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

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Abstract

This study develops an integrated framework to evaluate the relative effectiveness of alternative land use policies that target the management of natural resources in the face of climate change pressures. This framework is then applied to evaluate the relative performance of three different land use regulations that protect natural resources and alter current trends of urbanization using data from three rapidly urbanizing coastal counties in the southeastern United States facing growing risks of flooding.

The framework developed in this study is an iterative procedure that integrates a spatially explicit econometric model of land use change, local ecosystem service delivery, and feedback mechanisms among land use, ecosystem services, and land values in a dynamic framework. The study uses landscape simulations to examine 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.

The results indicate that price instruments based on land value and depending on landscape composition are mostly not cost–effective strategies. However, other policies can be modestly effective in altering urban development patterns; such policies may also be effective at reducing the cost of property repairs after a major flood, raising tax revenues, or delivering a marginally more equal spatial distribution of damages. The findings also illustrate how natural infrastructure, such as wetlands, is beneficial to coastal communities in terms of flood control.
Key words: Flood risk, wetland conservation, urban development, land use policy.
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1 Introduction

There are few examples of natural resources or environmental science research analyzing the dynamic behavioral implications of land use policy for land development and conservation, particularly in the face of changing climatic pressures. Moreover, few studies have developed methods to connect the impacts of land use policy with changes in ecosystem services provision resulting from altered urbanization patterns.[1] This study contributes to a growing area of research in land use and environmental economics by developing a new, comprehensive framework to evaluate the relative effectiveness of alternative land use policies that target the management of natural resources in the face of climate change pressures. This framework is then applied to evaluate the relative performance of three different land use regulations that protect natural resources and alter current trends of urbanization using data from three rapidly urbanizing coastal counties in the southeastern United States facing growing risks of flooding.

According to the National Oceanic and Atmospheric Administration, flooding is the costliest and fastest growing climatic threat in the United States.[2] 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, economic damages, and natural and human losses.

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.[3] 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

[1]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 limitations. In turn, the growing body of literature on the economics of urban sprawl is surveyed in Glaeser and Kahn (2004) and Nechyba and Walsh (2004).

[2]Since 1960, the number of 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 already 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).

[3]The most common effects of urbanization on stream characteristics are reduced infiltration of precipitation into the soils and more rapid runoff, which substantially increase runoff volume and flood frequency. See Appendix G for a thorough discussion of the relationship between impervious surfaces and flooding.

ecosystems that decrease the landscape's vulnerability to floods—like wetlands, for instance, which reduce flooding risks by promoting infiltration or absorption, reducing runoff, attenuating wave setup, and facilitating sediment accretion (which reduces water depth and wave height).[4] 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.

At the federal level, the National Flood Insurance Program (NFIP) exists to relieve American households residing in flood-prone areas. The NFIP provides flood coverage to more than 5 million property owners nationwide and 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. In contrast, 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). This study is concerned with three mitigation–oriented policies that address urbanization patterns and promote the types of land cover that ameliorate flooding risks.

At the local level, 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 limit the damage to private properties from flooding events. 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. Moreover, local mitigation efforts and policy interventions can relieve the federal government and taxpayers of flood–related expenses.

This study 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. The focal areas are the three coastal counties that encompass the

[4] Land development and new impervious surfaces prevent water, sediments, organic matter and nutrients from percolating into the soil, therefore inhibiting the formation of wetlands. Additionally, the construction of physical structures like bulkheads, sea walls, jetties and sandbags pose a physical impediment for wetlands and marshes to migrate inland, which further impairs the landscape's capacity to prevent flooding.

Charleston metropolitan area, which is a region subject to rapid urbanization and rising flooding threats. Specifically, three questions are posed by this study: (1) which policy is more cost–effective at reducing future damages; (2) whether there are differences across policy scenarios in the spatial distribution of damages; and (3) whether these answers differ when considering short–term and long–term planning horizons.

To answer these questions, the analytical work conducted here builds 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 framework, parameter estimates from an econometric model of land use choice are used to iteratively simulate alternative physical landscapes to determine whether expected flooding damages can be ameliorated through policy mechanisms that alter land values and hence affect decisions to develop agricultural land for residential uses.

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.

This application brings novelty into the literature on multiple ways. 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 applying econometric methods to 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 this spatial data, this study represents 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.

The rest of the paper is organized as follows: section 2 presents theoretical and empirical frameworks used to study how various land use policies impact urbanization patterns and future flood damages. The discussion includes a thorough description of a two–stage predictive model, validated with machine learning methods, developed to project land values under alternative uses, and a detailed presentation of the estimators used to fit models of land use choice. The results from estimating the models developed in section 2 are shown and discussed in section 3. Section 4 describes the process followed to simulate future landscapes and defines the alternative land use policies evaluated in this study. Results from the comparative analysis are also discussed in section 4. Section 5 concludes by summarizing findings and discussing opportunities for future work. The appendix can be found online following the link speficied in the references section.

2 Economic theory and empirical methods

2.1 Economic theory

The centerpiece of the analysis is an econometric decision model of land conversion.[5] 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.

Rational forward–looking landowners in a deterministic environment decide to convert an undeveloped parcel to urban uses if the net present value of the land when developed is greater than

[5]Typically, models of land use change treat urbanization as a phenomenon that naturally occurs in space and depends solely on the distribution of existing land uses. In contrast, econometric models of conversion link physical changes in the landscape to behavioral motives. Thus, urbanization is the aggregation of individual decisions.

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.[6] Furthermore, it is assumed that land development is irreversible.

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}.

[6] Commercial development is not considered in this study as suburbanization is generally thought to be led by residential development (Benson, 2009).

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.[7] In this study, market data is used to estimate separate predictive hedonic models of land value and generate proxies for π_{it}^D and π_{it}^U.

2.2.1 Predictive hedonic models of property value

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).

This study follows 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 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.[8] 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

[7]This is an increasingly popular approach to modeling 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 valid but also preferable, under certain conditions, to alternative methods such as the use of randomized control trials (Antle, 2018).

[8]The hedonic method is a revealed preference approach for recovering the implied value of the individual attributes that compose a heterogeneous or differentiated good (Taylor, 2003). The idea 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 that gives rise to variations in product prices. Rosen (1974) showed how regressing product prices on their attributes could reveal consumers' willingness to pay for a marginal change in a continuous attribute of a differentiated product.

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 designed 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 for land values instead of using reduced–form estimates of land rents in the land use change model (Bigelow, 2015).

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 is sold and 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 is sold and is not converted to an urban use, π_{it}^U can be inferred from the observed sales price but the value of the land if it had been developed, π_{it}^D, is not observed. Thus, 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 before and after an observed sale.

To understand how π_{it}^U and π_{it}^D are inferred from sales prices using the hedonic method, consider the first of two types of sales that are observed in transaction data: the case of undeveloped parcels that remain undeveloped after being sold. The second case is that of developed parcels that remain developed after being sold.[9] Under the hedonic framework, land values can be decomposed into attributes that explain the variation in land prices. These attributes can be classified as structural characteristics of improvements on the 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:

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

[9]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. Fortunately, this study is not concerned with the subdivision of parcels. Thus, case three is outside the scope of this research.

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 generated.

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:

$$P_{jt}^U = \alpha^U + \varphi_j^U + \tau_t^U + \beta_S^U S_{jt}^U + \beta_L^U L_{jt}^U + \beta_G^U G_{jt}^U + \nu_{jt}^U, \tag{2.4}$$

where α^U is an intercept term, φ_j^U captures fixed effects specific to the census tract where parcel j is located, and 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 (2.4) 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 predicted from estimating (2.4), or:

$$\widehat{P_{jt}^U} = \widehat{\alpha^U} + \widehat{\varphi_j^U} + \widehat{\tau_t^U} + \widehat{\beta_S^U} S_{jt}^U + \widehat{\beta_L^U} L_{jt}^U + \widehat{\beta_G^U} G_{jt}^U. \tag{2.5}$$

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

$$\widetilde{P_{kt}^U} = \widehat{\alpha^U} + \widehat{\varphi_k^U} + \widehat{\tau_t^U} + \widehat{\beta_S^U} S_{kt}^D + \widehat{\beta_L^U} L_{kt}^D + \widehat{\beta_G^U} G_{kt}^D, \tag{2.6}$$

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 (2.5). Note that (2.5) is also applied out–of–sample to undeveloped parcels which have not sold.[10]

To finalize the first stage of the two–step land use change model, it is necessary 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.

A linear specification of the price function, P_{kt}^D, shows:

$$P_{kt}^D = \alpha^D + \varphi_k^D + \tau_t^D + \beta_S^D S_{kt}^D + \beta_L^D L_{kt}^D + \beta_G^D G_{kt}^D + \nu_{kt}^D, \tag{2.7}$$

where S_{kt}^D is a vector with structural or building characteristics of developed parcels, such as residential square footage, number of bedrooms, and number of bathrooms; L_{kt}^D contains land characteristics, such as parcel size and elevation; and G_{kt}^D represents geospatial characteristics, such as proximity to major cities and environmental amenities, or urbanization density in the surrounding neighborhood. Similarly to (2.4), α^D is an intercept term; φ_k^D captures block group fixed effects; β_S^D, β_L^D, and β_G^D are vectors of coefficients corresponding to the covariate matrices S_{kt}^D, L_{kt}^D and G_{kt}^D; and ν_{kt}^D is the error term.

To retrieve $\widehat{\pi_{kt}}^D$, the hedonic price function in (2.7) is estimated using data from developed parcels. To get the fitted value of land, the value of buildings on the parcel is netted out by manually

[10] It is worth noting that the predicted agricultural land values generated from estimating hedonic price models are not equivalent to predicted agricultural land rents. Predicted land values are greater than predicted agricultural rents by the amount equivalent to the option value of developing agricultural parcels. Deflating predicted agricultural land prices by the option value would imply that landowners have no reason for waiting to develop their lands and would lead to the generation of future urban scenarios that are not consistent with current market expectations. This is an important consideration, and one that distinguishes this research from previous works.

setting the value of the corresponding coefficients equal to zero. The resulting estimate, $\widehat{P_{kt}}^D$, is used as a proxy of π_{kt}^D. In turn, to construct proxies of π_{jt}^D for parcels that are in agricultural use, their information about factors in the covariate matrices S_{kt}^D, L_{kt}^D, and G_{kt}^D is used together with the coefficients derived from estimating equation (2.7), or $\widehat{\beta_S^D}$, $\widehat{\beta_L^D}$, and $\widehat{\beta_G^D}$.

The constructed proxies for π_{it}^D are:

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

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

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:

$$\widetilde{P_{jt}^D} = \widehat{\alpha^D} + \widehat{\varphi_j^D} + \widehat{\tau_t^D} + \widehat{\beta_S^D} S_{jt}^U + \widehat{\beta_L^D} L_{jt}^U + \widehat{\beta_G^D} G_{jt}^U, \tag{2.9}$$

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 (2.8) are combined with characteristics of agricultural land to determine its value in residential use. Naturally, some components of the coefficient vector in (2.8) are not used as they are unavailable for the sample of undeveloped parcels (e.g., size of residential building).

2.2.2 Choice models of land use: the proportional hazard model

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.

For estimation of the land conversion decision model, the RUM framework is employed because it accommodates incomplete information about private returns (Lewis, 2010).[11] As in equation (2.3), values of a parcel under use j (where $j \in \{D, U\}$) can be decomposed as:

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

[11] As shown in equation (2.1), landowners in the model convert an agricultural parcel to residential use if development yields the greater net present value of the land.

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

$$\begin{aligned} Pr(d_{it} = 1) &= Pr(V_{it}^{D} > V_{it}^{U}) \\ &= Pr(\pi_{it}^{D}(\cdot) + \epsilon_{it}^{D} > \pi_{it}^{U}(\cdot) + \epsilon_{it}^{U}). \end{aligned} \tag{2.10}$$

Rearranging terms and gathering the random components, equation (2.10) becomes:

$$Pr(d_{it} = 1) = Pr(\pi_{it}^{D}(\cdot) - \pi_{it}^{U}(\cdot) > \mu_{it}). \tag{2.11}$$

Equation (2.11) 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 is developed if originally undeveloped (δ); the probability that it becomes agricultural if currently developed (γ); and the probability that it remains in residential use 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 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 estimators such as conditional or fixed effects logit (Lewis and Plantinga, 2007), multinomial logit (Newburn et al., 2006), fixed effects linear probability (Bigelow et al., 2017), pooled logit (Bigelow, 2015), random parameters or mixed logit

(Lewis et al., 2011), combination of probit and Poisson (Lewis, 2010; Bockstael, 1996), nested logit (Lubowski et al., 2008), and the proportional hazard or Cox regression estimator (Irwin et al., 2003; Towe et al., 2008). Ultimately, the choice of estimator largely depends on the structure of the data and the advantages of different estimators.

An estimator found in the recent literature that seems well suited for the problem at hand is the proportional hazards or duration model (also referred to as Cox's regression estimator). In a proportional hazards model, the duration for which a parcel has been in an undeveloped state influences the estimated probability of development. Thus, unlike the more common conditional logit, it allows direct incorporation of temporal considerations into the model of land conversion. For this reason, in this research, results from a proportional hazard estimation are used to build the scenario comparison analysis that will be presented in section 5.

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 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 is 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:

$$h_t = \lim_{\Delta t \to 0} \frac{Pr(T < t + \Delta t | T \geq t)}{\Delta t}, \tag{2.12}$$

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

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, $S_t = \exp(-\Lambda_t)$.

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 duration, 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 with h_t and for the change in risk associated with a change in a particular covariate to be constant for all time durations T.[12] This model is called the Cox proportional hazards model. Cameron and Trivedi (2005) provide a thorough derivation and discussion of it.

When the proportional hazard assumptions are imposed, (2.12) can be written as:

$$h_t = h_{0t} \cdot \exp(X^{'}\beta), \tag{2.13}$$

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 (2.13) is therefore:

$$S_t = \exp\Big(- \int_0^t h_{0t} \exp(X^{'}\beta) dt \Big). \tag{2.14}$$

To estimate the parameters in (2.13), the partial likelihood function of the proportional hazard rate function, or L_p, is minimized.[13] 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:

$$L_p = \prod_{j=1}^{k} \frac{\prod_{m \in D_{t_j}} \exp(X^{'}\beta)}{\Big[\sum_{l \in R_{t_j}} \exp(X^{'}\beta) \Big]^{d_j}}, \tag{2.15}$$

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.

[12]The assumption that changes in risk are constant across T implies that the duration between events of development does not make a difference in calculating the likelihood that a given parcel develops.

[13]The proportional hazards assumptions are particularly advantageous because they allow a semi–parametric estimation of (2.13) without requiring specification of 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. A discussion of the baseline estimation is found in Appendix F.

The partial log–likelihood corresponding to (2.15) is defined by:

$$\ln(L_p) = \sum_{j=1}^{k} \Big[\sum_{m \in D_{t_j}} (X'\beta)) - d_j \ln\Big(\sum_{l \in R_{t_j}} \exp(X'\beta) \Big) \Big]. \tag{2.16}$$

The minimization of (2.16) results in estimates of the β coefficients in (2.13).[14] 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.[15] 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 k^{th} 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.[16]

Modified for the context of this study, $\exp(X'\beta)$ 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. It is important to note that the hazard rate shown in (2.13) 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. Appendix F includes a brief explanation of the methods used to obtain the development probabilities from the hazard model estimates.

[14]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).

[15]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).

[16]It follows that $\exp(\beta_k) = 1$ 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.

3 Empirical analysis and results

3.1 Predictive hedonic models of land value

The study area is confined to 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.

Though rich in protective natural capital, counties in the study area face increasing flooding risks and increasing risks of flooding damage. Figure 3.2 shows the location of flooding events in the study area since 1996 in relation to the parcels available for analysis. Increased flood risks are partly due to rising pressures from urbanization and subsequent changes in land cover. 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. In Georgetown, urban population growth was much slower, at 2.1%.[17] An examination of the most recent national land cover data indicates that much of the new development is dominated by medium– and high–intensity growth, although it is accompanied by growth that is more suburban in nature. Table 2.1 summarizes change in land cover composition in the three counties between 2001 and 2011 and makes clear that forest cover, pasture lands, and woody wetlands are decreasing, likely giving way to the observed increase in medium– and high–intensity development land uses.

3.1.1 Data

The hedonic price functions used to construct proxies for land values are estimated using repeated cross–section data of the most recent recorded sales prices made available by tax assessor offices in the three counties that comprise the study area.[18] The data used in the statistical property–value

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

[18] Cross–sectional data is used 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 for this 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. These methods, like the Hausman–Taylor and the Mundlack estimators, 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).

models can be organized into 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). A full list of the sources of data is presented in the appendix table A.1.

Land market data for the hedonic analyses was obtained from County tax assessor databases and County GIS offices. 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, including square footage of the 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. These GIS and NLCD shapefiles were used 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., 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 and around the parcel 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.

3.1.2 Sample selection

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 assigned 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.

A five–step process partly relying on geospatial data availability was followed to select the parcels used in the empirical analysis. A detailed description of these steps is included in appendix A. Table 2.2 shows the number of parcels in each County that remain after each restriction in the construction of the dataset is imposed. Figure 3.3 shows the location of parcels in the sample relative to parcels that were not included and are categorized by land use. Figure 3.4 provides supplementary location information. Specifically, panel (a) of figure 3.4 presents the location of only the parcels included in the final sample and indicates whether they were considered developed or undeveloped. Panel (b) shows the location of parcels in the sample relative to land cover classes. As shown by the figure, the landscape of parcels left out of the analysis is dominated by public lands, wetlands and marshes, and open water.

3.1.3 Model selection

This study's focus on prediction contrasts with the majority of studies employing hedonic models in environmental applications.[19] 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 on 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 on how to specify the models (i.e., whether 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, a standard machine learning algorithm known as the k–fold validation technique is employed.[20] In this application, k equals 10. Given tax assessor data

[19] 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. Appendix B includes a discussion of the accuracy of prediction attained in the first–stage estimation by analyzing the statistical properties of the generated proxies. Recall from section 2 that these proxies correspond to $\widehat{\pi^D}$ and $\widehat{\pi^U}$.

[20] The k–fold cross–validation technique is a technique used in statistics to assess 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. The cross–validation process is then repeated k times

availability, the modeling choices for all three counties were based on the results based on Charleston data. The output from the 10–fold cross–validation is used to progressively refine baseline hedonic models for residential and agricultural parcels.[21] The baseline models are:

$$P_t^U = \alpha^U + \varphi_j^U + \tau_t^U + \beta_S^U S_{jt}^U + \beta_L^U L_{jt}^U + \beta_G^U G_{jt}^U + \nu_{jt}^U, \tag{3.1}$$

$$P_t^D = \alpha^D + \varphi_k^D + \tau_t^D + \beta_S^D S_{kt}^D + \beta_L^D L_{kt}^D + \beta_G^D G_{kt}^D + \nu_{kt}^D, \tag{3.2}$$

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 choice of variables in the post–cross–validation step is made on the basis of several factors, including the coefficient of determination (or R–square value) and statistical significance of the explanatory variables.[22] 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. Below, the specifics of each hedonic model are discussed, starting with agricultural models.

(i.e., the number of 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. A recent survey of cross-validation results is Arlot and Celisse (2010).

[21]The 10–fold cross–validation technique results in 10 sets of predicted errors. Each set is then 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 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 $\sqrt{L}2$). To transparently select the statistical models that offer the better fit for the sample data, the distributions of L1, $\sqrt{L}2$, and MSE resulting from the validation process are examined. Appendix B includes figures that illustrate the resulting distributions.

[22]The final refinement is done outside the 10–fold validation procedure because it is computationally demanding.

3.1.4 Hedonic models for agricultural properties

For the hedonic model of agricultural land value, an ordinary least squares (OLS) estimator is employed on parcel data for each County. The OLS regressions include a rich set of explanatory variables representing 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. Explicitly, the regressions use data on structural characteristics contained in tax assessor data, such as parcel size and assessed value of improvements, together with land and geospatial features. The latter 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 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 2.3.

The estimated model has the following structure:

$$\ln(P^U_{jt}/\text{Acre}) = \alpha^U + \varphi^U_j + \tau^U_t + \beta^U_S S^U_{jt} + \beta^U_L L^U_{jt} + \beta^U_G G^U_{jt} + \nu^U_{jt}, \tag{3.3}$$

where α^U is an intercept term, φ^U_j captures fixed effects specific to the census tract where parcel j is located, τ^U_t is a vector of time dummies that captures year–specific fixed effects, S^U_{jt} represents characteristics of structures in the land, L^U_{jt} contains features of the land, G^U_{jt} includes geospatial variables, and ν^U_{jt} is the error term.

The structural or building characteristics included in S^U_{jt} 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.[23]

Variables related to productive capacity, L^U_{jt}, are dummy variables of land capability class 1 through 4,[24] elevation, an indicator of whether the parcel is in the 100–year flood plain, and

[23] 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 by only a few variables, such as whether the building has a central air system, a basement, or five or more rooms (Ihlanfeldt and Matinez-Vazquez, 1985).

[24] There are seven land capability classes (LCC) identified by the National Resource Conservation Service. Land capability class 1 describes prime soils for agriculture, while land capability 7 corresponds to poor soils for agriculture. LCC's 5 to 7 were left out of the regressions.

an indicator of whether a river runs through or by the parcel. Finally, geospatial variables in G^U_{jt} 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 and its surrounding area covered in wetlands, high–intensity developed surfaces, or pasture/crop covers. Throughout the empirical work, the aforementioned land cover variables are defined by a 0.25–mile buffer around the parcel's centroid (just over 125 acres), which therefore includes the area within the parcel's boundaries. The boundary choice was based on Bockstael (1996).[25]

Results from this estimation are presented in table 2.4. 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 adjacent to a river.

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 Berkeley—which could be indicating access to water is seen as an 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 to 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 supports the logic that agricultural lands within 100–year flood plains are worth more under agriculture and thus less likely to develop.[26]

[25] 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. The buffer measures are used in the final models as they capture both effects. Future research will explore whether disaggregated measures of land cover on–parcel and out–of–parcel influence the policy simulations in a meaningful way.

[26] This may be because floods carry nutrient-rich silt and sediment, and distribute it across the land, making flood plains fertile areas. Often, they are also flat and have few obstacles impeding agriculture.

Proximity to a wood–processing facility is important for determining the price of agricultural parcels only 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 to land values. The exception is Georgetown, where every additional mile between an agricultural parcel and Charleston's city center increases land value by $1.5 per–acre. This effect translates to less than $20 for the average parcel, and it is conditional on a parcel being within a specific census tract.

Distance to major roads is positively related to higher land values, suggesting that transportation costs do not affect agricultural profitability for parcels in the sample, 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 to land values but being farther from the coastline shows a positive relation. In Berkeley and Georgetown the opposite is observed in regard to proximity to the coastline, while proximity to beach access points has no effect on land values.

The effects of variables measuring landscape composition of a parcel's area and the area that surrounds it are intuitive, 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 may be related to landowners' expectations about future development options. 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). 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 higher prices. This is likely related to ease of access to public services.

3.1.5 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. The set of regressors used in the hedonic models of developed land values include representatives from three categories: 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 heterogeneous 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.[27]

The general residential hedonic model has the following structure:

$$\ln(P_{kt}^D/\text{Acre}) = \alpha^D + \varphi_k^D + \tau_t^D + \beta_S^D S_{kt}^D + \beta_L^D L_{kt}^D + \beta_G^D Gkt^D + \nu_{kt}^D, \tag{3.4}$$

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, and improvement value squared. Land variables related to land productive capacity contained in L_{kt}^D are 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 2.5.

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

Table 2.6 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. It is possible that in Georgetown, 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 river presence. An interesting finding is the effect of flood hazards on sales prices. In Charleston County, being within the 100–year flood plain is negatively and significantly related to sales prices, a result supported by recent findings in the literature.[28] This negative effect contrasts with what is found with the model of agricultural parcels, indicating that residential land markets may react differently to flood risks than agricultural land markets, perhaps due to reasons overlooked in this study, such as relative ease of access to crop insurance as opposed to flood insurance. In Berkeley and Georgetown counties, the effect of flood hazards is not significant, which could reflect differences in property markets across rural and more urban landscapes.

In general, proximity effects are negligible in terms of magnitude. However, they also suggest 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.

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 relationship between open space and forested covers and prices of residential lands.[29] In a recent study by Phaneuf and Kaliber (2009), the authors find

[28]Dei-Tutu and Bin (2002) also find that the market value of a house located within a floodplain is significantly lower than an equivalent house located outside the floodplain.

[29]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).

that heterogeneity within open space covers matters for identifying marginal willingness to pay for open space. The negative effect found here may be related to heterogeneity in open space in the Lowcountry. It is possible that forest and agricultural lands may be less of an amenity in more rural counties 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—an intuitive effect of urbanization. Finally, there is a heterogeneous effect of increases in the density of wetland covers in and around parcels. 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 wetlands are not perceived as an open space amenity in more rural places. This outcome is relevant when designing land use policies aimed at conserving natural infrastructure, as impacts may differ across counties based, for instance, on whether wetlands are perceived as desirable or undesirable open space.

3.2 Land use change model estimation results

As described in section 2.2, in this model of rational agents in a deterministic environment, landowners decide to convert an agricultural parcel to urban use if the net present value of their land is greater under residential than agricultural use, net of conversion costs. This is mathematically shown by:

$$d_{it} = \begin{cases} 1 & \text{if } \ln(\widehat{\frac{P_{it}^D}{Acre}}) - \ln(\widehat{\frac{P_{it}^U}{Acre}}) > 0, \\ 0 & \text{otherwise.} \end{cases} \tag{3.5}$$

Here, $\ln(\widehat{\frac{P_{it}^D}{Acre}})$ and $\ln(\widehat{\frac{P_{it}^U}{Acre}})$ 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 by estimating the hedonic models of land value presented in equations (3.3) and (3.4). The remainder of this section presents the results from modeling private land use decisions in a context that assumes no change in the current set of land use policies (i.e., under business–as–usual, or BAU, conditions).

Equation (3.5) 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 2.7. The first column in table 2.7 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 parcels are included. Note that this table shows estimated coefficients, which are not directly interpretable.

Overall, the direction of the relationships between land value and development are consistent with theory, and both variables are statistically significant. First, a 1% increase in the predicted per–acre developed value of land increases the hazard of development by 0.483% when all parcels are used for estimation. An alternative interpretation of this coefficient is that a parcel's expected hazard rate is 1.62 times higher after a 1% increase in its per–acre developed value, holding its undeveloped value constant.[30]

A second result, which is also consistent with theory, is the reduction in the development hazard rate following a 1% 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 the 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 section 4. 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 should be equal. However, what is found is that a 1% increase in the undeveloped price of land does not restrict development to the same degree that an increase of the same proportion in the developed price of land encourages development. This gap could reflect the difference in starting alternative values of land, or it could mask a particular appetite for land conversion in the study area. The difference in magnitude of coefficients 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.

[30]This is so because $\exp(0.483) = 1.62$.

4 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.[31] In this section, simulations are used to investigate the predicted effects of various land use policies (e.g., policies that discourage development in densely urbanized areas or that encourage the protection of ecosystems) and evaluate their relative ability to influence spatial patterns of land use and the landscape's ability to mitigate flood damages. Specifically, this study addresses what policies are more cost–effective at reducing future damages, the spatial distribution of damages associated with various policies, and how these measures differ across time.

4.1 Description of alternative policies

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.[32] Without clear ex–ante expectations about the effects of urban growth policies, this study considers different forms of price instruments, leaving quantity instruments as an area of interest for future research.[33] Specifically, the scenarios evaluated are:

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.[34]

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,

[31] 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).

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

[33] A comprehensive discussion on this topic can be found in Villegas, 2018.

[34] Currently, none of the three counties studied here have land use policies aimed at flood mitigation or adaptation.

this will be referred to 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).[35]

3. Scenario 3: Tax on developed covers (DCT). This instrument is a heterogeneous impact fee linked to density of development around a parcel. It is meant to discourage development in areas that are already highly developed and in that way help preserve the ecological functions of the landscape. As opposed to the 10% DT, the DCT is 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) covered by hard surfaces.[36] Since the tax disproportionately penalizes development in places with relatively large paved areas, it may not necessarily obstruct development but instead may 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). By inflating the undeveloped value of land, this scheme encourages owners of agricultural land to conserve natural covers that are critical for flood prevention.[37] Effectively, this subsidy increases the opportunity cost of developing land; thus, if the demand for land is not perfectly inelastic, such a subsidy would reduce 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.

[35] 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 undeveloped (or 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%.

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

[37] 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.

4.2 Procedure for simulating future landscapes

To answer the questions posed in this study, multiple alternative landscapes are generated. The simulation exercise relies on a comprehensive algorithm that takes as inputs the parameter estimates from econometric models derived from those developed in section 3. There are five steps in the procedure: (1) a standard Monte Carlo exercise to predict future urban patterns; (2) the incorporation of land use considerations at the marginal level using historical geospatial data; (3) adding the various policy rules to the model parameters; (4) iterating over the procedure to generate landscapes further into the future in time steps of five years; and (5) the creation of confidence intervals by generating 200 landscapes per scenario.

Under a standard Monte Carlo simulation exercise, the probability that each agricultural parcel in the sample transitions from agricultural to residential uses, δ_i, is compared to a random draw from a standard uniform distribution, ξ.[38] If δ_i is greater than ξ, parcel i is determined to develop within a period of five years. Because this comparison 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. 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 use within five 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.[39]

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 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.

[38] The average probability of conversion is calculated using the estimated hazard ratios. Specifically, the probability of development within a 5–year period is 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.

[39] 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; Nelson and Hellerstein, 1997).

By allowing land use intensity or land cover to change endogenously, this study advances the literature. To account for the choice of development covers of various intensities in the development decision, in the second step of the simulation algorithm this study uses land cover data to determine the extent of changes to the physical composition of the landscape from recent development decisions and imposes that as an exogenous rule on all new development events. Specifically, spatial packages in R are used 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 five years (i.e., development that occurred between 2011 and 2016) and impose that average on parcels that are projected to develop.[40] This method also addresses a concern posed in the early work of environmental economists examining land use change that has not yet been resolved: it accounts for spatial dynamics in the hedonics relationships by directly incorporating updated land cover variables in the hedonics functions.

To generate future scenarios under each alternative land use policy, the processes described above are conducted with different parameters for the particular drivers that define each of the considered policies. For instance, under a 10% tax on development, the simulation uses as an 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.

The fourth step is to repeat the procedure described above multiple times to generate landscape at time $t+25$, starting with the recalculation of the predicted land values derived from the original hedonic estimation.[41] 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 $t+25$.[42]

[40] Previous work typically incorporates 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 be developed at the maximum density allowed by zoning. Other studies impose periodic fixed exogenous changes in the return derived from each use to internalize chosen technological improvements (Lawler et al., 2014).

[41] These predicted values are updated at each time step to reflect changes in the physical landscape. This is done because, as discussed above, the proportional hazard model does not include time–varying covariates in X, and because landowners who did not develop their parcels between t and $t+5$ may face different trade–offs at the end of $t+5$ than they did at the beginning of t.

[42] Note that the deep parameters determining transition probabilities in each simulation are the coefficients from the previous proportional hazard model estimation. A brief discussion on how these deep parameters are manipulated in the simulations to obtain the development probabilities is provided in appendix F.

A final step is to create some form of confidence intervals around the predicted urban patterns. 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. To characterize the range of potential outcomes, it is preferable to repeat the simulation *multiple* times. Under this view, *multiple* feasible landscapes are generated using different random draws from the U[0,1] distribution to capture both the range of potential landscape patterns and some uncertainty related to how the model is specified (i.e., uncertainty over how landowners make decisions). In this study, 200 alternative landscapes are generated in $t+5$ and $t+25$ for each policy scenario.[43] The distribution of these 200 scenarios is summarized in the results section. The summary tables report the average number of parcels expected to develop under each policy and the associated wetland cover change and developed cover change. Boxplots with the distribution of costs and benefits of each policy are also presented (figures 4.2 and 4.3, and 4.10 and 4.11). Intuitively, better predictive power would be associated with less variation in the distribution of simulated measures.

4.3 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, the 1,600 simulated landscapes are used 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 4.1 summarizes the steps in the comparison process.

In this study, economic costs and benefits reflect, correspondingly, the cost of limiting development by restricting land use choices, and subsequent avoided property damages after an event resembling 2017 Hurricane Irma. Mathematically, the costs of policy j at time T are defined as:

$$\text{Cost}_{jT} = \Big[\sum_{t=1}^{T}\sum_{i}\beta^t(V_{it}^D - V_{it}^U)\Big]_{BAU} - \Big[\sum_{t=1}^{T}\sum_{i}\beta^t(V_{it}^D - V_{it}^U)\Big]_{j}, \tag{4.1}$$

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. Hence, the cost of implementing policy j is defined as

[43] 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.

the difference in the net developed value added to the landscape at time T between a BAU scenario and a scenario where policy j is in place.

In turn, 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 revenues raised under the policy.[44] Formally, the benefits of policy j at time T are:

$$\text{Benefit}_{jT} = \Big[\sum_i \beta^T \text{FRI}_i \times \overline{\text{Damage}}\Big]_{BAU} - \Big[\sum_i \beta^T \text{FRI}_i \times \overline{\text{Damage}}\Big]_j \tag{4.2}$$

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.

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. This study uses 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). For the parcel–specific FRI, inundation models were developed to generate a measure of predicted flood risk. These models are described in appendix G. Finally, for $\overline{\text{Damage}}$, the 2016 average NFIP payment per claim in South Carolina is used. In 2016 dollars, this value is \$24,776.

4.3.1 Short–term (5 years) comparative analysis

The policies discussed in this section have the potential to alter urbanization patterns in different ways. 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 section 4, and a predicted developed value of land that has been reduced by 10% due to the tax. In short, in this

[44]This measure of benefit should be interpreted as a lower bound as it (1) ignores changes in ecosystem service values between BAU and other policy scenarios, and (2) uses 2016 NFIP statistics on total claim payments, which are much lower than the statistics for the 2017 fiscal year—when Hurricane Irma actually occurred. (NFIP 2017 data are not yet publicly available as some payouts are still being processed—it was a hectic year for NFIP with Hurricanes Harvey, Irma, and Maria, some of the most significant U.S. flood events in history.) For reference, in 2017, the average national claim payout was \$91,735, almost 50% more than in 2016 (\$62,247).

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 land use decision is simulated only for one time period for each policy scenario (recall that time steps in this model are five years). Table 4.1 reminds the reader of summary statistics for key characteristics 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.

Table 4.1 also shows approximations of the average effects on prices from a 1% increase in certain land covers. As reported in table 4.1, 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 the 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 4.2 describes the probabilities of development resulting from the simulations, one for each alternative policy scenario. The probabilities suggest that development decisions are generally non–responsive to land use controls, which is consistent with previous findings in the land development literature (Wrenn and Irwin, 2012).[45] The average probability of conversion under BAU is 16.2%, 15.8% under a 10%DT, and 8.8% and 15.6% with a DCT and a WPS, 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 4.3. Table 4.3 reports the number of parcels predicted to develop within a

[45] Wrenn and Irwin (2012) find that a development fee of 20% of the land price was predicted to reduce development by only 2%, and a fee of 40% of the land price by only 3%.

period of five 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 five years under a BAU scenario, which is consistent with estimates of population growth in the study area.[46] 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 in table 4.3, wetland cover loss is actually negative under all scenarios, meaning that wetland cover in the landscape actually increases 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. However, under the DCT scenario, there is a reduction in the overall amount of 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 suburban.

4.3.1.1 Short–term (5 years) benefit–cost comparison

To complete the benefit–cost analysis, each 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 patterns via land use policies are avoided damages measured as the difference in NFIP payments between BAU and each policy scenario. Table 4.4 shows the corresponding savings in NFIP payments associated with each regime relative to the BAU scenario.

Table 4.4 also shows expected costs of implementing policies that restrict development under different policy scenarios, which in this study are defined as forgone benefits of development due to land use restrictions, or the present value of the difference between BAU and each policy scenario

[46] Recall that population growth in the last five years was 13% in Charleston and 17% in Berkeley.

in added value to converted lands. Using these two measures, a Cost–Benefit Ratio (CBR) is calculated and is shown in table 4.4 as well. Table 4.4 also presents an "Augmented CBR." This ratio accounts for tax revenues raised in scenarios 2 and 3, and for subsidies as a cost in scenario 4.

The measures reported in table 4.4 correspond to the average values of the 200 simulated scenarios. Table 4.5 shows summary statistics of the distribution of benefits and costs that were generated with the 200 landscape simulations. Figure 4.2 shows boxplots comparing the distribution of benefits (i.e., avoided damages) generated in the 200 simulations, and figure 4.3 shows boxplots comparing the distribution of costs (i.e., foregone added value) generated in the 200 simulations.

A first look at the results in tables 4.4 and 4.5 and figures 4.2 and 4.3 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 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 the least favorable 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 criterion for choosing a land use policy were 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., forgone benefits of development) are considered, a 10%DT is the preferable policy among the three, as average reduction in value added is 4% rather than 51% or 12%.[47] 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.[48] 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 is raised

[47]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.

[48]The effect observed with the WPS stands out as a rather credible estimate, given recent findings in the literature.

in taxes, which is about 20% more than the amount raised with a DCT. Of course, under the WPS, raised revenues are actually negative and would therefore be considered costs. When government 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 one–tenth and two–fifths of benefits.

4.3.1.2 Short–term spatial patterns of development and distribution of damages

Figure 4.4 shows the location and number of parcels predicted to develop in a five–year period under each regime. It also shows rivers and major highways in the study area.[49] 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. 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 3.1). However, it is interesting to find that, relative to a 10%DT, a WPS does not reduce development 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 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 4.5 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. For ease of visual examination, maps of projected flood damages in three subregions of the study area are provided. Figure 4.6 defines three subregions of the study area and identifies key local features of the landscape.

[49] 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.

As shown in figures 4.7 to 4.9, 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, in addition 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. 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 landscape with a DCT in place is the better of the alternative scenarios in terms of spatial distribution of damages. The 10%DT and DCT show distributions that are marginally more unequal than the distribution delivered by the BAU.

4.3.2 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 above was repeated four times, so that all generated landscapes correspond to scenarios 25 years into the future. Tables 4.6 to 4.9 and figures 4.10 to 4.16 summarize the results from this exercise.

Table 4.6 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 relationship 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.

Table 4.7 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. Housing stock in most of the study area has increased between 75 and 350% since 1990. 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 4.7 shows how land use policies affect wetland conservation and the addition 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.

4.3.2.1 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 4.8 and 4.9, and illustrated in figures 4.10 and 4.11. Table 4.8 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 4.9 shows summary statistics for the 200 simulated measures of costs and benefits, and figures 4.8 and 4.9 illustrate 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 DCT.

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

4.3.2.2 Long–term spatial patterns of development and distribution of damages

Figure 4.12 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. Similarly to the short–term analysis, there is no clear indication that spatial tendencies in development are altered by the policies. In general, it 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). Although illustrative, the maps do not offer any conclusive insights in terms of differential impacts of the policies on the spatial tendencies of development.

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. Figure 4.13 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. Figures 4.14 to 4.16 show maps of two subregions where damages differed the most.

4.3.3 Policy implications

Table 4.10 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 4.11 summarizes pros and cons of all policies and ranks them in terms of relative capacity to deliver each 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.[50] 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 (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, in addition to the changes observed with the 10%DT, there are fewer clusters of parcels with high levels of damage on the coast of Charleston. Also, there are noticeable reductions of damages near the Waccamaw National Wildlife Refuge on 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 central–west 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 study (i.e., land use regulation via 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

[50]It was found that in the 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 the BAU. In the long run, there was a 49% reduction in payments relative to the BAU scenario. A WPS also reduces NFIP payments in both timelines, but to a lower degree than the DCT.

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.[51] 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. No local jurisdiction collects fees specifically tailored to address flood control projects, let alone flood control projects that target natural infrastructures, such as buffer areas of wetlands. 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, this type of revenue 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.[52]

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

[51] Appendix H includes a detailed discussion on the state's legislative timeline and reasons why the impact of coastal policies has been limited.

[52] As mentioned earlier, development outcomes are relatively insensitive to price–based policy. 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.

will likely not suffice to prevent losses. Instead, to address losses 25 or more years into the future, policy makers will 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 (for instance, a 10%DT is the 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 instruments that induce developers to provide flood prevention services by preserving additional wetland habitat.

The results of this study 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. 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 strengthening land use strategies, fiscal tools, and public–private partnerships to promote development in areas where impacts on wetlands can be mitigated. The Berkeley Plan recommends the use of subsidies for developers that engage in wetland-friendly practices, exactly the type of policy studied here.

Finally, there are interesting implications 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 indicate 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 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 consider urbanization trends when designing land use policies.

5 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 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 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).

The results 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 an interest in, 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.[53]

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. However, 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 community–centered, environmental, and fiscal goals—given a level of creativity and assertiveness that is feasible.

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

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 limiting the amount of forgone benefits of development. Such a policy is associated with lower costs in terms of lost development value and 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.

5.1 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 disaggregated data on localized relationships that account for spatial determinants of the land development process. However, there are limitations, as well as opportunities for future research.

In terms of the framework employed, there are a few key considerations. First, this is not an optimization exercise, in that it does not address the economic efficiency of alternative development patterns. In addition, the analysis is built on a partial equilibrium model and therefore does not capture price feedbacks or development spillovers to other locations, both effects that would likely affect the modeled system via population and income shifts following the imposition of these policies and the occurrence of large storms. Second, 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 and their geomorphological and biological dynamics are complex. Moreover, this study is completely agnostic to the impact that climate change.

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 possible extensions to the current modeling framework. 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. Land cover inside a parcel contributes to its value differently than landcover in the area that surrounds it.

Second, the construction of variables 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 constitute only a small share of the total cover. For instance, open–space developed covers (LC21) include areas where less than 20% of the total area is covered 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. 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.

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 on the impact of landscape features on flood vulnerability. This would also improve the methods for measuring the externalities associated with intensive land development and removal of wetlands, and the link between flood risks and property values.

References

[1] Antle, John (2018, August). *Data, Economics and Computational Agricultural Science.* Fellows Address at the 100^{th} Agricultural & Applied Economics Association annual meeting in Washington, D.C.

[2] Arrow, K. J., Cropper, M. L., Gollier, C., Groom, B., Heal, G. M., Newell, R. G., & Sterner, T. (2014). Should governments use a declining discount rate in project analysis? *Review of Environmental Economics and Policy, 8*(2), 145-163.

[3] Bengston, D. N., Fletcher, J. O., & Nelson, K. C. (2004). Public policies for managing urban growth and protecting open space: policy instruments and lessons learned in the United States. *Landscape and Urban planning, 69*(2), 271-286.

[4] Benson, Sonia, ed. (2009). "Suburbanization". UXL Encyclopedia of U.S History. pp. 1498–1501.

[5] Bento, A. M., Franco, S. F., & Kaffine, D. (2006). The efficiency and distributional impacts of alternative anti-sprawl policies. *Journal of Urban Economics, 59*(1), 121-141. doi:10.1016/j.jue.2005.09.004

[6] Bento, A. M., Franco, S. F., & Kaffine, D. (2011). Welfare effects of anti-sprawl policies in the presence of urban decline. *Agricultural and Resource Economics Review, 40*(3), 439-450. doi:10.1017/S1068280500002884

[7] Bertaud, A. and Richardson, A.W. (2004). Transit Density: Atlanta, the United States and Western Europe. *Urban Sprawl in Western Europe and the United States. London: Ashgate*, 293-310.

[8] Bigelow, D. P. (2015). How Do Population Growth, Land-Use Regulations, and Precipitation Patterns Affect Water Use? A Fine-Scale Empirical Analysis of Landscape Change. *Oregon State Institutional Repository.*

[9] Bigelow, D. P., Plantinga, A. J., Lewis, D. J., & Langpap, C. (2017). How does urbanization affect water withdrawals? Insights from an econometric-based landscape simulation. *Land Economics, 93*(3), 413-436.

[10] Bockstael, N. E. (1996). Modeling economics and ecology: the importance of a spatial perspective. *American Journal of Agricultural Economics, 78*(5), 1168-1180.

[11] Boutwell, J. L., & Westra, J. (2014). Economic Risk, Tropical Storm Intensity and Coastal Wetlands: A Factor Analysis. In *Selected Paper Prepared for Presentation at the 2014 Southern Agricultural Economics Association (SAEA) Annual Meeting.*

[12] Boutwell, J. L., & Westra, J. V. (2015). Evidence of Diminishing Marginal Product of Wetlands for Damage Mitigation. *Natural Resources, 6*(01), 48.

[13] Boyle, K. J., Poor, P. J., & Taylor, L. O. (1999). Estimating the demand for protecting freshwater lakes from eutrophication. *American Journal of Agricultural Economics, 81*(5), 1118-1122.

[14] Brown, J. T. (2016). Introduction to FEMA's National Flood Insurance Program (NFIP). *Congressional Research Service, 16.*

[15] Brueckner, J. K. (1995). Strategic control of growth in a system of cities. *Journal of Public Economics, 57*(3), 393-416. doi:10.1016/0047-2727(95)80003-R

[16] Brueckner, J. K., & Lai, F. (1996). Urban growth controls with resident landowners. *Regional Science and Urban Economics, 26*(2), 125-143. doi:10.1016/0166-0462(95)02125-6

[17] Burge, G. S., & Ihlanfeldt, K. R. Sustainable Urban Growth and Development Impact Fees. *Cityscape,* 83-105.

[18] Cameron, A. C., & Trivedi, P. K. (2005). *Microeconometrics: methods and applications.* Cambridge University Press.

[19] Carrion-Flores, C., & Irwin, E. G. (2004). Determinants of residential land-use conversion and sprawl at the rural-urban fringe. *American Journal of Agricultural Economics, 86*(4), 889-904.

[20] Carter, V. (1996). *Technical aspects of wetlands. Wetland hydrology, water quality, and associated functions.* United States Geological Survey Water Supply paper 2425. US Geological Survey, USA.

[21] Cassel, E., & Mendelsohn, R. (1985). The choice of functional forms for hedonic price equations: comment. *Journal of Urban Economics, 18*(2), 135-142.

[22] Chomitz, K. M., & Gray, D. A. (1996). Roads, land use, and deforestation: a spatial model applied to Belize. The World Bank Economic Review, 10(3), 487-512.

[23] Coastal Wetlands: Too Valuable to Lose. NOAA Fisheries. (n.d.). Retrieved from https://www.fisheries.noaa.gov/coastal-wetlands-too-valuable-lose

[24] Costanza, R., Pérez-Maqueo, O., Martinez, M. L., Sutton, P., Anderson, S. J., & Mulder, K. (2008). The value of coastal wetlands for hurricane protection. *AMBIO: A Journal of the Human Environment, 37*(4), 241-248.

[25] Council, M. M. (2017). Natural Hazard Mitigation Saves: 2017 Interim Report. *Multihazard Mitigation Council: Washington, DC, USA.*

[26] Cropper, M. L., Deck, L. B., & McConnell, K. E. (1988). On the choice of functional form for hedonic price functions. *The Review of Economics and Statistics,* 668-675.

[27] Cunningham, C. R. (2007). Growth controls, real options, and land development. *The Review of Economics and Statistics, 89*(2), 343-358.

[28] Dahl, T. E., & Allord, G. J. (1996). History of wetlands in the conterminous United States. *National summary on wetland resources. USGS, Springfield,* 19-26.

[29] Dei-Tutu, V. A., & Bin, O. (2002). Flood Hazards, Insurance, and House Prices-A Hedonic Property Price Analysis. *Research paper, East Carolina University.*

[30] Dickes, L. A., Allen, J., Jalowiecka, M., & Buckley, K. (2017). A Policy Lens of South Carolina Coastal Stormwater Management. *Journal of South Carolina Water Resources, 3*(1), 5.

[31] Donovan, G. H., & Butry, D. T. (2010). Trees in the city: Valuing street trees in Portland, Oregon. *Landscape and Urban Planning, 94*(2), 77-83.

[32] Environmental Protection Agency (2018). *Mitigation Banking Factsheet.* Retrieved from https://www.epa.gov/cwa-404/mitigation-banking-factsheet

[33] Feaster, T. D., Gotvald, A. J., & Weaver, J. C. (2014). *Methods for estimating the magnitude and frequency of floods for urban and small, rural streams in Georgia, South Carolina, and North Carolina, 2011* (No. 2014-5030). US Geological Survey.

[34] Forest Trends' Ecosystem Marketplace (2015, May 1). *Ecosystem Markets and Finance: A Global Primer.* Retrieved from http://www.ecosystemmarketplace.com/wp-content/uploads/2016/01/Ecosystem-Marketplace-Market-Primer-2015-Final.pdf

[35] Glaeser, E. L., & Kahn, M. E. (2004). Sprawl and urban growth. In *Handbook of regional and urban economics* (Vol. 4, pp. 2481-2527). Elsevier.

[36] Goerke, L. (2011). Commodity tax structure under uncertainty in a perfectly competitive market. *Journal of Economics, 103*(3), 203-219.

[37] Goulder, L. H., & Parry, I. W. (2008). Instrument choice in environmental policy. *Review of environmental economics and policy, 2*(2), 152-174.

[38] Hayashi, F. (2000). Econometrics (1st edn).

[39] Helsley, R. W., & Strange, W. C. (1995). Strategic growth controls. *Regional Science and Urban Economics, 25*(4), 435-460. doi:10.1016/0166-0462(95)02095-C

[40] Hoeting, J. A., Davis, R. A., Merton, A. A., & Thompson, S. E. (2006). Model selection for geostatistical models. *Ecological Applications, 16*(1), 87-98.

[41] Homer, C.G., Dewitz, J.A., Yang, L., Jin, S., Danielson, P., Xian, G., Coulston, J., Herold, N.D., Wickham, J.D., and Megown, K., 2015, Completion of the 2011 National Land Cover Database for the conterminous United States-Representing a decade of land cover change information. Photogrammetric Engineering and Remote Sensing, v. 81, no. 5, p. 345-354

[42] Horsch, E. J., & Lewis, D. J. (2009). The effects of aquatic invasive species on property values: evidence from a quasi-experiment. *Land Economics, 85*(3), 391-409.

[43] Ihlanfeldt, K. R., & Martinez-Vazquez, J. (1986). Alternative value estimates of owner-occupied housing: evidence on sample selection bias and systematic errors. *Journal of Urban Economics, 20*(3), 356-369.

[44] Ihlanfeldt, K. R., & Taylor, L. O. (2004). Externality effects of small-scale hazardous waste sites: evidence from urban commercial property markets. *Journal of environmental economics and management, 47*(1), 117-139.

[45] Intergovernmental Panel on Climate Change. (2018). Sixth Assessment Report: Special Report on Global Warming by 1.5C. *IPCC: Geneva, Switzerland.*

[46] Irwin, E. G. (2010). New directions for urban economic models of land use change: incorporating spatial dynamics and heterogeneity. *Journal of Regional Science, 50*(1), 65-91.

[47] Irwin, E. G., & Bockstael, N. E. (2002). Interacting agents, spatial externalities and the evolution of residential land use patterns. *Journal of economic geography, 2*(1), 31-54.

[48] Irwin, E. G., & Bockstael, N. E. (2004). Land use externalities, open space preservation, and urban sprawl. *Regional science and urban economics, 34*(6), 705-725.

[49] Irwin, E. G., & Wrenn, D. H. (2014). An assessment of empirical methods for modeling land use. *The Oxford Handbook of Land Economics*, 327.

[50] Irwin, E. G., Bell, K. P., & Geoghegan, J. (2003). Modeling and managing urban growth at the rural-urban fringe: a parcel-level model of residential land use change. *Agricultural and Resource Economics Review, 32*(1), 83-102.

[51] Irwin, E. G., Bell, K. P., Bockstael, N. E., Newburn, D. A., Partridge, M. D., & Wu, J. (2009). The economics of urban-rural space. *Annu. Rev. Resour. Econ.,1*(1), 435-459.

[52] Jeuck, J. A., Cubbage, F. W., Abt, R. C., Bardon, R. E., McCarter, J. B., Coulston, J. W., & Renkow, M. A. (2014). Assessing Independent Variables Used in Econometric Modeling Forest Land Use or Land Cover Change: A Meta-Analysis. *Forests, 5*(7), 1532-1564.

[53] Kaplan, E. L., & Meier, P. (1958). Nonparametric estimation from incomplete observations. *Journal of the American statistical association, 53*(282), 457-481.

[54] Kenworthy, J. R. (2003). Transport energy use and greenhouse gases in urban passenger transport systems: a study of 84 global cities.*Murdhoch University Institutional Repository.*

[55] Kiel, K., & Zabel, J. (2000). Estimating the demand for air quality in four United States cities. *Land Economics,* 76.

[56] Klaiber, H. A., & Phaneuf, D. J. (2009). Do sorting and heterogeneity matter for open space policy analysis? An empirical comparison of hedonic and sorting models. *American journal of agricultural economics, 91*(5), 1312-1318.

[57] Kong, F., Yin, H., & Nakagoshi, N. (2007). Using GIS and landscape metrics in the hedonic price modeling of the amenity value of urban green space: A case study in Jinan City, China. *Landscape and urban planning, 79*(3-4), 240-252.

[58] Kotsogiannis, C., & Serfes, K. (2014). The comparison of ad valorem and specific taxation under uncertainty. *Journal of Public Economic Theory, 16*(1), 48-68.

[59] Kuminoff, N. V., Parmeter, C. F., & Pope, J. C. (2010). Which hedonic models can we trust to recover the marginal willingness to pay for environmental amenities?. *Journal of Environmental Economics and Management, 60*(3), 145-160.

[60] Kunreuther, H. and Pauly, M. (2006). Rules rather than discretion: Lessons from Hurricane Katrina. *Journal of Risk and Uncertainty, 33*:101-116.

[61] Lawler, J. J., Lewis, D. J., Nelson, E., Plantinga, A. J., Polasky, S., Withey, J. C., & Radeloff, V. C. (2014). Projected land-use change impacts on ecosystem services in the United States. *Proceedings of the National Academy of Sciences, 111*(20), 7492-7497.

[62] Lewis, D. J. (2010). An economic framework for forecasting land-use and ecosystem change. *Resource and Energy Economics, 32*(2), 98-116.

[63] Lewis, D. J., & Plantinga, A. J. (2007). Policies for habitat fragmentation: combining econometrics with GIS-based landscape simulations. *Land Economics, 83*(2), 109-127.

[64] Lewis, D. J., Plantinga, A. J., & Wu, J. (2009). Targeting incentives to reduce habitat fragmentation. *American Journal of Agricultural Economics, 91*(4), 1080-1096.

[65] Lewis, D. J., Plantinga, A. J., Nelson, E., & Polasky, S. (2011). The efficiency of voluntary incentive policies for preventing biodiversity loss. *Resource and Energy Economics, 33*(1), 192-211.

[66] Lewis, D. J., Provencher, B., & Butsic, V. (2009). The dynamic effects of open-space conservation policies on residential development density. *Journal of Environmental Economics and Management, 57*(3), 239-252.

[67] Loerzel, J., Gorstein, M., Rezzai, A. M., Gonyo, S., Fleming, C. S., & Orthmeyer, A. (2017). Economic valuation of shoreline protection within the Jacques Cousteau National Estuarine Research Reserve. *NOAA Institutional Repository.*

[68] Lubowski, R. N., Plantinga, A. J., & Stavins, R. N. (2008). What drives land-use change in the United States? A national analysis of landowner decisions. *Land Economics, 84*(4), 529-550.

[69] Ming, J., Xian-Guo, L., Lin-Shu, X., Li-juan, C., & Shouzheng, T. (2007). Flood mitigation benefit of wetland soil—A case study in Momoge National Nature Reserve in China. *Ecological Economics, 61*(2-3), 217-223.

[70] Narayan, S., Beck, M. W., Wilson, P., Thomas, C. J., Guerrero, A., Shepard, C. C., & Trespalacios, D. (2017). The Value of Coastal Wetlands for Flood Damage Reduction in the Northeastern USA. *Scientific reports, 7*(1), 9463.

[71] National Ocean Service website, https://oceanservice.noaa.gov/facts/population.html, 02/09/18.

[72] National Oceanic and Atmospheric Administration. *Status and Trends of Wetlands in Coastal Watersheds.* Retrieved from http://www.nmfs.noaa.gov/stories/2013/11/11_21_13wetlands_habitat_report.html

[73] NC Department of Environmental Quality. *Wetlands.* Retrieved from https://deq.nc.gov/about/divisions/coastal-management/coastal-management-estuarineshorelines/ wetlands

[74] Nechyba, T. J., & Walsh, R. P. (2004). Urban sprawl. *Journal of economic perspectives, 18*(4), 177-200.

[75] Nelson, E., Polasky, S., Lewis, D. J., Plantinga, A. J., Lonsdorf, E., White, D., & Lawler, J. J. (2008). Efficiency of incentives to jointly increase carbon sequestration and species conservation on a landscape. *Proceedings of the National Academy of Sciences, 105*(28), 9471-9476.

[76] Nelson, G. C., & Hellerstein, D. (1997). Do roads cause deforestation? Using satellite images in econometric analysis of land use. *American Journal of Agricultural Economics, 79*(1), 80-88.

[77] Nelson, G. C., Harris, V., Stone, S. W., Barbier, E. B., & Burgess, J. C. (2001). Deforestation, land use, and property rights: empirical evidence from Darien, Panama. *Land Economics, 77*(2), 187-205.

[78] Netusil, N. R., Chattopadhyay, S., & Kovacs, K. F. (2010). Estimating the demand for tree canopy: a second-stage hedonic price analysis in Portland, Oregon. *Land Economics, 86*(2), 281-293.

[79] New Climate Economy (2014). "The global commission on the economy and the climate." *Washington DC: World Resources Institute.*

[80] Newburn, D. A., Berck, P., & Merenlender, A. M. (2006). Habitat and open space at risk of land-use conversion: targeting strategies for land conservation. *American Journal of Agricultural Economics, 88*(1), 28-42.

[81] Newburn, D., Reed, S., Berck, P., & Merenlender, A. (2005). Economics and Land-Use Change in Prioritizing Private Land Conservation. *Conservation Biology, 19*(5), 1411-1420.

[82] NOAA (National Oceanic and Atmospheric Administration). Status and Trends of Wetlands Status and Trends of Wetlands. (2013).

[83] NOAA National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters (2018). https://www.ncdc.noaa.gov/billions/

[84] NOAA (2018). *What percentage of the American population lives near the coast?*

[85] Novitzki, R. P., Smith, R. D., & Fretwell, J. D. (1997). Restoration, Creation, and Recovery of Wetlands. *Wetland Functions, Values, and Assessment. USGS WSP, 2425.*

[86] Palmquist, R. B. (2005). Property value models. *Handbook of environmental economics, 2*, 763-819.

[87] Parsons, G. R. (1992). The effect of coastal land use restrictions on housing prices: a repeat sale analysis. *Journal of Environmental Economics and Management, 22*(1), 25-37.

[88] Phaneuf, D. J., & Requate, T. (2016). A course in environmental economics: theory, policy, and practice. Cambridge University Press.

[89] Pinchot, G. (1910). *The fight for conservation.*

[90] Polasky, S., & Segerson, K. (2009). Integrating ecology and economics in the study of ecosystem services: some lessons learned. *Resource*, 1.

[91] Roosevelt, F. D. (1937). *Message to Congress on National Planning and Development of Natural Resources.*

[92] Rosen, S. (1974). Hedonic prices and implicit markets: product differentiation in pure competition. *Journal of political economy, 82*(1), 34-55.

[93] Sander, H., Polasky, S., & Haight, R. G. (2010). The value of urban tree cover: A hedonic property price model in Ramsey and Dakota Counties, Minnesota, USA. *Ecological Economics, 69*(8), 1646-1656.

[94] Sharma, B., Rasul, G., & Chettri, N. (2015). The economic value of wetland ecosystem services: evidence from the Koshi Tappu Wildlife Reserve, Nepal. *Ecosystem Services, 12*, 84-93.

[95] Silver, N. (2012). *The signal and the noise: why so many predictions fail–but some don't.* Penguin.

[96] Singer, J. D., & Willett, J. B. (1993). It's about time: Using discrete-time survival analysis to study duration and the timing of events. *Journal of educational statistics, 18*(2), 155-195.

[97] Taylor, L. O. (2003). The hedonic method. In *A primer on nonmarket valuation* (pp. 331-393). Springer Netherlands.

[98] Taylor, L.O., Phaneuf, D.J., & Liu, X. (2016). Disentangling property value impacts of environmental contamination from locally undesirable land uses: Implications for measuring post-cleanup estimates. *Journal of Urban Economics, 93* 85-98.

[99] Towe, C. A., Nickerson, C. J., & Bockstael, N. (2008). An empirical examination of the timing of land conversions in the presence of farmland preservation programs. *American Journal of Agricultural Economics, 90*(3), 613-626.

[100] Turnbull, G. K. (2004). Urban growth controls: Transitional dynamics of development fees and growth boundaries. *Journal of Urban Economics, 55*(2), 215-237. doi:10.1016/j.jue.2003.10.001

[101] Turner, B. L., Lambin, E. F., & Reenberg, A. (2007). The emergence of land change science for global environmental change and sustainability. *Proceedings of the National Academy of Sciences, 104*(52), 20666-20671.

[102] Tversky, A. and Kahneman, D. (1974). Judgment under uncertainty: heuristics and biases. *Science, 185*(4157):1124-1131.

[103] U.S. Census Bureau (2010). *General Population and Housing Characteristics, 2010 Demographic Profile Data, 2010-2016 American Community Survey 5-year estimates.*

[104] Villegas, L. (2018). Integrating econometric land use models with ecological modeling of ecosystem services to guide coastal management and planning. *North Carolina State University Institutional Repository.* Online Appendix.

[105] Walls, M., Rezaie, A. M., Chu, Z. and Ferreira, C. M. (2017) "Valuing Flood Protection Services from Coastal Wetlands" *PlosONE (under 2nd review).*

[106] Watson, K. B., Ricketts, T., Galford, G., Polasky, S., & O'Niel-Dunne, J. (2016). Quantifying flood mitigation services: The economic value of Otter Creek wetlands and floodplains to Middlebury, VT. *Ecological Economics, 130*, 16-24.

[107] Wooldridge, J. M. (2015). *Introductory econometrics: A modern approach.* Nelson Education.

[108] Wrenn, D. H., & Irwin, E. G. (2012). How do land use policies influence fragmentation? An econometric model of land development with spatial simulation. *Environmental Economics, 3*, 82-96.

[109] Wu, J. (2014). *The Oxford handbook of land economics.* Oxford University Press.

[110] Zhang, B., Shi, Y. T., Liu, J. H., & Xu, J. (2017). Economic values and dominant providers of key ecosystem services of wetlands in Beijing, China. *Ecological Indicators, 77*, 48-58.

Tables and Figures

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
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: 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 3.3: 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]
	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]

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Table 3.3 (continued).

		Charleston	Berkeley	Georgetown
# obs		2,401	2,366	1,959
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]
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 3.4: 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 valueˆ2	-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 riverˆ2 (mi)	X	-1.235***	0.800
		(0.383)	(0.741)
Dist. to mill (mi)	-0.046**	X	X
	(0.024)		
Dist. to Charleston (mi)	-0.056	-0.181**	0.403**
	(0.041)	(0.083)	(0.175)
Dist. to Charlestonˆ2 (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)

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Table 3.4 (continued).

	Charleston	Berkeley	Georgetown
Dist. to roadˆ2 (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 beachˆ2 (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 coastlineˆ2(mi)	X	X	-0.006**
			(0.004)
Wetland cover within a 0.25-mile radius area	0.002 (0.001)	-0.004*** (0.002)	-0.004*** (0.001)
Developed cover within a 0.25-mile radius area*	0.010*** (0.001)	0.007*** (0.001)	0.006*** (0.001)
Pasture/crop cover within a 0.25-mile radius area	-0.008*** (0.002)	-0.015*** (0.002)	-0.003 (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
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 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]
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]

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Table 3.5 (continued).

		Charleston	**Berkeley**	**Georgetown**
# obs		16,300	12,315	3,627
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]
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]

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Table 3.5 (continued).

		Charleston	Berkeley	Georgetown
# obs		16,300	12,315	3,627
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: 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)
Ageˆ2	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)
SQFTˆ2	$-0.003e^{-5}$***	$0.006e^{-6}$*	$0.003e^{-6}$***
	$(0.003e^{-6})$	$(0.003e^{-6})$	$(0.007e^{-7})$
Building value	0.00001***	$0.003e^{-4}$***	$0.003e^{-3}$***
	$(0.006e^{-4})$	$(0.006e^{-5})$	$(0.002e^{-4})$
Building valueˆ2	$-0.006e^{-11}$***	$-0.026e^{-12}$	$-0.001e^{-9}$***
	$(0.001e^{-11})$	$(0.005e^{-11})$	$(0.002e^{-10})$
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 Charlestonˆ2 (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)
Dist. to roadˆ2(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 beachˆ2 (mi)	0.003	0.007***	0.010***
	(0.003)	(0.001)	(0.002)

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Table 3.6 (continued).

	Charleston	Berkeley	Georgetown
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
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 3.7: 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 3.5 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.

Table 4.1: 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 3.4 and 3.6			
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 4.2: 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 4.3: Short–term (5 years): number of parcels predicted to develop under different policy regimes.

	Undeveloped parcels at starting point	Number of parcels predicted to develop: 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 4.4: 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 4.5: 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 4.6: 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 4.7: Long–term (25 years): number of parcels predicted to develop under different policy regimes.

	Undeveloped parcels at starting point	Number of parcels predicted to develop			
		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 4.8: 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 4.9: 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 4.10: 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 4.11: 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**.

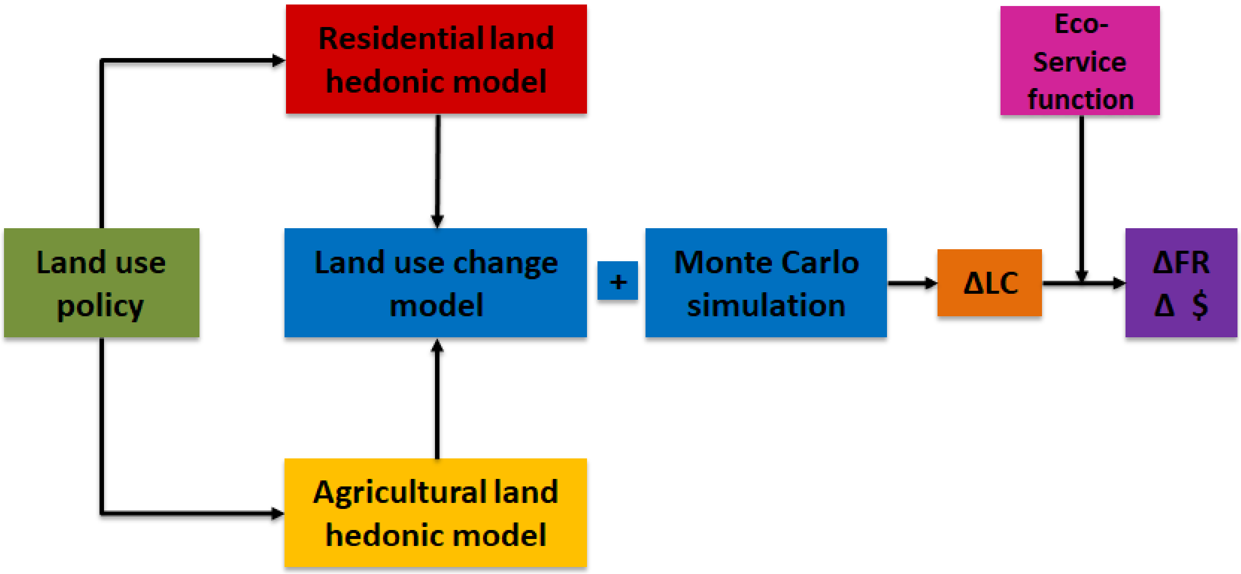


Figure 1.1: Analytical framework. The results from separate hedonic models of land value inform a model of land use change that is used in Monte Carlo simulation to generate future landscapes. Future landscapes may exhibit changes in land cover composition (ΔLC) which in turn influence land values and 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.

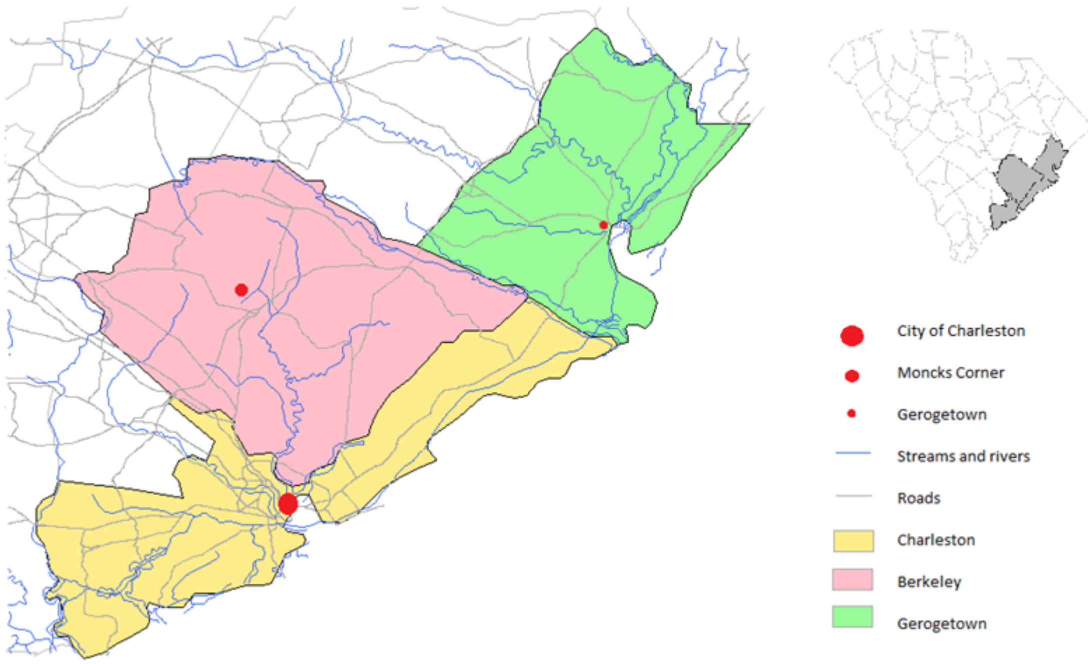


Figure 3.1: The study area.

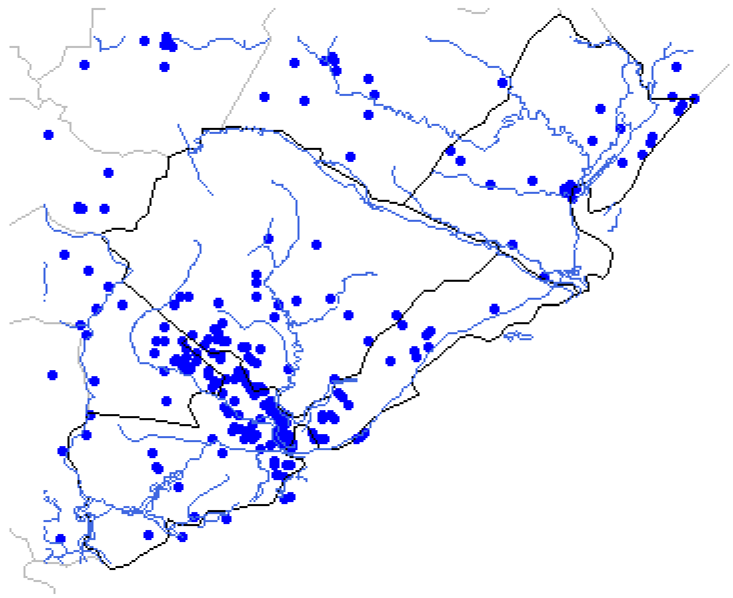


Figure 3.2: Location of flash floods, floods, and coastal flooding incidents (1996–2016).

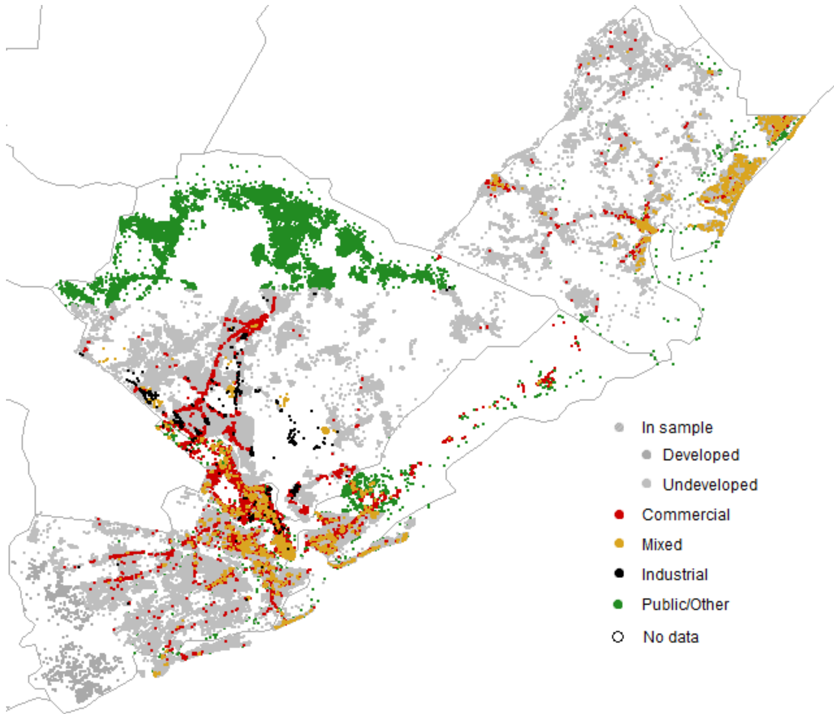
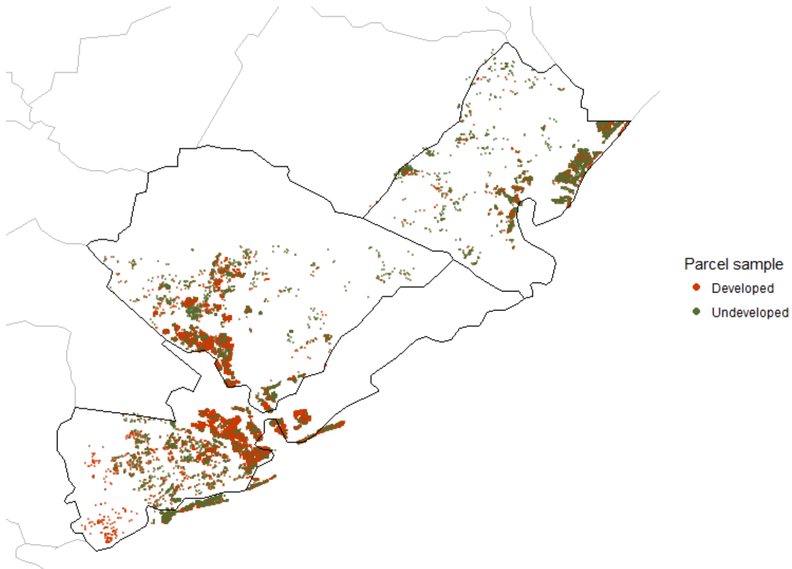


Figure 3.3: Location of selected parcels that are included in the final sample relative to parcels not included in the sample. Parcels that were excluded were zoned commercial, industrial, public, or were in mixed uses.

(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.

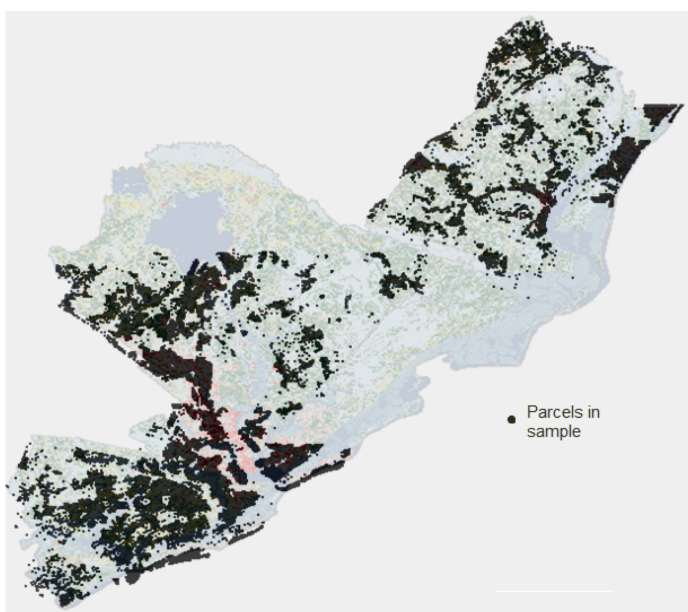


Figure 3.4: Parcel selection, land uses, and land covers.

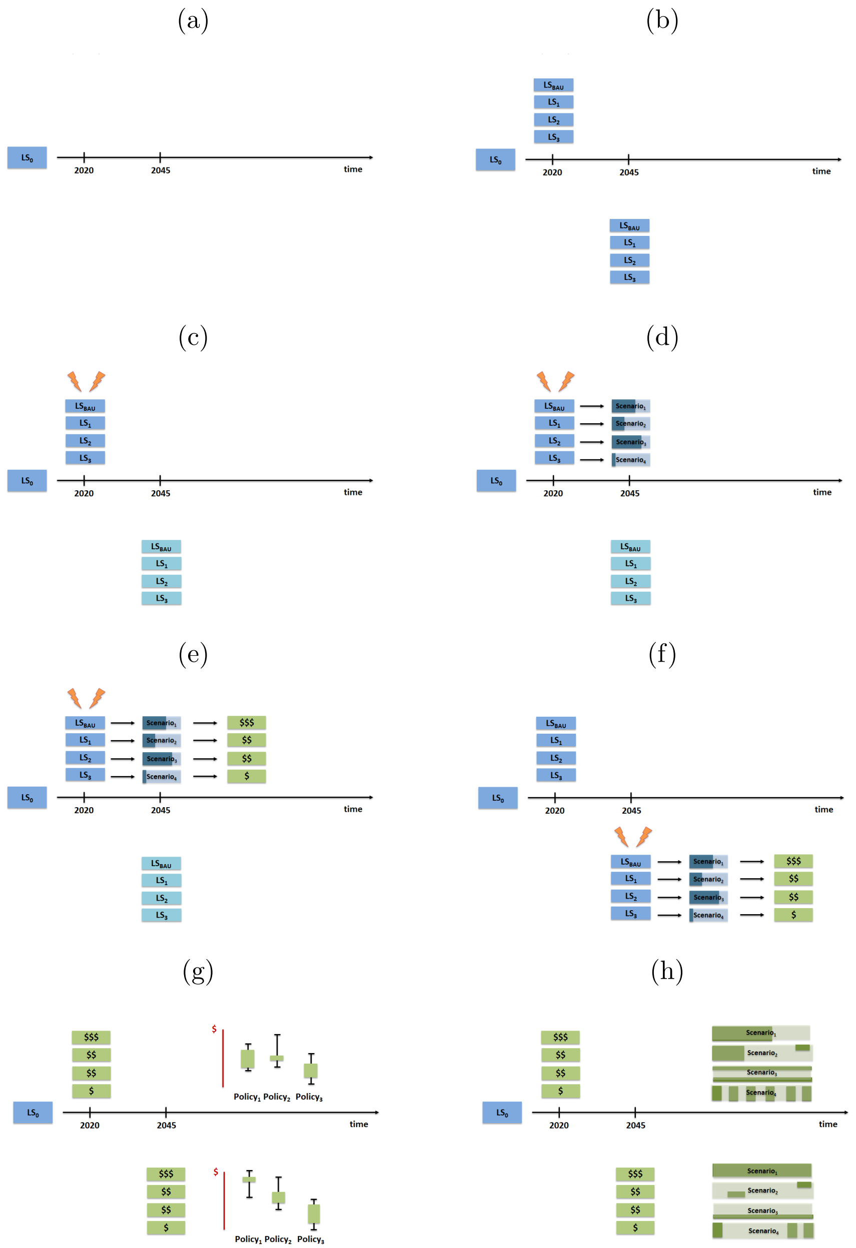


Figure 4.1: Steps for comparing alternative land use policies in their ability to mitigate risks and damages from major floods. Panel (a) shows the original state of the landscape. Panel (b) shows the starting point for policy comparison: the generated alternative future landscapes. Panel (c) shows step 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.

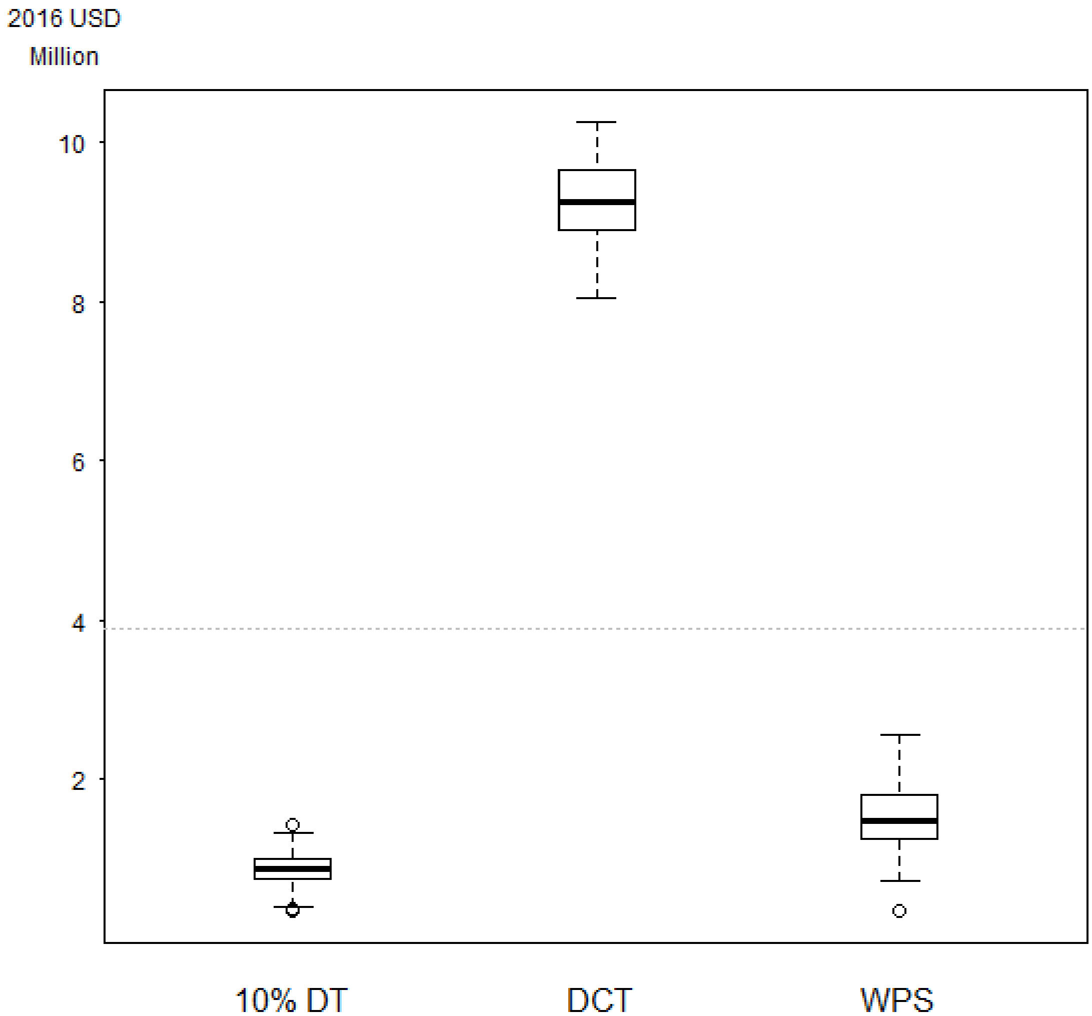


Figure 4.2: Short–term (5 years) benefits comparison: expected savings in NFIP payments using estimates of average NFIP claim in South Carolina ($2016). The average saving across all simulations is indicated by the dotted gray line. In the boxplot, the thick middle line corresponds to the median, and 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.

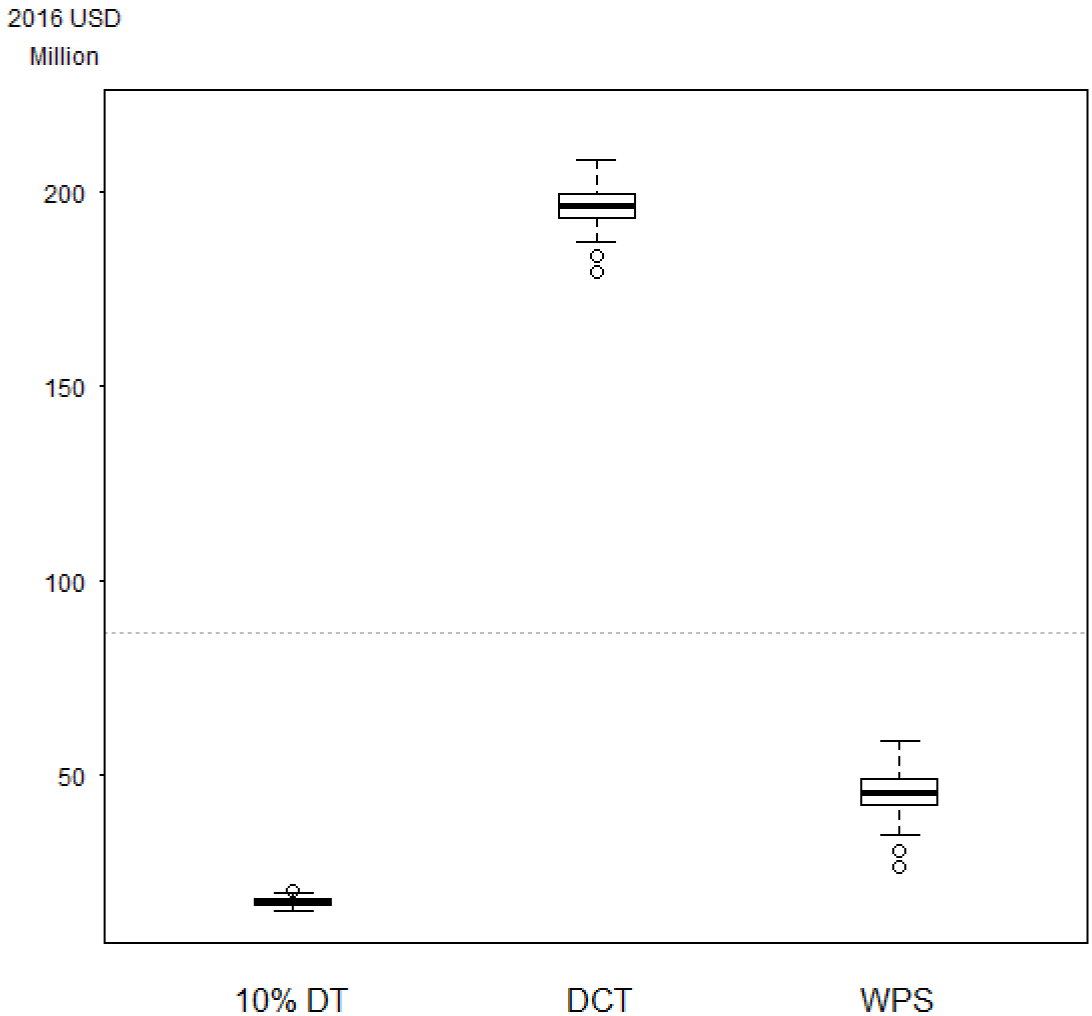
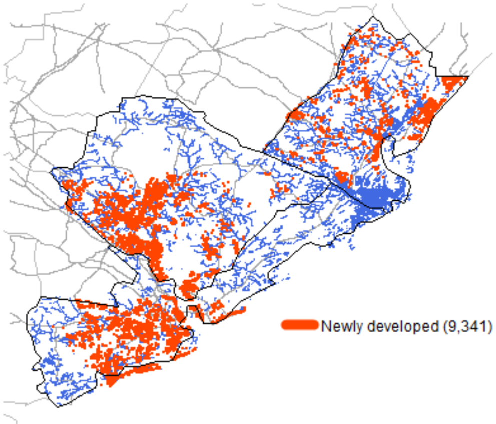
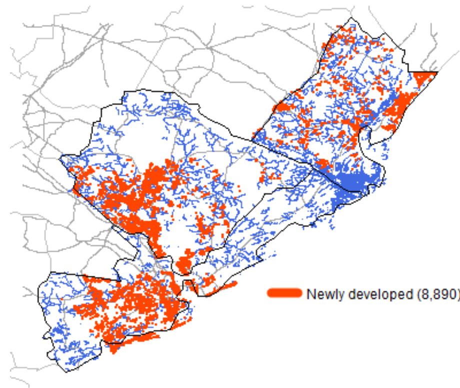


Figure 4.3: Short–term (5 years) costs comparison: foregone added value to the landscape (in \$2016). The average foregone added value across all simulations is indicated by the dotted gray line. In the boxplot, the thick middle line corresponds to the median, and the edges of the box to the first and 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.

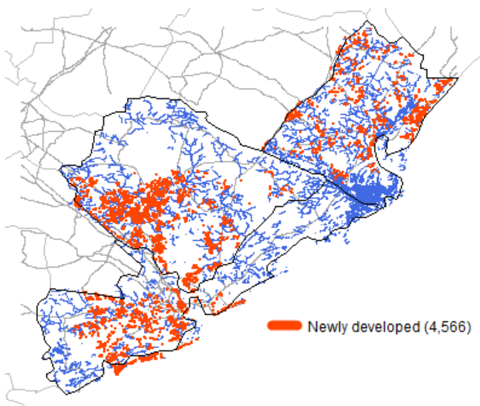
(a) Business as usual scenario.



(b) 10% tax on development.



(c) Tax on developed covers.



(d) Subsidy on wetland covers.

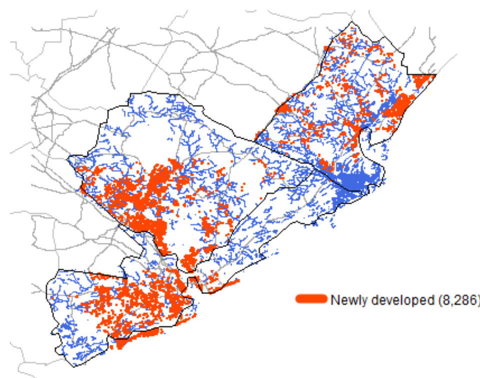
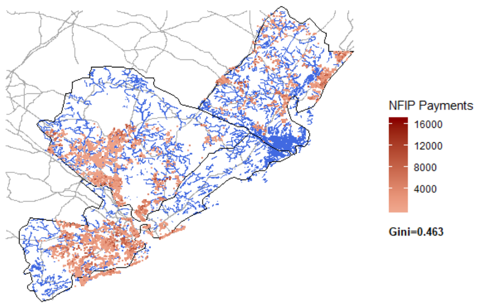
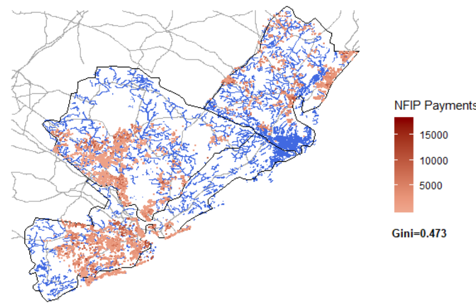


Figure 4.4: Short–term (5 years): maps of predicted development under various policy regimes. The number of developed parcels under each scenario are in parenthesis. Gray lines are major roads and blue lines are streams and rivers.

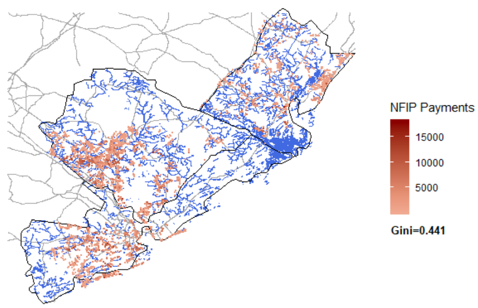
(a) Business as usual scenario.



(b) 10% tax on development.



(c) Tax on developed covers.



(d) Subsidy on wetland covers.

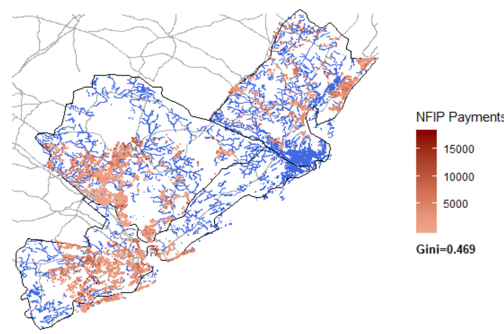
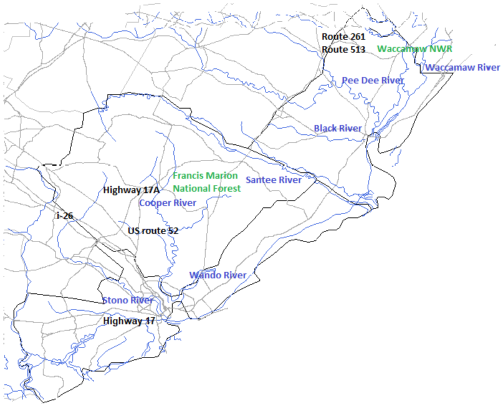
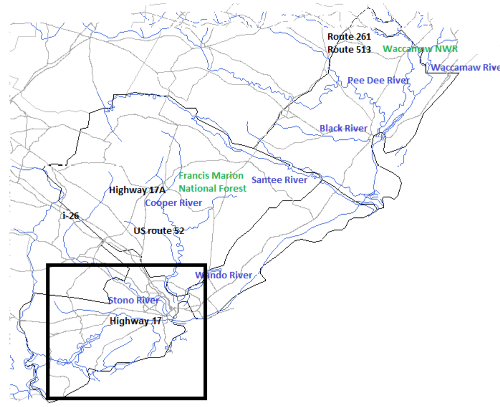


Figure 4.5: Short–term (5 years): maps of expected damages from a major flood under various policy regimes 5 years into the future. Maps show the Gini coefficient associated with each scenario. Gray lines are major roads and blue lines are streams and rivers.

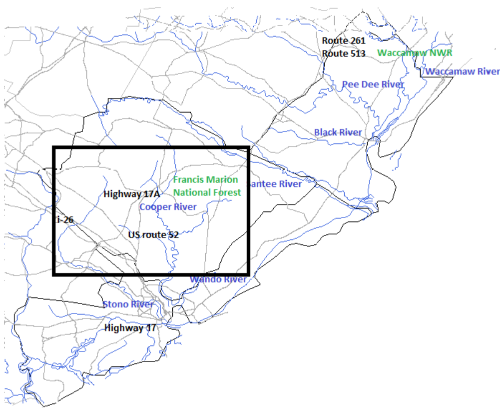
(a) Region with key features.



(b) Southern coast Charleston.



(c) Central and West Berkeley.



(d) Georgetown proper.

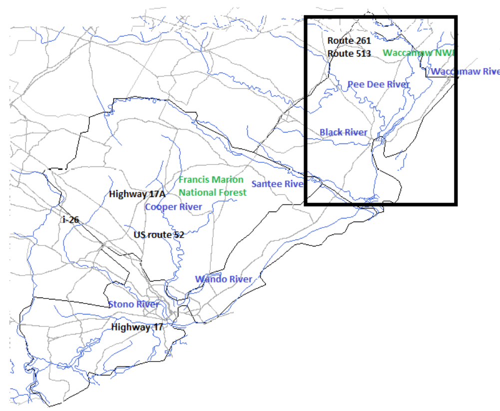
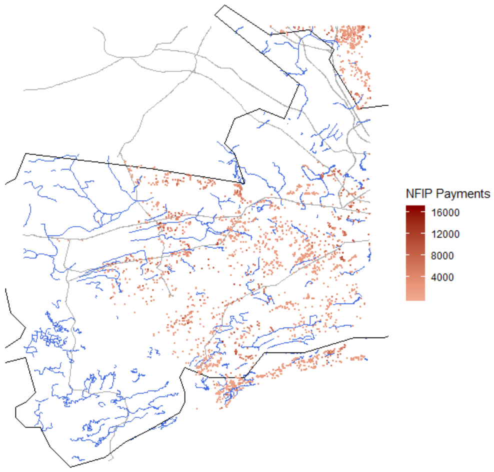
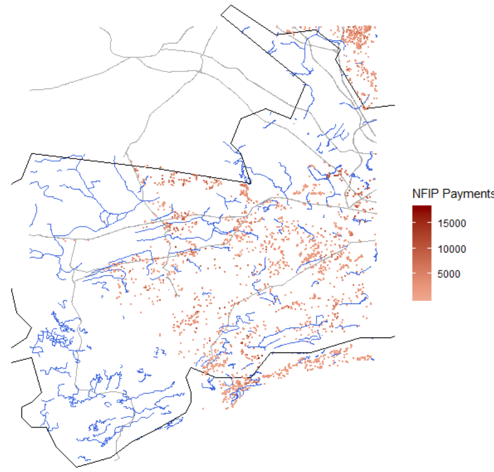


Figure 4.6: Selected regions of study area where impacts from policies differ the most.

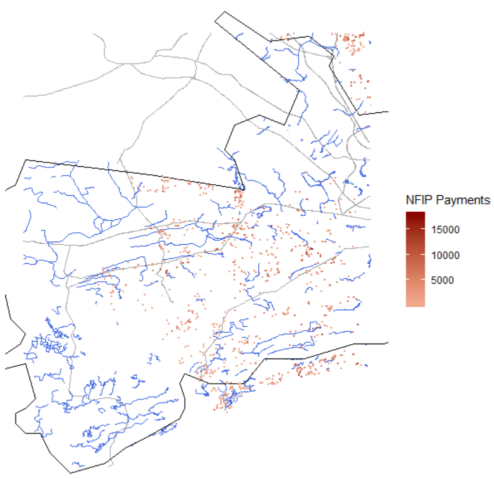
(a) Business as usual scenario.



(b) 10% tax on development.



(c) Tax on developed covers.



(d) Subsidy on wetland covers.

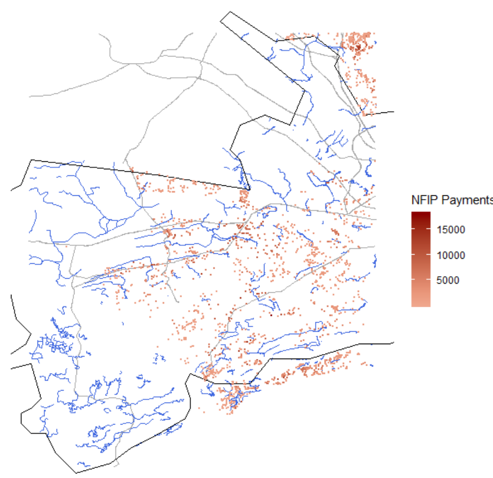
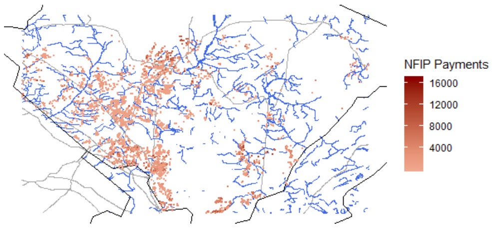
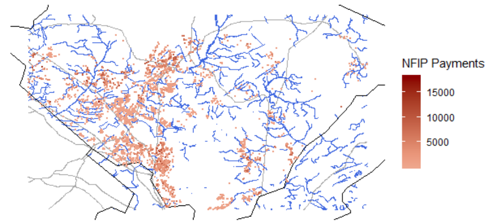


Figure 4.7: Short–term (5 years): maps of expected damages from a major flood under various policy regimes in the South Charleston subregion. Gray lines are major roads and blue lines are streams and rivers.

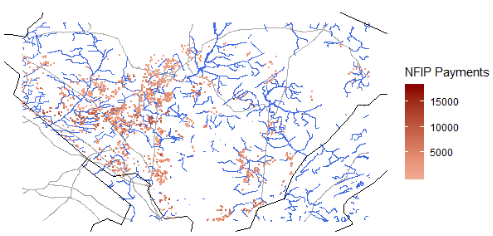
(a) Business as usual scenario.



(b) 10% tax on development.



(c) Tax on developed covers.



(d) Subsidy on wetland covers.

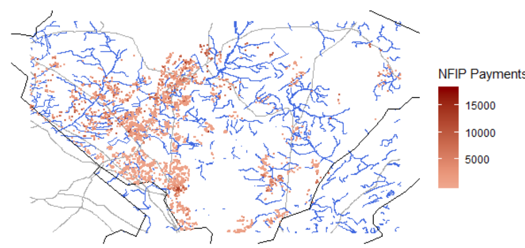
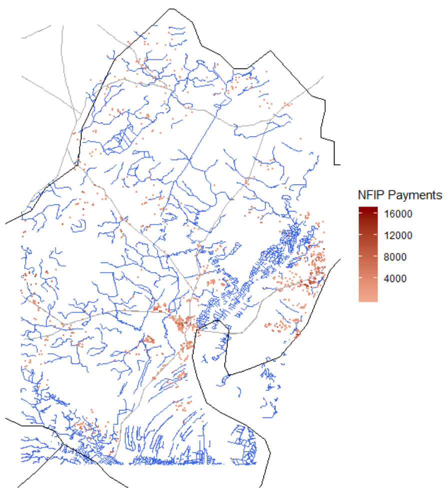
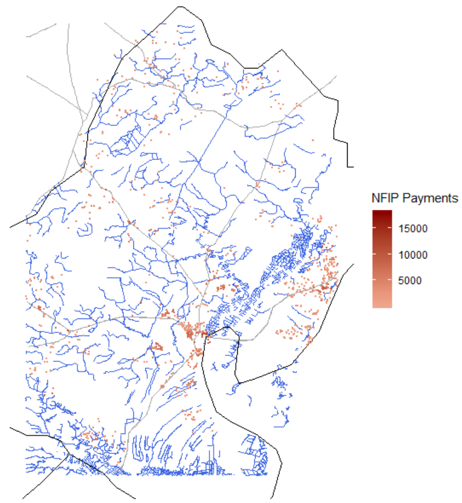


Figure 4.8: Short–term (5 years): maps of expected damages from a major flood under various policy regimes in the Central Berkeley subregion. Gray lines are major roads and blue lines are streams and rivers.

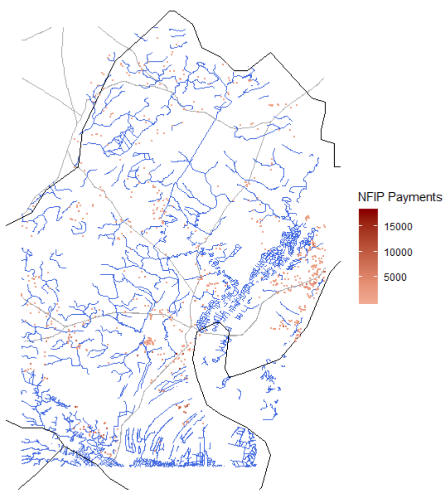
(a) Business as usual scenario.



(b) 10% tax on development.



(c) Tax on developed covers.



(d) Subsidy on wetland covers.

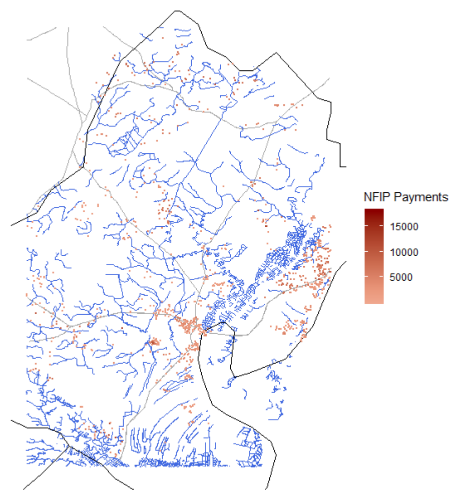


Figure 4.9: Short–term (5 years): maps of expected damages from a major flood under various policy regimes in a subregion of Georgetown. Gray lines are major roads and blue lines are streams and rivers.

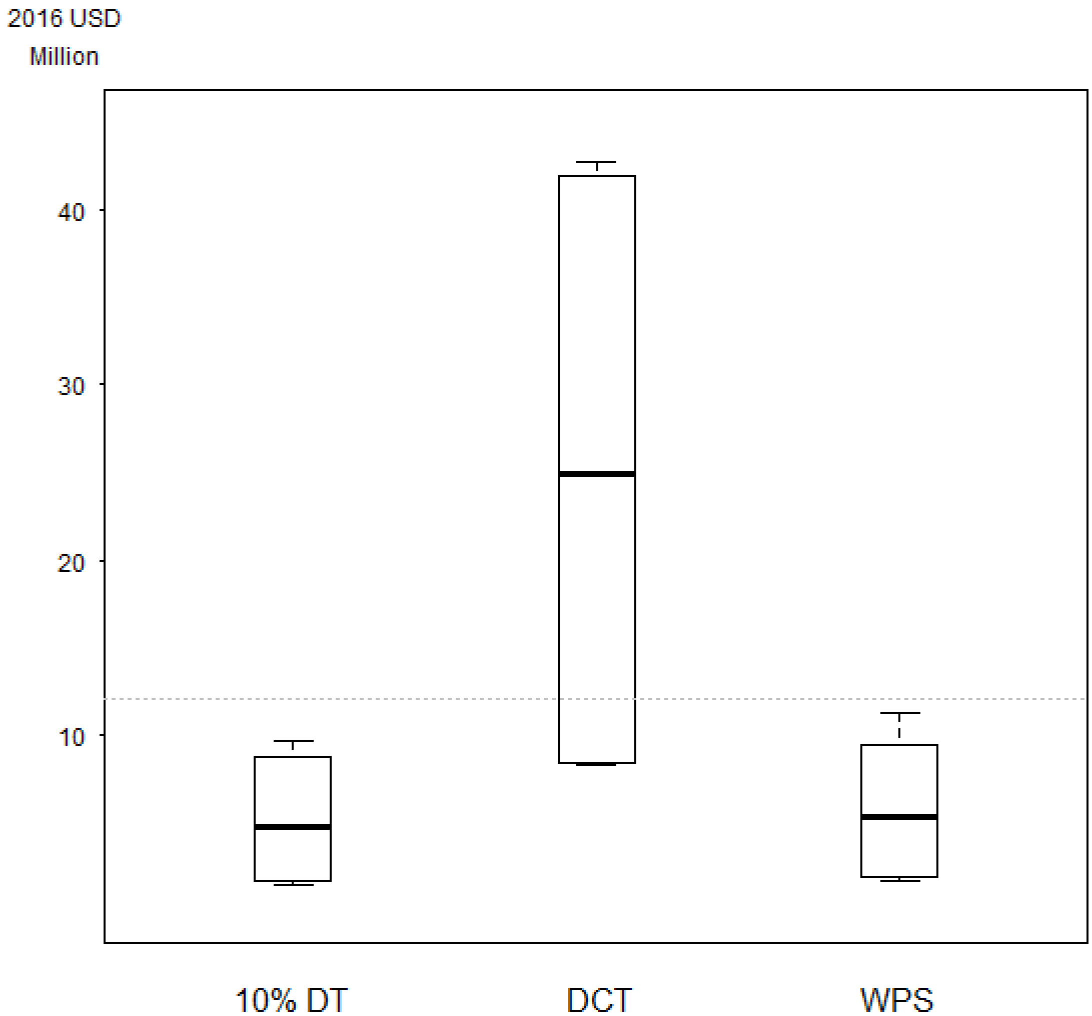


Figure 4.10: Long–term (25 years) benefits comparison: expected savings in NFIP payments using estimates of average NFIP claim in South Carolina ($2016). The average saving across all simulations is indicated by the dotted gray line. In the boxplot, the thick middle line corresponds to the median, and 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.

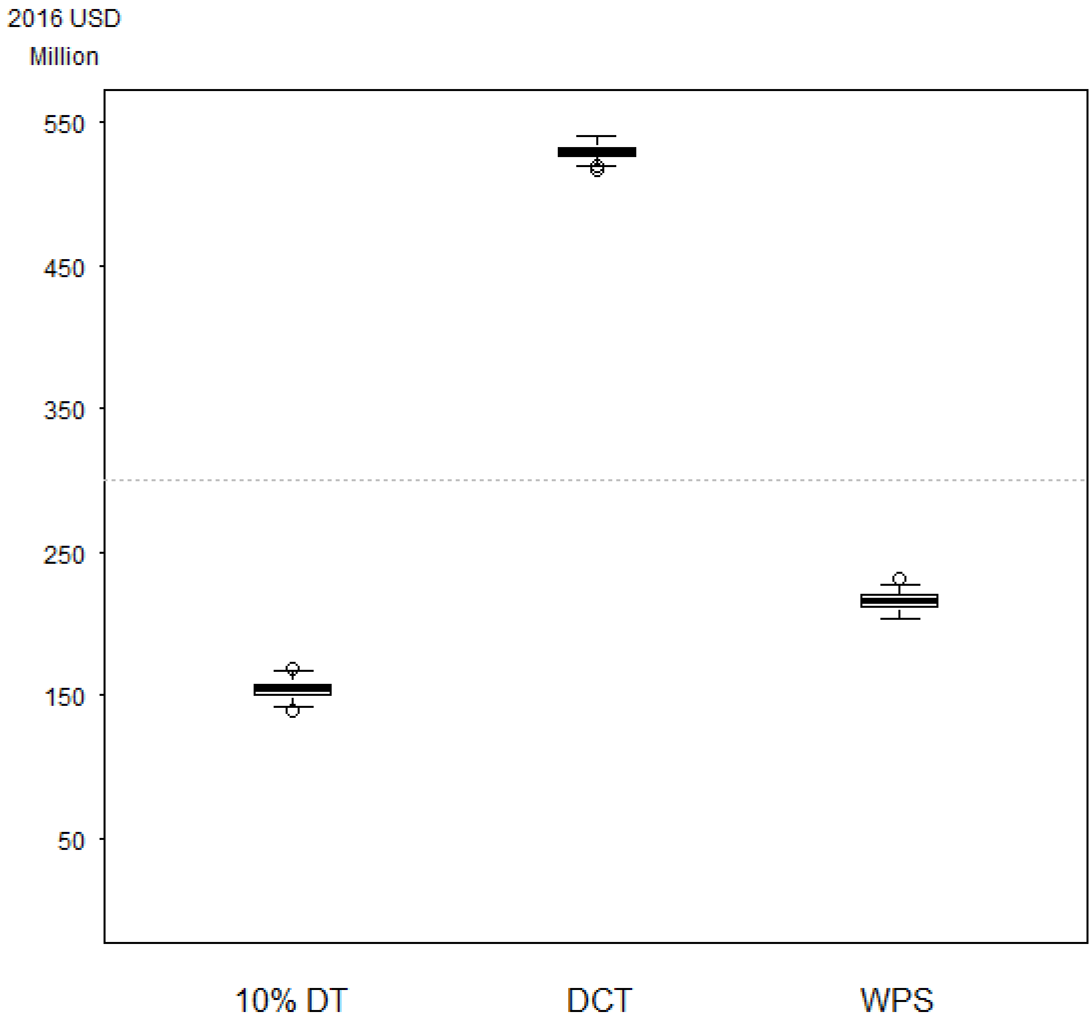
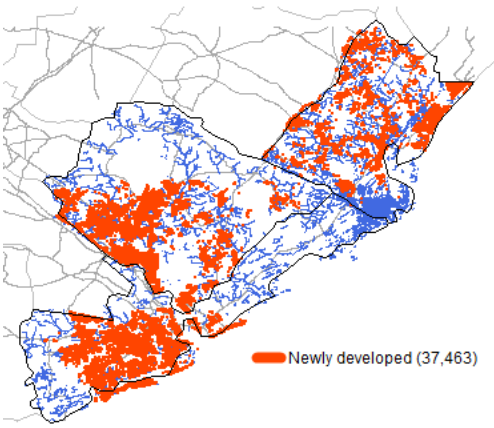
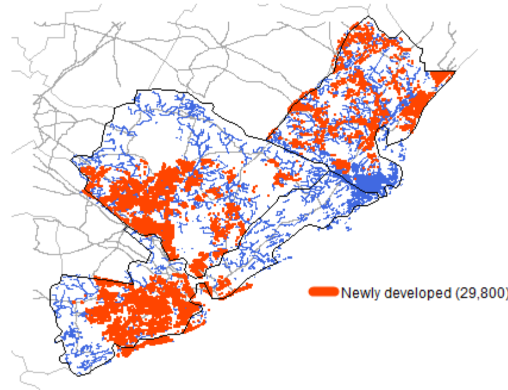


Figure 4.11: Long–term (25 years) costs comparison: foregone added value to the landscape (in $2016). The average foregone added value across all simulations is indicated by the dotted gray line. In the boxplot, the thick middle line corresponds to the median, and the edges of the box to the first and 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.

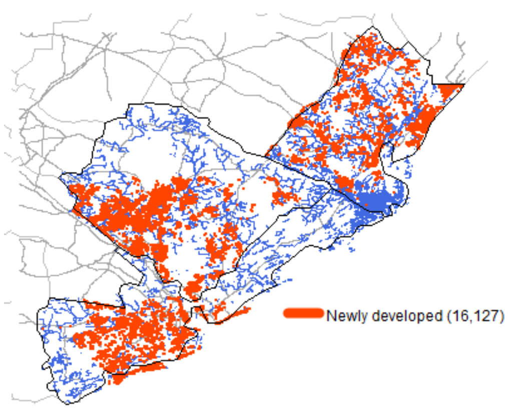
(a) Business as usual scenario.



(b) 10% tax on development.



(c) Tax on developed covers.



(d) Subsidy on wetland covers.

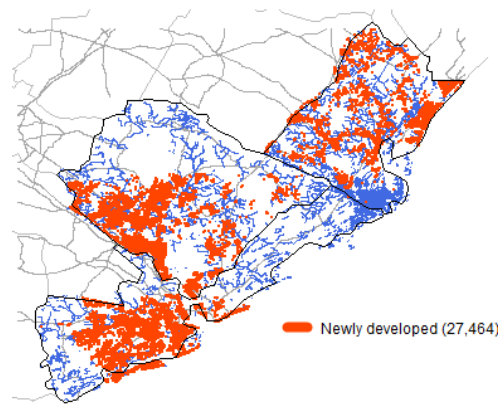
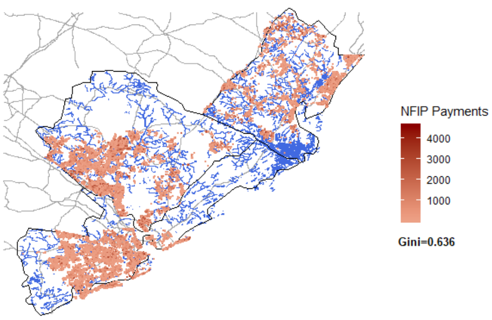
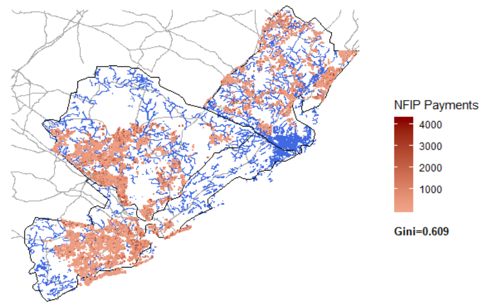


Figure 4.12: Long–term (25 years): maps of predicted development under various policy regimes. The number of developed parcels under each scenario are in parenthesis. Gray lines are major roads and blue lines are streams and rivers.

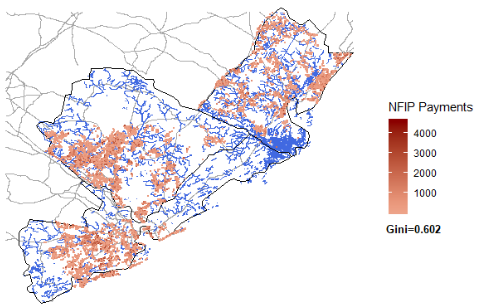
(a) Business as usual scenario.



(b) 10% tax on development.



(c) Tax on developed covers.



(d) Subsidy on wetland covers.

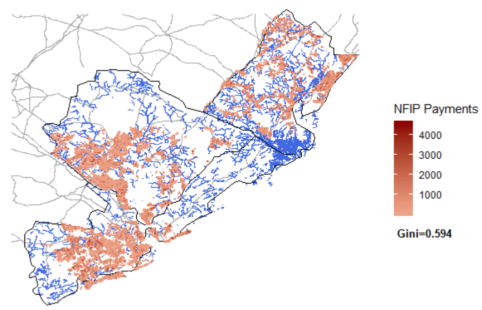
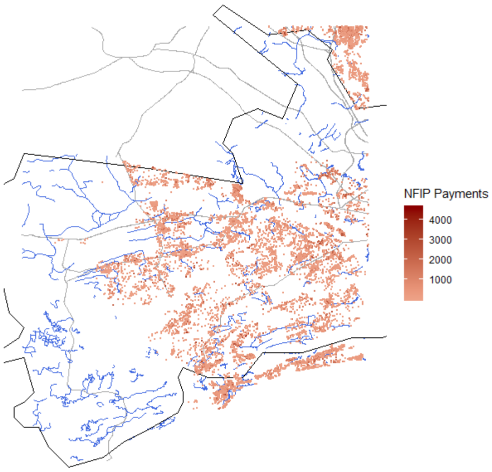
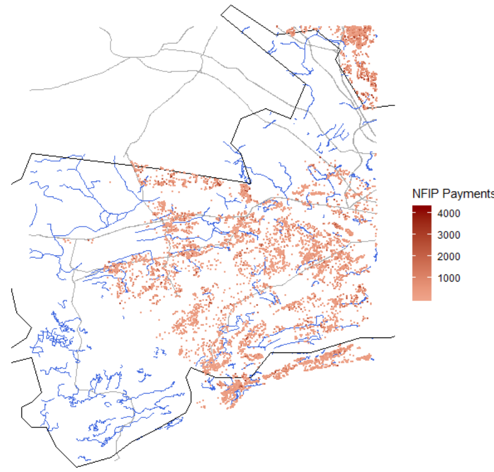


Figure 4.13: Long–term (25 years): maps of expected damages from a major flood under various policy regimes 25 years into the future. Maps show the Gini coefficient associated with each scenario. Gray lines are major roads and blue lines are streams and rivers.

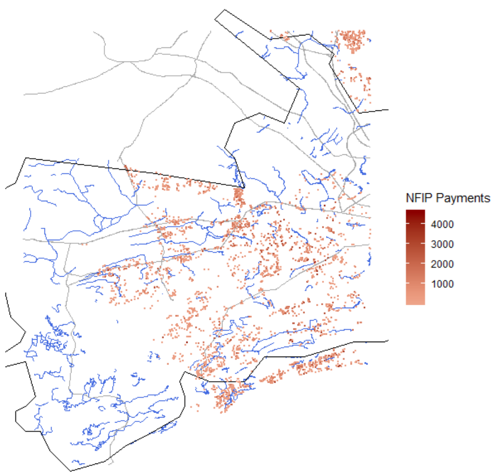
(a) Business as usual scenario.



(b) 10% tax on development.



(c) Tax on developed covers.



(d) Subsidy on wetland covers.

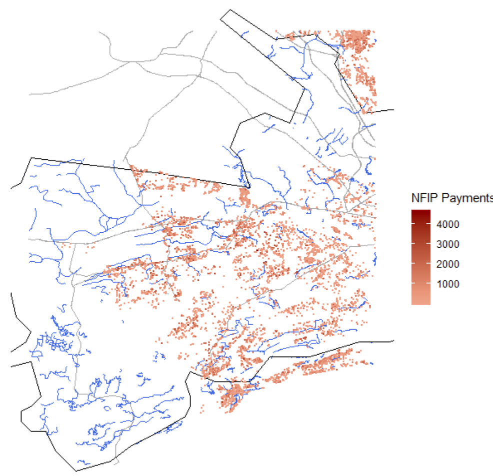
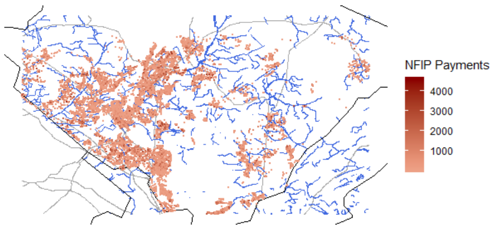
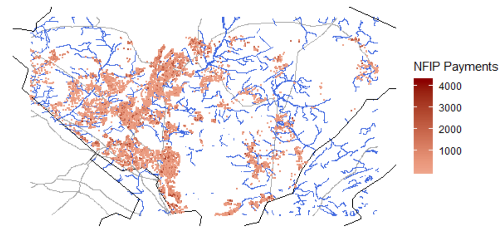


Figure 4.14: Long–term (25 years): maps of expected damages from a major flood under various policy regimes in the South Charleston subregion. Gray lines are major roads and blue lines are streams and rivers.

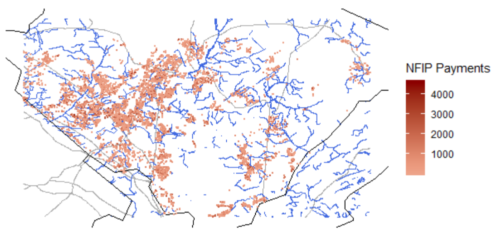
(a) Business as usual scenario.



(b) 10% tax on development.



(c) Tax on developed covers.



(d) Subsidy on wetland covers.

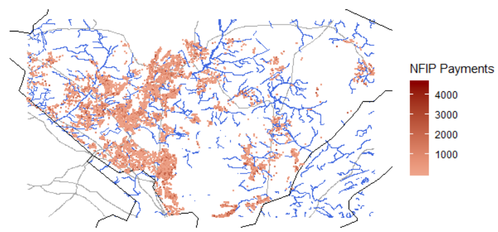
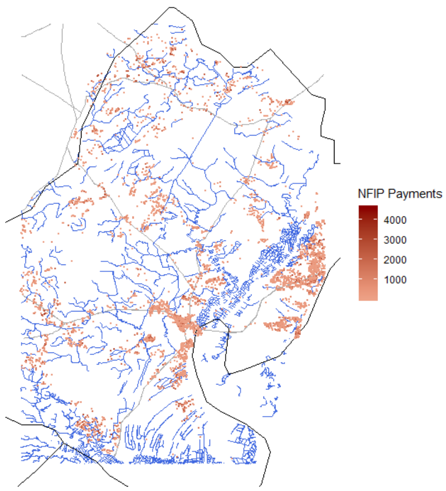
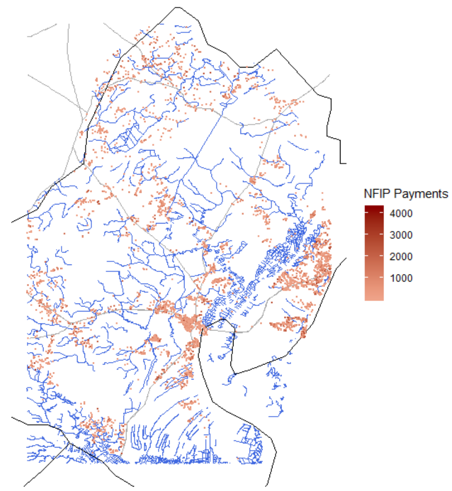


Figure 4.15: Long–term (25 years): maps of expected damages from a major flood under various policy regimes in the Central Berkeley subregion. Gray lines are major roads and blue lines are streams and rivers.

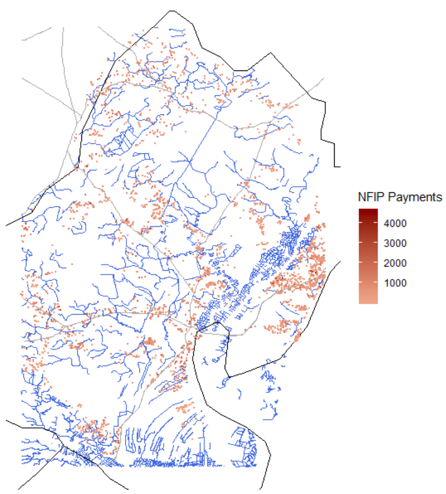
(a) Business as usual scenario.



(b) 10% tax on development.



(c) Tax on developed covers.



(d) Subsidy on wetland covers.

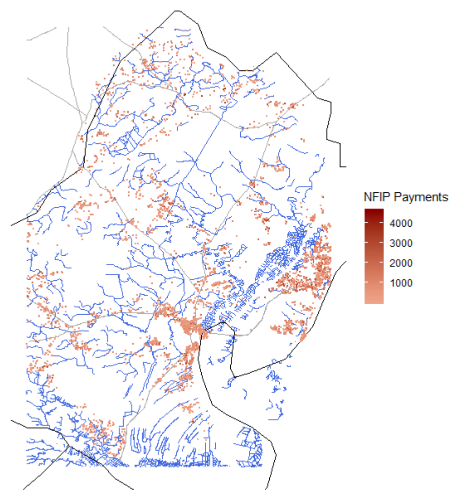


Figure 4.16: Long–term (25 years): maps of expected damages from a major flood under various policy regimes in a subregion of Georgetown. Gray lines are major roads and blue lines are streams and rivers.