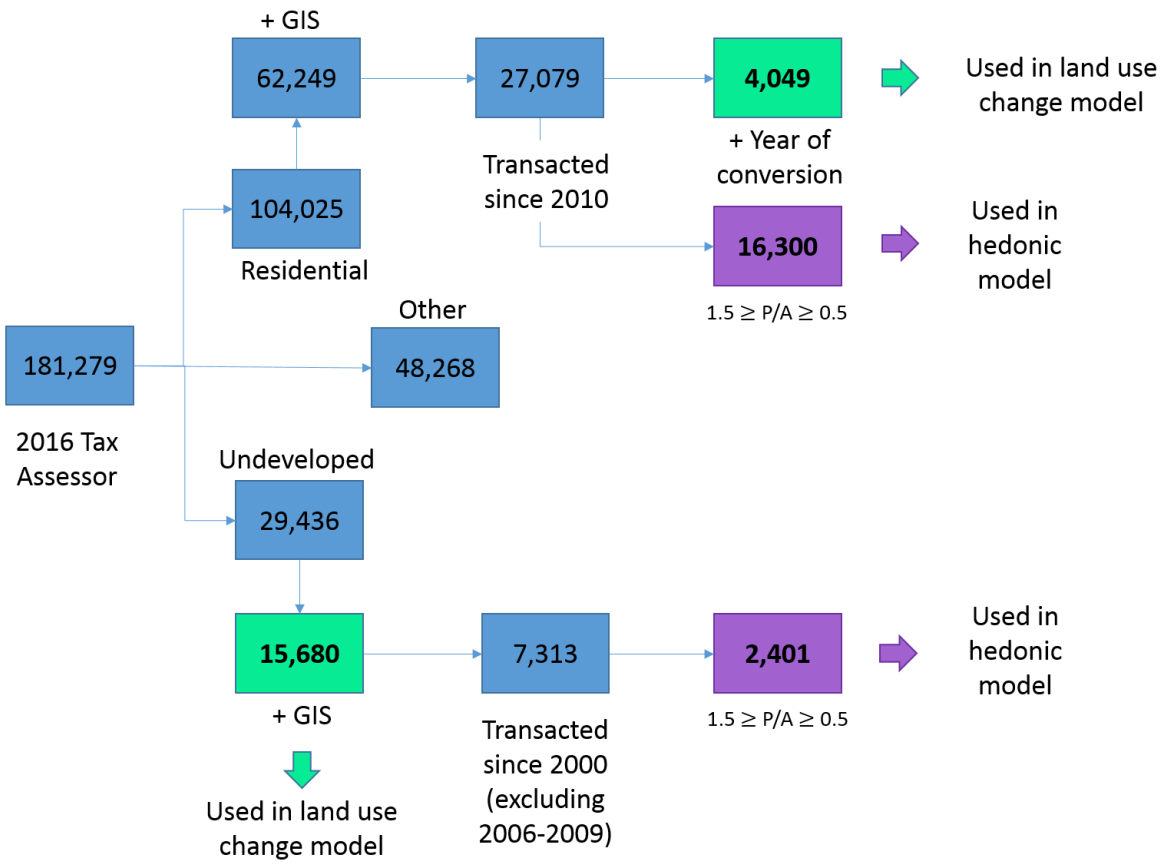


Figure 3.10: Parcel selection for Charleston county data.

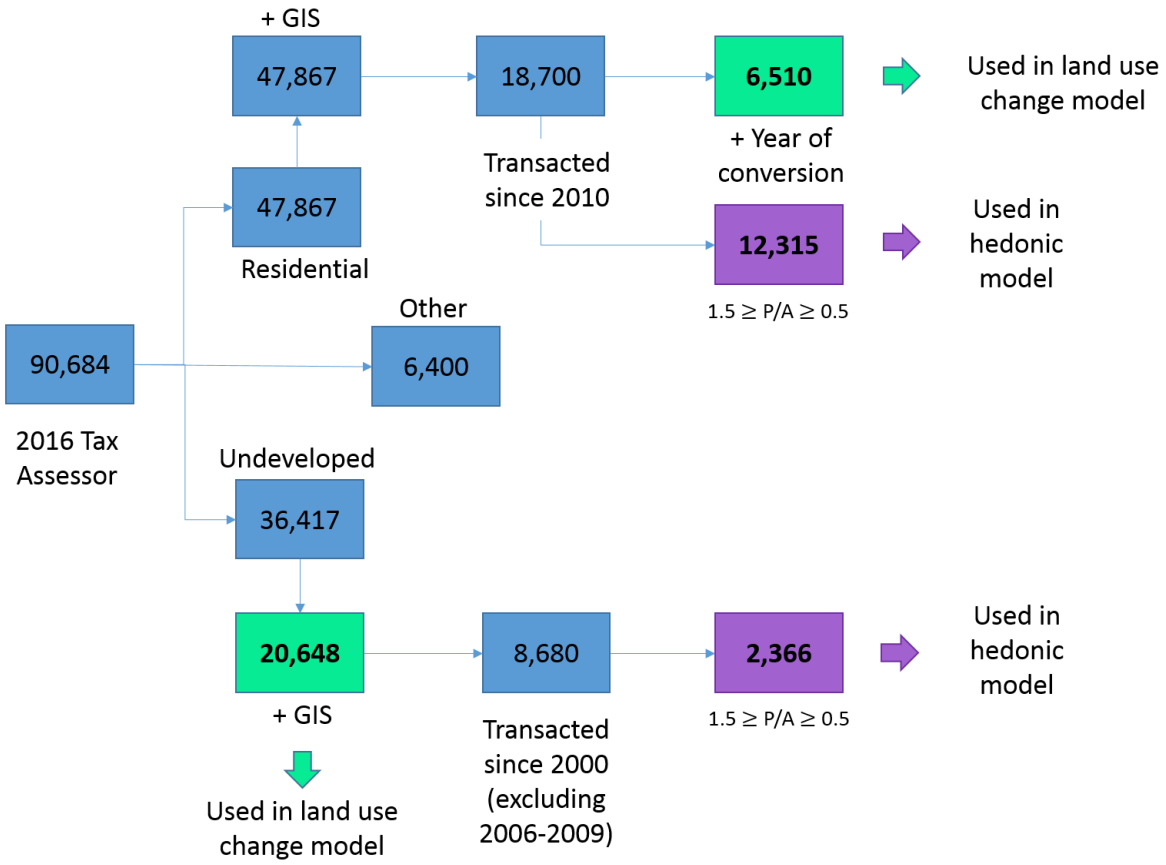


Figure 3.11: Parcel selection for Berkeley county data.

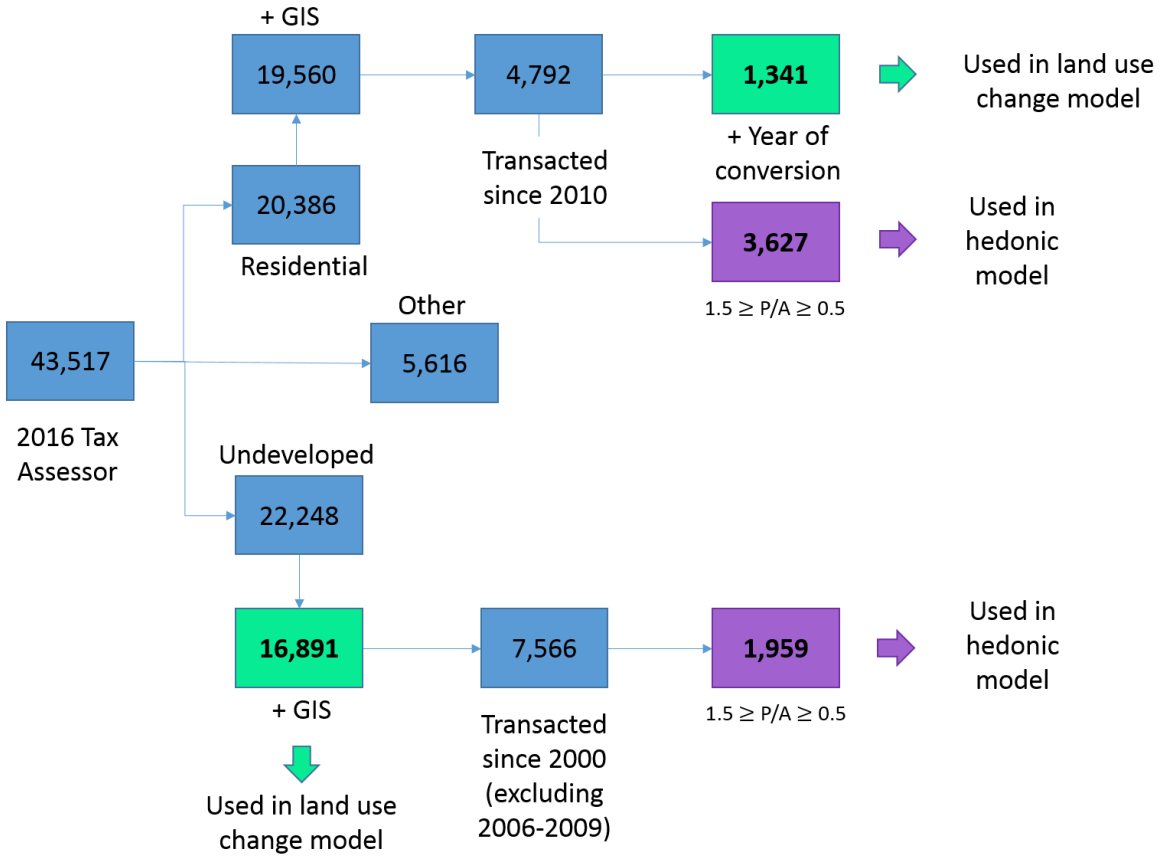


Figure 3.12: Parcel selection for Georgetown county data.

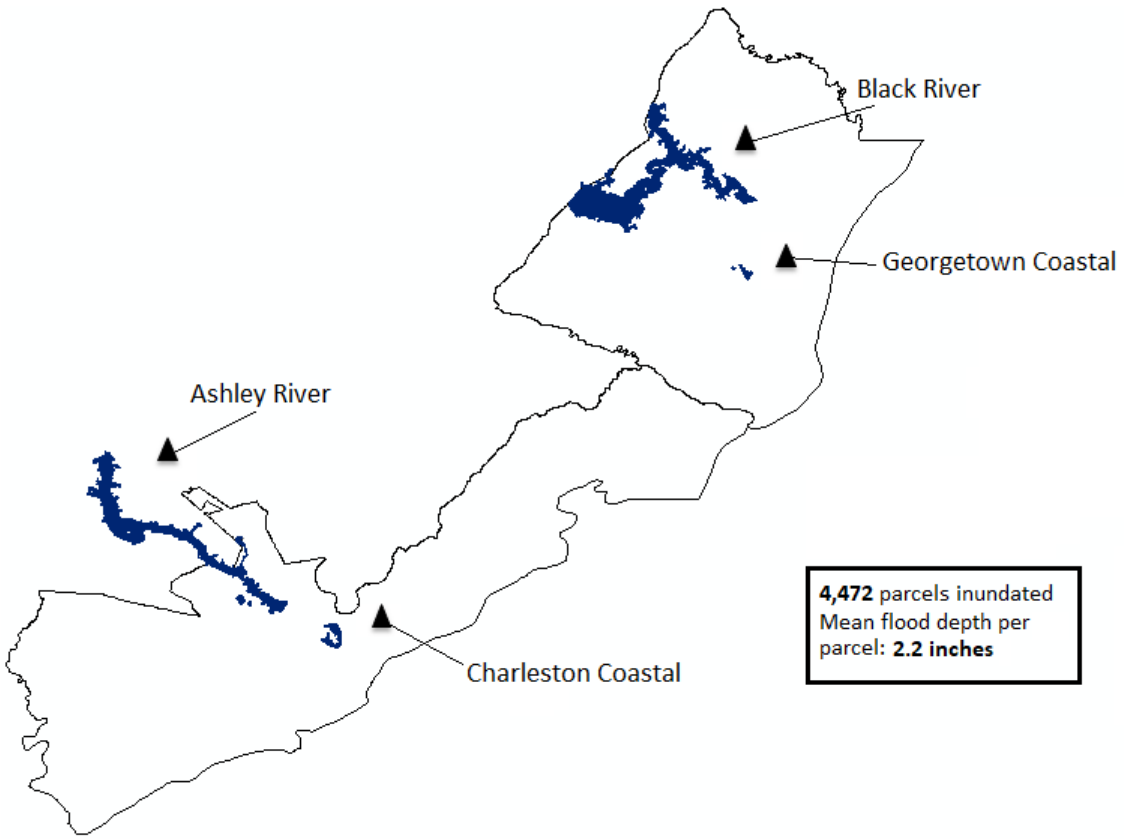


Figure 3.13: Inundation maps of Hurricane Joaquin used in developing a flood risk index. Source: USGS, 2016.

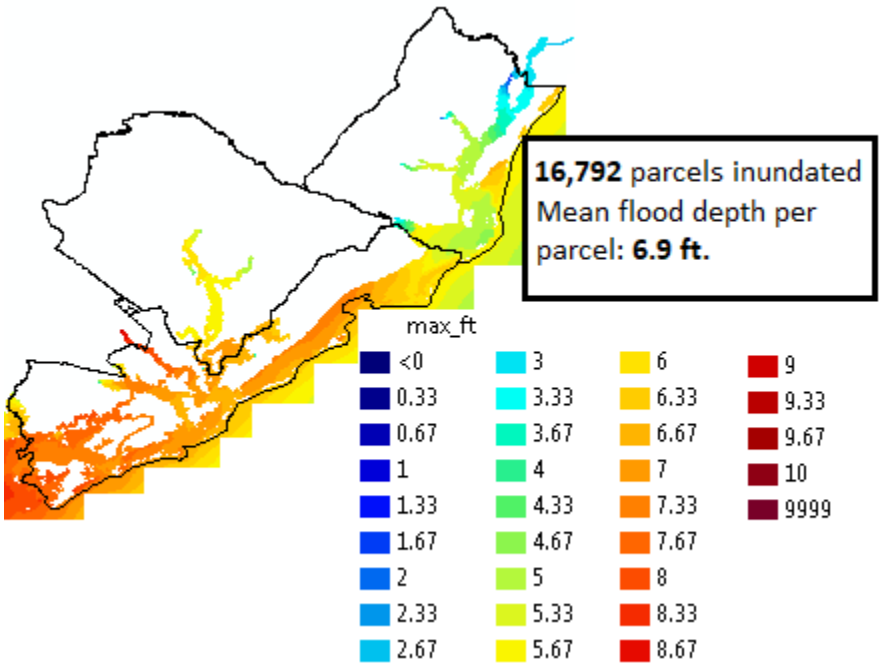


Figure 3.14: Storm simulation of Hurricane Irma used in developing a flood risk index. Source: CERA, 2017.

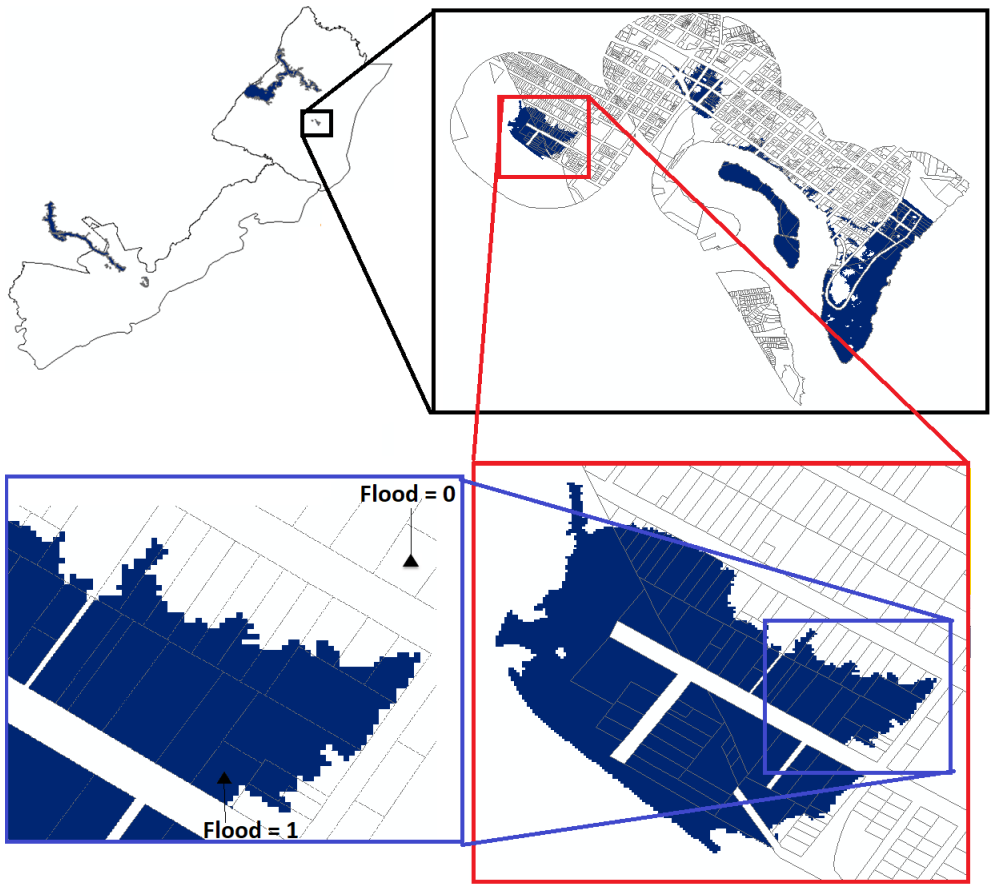


Figure 3.15: Parcel selection for probit model of flood risk during Hurricane Joaquin.

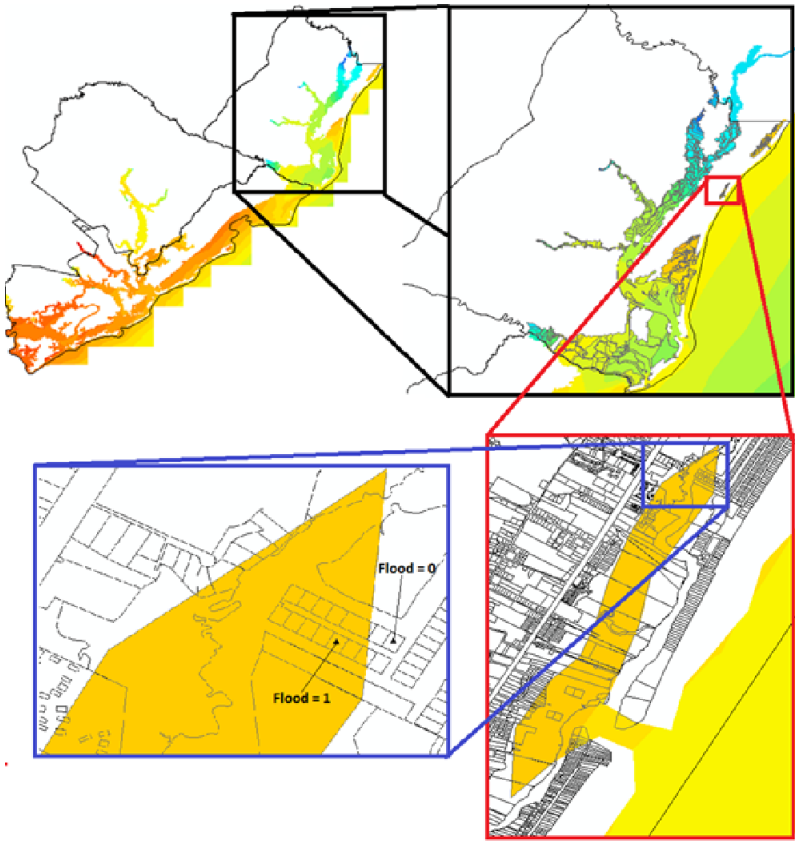


Figure 3.16: Parcel selection for probit model of flood risk during Hurricane Irma.

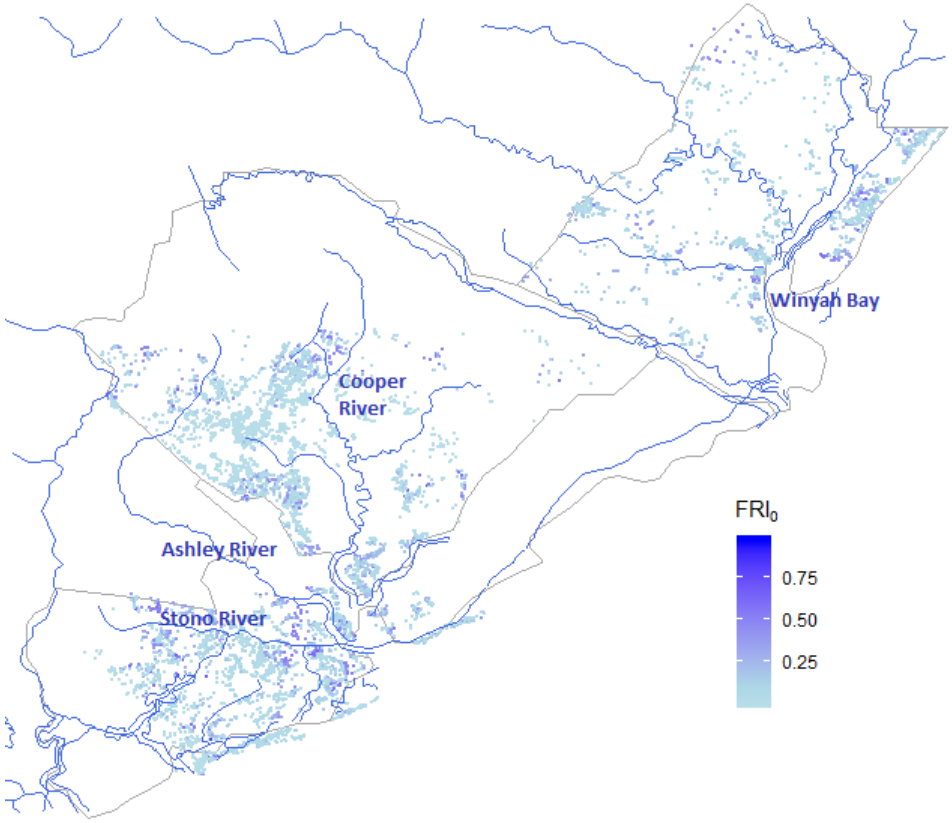


Figure 3.17: Predicted FRI_0.

4 EMPIRICAL RESULTS

4.1 PREDICTIVE HEDONIC MODELS OF LAND VALUE

In this dissertation, hedonic price functions are estimated and used to predict proxies for land values. My focus on prediction contrasts with the majority of studies employing hedonic models in environmental applications. As described in Taylor et al. (2016) and Phaneuf and Requate (2016), the focus tends to be on the estimation of specific regression coefficients of interest instead of forecast. Hence, there is little direction in the literature on what data structure is preferred for prediction (e.g., panel, cross–section, or repeated sales) or how to systematically determine what models are best suited for prediction.

In the empirical analysis, I build a repeated cross–section database with the most recent recorded sales price for each property in the sample (i.e., last–price data). I use cross–sectional data instead of panel data because the latter requires assuming that deep parameters in the property market are fixed over time, which is not realistic. In addition, the explanatory variables available in my application, are generally not well suited for exploiting time–variation in the regressors, which is required for hybrid econometric estimators for panel and pooled panel data that are advantageous for the identification of causal effects in modeling land values (which is not the objective of using price hedonic functions in this study), such as the Hausman–Taylor and the Mundlack estimators.[1]

In turn, to select the model that best fits this data, I follow a 10–fold cross validation technique and examine various measures of prediction error to determine which functional

[1]Considerable effort was devoted to arrive at the final parcel sample used in estimation as each dataset had to be carefully curated to accurately characterize the use given to each parcel in the study area. The final selection for the land use change model had 53,228 undeveloped parcels and 129,634 developed parcels. In turn, the sample for the hedonics models had 33,364 parcels for the developed model, and 6,725 for the undeveloped model. The five–step process followed to select the parcels used in the empirical analysis is described in chapter 3.

form to use, to guide the removal of outliers, and to decide which regressors to include in the model. In this chapter, I first present the modeling decisions that were determined using the 10–fold cross validation technique and describe this approach in detail. I also introduce the various measures of modeling error that were used to finalize the model selection process and present their properties. In a second section, I present the final models used to the generate proxies of land values (proxies that were in turn used as inputs in a subsequent probabilistic model of land use change). I also present the results corresponding to the estimated hedonic models for agricultural and residential land.

In a third section, I discuss the performance of the hedonic models at predicting land values and compare original data to predicted land values. I separate the discussion into a comparison of the original data against in–sample predictions and a juxtaposition of in–sample predictions to out–of–sample predictions. I further split the discussion to assess the predictive capacity of agricultural and residential models. Finally, I conclude the chapter with a discussion over estimation results of a baseline model of land use change that takes as inputs the generated, and validated, proxies.

4.1.1 MODEL SELECTION

To use valid proxies of land value in the model of land use change, it is important to specify hedonic models with high predictive power. With this focus, three type of modeling decisions were made: (1) decisions over which dependent variable to use and what functional form it should take (i.e., whether the hedonic models were to predict sales price or assessed values and whether these should be absolute or on a per acre basis, and whether linear, semi–log, or log–log functional forms should be used); (2) decisions about how to restrict the sample of parcels used in estimation (i.e., what time restrictions should be applied to the observed transactions data and how to define outliers in the

sample); and (3) decisions over how to specify the models (i.e., whether to to use a set of variables from tax assessor data commonly available for all counties or a set of variables specific to each county). To inform the making of these decisions, I employ a standard machine learning algorithm known as the k–fold validation technique. In the paragraphs below, I describe the validation procedure and summarize the relevant findings from its employment. Then, I present the final models used in estimation and discuss their results.

The cross validation procedure

The k–fold cross validation technique is a technique used in statistics to asses how well the results of a model generalize to an independent data set. In k–fold cross-validation, the original sample is randomly partitioned into k equal size subsamples and the partitioning of data is done without replacement so that no observation in the data is found in two subsets. Of the k subsamples, a single subsample is kept as the validation data for testing the model, and the remaining $k - 1$ subsamples are used as training data.[2]

The cross–validation process is then repeated k times (i.e., the number folds) with each of the k subsamples used exactly once as the validation data. The advantages of this method for model evaluation are well documented, the more salient being that all observations are used for both training (or refining) and validation, that each observation is used for validation exactly once, and that the k results from the folds can then be averaged (or otherwise combined) to produce a single estimation. An excellent and comprehensive recent survey of cross-validation results is Arlot and Celisse (2010).

I follow this process with k equal to 10. The choice of 10 subsamples is largely pragmatic since partitioning the sample further would result in datasets with fewer obser-

[2]Training a model can be thought of as refining it. In machine learning, a model is trained using training data from a training set. To evaluate the trained model, the estimated coefficients are used to predict data in the test set. In my case, the test set is the same as the validation set.

vations and the time of computation would increase. Each of the 10 resulting sets of predicted errors is manipulated to generate three measures of dispersion summarizing the quality of each estimation: the absolute deviations norm (commonly referred to as L1); the euclidean norm (or square root of the sum of squares norm, also known as $\sqrt{L}2$); and the the mean squared error (MSE). Each one of these three statistics offers different advantages when evaluating the quality of an estimator as they give proportionally higher or lower penalties to large errors or to predictions derived from small samples (for example, the $\sqrt{L}2$ measure will penalize large errors more heavily than the L1 , and the MSE will penalize errors based on smaller samples more heavily than the $\sqrt{L}2$).

The formal definition of these three measures of modeling error is:

$$L1 = \sum |Y - X\beta|, \tag{4.1}$$

$$\sqrt{L2} = \sqrt{\sum (Y - X\beta)^2}, \tag{4.2}$$

$$MSE = \frac{1}{N} \sum (Y - X\beta)^2. \tag{4.3}$$

There is a debate of whether simple but sound and robust models are preferred to more complex models that are more data driven and more sensitive to idiosyncratic conditions but are also more accurate. Given my interest in prediction, and that hedonic price functions are envelope forms without theoretical properties, I choose the latter strategy. To transparently select the statistical models that offer the better fit for the sample data, I examined the distribution of L1, $\sqrt{L}2$, and MSE resulting from the validation process. In Appendix D, I include figures that illustrate the resulting distributions.

Modeling choices

Baseline hedonic models for residential and agricultural parcels were progressively refined using output from the 10–fold cross validation. The baseline models are, as shown in equations (2.6) and (2.9):

$$P_t^U = \alpha^U + \varphi_j^U + \tau_t^U + \beta_S^U S_{jt}^U + \beta_L^U L_{jt}^U + \beta_G^U G_{jt}^U + \nu_{jt}^U, \tag{4.4}$$

$$P_t^D = \alpha^D + \varphi_k^D + \tau_t^D + \beta_S^D S_{kt}^D + \beta_L^D L_{kt}^D + \beta_G^D G_{kt}^D + \nu_{kt}^D, \tag{4.5}$$

where S_t^D and S_t^U are vectors with structural or building characteristics available from all tax assessor databases; L_t^D and L_t^U contain land characteristics available for all parcels in the sample; and G_t^D and G_t^U include measures of geospatial features. Variables in S_t^D include assessed building values and age of structures; variables in L_t^D and L_t^U are area of land, elevation, and whether parcels are located within a flood plain; and variables in G_{kt}^D and G_t^U are measures of proximity to rivers, mills, markets, roads, beaches, and the coastline, and measures of landscape composition of the parcel and its surrounding area.

The types of choices that were informed by the 10–fold cross validation are: (1) whether the hedonic models were to predict sales price or assessed values, and whether linear, semi–log, or log–log functional forms should be used; (2) what time restrictions should be applied to the observed transactions data, and how to define outliers in the sample; and (3) whether to to use a set of variables from tax assessor data commonly available for all counties or a set of variables specific to each county.

In terms of the choosing a dependent variable, the model selection process indicates the preferred model is not better or worse at predicting sales prices than assessed values for either agricultural or residential parcels, thus sales prices are selected as the dependent

variable, and to remain consistent with similar literature, price per acre was used as the dependent variable. Also, unsurprisingly, the logarithmic transformation of prices is more normally distributed that the non–transformed data. Thus, the functional form chosen for the hedonic models was log–linear. This choice also facilitates the interpretation of parameter estimates as semi–elasticities.[3]

To inform the decision of restricting the use of historical data, the selection process was slightly different from the 10–fold cross validation approach previously described. Before of partitioning the data into 10 samples, the data was split into two subsamples, one with price data from properties that sold in 2015 and 2016, and one with price data from parcels that sold before 2015. The latter subsample (i.e., the pre–2015 data) was partitioned into 10 random samples, and each random sample was used as a training set to test the set with the 2015 and 2016 prices. Five historical subsets were tested: those with sales occurring between 1996 and 2014, 2000 and 2014, 2010 and 2014, sales after 1996 but excluding the years of the housing market crisis, and those after 2000 but excluding sales from 2006 to 2009. Results from the selection process suggest the preferred time frame for building predictive models of residential land value includes sales that occurred between 2010 and 2016. For the model of agricultural land value, it includes sales that occurred between 2000 to 2016 but exclude transactions during housing market crisis (which is defined as the years between 2006 and 2009).

[3]Within the literature, there is a history of swinging between advocating the use computationally feasible forms such as linear, semi–log, and log-linear, and favoring more general and flexible functional forms nested within the general quadratic Box–Cox form. The issue of complexity has been the focus of prior literature. For many years it seemed to be that simpler forms tend to perform best in the presence of omitted variables (Cassel and Mendelshn, 1985; Cropper et al, 1988). However, in more recent years, other researchers have found that large gains in accuracy can be realized by moving from the standard linear specifications for the price function to a more flexible framework that uses a combination of spatial fixed effects, quasi-experimental identification, and temporal controls for housing market adjustment (Kuminoff, Parmeter, and Pope, 2010). Given the lack of consensus, I follow the general advice in econometrics texts, which is for the functional form to be determined from the data (Palmquist, 2005).

As with the decision over use of historical data, to inform the decision of removing outliers (i.e., unusually high or low prices), subsets of the data were created before partitioning the data into 10 random subsamples. Specifically, the data was split into five subsets containing different price ranges, each range incrementally more restricted than the previous. These ranges were defined to filter anomalous transactions that are known as "not at arm's length."In general, an arm's length transaction is one in which the buyers and sellers of a product act independently. Thus, they have no relationship to each other and are acting in their own self–interest. For filtering purposes, out of arm's length transactions in the sample were defined as those for which the reported sales price differs greatly from the value estimated by tax assessors, and five restriction rules were made based on the ratio of these two values (both expressed in 2016 dollars).[4]

[4]In the three counties studied, out of transactions that are not at arm's length are rather prevalent. To get a sense of how normal it is to observe anomalous transactions in the study area, I compared data from the three counties to data from property sales in Wake county, NC. In 2015, 1.8% of transactions in Wake county were considered "disqualified."Wake county defines disqualified transactions as those that are typically out of arm's length. Officially, these are transactions between parties of the same family, transactions that are the result of forced sale, transactions involving a loan or trade, or other transactions not considered arm's length. Unfortunately, counties in the study area do not have a standard way to codify arm's length transaction. However, using prices–to–assessed value ratios as an indicator of arm's length transactions, I found that in Charleston county, 17.5% of transactions in 2015 occurred at prices that were below 10% of the assessed value. In Berkeley county, the share was 26.5% in 2015, and in Georgetown county it was 32.5%. Compared to Wake county, the share of abnormal transactions is evidently disproportionate in the South Carolina Lowcountry region and this observation holds when the Lowcountry is compared to a other regions in the US. Communication with local experts in tax assessor offices, GIS offices, and civic groups suggest that this anomaly is related to poorly defined property rights that are associated with local historical institutions such as the prevalence of "Heirs Property."Heirs property is a legal definition of property rights closely tied with the history of slavery in the American South. In general, it refers to any land passed without a will, and in South Carolina, it most often refers to land in the Lowcountry handed down by former slaves that eventually ended up being owned jointly by dozens of descendants each of whom owns a percentage (not a portion) of the whole property regardless of whether they live on the land, pay or not pay taxes, etc. Each heir has the right to sell his/her percentage of ownership to another party who can then force a property partition and sale of the entire property in the courts (there is recorded evidence that this practice is exploited by developers to buy land below market value which is behind the drafting of the Uniform Partition of Heirs Property Act). According to a 2012 mapping project by the Center for Heirs Property Preservation, there are more than 40,000 acres of heirs' property in the Lowcountry, 51.6% of which are Charleston, Berkeley, and Georgetown counties (12,003 in Berkeley, 4,812 in Georgetown, and 4,230 in Charleston). The effects of unclear property rights on local property markets is beyond the scope of this

The restriction rules to define unusable transactions are:

1. no exclusion rule (i.e., all sales are included in the model),
2. exclude parcels whose corresponding sales price is less than 10% of the assessed value (or parcels with a price-to-assessed value ratio less than 0.1),
3. exclude parcels with a price–to–assessed value ratio less than 0.25,
4. exclude parcels with a price-to-assessed value ratio less than 0.5, and
5. exclude parcels with a price–to–assessed value ratio less than 0.5 and greater than 1.5 (or parcels whose price is less than 50% or over 150% of their assessed value).

The selection mechanism indicates the preferred range of values for both models of land value (i.e., agricultural and residential), is the more restrictive of the five: the one with transactions were the ratio between prices and assessed values is between 0.5 and 1.5.

Finally, the process to guide the decision over which independent variables to include in the model results in similar but different specifications for each county. Results from the cross validation validation suggest that exploiting specificity of data on house characteristics at the county level does not necessarily offer an advantage over using a general model with a set of variables common to all counties. Thus, a single baseline model is applied to all counties, and once a common set of property variables is chosen, further modifications are applied on the set of explanatory variables for each hedonic price function in each county. The choice of variables in the post–cross validation step, is made on the basis of several factors including the coefficient of determination (or R–

analysis, however, its economic importance and relevance for studying generational poverty appear to be nontrivial and may be an interesting aspect to study in future research.

square value), and statistical significance of the explanatory variables.[5] To arrive at the final selection of variables, the most complex version of each model is progressively made more parsimonious and is tested to determine whether extra predictors or interactions improve the model. Variables that are not significant in specifications that involve minor modifications are discarded for the final estimation. In the section below, I discuss the specifics of each hednoic model, starting with a discussion of agricultural models followed by a discussion of residential models.

4.1.2 HEDONIC MODELS FOR AGRICULTURAL PROPERTIES

For the hedonic model of agricultural land value, I use an ordinary least squares (OLS) estimator on parcel data for each county. The choice of explanatory variables was guided by existing literature, theory, and results from the validation process described above. The literature using the hedonic method in agricultural applications is small, and it is even smaller for studies focused at the parcel-level of analysis, but the general procedure is to divide observable drivers of land value into three types of factors: those that increase returns to land (net of opportunity costs), those that decrease investment costs, and those that impact option values (Towe et al., 2008). Empirically, the major determinants of farm land value are climatic factors (e.g., average rainfall), physical parcel characteristics (e.g., soil productivity), farm management practices, government payments, urban accessibility, the likelihood of future development, and exogenous population pressures (Jeuck et al., 2014; Doye and Brorsen, 2011).

I include a rich set of regressors that represent the three categories mentioned above. Explicitly, I use structural characteristics contained in tax assessor data, like parcel size

[5]The final refinement of the models is done out of the validation procedure because 10–fold cross validation is computationally demanding.

and assessed value of improvements in the parcel, together with land and geospatial features. These include raster data of soil quality classes, elevation, proximity to streams and rivers, and land cover types. I also include other spatial variables such as proximity to near employment centers (e.g., the center of the City of Charleston), main roads, and public access points to recreational beaches. Description and summary statistics of selected variables are shown in table 3.4 in the previous chapter.

The estimated model has the following structure:

$$\ln(P_{jt}^U/\text{Acre}) = \alpha^U + \varphi_j^U + \tau_t^U + \beta_S^U S_{jt}^U + \beta_L^U L_{jt}^U + \beta_G^U G_{jt}^U + \nu_{jt}^U, \tag{4.6}$$

where α^U is an intercept term, φ_j^U captures fixed effects specific to the census tract where parcel j is located, τ_t^U is a vector of time dummies that captures year–specific fixed effects, S_{jt}^U represents characteristics of structures in the land, L_{jt}^U contains features of the land, G_{jt}^U includes geospatial variables, and ν_{jt}^U is the error term.

The structural or building characteristics included in S_{jt}^U are assessed improvement value and its squared term. All three separate models are estimated using building assessed values as proxies for improvement characteristics instead of direct structural measures such as number of bedrooms, bathrooms, etc., because the latter set of variables is missing from Berkeley's tax assessor data and for many parcels in Georgetown.[6]

Variables related to productive capacity, L_{jt}^U, are dummy variables of land capability class 1 through 4, elevation above sea level, an indicator of whether the parcel is in the 100–year flood plain, and an indicator of whether a river runs through or by the parcel.[7]

[6]There are concerns of measurement error in using assessed values of building characteristics, however, evidence shows that using assessed values in hedonic equations has negligible impacts for inference and that the use of assessed values is likely to be affected only by few variables, such as whether the building has a central air, a basement, or 5 or more rooms (Ihlanfeldt and Matinez-Vazquez, 1985).

[7]There are 7 land capability classes identified by the National Resource Conservation Service. Land capability class 1 describes prime soils for agriculture while land capability 7 corresponds to poor soils

Finally, geospatial variables in G_{jt}^{U} are measures of proximity to features of interest, measures of land cover composition, and a dummy variable indicating whether or not a parcel is inside the Charleston urban growth boundary. Proximity measures include distance to a river, to the nearest mill, to Charleston's city center, to the nearest primary or secondary road, to the nearest public access point to a recreational beach, and to the coastline; and the variables describing the physical landscape are the share of the parcel's and its surrounding area covered in wetlands, high–intensity developed surfaces, or pasture/crop covers. Throughout the empirical work, I define the aforementioned land cover variables with a 0.25–mile buffer around the parcel's centroid (just over 125 acres), which therefore includes the area within parcel's boundaries. The boundary choice was based on Bockstael (1996).[8]

Results from this estimation are presented in table 4.1. Overall, estimation results are in line with expectations. In general, in a per acre measure, soil quality tends to have a positive relationship with price, although the effect is not always significant. However, in the case of Georgetown county, it is not clear that parcels with good quality soils tend to sell for higher prices, as shown by the fluctuation in signs and significance level associated with land capability class variables—this could be explained by the low variability in these soil quality indicators. Parcels in lower elevations are associated with lower prices, as are parcels with a river passing through or by (which is highly correlated with low elevations).

Interestingly, conditional on having a river go through or by the parcel, being closer to a river was associated with higher prices in Charleston and Georgetown but not in

for agriculture. LCC's 5 to 7 were left out from the regressions.

[8]In the model selection process, models that separated on–site from off–site measures of landscape composition were also estimated. Between the final model and those alternative models, there are almost no differences in significance and sign of landscape composition measures. Thus, given that my main interest is prediction and not the identification of a particular coefficient, I proceed with the buffer measures in the final models as it captures both effects. Future research will explore whether disaggregate measures of land cover on-parcel and out-of-parcel influence the policy simulations in a meaningful way.

Berkeley—which could be indicating access to water is seen as amenity in some places of the study area. This could be related to the finding that being within the 100–year flood plain is positively related with prices. Although seemingly counterintuitive, this result is consistent with relevant findings in the recent literature. In a similar study of land use change in fast–growing area in Maryland, Wrenn and Irwin (2012) find that being located in a 100–year flood plain decreases the likelihood of development. The positive result from my estimation could point towards a mechanism of causality: agricultural lands within 100–year flood plains may be less likely to develop because they are worth more under agriculture. This may be because floods carry nutrient-rich silt and sediment, and distribute it across th land, making flood plains fertile areas. Often, they are also flat and have few obstacles impeding agriculture.

Proximity to a wood processing facility is only important for determining the price of agricultural parcels in Charleston county, which tend to be farther from these centers than parcels in Berkeley or Georgetown. The relationship shows the expected sign, indicating that proximity to a mill increases the value of agricultural land. Similarly, proximity to important market centers, as indicated by distance to Charleston's city center, is generally positively related with land values. The exception being Georgetown, where every additional mile between an agricultural parcel and Charleston's city center increases land value by $1.5 per acre. This effect is small and translates to less than $20 for the average parcel, also it is conditional on a parcel being within a specific census tract.

Distance to major roads is positively related with higher land values, suggesting that transportation cost do not affect agricultural profitability for parcels in the sample, specifically, conditional on census tract fixed effects. However, the relationship is not significant in Berkeley. The reason may be that an additional mile represents a smaller part of the trip in areas that are more rural.

Proximity to public access points to recreational beaches or to the coastline are not consistently related to agricultural land values across counties. For instance, in Charleston, proximity to public beach access points is negatively related with land values but being farther from the coastline is positively related with land values, while in Berkeley and in Georgetown the opposite is observed in regards to proximity to the coastline, and there is no effect associated with proximity to beach access points.

The effects of variables measuring landscape composition of a parcel's area and the area that surrounds it are consistent with intuition, showing that larger shares of wetland cover in the area surrounding the parcel are negatively related to land values while larger shares of developed covers are positively related to land values. The latter effect is probably related to landowners' expectations over the potential for future development. Surprisingly, larger shares of pasture and crop lands are negatively related to land values (although the relationship is positive in models where variables measuring in–parcel composition are separated from variables measuring in–and–surrounding composition).[9] Although counterintuitive, the negative may suggest pastures and crop covers are signals of less development interest or opportunity, thus reducing the option value of the land.

Finally, parcels inside Charleston's urban growth boundary are found to sell for larger prices. This is likely related to ease of access to public services.

[9]In agricultural land models where on-parcel forest, wetland, and pasture were included separately from surrounding buffers, coefficient estimates for surrounding land cover measures remain qualitatively and quantitatively very similar with the exception of the percentage of surrounding land that is wetland in Berkeley and Georgetown which becomes insignificant, but the amount of wetland on-the-parcel is negative and significant with a bigger magnitude than the combined measure reported in Table 4.1. Also, the estimates for Georgetown indicate that more developed cover on the parcel and around the parcel increase agricultural land value in that county. Further, and increase in pasture/crop cover on the parcel significantly increases its sales price, while the amount of pasture/crop in the 0.25 mile buffer around the parcel decreases sales price. The net effect (as reported in Table 4.1) is negative and not statistically significant.

4.1.3 HEDONIC MODELS FOR RESIDENTIAL PROPERTIES

As in the analysis of agricultural land value, in the analysis of residential land value, three separate OLS models are estimated on sales price data from each county using a wide range of variables. These variables are chosen largely based on empirical findings from the hedonics literature and land use conversion studies. Empirical findings in the urban economics field, show that central factors that influence residential land prices, residential land conversion, and patterns of urban development (e.g., urban sprawl) include zoning laws and other urban development policies (e.g., clustering regulations, smart growth policies, minimum density limits, and programs that preserve open space); spatially varying heterogenous features of parcels (e.g., proximity to urban centers, soil quality, and lot size); and spatial interactions between neighboring parcels due to the effects of land use externalities.[10] The set of regressors used in the hedonic models of developed land values include representatives from all these three categories.

The general residential hedonic model has the following structure:

$$\ln(P_{kt}^{D}/\text{Acre}) = \alpha^{D} + \varphi_{k}^{D} + \tau_{t}^{D} + \beta_{S}^{D} S_{kt}^{D} + \beta_{L}^{D} L_{kt}^{D} + \beta_{G}^{D} Gkt^{D} + \nu_{kt}^{D}, \tag{4.7}$$

where, α^{D} is an intercept term, φ_{k}^{D} captures fixed effects specific to the census block group where parcel k is located, τ_{t}^{D} is a vector of time dummies that captures year–specific fixed effects, S_{kt}^{D} represents characteristics of structures in the land, L_{kt}^{D} contains features of the land, G_{kt}^{D} includes geospatial variables, and ν_{kt}^{D} is the error term.

Structural or building characteristics in S_{kt}^{D} are age of the structure and its squared term, residential square footage in the land and its square, assessed improvement value,

[10] These results are found in Bockstael (1996), Taylor (2003), Palmquist (2005), Newburn et al. (2006), Wrenn and Irwin (2012), Bigelow (2015).

and improvement value squared. Land variables related to land productive capacity contained in L_{kt}^{D} are a dummy variables indicating whether the parcel is inside the 100–year flood plain, elevation above sea level, and a dummy indicator of whether a river runs through or by the parcel. Finally, geospatial variables in G_{kt}^{D} are distance to Charleston's city center, to the nearest primary or secondary road, to the nearest public access point to a recreational beach, to the coastline, and to a river; and the share of a parcel's area and the area that surrounds it that is covered in wetlands, high–intensity development surfaces, pasture or crops, and forests. Definitions and summary statistics for these variables are shown in table 3.5.

Table 4.2 shows estimation results for the hedonic equations of residential properties. Across counties, age of residential buildings in the parcel, square footage of the structure, and assessed value of the structure show a significant quadratic relationship with prices. Younger structures are associated with higher prices as are structures with higher assessed values. However, building size has different effects across counties. In Charleston, it is positively related to price while the main effect is not significant in Berkeley, and in Georgetown it is negative. Although that an increase in the size of buildings would cause a drop in the price of residential parcels is counterintuitive, it is possible that an increase in the square footage may be signaling lower quality of structures, given that building assessed values are being held constant.

Parcel elevation is negatively related to sales prices as is the dummy variable indicating whether a river runs through or is adjacent to the parcel. An interesting finding is the effect of flood hazards on sales prices, as indicated by whether parcels are located within the 100–year flood plain. In Charleston county, being within the flood plain is negatively and significantly related with sales prices, a result supported by recent findings in the

literature.[11] This negative effect contradicts the effect found among agricultural parcels, providing indication that residential land markets may react differently to flood risks than agricultural land markets, perhaps due to underlying reasons overlooked in this study, like relative ease of access to crop insurance compared to access to flood insurance for residential properties. In Berkeley and Georgetown counties, the effect of flood hazards on property values is not significant, which could be reflecting fundamental differences in property markets across rural and more urban landscapes.

In general, proximity effects are negligible in terms of magnitude. However, they also point towards the existence of structural differences in land markets across counties. In Charleston county, proximity to Charleston's city center, major roads, access points to public beaches, the coastline, and the nearest river, positively affect sales prices. In Berkeley county, almost all these relationships show the opposite direction. In Georgetown county, the effect of proximity variables resemble those from Charleston, except for proximity to downtown Charleston, which is positively related to sales prices.

The effects of landscape composition variables on sales prices are more consistent across counties. Increases in the density of crop and forest covers negatively influence sales prices, in spite of the long list of empirical evidence on the positive relation between open space and forested covers and prices of residential lands.[12] In a recent study by Phaneuf and Kaliber (2009), the authors find that heterogeneity within open space covers matters for identifying marginal willingness to pay for open space. In particular, they find a negative marginal willingness to pay for agricultural open spaces. The negative effect

[11] In their study of the effects of flood hazards on residential property values, Dei-Tutu and Bin (2002) find that the market value of a house located within a floodplain is significantly lower than an equivalent house located outside the floodplain. Furthermore, using sales data from North Carolina, the authors find that the price differentials are greater than the present value of the future flood insurance costs.

[12] The positive relation is found, for example in Donovan and Butry (2010), Netusil et al. (2010), Sander et al. (2010), and Kong et al. (2007).

found in my estimation may be related to such kind of heterogeneity in open space in the Lowcountry, and may be alluding to the idea that in more rural counties additional forest and agricultural lands may be less of an amenity than in urban spaces—after all, other studies of the amenity effect tend to focus on highly urban areas.

Higher densities of developed land cover inside a parcel and in the area that surrounds it are positively related to sales prices. This is an intuitive effect of urbanization, which captures many effects, for instance, easier access to retail. Finally, the effect of increases in the density of wetland covers in and around parcels is heterogenous. This variable has a positive effect on sales prices in Charleston, which can be explained by the biophysical connection between wetlands and water features—features that tend to be an amenity of interest in urban areas. However, wetland covers have a negative effect in Berkeley, and are insignificant determinants of price in Georgetown, possibly indicating that in more rural places, wetlands are not perceived as an open space amenity. This outcome is of particular interest for designing land use policies aimed at conserving natural infrastructure with flood protective capacity, and the fluctuation in signs and significance suggests there may be heterogenous impacts of such a policy across counties.[13]

4.1.4 ARE PREDICTED VALUES VALID PROXIES OF LAND VALUE?

A major interest of this study is to use the hedonics framework for predictive purposes and to generate valid proxies of land value that are then used as inputs in a second–stage probabilistic model of land use choice. Hence, in the paragraphs below, I assess the accuracy of prediction attained in the first–stage estimation by analyzing the statistical

[13]In residential land models where on–parcel forest, wetland, and pasture were included separately from surrounding buffers, coefficient estimates for surrounding land cover measures remain qualitatively and quantitatively very similar with the exception of the percentage of surrounding land is developed in Berkeley (which becomes insignificant).

properties of the generated proxies.[14] In this section, I first examine the performance residential and agricultural models by comparing in–sample predictions against original data. Then, I contrast in–sample predictions to out–of sample–predictions and analyze differences in performance between residential and agricultural models.

In evaluating the internal validity of the models, I find that that, in general, the hedonic model for residential land value does not perform poorly at predicting in–sample values, and that it performs better than the hedonic model of agricultural land value. This is shown in table 4.3 and further illustrated in figures 4.1 to 4.3.

Table 4.3 presents different measures of prediction error for both models and shows how these statistics are substantially larger for agricultural models, with magnitudes that are between 4.5 to 12 times larger. Figure 4.1 compares simple prediction errors (i.e., $Y - X\hat{\beta}$) for both models using boxplots and clearly shows that errors from the residential land model are more normally distributed with the mean near zero.

Figure 4.2 compares the kernel densities of the original data to those of the predicted values and includes a measure of bandwidth for each kernel density which represents the standard deviation of the kernel. This comparison is shown for results of the residential model in panel (a) and of the agricultural model in panel (b). As shown in the figure, differences in bandwidths between kernels of original and predicted data are negligible for the residential model (0.007 instead of 0.09), while the difference between in bandwidths across agricultural values are rather pronounced (0.6 instead of 0.2). Panel (a) shows that, in general, the hedonic model for residential land value generates predictions that are closely related to in–sample values, while panel (b) shows that the agricultural model seems to largely misrepresent the group of parcels with lower prices—which is

[14]Recall from chapter 2 that these proxies correspond to $\widehat{\pi^D}$ and $\widehat{\pi^U}$. Specifically, they are $\ln(\widehat{\frac{P^D}{Acre}})$, $\ln(\widetilde{\frac{P^D}{Acre}})$, $\ln(\widehat{\frac{P^U}{Acre}})$, and $\ln(\widetilde{\frac{P^U}{Acre}})$ in chapter 2.

a particularly noise part of the sample (see reference to Heirs Property transactions). Nevertheless, predicted values for parcels with higher prices are do not differ drastically from the original data.

Figure 4.3 shows the spatial distribution of predictive error. Darker colors indicate larger errors. Interestingly, the agricultural model tends to under–predict values disproportionately for parcels in Georgetown county and over–predict them elsewhere.

In terms of external validity, both hedonic models seem perform similarly for out–of–sample prediction. Table 4.4 shows descriptive statistics for in–sample and out–of sample models of residential and agricultural parcels while figure 4.4 juxtaposes kernel densities of in–sample and out–of–sample predicted values. As shown by table 4.4 and figure 4.4, the predicted out–of–sample values do not stand out as strikingly poor counterfactuals for either model, although again, there is some indication that residential and agricultural land models have slightly different predictive powers. Based on summary statistics and kernel distributions, in–sample predictions are slightly larger than out–of–sample predictions, however, that difference seems smaller for predictions of residential land value.

To summarize, there is indication that hedonic models for residential land have greater predictive power than models for agricultural land. I suspect this to be partly explained by the infrequency of transaction data for agricultural properties as well as by the greater uncertainty regarding their price is agreed on relative to residential parcels. However, both models generate out–of–sample predictions that are consistent with tendencies and distributions of in–sample estimates and original values.

4.2 LAND USE CHANGE MODEL ESTIMATION RESULTS

The predicted values generated in the estimation of the hedonic models of land value presented in equations (4.1) and (4.2) are used as explanatory variables in a series of land use change models. In this section, I focus on the results from modeling land use decisions by private landowners in a context that assumes no change in the current set of land use policies (i.e., under a business–as–usual, or BAU, conditions).

As described in section 2.2 of this dissertation, I model land use decisions of private landowners whose objective is to maximize the expected net present value of their land, and they do so by choosing the use given to their land (i.e., agricultural or residential). In this model of rational agents in a deterministic environment, landowners decide to covert an agricultural parcel to urban uses if the net present value of their land is greater under residential uses than when used in agriculture, net of conversion costs. In the paragraphs to come, I discuss the results from estimating the following model of land use choice:

$$d_{it} = \begin{cases} 1 & \text{if } \widehat{\ln(\frac{P^D_{it}}{Acre})} - \widehat{\ln(\frac{P^U_{it}}{Acre})} > 0, \\ 0 & \text{otherwise.} \end{cases} \tag{4.8}$$

Here, $\widehat{\ln(\frac{P^D_{it}}{Acre})}$ and $\widehat{\ln(\frac{P^U_{it}}{Acre})}$ are the predicted proxies of alternative land values for parcel i in 2016 (which is the last year in tax assessor databases). These proxies were generated earlier in this chapter.

Equation (4.8) is estimated using a proportional hazards model, which was introduced and discussed in section 2.2, and results from this estimation are shown in table 4.5.[15] The first column in table 4.5 corresponds to estimates from the proportional hazards model

[15]This model was estimated using the survival package in the statistical software R.

when only parcels from Charleston county are considered, the second column applies to the subset of the data with Berkeley and Georgetown parcels, and the third column shows coefficient estimates when all parcels are included.[16] Note that this table shows estimated coefficients, which are not directly interpretable.

Overall, the direction of the relations between land value and development are consistent with theory, and both variables are statistically significant. A one percent increase in the predicted per acre developed value of land (i.e. a unit increase in the predicted natural log of the per acre developed value of land), increases the hazard of development. When all parcels are used for estimation, a 1% increase in the predicted per acre developed value of land increases the hazard rate of development by 0.483%.[17]

Note that an effect on the hazard rate is not equal to (or has the same statistical significance as) an effect on the probability that a parcel develops, although the effects will always be of the same sign. To find the change in the probability that parcel develops further manipulations of the model outputs are required. Specifically, as discussed in chapter 2, the probability that a parcel develops within 5 years is $\delta = 1 - S_5$, where S_5 is the probability that a parcel remains undeveloped for 5 years. In the appendix, I include a brief explanation on the methods used to get the survival probabilities.

The effect on the hazard rate from a 1% increase in the predicted per acre developed value of land is substantially smaller for parcels in Charleston county than for parcels in Berkeley and Georgetown. According to estimates from the proportional hazards model, a one percent increase in the developed value of land increases the hazard rate of devel-

[16] By virtue of the selection criteria described in the data section, most of the parcels selected for analysis in Charleston county are located in John's Island, the largest island in South Carolina. Johns Island is 84 square miles in area, with a population of 21,500 people. It is a sensitive region in terms of historical, cultural, and environmental considerations.

[17] Alternatively, taking the exponent of the coefficient yields the effect on the relative hazard of development. In this case, $\exp(0.483) = 1.62$, which means the expected hazard rate is 1.62 times higher for parcels after a 1% increase in their per acre developed value, holding their undeveloped value constant.

opment by 0.236% in Charleston county, while in Berkeley and Georgetown, the hazard increases by a 0.637%.[18] The difference in predicted coefficients from separate samples shown in table 4.5 supports the hypothesis developed during the hedonic estimation that land markets in Georgetown and Berkeley are structurally different from land markets in Charleston. However, the direction of the effect differential is counterintuitive. Charleston is more developed than Berkeley and Georgetown, thus, undeveloped land is more scarce and more valuable to developers.[19] Developers would theoretically be willing to invest more in Charleston than in Berkeley and Georgetown, and yet, the results suggest developers are more likely to buy land for development in Berkeley and Georgetown.

To understand this discrepancy, it is important to note that the reported effect constitutes a change in risk at the margin. In other words, the baseline risk of conversion in Charleston county may already be higher than that in Berkeley and Georgetown counties. To further explain this divergence, it is useful to consider an additional factor: the concept of economies of scale, which describes a situation where a proportionate saving in costs in gained by an increased level of production. In other words, the average costs of developing one parcel are lower when the fixed costs of development (which are incurred to cover costs of permitting, bank loans, office managers, transportation of construction materials, etc.) are spread across many parcels. When this idea is taken into account, then it is easier to see how a one percent increase in the value that a residential parcel can fetch in Berkeley and Georgetown counties may seem more attractive to developers than a similar increase in the value that residential parcels can sell for in Charleston county. Developers prefer to locate their projects where they can find larger areas of land to spread fixed costs over more potential subdivisions.

[18] As shown in Appendix F, the effect differential is also found when estimating the conditional logit.

[19] According to the latest land cover data, 11.5% of Charleston county's surfaces are developed covers, while in Berkley and Georgetown developed covers comprise 6.3% and 4.3% of the area, respectively.

A second result that is also consistent with theory, is the reduction in the development hazard rate from a percent increase in the predicted per acre agricultural value of a parcel. The effect is similar for Charleston parcels and for Berkeley and Georgetown parcels, at 0.063% and 0.092% respectively. When all parcels are included in estimation, a 1% increase in agricultural value reduces the risk of development by 0.105%, holding constant the developed value of land.

The results from this original proportional hazard estimation can help develop ex–ante expectations for the results of the policy comparison analysis that will be presented in chapter 5. The 0.105% reduction in risk from an increase in the agricultural value of land stands out as substantially smaller than the 0.483% increase in risk from an analogous change in the developed value of land. Theoretically, the absolute magnitude of these coefficients is be equal. However, what is found is that a 1% in the undeveloped price of land does not restrict conversion to the same degree that an increase in the developed price of land of the same proportion encourages development. This gap could be reflecting the difference in starting alternative values of land, or it could also be masking a particular appetite for land conversion in the study area that is explained by reasons not specified in the land value functions (e.g., shifting demographics in the country or the region that drive external populations towards the study area). Whatever the case may be, the difference in magnitude of coefficients is thought provoking and may turn out to be an important factor in determining the relative effectiveness of land use policies, suggesting that policies reducing developed values may have stronger effects in altering the urban landscape than policies that increase agricultural values.

4.3 ADDITIONAL ECONOMETRIC CONSIDERATIONS

4.3.1 SPATIAL DEPENDENCE IN THE ERROR TERM

The role of spatial processes is strong in determining how land is valued, how developers make decisions, and how natural landscapes evolve. When important covariates with spatial effects are not included in the model, or when the model is misspecified in another way, residuals will show spatial autocorrelation. For instance, consider the idea that proximity to sea walls determines the likelihood that a parcel gets flooded and therefore how landowners and developers value the parcel. If the location of sea walls is unknown, the effect of proximity to sea walls will be captured by the error term in a model of land value and the error term will exhibit spatial dependence. Specifically to this study, if an important covariate explaining spatial correlation among land values, development decisions, or the ecology of the landscape is not observed, spatial correlation in the error term can be a threat to the validity of any statistical inferences.

There are well supported ways to accommodate for spatial dependence in linear models, such as adding spatial weights to the error term (what is commonly known as using a spatial autoregressive error). However, the preferred solution for dealing with residual spatial autocorrelation is to find any missing covariates that explain spatial processes and include them in the model (Hoeting et al., 2006). Thus, before adding more structure to the error term in the hedonic models of land prices, and possibly introducing new randomness into the analysis, I first add spatial structure to the mean function by including multiple landscape attributes (for example the measures of surrounding land covers and measures of proximity) and spatial fixed effects at the census tract and block group level in the reduced form equation (see discussion over equations 4.1 and 4.2). Then, using standard diagnostic tools, I test whether adding spatial structure to the mean function is

enough to account for the unobserved spatial autocorrelation in the process determining property values. Specifically, I use QQ–plots, bubble plots, spatial correlograms, and variograms to detect residual spatial autcorrelation in the hedonic models. Using these tools, I find that including a rich set of spatial explanatory variables in the hedonic models is enough to remove any spatial dependence in the residuals.

In regards to modeling land use decisions, failing to address spatial correlation in land features that facilitate development could even result in biased coefficient estimates, and not just flawed standard errors (Bigelow, 2015). There are well documented ways to address the error dependence problem in a binary choice model.[20] However, there is evidence in the literature that in two–stage study, like the one conducted here, accounting for spatial correlation in the first–stage (i.e., in how land prices are generated) can be enough to fully capture spatial processes that influence the second–stage process, therefore obviating the need to use complicated techniques that make a model more complex and the analysis more prone to error (Newburn et al., 2006).

Furthermore, to the extent that land use patterns and the spatial configuration of aggregated development decisions are perceived as disorganized and unpredictable, and that the study of individual landowner conversion decisions appears insufficient for understanding sprawl, there may not be any gain from separately addressing spatial au-

[20]For instance, Lewis et al. (2011) address this issue by adding components to the random error term in the RUM that allow land values to be correlated spatially (i.e., all parcels within a county share a common value for a given term) and temporally (i.e., each parcel has a common value for another term across time periods). An alternative way to address spatial dependence is to extract subsamples of the data that are less likely to be spatially correlated with each other, and then estimate the land use model on these subsamples. The justification behind this approach is that the spatial autocorrelation in the residuals is likely to be lower if the samples used for estimation are farther apart in a spatial sense. There are multiple options for selecting the samples that are to be included in the estimation. For example, Carrion-Flores and Irwin (2004) follow the so-called "work-around"method, creating a subsample of the data by removing nearest neighbors within a fixed distance. In a different study, Newburn et al. (2006) perform multinomial logit regression on random stratified bootstrapped samples taken from the full dataset to correct the error term. More recently, Bigelow (2015) constructs a block-stratified random sample and uses it to estimate the econometric land use models.

tocorrelation in the second stage of the analysis.[21] Therefore, for the purpose of this dissertation, relying on results of the diagnostics tests for the hedonic estimations and including in the land price equations important spatial features thought to influence the formation of aggregated pockets of development, such as proximity to large urban centers and presence of development in neighboring areas, is considered enough to address potential spatial autocorrelation in the development decision. In Appendix D, I discuss statistical strategies to model spatial processes. I also present present the tools used to diagnose spatial autocorrelation in my application and the results that support my conclusion of continuing without further corrections.

4.3.2 SAMPLE SELECTION CORRECTION

By necessity, the hedonic model of residential property value is estimated using observed sales prices of parcels that have been converted to residential use. Thus, there is an inherent selection bias that threatens the estimation of coefficients. To estimate valid (i.e., unbiased) coefficients in a hedonic model for developed parcels, the corrective procedure proposed by Heckman (1979) can be used. This procedure calls for the identification of at least one exclusion variable (i.e., a variable that affects the probability that parcels develop but not the sales price of residential parcels).

To implement Heckman's sample selection corrective method to my empirical application, I use as the exclusion restriction variables measures soil quality and proximity to agricultural processing facilities, both factors that are expected to affect agricultural land value but not residential land value. Despite the theoretical strength behind the logic

[21] Disproportionate growth of urban areas and excessive leapfrog development are examples of such inefficient patterns, and the term to describe this inefficiency is "sprawl."Several hypotheses to explain sprawl have been tested but empirical evidence of what factors influence sprawl per se remains limited (Carrion–Flores and Irwin, 2004).

used to select these instruments, a close examination of the data offers weak support for the choice of instruments, questioning whether any instrument should be used at all. Evidence shows that using weak instruments is likely to produce inconsistent and sometimes biased (Bound, Jaeger and Baker, 1995). Thus, to minimize introduced damage in the estimation and avoid the risk of over-fitting the model, I chose not to pursue any corrective steps in the final estimation of the hedonic model for residential properties.

Other works in the literature have opted to proceed with the non–corrective method (Wrenn and Irwin, 2012; Newburn et al., 2004-2006; and Bockstael, 1996). In fact, few works empirically address the issue of sample selection bias, even though the literature clearly recognizes the problem. A theoretical justification for abstracting away from the sample selection problem is the idea that a hedonic model of residential land value may be unbiased if developers' ignorance of omitted variables that drive the selection problem matches the ignorance of the researcher (Bockstael, 1996). In Appendix E, I include findings from the exploratory analysis of instruments for a selection bias correction, and to illustrate the trivial effect of including or excluding these weak instruments from estimation, I present results from hedonic regressions that correct for sample selection bias using the proposed weak instruments and the Heckman methodology.

Table 4.1: Hedonic models of agricultural land.

	Dependent variable: $\ln(\frac{\text{Price}}{\text{Acre}})$ in 2016 dollars		
	Charleston	Berkeley	Georgetown
Constant	12.363***	10.425***	-5.531
	(0.373)	(1.183)	(5.367)
Building value	0.0001***	0.00001***	0.00003***
	(0.00002)	(0.000001)	(0.000003)
Building value^2	-0.017e^{-10}***	-0.021e^{-9}***	-0.088e^{-9}***
	(0.004e^{-10})	(0.005e^{-8})	(0.004e^{-8})
LCC1 (=1)	-0.336	0.269	0.405
	(0.649)	(0.375)	(0.310)
LCC2 (=1)	0.067	0.424	-0.206*
	(0.078)	(0.363)	(0.116)
LCC3(=1)	-0.011	0.209	-0.037
	(0.058)	(0.368)	(0.118)
LCC4 (=1)	0.380***	0.533	-0.040
	(0.093)	(0.373)	(0.116)
Elevation (m)	-0.013	-0.003	-0.089***
	(0.020)	(0.011)	(0.014)
100-year flood plain	0.780***	0.181**	0.273***
	(0.079)	(0.080)	(0.058)
River (=1)	-0.953***	-0.199*	-0.598***
	(0.127)	(0.117)	(0.141)
Dist. to river (mi)	-0.575***	1.263***	-0.790*
	(0.171)	(0.330)	(0.430)
Dist. to river^2 (mi)	X	-1.235***	0.800
		(0.383)	(0.741)
Dist. to mill (mi)	-0.046**	X	X
	(0.024)		

Continued on next page

Table 4.1 (continued).

	Charleston	Berkeley	Georgetown
Dist. to Charleston (mi)	-0.056	-0.181**	0.403**
	(0.041)	(0.083)	(0.175)
Dist. to Charleston^2 (mi)	0.004***	0.003	-0.002*
	(0.002)	(0.002)	(0.001)
Dist. to road (mi)	0.309***	0.055	0.268**
	(0.026)	(0.114)	(0.116)
Dist. to road^2 (mi)	X	0.013	-0.054
		(0.030)	(0.043)
Dist. to beach (mi)	-0.172***	0.239***	-0.027
	(0.023)	(0.091)	(0.079)
Dist. to beach^2 (mi)	X	-0.006***	0.008***
		(0.002)	(0.002)
Dist. to coastline (mi)	0.075***	X	-0.110
	(0.028)		(0.079)
Dist. to coastline^2(mi)	X	X	-0.006**
			(0.004)
Wetland cover within	0.002	-0.004***	-0.004***
a 0.25-mile radius area	(0.001)	(0.002)	(0.001)
Developed cover within	0.010***	0.007***	0.006***
a 0.25-mile radius area*	(0.001)	(0.001)	(0.001)
Pasture/crop cover within	-0.008***	-0.015***	-0.003
a 0.25-mile radius area	(0.002)	(0.002)	(0.003)
UGB (=1)	0.592***	X	X
	(0.104)		
Year fixed effects	YES	YES	YES
Tract fixed effects	YES	YES	YES
Observations	2,041	2,366	1,959
R^2	0.591	0.723	0.741

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Table 4.1 (continued).

	Charleston	Berkeley	Georgetown
Adjusted R^2	0.584	0.715	0.734
Residual Std. Error	1.06	0.94	0.91
	(df = 2008)	(df = 2294)	(df = 1910)
F Statistic	90.6^{***}	84.5^{***}	113.7^{***}
	(df = 32; 2008)	(df = 71; 2294)	(df = 48; 1910)

*Includes open space-, low-, medium-, and high-intensity development.
Significance codes: *p<0.1; **p<0.05; ***p<0.01
The errors in parenthesis are robust standard errors.
An "X"in place of coefficients means the variable was left out as indicated by results of the 10–fold cross validation.

Table 4.2: Hedonic models of residential land.

	Dependent variable: $\ln(\frac{\text{Price}}{\text{Acre}})$ in 2016 dollars		
	Charleston	Berkeley	Georgetown
Constant	16.773***	13.222***	-11.735**
	(0.205)	(0.414)	(6.119)
Age	-0.032***	-0.059***	-0.032***
	(0.001)	(0.003)	(0.003)
Age^2	0.0003***	0.001***	0.0003***
	(0.00001)	(0.0001)	(0.00005)
SQFT	0.0002***	-0.00001	-0.0002***
	(0.00003)	(0.00003)	(0.00003)
SQFT^2	$-0.003e^{-5}$***	$0.006e^{-6}$*	$0.003e^{-6}$***
	($0.003e^{-6}$)	($0.003e^{-6}$)	($0.007e^{-7}$)
Building value	0.00001***	$0.003e^{-4}$***	$0.003e^{-3}$***
	($0.006e^{-4}$)	($0.006e^{-5}$)	($0.002e^{-4}$)
Building value^2	$-0.006e^{-11}$***	$-0.026e^{-12}$	$-0.001e^{-9}$***
	($0.001e^{-11}$)	($0.005e^{-11}$)	($0.002e^{-10}$)
100-year flood plain (=1)	-0.069***	0.029	-0.0012
	(0.013)	(0.024)	(0.033)
Elevation (m)	-0.022***	0.001	-0.106***
	(0.006)	(0.003)	(0.010)
River (=1)	-0.401***	-0.230***	-0.292***
	(0.037)	(0.034)	(0.069)
Dist. to Charleston (mi)	-0.166***	0.078**	0.576***
	(0.027)	(0.033)	(0.178)
Dist. to Charleston^2 (mi)	0.005***	-0.011***	-0.004***
	(0.001)	(0.001)	(0.001)
Dist. to road (mi)	-0.062***	0.141***	-0.08
	(0.027)	(0.031)	(0.057)

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Table 4.2 (continued).

	Charleston	Berkeley	Georgetown
Dist. to road^2(mi)	0.008	-0.027**	0.03
	(0.007)	(0.010)	(0.020)
Dist. to beach (mi)	-0.126***	0.012	-0.061
	(0.036)	(0.049)	(0.046)
Dist. to beach^2 (mi)	0.003	0.007***	0.010***
	(0.003)	(0.001)	(0.002)
Dist. to coastline (mi)	-0.107**		-0.155***
	(0.043)	X	(0.042)
Dist. to coastline^2 (mi)	0.009**		-0.006*
	(0.004)	X	(0.003)
Dist. to river (mi)	-0.327**		-0.263
	(0.132)	X	(0.222)
Dist. to river^2 (mi)	0.446*	X	0.822**
	(0.231)		(0.395)
Wetland cover within	0.002***	-0.002***	-0.001
a 0.25-mile radius area	(0.0005)	(0.0003)	(0.001)
Developed cover within	0.003***	0.001***	0.004***
a 0.25-mile radius area*	(0.0004)	(0.0003)	(0.001)
Pasture/crop cover within	-0.005***	-0.020***	-0.005
a 0.25-mile radius area	(0.001)	(0.001)	(0.003)
Forest cover within	-0.002***	-0.002***	-0.003**
a 0.25-mile radius area	(0.0005)	(0.0002)	(0.001)
Year fixed effects	YES	YES	YES
Tract fixed effects	YES	YES	YES
Block group fixed effects	YES	NO	NO
Observations	16,300	12,315	3,627
R^2	0.765	0.695	0.709
Adjusted R^2	0.763	0.694	0.705

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Table 4.2 (continued).

	Charleston	Berkeley	Georgetown
Residual Std. Error	0.516	0.453	0.575
	(df = 16125)	(df = 12248)	(df = 3582)
F Statistic	301.9***	423.4***	198.2***
	(df = 174; 16125)	(df = 66; 12248)	(df = 44; 3582)

*Includes open space-, low-, medium-, and high-intensity development.
Significance codes: *p<0.1; **p<0.05; ***p<0.01
The errors in parenthesis are robust standard errors.
An "X"in place of coefficients means the variable was left out as indicated by results of the 10–fold cross validation.

Table 4.3: Measures of prediction error from in–sample estimation of hedonic models.

	Agricultural parcels	Residential parcels
$L1 = \sum \lvert Y - \hat{Y} \rvert$	214,996.1	17,708.5
$\sqrt{L2} = \sqrt{\sum \left(Y - \hat{Y}\right)^2}$	1,452.92	379.72
$MSE = \frac{1}{N} \sum (Y - \hat{Y})^2$	63.13	13.93

Table 4.4: Summary statistics: in–sample against out–of–sample.

	Residential		Agricultural	
	in–sample	out–of–sample	in–sample	out–of–sample
	$\ln(\widehat{\frac{P^D}{Acre}})$	$\ln(\widetilde{\frac{P^D}{Acre}})$	$\ln(\widehat{\frac{P^U}{Acre}})$	$\ln(\widetilde{\frac{P^U}{Acre}})$
min	9.85	8.25	6.69	7.28
1st Quantile	13.49	12.67	10.55	10.55
Median	13.88	13.51	11.81	11.2
Mean	13.91	13.38	12.57	11.87
3rd Quantile	14.25	14.18	14.56	12.13
Max	16.81	16.82	19.48	19.38

Table 4.5: Land use change model - proportional hazards.

	Dependent variable: hazard rate		
	Charleston parcels	Berkeley and Georgetown	All parcels
$\ln(\widehat{\frac{P^D}{Acre}})$	0.236***	0.637***	0.483***
	(0.012)	(0.019)	(0.011)
$\ln(\widehat{\frac{P^U}{Acre}})$	−0.063***	−0.092***	−0.105***
	(0.002)	(0.002)	(0.002)
Observations	19,729	45,390	65,119
R^2	0.009	0.072	0.049
Log Likelihood	-39,575	-81,764	-129,158
Wald Test (df = 2)	170.4***	2,884.4***	2,952.1***
LR Test (df = 2)	170.1***	3,402.4***	3,301.2***
Score (Logrank) Test (df = 2)	170.4***	3,017.7***	3,018.8***

Significance codes: *p<0.1; **p<0.05; ***p<0.01
The errors in parenthesis are robust standard errors.
The first column in table 4.5 corresponds to estimates from the proportional hazards model when only parcels from Charleston county are considered, the second column applies to the subset of the data with Berkeley and Georgetown parcels, and the third column shows coefficient estimates when all are included.

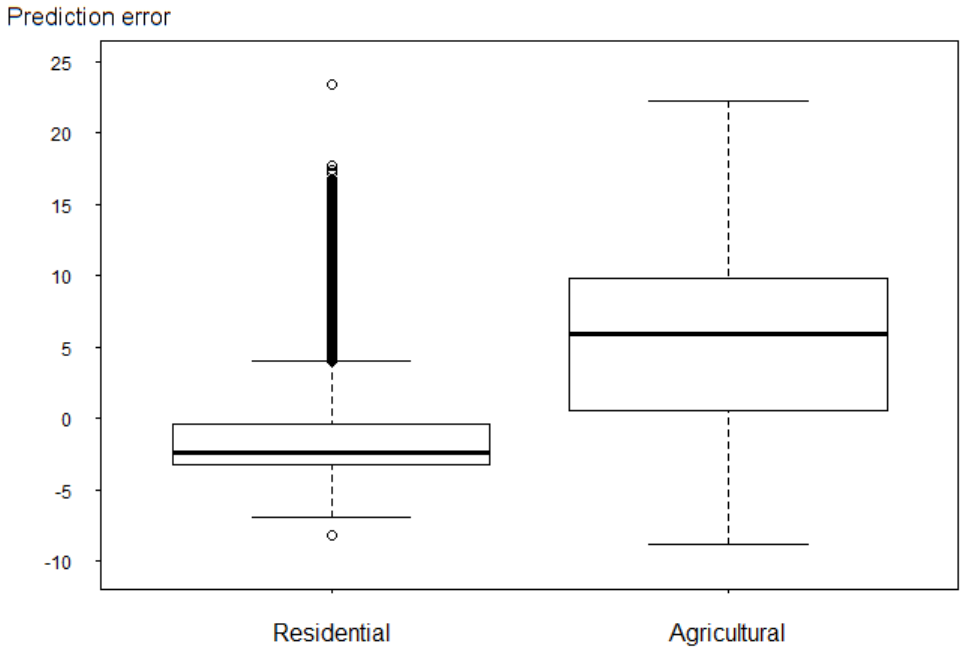
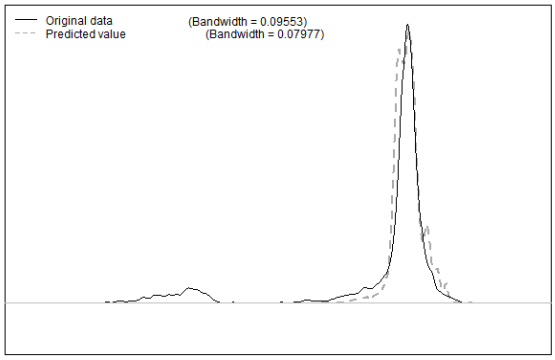


Figure 4.1: Boxplots of in–sample prediction error of parcels in the sample. In the boxplot, the thick middle line corresponds to the median, and the edges of the box to the first and third quartiles. For the residential model, whiskers are the inner fence (1.5 times the interquartile range above the upper quartile and below the lower quartile), and the dots are outliers. For the agricultural model, whiskers and the minimum and maximum observations.

(a) Predictions from the hedonic model of residential land value.



(b) Predictions from the hedonic model of agricultural land value.

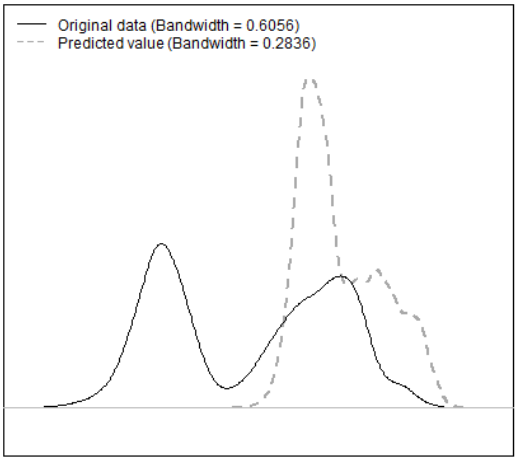
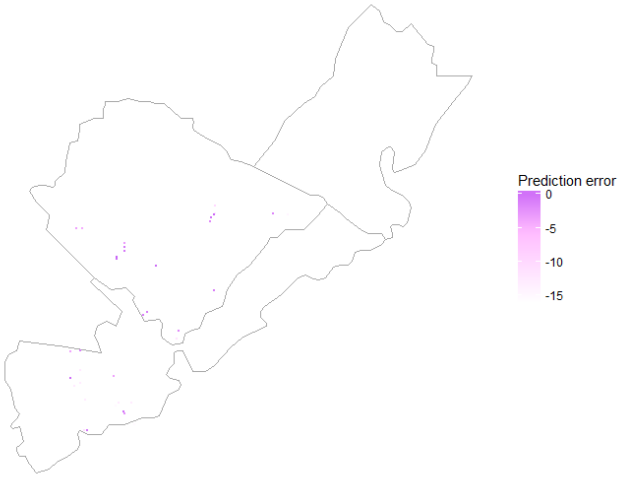


Figure 4.2: Densities of observed and predicted land values for parcels in the sample.

(a) Predictions from the hedonic model of residential land value.



(b) Predictions from the hedonic model of agricultural land value.

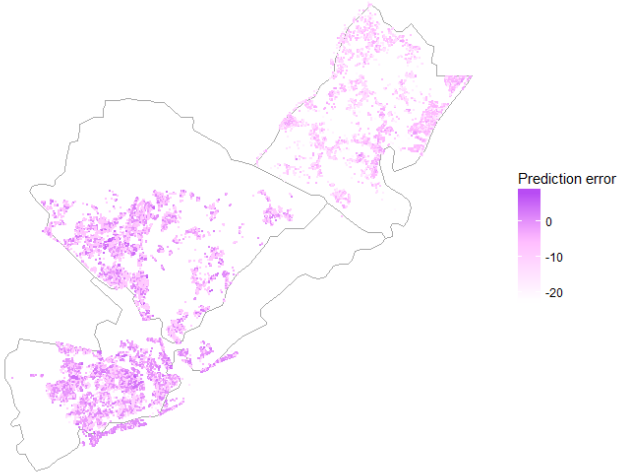
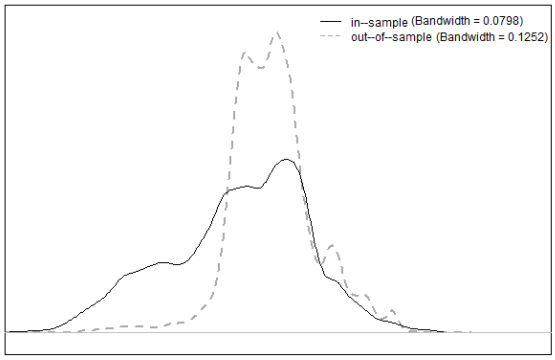


Figure 4.3: Prediction error of land values for parcels in sample.

(a) Predictions from the hedonic model of residential land value.



(b) Predictions from the hedonic model of agricultural land value.

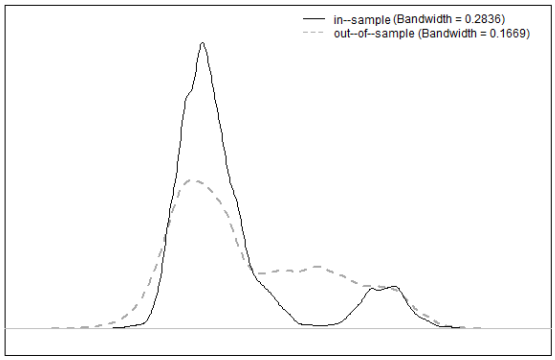


Figure 4.4: Densities of in–sample and out–of sample prediction of land value.

5 SCENARIO BUILDING AND POLICY COMPARISON

Landscape simulations are a versatile tool for analyzing the effects of policy on patterns of urbanization and for predicting changes in the biophysical composition of a geographic area under baseline and alternative scenarios. Recent studies have adopted this approach to measure the effects of economic incentives on land conservation and to analyze the impact of habitat restoration on economic outcomes.[1] In this chapter, I investigate the predicted effects of various land use policies and evaluate their relative ability to influence spatial patterns of land use and the landscape's ability to mitigate flood damages. Specifically, I explore what policies are more cost–effective at reducing future damages; the spatial distribution of damages associated with different policies; and how these measures differ when considering different time horizons. I use a comprehensive algorithm that relies on parameter estimates from econometric models derived from those developed and discussed in chapter 4.

This chapter is organized as follows: first, I describe the policies being compared and relate them to the current policy environment in the United States and South Carolina. Next, I describe the simulation procedure used to generate alternative future urban landscapes. This is followed by results from the simulation exercise. I separate the discussion of results into two parts: a short–term analysis and a long–term analysis. The short–term analysis begins with a discussion of the changes in land development probabilities within a 5–year period after the introduction of different policy rules. Using the 5–year period calculations, I set up a comparative analysis to evaluate the effectives of each policy at altering urbanization patterns, reducing damages from a hypothetical 100–year storm that occurs 5 years into the future, and delivering more equal spatial distribution of

[1] See for instance Loerzel et al. (2017), Lewis et al. (2011), Lewis (2010), Lewis Provencher, and Bustic (2009), Nelson et al. (2008), Newburn et al. (2006).

damages after such an event. The short–term comparison of policy regimes is followed by a long–term analysis that predicts land use change over a 25–year period. Using results from this multi–period simulation, I compare benefits and costs of development restrictions, the resulting natural provision of flood damage mitigation services, and the spatial distribution of damages that result from a potential 100–year storm that occurs 25 years into the future. The chapter concludes with a summary of findings and a discussion on policy implications.

5.1 DESCRIPTION OF ALTERNATIVE POLICIES

Policy makers have two ways to influence flood risks via land use management: they can relieve pressures on coastal environmental resources by investing in natural capital that protects against inundation of developed land (e.g., protect or invest in wetlands), or they can influence land development decisions of residents (e.g., where and how they develop) to reduce losses from flooding. Local governments in the United States have a versatile set of fiscal and regulatory tools that can do both. Examples include urban growth boundaries, development taxes, impact fees, zoning ordinances, and building standards. In Appendix H, I provide background information on the national legal framework for wetland conservation in the United States in general, and in South Carolina specifically.

Growth control policies fall into two general categories: those that control the quantity of development, and those that affect the price of development. Quantity controls, or prescriptive regulations, include designation of urban growth boundaries, minimum lot size restrictions, building standards, and building permits. In turn, price controls, or tax instruments, include development cost charges and impact fees.

Price instruments can be set as per unit taxes, but they can also be determined to

depend on parcel characteristics, such as square footage of buildings on the land or the rental value of the land (i.e., they can be set as *ad valorem* schemes).[2] Price instruments can also include subsidy policies similar to the US Department of Agriculture's Conservation Reserve Program or the Agricultural Conservation Easement Program (CRP), which pay farmers an annual amount linked to the rental value of the land to conserve sensitive ecosystems. The CRP offers payments that are "roughly equivalent to the rental value of the land"to remove sensitive land from agricultural production and plant species that will improve environmental quality. In turn, the ACEP provides financial and technical assistance to help conserve agricultural lands and wetlands.[3]

The general conclusion from the literature on growth control policies is that no single instrument is clearly superior along all the dimensions relevant to policy choice (Goulder and Parry, 2008). Moreover, administrative efficiency and other details of policy implementation are also important in determining policy effectiveness.[4]

Without clear ex–ante expectations over the effects of urban growth policies, I consider

[2]In South Carolina, for instance, the Development Impact Fee Act of 1999, defines development impact fees as payment for a "proportionate share"of the government's cost of providing new or improving existing infrastructure. If government's cost of providing new or improving existing infrastructure is tied to the value of the land, then, an impact fee can be set to be proportional to the rental value of the land. Typically, however, these fees are not tied to the value of the land and depend only on construction costs on a per square foot basis. In South Carolina, building permit fees are based on official construction valuation data published by the International Code Council. Upon the valuation, the local Building Official sets the amount of the permit fee. According to the Building Valuation Data, the Square Foot Construction Cost takes does not include the price of the land on which the building is built. That is, currently, building permits and impact fees are set more like property taxes than like land value taxes. In other words, they are set independently from the cost of the land. It is worth noting that land value taxes are generally favored by economists over per–unit (or specific) property taxes as they do not cause further distortions of landowners' development incentives and are considered welfare enhancing under uncertainty (Goerke, 2011; Kotsogiannis and Serfes, 2014).

[3]Although conservation subsidies typically face more political opposition than other regulatory tools, there are current developing examples of states using this type of policies for flood mitigation. For instance, in Florida, a state facing disproportionate risks of sea level rise and chronic flooding, officials in Biscayne beach are considering surrendering developed land to nature by funding a $275 million project to purchase and demolish properties and turn them into parks and retention basins.

[4]These institutional details include managerial coordination, stakeholder participation, and political transparency (Bengston, Fletcher, and Nelson, 2004).

a set of policies for urban development that includes different forms of price instruments, leaving quantity instruments as an area of interest for future research. Specifically, I evaluate four scenarios:

1. Scenario 1: Business–as–usual, or BAU. This scenario is the baseline to which I compare scenarios 2, 3, and 4 below, and it assumes no change in the current set of land use policies (which in the case of the three counties studied here, do not include a flood mitigation plan).

2. Scenario 2: Tax on development that reduces the value of developable land by 10% (10%DT). Under this scenario, a tax on development is imposed. The tax is assumed to be large enough to decrease the developed value of land by 10%. This rate was chosen to match South Carolina's property tax rates, which vary between 4 and 10.5 percent. For ease of exposition, I will refer to this tax as a 10%DT, even though the tax rate τ is likely to be larger than 10% (because the supply of land for development is likely to be somewhat elastic).[5]

3. Scenario 3: Tax on developed covers (DCT). This instrument is a heterogenous impact fee linked to density of development around a parcel. It is meant to discourage development in areas that are already highly developed and that way help preserve the ecological functions of the landscape. As opposed to the 10% DT, the DCT is

[5]Given the general result that the incidence of the tax will be split between the land owner and the purchaser (the developer and ultimate buyer), a 10% tax will only result in a 10% decline in the price of land if the supply of land into development is perfectly inelastic. In that case, the developer will pay the same price for a parcel to be developed after the tax as before. Alternatively, if the supply of land for development is not perfectly inelastic, inducing a 10% decrease in the price received for vacant land would require the imposition of a tax that is greater than 10% of the land's original value. In this case, land developers would also be impacted by the tax policy and they would pay the difference between the tax and the amount paid by original landowners. The more inelastic the supply, the closer τ would be to 10%.

not meant to discourage development altogether but to discourage adding developed covers to the original landscape. The tax reduces the developed value of land by a percentage equal to the share of the parcel's surrounding area (which includes the area within the parcel's limits) that is covered by developed surfaces.[6] Thus, a parcel with an undistorted expected developed value of $1,000 that is located in an area that is 5% covered in developed surfaces, has an effective expected developed value of $950, which is 95% of the original value. Since the tax disproportionately penalizes conversion in places with relatively large paved areas, it may not necessarily obstruct development but instead induce spatial patterns of development associated with lower flood risks. Thus, it is possible that under scenario 3, more development and lower aggregate flood risks occur in tandem.

4. Scenario 4: Subsidy on wetlands preservation (WPS). This scheme encourages owners of agricultural land to conserve natural covers that are critical for flood prevention by inflating the undeveloped value of land.[7] Effectively, this subsidy increases the opportunity cost of developing land, thus, if the demand for land is not perfectly inelastic, such a subsidy would lower the number of parcels that get developed. In addition, it is meant to discourage development in areas with relatively large wetland covers by linking the subsidy to the share of the parcel's neighborhood that is covered in wetlands. Hence, the value of a parcel with an undistorted expected agricultural value of $1,000 that is 25% covered in wetlands, will be adjusted to have an effective expected undeveloped value of $1,250.[8]

[6]Similarly to the 10%DT, the exact size of a DCT instrument would be determined by the elasticities of land supply and land demand.

[7]Since agricultural activities are generally not conducted in wetland areas, the subsidy does not per se raise the agricultural value of land. Instead, it raises the undeveloped value of land.

[8]Once more, the exact size of the subsidy and its incidence would depend on the elasticities of land supply and land demand.

To understand the construction of the instruments listed above, first consider a simple development model where the expected economic value of developing a parcel is the difference between the developed value of the land, net of development costs, and the agricultural value of the land (or d^* in equation 2.1). In this simple model, benefits are:

$$d^* = V^D(\mathrm{P}, \mathrm{C}) - V^U(\mathrm{LC}, \mathrm{WC}, \mathrm{O}), \tag{5.1}$$

where $V^D(\cdot)$ is the market value for developed land minus the cost of developing the land, and $V^U(\cdot)$ is the agricultural value of the land. In equation 5.1, $V^D(\cdot)$ is a function of market price (P) and development costs (C), while $V^U(\cdot)$ is a function of land characteristics (LC), wetland cover (WC), and an option value component (O).

Note that price is itself a function of land characteristics (LC), wetland cover (WC), and the value of structural improvements in the land (I) such as buildings, driveways, patios, and pools. Improvements to the land can be characterized by the amount of developed cover (DC) they constitute. In turn, costs of development can be written as a function of land characteristics (LC) such as slope and amount of forest cover, improvement costs (I(DC)), and wetland cover (WC). It is generally expected for price and cost to increase with improvements and for improvements to be positively related with amount of developed surfaces, or $\frac{\partial \mathrm{I}}{\partial \mathrm{DC}} \geq 0$. Costs are also thought to increase in wetland covers, as more wetland covers call for additional filling, dredging, and permitting.

If the cost function is separable in improvements, (5.1) can be written as:

$$d^* = \mathrm{P}(\mathrm{LC}, \mathrm{WC}, \mathrm{DC}) - C(\mathrm{DC}) - C(\mathrm{LC}, \mathrm{WC}) - V^U(\mathrm{LC}, \mathrm{WC}, \mathrm{O}). \tag{5.2}$$

The first order conditions with respect to developed covers and wetland covers are:

$$\begin{aligned}\frac{\partial d^*}{\partial \mathrm{DC}} =& \frac{\partial \mathrm{P}}{\partial \mathrm{DC}} - \frac{\partial \mathrm{C}}{\partial \mathrm{DC}} \\ & (+) \ - \ (+)\end{aligned} \tag{5.3}$$

$$\begin{aligned}\frac{\partial d^*}{\partial \mathrm{WC}} =& \frac{\partial \mathrm{P}}{\partial \mathrm{WC}} - \frac{\partial \mathrm{C}}{\partial \mathrm{WC}} - \frac{\partial V^U}{\partial \mathrm{WC}} \\ & (+/-) - (+) - (+/-)\end{aligned} \tag{5.4}$$

The signs of (5.3) and (5.4) are ambiguous. Thus, a simple comparative statics analysis indicates landowners who consider conversion do not necessarily find it beneficial to add developed covers to their land or to remove existing wetlands on the parcel.

In terms of adding developed cover surfaces, the attractiveness of development will increase only if the increase in price from adding new structures outweighs the increase in construction costs. Regarding wetland covers, there may be gains to developers from restoring or conserving wetlands, even though the general assumption is that, absent regulation, developers do not retain wetland cover in the parcel. For the sign to be positive, the price of developed land should positively related to presence of wetlands (perhaps because landowners value flood prevention services) and outweigh change in costs associated with more wetlands (e.g., additional filling and permitting). Alternatively, the undeveloped value of land should be sufficiently negatively associated with wetland cover (which is hypothesized given that no farming occurs on wetlands).[9]

As discussed above, the relation between d^* and DC intensification or WC restoration is unclear and no predictions can be made about the direction of changes in the attractiveness of development decisions from changes in landscape composition. However, this

[9]The hedonic analysis in chapter 4 hows that prices of agricultural lands tend to decrease with wetland cover while the price of residential lands may increase, decrease, or not change (see tables 4.1 and 4.2).

simple framework can be extended to explore how the policies studied here interact with the value of development.

Consider the first instrument: a tax on development that is separable from land characteristics. In this case, conversion benefits are:

$$d^* = (1-\tau)V^D(\cdot) - V^U(\cdot), \tag{5.5}$$

where tax rate τ is between 0 and 1, and where the value of development increases in prices at a rate that decreases with the level of tax, or $\frac{\partial d^*}{\partial V^D} > 0$ and $\frac{\partial^2 d^*}{\partial V^D \partial \tau} < 0$.

An interesting property of (5.5), is the relation between the value of development and taxes. Development taxes are presented as instruments that discourage growth. However, development taxes or impact fees may actually positively impact d^*. This is shown by making explicit the role of τ in the formation of option values:

$$d^* = (1-\tau)V^D(\cdot) - V^U\Big(\mathrm{O}(\tau)\Big), \tag{5.6}$$

where O represents the option value of developing a parcel and is a function of tax τ. Having made this explicit, the first order condition with respect to τ is:

$$\begin{aligned} \frac{\partial d^*}{\partial \tau} = &- V^D - \frac{\partial V^U}{\partial \mathrm{O}}\frac{\partial \mathrm{O}}{\partial \tau} \\ &- (+) - (+ \cdot + / -) \end{aligned} \tag{5.7}$$

As shown by (5.7), introducing a tax may encourage development, depending on the sign of $\frac{\partial \mathrm{O}}{\partial \tau}$ and the relative magnitude of price, cost, and the effect of τ on option values. The theoretical and empirical literature that examine the effect of policy instruments on growth has found that development fees tend to make development today more attrac-

tive relative to development in the future by reducing the option value of vacant land (Cunninghan, 2007; Turnbull, 2004). In this case, $\frac{\partial \mathrm{O}}{\partial \tau} < 0$ and $\frac{\partial d^*}{\partial \tau}$ may be positive.

Now consider policy instrument in scenario 3: a heterogenous tax where the tax rate increases with developed covers. In this case, the economic benefit of development is:

$$d^* = \Big(1 - \tilde{\tau}(\mathrm{DC})\Big) V^D(LC, WC, DC) - V^U, \tag{5.8}$$

where $\tilde{\tau}(\mathrm{DC})$ is a tax taking values from 0 to 1 and varying positively in DC, or $\frac{\partial \tilde{\tau}}{\mathrm{DC}} > 0$.

When a tax $\tilde{\tau}$ is introduced, the developed value of the parcel decreases with the tax rate and may deter future development (i.e., $\frac{\partial d^*}{\partial \tilde{\tau}} < 0$) by changing the expectations that owners of agricultural land have about the value of their land under urban uses. However, introducing $\tilde{\tau}(\mathrm{DC})$ does not necessarily discourage the intensification of development:

$$\frac{\partial d^*}{\partial \mathrm{DC}} = \underset{(+\cdot+)}{(1-\tilde{\tau})\frac{\partial V^D}{\partial \mathrm{DC}}} \underset{-}{-} \underset{(+\cdot+)}{V^D \frac{\partial \tilde{\tau}}{\partial \mathrm{DC}}}. \tag{5.9}$$

As FOC (5.9) shows, a tax $\tilde{\tau}(\mathrm{DC})$ may discourage landowners from adding more developed covers to their parcels if the tax rate is not large enough or not sensitive enough to existing developed covers (assuming $\frac{\partial V^D}{\partial \mathrm{DC}}$ is positive and V^D sufficiently small). The answer remains empirical, but results from the hedonics analysis shown in table 4.2 indicate prices of residential parcels increase as surrounding areas become more intensively developed. Suggesting that the sign for (5.9) is not necessarily negative.

Finally, consider the policy in scenario 4. When a subsidy to encourage wetland conservation is introduced, the economic benefit of development is:

$$d^* = V^D(\mathrm{LC,\ WC,\ DC}) - \Big(1 + \omega(WC)\Big) V^U(\mathrm{LC,\ WC,\ O}), \tag{5.10}$$

where $\omega(\cdot)$ is between 0 and 1 and is equal to the percentage of the area in and around the parcel that is under wetland cover.

Intuitively, introducing ω makes the expected economic returns to agricultural uses in the land higher relative to expected economic returns to residential uses, therefore providing incentives to conserve the land.[10] This is shown by $\frac{\partial d^*}{\partial \omega} < 0$. However, new development may or may not protect existing wetland covers, as shown by the ambivalent relation between the value of development and the conservation of wetland cover.

The relation between d^* and wetland cover is given by:

$$\frac{\partial d^*}{\partial \mathrm{WC}} = \frac{\partial V^D}{\partial \mathrm{WC}} - \omega \frac{\partial V^U}{\partial \mathrm{WC}} - V^U \frac{\partial \omega}{\partial \mathrm{WC}}. \tag{5.11}$$

The sign of (5.11) is theoretically ambiguous and depends on the sign of $\frac{\partial V^D}{\partial \mathrm{WC}}$ as well as the relative magnitude of the subsidy's effects, the size of the subsidy, and the undeveloped value of land. This ambiguity implies that introducing a subsidy may not always encourage conservation of wetlands.

As shown in the discussion above, even with a simple model, the effects of the suggested policies over landowners' decisions to develop a parcel, to further intensify its use, or to conserve naturally occurring habitats, are ambiguous and generally difficult to isolate without additional knowledge about magnitude of the relationships between variables involved, such as the value of the land, biophysical characteristics of the area, construction costs, and landowner preferences regarding the composition of the physical landscape. Greater precision would require further assumption about the landowner preferences and restrictions over the domain of the parameters. The absence of unambiguous predictions obtained from the simple theoretical analysis highlights the need for empirical

[10]Note, in this policy, only owners of agricultural undeveloped land receive the subsidy. Owners of residential do not receive the subsidy even is there are wetland covers in the residential parcel.

research to assess the effects of land use policy on urbanization tendencies and patterns, the protection of natural ecosystems, and the resulting changes in flood risk. In the next section, I describe the simulation procedure used to advance the understanding over the theoretical issue presented above.

5.2 PROCEDURE FOR SIMULATING FUTURE LANDSCAPES

To answer the questions posed in this study, I generate multiple alternative landscapes. Originally, I simulate four landscapes, each corresponding to a scenario with a different policy rule. In addition, to answer how the effect of policies compare over time, I examine two different time horizons for each scenario: 5 years into the future and 25 years into the future. The generation of landscapes 5 years into the future requires a one–period simulation, where one period is defined as five years. In turn, generating landscapes 25 years into the future requires multiple iterations of the one–period procedure. The time–step–length for the simulations was chosen to match the time frame of tax assessor offices in South Carolina, who by law, assess the value of personal property every 5 years. In the sections below, I describe the procedure to generate future landscapes 5 and 25 years into the future. Then I proceed to discuss results from the simulations.

5.2.1 THE MONTE CARLO APPROACH

To predict future urban patterns, I follow a standard Monte Carlo simulation approach. Under this approach, the probability that each agricultural parcel in the sample transitions from agricultural to residential uses, δ_i, is compared to to a random draw from a standard uniform distribution: $\xi \sim U[0, 1]$. If δ_i is greater than ξ, parcel i is determined

to develop within a period of 5 years.[11] Instead, if $\xi \leq \delta_i$, the parcel is assumed to remain undeveloped and is eligible for development in the next transition period.[12] Thus, for an agricultural parcel with a 30% probability of conversion in 2016, a random draw from a standard uniform distribution U[0,1] that is between 0 and 0.3 would indicate the that the parcel stays in agriculture in the 2021 landscape, while a draw between 0.31 and 1 indicates it will be converted to urban development by 2021.

To complete the single–period Monte Carlo simulation, the comparison of δ_i to a ξ is done for every undeveloped parcel in the sample. Because this process is applied to each parcel individually, the resulting generated landscape in time $t+5$ is consistent with the underlying transition probabilities of each individual parcel.[13] Furthermore, in this study, the simulated landscape in $t+5$ is also consistent with market forces and behavioral motives because the probability that each agricultural parcel in the sample transitions to residential uses within 5 years, δ_i, is directly derived using estimated coefficients from a hazard model that is built over proxies of land value that reflect landowner preferences and responses to changes in the land market.[14]

[11]In this study, the probability that a parcel develops in the next 5 years does not depend on how likely it was to develop in previous time periods. This is due to the memoryless property of the Markov Decision Process that characterizes landowners' decisions under a RUM.

[12]For the special case examined here, in which development is irreversible, the probability that currently developed parcels transition back into undeveloped uses is zero. Thus, once a parcel is simulated to develop, it remains under residential uses for the rest of the simulation exercise (refer to section 2.2).

[13]The average probability of conversion is calculated using the estimated hazard ratios. Specifically, I calculate the probability of development within a 5 year period as one minus the survival probability, or $1 - S_5 = 1 - \exp(-\Lambda_5)$ where Λ_5 is the cumulative hazard at time 5 as discussed in section 2. It follows that the estimation of the hazard model can be specified to derive annual probabilities of development. If this is the case, they must be transformed to reflect a 5–year time–step using the following formula: $\delta_i = 1 - (1 - \hat{\delta}_i)^5$, where $\hat{\delta}_i$ is the annual probability that parcel i develops resulting from the estimation of a hazard model, and δ_i is the adjusted development probability indicating the likelihood that parcel i develops *any time* within the next 5 years. Hence, if the annual probability that parcel i develops is 0.03 (i.e., $\hat{\delta}_i = 0.03$), over a 5 year period, its probability of development is 0.14 (or $\delta = 0.14$).

[14]In the past, Bigelow et al. (2017), Bigelow (2015), Lewis et al. (2011), Lewis, Plantinga and Wu (2009), Nelson et al. (2008), and Lewis and Plantinga (2007) have followed this procedure of characterizing the spatial distribution of conversion of undeveloped lands with probabilistic transition rules. Other authors have formed deterministic rules of transition (Irwin and Bockstael, 2002; Nelson et al., 2001;

Notice that the physical landscape in $t + 5$ may have changed due to modifications to the land made by landowners who developed between t and $t + 5$. For example, the landscape may exhibit more developed covers and less wetland covers in $t+5$ than it did in t. If this is the case, the physical landscape in $t+5$ may be have a different capability of preventing floods than it did in t. Thus, it is important for the purpose of this study, that once a future landscape has been simulated, its physical characteristics are updated to reflect new development choices. In the subsection below, I explain how considerations of land use decisions at the intensive margin are incorporated into the simulation process.

5.2.2 INCORPORATING THE INTENSIVE MARGIN

In addition to choosing what use to give to their land (i.e., a decision at the extensive margin), landowners make decisions at the intensive margin. For instance, landowners that choose to develop a parcel must also decide whether or not to subdivide the parcel and if so into how many plots. Alternatively, a landowner choosing to keep land in agriculture, must choose which crops to produce and what technologies to employ in cultivation. In this study of land use change, accounting for intensity of land development is important as it is directly related to the ecological capacity of the landscape to provide flood prevention services: the extent of hard surfaces in the landscape (e.g., parking lots) and the degree of connectivity between these patches of impervious surfaces are critical at determining whether or not present wetlands can provide flood prevention services.

Most studies of land use change found in the literature do not account for changes in land use intensity or its impact on the ecology of the landscape (e.g., Lewis et al., 2011; Nelson et al., 2009; Lubowski et al., 2008).[15] Yet, distinguishing between types of

Nelson and Hellerstein, 1997; and Chomitz and Gray, 1996).

[15]Land use change models are typically examined in a binary framework where the outcome is whether or not a parcel gets developed. This outcome does not differentiate between types of development (e.g.,

developed covers is of particular importance when considering the impacts of urbanization on flood risk. For instance, the functionality of a particular wetland will not be affected if an adjacent agricultural parcel is converted a single family house in a large lot but will be compromised if the parcel is turned to a high–density complex of apartments.[16]

In this research, I advance the literature by allowing land use intensity or land cover to change endogenously. Previous works typically incorporate this aspect by assuming that land use intensity decisions are reflected by the net returns to each use (Lubowski, Plantinga, and Stavins, 2006). Under this strategy, if a parcel is developed, it is assumed to get developed at the maximum density allowed by zoning. Other studies impose periodic fixed exogenous changes in the return derived from each use to internalize changes in the endogenous decision of using technological improvements (Lawler et al., 2014).

To account for the choice over development covers of various intensities in the development decision, I use land cover data to determine the extent of changes to the physical composition of the landscape from recent development decisions and impose that as an exogenous rule on all new development events. Specifically, I use ArcMap and spatial packages in R to compute the average share of impervious surface cover, forest cover, wetland cover, and crop and pasture cover for parcels in the sample that developed in the most recent 5 years (i.e., development that occurred between 2011 and 2016) and impose that average on parcels that are simulated as developed in the future.

To illustrate the process, consider the case of Charleston parcel i which was undeveloped in time t but simulated to develop in time $t + 5$. The original composition of

exurban and high–intensity types of development are treated equally). The exceptions are Lewis et al. (2009) and Lewis (2010), in which the authors use probit and poisson models to estimate a joint model of land use and the decision to further subdivide residential parcels, and a nested logit where the landowner simultaneously chooses land use and number of subdivisions.

[16] As a note, keep in mind that FEMA's flood risk maps have been criticized for not accounting for how buildings are constructed, among other things.

parcel i at time t is 11.8% developed covers, 28.2% forest covers, 16.2% crops and pasture covers, 16.4% wetland covers, and 27.4% others (e.g., open water or rocky soils). The average composition of parcels that developed in Charleston county between 2006 and 2011 was 32.9% developed covers, 21.4% forest covers, 2.9% crops and pasture covers, 28.5% wetland covers, and 14.3% others (e.g., open water or rocky soils), hence, I use those percentages as the new values for parcel i at time $t + 5$. In this case, parcel i exhibits more developed covers, less forest covers and crop/pasture covers, and more wetlands.

Using this method in the simulation analysis, I am able to account for spatial dynamics in the hedonics relationships as they would occur in a recursive setting by directly incorporating updated land cover variables in the hedonics functions (as shown in figure 1.1). This is a concern posed in the early work of environmental economists examining land use change that to my knowledge, has not yet been addressed (Bockstael, 1996).

5.2.3 INCORPORATING POLICY RULES

The processes described above, explains how a future landscape corresponding to the baseline scenario, or BAU, is generated and how its physical characteristics updated. To generate future scenarios under each alternative land use policy, the same simulation exercise is conducted with different parameters for the particular drivers that define each one of the considered policies. For instance, under a 10% tax on development, the simulation uses as input a developed value of land that has been reduced by 10%. In turn, under a policy discouraging developed covers, the predicted developed value of land is reduced by the percentage area of the parcel covered by developed surfaces. Similarly, under a policy subsidizing wetland conservation, the predicted agricultural value of land is increased by the percent corresponding to the share of the parcel covered in wetlands. The result is the generation of four separate scenarios.

5.2.4 ITERATING THE PROCEDURE

To generate landscape at time $t + 25$, the entire procedure described above is repeated multiple times, starting with the recalculation of the predicted land values derived from the original hedonic estimation. Recall that at each time step, these values are updated to reflect changes in the physical landscape. It is so because the proportional hazard model I use does not include time–varying covariates in X, and because different landscape features (which are updated in the final step of the 5–year simulation) may impact land values and therefore alter the trade–offs faced by landowners of undeveloped land in future time periods (i.e., landowners who did not develop their parcels between t and $t+5$ may face different incentives at the end of $t+5$ than they did at the beginning of t). Hence, to generate a potential landscape 25 years into the future, the process is repeated four times and results in the generation of landscapes in $t+10$, $t+15$, $t+20$, and $t+25$. As with the simulation in $t+5$, the procedure results in four alternative landscapes in $t+25$, one for each of the policy rules. Note that the deep parameters determining transition probabilities in each simulation are the coefficients from the proportional hazard model estimation in chapter 4.[17]

5.2.5 DEVELOPING CONFIDENCE INTERVALS

Notice that each of the eight generated landscapes is only one of many possible future outcomes, each varying by the random draw of ξ for each parcel in each time–step. Some researchers in the natural resources economics literature suggest that to characterize the range of potential outcomes, it is preferable to repeat the simulation *multiple* times in order to generate a large number of feasible future landscapes, each of which would be

[17] A brief discussion on how these deep parameters are manipulated in the simulations to obtain the development probabilities is provided in Appendix G.

consistent with the estimated transition probabilities. Under this view, *multiple* feasible landscapes are generated using different random draws from the U[0,1] distribution to capture the range of potential landscape patterns and create a confidence interval around the projections. Prior literature tends to assume conversion to the use with higher probability, which is convenient but negates the notion of probability (Lewis, 2010). By generating an empirical distribution of outcomes, the simulations approach does not generate a single forecast but allows to capture some uncertainty that may be related with how the model is specified (i.e., uncertainty over how landowners make decisions). Intuitively, better predictive power would be associated with less variation in the distribution of simulated measures. However, as it relates to my application, it is important to note that some areas in the study region are characterized by a "random appeal"that could lead to circumstantial development clusters that may seem atypical.

Determining the number of repetitions that are sufficient has not yet been resolved in the literature. In a study of biodiversity and fragmentation, Lewis et al. (2011) generate 500 feasible landscapes. In a similar study of land subdivision, Wrenn and Irwin (2012) generate 200. In turn, Bigelow et al. (2017) generate 100 rounds of the simulation. In this study, I generate 200 alternative landscapes in $t + 5$ and $t + 25$ for each policy scenario. The distribution of these 200 scenarios will be summarized in the results section by examining averages and the discussion will focus on this key statistics. Specifically, in summary tables, I will report average number of parcels expected to develop under each policy and the associated wetland cover change and developed cover change. I will also present boxplots with the distribution of costs and benefits associated with each policy.

5.3 RESULTS FROM THE LANDSCAPE SIMULATIONS

Three policy levers are explored in this analysis, all of them tools that are available to regulators in South Carolina. To investigate the potential environmental and economic implications of each of these policies, I use the 1,600 simulated landscapes (200 per scenario per time horizon) to compute a distribution of costs and benefits associated with each scenario in $t + 5$ and in $t + 25$ and to examine the spatial distribution of benefits under each scenario. Figure 5.1 summarizes the steps in the comparison process.

In this study, I use measures of economic costs and benefits that reflect the cost of limiting development by restricting land use choices, and the savings from implementing these policies in terms of avoided property damages after a storm event resembling Hurricane Irma in 2017. These costs and benefits are computed using data on property sales prices from tax assessor offices, and estimates of predicted damages using NFIP payments in South Carolina. In the sections below, I first include a thorough discussion over the definition of costs and benefits used in the comparative study. Next, I present and discuss the results from simulating 200 landscapes for each policy scenario 5 years into the future. Then, I expose the results from analogous simulations of the urban landscape 25 years into the future. I conclude chapter 5 with a discussion of policy implications.

5.3.1 DEFINITION OF COSTS AND BENEFITS

For this study, the cost of implementing policy j (i.e., the cost of limiting development by restricting land use choices) is defined as the difference between a BAU scenario and a scenario where policy j is in place in the net developed value added to the landscape at time T. The net developed value added to the landscape at time T is defined as the aggregate developed value of parcels converted to development as of time T, net of

opportunity costs. Notice that administrative costs or costs related to passing legislative action are ignored. Mathematically, costs of policy j at time T are defined as:

$$\text{Cost}_{jT} = \Big[\sum_{t=1}^{T}\sum_{i}\beta^t(V_{it}^D - V_{it}^U)\Big]_{BAU} - \Big[\sum_{t=1}^{T}\sum_{i}\beta^t(V_{it}^D - V_{it}^U)\Big]_j, \tag{5.12}$$

where β is the discount factor and $\beta^t(V_{it}^D - V_{it}^U)$ is the discounted net added value of development to a parcel that was originally undeveloped.

Benefits of policy j are defined as the difference between the BAU scenario and policy j scenario in the sum of expected property damages from a 100–year flood. The value of expected flood damages is calculated by interacting a parcel–specific probability of flooding with an estimate of the average property damage caused by flooding. Notice that this definition does not include raised revenues associated with the policy. Formally, benefits of policy j at time T are:

$$\text{Benefit}_{jT} = \Big[\sum_{i}\beta^T \text{FRI}_i \times \overline{\text{Damage}}\Big]_{BAU} - \Big[\sum_{i}\beta^T \text{FRI}_i \times \overline{\text{Damage}}\Big]_j \tag{5.13}$$

where where β is the discount factor, FRI_i is a measure of flood risk for parcel i, or the parcel's flood risk index (FRI), and $\overline{\text{Damage}}$ is the average property damage associated with a major flood in the study area.

As dictated by (5.12) and (5.13), the parameters required to complete the cost–benefit calculations are: a discount factor, a parcel–specific FRI, and an average cost of property damages from flooding. In this study, I use a constant annual discount factor of 0.93, which translates into an annual discount rate of 7% (which is the historical average real annual return to capital in the stock market).[18] For the parcel–specific FRI, I use the

[18]This choice of discount rate is also consistent with recommendations in the literature. Theoretically, the discount rate reflects the annual rate of return to private investment (which is the opportunity cost

predicted measure of flood risk derived from inundation models that are described in chapter 3. Finally, for $\overline{\text{Damage}}$, I use the 2016 average NFIP payment per claim in South Carolina. In 2016 dollars, this value is $24,776.[19]

Notice that the resulting measure of benefit as described by equation (5.16) should be interpreted as a lower bound of the gains from altering urbanization patterns in the study area. There are two reasons for this. First, the definition is missing a very important component: changes in ecosystem service values between BAU and other policy scenarios. Theoretically, the FRI variable captures one such ecosystem service: flood risk mitigation, and although an important service, it is only one of many provided by wetland habitats such as value of habitat for species, carbon sequestration, scenic beauty and open space values, among other. Additionally, NFIP statistics on total claim payments for the 2017 fiscal year, the year Hurricane Irma occurred, are not yet publicly available as some payouts are still being processed.[20] Given the impact of Irma (FEMA has already paid $1 billion in payments), it is expected that the 2017 claim payments statistics will exceed those from 2016. For reference, in 2017, the average national claim payout was $91,735, almost 50% more than in 2016 ($62,247).

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of consumption and reflects key parameters of the private utility function and growth in the economy, such as the intertemporal elasticity of substitution between consumption today and consumption in the future, the coefficient of relative risk aversion, the rate of change of consumption, and the rental growth of capital). Recent empirical estimates suggest the private consumption rate of discount is approximately 6.5 % for 2015 (Arrow et al., 2014). In the US, the Office of Management and Budget recommends that costs and benefits be discounted at a constant rate of 7% (OMB, 2003). In an article of advice to the EPA, Arrow et. al (2014) provide a thorough discussion on the choice of discount factor for public projects.

[19]Other measures of cost were explored to develop an idea of confidence around the estimate. Justification for this choice of value is found in the fact that the NFIP payment measure is similar in magnitude to available estimates of average flood damage to residential properties. For instance, Loerzel et al. (2017) estimate the average flood damages form Hurricane Sandy to residential properties in three coastal counties of New Jersey to be $22,672.

[20]The year 2017 was a hectic year for NFIP with Hurricanes Harvey, Irma, and Maria. Hurricane Harvey ranks as the third most significant U.S. flood event in history, as about 76,000 NFIP policyholders filed claims. FEMA has paid $8.7 billion to those policyholders. Flooding from Hurricane Irma in September ranks as number 9, with about 22,000 policyholders filing claims.

5.3.2 SHORT–TERM (5 YEARS) COMPARATIVE ANALYSIS

The policies discussed in this chapter have the potential to alter urbanization patterns in different ways. Recall from chapter 2 and 4, that in the land use change analysis I use a proportional hazard model to estimate a decision model of the form:

$$\delta = \Pr[\widehat{V^D} > \widehat{V^U}]. \tag{5.14}$$

Under a baseline scenario, the probability of development δ depends on $\widehat{V^D}$ and $\widehat{V^U}$. When a policy is introduced to model, δ depends on adjusted versions of these values. In the simulation corresponding to the 10% tax on development scenario (scenario 2), the inputs are original predicted agricultural value of land resulting from the hedonic estimation discussed in chapter 4, and a predicted developed value of land that has been reduced by 10% due to the tax. In short, in this simulation, alternative land values are $\widehat{V^U}$ and $0.9 \times \widehat{V^D}$. It follows that under a policy discouraging impervious surfaces, the predicted developed value of land that is used as an input in the simulation is reduced proportionately to the percentage area surrounding the parcel that is covered by developed surfaces. So that, for a parcel that is 4% covered in hard surfaces, the corresponding land values are $0.96\times\widehat{V^D}$ (instead of $\widehat{V^D}$) and $\widehat{V^U}$. Similarly, under a policy subsidizing wetland conservation, the predicted agricultural value of land is increased by the percent corresponding to the share of the parcel covered in wetlands. Hence, simulating conversion of a parcel that is 15% covered in wetlands uses as inputs $1.15\times\widehat{V^U}$ and $\widehat{V^D}$.

In a short–term analysis, the decision of land use is simulated only for one time period for each policy scenario (recall from the discussion in 5.2 that time–steps in this model are of 5 years). Table 5.1 reminds the reader of summary statistics for key characteris-

tics of undeveloped parcels in the estimation sample to ease interpretation of estimated coefficients for alternative scenarios. These variables are sales price, wetland protection subsidy rates, and developed cover tax rates. Recall wetland and developed cover subsidy and tax rates are equal to the percentage of that land cover within a 0.25 mile buffer from the centroid of each parcel.

Table 5.1 also shows presents approximations of the average effects on prices from a 1% increase in certain land covers. These effects are directly taken from the estimates of hedonic models presented in chapter 4. As reported in table 5.1, a 1% increase in developed covers increases the value of agricultural parcels by approximately 1% in all three counties. In turn, a 1% increase in wetland covers decreases value of agricultural parcels by 0.4 percent in Berkeley and Georgetown counties and has no effect in Charleston. Relative to these average effects the average DCT and WPS rates are high, suggesting that the imposition of a tax or a subsidy would outweigh the potential effects on land values from changes in land cover induced by the policies.

Table 5.2 describes the probabilities of development resulting from the simulations, one for each alternative policy scenarios. The probabilities shown in table 5.2 suggest development decisions to be generally non–responsive to land use controls, which is consistent with previous findings in the land development literature (Wrenn and Irwin, 2012).[21] The average probability of conversion under the BAU scenario is 16.2%. Under a 10%DT, it is 15.8%, with a DCT and a WPS, these averages are 8.8% and 15.6% respectively.

However, despite the relative non–responsiveness of the simulations to moderate land use controls, all policy instruments are effective at altering development patterns, as revealed by the projections in table 5.3. Table 5.3 reports the number of parcels predicted

[21] In a similar study of land conversion, the authors found that a development fee of 20% of the land price was predicted to reduce development by only 2%, while a fee of 40% of the land price by only 3%.

to develop within a period of 5 years under each policy scenario and the corresponding predicted loss of wetland cover and predicted increment of developed covers. About 17% of parcels are predicted to develop in 5 years under a BAU scenario, which is consistent with estimates of population growth in the study area.[22] That percentage is slightly lower (by 0.8 percentage points) with a 10%DT, and it is distinctively lower under the remaining instruments with the biggest effect being experienced under a DCT. Compared to the BAU scenario, under the DCT and the WPS, predicted development slows down by approximately 9 and 2 percentage points, respectively.

In terms of additional impacts, not only do the three policies alter development outcomes, they also have an effect on wetland conservation and the intensity of land development. As shown by the third–to–last two row in table 5.3, wetland cover loss is actually negative under all scenarios, meaning that wetland cover in the landscape actually increased in the near future, but only by a trivial amount. This is a technical artifact of how new land cover composition is mechanically assigned post–development in the simulation. As a result, land that previously did not have any wetland cover can now exhibit positive wetland covers.

In terms of developed covers, most alternative future scenarios are characterized by more developed covers (they are defined in chapter 3). However, under the DCT scenario, there is a reduction in the amount of general developed covers that are added to the landscape. Under this policy, there is an even more dramatic reduction (relative to the BAU) in high intensity developed covers, perhaps suggesting that the policy encourages new growth in the study area to be of the kind characterizing suburban landscapes.

[22]Recall from the discussion in chapter 3 that population growth in the last five years is 13% in Charleston and 17% in Berkeley.

Short–term (5 years) benefit–cost comparison

To complete the benefit–cost analysis, each of simulated landscapes in $t+5$ is shocked by a hypothetical hurricane identical to Hurricane Irma in 2017, which was a 100–year storm. In this context, the benefits from altering development patters via land use policies are avoided damages measured as the difference in NFIP payments between BAU and each policy scenario. Table 5.4 shows the corresponding savings in NFIP payments associated with each regime relative to the BAU scenario.

Table 5.4 also shows expected costs of implementing policies that restrict development under different policy scenarios, which in this study are defined as foregone benefits of development due to land use restrictions, or the present value of the difference between BAU and each policy scenario in added value to converted lands. Using these two measures, a Cost–Benefit ratio (CBR) is calculated and is shown in table 5.4 as well. Table 5.4 also presents an "augmented CBR."This ratio accounts for raised tax revenues in the case of scenarios 2 and 3, and for subsidies as a cost in the case of scenario 4.

The measures reported in table 5.4 correspond to the average values of the 200 simulated scenarios. In table 5.5, I show summary statistics of the distribution of benefits and costs that were generated with the 200 landscape simulations. Figure 5.2 shows boxplots comparing the distribution of benefits (i.e., avoided damages) generated in the 200 simulations, and figure 5.3 shows boxplots comparing the distribution of costs (i.e., foregone added value from development) generated in the 200 simulations.

A first look at the results in tables 5.4 and 5.5, and figures 5.2 and 5.3 would indicate that no policy is cost effective. That is, under all policies, costs outweigh benefits. Of the three policies, the one with the more favorable cost–benefit ratio (CRB) is the 10%DT. Under this scenario, the CBR is 19.7, indicating that costs are about 20 times higher

than benefits. The DCT instrument performs similarly with a CBR of 21, while the WPS is evidently the least favorable of the three policies with a CBR of 29.

In summary, while the policies have modest effects on the pace of development, when the region experiences a 100–year storm, the expected benefits of implementing mitigation policies are much smaller their costs. In other words, the avoided damages that stem from preventing general land conversion, discouraging certain types of land covers, or protecting wetlands, cannot offset the loss in development values. Thus, if the only criteria for choosing a land use policy was the CBR, no policy would yield the preferred scenario.

Nevertheless, when indicators other than CBR are studied separately, conclusions change in an important manner. When only policy costs (i.e., foregone benefits of development) are considered, a 10%DT is the more preferable policy of the three, as average reduction in value added is 4% rather than 51 or 12%.[23] When only benefits are considered, the preferred policy is evidently the tax on developed covers, and the second most effective policy at reducing damages is a subsidy on wetland. Under the DCT scenario, average expected damages from a storm resembling Hurricane Irma represent about 39.6% savings from the BAU scenario. In turn, savings are 6.6% with a WPS.[24] Finally, when policies are compared in their ability to raise tax revenues, a 10%DT and the DCT scenarios deliver similarly preferable outcomes. Under a 10%DT, $152,240,261 are raised in taxes, which is about 20% more than the amount raised with a DCT. Of course, under

[23]Average added values to the land are $17,078,526 lower under a 10%DT than under the BAU, while the average loss under a DCT and a WPS regime is $196,590,241 and$45,050,034, respectively.

[24]The effect observed with the WPS stands out as a rather credible estimate, given recent findings in the literature. For reference, Loerzel et al. (2017) find that adding marsh habitats to the landscape (about 53% of their study area, which is 11 percentage points larger than the wetland cover in my study area) reduced damages between 0.36% and 11.98% of the baseline damage during a 100– and a 25–year storm. A 6.6% reduction in costs from protecting wetland covers (which constitute approximately 42% of the study area) is between the 100–year and the 25–year estimates found in Loerzel et al. (2017). Considering that wetland covers in the my study area is 11 percentage points smaller than that in the New jersey case, a smaller effect than the 11.98% reduction in costs is reasonable.

the WPS raised revenues are actually negative and would therefore be considered costs. When govenrment expenditures and revenues are accounted for, the augmented CBR indicates a 10%DT policy is marginally preferred over a DCT, as the augmented CBR is 0.11 for the 10%DT and 0.38 for the DCT—suggesting that costs are between a 10th and two fifths of benefits.

Short–term spatial patterns of development and distribution of damages

Figure 5.4 shows the location and number of parcels predicted to develop in a 5–year period under each regime, it also shows rivers and major highways in the study area.[25] As shown in the figure, differences in patterns of land development are subtle across scenarios at the regional level but it is possible to see that the policies induce less dense growth in certain areas.

Overall, it is difficult to identify whether or not development follows a spatial pattern that reflects conservation around waterways or concentration around important local features, such as US–routes 17, 17A, and 52, and interstate I–26.[26] The main observations are that there is not much difference between the 10%DT and the BAU and that there is less development under the DCT than under the WPS. Generally, this is not surprising given the size of the instruments (refer to table 5.1). However, it is interesting to find that, relative to a 10%DT, a WPS does not reduce development in in Berkeley and Georgetown counties as much as in Charleston county (where the average size of the subsidy is much lower and is rather close to 10%). This may be related to the negative association between agricultural land values and density of wetland cover in Berkeley and

[25]Note that this and the rest of the maps in the figures presented here correspond to one of the 200 simulated landscapes used to generate the distribution and summary statistics discussed above

[26]US–route 17 connects the City of Charleston to the City of Georgetown following the coastline, 17A is an alternate route that does not follow the coastline; route 52 also flows S–N from the City of Charleston, and interstate i–26 connects the City of Charleston to the West boundary of Berkeley county.

Georgetown, as suggested by the hedonic analysis. It could be that the WPS's negative effect on agricultural land values is enough for landowners to accelerate development.

In terms of the spatial distribution of expected damages, there are noticeable differences across policies. Figure 5.5 shows maps with the spatial distribution of damages corresponding to a single simulation and indicates the Gini coefficient associated with each particular scenario. It also shows major rivers and roads in the study area. To ease the visual examination, I provide maps of projected flood damages in three subregions of the study area. Figure 5.6 defines three subregions of the study area and identifies key local features of the landscape. The subregions are the Southeast region of Charleston county, the Central–West region of Berkeley, and the core of Georgetown.

As shown in figures 5.7 to 5.9, besides very particular focal areas of increased damage, such as near the intersection of SC highways 261 and 513 in Georgetown and near Moncks Corner where route 17A meets US–route 52 in Central–West Berkeley, expected damages are lower and more uniformly distributed across the region when a land use policy is in place. Under a 10%DT there are fewer clusters of parcels with high damage in CW Berkeley and in Georgetown. With the DCT and the WPS, additional to the changes observed with the 10%DT, there are fewer clusters of parcels with high damage in the coast of Charleston. Also there are noticeable reductions near the Waccamaw National Wildlife Refuge in the Northeast boundary of Georgetown, along the Santee River on the North edge of the Francis Marion National Forest in Berkeley, along the Cooper River in CW Berkeley, and near the delta of the Stono River in Charleston.

As a final note on the spatial distribution of damages, there is very little difference across scenarios in terms of how equally distributed are expected damages: the Gini coefficients of all scenarios are between 0.44 and 0.47. A Gini coefficient of zero would imply perfect equality among values of a frequency distribution (i.e., all parcels experience

the same level of damages), and a Gini coefficient of 1 (or 100%) would imply only one parcel experiences all the damages. A Gini coefficient indicating the distribution of damages is almost exactly between perfectly equal and perfectly unequal could be due to the very localized nature of flooding. Essentially, the Gini coefficient is incapable of capturing the variation in spatial distribution of damages because of the enormity of the study area, but overall, it seems that the better of the alternative scenarios in terms of spatial distribution of damages is the landscape with a DCT in place. The 10%DT and DCT show distributions that are marginally more unequal (and perhaps less desirable from a social perspective) than the distribution delivered by the BAU.

5.3.3 LONG–TERM (25 YEARS) COMPARATIVE ANALYSIS

In the long–term analysis, four alternative scenarios were modeled again, except this time the one–period Monte Carlo simulation described in section 5.2 was repeated four times, so that all generated landscapes correspond to scenarios 25 years into the future. Tables 5.6 to 5.9, and figures 5.10 to 5.16 summarize the results from this exercise.

Table 5.6 shows the average development probabilities for each time period and for all policy scenarios. It also shows standard deviations. In general, there is no evident relation between policy rules that persists across time periods. Under the BAU, the 10%DT, and the WPS probabilities of development tend to be decreasing in time. The main difference between scenarios is that the DCT has larger impacts on land conversion than the other two policies, which have almost identical effects across time.

Table 5.7 shows the number of parcels predicted to develop, the amount of wetland acres lost, and the amount of added developed covers under each policy. As revealed in the table, about 70% of the parcels in the sample develop within 25 years under the BAU scenario. This projection is consistent with observed growth trends in the study

area. Recall from the discussion in chapter 3 that housing stock in most of the study area has increased between 75 and 350% since 1990 (as shown in panel b of figure 3.2). Interestingly, in a long–term horizon, the policies have an important effect at slowing down development. The DCT has the strongest effect, reducing the number of parcels that develop by almost 57%, relative to the BAU. The 10%DT and the WPS have similar effects, reducing development by 20% and 27%, respectively.

The lower panel of table 5.7 shows how land use policies affect wetland conservation and the adding of developed surfaces in the long run. Relative to the baseline, wetland loss is higher under all scenarios. Unsurprisingly, the WPS induces less wetland loss than the other two policies. Added developed covers are lower under all scenarios relative to the BAU. In addition, it seems that future development is characterized by low–density urbanization under all scenarios.

Long–term (25 years) benefit–cost comparison

Similar to the short–term analysis, in the long–term analysis, each generated urban landscape was shocked with a storm resembling Hurricane Irma to measure the economic impact of implementing alternative land use policies. Results for the benefit–cost analysis are summarized in tables 5.8 and 5.9, and illustrated in figures 5.10 to 5.11. Table 5.8 shows average (from the 200 simulations) property damages caused by a major flooding event, expected avoided damages under different policy scenarios, average added value to the landscape for each scenario, and expected cost of each policy in terms of foregone added value. Table 5.9 shows summary statistics for the 200 simulated measures of costs and benefits, and figures 5.11 and 5.12 illustrates these distributions.

When only benefits are considered, the preferable policy is a DCT. Under this policy, there is a 49% reduction in damages relative to the BAU. It is important to recognize

that the only component of flood damages being measured is insurance payments: that is, other non-market, non-insurance measures of economic benefit are neglected. When tax revenues and subsidy costs are considered, under a 10%DT, the augmented CBR is just 0.3 and the amount of raised tax revenue is about 20% more than with a the DCT.

Considering benefits and raised tax revenue seems to indicate a DCT or a 10%DT can deliver the preferred outcome 25 years into the future. However, only looking at these measures may be a misleading strategy for policy design. When considering lost development values, none of the policies pass a benefitcost test. Similarly to the short-term case, findings from a simple cost-benefit comparison suggest that 25 years into the future, the policies are not an effective approach to address increased risks of flooding. In the long-term, the CBR associated with the DCT is 21 (as in the 5–year analysis). In turn, the CBR is 30 for the 10%DT and 38 for the WPS. These ratios indicate that costs are 21 to 37 times the benefits, and that the least undesirable policy is a DCT.

Long–term spatial patterns of development and distribution of damages

Figure 5.12 illustrates the location and number of predicted developments in the study area 25 years into the future. The maps also show major rivers, streams, and roads. Similar to the short–term analysis, there is no clear indication that spatial tendencies in development are altered by the policies. In general, it just seems that development is less dense when a policy is in place, particularly with the DCT and the WPS (these are the same trends observed in the short–term analysis). In general, although illustrative, the maps do not offer any conclusive insights in terms of differential impacts of the policies on the spatial tendencies of development.

Conversely, the policies do seem to have different effects in terms of which areas are expected to experience higher or lower damages. Nevertheless, as with the short–

term analysis, there is very little difference across scenarios in terms of inequality in distribution of expected damages, as indicated by the Gini coefficients. However, I suspect the variation in space is absorbed by the scale of the region.

Figure 5.13 shows the spatial distribution of damages under each policy scenario. Most noticeable are the reduction in extreme damages with a DCT and the more homogeneous distributions of damages under the WPS scenario, relative to the BAU. To facilitate the view of these differential impacts, figures 5.14 to 5.16 show maps of two subregions in the study area where damages differed the most.

5.3.4 SUMMARY AND POLICY IMPLICATIONS

Table 5.10 summarizes the short– and long–run benefits and costs of imposing different land use policies. A first look at the results would indicate a BAU scenario is the preferred alternative. However, a closer look at the results reveals a more nuanced story. Table 5.11 summarizes advantages and disadvantages of all policies and ranks them in terms of relative capacity to deliver each itemized objective.

An examination of the CBR indicates that the 10%DT is the policy with the lowest CBR, (i.e., the least costly at reducing flood damages from a large storm while limiting the amount of foregone benefits of development) in the short–run. In addition, this policy protects wetland covers. In the long–run, the DCT has the lowest CBR as it delivers the largest savings in terms of insurance payments. It also deters development the most.

When other indicators of performance are explored, it is found that no policy dominates across all criteria. For example, a 10%DT outperforms the DCT in terms of raising tax revenues but it delivers lower savings in NFIP payments than the other two policies.[27]

[27]It was found that in the a 10%DT raises about 20% more tax revenue than a DCT. In turn, a DCT is associated with savings that are between 4 and 10 times the size of those delivered by the 10%DT and the WPS. In the short run, a DCT generated savings equal to 39.6% of the damages experienced under

Also, the DCT and the WPS can deliver more equal spatial distribution of damages than the 10%DT. However, all policies were associated with lower Gini coefficients, relative to the baseline. Finally, a WPS outperforms the other policies in terms of encouraging dense development, which may have more desirable implications for the environment than low–intensity type of development (Bertraud and Richardson, 2004; Kenworthy, 2003).

In terms of urbanization patterns, findings show that the policies tend to slow down development in Charleston, both in the short and the long run. Yet, there is no evident difference across scenarios in terms of the spatial tendencies of development. In terms of spatial distribution of expected damages, expected damages are lower and more uniformly distributed across the region when a land use policy is in place. With the DCT and the WPS, additional to the changes observed with the 10%DT, there are fewer clusters of parcels with high damage in the coast of Charleston. Also, there are noticeable reductions near the Waccamaw National Wildlife Refuge in the Northeast boundary of Georgetown, along the Santee River on the North edge of the Francis Marion National Forest in Berkeley, along the Cooper River in CW Berkeley, and near the delta of the Stono River in Charleston. In the long run, there are noticeable reductions in extreme damages with a DCT. In turn, with a WPS, damages seem to be more homogeneously distributed.

The results presented here may have interesting implications for designing future national flood mitigation incentives, such as those supported by the NFIP's Community Rating System (CRS), or future local land use policy. The CRS is a voluntary incentive program that offers flood insurance premium discounts to provide an incentive for communities to implement flood protection activities that exceed the minimum NFIP requirements. The type of activities studied in this dissertation (i.e., land use regulation via

the BAU. In the long run, there was a 49% reduction in payments relative to the BAU scenario. A WPS also reduces in both time lines, but to a lower degree than the DCT.

price instruments) would be classified as 530 activities: those that further the flood protection goals of the CRS. Interestingly, "Flood Protective"activities as currently defined in the CRS do not include modifications to the natural landscape or natural structure restoration. Flood protective activities only include building or restoring levees and dams, however, as shown above, extending the CRS definition of 530 activities to include land use regulation via price instruments could lead to important savings in insurance costs.

The State of South Carolina has been a pioneer in addressing shoreline change and other coastal hazard management issues.[28] In South Carolina, land use planning authority, which includes comprehensive planning, zoning, and adoption of building codes, is delegated to local communities by The Planning Enabling Act of 1994. The Act establishes the baseline requirements for adoption of various ordinances and rules, which can include price controls of the type studied here. However, in spite of a comprehensive list of regulatory powers explicit in the state's legislation, no county in South Carolina has established prescriptive regulation of the type proposed here.

In terms of price controls, only three municipalities within the study area (Mount Pleasant, the City of Charleston, and the City of Summerville in Berkeley county) collect impact fees but none of them collects fees specifically tailored to address flood control projects, let alone flood control projects that target natural infrastructures, such as buffer areas of wetlands. The findings from this work illustrate how various land use policies are beneficial in terms of slowing down development and enabling the region to save on property repairs, either through promoting the conservation of wetlands, which provide flood mitigation services, preventing the imposition of additional impervious surfaces, which lead to increased run–off and inhibit the infiltration of excess water, or through

[28]In Appendix H, I include a detailed discussion on the state's legislative time–line and reasons for why the impact of coastal policies has been limited.

the imposition of a tax on new development that can enhance local government's capacity to raise revenues (revenues that can be tied to flood risk mitigation efforts).

In Mount Pleasant, impact fees for developing a single family home sum to $3,850, most of which goes to the water and sewer utility. In Summerville, impact fees for one house are just under $1,400. If expected property damages after a flooding are taken to be to $24,776, the revenue local governments in South Carolina raise from impact fees seems insufficient to cover the cost of flooding.

As a short run solution, local governments can frame a 10% tax on development as a development impact fee. In the eyes of developers, impact fees and development taxes are an expense that lowers the profitability of a project. However, the results presented here, suggest that impact fees do not slow down development significantly, and that it could be cost effective for county planners to implement or ramp up existing fees.[29]

Policy makers can also use impact fees to design long–term flood mitigation plans. Addressing the threat of climate change and increased flood risks in the long run will likely require policy makers to take a different approach to planning urban growth. In the long run, short–term mitigation efforts will likely not suffice to prevent future losses . Instead, to address losses 25 or more years into the future, policy makers will likely have to take a more preventative stance when designing land use regulations. At least, this is what results from the 25–year simulation exercise indicate (this is shown for instance in that a 10%DT is the more preferable policy in the short term, but a DCT has the lowest CBR in the long term). Combining the economic principles of impact fees with the standing legal mechanisms available to local governments may result in novel policy

[29] As mentioned earlier, that development outcomes are insensitive to price–based policy, is a result found elsewhere in the academic literature and in particular case studies. In the case of Florida, which among the states that most heavily relies on impact fees for financing new capital improvements, the imposition of impact fees in the late 1970's was followed by decades of the state's highest growth.

instruments that induce developers to provide flood prevention services by preserving additional wetland habitat, the type of conservation policy here.

The results of the efforts undertaken in this dissertation can also offer local managers valuable insights on how to design and evaluate schemes aimed at protecting local coastal resources and reducing flood risks. In South Carolina, wetlands account for an important share of the surface area of the state.[30] Yet, current coastal zone management agencies in the state are not well prepared to address wetland protection, particularly as they face pressure from sea level rise, rapid population growth, and fast development of waterfront properties. Currently, there is no state–specific program recommending particular strategies for coastal management or for regulating wetlands in South Carolina. Thus, federal rules continue to provide the only real legal protection for wetlands, and the federal government remains the practical manager of critical wetland areas. However, the most recent County Comprehensive Plans for counties in the study area acknowledge the impact on wetlands from urbanization and climate change, and are not shy in calling for the strengthening of land use strategies, fiscal tools, and public–private partnerships to promote development in areas where impacts on wetlands can be mitigated. The Berkeley Plan goes as far as to recommend the use of subsidies for developers that engage in wetland-friendly practices, exactly the type of policy studied here.

Finally, there are interesting implications from this work for effective future urban and climate policy. In the baseline scenario, about 16% of parcels are predicted to develop in 5 years and 70% in 25 years, and results from this study provide indication that future development in the Charleston metropolitan area is of the suburban type. There is evidence that cities that follow unstructured urban expansion development patterns

[30] About 4.6 million acres, or 23.4% of the surface area of the state, is covered by wetlands. Only two other states, Florida and Louisiana, had a higher percentage (USGS, 1996).

are less resilient to climate events and have higher emissions of greenhouse gases—which further accelerates climate change (Bertraud and Richardson, 2004; Kenworthy, 2003). Thus, based on the findings shown here, future policies aimed at mitigating the effects of climate change should further account consider the type of development when designing land use policies.

Table 5.1: Summary statistics of selected characteristics for undeveloped parcels used to model land use change.

	Charleston	**Berkeley**	**Georgetown**
Recorded sales price*	216,142/11,905	137,567/5	149,753/3,231
(in 2016 dollars)	[0/2,186,066]	[0/27,680,376]	[0/33,022,142]
Area	7.18/0.6	1.4/0.7	10.4/0.7
(in acres)	[0.00/14,525]	[0.00/9.99]	[0.003/7,541]
Developed Cover	61.4/96	39/7.6	33.5/7.9
Tax (%)**	[0/100]	[0/100]	[0/100]
Wetland Protection	11.4/0	20.3/0	18.9/0
Subsidy (%)	[0/100]	[0/100]	[0/100]
# obs	15,680	20,648	16,891
Elasticities from tables 4.1 and 4.2			
Mean effect of DC on Ag prices^{+}	1***	0.7***	0.6***
Mean effect of WC on Ag prices^{+}	0.2	-0.4***	-0.4***
Mean effect of DC on Res prices^{++}	0.3***	0.1***	0.4***
Mean effect of WC on Res prices^{++}	0.2***	-0.2***	-0.1

Statistics outside brackets represent mean/median; and inside brackets [min/max].
* The sample for the land use change model includes more parcels than the hedonic model, some of them had not sold as of 2016 and some sold for unusual prices.
** Tax is based on developed covers development (LC21–to–LC24 in the NLCD).
$^{+}$Expected percentage change in Price/Acre for a 1% increase in land cover class. It is the transformation of the estimates from the hedonic model on agricultural land
$^{++}$Expected percentage change in Price/Acre for a 1% increase in land cover class. It is the transformation of the estimates from the hedonic model on residential land

Table 5.2: Short–term (5 years): development probabilities under alternative policies.

	BAU	10%DT	DCT	WPS
mean/med	0.162/0.151	0.158/0.148	0.088/0.067	0.156/0.145
[min/max]	[0.0028/0.57]	[0.0053/0.55]	[0.00001/0.56]	[0.005/0.599]
std. dev.	0.087	0.083	0.088	0.0870
$\Delta\hat{\delta}$		0.004	0.074	0.006

$\Delta\hat{\delta}$ represents the percentage point difference from BAU.

Table 5.3: Short–term (5 years): number of parcels predicted to develop under different policy regimes.

		Number of parcels predicted to develop			
	Undeveloped parcels at starting point	BAU scenario	10%DT scenario	DCT scenario	WPS scenario
Charleston	15,680	3,097 (19.8%)	2,983 (19%)	1,018 (6.5%)	2,430 (15.5%)
Berkeley	20,648	4,602 (22.3%)	4,312 (20.9%)	2,553 (12.4%)	4,355 (21.1%)
Georgetown	16,891	1,642 (9.7%)	1,595 (9.4%)	995 (5.9%)	1,501 (8.9%)
Total	53,219	9,340 (17.6%)	8,890 (16.7%)	4,566 (8.6%)	8,286 (15.6%)
% relative to BAU			−4.8%	−51.1%	−11.3%
Wetland cover loss (acres)		−4,336	−1,917	−5,258	−1,083
% relative to BAU			−55.8%	+21.3%	−75%
Developed cover added (acres)*		37,106	27,138	−5,482	28,079
% relative to BAU			−26.9%	−114.8%	−24.3%
Intensive development added (acres)+		344	216	-405	291
% relative to BAU			−37.2%	−217.7%	−15.4%

Shares in parenthesis are percentages of land cover change relative to total area.
* Includes, open space, low–, medium–, and high–intensity development (i.e., land cover classes 21 to 24).
+ Includes high–intensity development only (i.e., LC class 24).

Table 5.4: Short–term (5 years): expected benefits and costs under different policy scenarios.

	BAU	10%DT	DCT	WPS
Expected damages and savings				
Average NFIP payments	23,399,384	22,531,926	14,132,178	21,851,824
Avoided payments		867,458	9,267,206	1,547,560
Savings as percent of BAU damages		3.7%	39.6%	6.61%
Expected added value from development				
Added value to the land	386,376,257	369,297,731	189,786,016	341,326,223
Foregone added value		17,078,526	196,590,241	45,050,034
Foregone value as percent of baseline		4%	50.9%	11.7%
Cost–Benefit Ratio		19.7	21.2	29.1
Raised revenue		152,240,261	127,812,019	−207,553,252
Augmented CBR		0.11	0.38	163.23

Table 5.5: Short–term (5 years): summary statistics of benefits and costs under different scenarios.

		BAU	10% DT	DCT	WPS
Expected NFIP payments	Min	22,338,461	21,766,575	13,813,227	21,046,542
	1st Qu.	23,177,191	22,331,142	13,984,228	21,626,114
	Median	23,431,304	22,536,802	14,171,685	21,956,014
	Mean	23,399,384	22,531,926	14,132,178	21,851,824
	3rd Qu.	23,623,131	22,765,829	14,295,537	22,077,027
	Max.	24,181,598	23,122,886	14,303,487	22,358,467
Expected sales revenues	Min	373,504,670	357,259,889	183,035,663	329,948,613
	1st Qu.	383,965,640	366,760,371	188,151,307	339,135,892
	Median	386,513,022	369,474,795	189,675,560	341,537,113
	Mean	386,376,257	369,297,731	189,786,016	341,326,223
	3rd Qu.	388,924,683	371,708,974	191,356,415	343,948,774
	Max.	395,094,776	378,014,789	196,315,458	349,325,421

Table 5.6: Long–term (25 years): development probabilities for different periods under alternative policies.

	BAU	10%DT	DCT	WPS
0-to-5–year	0.162	0.158	0.088	0.157
	(0.087)	(0.083)	(0.089)	(0.087)
5-to-10–year	0.157	0.151	0.081	0.148
	(0.083)	(0.08)	(0.085)	(0.083)
10-to-15–year	0.148	0.144	0.075	0.141
	(0.08)	(0.078)	(0.082)	(0.08)
15-to-20–year	0.136	0.138	0.07	0.135
	(0.078)	(0.076)	(0.079)	(0.078)
20-to-25–year	0.126	0.133	0.065	0.13
	(0.071)	(0.074)	(0.077)	(0.076)

Results shown in the table are average probabilities.
Numbers in parenthesis are standard deviations.

Table 5.7: Long–term (25 years): number of parcels predicted to develop under different policy regimes.

		Number of parcels predicted to develop			
	Undeveloped parcels at starting point	BAU scenario	10%DT scenario	DCT scenario	WPS scenario
Charleston	15,680	12,439 (79.3%)	9,751 (62.2%)	3,476 (22.2%)	7,699 (49%)
Berkeley	20,648	17,331 (85%)	13,780 (66.7%)	8,641 (41.8%)	13,693 (66.3%)
Georgetown	16,891	7,693 (45.5%)	6,269 (37%)	4,010 (23.7%)	6,072 (36%)
Total	53,219	37,463 (70.4%)	29,800 (56%)	16,127 (30.3%)	27,464 (51.6%)
% relative to BAU			−20.5%	−57%	−26.7%
Wetland cover loss (acres)		847	2,947	3,053	2,644
% relative to BAU			248%	260%	212%
Developed cover added (acres)*		25,536	17.676	2,776	20,668
% relative to BAU			−30.8%	−89%	−19%
Intensive development cover added (acres)+		140	−7	−307	32
% relative to BAU			−105%	−319%	−77%

Shares in parenthesis represent percentage of land cover change relative to total area.
* Includes, open space, low–, medium–, and high–intensity development (i.e., land cover classes 21 to 24).
+ Includes high–intensity development only (i.e., LC class 24).

Table 5.8: Long–term (25 years): expected benefits and costs under different policy scenarios.

	BAU	10%DT	DCT	WPS
Expected damages and savings				
Average NFIP payments	51,548,920	46,327,071	26,384,454	45,787,556
Avoided payments		5,221,849	25,164,466	5,761,364
Savings as percent of BAU damages		10%	48.8%	11.2%
Expected added value from development				
Added value to the land	958,338,082	803,808,551	428,620,585	741,964,796
Foregone added value		154,529,531	529,717,497	216,373,286
Foregone value as percent of baseline		16%	55.3%	22.6%
Cost–Benefit ratio		29.6	21	37.6
Raised revenue		508,577,985	410,877,451	−694,682,671
Augmented CBR		0.3	1.2	158.1

Table 5.9: Long–term (25 years): summary statistics of benefits and costs under different policy scenarios.

		BAU	10% DT	DCT	WPS
Expected NFIP payments	Min	17,188,241	15,486,068	8,845,862	15,131,485
	1st Qu.	17,295,507	15,635,003	8,889,447	15,420,510
	Median	51,272,633	45,963,663	26,353,737	45,238,199
	Mean	51,548,920	46,327,071	26,384,454	45,787,556
	3rd Qu.	85,798,322	77,032,257	43,881,914	76,289,790
	Max.	86,556,430	77,801,487	44,092,780	76,894,036
Expected added value	Min	948,470,267	795,633,202	423,040,580	734,144,657
	1st Qu.	955,480,457	801,504,189	427,273,367	739,879,162
	Median	958,409,902	803,486,438	428,490,534	742,323,898
	Mean	958,338,082	803,808,551	428,620,585	741,964,796
	3rd Qu.	960,806,679	805,822,750	429,954,540	744,246,801
	Max.	969,123,393	812,132,317	435,674,925	750,521,124

Table 5.10: Expected damages and savings under different policy scenarios at two different points in time.

	10%DT	DCT	WPS
5–year			
% of parcels developed relative to BAU	−2.9%	−39.4.3%	−8.6%
Δ wetland cover relative to BAU	−55.8%	21.3%	−75%
Δ general development relative to BAU$^+$	−26.9%	−114.8%	−24.3%
Δ impervious surface relative to BAU	−37.2%	−217.7%	−15.4%
Savings in NFIP payments	867,458	9,267,206	1,547,560
Savings as % of BAU	3.7%	39.6%	6.6%
Cost–Benefit ratio	19.7	21.2	29.1
Raised revenue	152,240,261	127,812,019	−207,553,252
Augmented CBR	0.1	0.4	163.2
Gini coefficient of damage distribution*	0.473	0.44	0.47
25–year			
% of parcels developed relative to BAU	−18.5	−47.9	−21.1
Δ wetland cover relative to BAU	248%	260%	212%
Δ general development relative to BAU	−31%	−89%	−19%
Δ impervious surface relative to BAU	−105%	−319%	−77%
Savings in NFIP payments	5,221,849	25,164,466	5,761,364
Savings as % of BAU	10.1%	48.8%	11.2%
Cost–Benefit ratio	29.6	21.1	37.6
Raised revenue	508,577,985	410,877,451	−694,682,671
Augmented CBR	0.3	1.2	158
Gini coefficient of damage distribution$^+$	0.61	0.6	0.59

* Gini for BAU is 0.46 5years into the future, and 0.64 25 years ahead.
$^+$ Gini for BAU is 0.64 25 years ahead.

Table 5.11: Summary of advantages and disadvantages of policies and their ranking.

	10%DT	DCT	WPS
5–year			
Reduces insurance payments	yes	YES	Yes
Raises tax revenues	Yes	yes	no
Avoids losses in added developed value	no	NO	No
Slows down urbanization	yes	YES	Yes
Protects/restores wetlands	yes	no	Yes
Encourages dense development	no	No	yes
More equal spatial distribution of damages	No	yes	no
25–year			
Reduces insurance payments	yes	YES	Yes
Raises tax revenues	Yes	yes	no
Avoids losses in added developed value	no	NO	No
Slows down urbanization	yes	YES	Yes
Protects/restores wetlands	No	NO	no
Encourages dense development	yes	Yes	YES
More equal spatial distribution of damages	yes	Yes	YES

This table ranks policies based on relative performance. Capitalization of "yes"and "no"indicates capacity, so that a **YES** is stronger than **Yes**. In turn, both have larger impacts than a policy that delivers **yes**.

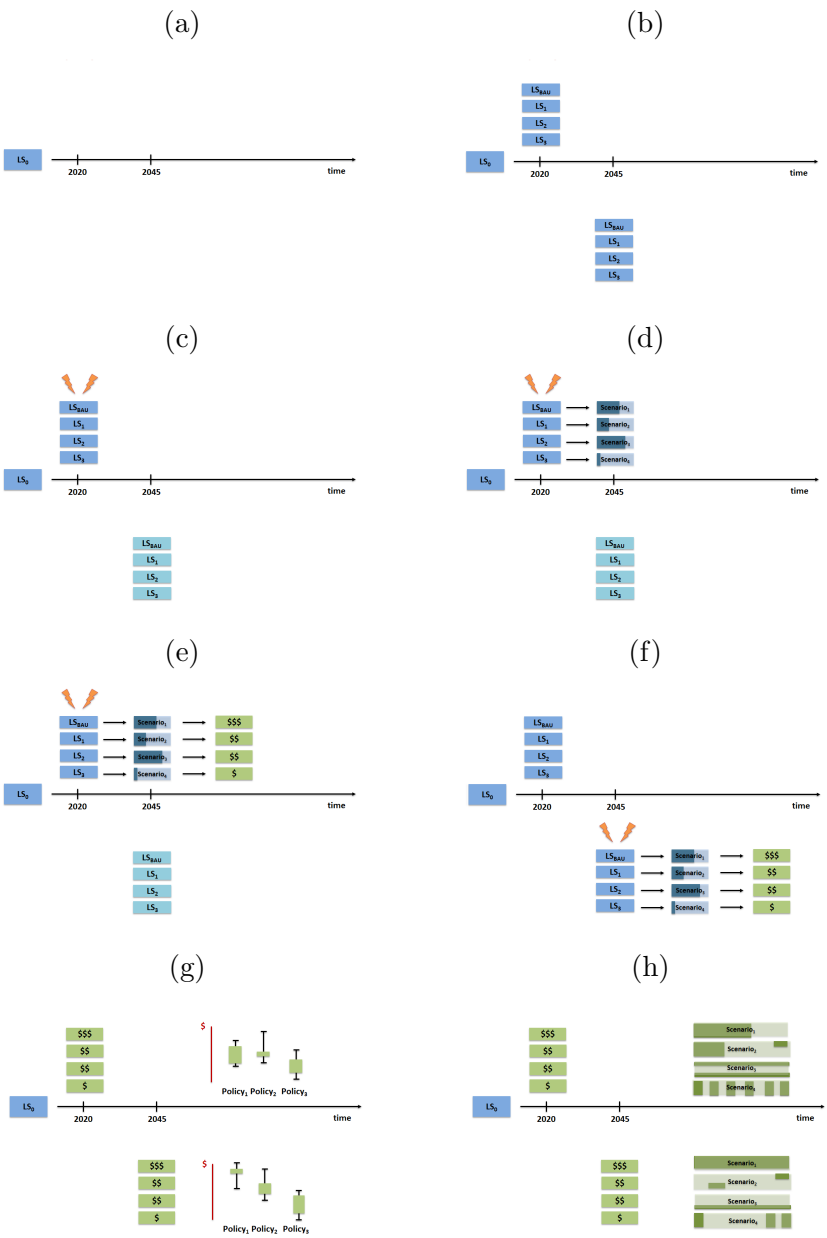


Figure 5.1: Steps for comparing alternative land use policies in their ability to mitigate risks and damages from major floods. Panel (a) shows the original state of the landscape. Panel (b) shows the starting point for policy comparison: the generated alternative future landscapes. Panel (c) shows step 2: the system is shocked with a flood in the short term. Panel (d) shows step 3: alternative landscapes and their propensity to flood. Panel (e) shows step 4: estimated costs and benefits. Panel (f) shows steps 2 to 4 when the system is shocked with a storm in the long run. Panel (g) shows step 5: the final cost-benefit comparison between policies and across time. Panel (h) shows the final analysis of differences in spatial distribution of damages between policies and across time.

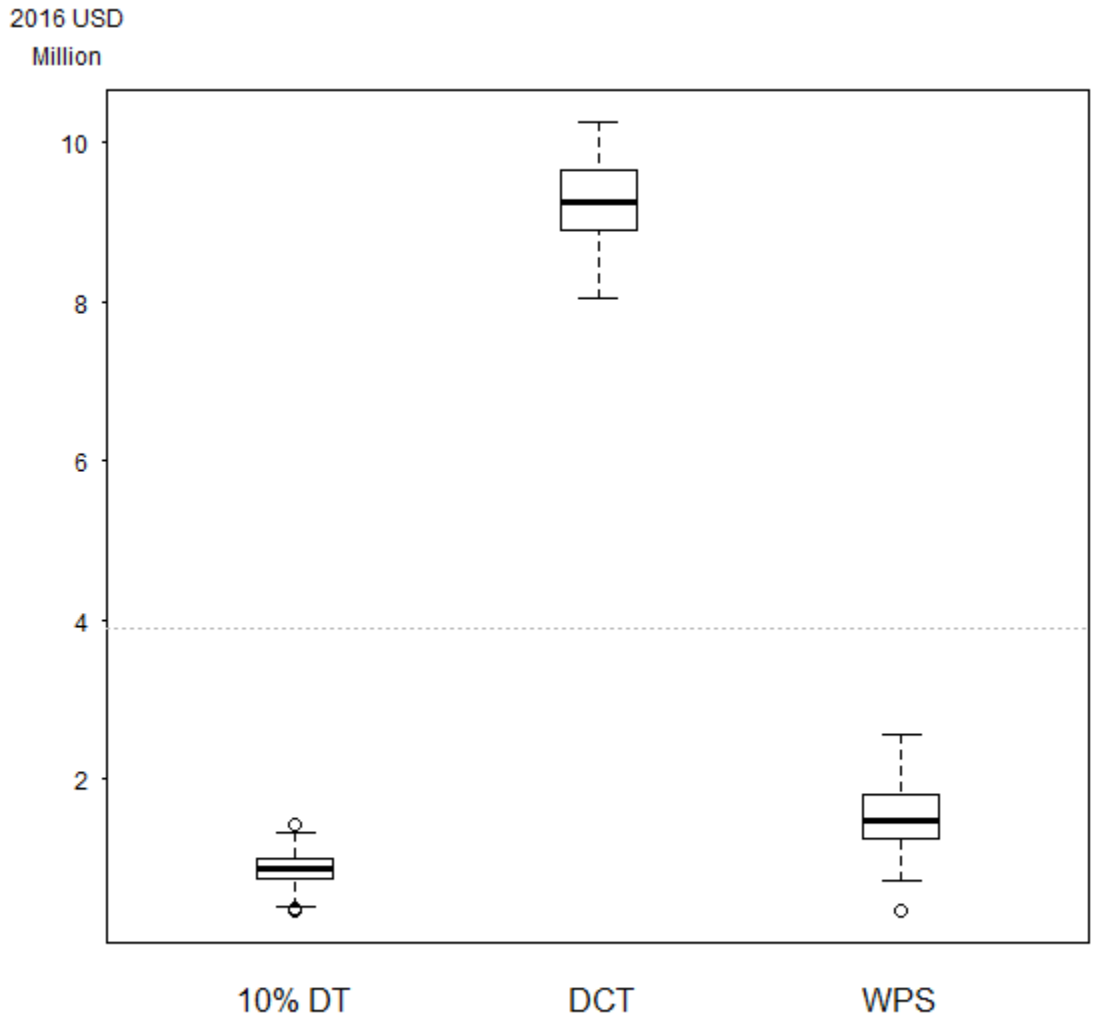


Figure 5.2: Short–term (5 years) benefits comparison: expected savings in NFIP payments using estimates of average NFIP claim in South Carolina ($2016). The average saving across all simulations is indicated by the dotted gray line. In the boxplot, the thick middle line corresponds to the median, and the edges of the box to the first and third quartiles; whiskers are the inner fence (1.5 times the interquartile range above the upper quartile and below the lower quartile), and the dots are outliers.

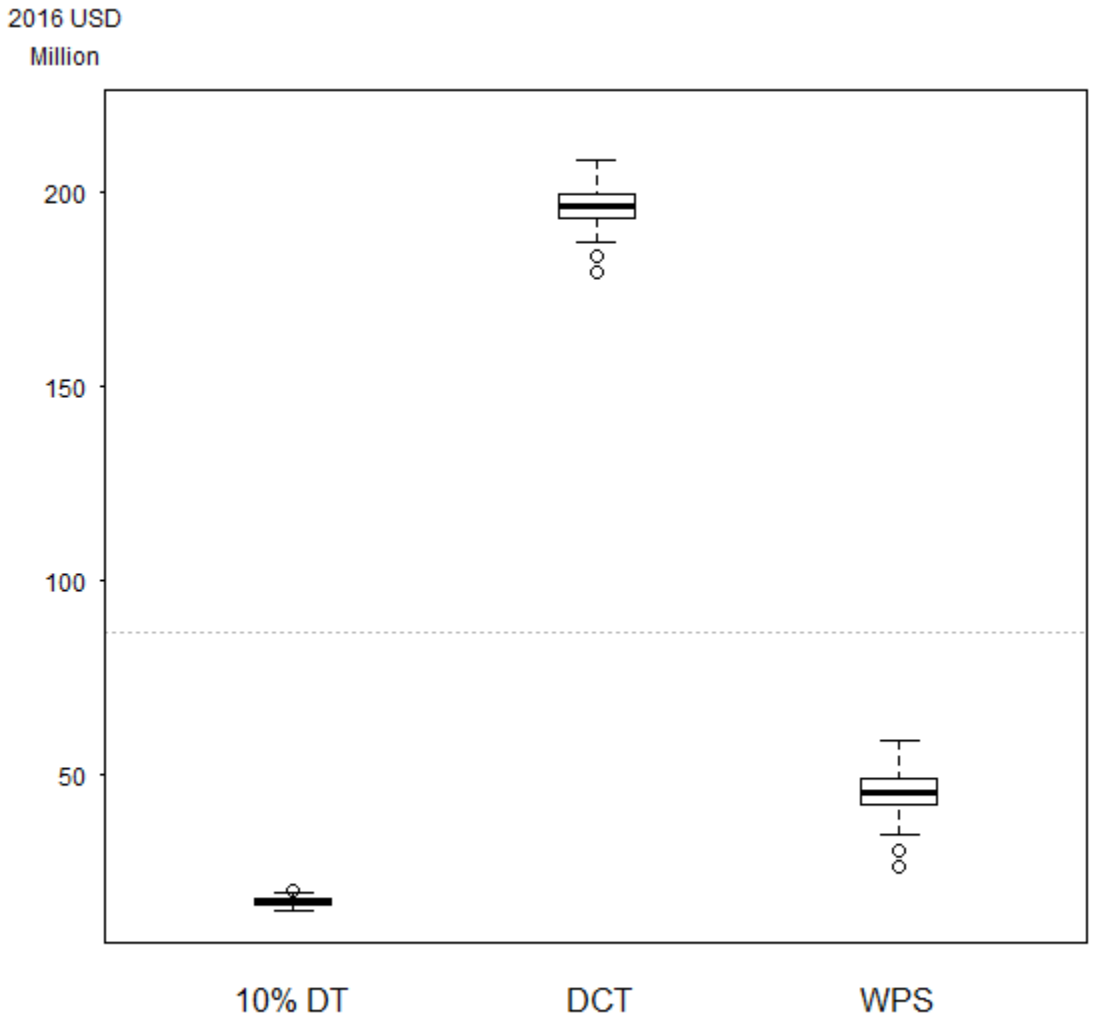
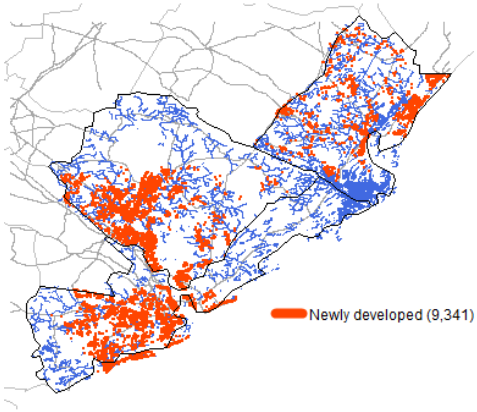
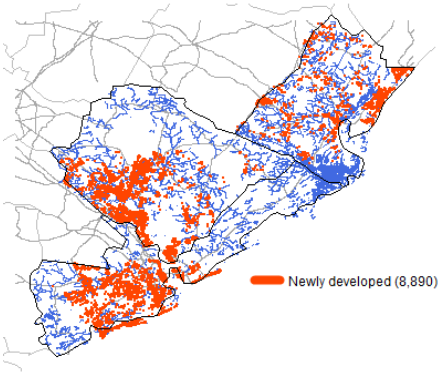


Figure 5.3: Short–term (5 years) costs comparison: foregone added value to the landscape (in $2016). The average foregone added value across all simulations is indicated by the dotted gray line. In the boxplot, the thick middle line corresponds to the median, and the edges of the box to the first and third quartiles; whiskers are the inner fence (1.5 times the interquartile range above the upper quartile and below the lower quartile), and the dots are outliers.

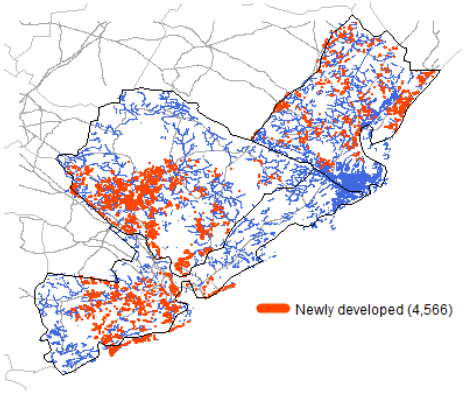
(a) Business as usual scenario.



(b) 10% tax on development.



(c) Tax on developed covers.



(d) Subsidy on wetland covers.

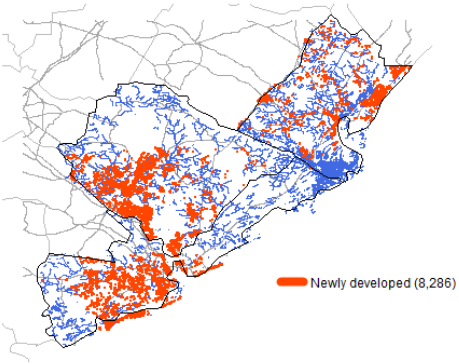
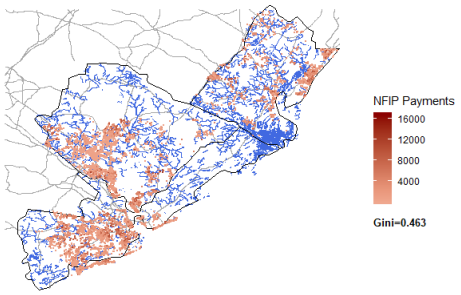
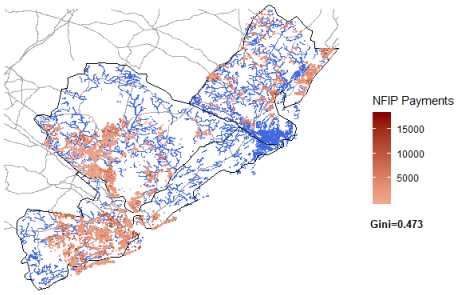


Figure 5.4: Short–term (5 years): maps of predicted development under various policy regimes. The number of developed parcels under each scenario are in parenthesis. Gray lines are major roads and blue lines are streams and rivers.

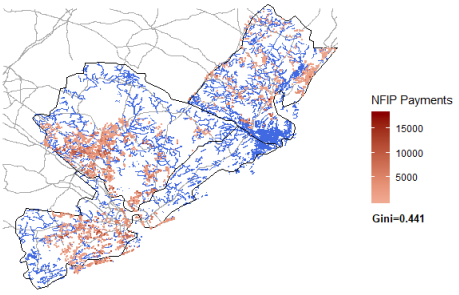
(a) Business as usual scenario.



(b) 10% tax on development.



(c) Tax on developed covers.



(d) Subsidy on wetland covers.

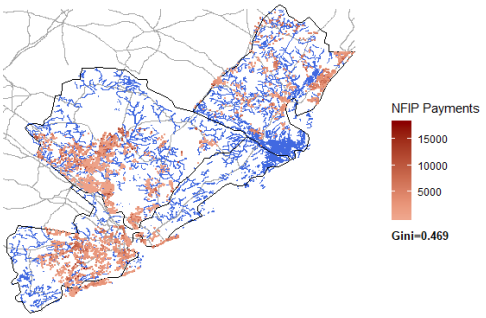
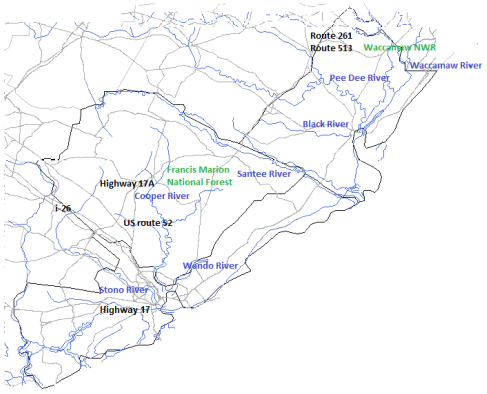
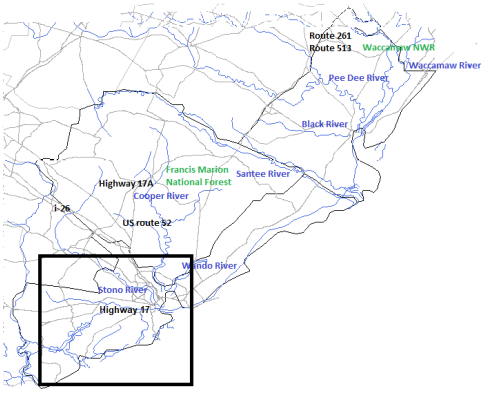


Figure 5.5: Short–term (5 years): maps of expected damages from a major flood under various policy regimes 5 years into the future. Maps show the gini coefficient associated with each scenario. Gray lines are major roads and blue lines are streams and rivers.

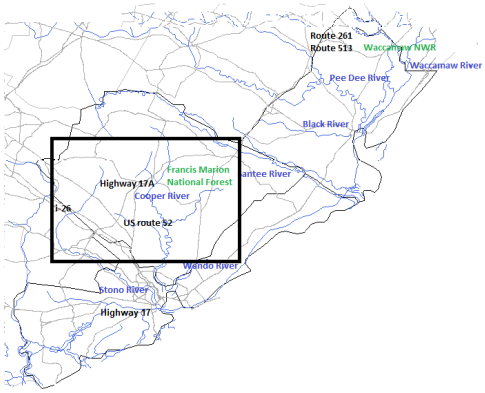
(a) Region with key features.



(b) Southern coast Charleston.



(c) Central and West Berkeley.



(d) Georgetown proper.

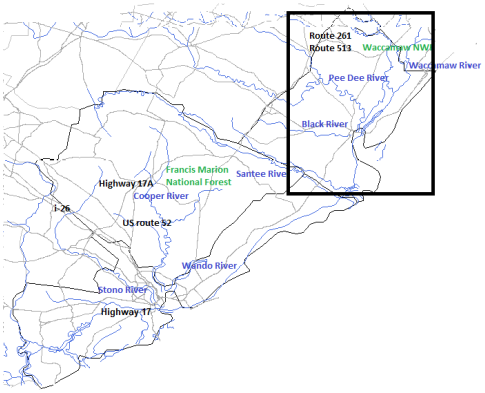
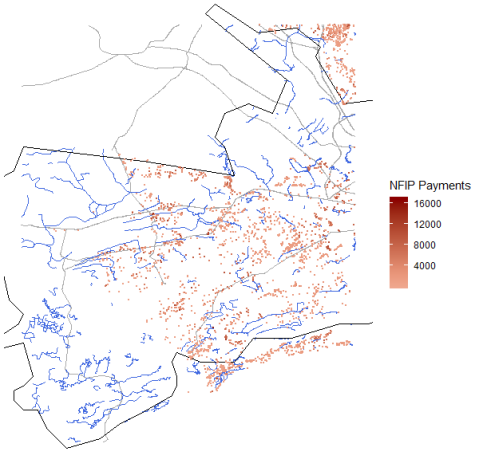
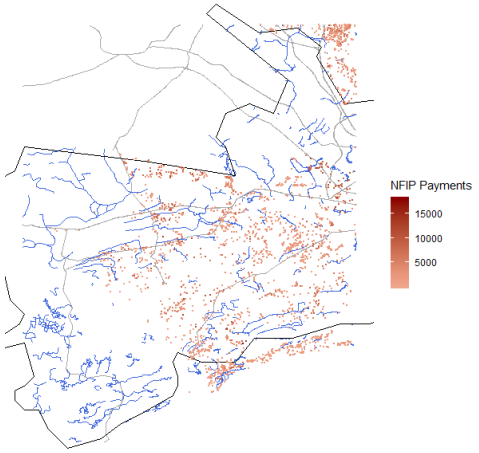


Figure 5.6: Selected regions of study area where impacts from policies differ the most.

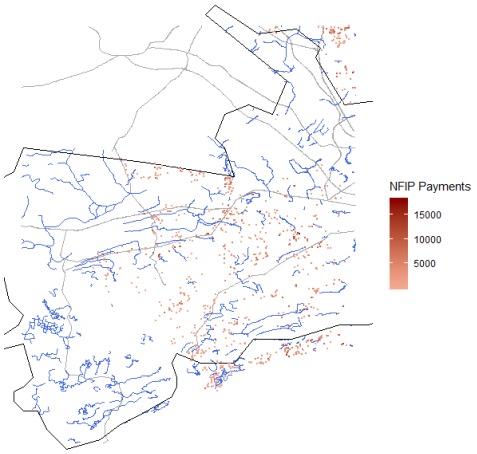
(a) Business as usual scenario.



(b) 10% tax on development.



(c) Tax on developed covers.



(d) Subsidy on wetland covers.

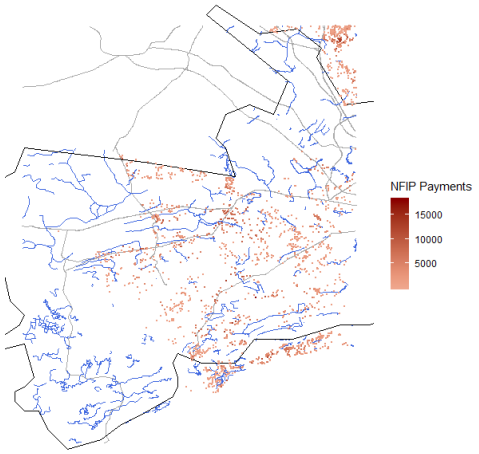
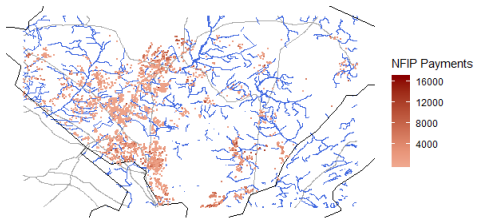
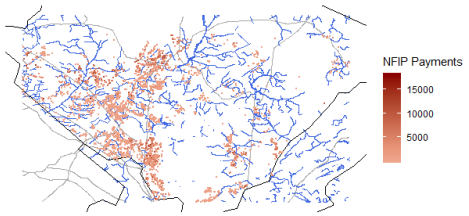


Figure 5.7: Short–term (5 years): maps of expected damages from a major flood under various policy regimes in the South Charleston subregion. Gray lines are major roads and blue lines are streams and rivers.

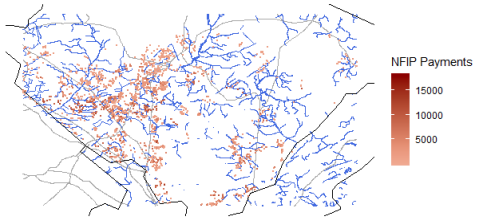
(a) Business as usual scenario.



(b) 10% tax on development.



(c) Tax on developed covers.



(d) Subsidy on wetland covers.

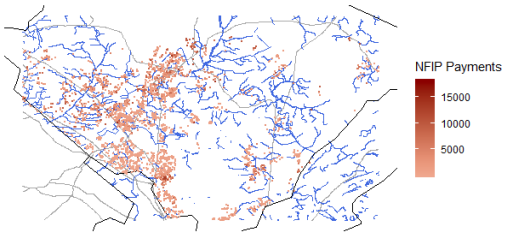
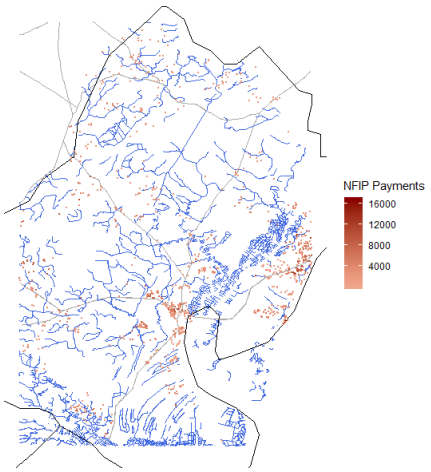
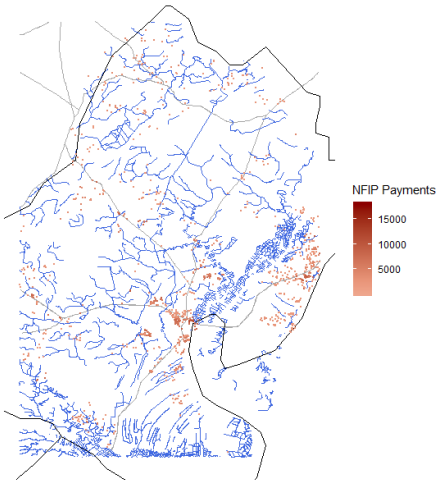


Figure 5.8: Short–term (5 years): maps of expected damages from a major flood under various policy regimes in the Central Berkeley subregion. Gray lines are major roads and blue lines are streams and rivers.

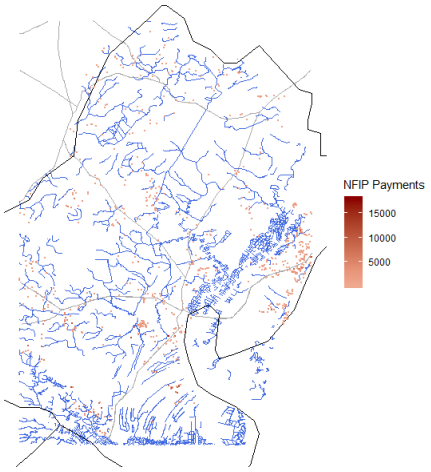
(a) Business as usual scenario.



(b) 10% tax on development.



(c) Tax on developed covers.



(d) Subsidy on wetland covers.

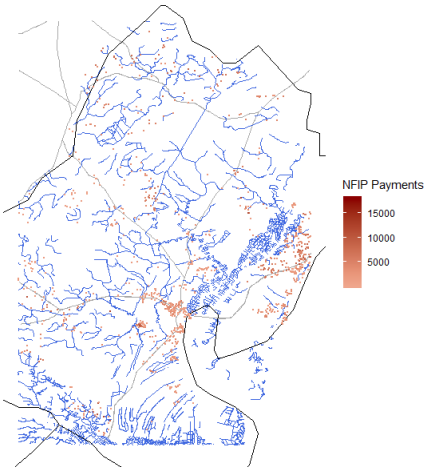


Figure 5.9: Short–term (5 years): maps of expected damages from a major flood under various policy regimes in a subregion of Georgetown. Gray lines are major roads and blue lines are streams and rivers.

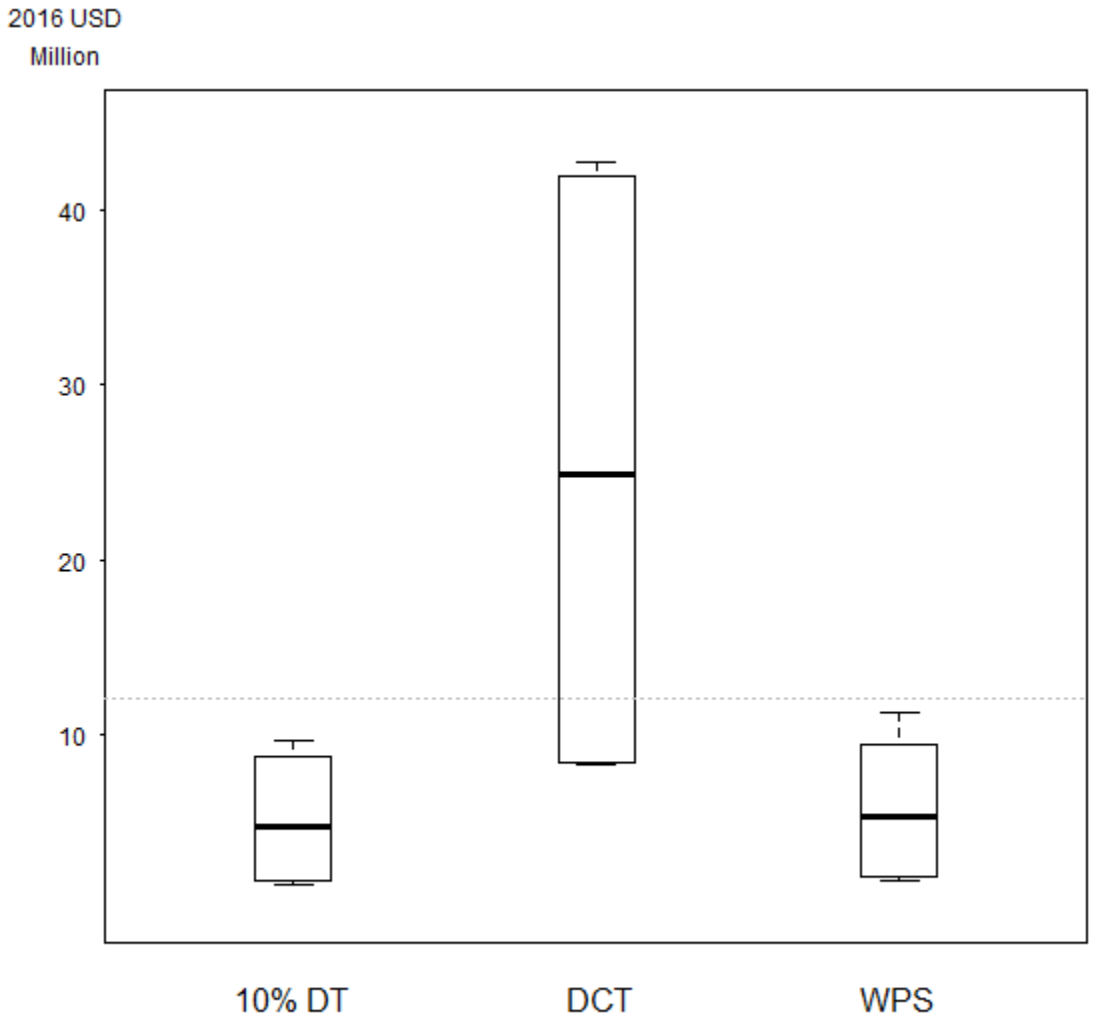


Figure 5.10: Long–term (25 years) benefits comparison: expected savings in NFIP payments using estimates of average NFIP claim in South Carolina ($2016). The average saving across all simulations is indicated by the dotted gray line. In the boxplot, the thick middle line corresponds to the median, and the edges of the box to the first and third quartiles; whiskers are the inner fence (1.5 times the interquartile range above the upper quartile and below the lower quartile), and the dots are outliers.

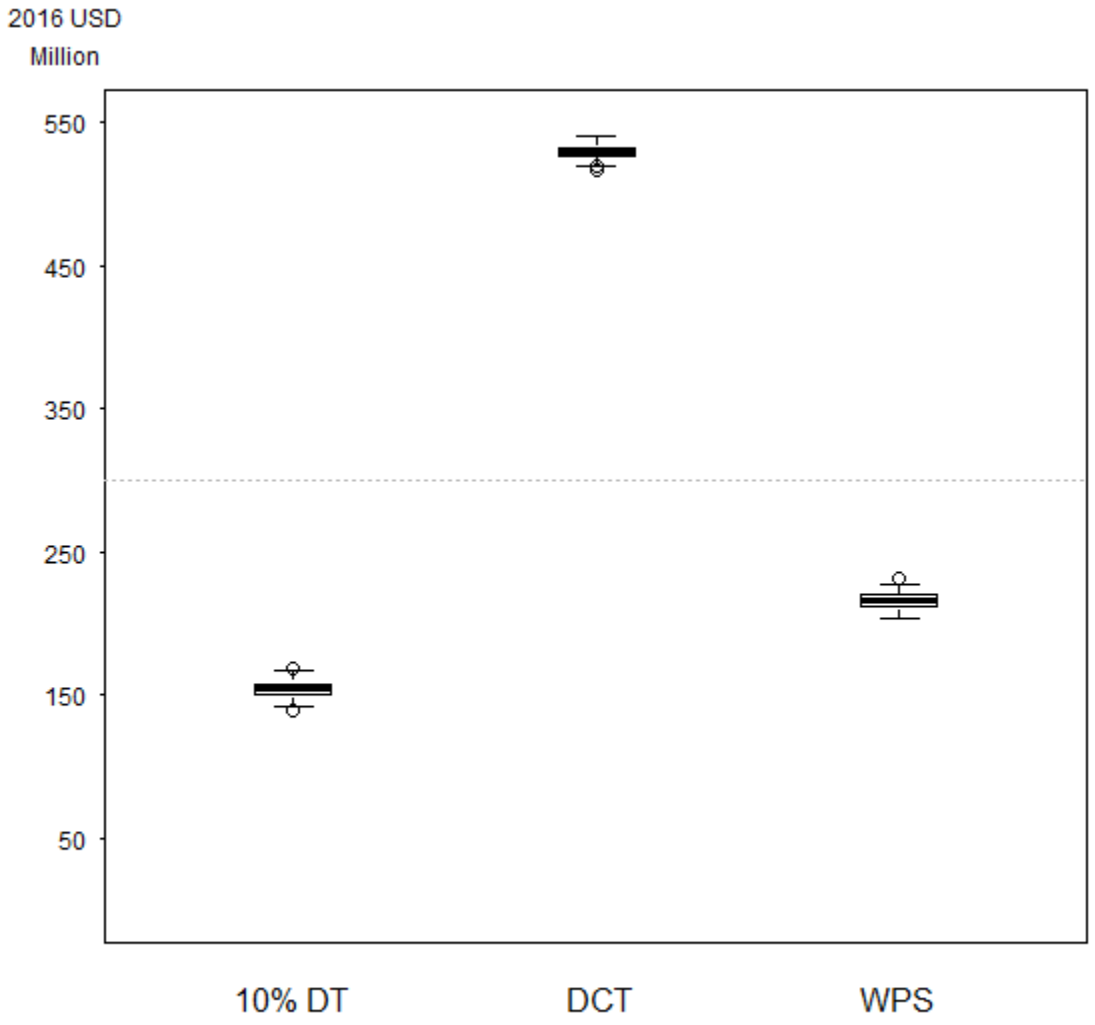
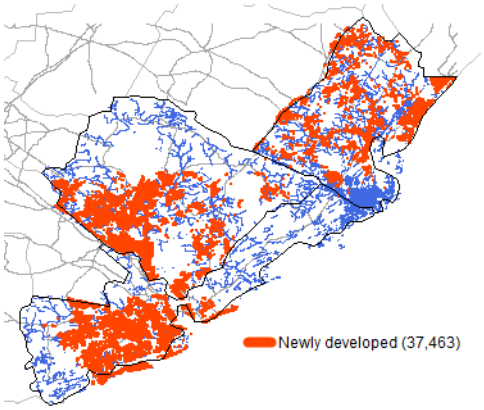
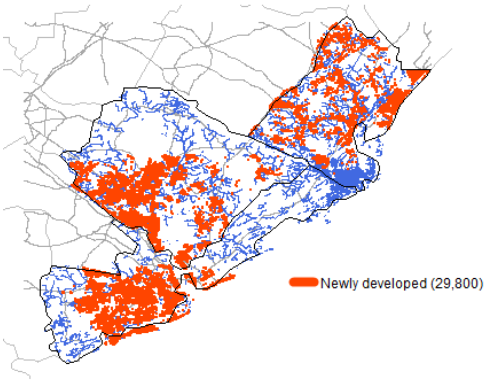


Figure 5.11: Long–term (25 years) costs comparison: foregone added value to the landscape (in $2016). The average foregone added value across all simulations is indicated by the dotted gray line. In the boxplot, the thick middle line corresponds to the median, and the edges of the box to the first and third quartiles; whiskers are the inner fence (1.5 times the interquartile range above the upper quartile and below the lower quartile), and the dots are outliers.

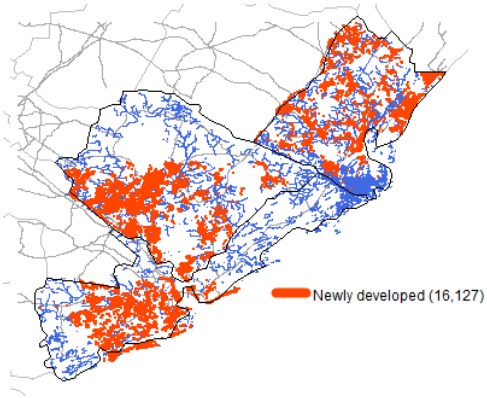
(a) Business as usual scenario.



(b) 10% tax on development.



(c) Tax on developed covers.



(d) Subsidy on wetland covers.

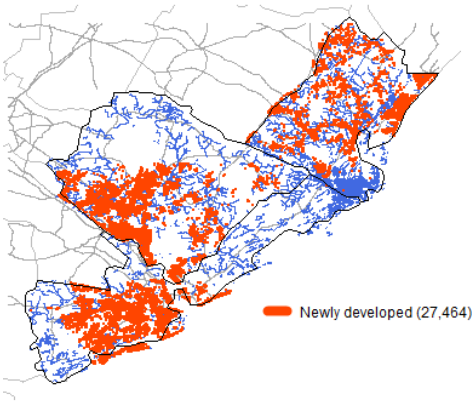
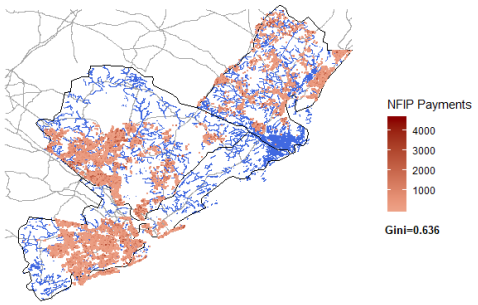
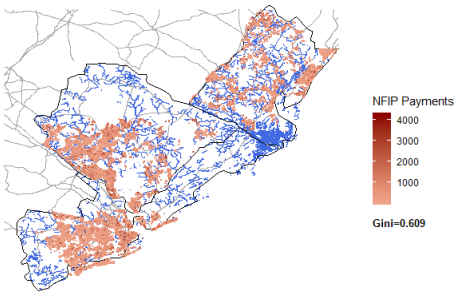


Figure 5.12: Long–term (25 years): maps of predicted development under various policy regimes. The number of developed parcels under each scenario are in parenthesis. Gray lines are major roads and blue lines are streams and rivers.

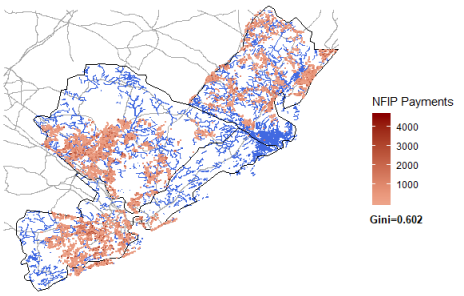
(a) Business as usual scenario.



(b) 10% tax on development.



(c) Tax on developed covers.



(d) Subsidy on wetland covers.

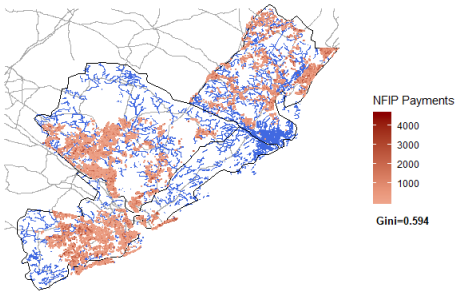
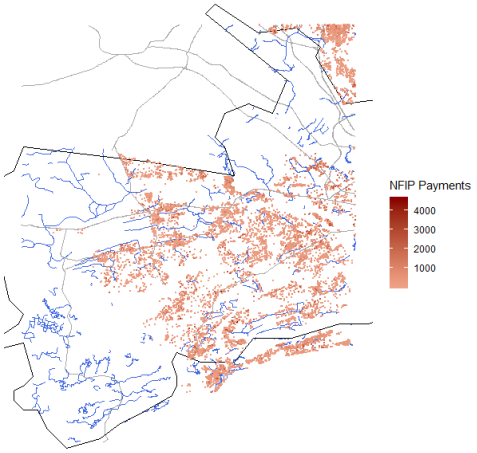
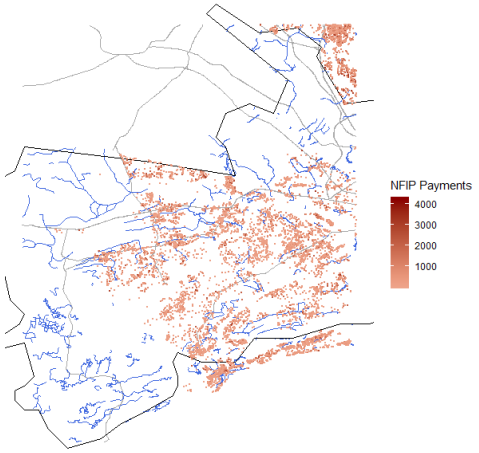


Figure 5.13: Long–term (25 years): maps of expected damages from a major flood under various policy regimes 25 years into the future. Maps show the gini coefficient associated with each scenario. Gray lines are major roads and blue lines are streams and rivers.

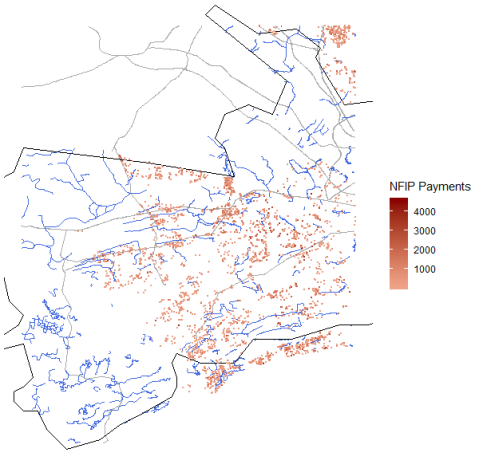
(a) Business as usual scenario.



(b) 10% tax on development.



(c) Tax on developed covers.



(d) Subsidy on wetland covers.

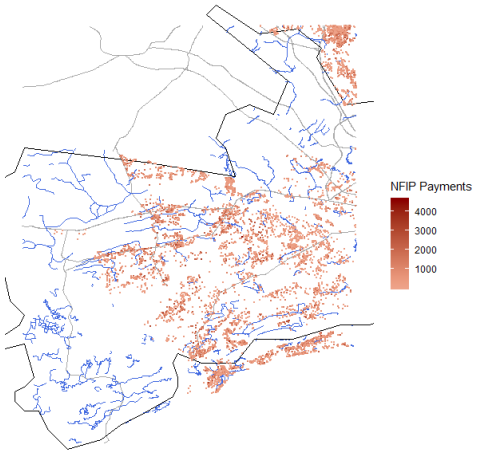
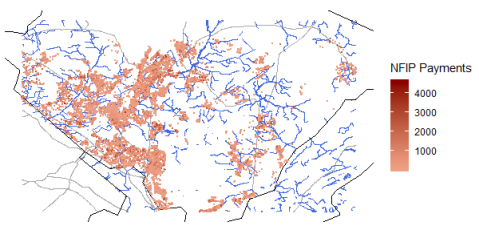
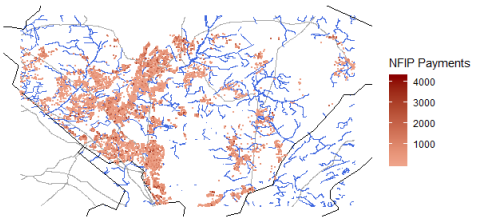


Figure 5.14: Long–term (25 years): maps of expected damages from a major flood under various policy regimes in the South Charleston subregion. Gray lines are major roads and blue lines are streams and rivers.

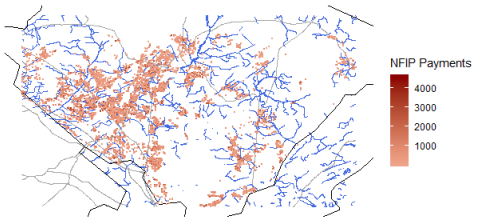
(a) Business as usual scenario.



(b) 10% tax on development.



(c) Tax on developed covers.



(d) Subsidy on wetland covers.

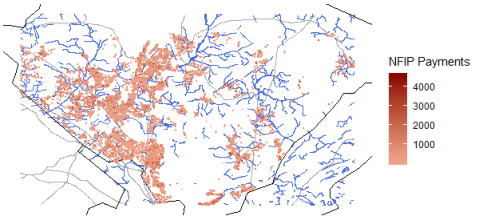
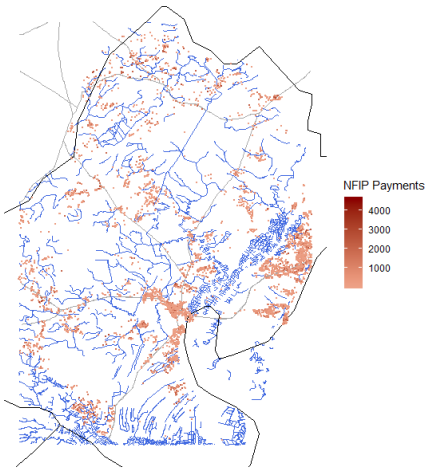
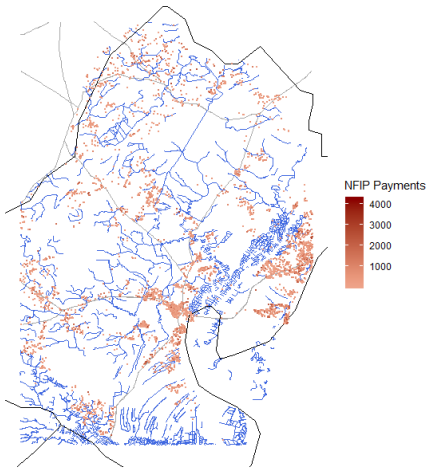


Figure 5.15: Long–term (25 years): maps of expected damages from a major flood under various policy regimes in the Central Berkeley subregion. Gray lines are major roads and blue lines are streams and rivers.

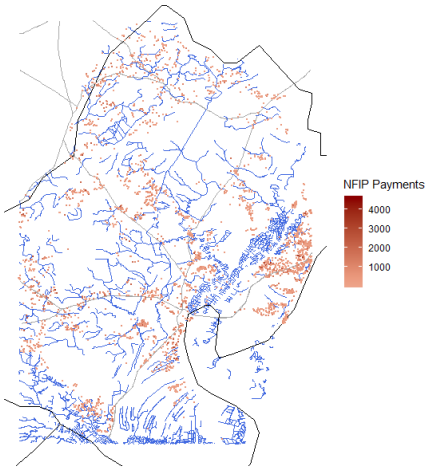
(a) Business as usual scenario.



(b) 10% tax on development.



(c) Tax on developed covers.



(d) Subsidy on wetland covers.

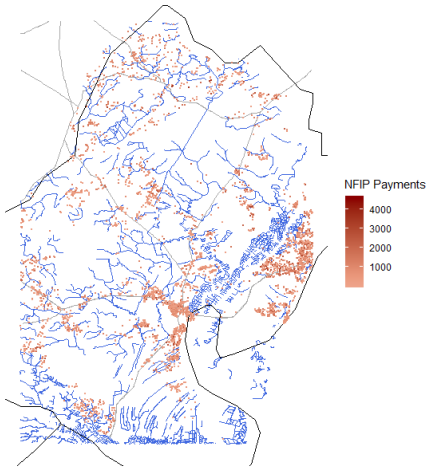


Figure 5.16: Long–term (25 years): maps of expected damages from a major flood under various policy regimes in a subregion of Georgetown. Gray lines are major roads and blue lines are streams and rivers.

6 CONCLUSION

The purpose of this study is to develop and apply an integrative analysis using spatial simulation, economic models, and models of ecosystem services provision that can provide an initial evaluation of the relative effectiveness of three market–based land use policies in their ability to alter development outcomes, protect natural infrastructure, and reduce flood damages among coastal properties in the Charleston metropolitan area. The results of this study indicate that price instruments based on land value and that vary by landscape composition are mostly not a cost effective strategy for addressing increased risks of flooding in the study area. However, when examining various outcomes that policy makers may have interest on, these instruments can be modestly effective at altering urban development patterns, enabling the region to reach economic savings on property damages when a flood occurs, raising tax revenues, or delivering a marginally more equal spatial distribution of damages. The findings from this work also provide supportive evidence to research illustrating how natural infrastructures, such as coastal wetlands, are beneficial to coastal communities in terms of flood damage reduction.[1]

More specifically, the findings presented here imply that policy makers face interesting trade–offs in designing forward–looking land use policy aimed at mitigating flood damages, and that they can take better advantage of the economic benefits different policies offer by differentiating between fiscal, environmental, and social objectives, and between short term and long term objectives. In general, no policy dominates across all criteria, thus, this work cannot give indication on what is the preferred route of action. However, the framework and analysis established here serve as a strong starting ground for research trying to answer the questions of how can planners choose among policies, and what is the optimal policy for meeting community–centered, environmental, and fiscal goals—given a level of creativity and assertiveness that is both socially and legally feasible.

Among the three policies, a tax on development that would reduce the value of developable land by 10% is the most cost–effective approach to reducing flood damages from a storm while

[1]See Loerzel et al.,(2017), Walls et al., (2017), Narayan et al., (2016), Boutwell and Westra, (2015).

limiting the amount of forgone benefits of development. Such a policy is associated with lower costs in terms of lost development value, moderate savings in terms of flood damages, and it delivers positive tax revenues (which can be tied to flood–preventive investments). In addition, it protects wetland covers in the short run. However, such a tax is not the most effective policy for reducing damages, deterring urban growth, or equalizing damages across the region. Alternatively, a heterogeneous tax based on developed cover surfaces discourages development, delivers a more equal spatial distribution of damages, and is the most effective at reducing damages. Yet, it is associated with high costs in terms of losses in development value. Finally, a subsidy on wetland covers delivers outcomes that are generally between those associated with the 10%DT and the DCT, with the main difference being its high cost to local governments.

6.1 LIMITATIONS AND FUTURE RESEARCH

The analysis shown here is innovative and provides new insights on the potential impact of land use policy on flood prevention by examining highly disaggregate data on localized relationships that account for spatial determinants of the land development process. However, there are several limitations to mention and opportunities for future research.

In terms of the overall framework employed, there are a few key considerations. First, it is important to highlight that this is not an optimization exercise and that I do not address the economic efficiency of alternative development patterns. In addition, the analysis shown here is built on a partial equilibrium model and therefore does not capture the price feedbacks or development spillovers to other locations, both effects that would likely affect the modeled system via population and income shifts that would follow the imposition of these policies and the occurrence of large storms in the study area.

Second, it is important to note that the selected storm event used as a basis for developing flood risks and determining damages (i.e., Hurricane Irma) is unique. Thus, the analysis in this study is not representative of all possible storms and does not identify the general impact of

landscape features on coastal communities. It is not expected that property damages in the short and long term scenarios will respond similarly under other storm events. There are variabilities in surge reduction potential of landscape features, such as wetlands and hard covers, and their geomorphological and biological dynamics are complex. Moreover, this study is completely silent on the impact that climate change and sea–level–rise will have on future flood risks.

Third, the analysis conducted here also abstracts away from the effect price instruments have on development decisions at the intensive margin. Recognizing that the share of developed surfaces covering land is endogenous, and that landowners can be strategic about their choice to intensify density of development in order to modify the tax rate they receive, ignoring the intensive margin is an important limitation of this framework. Finally, the non–flooding externality costs associated with land development are not estimated, nor is a welfare analysis conducted—thus, this work is silent on the potential policy incidence on different income groups or populations residing in locations with different environmental sensitivities.

There are a number of extensions to the current modeling framework that can also be considered. First, in the hedonic analysis, variables measuring land cover composition of the landscape can be separated to measure composition in the parcel and around the parcel, rather than using a measure that aggregates both. Land cover inside a parcel contributes to its value differently than landcover in the area that surrounds it, and should thus be considered separately. While coefficients estimates did not change much when land cover variables were separated by on–parcel versus off–parcel, future research can include them separately.

Second, the construction of variable measuring developed covers can be improved. The definition used in this study included areas covered in land classes LC21, LC22, LC23, and LC24 in the National Land Cover Database. For most of these land classes, impervious surfaces constitutes only a small share of the total cover. For instance, open–space developed covers (LC21) include areas where less than 20% of the total cover is accounted for by impervious surfaces. An index variable can be used to improve the measure of impervious surface cover.

Third, while continuous–time proportional hazard models offer many benefits, they have some limitations, one of them being that they do not adapt readily to contexts where time is measured discretely. Thus, a technical improvement to the estimation may involve using a discrete–time proportional hazard model, as opposed to a continuous–time model. Future models can also explore enriching the explanatory variable set with spatial fixed effects.

Fourth, the mechanism used to update land cover composition of parcels post–development can be strengthened by formally modeling density of development in the conversion decision. This can be done by incorporating a hurdle model into the framework. With the current method, strange results that are not possible to explain with the data at hand may arise—like the predicted increment in wetlands post–development. Although it is possible to explain such an increment by natural migration of wetlands or by active modification of the landscape by landowners (perhaps with the intent of acquiring tradable wetland credits, which are part of the largest ecosystem services market in the U.S. and the world), it contradicts existing reports of coastal watersheds in the continental US, which show a loss of wetland coverage area at a rate of 1% in the years between 2004 and 2009 (NOAA and F&WS, 2013).

Fifth, the empirical framework developed here is sufficiently flexible to be used in the study of other types of policies, including modifications to the price policies explored here, and quantity–based policies such as density controls. Lastly, coupling the modeling of future urban landscapes with simulated alternative storm scenarios and a model of flood risk that is more strongly based on ecological and geological knowledge could help derive more realistic conclusions over the impact of landscape features on flood vulnerability. This would also improve the methods for measuring the externality associated with intensive land development and removal of wetlands, and the link between flood risks and property values.

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APPENDICES

A DATA SOURCES

In this appendix I include a brief overview of differences in local demographic and socioeconomic conditions among the three counties that supplements the discussion presented in chapter 3. Table A.1 specifies name and website for the sources consulted. Tables A.2–A.4 present county land use and zoning codes. Figure A.1 shows activity in the property markets in all three counties from 1950 to 2016.

A.1 OVERVIEW OF COUNTY DIFFERENCES

Charleston county is the largest county in SC by land and water area. The county has a total area of 1,358 square miles, 33% of which are covered in water, leaving approximately 916 square miles of land. It is also the third most populous county in the state with an estimated population of 389,262 people, or 8% of the state's population. In 2015, the median household income in Charleston is $57,079, just below the US median household income ($57,230 in 2015) but above the median household income in South Carolina ($47,238), and 7.07% higher than the previous year.

Charleston is also densely populated, with about 89% of the county's population being classified as urban, which is well above the state's share of urban residents (71% in the 2010 Census). In the 2014 ACS, population density was 416 people per square mile, which is over 4.5 times the national average of 88.8 people per square mile. Between 2000 and 2015, the population in Charleston county grew by 25%, or at an annual rate of 8.8%, and the housing stock grew by almost 34,600 units, or 24.5%. Finally, Charleston county is the fastest growing county in the state and the county's seat, the City of Charleston, is one of the fastest growing metropolitan areas in the nation.

Berkeley county is adjacent to Charleston county (see figure 1.1) and has an area of 1,229 square miles, most of which are terrestrial (1,099 square miles). Seventy–one percent of the county's population is classified as urban, and with a population of 202,786, population density

in the county is 180.4 people per square mile, making Berkeley county less than half as densely populated as Charleston county.

In 2015, the median household income of the 69,030 Berkeley households was $52,506, which is less than the median annual income in Charleston but represents a 1.3% increase from the previous year. Berkeley county also remains behind Charleston county in terms of absolute population and construction levels. However, in relative terms, Berkeley county has experienced faster population and development growth than Charleston county. Between 2000 and 2015, the population in Berkeley grew by 41.7% (i.e., 11.4% annually), and the housing stock grew by almost 40% (or 22,000 units).

Georgetown county, the northern–most county in the study area, has a total area of 1,035 square miles, of which 814 are terrestrial. Georgetown county is similar in area and physical characteristics to Charleston and Berkeley, but is very different in terms of socioeconomic conditions and economic history. Georgetown's population growth of approximately 1% per year is much slower than that of Charleston and Berkley (8.8% and 11.4%, respectively). With a population of 60,572 and a population density of 74.2 people per square mile, Georgetown is much more rural than both Berkeley and Charleston, and only 58.8% of the county was classified as urban in the 2010 Census.

The median household income in Georgetown in 2015 grew faster than in Berkeley, with a growth of 3.02%. Nevertheless, at $42,835, it remained well below the median income in the other two counties. Between 2000 and 2015, population grew much slower in Georgetown than in Charleston and Berkeley counties, while growth in the housing stock was half the growth in Berkeley but similar to that in Charleston (however, Charleston county is much more densely populated and therefore has smaller margins to expand in this regard). In this time period, the population in Georgetown grew by 9.4% (i.e., half as fast as in Charleston and even slower compared to Berkeley) and the housing stock grew by almost 20% (or 5,650 units).

Figure A.1 shows market trends and differences in sales volumes across counties. Panel

(a) shows the number of market transactions per year in Charleston county, panel (b) shows historical sales in Berkeley county, and panel (c) presents the number of market transactions in Georgetown county. In general, market tendencies shown by the number of transactions of residential or agricultural parcels are mirrored across counties. However, much of the difference between counties is found in the volume of sales and recorded prices (prices are not shown in the figure). Overall, Charleston and Berkeley have more active markets than Georgetown.

As shown in figure A.1, there was limited activity in property markets in all three counties until late 1970's, when they started to rapidly pick up.[1] The early 2000's saw the end of that period of rising market activity. After a short slump, there was a second boom period where market activity increased more rapidly than before and in which the number of transactions overpassed the 2000 level, reaching a maximum number of transaction in 2005. There was a sharp decline around the time of the financial crisis with the minimum number of sales being recorded in 2008 for Charleston, 2012 for Berkeley, and 2009 in Georgetown. Sales began to recover in 2012, and in 2015, the number of transactions was already above 2005 levels.

[1]This could be because transactions were not recorded into tax assessors' databases.

Table A.1: Data sources.

Layer	Source	Website
Land cover data	National Land Cover Database	www.mrlc.gov/finddata.php
Soil data	National Resources Conservation Service	www.nrcs.usda.gov/wps/portal/nrcs
Geographic names	United States Geological Survey	gdg.sc.egov.usda.gov
National hydrography dataset	United States Geological Survey	gdg.sc.egov.usda.gov
2015 Primary and secondary roads	United States Geological Survey	gdg.sc.egov.usda.gov
National Elevation dataset	United States Geological Survey	gdg.sc.egov.usda.gov
SC public access to beaches	SC Dept. of Health and Environ. Control	www.scdhec.gov
Socioeconomic data	American Community Survey	factfinder.census.gov
Housing Price Index	Federal Reserve Bank	fred.stlouisfed.org/series
Tax assessor data Charleston	Tax assessor office	www.charlestoncounty.org
Tax assessor data Berkeley	Tax assessor office	www.berkeleycountysc.gov
Tax assessor data Georgetown	Tax assessor office	www.georgetowncountysc.org
Charleston county GIS office	GIS office	www.charlestoncounty.org
Berkeley county GIS office	GIS office	gis.berkeleycountysc.gov
Georgetown county GIS office	GIS office	www.georgetowncountysc.org
Other consulted sources		
Wood Mills in South US 2015	Forest economics and policy research	www.srs.fs.usda.gov/econ/data/mills/
SC hurricane evacuation routes	SC Emergency Management Division	www.scdhec.gov/HomeAndEnvironment/

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Table A.1 (continued).

Layer	Source	Website
Storm database	NOAA's National Weather Service	www.ncdc.noaa.gov/stormevents/ftp.jsp
Building permits database	State Of the Cities Data Systems	socds.huduser.gov/permits/
SC department of transportation		info.scdot.org/sites/GIS/
Unites States National Conservation Easement Database		www.conservationeasement.us/
South Carolina Department of Natural Resources		www.dnr.sc.gov/
Flood hazard maps	Federal Emergency Management Agency	www.floodmaps.fema.gov/NFHL/
USGS Inundation maps	United States Geological Survey	water.usgs.gov/floods/events/2015/Joaquin/
CERA group storm simulations	Coastal Emergency Risk Assessment	nc-cera.renci.org/cgi-cera/cera-nc.cgi

Table A.2: Zone codes and land uses in Charleston county, 2016.

Class Code	General Definition	obs
101 - RESID-SFR	Single family residential	103,222
905 - VAC-RES-LOT	Vacant residential lot	24,644
160 - RESID-CNU	Residential condo (near Kiawah island)	15,581
120 - RESID-TWH	Residential (town houses)	8777
500 - General Commercial	General commercial	4,476
990 - UNDEVELOPABLE	Edges and awkward shapes	3,813
800 - AGRICULTURAL	Rural residential and resource management	3,131
952 - VAC-COMM-LOT	Vacant commercial zone	2,645
130 - RESID-DUP/TRI	Residential duplex/triplex	2,444
110 - RESID-MBH	Residential mobile home	1,722
750 - SPCLTY-REC	Agricultural residential/recreational	1,710
250 - SPCLTY-COMMCONDO	Residential condominium	1617
742 - HOA-PROP	Home owner association	889
691 - RELIGIOUS	Religious	684
210 - SPCLTY-SMA	Small apartment complexes	642
650 - SPCLTY-OFC	Office building	615
900 - RES-DEV-ACRS	Residential development acres	570
460 - AUTO-PARKING	Big lots with buildings that can be residential	563
220 - SPCLTY-TAMSBERG	Townhouses appraised as apartments	518
225 - SPCLTY-CNU-TMSBRG	Condos appraised as apartments	413
530 - SPCLTY-RTL	Retail	409
630 - SPCLTY-WHS	Warehouse	396
580 - SPCLTY-RST	Restaurant	355
200 - SPCLTY-APT	Large apartment complexes	323
671 - GOVT-BLDG	Government building	197
700 - SPCLTY-HTL	Hotel	178
140 - MH-PARKS	Mobile home park	171
195 - COMM-APP-RES	Residential use on commercially zoned land	160
681 - SCHOOLS	Schools	149
910 - COM-DEV-ACRS	Commercial development acres	142
170 - RESID-ROW	Residential rowhouse	97
481 - PUBLIC-UTIL	Public utility	91
304 - MFG/INDUST	Manufacturing/Industrial	64
121 - GROUP-LIV	Residential group living quarters	58
624 - CEMETERIES	Cemeteries	56
451 - ROAD-ROW	Roads	54
711 - MUSEUM-CULT	Public building	46
999 - Not Currently Classified	Not classified	40
300 - BUILDNG-ONLY	Rented buildings	38
471 - TELEPH-COMM	Company	16
411 - RAILRD/TRAIN	Train	9
150 - HOTELS	Hotel	3
10M-Mobile Home taxed as Real	Mobile home	1
Total		181,725

Table A.3: Zone codes and land uses in Berkeley county, 2016.

Zone	Type	Definition	obs
Berkeley County - Flex1	QR	Agricultural district	1,127
Berkeley County - R2	QR	Manufactured residential district	558
Moncks Corner - PD-R	QR	Residential Zone Districts	496
Summerville - R-4	QR	Multifamily residential district small-scale	388
Moncks Corner - R-1	QR	Single family residential district	313
Berkeley County - R2-R(F)	QR	Mobile home rural residential district	161
Moncks Corner - R-2	QR	Manufactured residential district	156
Moncks Corner - R-3	QR	Mobile home park	155
Berkeley County - R4	QR	Multifamily residential district small-scale	74
Berkeley County - R5	QR	Multifamily residential district (large-scale)	65
Berkeley County - R1-R	QR	Rural single-family residential district	60
Berkeley County - GC	QR	General Commercial district	37
Berkeley County - R1-MM	QR	Multisection manufactured residential district	23
St Stephen - TNR	QR	Temporary Neighborhood Residential	23
Moncks Corner - C-1	QR	Office Institutional District	15
Berkeley County - RNC	QR	Rural and neighborhood commercial district	12
Moncks Corner - TD	QR	Transitional District	11
Moncks Corner - C-2	QR	General Commercial District	10
Berkeley County - R15	QR	Preservation residential district	4
OUT	QR		4
Bonneau - AGRICULTURE	QR	Agricultural district	3
Berkeley County - R3	QR	Mobile home park	1
Bonneau - MOBILE HOME	QR	Mobile home park	1
Bonneau - SINGLE FAMILY	QR	Single family residential	1
St Stephen - HC	QR	Highway Commercial/Contiguous	1
Berkeley County - Flex1	AC	Agricultural district	28
Berkeley County - PD-MU	AC	Planned development /Mixed use	12
Summerville - I-1	AC	limited industrial	10
Berkeley County - HI	AC	Heavy industrial	1
Berkeley County - PD-OP/IP	AC	Office park/ Industrial park	1
Goose Creek - GC	AC	General Commercial district	1
Summerville - B-3	AC	General Business	1
Summerville - R-4	AC	Multifamily residential small-scale	1
Berkeley County - Flex1	AQ	Agricultural district	494
Berkeley County - R2	AQ	Manufactured residential	39
Berkeley County - HI	AQ	Heavy industrial	21
Berkeley County - R1	AQ	Single family residential	18
Moncks Corner - R-3	AQ	Mobile home park	13
Berkeley County - R15	AQ	Preservation residential	9
Berkeley County - GC	AQ	General Commercial district	8
Moncks Corner - PD-R	AQ	Residential Zone Districts	8
Berkeley County - R1-R	AQ	Rural single-family residential	5
Moncks Corner - C-2	AQ	General Commercial District	5
Goose Creek - PD	AQ	Planned District	4

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Table A.3 (continued).

Moncks Corner - R-2	AQ	Manufactured residential	4
St Stephen - TNR	AQ	Temporary neighborhood residential	4
Berkeley County - PD-MU	AQ	Planned development /Mixed use	3
Berkeley County - PD-OP/IP	AQ	Office park/ Industrial park	2
Berkeley County - R1-MM	AQ	Multi-section manufactured residential	2
Goose Creek - GC	AQ	General Commercial	2
Goose Creek - R-3	AQ	Mobile home park	2
Moncks Corner - C-1	AQ	Office institutional	2
Moncks Corner - PD-C	AQ	Planned district commercial	2
Berkeley County - R2-R(F)	AQ	Mobile home rural residential	1
Berkeley County - RNC	AQ	Rural and neighborhood commercial	1
Berkeley County - Flex1	OT	Agricultural district	1,870
OUT	OT		10
Bonneau - AGRICULTURE	OT	Agricultural	1
Berkeley County - R1	OT	Single family residential	1,052
Berkeley County - R2	OT	Manufactured residential	823
Berkeley County - PD-MU	OT	Planned development /Mixed use	600
Moncks Corner - R-3	OT	Mobile home park	355
Berkeley County - GC	OT	General commercial	296
Summerville - R-4	OT	Multifamily residential small-scale	210
Moncks Corner - R-1	OT	Single family residential	188
Berkeley County - R2-R(F)	OT	Mobile home rural residential	149
Moncks Corner - C-2	OT	General commercial	143
Moncks Corner - PD-R	OT	Residential	143
Moncks Corner - R-2	OT	Manufactured residential	116
Berkeley County - R5	OT	Multifamily residential (large-scale)	105
Berkeley County - RNC	OT	Rural and neighborhood commercial	53
St Stephen - TNR	OT	Temporary neighborhood residential	53
Berkeley County - R4	OT	Multifamily residential small-scale	50
Berkeley County - HI	OT	Heavy industrial	45
Summerville - B-3	OT	General business	45
Moncks Corner - C-1	OT	Office Institutional District	41
Berkeley County - R1-MM	OT	Multi-section manufactured residential	25
Berkeley County - R1-R	OT	Rural single-family residential	23
Berkeley County - PD-OP/IP	OT	Office park/ Industrial park	20
Berkeley County - LI	OT	Light industrial	19
Moncks Corner - TD	OT	Transitional	19
Berkeley County - R15	OT	Preservation residential	10
Summerville - I-1	OT	limited industrial	8
Summerville - PUD	OT	Planned unit development	8
Goose Creek - PD	OT	Planned	7
Berkeley County - OI	OT	Office institutional	6
Berkeley County - OIGC	OT	Office institutional /General commercial	6
Berkeley County - R3	OT	Mobile home park	6
Moncks Corner - M-1	OT	Light Industrial District	6
St Stephen - HC	OT	Light Industrial Office	6
Bonneau - MOBILE HOME	OT	Mobile home park	5

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Table A.3 (continued).

Goose Creek - R-3	OT	Mobile home park	4
Goose Creek - GC	OT	General Commercial district	3
Moncks Corner - MH-1	OT	Mobile home park	3
Moncks Corner - PD-C	OT	Planned District Commercial	3
Bonneau - SINGLE FAMILY	OT	Single family residential	2
St Stephen - LIO	OT	Light Industrial Office	2
St Stephen - M	OT	Light industrial	2
Summerville - R-6	OT	Multifamily residential	2
Bonneau - COMMERCIAL	OT	General commercial	1
St Stephen - TC	OT	Temporary commercial	1

Table A.4: Zone codes and land uses in Georgetown county, 2016.

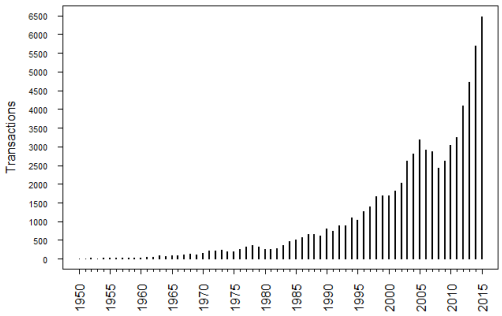
Primary Land Use Code	Definition	obs
Q100	Improved residential lot	17,272
Q000	Vacant residential lot	7,240
Q650	Mobile home	6,528
Q200	Rural (less than 5 AC)	4,673
N450	Condominium	4,582
Q302	More than 5 AC with AG use	2,257
N65	Mobile home on property	2,046
N500	Improved resort lot	1,745
N300	Rural (more than 5 AC)	1,125
N455	Townhouses	774
N003	Vacant commercial	571
N451	Common area	488
E890	Church/Religious, etc	481
N700	Multiple lot discount value	475
N400	Vacant resort lot	316
N280	Office building	288
Q165	Mobile home	260
Q202	Rural (less than 5 AC with AG use)	245
E940	State	245
N456	Subdivision common area	240
Q657	MH on as storage	240
E930	County	239
N231	Retail Shop	233
N380	Marinas	214
E920	Veteran	207
E970	Georgetown water & sewer	200
E960 /Misc	187	
E452	HPR	173
N001	No infrastruature	168
N101	Improvement on lot	129
N050	Building only	120
Q009	Wetlands/ unbuildable	116
E950	City	114
N800	Duplex	110
N240	Warehouse	108
T600	Tax commission property	104
N150	Restaurant	72
N381	Boat storage	70
Q659	MH on as storage	68
N180	Convince store	67
N490	Garage/Storage	63
N370	Mobile home park	61
N651	Mobile home	55
E941	SC Public service	52

Continued on next page

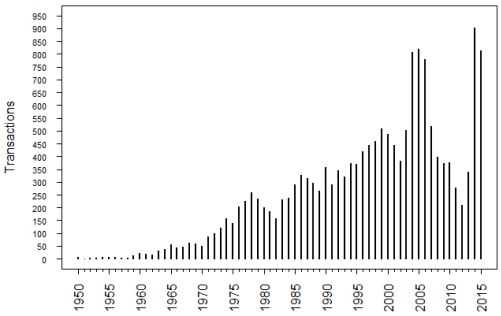
Table A.4 (continued).

E910	Cemetery	44
N480	Storage warehouse	42
N701	Homeowners association	41
E980	Georgetown Hospital	40
N550	Medical Building	36
N004	Street, road or right of way	33
N453	Villa's	33
N383	Boat slip	32
N260	Garages & Auto center	28
E931	Georgetown board of education	28
N330	Banks	27
N440	Golf course	27
N460	Shopping center	27
E961	Federal government	26
N410	Apartments	25
N130	Club house	16
Q10	Unbuildable	15
N360	Barber/Beauty Shop	15
N250	Mini warehouse	14
N510	Auto center	14
N530	Auto dealer	14
Q653	Residential and commercial	14
N350	Service stations	13
N120	Motel	12
N190	Department store	12
N804	Quadplex	12
N340	Lumber Yard	11
N220	Discount store	10
N230	Shopping center	10
Q384	Boat at residence	10
N160	Fast food restaurant	7
N430	Day care center	7
E658	MH used with church	7
N170	Laundromat	6
N390	Nursery/Greenhouses	6
N570	Veterinary building	6
N140	Homes for elderly	5
N656	Commercial Property	5
Q652	Mobile Home on as R/E for Homestead	4
E990	PHONE, CABLE, POWER, ETC	4
N803	Triplex	3
N580	Fraternal building	2
N110	Hotel	1
N382	Boat ramp	1
Q385	Motor home/Ag 4%	1
N560	Convalescent hospital	1
Total		55,770

(a) Historical sales – Charleston.



(b) Historical sales – Berkeley.



(c) Historical sales – Georgetown.

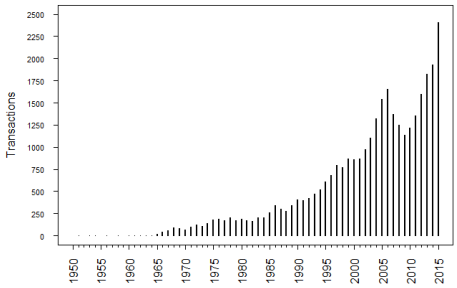


Figure A.1: Historical sales in study area (1950–2015).

B DATA ON PROPERTY DAMAGE FROM FLOODS

One data component needed for this research is data on damages that result once a flood occurs. In the estimation of economic losses from floods, I test three types of cost data. I use data from (1) the HAZUS®–MH Flood model, (2) estimates from a recent economic valuation project of shoreline protection in New Jersey by Loerzel et al. (2017), and (3) National Flood Insurance Program data on insurance claims and payments.

The HAZUS®–MH is the most recent recent flood model being used by FEMA. It is an estimation software that provides a flood loss estimation analysis. The HAZUS software makes available data bases that contain important information for estimating losses from floods. These data include an inventory of building stock, infrastructure, and population exposed to flood hazard at the census block level.

The data on General Building Stock (GBS) made available by HAZUS includes residential, commercial industrial, agricultural, religious, government, and education buildings. However, for this study, only information from single family residential is relevant. The key GBS databases include a full replacement value for single family residential buildings.[1] The Flood Model uses a general construction classification strategy and considers building characteristics and regional income distribution to develop a valuation method to estimate these replacement values.[2]

The HAZUS Flood Model uses the developed replacement values to estimate the dollar exposure of the building stock by census block and by occupancy type (i.e., for single family residential buildings, mobile homes, commercial buildings, etc.). Specifically, the HAZUS valuation algorithm directly includes data on floor area by construction class, number of stories, replacement costs by construction class and for a particular story class, and additional costs for finished basements of a given construction class and for various combinations of garage types.[3]

[1] To develop the GBS inventory, the HAZUS project used US Census data, reports from the Department of Energy, data from the Energy Information Administration, and Dun & Bradstreet surveys.

[2] Detailed information on data gathering and methodology can be found in the technical manual.

[3] This algorithm is summarized in equation 14-1 of the technical manual, and the valuation parameters are presented in section 14.2.1.1.4 of that document.

I use these estimates of dollar exposure for single family residential buildings in the census blocks that comprise the study area to arrive at an average regional dollar exposure measure that is directly used in the economic analysis presented in chapter 5.[4] Table B.1 presents basic inventory characteristics from the HAZUS database for the study area.

The second type of property damage data comes from a recent study of economic valuation of shoreline protection within the Jacques Cousteau national estuarine research reserve conducted by Loerzel et al. (2017), a group of NOAA researchers. In this study, researchers gathered data on residential properties to calculate the average property damage during various simulated storm events.[5] In this study, researchers found that residential property owners suffered an average loss of $22,390 during a simulated hurricane Sandy event, $976 during a simulated 50–year storm, and $837 during a simulated 25–year storm event.[6] Tables B.2 and B.3 provide basic characteristics of the property data used in this calculation.

The last type of cost data used to estimate damages from floods is data from the National Flood Insurance Program (NFIP). This data was described in chapter 4).

[4]In selecting the census blocks, I do not consider blocks within census tract 00500 in Charleston county, and within tracts 020101, 020201, and 020202 in Berkeley county.

[5]The objective of this study was to use a damages avoided method to measure the benefits provided by an ecosystem. In a damages avoided method, the ameliorating benefits of a natural habitat are measured by using the value of property protected, or the cost of actions taken to avoid damages. This approach does not provide strict measures of economic value, which are based on people's willingness to pay for a service, but it assumes that society is willing to pay at least as much as they would avoid losing if no preventive actions were taken.

[6]These are in 2015 dollars and do not take into account the value of contents of the structure.

Table B.1: Average census block inventory characteristics (HAZUS® Flood Model).

	Charleston	Berkeley	Georgetown	All
# of census blocks	6,416	2,831	1,431	10,678
Dollar exposure*	$3,853	$3,983	$2,898	$3,741
SFR SqFt**	26,000	28,000	18,000	25,000
Dollar exposure / SqFt	0.148	0.142	0.161	0.15
Dollar exposure per property+	$266.7	$256.1	$289.8	$269.4

* These are expressed in 2014 dollars.
** The HAZUS default data on square footage for single family residences is derived from a detailed, unpublished database provided by the EIA. The database includes the number of households by region, income category, and housing floor space and is aggregated across all foundations/basement types.
+HAZUS assumes a typical size of 1,800 SqFt for single family residential buildings. For reference, the average building size by county in the tax assessor data is: 2,036 SqFt in Charleston, 1,838 in Berkeley, and 1,973 in Georgetown. Making the average property exposure $301.7, $261.5, and $337.9 in each county (using $2014).

Table B.2: Building characteristics of parcels in Loerzel et al. (2017).*

Characteristic	Number of parcels
One Story	42,039
2+ stories	60,823
Split level**	1,065
Total	103,927

*Property parcels on lands that are vulnerable to wave induced erosion and/or storm damage.
**A split level property is a style of house with the floor levels are staggered.

Table B.3: Summary statistics for parcels in Loerzel et al. (2017).

Statistic	Value of building*
Mean	$151,898
Median	$120,700
Std deviation	$127,158
Minimum	$15
Maximum	$5,687,300

*Due to inconsistent data on presence of a basement, the losses are estimated as if properties had no basement.
*Values are in 2015 dollars.

C OUTPUT FROM 10–FOLD VALIDATION

In the empirical analysis, I build a repeated cross–section database with the most recent recorded sales price for each property in the sample (i.e., last–price data), and to select the model that best fits this data, I follow a 10–fold cross validation technique and examine different measures of error (L1, L2, and MSE) to determine which regressors to include in the model and to guide the removal of noisy observations. Below, I include output figures used to arrive at the final choice of model.

Output from 10–fold cross validation procedure used for guiding the selection of the hedonic model for agricultural land value

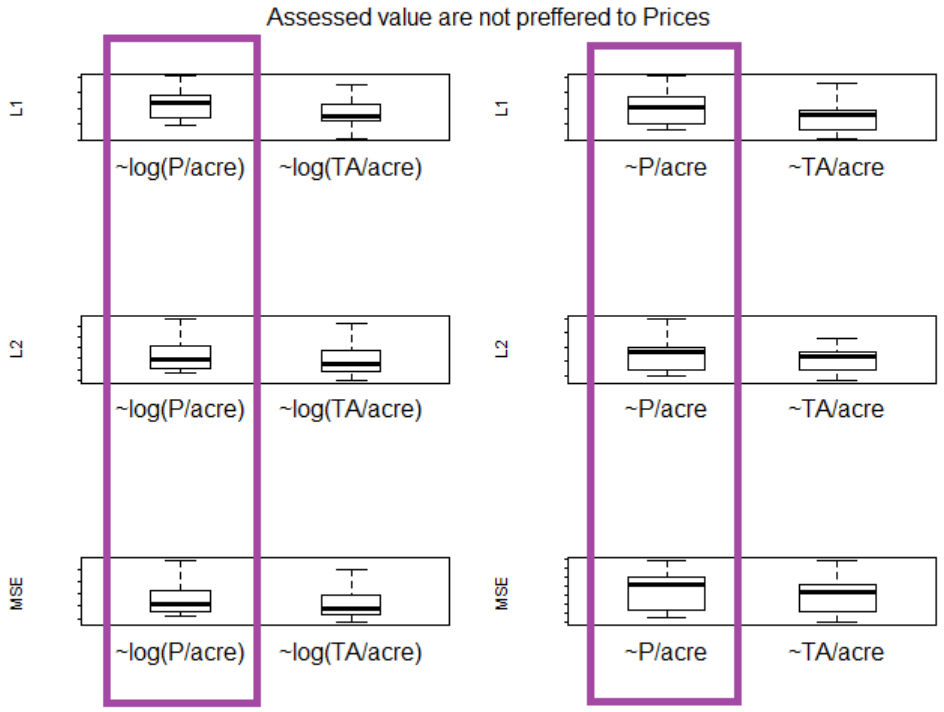


Figure C.1: Dependent variable choice (price vs. assessed values).

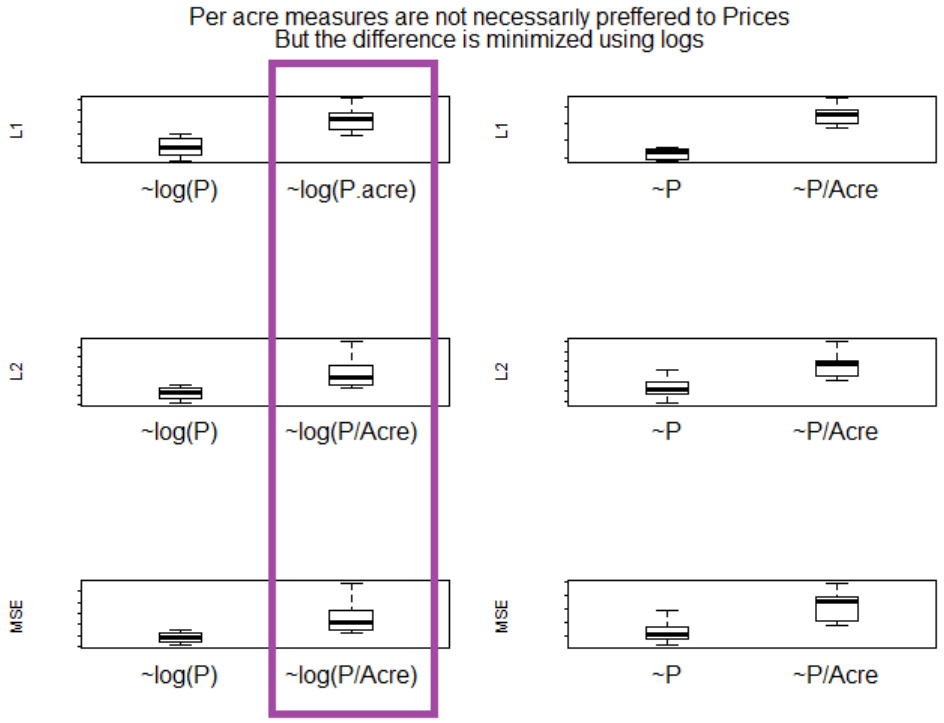


Figure C.2: Choice of dependent variable form (log vs levels).

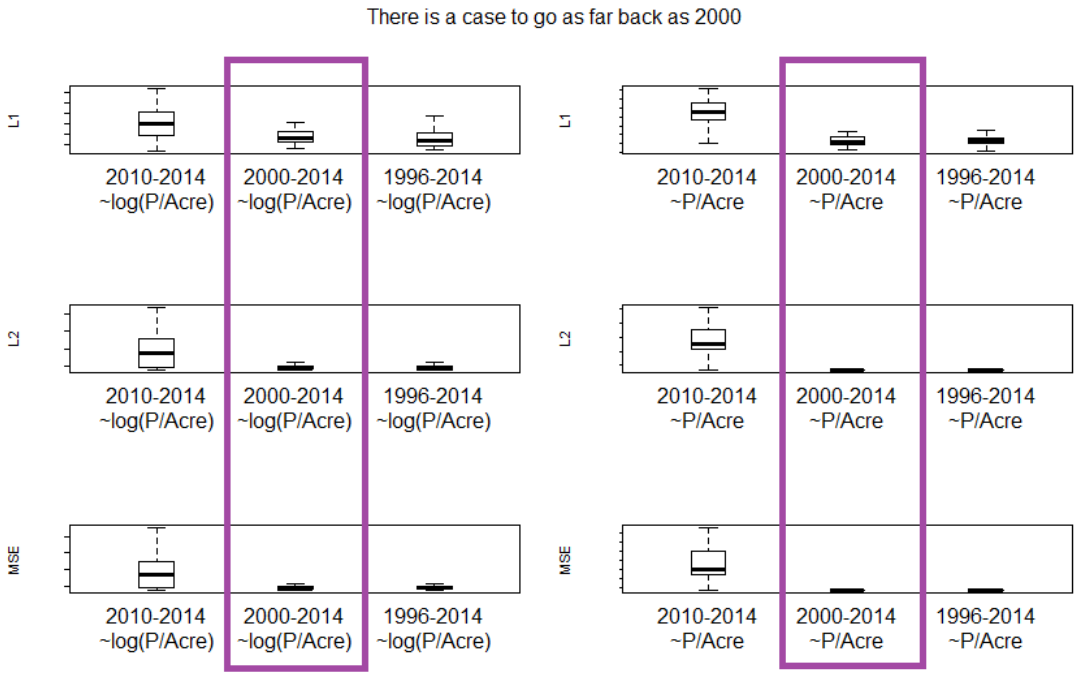


Figure C.3: Choice of historical data.

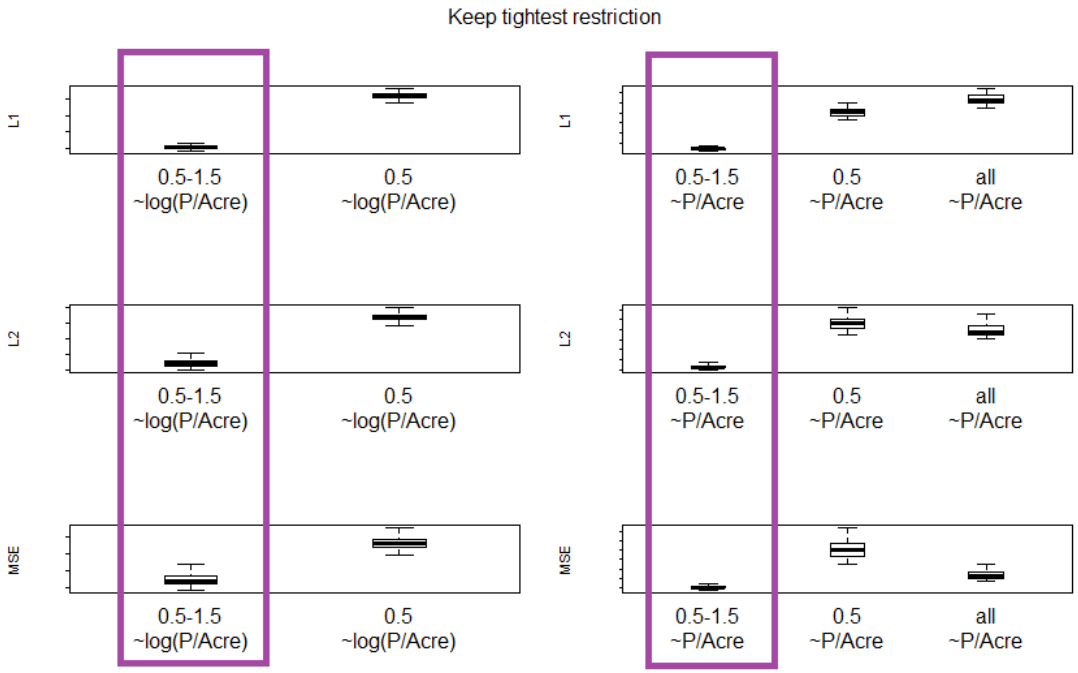


Figure C.4: Price range restriction.

Output from 10–fold cross validation procedure used for guiding the selection of the hedonic model for residential land value

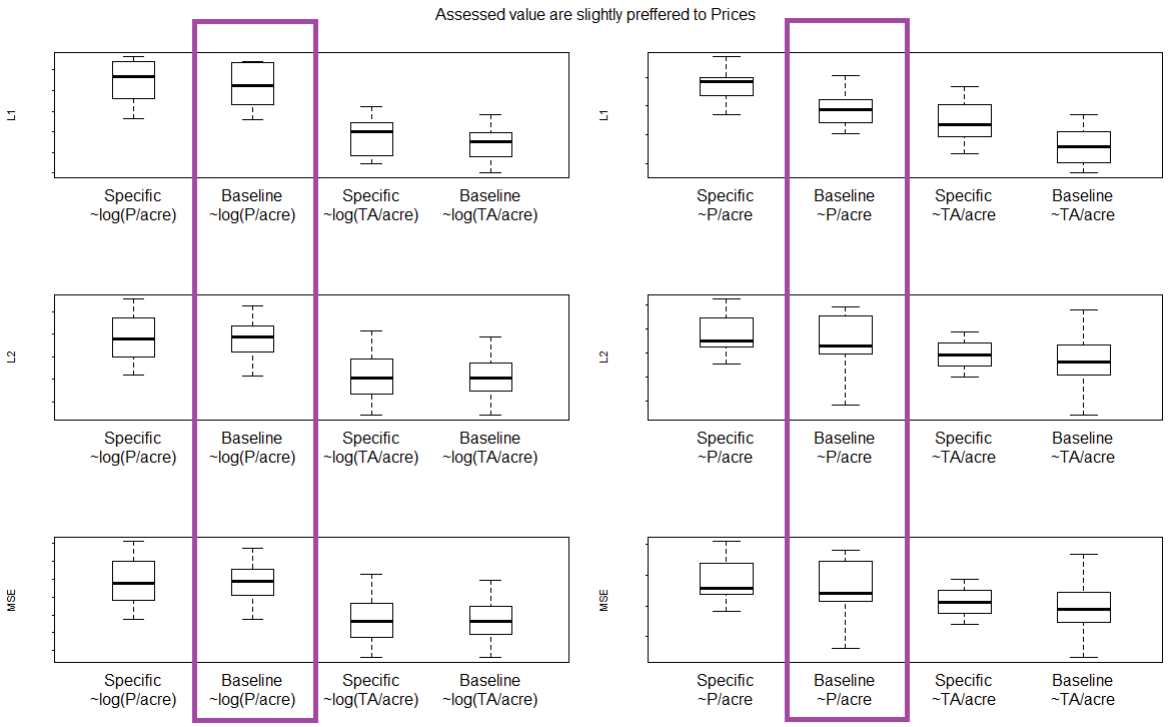


Figure C.5: Dependent variable choice (price vs. assessed values, logs vs. levels).

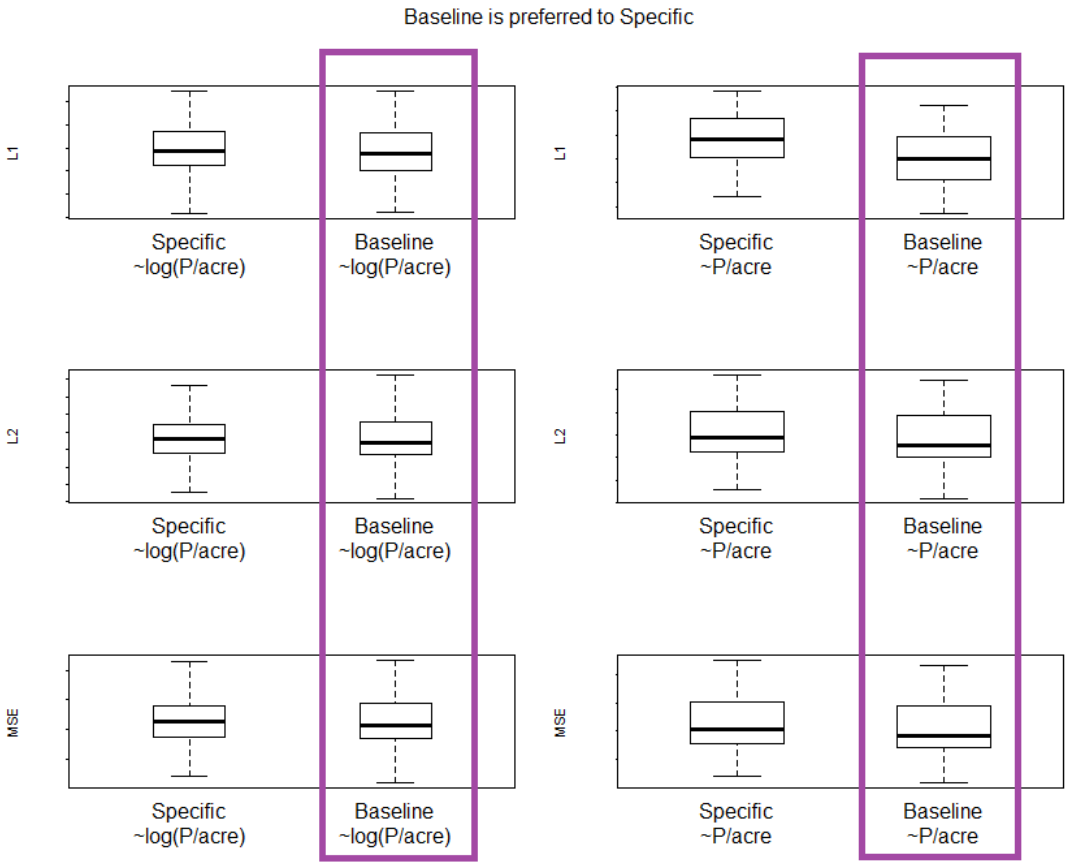


Figure C.6: Choice of county specific variables.

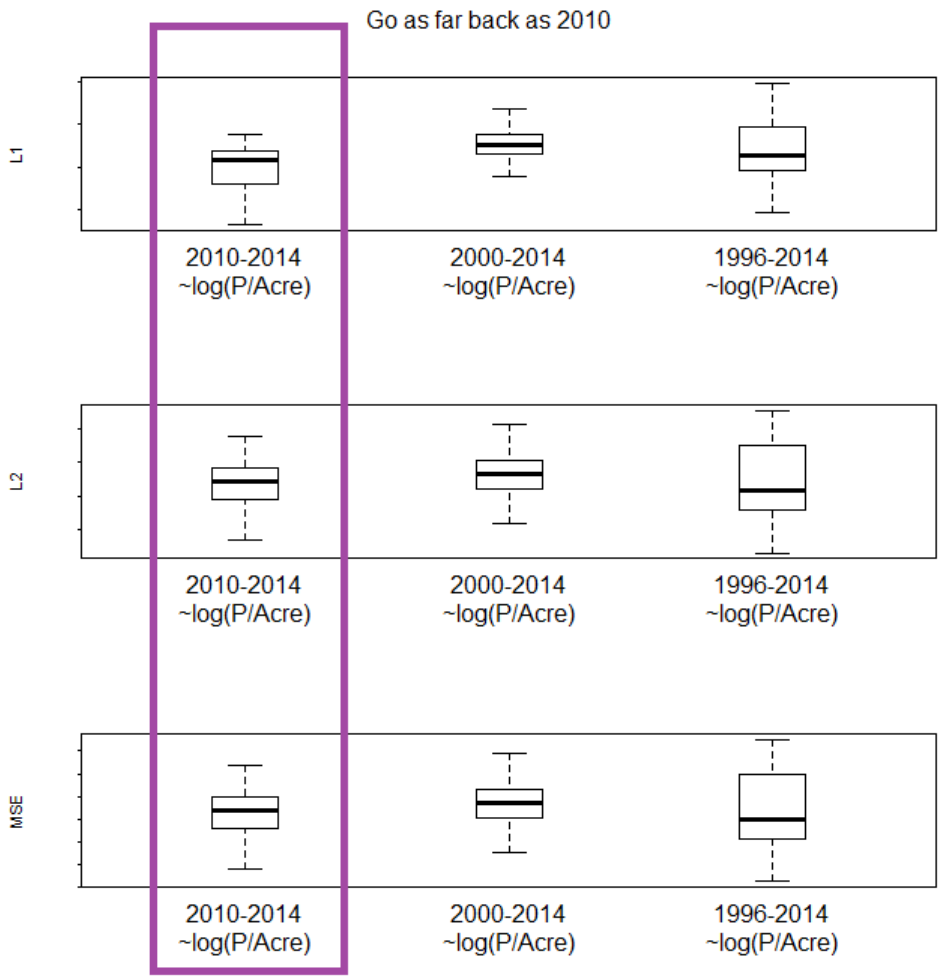


Figure C.7: Choice of historical data.

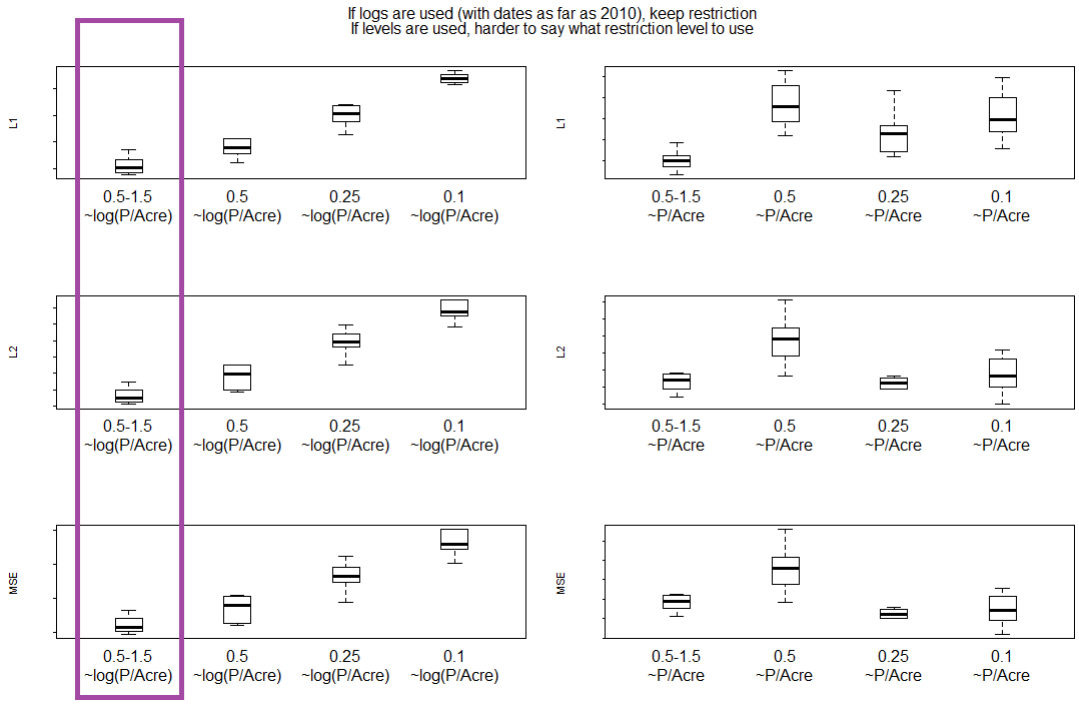


Figure C.8: Price range restriction.

D SPATIAL DEPENDENCE DIAGNOSTICS

The role of spatial processes is strong in determining how land is valued, how developers make decisions, and how natural landscapes evolve. Land use decisions and land values may be correlated across space if there are gradual changes in local or regional features, such as distance to processing facilities and soil quality. In turn, when it comes to environmental processes, the ecological value of a given parcel may be contingent on the land use status of neighboring parcels. For instance, when concerned with managing wetlands for flood protection, the ecological value of a given parcel may not justify the costs of protection if the parcel is surrounded by parcels that have already been developed.

When important covariates with spatial effects are not included in the model, or when the model is misspecified in another way, residuals will show spatial autocorrelation. For instance, consider the idea that proximity to sea walls determines the likelihood that a parcel gets flooded. If the location of sea walls is unknown, the effect of proximity to sea walls will be captured by the error term in a model of land value and the error term will exhibit spatial dependence. Spatial autocorrelation in land features that facilitate development can be a threat to the validity of any statistical inferences. Thus, spatial relationships must be accounted for in the econometric analysis.

When the hedonic models are specified as spatial processes, the price models are:

$$\begin{aligned} P_{it}(s) &= \alpha_i + X_{it}\beta + \nu_{it} \\ &= \alpha_i + \mu_{it}(s) + \eta_{it}(s) + \epsilon_{it}, \end{aligned} \tag{D.1}$$

where $X_{it}\beta$ constitute what in spatial statistics is known as the mean function $\mu_{it}(s)$, which explains large–scale spatial variation, while small–scale spatial variation is captured by the error term, ν_{it}. The latter can be decomposed as $\nu_{it}(s) = \eta_{it}(s) + \epsilon_{it}$. Where $\eta_{it}(s)$ captures spatial variation in the residuals, and ϵ_{it} is the uncorrelated error term.

If $\eta_{it}(s)$ is unobserved, then, its effect on prices is captured by $\nu_{it}(s)$, and ν_{it} exhibits spatial

dependence. Also,$\nu_{it}(s)$ would be correlated with unobservables in $\eta_{it}(s)$.

In linear models, like the hedonic models in this study, uncorrected spatial dependence in the error term does not necessarily lead to bias of the coefficients but affects the standard errors. Thus, failing to account for local spatial processes driving property prices may result in inaccurate inference.

In non–linear models, like binary choice models of land use, spatial correlation may even result in biased coefficient estimates (Bigelow, 2015).[1] However, in a two–stage process like the one conducted here, it is possible that correcting for spatial correlation in the first–stage models is enough to fully capture spatial processes in the second–stage process, therefore obviating the need to use complicated techniques that make a model more complex and the analysis more prone to error (Newburn et al., 2006).

There are well supported ways to accommodate for spatial dependence for linear models, such as adding spatial weights to the error term (what is commonly known as using a spatial autoregressive error). However, the preferred solution for dealing with residual spatial autocorrelation is to find any missing covariates that explain spatial processes and include them in the model (Hoeting et al., 2006). Thus, before adding more structure to the error term in the hedonic models of land prices and possibly introducing new randomness into the analysis, I first add spatial structure to the mean function by including multiple landscape attributes (for example

[1]There are well documented ways to address the error dependence problem in a choice model. For instance, Lewis et al. (2011) address this issue by adding components to the random error term in the RUM that allow land values to be correlated spatially (i.e., all parcels within a county share a common value for a given term) and temporally (i.e., each parcel has a common value for another term across time periods). An alternative way to address spatial dependence is to extract subsamples of the data that are less likely to be spatially correlated with each other, and then estimate the land use model on these subsamples. The justification behind this approach is that the spatial autocorrelation in the residuals is likely to be lower if the samples used for estimation are farther apart in a spatial sense. There are multiple options for selecting the samples that are to be included in the estimation. For example, Carrion-Flores and Irwin (2004) follow the so-called "work-around"method, creating a subsample of the data by removing nearest neighbors within a fixed distance. In a different study, Newburn et al. (2006) perform multinomial logit regression on random stratified bootstrapped samples taken from the full dataset to correct the error term. More recently, Bigelow (2015) constructs a block-stratified random sample and uses it to estimate the econometric land use models.

the measures of surrounding land covers) and spatial fixed effects at the census tract and block group level in the reduced form equation. Then, using standard diagnostic tools, I test whether adding spatial structure to the mean function is enough to account for the unobserved spatial autocorrelation in the process determining property values.

Specifically, I use QQ–plots, bubble plots, spatial correlograms and variograms to detect residual spatial autcorrelation in the hedonic models. Using these tools, I find that including a rich set of spatial explanatory variables in the hedonic models is enough to remove any spatial dependence in the residuals.

D.1 VISUAL INSPECTION

To study whether or the estimated hedonic models are appropriate for representing the spatial process determining land values in the sample, I first make a visual exploration of the residuals. Standard QQ–plots showed that residuals from models rich in spatial variables were in general normally distributed, suggesting the models are appropriate for the data in the sample and that it is not inadequate to proceed to make inference from these models. This conclusion was supported by results from complementary "bubble plots."[2] These plots showed that positive and negative residuals, large or small, do not seem to be clustered nor perfectly dispersed, suggesting that the independence assumption made in the standard regression model is met (i.e that residuals are randomly distributed). This was observed for models on residential and agricultural properties in all three counties.

D.2 SPATIAL CORRELOGRAMS

A more formal way of detecting residual spatial autocorrelation is a spatial correlogram. A spatial correlogram is a plot of the Moran's Index, or Moran's I, as a function of distance.

[2]Bubble plots are an intuitive informal diagnostic tool provided by the package gstat in the statistical software R. They plot the residuals against their spatial coordinates. The size of the dots is proportional to the value of the residuals, and different colors are used for positive and negative residuals.

Moran's I is computed with following formula:

$$I = \frac{n}{W} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{n} (y_i - \bar{y})^2},$$

where n equals the total number of parcels in the study area, y_i is the land value of parcel i, $\bar{y}$ is the mean land value in the sample, w_{ij} represents the spatial weights, and W is the sum of all weights in the study area. When using Moran's I, the null hypothesis is that there is no spatial correlation and it can be tested using a permutation test. [3]

The way the weights w_{ij} are defined has a strong influence on the actual value of I. In the simplest case, the weights have the values 1 when parcels i and j are neighbors or 0 when they are not neighbors. However, there are more possible definitions what makes two parcels neighbors. For instance, one option is to consider two parcels as neighbors ($w_{ij} = 1$) if they are within 0.5 miles or 0.25 miles from each other. A spatial correlogram plots values of I as a function of the distance used to define the weights, w_{ij}'s.[4]

What I find from using spatial correlograms, is that there is no strong autocorrelation in the residuals for any of the distances considered for defining the weights.[5] Furthermore, starting at a distance of 0.3 miles, land values of neighboring parcels clearly appear to be independent from each other.

[3] If there is no spatial autocorrelation, the expected value of I is $E[I] = -1/(n-1)$, which is close to 0 when n tends to infinity. When $E[I] = -1$, the process exhibits perfect dispersion, that is, similar values repel each other. Instead, when $E[I] = +1$, the process exhibits perfect clustering. A permutation test is a statistical tool similar to bootstrapping where the observed data is resampled a large number of times to generate a distribution from which to assess whether or not the tested effect is random. Unlike boostrapping the resampling in a permutation test is done without replacement.

[4] To produce a meaningful correlogram, the width of the distance bands should be greater than the minimum distance between parcels in the study area. The correlog function of the ncf package in R allows computing a spatial correlogram and tests the significance of the different I values with permutation. Results from hypothesis testing using the correlog function include plots indicating when values of I significantly larger or smaller than expected under the null hypothesis of no autocorrelation. Black dots in the plot indicate that the corresponding values of I are significantly different from $-1/(n-1)$.

[5] I test I's corresponding to weights set on distances between 0.3 and 60 miles with 0.3 mile increments. The spatial correlograms show intermitently significant although weak autocorrelation in the residuals (i.e., I's are close to zero). But because the values are so close to zero, it is difficult to conclude there is a case of autocorrelation.

D.3 SPATIAL VARIOGRAMS

Another common tool used in geostatistical data analysis used to detect residual spatial autocorrelation are variograms (or semi-variogram). Variograms are plots of the semivariance as a function of distance. The semivariance of a function expresses the degree of relationship between parcels on a surface and it equals half the variance of the differences between all possible parcels spaced at a constant distance apart. The semi-variance between two sites is defined by:

$$\gamma(x_1, x_2) = \frac{1}{2}E[(Z(x_1) - Z(x_2))^2],$$

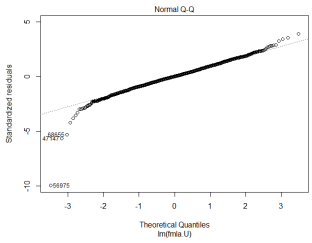
where x_1 and x_2 are the coordinates of the parcel and Z is a random function modeling the process of how land values are determined. If there is strong spatial dependence, parcels that are closer together show a smaller semivariance.

What I find from examining variograms is that the semi-variance does not seem to change with distance, suggesting that parcels are not more or less similar to parcels that are close to each other than they are to parcels that are more distant, therefore supporting the assumption of no spatial autocorrelation.[6]

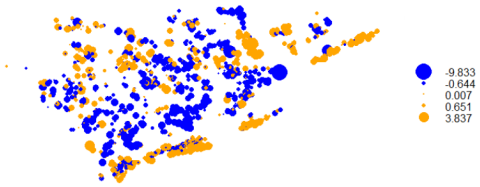
Having performed these three types of tests, I conclude that that spatial autocorrelation is not present in the residuals from the selected hedonics models and therefore I take no further steps in the structural correction of residuals in the empirical analysis.

[6]The gstat package in R also has functions for variogram analyses. Namely, I used two types of variogram tools: variogram clouds and experimental variograms. A variogram cloud plot the semi-variance as a function of distance for every possible pair of parcels. These plots can be difficult to interpret due to the massive density of possible parcel pairs. Thus, to improve the ease of analysis, I also used experimental variograms, which are like variograms that group distances into distance classes.

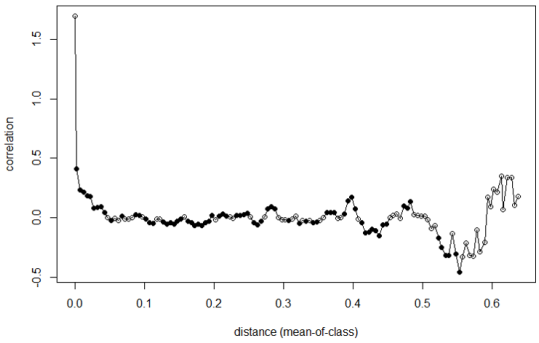
(a) Standard QQ plot showing that residuals are close to normally distributed.



(b) Bubble plot. The size of the dots is proportional to the value of the residuals, and different colors are used for positive and negative residuals.



(c) Spatial correlogram. It plots Moran's Index as a function of distance (1 in x-axis = 60 miles).



(d) Experimental variogram. It groups distances into classes and displays the average semi-variance among each class (1 in x-axis = 60 miles).

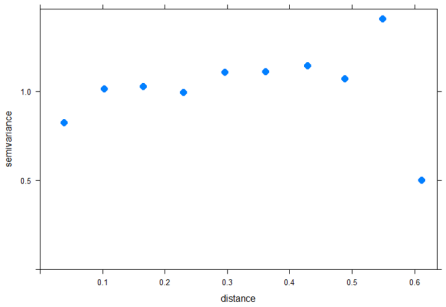
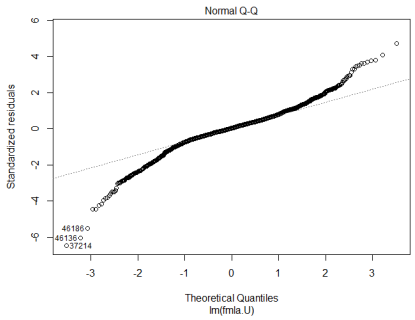
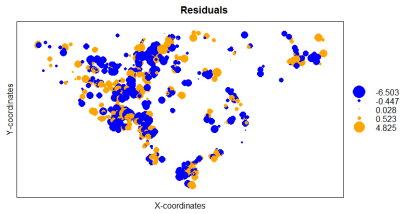


Figure D.1: Diagnostic tools used to visually assess existence of spatial dependence in the error term of the hedonic model of undeveloped parcels in Charleston county.

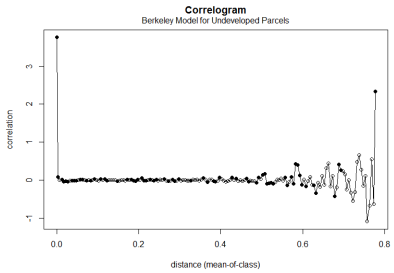
(a) Standard QQ plot showing that residuals are close to normally distributed.



(b) Bubble plot. The size of the dots is proportional to the value of the residuals, and different colors are used for positive and negative residuals.



(c) Spatial correlogram. It plots Moran's Index as a function of distance (1 in x-axis = 60 miles).



(d) Experimental variogram. It groups distances into classes and displays the average semi-variance among each class (1 in x-axis = 60 miles).

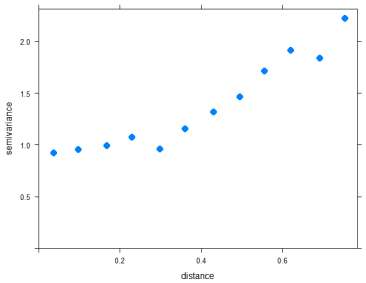
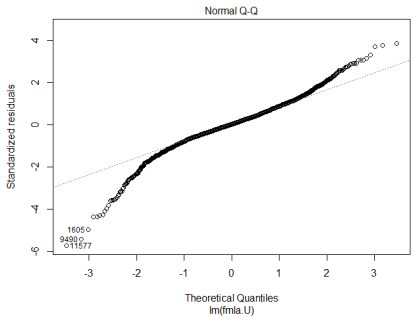
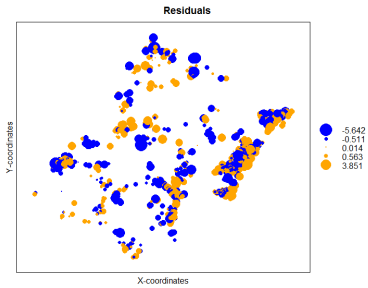


Figure D.2: Diagnostic tools used to visually assess existence of spatial dependence in the error term of the hedonic model of agricultural parcels in Berkeley county.

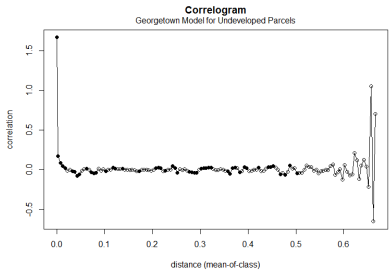
(a) Standard QQ plot showing that residuals are close to normally distributed.



(b) Bubble plot. The size of the dots is proportional to the value of the residuals, and different colors are used for positive and negative residuals.



(c) Spatial correlogram. It plots Moran's Index as a function of distance (1 in x-axis = 60 miles).



(d) Experimental variogram.It groups distances into classes and displays the average semi-variance among each class (1 in x-axis = 60 miles).

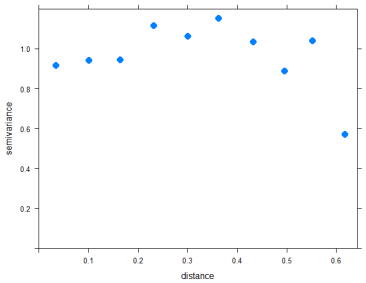
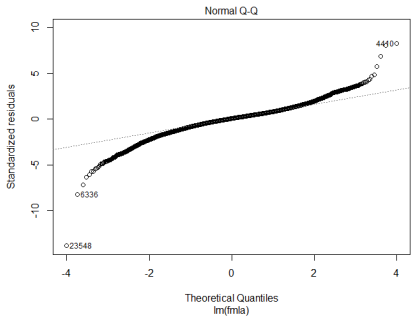
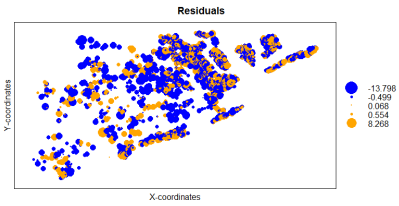


Figure D.3: Diagnostic tools used to visually assess existence of spatial dependence in the error term of the hedonic model of agricultural parcels in Georgetown county.

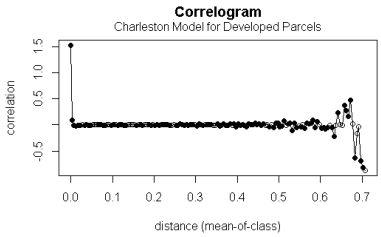
(a) Standard QQ plot showing that residuals are close to normally distributed.



(b) Bubble plot. The size of the dots is proportional to the value of the residuals, and different colors are used for positive and negative residuals.



(c) Spatial correlogram. It plots Moran's Index as a function of distance (1 in x-axis = 60 miles).



(d) Experimental variogram.It groups distances into classes and displays the average semi-variance among each class (1 in x-axis = 60 miles).

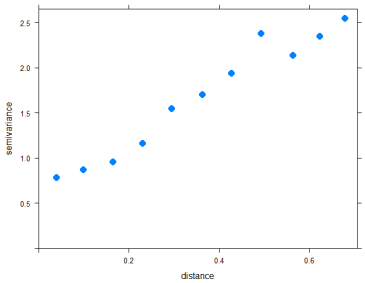
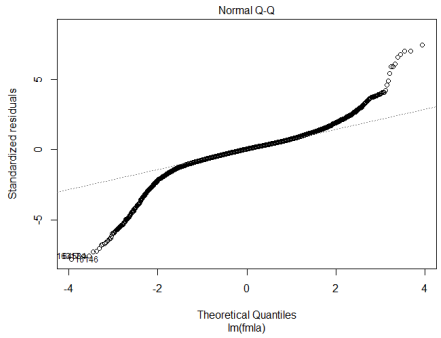
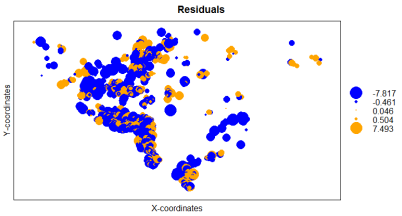


Figure D.4: Diagnostic tools used to visually assess existence of spatial dependence in the error term of the hedonic model of residential parcels in Charleston county.

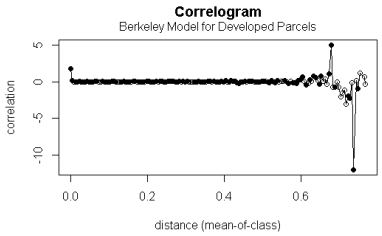
(a) Standard QQ plot showing that residuals are close to normally distributed.



(b) Bubble plot. The size of the dots is proportional to the value of the residuals, and different colors are used for positive and negative residuals.



(c) Spatial correlogram. It plots Moran's Index as a function of distance (1 in x-axis = 60 miles).



(d) Experimental variogram.It groups distances into classes and displays the average semi-variance among each class (1 in x-axis = 60 miles).

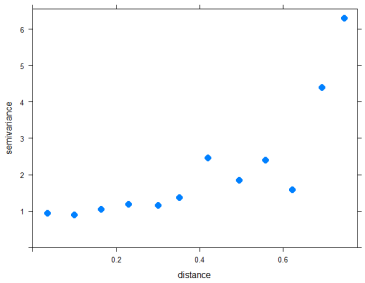
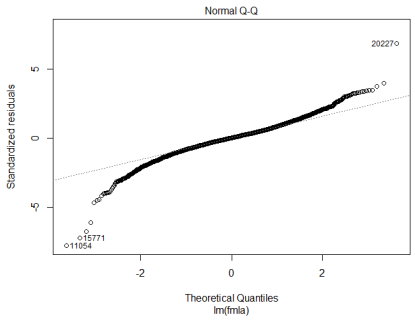
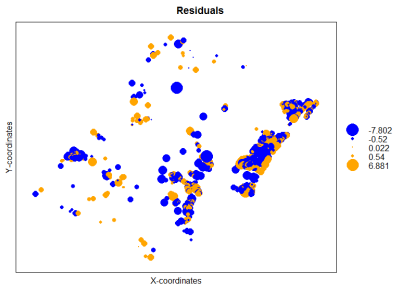


Figure D.5: Diagnostic tools used to visually assess existence of spatial dependence in the error term of the hedonic model of residential parcels in Berkeley county.

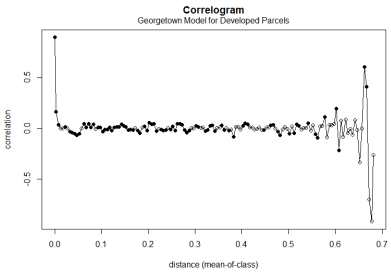
(a) Standard QQ plot showing that residuals are close to normally distributed.



(b) Bubble plot. The size of the dots is proportional to the value of the residuals, and different colors are used for positive and negative residuals.



(c) Spatial correlogram. It plots Moran's Index as a function of distance (1 in x-axis = 60 miles).



(d) Experimental variogram.It groups distances into classes and displays the average semi-variance among each class (1 in x-axis = 60 miles).

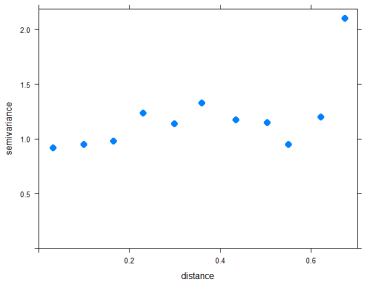


Figure D.6: Diagnostic tools used to visually assess existence of spatial dependence in the error term of the hedonic model of residential parcels in Georgetown county.

E SAMPLE SELECTION BIAS IN HEDONIC EQUATIONS

Developed land is not assigned across the landscape at random. Moreover, it is likely that unobserved characteristics inherent to a parcel, are correlated with both its current–use and its value. For example, an owner of agricultural land that perceives risk of flood hazard to be high, may purchase protective insurance or incur further investments on the property that make it more valuable in the eyes of developers. Thus, this particular parcel, is more likely to be developed and sell for higher prices than other parcels.

The hedonic price model for developed land is estimated on data from parcels that are already developed. Thus, if there are unobserved factors that influence both the decision to develop a parcel and its subsequent market value, the estimated coefficients will be biased. For instance, if residential parcels tend to fetch higher prices than agricultural prices, and if parcels that are closer to the beach are more likely to develop,then, the effect of proximity to the beach on sales prices will seem larger than its true effect. This is problematic because the purpose of estimating the residential hedonic models is to infer unknown sales values for lands that are currently in agriculture, but if the sample of developed parcels is not representative of the general parcel population, the estimated coefficients are biased and lead to invalid inference.

The problem of sample selection bias calls for corrective measures. Other works in the literature have opted to proceed to develop land use change models without taking corrective measures (Irwin and Wrenn, 2014; Newburn et al., 2004-2006; Bockstael, 1996). In fact, few works empirically address the issue of sample selection bias, even though the literature clearly recognizes the problem. A theoretical justification for abstracting away from the sample selection problem, is the idea that a hedonic model of residential land value may be unbiased if developers' ignorance of omitted variables that drive the selection problem, matches the ignorance of the researcher (Bockstael, 1996). In this Appendix, I include findings from the exploratory analysis of instruments for a selection bias correction and to illustrate the trivial effect of including or excluding weak instruments from estimation, I present results from he-

donic regressions that correct for sample selection bias using the proposed weak instruments and the Heckman methodology. In general, they are note different in direction, magnitude, or significance from results kept for the main estimation in this study.

To estimate valid (i.e., unbiased) coefficients in a hedonic model for developed parcels, the corrective procedure proposed by Heckman (1979) can be used. There are two steps in this procedure. First, a selection equation describing the probability that a parcel is developed is estimated using a standard probit model using maximum likelihood estimation (MLE).[1] Second, using the results from the probit estimation, an Inverse Mill's Ratio variable is formed and included as one of the explanatory variables in the hedonic price model for developed parcels.[2]

The selection model can be formalized as:

$$s_i y_i = X_i \beta + \upsilon, \tag{E.1}$$

where s_i is a selection indicator, y_i is a latent variable reflecting the sales price of residential properties, $X_i\beta$ is the deterministic component that defines sales prices, and υ is a random component. The latent variable y is not observed for every parcel, instead, it is only observed for parcels that are already developed. Therefore, the selection indicator s_i is equal to 1 for developed parcels, and is equal to 0 for undeveloped parcels.

This type of sample selection is called incidental truncation. It receives that name because the rule determining whether or not sales prices of residential properties are observed, does not directly depend on the actual sales price. The usual approach to incidental truncation is to add an explicit selection equation to the model shown above. Explicitly, the selection model

[1]The probit representation is valid under the assumption that disturbances in the data generating process behind the value of developing a parcel are normally distributed.

[2]The Inverse Mill's Ratio variable (IMR) is the ratio is the ratio of the probability density function to the cumulative distribution function of a distribution. It is probability that a landowner decides to develop his land over the cumulative probability of the landowner's decision. The IMR's coefficient is interpreted as the fraction of the covariance between the decision to develop a parcel and the net benefit from developing that parcel relative to the variation in the decision to develop it.

becomes:

$$y = X\beta + \upsilon, \mathrm{E}(\upsilon|X) = 0 \tag{E.2}$$

$$s = \mathbf{1}[Z\gamma + \nu], \tag{E.3}$$

where $s = 1$ if y is observed, and zero otherwise. In turn, Z is a matrix of covariates containing parcel characteristics that are exogenous to residential property values and of which X, in equation (E.2), is a strict subset.

Under Heckman's procedure, to properly identify the effects of the IMR variable, Z must include an instrumental variable that is sufficiently correlated with the selection decision, shown in equation (E.3), but not with the sales price of residential properties, shown in equation (E.2). This instrument, Z_j, is referred to as the exclusion restriction variable (i.e., the element in Z that is not in X).[3]

To implement Heckman's sample selection corrective method to my empirical application, I use as the exclusion restriction variables multiple factors that affect agricultural land value but not residential land value. This rationale for instrument choice (i.e., using variables that affect agricultural value of a parcel and therefore its probability of development but are not related to the residential value of land) is found in the literature.

Explicitly, as instruments, I use measures soil quality and proximity to agricultural processing facilities. Intuitively, soils that are better for agriculture would discourage conversion of agricultural land but do not impact the developed value of a parcel (to my knowledge, there are no studies suggesting that different soil qualities, at least as defined by the USDA nomenclature, facilitate or hinder construction). Similarly, proximity to processing facilities makes agricultural production more attractive by reducing transportation costs.

Table E.1 shows the findings from the exploratory analysis to determine the exclusion

[3]This is required to avoid problems with large standard errors when estimating (E.2). Because the IMR is a linear function of X, having every Z_j in X would result in multicollinearity. A thorough exposition of this method can be found in Wooldridge's Introductory Econometrics.

variables. Despite the theoretical strength behind the logic used to select these instruments, a close examination of table E.1 offers weak support for the choice of instruments.

The condition for a valid instrument is that is is significantly related to the selection equation but has no direct association with sales prices. For all counties, I find that none of the instruments is empirically sound as most of the time (that is, with the more parsimonious model and with a model that is highly specified), they are significantly related to probability of development and to sales prices.

Using weak instruments is likely to produce inconsistent estimates (Bound, Jaeger and Baker, 1995). In addition, even with large data sets, using weak instruments can lead to estimates that are biased in the same direction as OLS estimates, with the magnitude of the bias approaching that of OLS. This is evident in the minimal difference between the results from hedonic equations that use a corrective step and the hedonic equations used to estimate the results shown in the main text of this dissertation.

Table E.2 shows the results from the probit estimations to correct for sample selection bias in the hedonic models for residential properties. The probit results are used to construct an IMR that is then used as an explanatory variable in the hedonic equation.

The results from the sample selection models generally conform to prior expectations. Most important for the sample selection results, is the fact that the coefficients of most exclusion variables are significant and have the appropriate negative sign for the models of Charleston and Berkeley counties. For Georgetown, some have positive signs and some are not significant.

The factors that are more important in determining probability of development across all three counties are parcel size, elevation, proximity to major roads and beaches with public access, as well as spatial measures of landscape composition. Overall, relative to undeveloped parcels, developed lands in all three counties are smaller and are located in higher elevations. Also, parcels more heavily surrounded by by developed covers are more likely to develop.

In Charleston county, developed parcels tend to be more proximal to major roads, and

parcels that are closer from public beach access point are less likely to develop. In Berkeley and Georgetown counties, being further from Charleston city center is positively associated with the probability of development, as is being further away from major roads. This discrepancy may indicate that open space and distance from noise and pollution corridors (e.g., major roads) are more valuable features for landowners in Berkeley and Georgetown counties than in Charleston. Nevertheless, this effect is small.

In Berkley and Georgetown, parcels that are closer to the beach are more likely to be developed. Also, the further a parcel is from a hurricane evacuation route, the more likely it is to be developed. This result may provide early indication that landowners and developers take into consideration risks of flooding when choosing to develop a parcel, a finding supported by recent empirical evidence (McCoy and Zhao, 2018). In their research, McCoy and Zhao use data on capital investment projects in homes located in flood risk areas. They find evidence that recent flooding may increase perceived risks and investment in buildings.

Finally, results regarding the effect of landscape composition on development offer important insight for the design of land use policies aimed at slowing down development in areas vulnerable to flood risks. First, wetland covers are generally significantly related to the probability that a parcel develops, although the effect is small. In Georgetown county the effect is negative, which could be related to conversion costs that can include legal costs of obtaining 404 permits (i.e., permits to dredge or fill resources that may include wetlands) or expenses to cover required compensatory mitigation (these legislative costs are described in detail in chapter 5).

Second, the prevalence of developed covers (which include a mixture of construction materials and vegetation) in neighboring spaces positively and significantly influences the probability that parcels develop in all three counties. That wetland cover sometimes significantly decreases the likelihood of parcels developing suggests that implementing policies that encourage the conservation of wetland habitats may be an effective tool for managing urban growth in coastal counties like Charleston and Georgetown. In turn, the positive effect of developed covers on

conversion suggests that designing policies that discourage dense development (for instance a tax on high intensity developed covers) may also slow down urban growth in counties similar to those studied here.

Table E.3 shows the results from the estimation of hedonic equations for residential properties. Importantly for the empirical validity of this study, the coefficient on the IMR variable derived from the sample selection model is positive and significant in the estimation of models for Charleston and Berkeley counties, as expected.

Across counties, age of residential buildings in the parcel, square footage of the structure, and assessed value of the structure show a significant quadratic relationship with developed sales prices. Younger structures are associated with higher prices as are structures with higher assessed values. However, building size has different effects across counties. In Charleston county, building square footage is positively related to sales price while the opposite is true for the other counties, although the effect is not significant in Berkeley.

Parcel elevation is negatively related to sales prices as is the dummy variable indicating whether a river runs through or is adjacent to the parcel. The landscape variables measuring crop and pasture cover as well as percent of forested area are also negatively related to sales prices. Whether a river is present and the proportion of crop and forest cover in a parcel are variables that may play a role in conversion costs, hence their sign.

An interesting finding is the effect of flood hazards on sales prices (as indicated by a binary measure of whether parcels are located within the 100–year flood plain). In Charleston county, being within the flood plain is negatively and significantly related with sales prices. This negative effect provide indication that residential land markets may react differently to flood risks than agricultural land markets due to fundamental reasons that have not yet been studied. In Berkeley and Georgetown counties, the effect of flood hazards on property values is not significant, suggesting property markets in these two counties may be fundamentally different from that of Charleston, favoring the use of separate land use change models in the second stage of

the empirical analysis.

In general, proximity effects are negligible in terms of magnitude. However, they point towards the existence of underlying differences in land markets across counties. In Charleston county, proximity to downtown Charleston, major roads, access points to public beaches, the coastline, and the nearest river positively affect sales prices. In Berkeley county, almost all these relationships show the opposite direction. In Georgetown county, the effect of proximity variables resemble those from Charleston, except for proximity to downtown Charleston which is positively related to sales prices.

The effects on sales prices from landscape composition variables are more consistent across counties. Increases in the density of developed covers surrounding parcels has a positive effect on sales prices, an intuitive effect of urbanization that can work by lowering distribution costs of public utilities, for instance. Finally, increases in the density of wetland covers surrounding parcels has a positive effect on sales prices in Charleston, a negative effect in Berkeley, and an insignificant effect in Georgetown. This outcome is of interest for designing land use policies aimed at conserving natural infrastructure that provides flood protection services. It suggests there may be larger gains from imposing such a policy in Charleston than in Berkeley or Georgetown counties.

Table E.1: Correlation between exclusion variable and selection and value processes.

Exclusion	Process						
	$s = \mathbf{1}[Z\gamma + \nu]$			$y = X\beta + \upsilon$			
variable	Charleston	Berkeley	Georgetown	Charleston	Berkeley	Georgetown	Controls^{+}
Soil quality^{++}	-0.262	-0.616**	1.286***	-0.078	-0.330***	-0.759**	YES
	(0.293)	(0.240)	(0.457)	(0.107)	(0.089)	(0.372)	
	-0.168	0.351**	1.158***	-1.995***	-0.310**	-1.807***	NO
	(0.254)	(0.165)	(0.307)	(0.220)	(0.123)	(0.321)	
Dist. to mill (mi)	-0.136*	-0.044**	0.127***	-0.172***	-0.044***	0.020	YES
	(0.080)	(0.021)	(0.030)	(0.026)	(0.011)	(0.028)	
	-0.076***	-0.027**	0.072***	-0.022***	-0.043***	0.103***	NO
	(0.006)	(0.011)	(0.010)	(0.006)	(0.008)	(0.010)	
Soil quality * Dist. mill	0.024	0.043	-0.018	0.006	0.017	0.011	YES
	(0.021)	(0.031)	(0.033)	(0.010)	(0.014)	(0.026)	
	-0.004	-0.049**	-0.131***	0.116***	-0.063***	-0.110***	NO
	(0.019)	(0.022)	(0.024)	(0.021)	(0.017)	(0.023)	

Significance codes: *p<0.1; **p<0.05; ***p<0.01
The errors in parenthesis are robust standard errors.
$^{+}$"NO" means only the exclusion variables were included. "YES" means the model is as shown in table E.2
$^{++}$ Soil quality is constructed as a weighted sum of soil quality. Higher scores are better for agriculture.

Table E.2: Sample selection correction model.

	Dependent variable: Prob(Developed = 1)		
	Charleston	Berkeley	Georgetown
Constant	1.951***	-0.490	-11.654**
	(0.745)	(0.693)	(4.694)
Soil quality	-0.262	-0.616**	1.286***
(exclusion variable)	(0.293)	(0.240)	(0.457)
Dist. to mill (mi)	-0.136*	-0.044**	0.127***
(exclusion variable)	(0.080)	(0.021)	(0.030)
Soil quality * Dist. to mill	0.024	0.043	-0.018
(exclusion variable)	(0.021)	(0.031)	(0.033)
Acreage	-0.025**	-0.21***	-0.001*
	(0.01)	(0.048)	(0.001)
Acreage^2	0.00003***	0.013**	$0.005e^{-4}$
	(0.00001)	(0.006)	$(0.003e^{-4})$
Elevation (m)	0.065***	0.013**	0.029**
	(0.015)	(0.006)	(0.011)
River (=1)	0.061	-0.027	-0.022
	(0.081)	(0.061)	(0.081)
Dist. to Charleston (mi)	-0.052	0.047	0.282**
	(0.08)	(0.08)	(0.136)
Dist. to Charleston^2 (mi)	0.008***	-0.003*	-0.002*
	(0.003)	(0.002)	(0.001)
Dist. to road (mi)	-0.381***	0.192***	0.323***
	(0.063)	(0.06)	(0.078)
Dist. to road^2 (mi)	0.057***	-0.061***	-0.107***
	(0.012)	(0.016)	(0.028)
Dist. to beach (mi)	0.407***	-0.232***	-0.098***

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Table E.2 (continued).

	Charleston	Berkeley	Georgetown
	(0.058)	(0.086)	(0.036)
Dist. to beach^2 (mi)	-0.279***	-0.312***	-0.084**
	(0.065)	(0.104)	(0.038)
Dist. to evacuation route (mi)	X	0.185***	0.166***
		(0.043)	(0.041)
Surrounding wetland cover	0.002***	0.004***	-0.003**
	(0.001)	(0.001)	(0.002)
Surrounding developed cover+	0.01***	0.01***	0.005***
	(0.001)	(0.001)	(0.001)
Surrounding pasture/crop cover	0.003*	0.0001	0.002
	(0.002)	(0.002)	(0.003)
Surrounding forest cover	-0.001	-0.005***	-0.002
	(0.001)	(0.001)	(0.002)
Year fixed effects	YES	YES	YES
Tract fixed effects	YES	YES	YES
Block group fixed effects	YES	NO	NO
Observations	17,111	16,793	6,065
Log Likelihood	-4,768.4	-6,516.6	-3,356.5
Akaike Inf. Crit.	9,880.8	13,163.2	6,792.9

The above results correspond to binary probit models.
Coefficients do not show marginal effects.
+Includes open space-, low-, medium-, and high-intensity development.
Significance codes: *p<0.1; **p<0.05; ***p<0.01
The errors in parenthesis are robust standard errors.

Table E.3: Corrected hedonic model for residential parcels.

	Dependent variable: $log(\frac{Price}{Acre})$		
	Charleston	Berkeley	Georgetown
Constant	16.136***	13.075***	-11.73*
	(0.241)	(0.415)	(6.125)
IMR	0.0024	0.025·	-0.008
	(0.017)	(0.013)	(0.024)
Age	-0.03***	-0.059***	-0.032***
	(0.001)	(0.003)	(0.003)
Age^2	0.00032***	0.001***	0.0003***
	(0.00001)	(0.0001)	(0.00005)
SQFT	0.0002***	-0.00001	-0.0002***
	(0.00003)	(0.00003)	(0.00003)
SQFT^2	$-0.003e^{-5}$***	$0.006e^{-6}$*	$0.003e^{-6}$***
	($0.003e^{-6}$)	($0.003e^{-6}$)	($0.007e^{-7}$)
Building value	0.00001***	$0.003e^{-4}$***	$0.003e^{-3}$***
	($0.006e^{-4}$)	($0.006e^{-5}$)	($0.002e^{-4}$)
Building value^2	$-0.006e^{-11}$***	$-0.026e^{-12}$	$-0.001e^{-9}$***
	($0.001e^{-11}$)	($0.005e^{-11}$)	($0.002e^{-10}$)
100-year flood plain (=1)	-0.062***	0.038	-0.007
	(0.013)	(0.024)	(0.033)
Elevation (m)	-0.017***	0.002	-0.106***
	(0.007)	(0.003)	(0.010)
River (=1)	-0.401***	-0.224***	-0.284***
	(0.039)	(0.034)	(0.069)
Dist. to Charleston (mi)	-0.063***	0.078**	0.639***
	(0.039)	(0.033)	(0.174)

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Table E.3 (continued).

	Charleston	Berkeley	Georgetown
Dist. to Charleston^2 (mi)	0.005	-0.011***	-0.004***
	(0.002)	(0.001)	(0.001)
Dist. to road (mi)	-0.044	0.138***	-0.073
	(0.029)	(0.031)	(0.058)
Dist. to road^2(mi)	0.007	-0.025**	0.032
	(0.007)	(0.010)	(0.020)
Dist. to beach (mi)	-0.138***	0.014	-0.065
	(0.037)	(0.049)	(0.046)
Dist. to beach^2 (mi)	0.004	0.007***	0.010***
	(0.003)	(0.001)	(0.002)
Dist. to coastline (mi)	-0.193**	X	-0.153***
	(0.044)		(0.042)
Dist. to coastline^2 (mi)	0.012**	X	-0.007**
	(0.004)		(0.003)
Dist. to river (mi)	-0.406***	X	-0.287
	(0.134)		(0.222)
Dist. to river^2 (mi)	0.537**	X	0.847**
	(0.235)		(0.391)
Surrounding wetland cover	0.003***	-0.001***	0.001
	(0.0004)	(0.0003)	(0.001)
Surrounding developed cover^{+}	0.005***	0.002***	0.006***
	(0.0003)	(0.0002)	(0.001)
Surrounding pasture/crop cover	-0.002***	-0.019***	-0.003
	(0.001)	(0.001)	(0.003)
Surrounding forest cover	-0.0035***	-0.0018***	-0.0028**
	(0.0004)	(0.0003)	(0.001)

Continued on next page

Table E.3 (continued).

	Charleston	Berkeley	Georgetown
Year fixed effects	YES	YES	YES
Tract fixed effects	YES	YES	YES
Block group fixed effects	YES	NO	NO
Observations	14,429	12,315	3,627
R^2	0.769	0.695	0.709
Adjusted R^2	0.766	0.694	0.705
Residual Std. Error	0.51	0.45	0.575
	(df = 14254)	(df = 12247)	(df = 3581)
F Statistic	273***	423***	194***
	(df = 174; 14254)	(df = 67; 12247)	(df = 45; 3581)

Building values are assessed values and are adjusted to inflation to $2016.
+Includes open space-, low-, medium-, and high-intensity development.
Significance codes: *p<0.1; **p<0.05; ***p<0.01
The errors in parenthesis are robust standard errors.

F THE CONDITIONAL LOGIT MODEL

I provide in this appendix the results of estimating the land use change model obtained using a conditional logit framework as robustness check.

To estimate equation (2.13) using a standard conditional logit estimator, it is necessary to assume the error term, μ_i, is distributed logistically. This can be shown to be true if the error terms in (2.12) follow a standard Type I extreme value distribution distribution with density $\exp\{-\epsilon_i^j\} - \exp\{-\epsilon_i^j\}$. Under this assumption about error terms, the coefficients that describe how attributes contribute to the probability that land is converted can be estimated via MLE, where it is typically assumed that $\pi_i^j(\cdot)$ is linear in the parameters. If these conditions are met, equation (2.13) becomes:

$$Pr(d_i = 1) = \frac{\exp[\pi_i^D(\cdot)]}{\sum\limits_{j=D,U} \exp[\pi_i^j(\cdot)]}. \tag{F.1}$$

The estimation of (2.17) yields the probability that an agricultural parcel develops, δ, and the probability that it remains in agricultural uses, $1 - \delta$.

In table F.1, I present results from a conditional logit regression to show as a robustness check. These estimates are also not interpretable as marginal effects. As indicated by results in the table, for Charleston parcels, a 1% increase in the developed value of land is linked with an increase in the odds of a parcel developing of 32%, while for for Berkeley and Georgetown parcels the increase is of 114%. The effect is found by taking the exponent of the coefficients (i.e., $\exp\{0.28\}$ approximates 1.32 and $\exp\{0.76\}$ is close to 2.13). The negative coefficient of the $ln(\widehat{\frac{P^U}{Acre}})$ indicates that have lower odds of getting developed as the undeveloped value of parcels increase.

Table F.1: Land Use change model - conditional logit.

	Dependent variable: choice of land use		
	status		
	(1)	(2)	(3)
$ln(\widehat{\frac{P^D}{Acre}})$	0.282^{***}	0.761^{***}	0.580^{***}
	(0.023)	(0.016)	(0.011)
$ln(\widehat{\frac{P^U}{Acre}})$	-0.074^{***}	-0.107^{***}	-0.120^{***}
	(0.020)	(0.005)	(0.005)
Observations	19,729	45,390	65,119
Log Likelihood	-9,936	-19,089	-29,212
Note:	*p<0.1; **p<0.05; ***p<0.01		

G DERIVATION OF DEVELOPMENT PROBABILITIES

As presented in chapter 3, a hazard function is also the derivative of a survivor function S_t. A survivor function is the probability that an event (e.g., development of a parcel) does not occur until after period t, and it is equivalent to $1 - Pr(T \leq t)$, or $Pr(T > t)$, where $Pr(T \leq t)$ is the probability that the duration is less than t, or the cumulative distribution function of T, or of how long a parcel remains undeveloped. The survival function is also related to the cumulative hazard or integrated hazard function, Λ_t, which shows the expected number of events (in this case developments) for a given set of covariates at a particular time and is equal to $-\ln S_t$, or equivalently, $S_t = \exp(-\Lambda_t)$.

To derive development probabilities in this study, I manipulate the hazard model estimates to compute survival probabilities for each undeveloped parcel in the sample and simply set the probability of development to be the probability that a parcel does not survive in an undeveloped state up to time t, or that it is converted within time period t (i.e., $\delta_{it} = 1 - S_{it}$).

With the proportional hazard assumptions, the survival function at time t is:

$$\begin{aligned} S_t &= \exp\Big(- H_{0t} \exp(X^{'}\beta)\Big) \\ &= \exp(-H_{0t})^{\exp(X^{'}\beta)}, \end{aligned} \tag{G.1}$$

where H_{0t} is the baseline cumulative hazard function at time t (an intercept–like term that describes the risk for parcels with covariates X equal to zero); X is a set of covariates; and β is a vector of coefficients that measure the impact of covariates.

The R function basehaz() provides the estimated hazard function H_{0t}, while the coxph() function yields coefficient estimates β for a given sample.

Because of the proportional nature of the proportional hazard model, to obtain sur-

vival curves of the 2 groups defined by their values of a particular covariate, say the developed value of land, the $\widehat{H_{0t}}$ can be raised to the power of the estimated coefficients for that covariate. For example, for $\ln \frac{P^D}{Acre} = \{\$10,000, \$9,000\}$, the survival curves are:

$$S_{t|\$10,000} = \exp(-\widehat{H_{0t}})^{\exp(\hat{\beta}\cdot 10,000)} \tag{G.2}$$

$$S_{t|\$9,000} = \exp(-\widehat{H_{0t}})^{\exp(\hat{\beta}\cdot 9,000)} \tag{G.3}$$

Presumably, the group of parcels with higher developed values has a lower survival curve than the group with lower developed values.

Using the predict() function, I derive the cumulative hazard rate for a given set of covariates at a particular time that is associated with the $\hat{\beta}$ that were estimated with the coxph() function. I specify the prediction command so that the prediction of the cumulative hazard rate incorporates the baseline hazard. Thus, the predicted cumulative hazard represents the absolute hazard, instead of the hazard relative to the sample average. Moreover, I specify the coxph() command to use the baseline hazard for time 5. Explicitly, I predict the probability that a parcel survives development for 5 years using the following statements:

$$\begin{aligned}\hat{S}_5 &= \exp\big(-\widehat{H_{05}}\exp(X'\hat{\beta})\big)\\ &= \exp\Big(\text{-predict}\big(\text{coxph}(h_t = h_{0t}\exp[\beta_D \ln\frac{P^D}{Acre} + \beta_U \ln\frac{P^U}{Acre}],\ \text{data}_{t=5})\big)\Big).\end{aligned} \tag{G.4}$$

The predicted development probabilities are:

$$\hat{\delta}_5 = 1 - \hat{S}_5. \tag{G.5}$$

To extract development probabilities in the simulation exercise, I input into the calculation values of land that have been modified to reflect the policy rules in each scenario.

Specifically, I take the coefficients resulting from estimating the proportional hazards model on the original data and interact them with parcel characteristics that have been altered according to the policy. The alternative survival probabilities are:

$$\begin{aligned}\tilde{S}_5 &= \exp(-\widehat{H_{05}}\exp(\tilde{X}'\hat{\beta})) \\ &= \exp\Big(\text{-predict}\big(\text{coxph(model), data}_{X=\tilde{X}}\big)\Big).\end{aligned} \tag{G.6}$$

where the model is $h_t = h_{0t}\exp[\beta_D \ln \frac{P^D}{Acre} + \beta_U \ln \frac{P^U}{Acre}]$, and is estimated using original data where time has been set to 5, or $\text{data}_{t=5}$.

There are concerns over using the predicted baseline hazard to project out of sample development patterns (i.e., to use it for future time periods not observed in the data used to estimate the econometric model). Strictly speaking, the estimated proportional hazards model with time invariant regressors X and baseline hazard estimate $\widehat{H_{05}}$, is only suitable for predicting counterfactual development probabilities within the time period observed in the data, not for predicting future development probabilities for time periods not observed in the data.

The basehaz() function estimates the cumulative baseline hazard and not the baseline hazard rate itself. When plotted, there is a time trend in the cumulative baseline hazard. This is shown in figure G.1. In the simulation of scenarios 5 years into the future, I use the cumulative baseline hazard for $t = 5$, also shown in figure G.1.

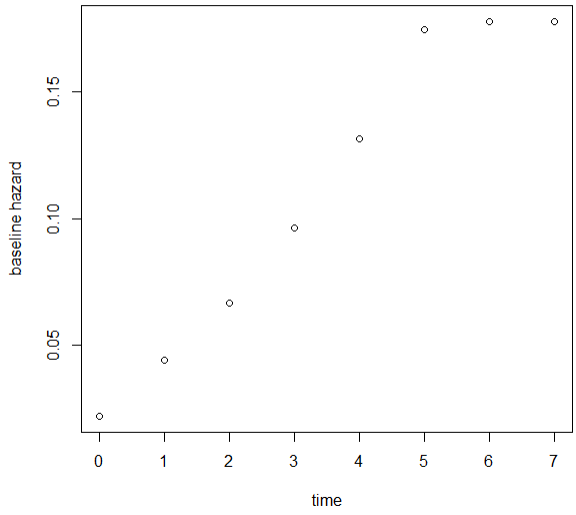

Figure G.1: Cumulative baseline hazard using basehaz() function on original data.

H LEGAL FRAME FOR WETLAND CONSERVATION

Protecting and restoring quantity and quality of coastal wetlands can play a critical role in reducing flood damages in coastal areas. In the US, the federal government derives authority to regulate wetlands from the Commerce Clause and the Clean Water Act (CWA).[1] Since 1990, when George H.W. Bush incorporated into The Clean Air Act pronouncements in Memorandum of Agreement between the U.S. Army Corps of Engineers (ACOE) and the Environmental Protection Agency (EPA) concerning the determination of the requirements for mitigating losses to wetlands, the nation's wetlands are protected by the federal government under Section 404 of the Federal Water Pollution Control Act (33 U.S.C. 1344).[2] The Memorandum established the national policy goal of no–net–loss of wetlands, a principle that enables the ACOE to ensure environmental impacts to aquatic resources are avoided or minimized as much as possible when reviewing proposed development projects.

The goal of the no–net–loss policy is to balance the protection, restoration and creation of wetlands and the need for sustained economic growth. To achieve its objectives, the no–net–loss policy establishes a flexible framework under which a variety of instruments, including tradeable wetland credits, can be utilized by federal, state and local government agencies as well as the private sector to protect and restore wetlands.

Following the 1989 directive, the ACOE and the EPA began to explicitly require property owners and developers looking to obtain a 404 permit (i.e., a permit to dredge or fill "waters of the US") to restore, establish, enhance, or preserve other aquatic resources

[1] The United States is not the only nation interested in the conservation of wetlands. International cooperation exists. The Ramsar Convention on Wetlands is an international treaty between 170 contracting parties for the conservation and sustainable use of wetlands. It is the oldest multilateral international conservation convention and the only one to deal with one habitat or ecosystem type.

[2] The first legal protection of wetlands came from President Jimmy Carter in 1977. However, it was not until the 1989 move that the government made explicit its policy goal regarding wetlands preservation.

in order to replace those unavoidably impacted by proposed development projects.[3] Under the no–net–loss policy, each newly impacted wetland is to be replaced with a surrogate wetland so that the total acreage of wetlands and the quality of wetland resources in the country does not decrease but remains constant or increases.[4] This is known as compensatory mitigation.

Despite apparent legislative clarity, even today, the level of federal involvement in wetland conservation is subject to the scope of *what* constitutes a regulated wetland (i.e., whether or not a particular wetland is part of the "waters of the United States") and that definition has changed over time.[5] For instance, two recent Supreme Court decisions (in 2001 and 2006) invalidated federal wetland regulation authority over some "isolated and non–navigable waters," and removed federal authority to protect the waters for migratory bird species. With these two rulings, the Court determined that migratory bird habitats do not constitute interstate waters, and that only wetlands that are adjacent to *navigable waters* are waters of the US and are therefore inside the scope of authority granted in the CWA. The outcome of these cases could either confirm or narrow the reach of federal regulatory jurisdiction over wetlands under the CWA.[6]

[3]Section 404 of the CWA requires a permit before dredged or fill material may be discharged into "waters of the United States."

[4]Currently, most states (including South Carolina), rely on the 1987 ACOE's Delineation Manual and Regional Supplements to guide delineation of wetlands. These guidelines include the three parameter approach using soils, hydrology, and plants.

[5]With the federal Water Pollution Control Act Amendment of 1972 (when the CWA took its modern form), Congress authorized the EPA to regulate wastewater discharges as well as wetland habitat damages. The EPA's jurisdiction is limited to the "waters of the United States," which are determined as navigable or potentially navigable rivers, tidal waters, interstate wetlands, and intrastate water and wetlands that have some permanent connection or "significant nexus" with interstate commerce. Waters that lack these connections remain solely under state jurisdiction.

[6]In the 2001 Solid Waste Agency of Northern Cook County v. United States Army Corps of Engineers case, the US Supreme Court ruled that the CWA could not block Chicago area governments from turning an isolated wetland into a landfill because the wetland did not nourish interstate waterways. In the Rapanos et al v. United States (2006) case, the Court ruled to prosecute the plaintiffs, developers John A Rapanos and June Carabell, for filling 22 acres of wetland with sand in preparation for the construction of a mall, without filing for a permit. However, the Court was split over further details regarding the

Following the 2001 and 2006 outcomes, in 2008 the US ACOE and the EPA released a new rule to clarify how to provide compensatory mitigation for unavoidable impacts to the nation's wetlands and streams. The rule defined new standards and expanded the agencies' role in regulating mitigation projects under the CWA.

More recently, in 2015, Ex–President Obama finalized the Water of the United States (WOTUS) rule, which gives the EPA and the ACOE broad authority over regulating the pollution of wetlands and tributaries that run into the nations largest rivers. The WOTUS rule covers wetlands adjacent to either traditional navigable waters or interstate waters, as well as streams serving as tributaries to navigable waters. The rule says that wetlands and tributaries must be "relatively permanent,"which means they can be intermittent. Defining wetlands this way extends federal jurisdiction to 60 percent of the water bodies in the United States. However, the relevance of this rule for future environmental policy is in question as the current administration is moving to craft a new more "industry-friendly"version.[7]

Besides the mitigation tools established by the CWA, there are other federal policy instruments for protecting wetland habitats. These include conservation easement programs (such as the Conservation Reserve Program, the Water Bank Act, and the Wetlands Reserve Program),[8] land use programs intending to reduce wetland conversion

term "navigable waters."

[7]Among Mr. Trump's first actions in office was an executive order directing his EPA administrator to begin the legal process of rescinding the rule and replacing it. Having suspended the water rule, in January of 2019, the EPA is now crafting a Trump administration version, which is expected to include much looser regulatory requirements on how farmers, ranchers and real estate developers must safeguard the streams and tributaries that flow through their property and into larger bodies of water. The Obama WOTUS regulation, which would have limited the use of pollutants like chemical fertilizers that could run off into small streams, came under fierce criticism from the rural landowners that make up a key component of Mr. Trump's political base.

[8]The Conservation Reserve Program is a land conservation program administered by the Farm Service Agency. In exchange for a yearly rental payment, farmers enrolled in the program agree to remove environmentally sensitive land from agricultural production and plant species that will improve environmental health and quality. The Water Bank Act authorizes the US Department of Agriculture to

to agricultural uses by removing incentives to produce agricultural commodities on converted wetlands (such as the Swampbuster Provision of the 1985 Farm Bill),[9] Fish and Wildlife Service conservation acts (such as the Migratory Bird Hunting and Conservation Stamp Act),[10] legal rulings (such as the Migratory Bird Rule),[11] and conditional federal grants (such as the Coastal Zone Act Reauthorization Amendments).[12]

At the state level, governments also have the authority to use various tools for addressing wetland protection, including policing powers to regulate the use of water and land (such as the administration of FEMA's building requirements), zoning authority, setting benchmarks for regulating net gain or loss of habitat, State Wetland Protection Plans, and the use of tradable wetlands credits. Additional policy instruments include private–public sector collaborations, such as educational efforts, conservation easement programs, land banking, and voluntary programs.[13] Similarly, at the local level, county and municipal governments can address wetland protection through stakeholder involvement, ordinances regarding land use, zoning and development standards, local Wetland

enter into 10–year contracts with landowners to preserve wetlands and retire adjoining agricultural lands. The Wetlands Reserve Program (valid until 2014) was a voluntary program that offered landowners the opportunity to protect, restore and enhance wetlands on their property.

[9]Under the Swampbuster Provision, farmers that plant agricultural commodities on wetlands that were converted between 1985 and 1990 are rendered inelegible for program benefits until the functions of the wetlands are repaired, unless an exemption applies.

[10]The Act requires revenues from sales of duck hunting stamps to be used in the acquisition of waterfowl production areas.

[11]Until 2001, this ruling extended the jurisdiction of the CWA to wetlands for being habitats used by migratory birds that cross state lines.

[12]This program is jointly administered by NOAA and the EPA and requires states or territories to implement solutions to non–point pollution problems in coastal water.

[13]As of 2015, twenty states (including South Carolina) had formally adopted the no–net–loss goal, and six states had adopted a net–gain–focused goal. Twenty–five states had EPA–approved Wetland Protection Plans. Twenty–three states had formal wetland permitting programs that serve as their primary regulation mechanism for protecting wetlands from dredges and fill impacts. An additional 21 states relied exclusively on provisions of Section 401 of the CWA on Water Quality Certification to provide input into the dredge and fill permitting process. Six additional states (including SC) relied on 401 Certification primarily but had some other state permitting program protecting at least some portion of the state's coastal wetlands. (Association of State Wetland Managers, 2015).

Strategic Plans, and wetland mitigation banking tools (e.g., tradable wetland credits).[14]

H.1 COASTAL MANAGEMENT IN SOUTH CAROLINA

The State of South Carolina has been a pioneer in addressing shoreline change and other coastal hazard management issues. In 1977, the SC Coastal Zone Management Program was established through the Coastal Tidelands and Wetlands Act. The Program authorized the SC Coastal Council (now the Department of Health and Environmental Control–Office of Ocean and Coastal Resource Management) to administer a permitting program for designated *critical areas* (i.e., coastal waters, tidelands, beaches and beach/dune systems) in the coastal zone (SC DHEC, 2017). Initially, the law provided limited beachfront jurisdiction and limited guidance for decisions on beachfront development and erosion control approaches. Then, in 1987, recognizing the threats of chronic erosion, sea level rise, increased shoreline development and a lack of comprehensive beachfront planning and management, the State supported the creation of the Blue Ribbon Committee on Beachfront Management to make recommendations for regulators and legislators about development and beach management policies.

Many of the recommendations of the Blue Ribbon Committee made their way into law through the 1988 SC Beachfront Management Act (BMA), which expanded state jurisdiction.[15] However, an examination of South Carolina's recent history shows that coastal management policies have had little practical power on restricting construction

[14]According to the ACOE database, in South Carolina, there are 28 approved mitigation banks, 17 pending mitigation banks, 3 mitigation banks and 1 in-lieu fee program that have sold all their credits.

[15]The new enacted law defined beachfront policies that limited development and established regulatory standards for construction along the coastline. The BMA also required the SC Coastal Council to develop a state–wide, long–range comprehensive beach management plan after having established a baseline from which to measure erosion setbacks. The baseline is typically placed as running parallel to the shore along the crest of the primary sand dune (the dune immediately adjacent to the ocean). The BMA included a provision for resetting the act within ten years and every five to ten years thereafter. The SC DHEC completed the most recent review for baseline and set back line positions in 2010.

and reconstruction decisions. For instance, in 1990, South Carolina eliminated a 20–feet dead zone within which the BMA established new structures could not be built and existing structures damaged beyond repair (i.e., when there has been a loss of two thirds of the value of the structure) could not be reconstructed, in response to demands of coastal landowners who, in the aftermath of Hurricane Hugo, demanded the right to rebuild their homes. The elimination of the 20–feet dead zone constitutes a clear weakening of South Carolina's coastal regulatory power.[16]

The impact of South Carolina's coastal policies has also been limited by other more stringent state policies that restrict reconstruction of coastal property, like the SC Septic System policy, and by outcomes of local law case rulings, like the 1992 case *Lucas* v. *South Carolina Coastal Council*, where the Supreme Court of the United States established that the BMA constituted a regulatory taking requiring compensation as it deprived a landowner (David Lucas) of the economically viable use of his property.[17]

Having found that local governments in coastal counties of South Carolina are virtually silent on the issue of land regulation for flood mitigation purposes, this work and its results have opened up a potential discussion over the role of federal legislation on environmental outcomes in coastal communities. More precisely, as discussed in this Appendix, a careful review of the legal history regarding wetland protection and restoration

[16]The 20–feet dead zone established by the BMA extended 20–feet landward of the point of furthest erosion on the previous three decades. The BMA also established a 40–feet zone, a landward area to be 40 times the average annual erosion rate and *only* applied to eroding coasts (i.e., in an area where annual erosion rate was two feet a year, the setback line would be 80 feet behind the baseline). Within the 40–year zone, new construction is limited to 5,000 sq feet of heated space and rebuilt homes cannot exceed the size, lateral extent, or proximity to the ocean of those replaced.

[17]David Lucas challenged the BMA as an unconstitutional taking of his property, claiming that the Act prevented him from developing his land and rendered the property valueless. The case made it to the Supreme Court, where justices found the South Carolina Supreme Court had erred in holding that the BMA was a valid exercise of the police power of the state as the Act sought to avoid a public harm and was therefore constitutional. According to the US Supreme Court, the South Carolina Supreme Court's public harm test was unworkable because it was impossible to differentiate between regulation that prevent a harm and those that confer a benefit.

programs seems to indicate there is a high degree of institutional uncertainty regarding the extent and level of federal involvement in wetland conservation. Intuitively, legislative uncertainty adds risk to the market of tradable wetland credits, the largest ecosystem services market in the US and the world. Thus, the topic of regulatory uncertainty on efficiency of markets for ecosystem services is also relevant to the work conducted here.