1. Overview

1.1. Purpose

The overall purpose of this model is to explore how feedbacks between housing and land markets influence the conversion of undeveloped land (e.g., agriculture) to residential housing. The agent-based model (ABM) presented here is a version of the CHALMS model (Magliocca et al., 2011, 2012) that has been adapted to a coastal landscape subject to uncertain impacts from coastal storms (C-CHALMS). The goal of the model is not to simulate the development patterns and market dynamics of any particular location. Rather, the aim is to isolate psychological and perceptual factors that influence location and adaptation decisions and their effects on key interactions between housing and land markets (particularly the timing and proximity to the coast of land conversion. The model investigates how agent-level decisions and interactions through markets link to market- and landscape-level outcomes, such as housing and land prices and extent and configuration of residential development, respectively. Further, the goal is to understand how residential housing consumers make trade-offs between amenities and risks of damages from storms given location near the coast, and how those trade-offs do or do not influence adaptive decisions in response to storms, such as purchasing insurance and/or relocating to less risky areas.

1.2. Entities, state variables, and scales

Entities represented in the model include three types of agents (Table 1) and spatially-explicit land parcels of one acre in size (Table 2).

1.2.1. Agents

Three agents are represented: residential housing consumers (or simply ‘consumers’ from here on), landowners, and a representative housing developer. *Consumers* are heterogeneous in incomes and preferences for location and coastal amenity level. Consumers form individual, dynamic expectations of the annual probability of coastal storm occurrences (i.e., subjective risk perception), which are used to estimate associated expected damages for each available house given proximity to the coast. Based on these risk perceptions, new consumers make location decisions, and existing residents decide whether to relocate or purchase insurance in response to storm events. Each time step consumers observe all available houses and calculate their utility (see *Objective Function*) for all available housing given current housing asking prices, housing locations, and perceived risk of storm damages. Consumers also observe how many other consumers are bidding on the same houses on which they bid and adjust their bid to be more competitive (see *Interactions*).

Landowners decide each time step whether it is more profitable to sell their land holdings to a developer or continue to maintain ownership and the current land use. At the initialization of each simulation, all landowners are assumed to know the potential surplus above their reservation price that would be gained by selling their land given their proximity to the coast. As dynamic simulation commences, landowners update land prices expectations. Landowners form dynamic expectations of future land prices based on interactions with the developer and observations of past land transactions elsewhere on the landscape.

A single representative *developer* purchases land from landowners, building in locations that maximize expected profit, and sets the asking prices or newly constructed and/or vacated houses to sell to consumers. The developer observes the competitive bidding process among consumers for the existing housing stock, and forms expectations of future prices based on observed prices. The developer then extrapolates price expectations to all undeveloped locations on the landscape. Developer demand for land is then calculated as the difference between expected future population growth and the combination of currently vacant houses and owned but undeveloped land. If demand exceeds currently available housing, bid prices for land are formed for each undeveloped land parcel based on these price expectations net of construction costs. If a transaction is possible (see *Submodels*), the developer acquires land and recalculates expected profits for each housing type given the transaction price(s) for land. New housing is constructed and placed on the market the same year as the land purchase. This assumption simplifies the construction process, which can include an extended construction period from many possible and uncertain sources (e.g., weather, policy change). Using the price expectations formed before housing construction, the developer sets asking prices for available houses.

Table 1: Attribute of consumer, landowner, and developer agents.

Agent Type	Attribute	Description
Residential housing consumer	Income	Annual household income spent between housing and all other goods (i.e., 'consumer good'). Incomes are heterogeneous among agents and drawn randomly from a log-normal distribution with μ=\$86,450 and σ=\$39,095 and a range of [40,000, 200,000].
	Share of income spent on housing	Proportion of income spent on housing in Cobb-Douglas utility function. This proportion varies based on income level: \$40-\$80k is .35–.42; \$80-\$120k is .27–.34; and > \$120k is .18–.26 (see *Objectives*).
	Coastal amenity preference	Proportion of income spent on housing allocated proximity to coastal amenity with a range of [0.1,0.9]. Must sum to one in combination with house and lot size preferences.
	Subjective risk perception	Dynamically updated based on direct experience (or lack thereof) of storm events.
	Moving costs	Set to 10% of the consumer's annual income.
Landowner	Land holdings	The spatial location and total size of the land parcels owned by a landowner agent. Each landowner is assigned 100 acres each (10-by-10 cells).
	Reservation land price	The economic returns generated from the land parcels in the highest value, undeveloped state. Along the coast, this is equal to the speculative value of the land for development. Further inland, this may be equal to returns from agriculture.
	Willingness to accept (WTA) for land	Minimum price per acre that the landowner would be willing to sell to a developer. As development pressure increases, WTA and exceed the reservation price.
	Land price expectation models	Set of twenty price prediction models with five different prediction strategies. Predictions of price in *t+1* are based on past observations (see *Agent Prediction*).
Residential developer	Land holdings	Spatial locations and number of land parcels purchased from landowners for development.
	Housing price expectation models	Similar to landowners, the developer is assigned a set of twenty price prediction models with six different prediction strategies. Spatially explicit predictions of prices for each house and lot size combination in *t+1* are based on past observations (see *Agent Prediction*).
	Profit target	Equal to normal rate of return on investment, assumed to be 5%.

	Willingness to pay (WTP) for land	Maximum price per acre the developer is willing to pay for a landowners holdings based on expected profit.

1.2.2. Environment

The model landscape includes a central business district (CBD) with existing residential development at the start of the simulation periods, and a large area of undeveloped land that is gradually developed as population grows. The landscape is highly stylized and does not represent an actual region, but it is parameterized using information on agricultural values, incomes, house prices, and other information from the Mid-Atlantic region of the U.S. The coast is assumed to be the eastern most edge of the simulated landscape. Coastal amenity values and potential damages from storms vary with distance from the coast (Figure 1). The landscape is divided into 'damage classes' based on proximity to the coast (Figure 2): 'high damage' locations are immediately adjacent to the coast (i.e., waterfront); 'medium damage' locations are within 0.4 miles (10 cells) of the coast but are not on the coast (i.e., 'water view'); and 'low damage' locations are all other houses on the landscape (i.e., inland). High damage class areas are assumed to be at base flood elevation (BFE), and medium and low damage areas are assumed to be at 2 or more feet above BFE. These classifications are assumed to align with those reported in Walls and Chu (in prep) and differences in insurance premiums described by Kousky et al. (2016).

The annual probability of storm occurrence is based on historical averages reported by Costanza et al. (2008). Storms are randomly generated. A random number between 0 and 1 is selected each time step, and if that number is *less than* the historical annual probability a storm is simulated. The severity of storms is not considered here, so the annual probability of storm occurrence is the aggregate of historical probabilities of storms of any severity. Expected damages from a storm event, expressed as percent annualized property value loss, are estimated with an empirically-based, spatially-explicit damage function that decays with distance from the coast (see *Implementation Details*). Storm costs, C, as percent of property value and as a function of distance from coast, *d* (in 1000s of feet), are estimated as:

(1) $$C = 9.19 - 0.205d + 0.001d^2$$

The value of the coastal amenity, *a*, is specified with an exponentially declining function with distance from the coast:

(2) $$a = A_0^{-rd};$$

where *r* is the rate of decline, *d* is distance from the coast, and A_0 is a maximum amenity value at the coast. The general shape of the amenity function is based on the hedonic property value literature that has assessed the value of ocean views and proximity (e.g., Benson et al., 1998; Bin et al., 2008; Gopalakrishnan et al., 2011; Major and Lusht, 2004). This literature generally finds that the capitalization of the coastal amenity in house prices falls of steeply with distance to the coast. The parameterization of this amenity function sets the amenity level at the coast to double the value of 0.4 miles inland.

Table 2: Attributes of the landscape that vary by location.

Attribute	Description
Area	Each land parcel (i.e., grid cell) represents one acre.
Proximity to the central business district (CBD)	Spatial location relative to the centroid of the CBD, measured in miles.

Travel cost	Annual cost of transportation to and from house location and CBD at a rate of $25. 85 per cell ($1.30/mile, 0.0395 miles per cell, and 500 miles traveled per year; Magliocca et al., 2011).
Proximity to the coastline	Spatial location relative to the coast, measured in miles.
Coastal amenity level	Unit-free amenity level that decays with distance from the coast (Eq. 2). For baseline settings, the amenity level at the coast (A_o) is 500,000, and the rate of amenity decline with distance from the coast (r) is 0.08.
Housing price neighborhood	Contiguous developed land parcels from which the developer perceives housing prices for each housing type to inform future price expectations.
Housing size	Square footage of house built on one land parcels (all houses are 2,000 ft^2).
Lot size	All lot sizes are 1 acre.
Population growth	The number of potential consumers grows by 10% of residents each year. In other words, the number of located consumers (i.e., residents) may grow by more or less in a given year, but the number of consumers added to the pool of consumers bidding on housing grows by 10% of the resident population annually.
Annual storm probability	Based on historical averages reported by Costanza et al. (2008). Severity is not considered for simplicity, so the annual storm probability is the cumulative probability of a storm of any severity occurring. Four storm climates are implemented: Mid-Atlantic region (p=0.025; Maryland, Virginia, Delaware, New Jersey, and Pennsylvania), North Carolina (p=0.299), Texas (p=0.383), and Florida (p=0.714)
Storm damage classification	Categorization of locations based on potential damages from storms. Classifications are waterfront (immediately adjacent to coast), waterview (within 0.2 miles from coast), and inland.
Expected storm damages	Percent of annualized property value loss incurred by the resident if a storm should occur based on simulate flood depths from the Hazus-MH model based on a 100-year storm. Expected damages decay with increasing distance from the coast (Eq. 1).
Insurance coverage and premiums	Insurance coverage is assumed to be the minimum of $250,000 of building coverage or the housing price. Premiums are vary continuously over space based on distance to the coast. Waterfront properties and the inland-most cell (western edge) assume the maximum and minimum premiums for 100-yr floodplain properties as reported by Kousky et al. (2016). Premiums in between decrease linearly with distance from the coast at a constant rate.

1.2.3. Spatial and Temporal Scales

The landscape is modeled at a 1-acre resolution, and the full landscape covers 6,400 acres (80 acres square, or 10 square miles). In each period, land use and pricing decisions are made for each 1-acre cell. Simulation is executed for a total of thirty time steps – each time step representing a year – with the first ten time steps as model spin-up with a static landscape and the following twenty as dynamic simulation.

1.3. Process overview and scheduling

The following provides a simplified version of the process overview and scheduling. For more detail regarding each process or agent attribute involved (*italics*), please see the submodels section below. At initialization, agent attributes are assigned and landscape configuration set. The CBD is initialized with a mix of housing options and prices set through an iterative spin-up of the housing market (see *Initialization*). After initialization, the following sequence of processes repeat every time step.

- **Storm occurrence**: A random draw determines whether a storm occurs in the given period (see *Environment*).
- **Update risk perception**: Existing residents update perceived annual risk of storm events given the occurrence (or not) of a storm in the current time step (see *Dynamic Subjective Risk Perception*).
- **Adaptive resident decisions**: Currently located consumers (i.e., residents) re-evaluate the utility of their current house given updated perceived storm probability, expected damages given the location, choice to purchase insurance (or not), and alternative utilities from moving to another available house in the region or outside of the modeled region. Existing consumers that have not located and new incoming consumers account for update risk perception in location choices (see *Adaptive Responses*).
- **Spatially explicit rent expectations**: The developer observes transaction prices and demand for each housing type and location and for expectations for future rents accounting for expected population growth. Rent expectations are extrapolated to all undeveloped locations in the landscape (see section 2.2.1.2 and *Submodels*).
- **Land demand**: The developer observes the number of vacant housing and undeveloped but developer-owned land, and compares the sum of those two quantities to expected population growth in the next period. If more growth is expected than current housing capacity, then the develop proceeds to the land market.
- **Land sales**: Based on spatially-explicit rent expectations, the developer forms per acre bids prices for all undeveloped land based on the average expected profit across all housing types. Landowners observe developer bids and sell land if bid is above their willingness to accept price. The developer purchases the entire land holdings of the landowner.
- **Land price expectations**: Landowners update their land price expectations based on most recent offers from the developer and any transactions that occurred in previous periods.
- **New housing**: Based on transaction prices for land, the developer recalculates expected profits based on rent expectations and builds the profit-maximizing mix of housing on all or some of owned and undeveloped land. The number of houses built depends on expected population growth.
- **Housing sales**: Consumers calculate utility for every available housing option given asking prices, house and lot characteristics, and location. Consumers observe the number of other consumers competing for the same houses and adjust bid prices. The highest bidder for each house occupies the house. Newly located consumers also choose whether or not to purchase insurance against storm damages given their perception of risk.

2. Design concepts

2.1. Theoretical and empirical background

CHALMS synthesizes the advances from many ABMs into one framework capable of simulating development density patterns through coupled housing and land markets. Similar to Robinson and Brown

(2009), housing and land markets are linked through the supply and demand functions of the developer and consumer households, respectively; however, our agents respond directly to and create market prices subject to economic constraints. Mechanisms of land and housing transactions in CHALMS are built upon the bilateral transaction framework developed by Parker and Filatova (2008), but are expanded to link the developer's rent expectations in the housing market to his bid prices in the land market. Price expectations play a similar role in CHALMS as they do in Ettema's model (2010). Adaptive expectations of future prices and market conditions are used to compare the utility of present and potential future transactions – directly influencing the timing of transactions. In addition, our agents' price expectation models are designed to capture spatially dependent price trends that directly affect the location of housing and land sales.

Substantial empirical evidence suggests that individual risk perceptions are biased, or subjective (Ludy and Kondolf, 2012), and risk perceptions change over time as new risk information is presented through either direct experience of hazards or indirect information channels (e.g., social networks, management agencies, insurance companies) (Dillon and Tinsley, 2008; Dillon et al., 2011). Thus, subjective risk perception may diverge from the objective probability of a hazard event in response to the number and frequency of events over time. In particular, risk perception may undergo large and immediate changes after a hazard event (Gallagher, 2014). A common Bayesian learning model (Viscusi, 1991) provides a formalization of dynamic, subjective risk perception in which individual housing consumer agents observe the occurrence of a storm event and update their expected probability of future storms (Davis, 2004; DeGroot, 1970). Additionally, empirical evidence demonstrates that not only does risk perception diverge from objective levels over time, but also the rate at which it diverges varies in relation to time since a hazard event. Risk perception dynamics are attributed to homeowners either forgetting past events or not experiencing the full hazard history for a given location (Gallagher, 2014). This is modeled by modifying the Bayesian updating model with a weighting parameter that discounts past information (Camerer and Ho 1999; Malmendier and Nagel 2011).

A myriad of risk-based, economic decision theories have been proposed that incorporate concepts, such as loss aversion, probability weighting, and intra- and inter-personal influences, to explain decision patterns that diverge from predictions of expected utility maximization. Foremost among these is Prospect Theory (Kahneman and Tversky, 1979), which posits loss aversion results from an over-valuing of potential losses versus equal potential gains relative to a given reference point. This is often implemented by 'probability weighting', which over-weights low probability, high impact outcomes (e.g., Barseghyan et al., 2014; Kőszegi and Rabin, 2007; Sydnor, 2010). However, PT is limited in two important ways in the context of valuing alternative behavioral options under risk: 1) the reference point may be arbitrary and/or is difficult to estimate empirically (Barberis, 2013), and 2) it cannot explain observed risk-seeking behavior in situations of perceived high payoffs (Bordalo et al., 2012). For these reasons, we adopt Salience Theory presented by Bordalo et al. (2012), which formalizes probability weights as a function of payoffs. Rather than specifying outcomes relative to a reference point, each outcome is valued based on the relative salience of its payoffs (i.e., magnitude of change relative to one another), and perceived probabilities of each outcome are thus increased (decreased) for more (less) salient outcomes. This is consistent with the structural assumptions of many PT scholars that specify reference points based on expectations of future outcomes rather than stationary or internal value (Barseghyan et al., 2014). Salience Theory goes a step further to eliminate the need for a reference point and is instead based on the valuation of expected payoffs for each potential outcome, which has been demonstrated to predict situations of risk-seeking behavior in laboratory experiments (Bordalo et al., 2012). The ability to capture risk-seeking behavior is particular appealing in the context of the work presented here in which residential location decisions in close proximity to the coast can be interpreted as pursing the large payoffs of high coastal amenity values despite a risk of significant damages in the event of coastal storms.

2.2. Agent decision-making

2.2.1. Objective functions

The model is designed to accommodate two alternative consumer valuation methods for making location and adaptation decisions: utility maximization and salience value. Formalizations of each are presented in the next sections.

2.2.1.1. Residential housing consumer utility maximization

Residential housing consumers competitively bid with other consumers to maximize utility from housing given asking price, personal budget constraints, location, perceive risk of storm damage, and competition from other consumers. A consumer *c* calculates standard Cobb–Douglas utility derived from the consumption of a general consumption good and a housing good. Each housing good can be considered a 'bundle' of locational features and their associated utility (Table 2). Consumer c's utility function has a Cobb–Douglas form:

$$U(c,i) = x^{\alpha_c} a(d_i)^{\beta_c} \tag{3}$$

where α_c and β_c sum to one and are the consumer's idiosyncratic preferences for a consumer good (*x*) and amenity level (*a*) with distance (*d*) from the coast in location *i*, respectively. A consumer's budget constraint is given by:

$$I_c = x + P_{ask|i}\left[1 + \rho(C(d_i) - IP_{d_i}^{cov})\right] + \psi_i + IP_{d_i}^{cost} \tag{4}$$

I_c is income, ψ_i is the travel cost from the location *i* to the CBD, ρ is subjective risk perception of the occurrence of a storm (see *Dynamic Subjective Risk Perception*), *C* is the expected damage from a storm in location *i*, and IP^{cov} and IP^{cost} are the amount of coverage and cost of an insurance premium, respectively, in location *i* with distance from the coast *d*. If the consumer chooses not to purchase insurance, the *IP* terms are equal to zero. The willingness to pay (WTP) of a consumer for any given house is equal to the proportion of the consumer's income that goes towards housing:

$$WTP(c,i) = (I_c - \psi_i - IP_{d_i}^{cost})\left(\frac{\beta_c}{1-\rho(C(d_i)-IP_{d_i}^{cov})}\right) \tag{5}$$

The WTP represents the ceiling price a consumer would pay for the optimum (i.e., utility-maximizing) housing option. WTP is further discounted for each available house relative to the optimum housing option for form a bid price (see *Submodels*).

Resident consumer agents can respond to storm events by either doing nothing (i.e., no change), purchase insurance against future storm damage costs, or relocate to another available house within the region or outside of the region (i.e., removed from simulation). Relocation decisions within the region consider all available houses, and assessment of relocation to a house outside of the region is calculated utility based on an asking price for a house with zero coastal amenity. See *Adaptive Responses* for more detail.

2.2.1.2. Residential housing consumer salience-based valuation

Decision-making under risk is typically characterized by some type of bias, such as loss aversion, which results in decision outcomes that may different than if the decision-maker had full information about risks. Loss aversion is often formalized as an over-valuing of potential losses versus equal potential gains relative to a given reference point – implemented by ‘probability weighting’ – which over-weights low probability, high impact outcomes (e.g., Barseghyan et al., 2014; Kőszegi and Rabin, 2007; Sydnor, 2010).

Salience Theory (ST; Bordalo et al., 2012) formalizes probability weights as a function of payoffs. Rather than specifying outcomes relative to a reference point, each outcome is valued based on the relative salience of its payoffs (i.e., magnitude of change relative to one another), and perceived probabilities of each outcome are thus increased (decreased) for more (less) salient outcomes.

ST frames decisions under risk as a choice problem between payoffs from two or more ‘lotteries’. In this context, lotteries are analogous to different behavioral options for each current or potential residential location. Specifically, a new housing consumer agent will choose between locating in a particular location with or without insurance given their expected probability of storm damages. This is formalized as a set of possible states (S) where each state $s \in S$ occurs with a probability π_s and has payoffs of x_s^j for the behavioral options L_j. With these dimensions of the choice problem, a salience function is calculated as:

(6) $$v\left(x_s^j, x_s^{-j}\right) = \frac{\left|x_s^j - x_s^{-j}\right|}{\left|x_s^j\right| + \left|x_s^{-j}\right| + \theta}$$

where θ=1. The salience of a state for L_j increases in the distance between its payoff (x_s^j) and the payoff x_s^{-j} of the alternative lottery.

In this case, j=1,2 corresponding to locating in a location i without or with insurance with s=1,2 corresponding to no storm event and the occurrence of a storm event, respectively. Payoffs from these outcomes are enumerated as follows:

(7) $$x_1^1 = \left(I_c - \psi_i - P_{ask|i}\right)^{\alpha_c} a(d_i)^{\beta_c}$$

(8) $$x_2^1 = \left(I_c - \psi_i - P_{ask|i} - IP_{d_i}^{cost}\right)^{\alpha_c} a(d_i)^{\beta_c}$$

(9) $$x_1^2 = \Big(I_c - \psi_i - P_{ask|i} - C(d_i)\Big)^{\alpha_c} a(d_i)^{\beta_c}$$

(10) $$x_2^2 = \left(I_c - \psi_i - P_{ask|i} - IP_{d_i}^{cost} - \left(C(d_i) - IP_{d_i}^{cov}\right)\right)^{\alpha_c} a(d_i)^{\beta_c}$$

The decision-maker then ranks the salience σ of each state s for L_j. This is expressed as $k_s^j \in \{1, \dots, S\}$, with a lower k_s^j indicating higher salience. Given this ranking, decision weights are defined:

(11) $$\omega_s^j = \frac{\delta^{k_s^j}}{\left(\sum_{r=1:S} \delta^{k_r^j} \cdot \pi_r\right)}$$

where $\delta \in (0,1)$ represents a ‘local thinker’ coefficient that controls the distortion of perceived probabilities of each outcome given its salience (Bordalo et al., 2012). Decision weights ω_s^i then modify the perceived probabilities of outcomes by:

(12) $$\pi_s^j = \pi_s \cdot \omega_s^j$$

The salience function is then expressed as a salience value for each outcome $v\left(x_s^j\right)$, which is used to calculate the perceived value (V) of each behavioral option j given the perceived salience of lottery:

(13) $$V(L_j) = \sum_{s \in S} \pi_s^j v(x_s^j)$$

The housing consumer then chooses the behavioral option that maximizes V at each housing location. The more general case of more than two behavioral options is described in *Adaptive Responses*.

2.2.1.3. Developer profit-maximization with risk aversion

The developer uses housing information, which would be available from a listing service or similar source, to form expectations of annual rental payments for different housing types in the next period (see *Agent Prediction*). This information includes the average past and current rent, lot size, house size, number of bidders before sale, percentage that sale price was above (or below) the original asking price, the number of houses of each type, and an approximation of residents' income levels. For any given house, the developer uses financial prediction models (section 2.5.1) to form a rent expectation for that house in t + 1 given past rental information. Rent expectations are then used to make spatially explicit rent projections for all housing types in all undeveloped cells.

The developer forms expectations of rents ($E\langle R|h,i,t\rangle$) for each housing type (h) in each cell i in time t based on past rent information. Expected returns ($E\langle Ret|h,i,t\rangle$) before land purchase are calculated for each housing type net of construction and infrastructure costs (*ccost*), last period's carrying costs (C_{carry}), which are applied equally over all acres demanded (A_d) in time t, and a profit target (1− r) equal to a normal rate of return (r) of 5%:

(14) $$E\langle Ret|h,i,t\rangle = (1-r)\frac{(E\langle R|h,i,t\rangle - ccost)}{z} - \frac{C_{carry|t-1}}{A_{d,t}}$$

where z converts expected returns per lot to expected returns per acre. If newly bought land parcels or newly constructed houses remain vacant, carrying costs (C_{carry}) are incurred by the developer annually and do not compound over time. Carrying costs represent costs to the developer associated with holding vacant property; for example, interest accrued on loans financing the development project or foregone interest on an alternative safe investment. Carrying costs for vacant land equal 5% interest on the price paid for land. Carrying costs for vacant houses equal 5% interest on the combined price paid for land and annualized construction costs of the particular housing type. Thus, available capital in a given period is constrained by the amount of vacant land or houses the developer owns, which influences how much land the developer can acquire each period.

Loss-aversion is taken into account using the prediction error, σ, associated with the most successful rent prediction model for each housing type (see *Agent Prediction*). Based on this prediction error, expected returns are bracketed by high and low estimates for housing type h in cell i at time t.

(15) $$\text{high}E\langle Ret|h,i,t\rangle = (1-r)\frac{(\sigma_{t-1} + E\langle R|h,i,t\rangle - ccost)}{z} - \frac{C_{carry|t-1}}{A_{d,t}}$$

$$\text{low}E\langle Ret|h,i,t\rangle = (1-r)\frac{(E\langle R|h,i,t\rangle - \sigma_{t-1} - ccost)}{z} - \frac{C_{carry|t-1}}{A_{d,t}}$$

High and low estimates of expected returns are then considered in a risk-aversion framework modified from Ligmann-Zielinska (2009) to conform to prospect theory. Potential gains (potgain) and losses (potloss) are calculated relative to a reference point of zero, which represents meeting the profit target of a normal rate of return applied in the equations.

(16) $$\text{potgain}(h,i,t) = \begin{cases} \left(\frac{\text{high}E\langle Ret|h,i,t\rangle}{\omega_{gain}}\right)^{\frac{1}{\omega_{gain}}}, & \text{if high}E\langle Ret|h,i,t\rangle > 0 \\ 0, & \text{if high}E\langle Ret|h,i,t\rangle \leq 0 \\ \text{potgain}(h,i) + \left(\frac{\text{low}E\langle Ret|h,i,t\rangle}{\omega_{gain}}\right)^{\frac{1}{\omega_{gain}}}, & \text{if low}E\langle Ret|h,i,t\rangle \geq 0 \end{cases}$$

$$\text{potloss}(h,i,t) = \begin{cases} \left(\frac{\text{high}E\langle Ret|h,i,t\rangle}{\omega_{loss}}\right)^{\frac{1}{\omega_{loss}}}, & \text{if high}E\langle Ret|h,i,t\rangle \leq 0 \\ \text{potloss}(h,i) + \left(\frac{\text{low}E\langle Ret|h,i,t\rangle}{\omega_{loss}}\right)^{\frac{1}{\omega_{loss}}}, & \text{if low}E\langle Ret|h,i,t\rangle < 0 \\ 0, & \text{if low}E\langle Ret|h,i,t\rangle \geq 0 \end{cases}$$

where $\omega_{gain} = 3$ and $\omega_{loss} = 2.5$ are skewedness factors modified from Ligmann-Zielinska (2009) to reproduce the value function in figure 1. Expected utility from each housing type is then calculated as:

(17) $$E\langle U|h,i,t\rangle = \frac{\text{potgain}(h,i,t)}{\text{potgain}(h,i,t)+\text{potloss}(h,i.t)}$$

Housing types are ranked from highest to lowest expected utility to the developer excluding those with negative expected returns. This ranking gives the order in which housing types will be built.

In each landscape cell, an average of expected return is calculated, $E\langle\overline{Ret}|\hat{h},i,t\rangle$, from the set of housing types with positive expected rents, $\hat{h}$. The developer forms a WTP for each landowner's holdings (F_n) as the average of $E\langle\overline{Ret}|\hat{h},i,t\rangle$ across all cells contained within the landowner's holdings ($i \in F_n$) with total acres, A:

(18) $$WTP(F_n,t) = \frac{1}{A_{F_n}}\sum_{j=i\in F_n}\frac{\sum E\langle U|h,i,t\rangle E\langle\overline{Ret}|\hat{h},i,t\rangle}{E\langle U|h,i,t\rangle}$$

2.2.1.4. Landowner profit-maximization

Landowner expectations of land prices are formed using the same price prediction as the developer (see (*Agent Prediction*). A landowner's decision to sell to a developer or continue to hold the land in the same land use is based on the expected return from selling relative to the value of the land in its current use in perpetuity. The landowner's willingness to accept (WTA) price is set dynamically to the greater of the two values. This enables the landowner to capture speculative gains from sale of land when development pressure is high, while enforcing a rational threshold below which the landowner would be better-off continuing the current land use.

2.3. Learning

Developer and landowner agents form price expectations each time step (see *Agent Prediction*). Each agent has a diversity of methods for forming predictions. Predictions are compared with observed prices each time step to evaluate each prediction method and record its cumulative error. Using reinforcement learning, each agent selects the method that minimizes cumulative error over time.

2.4. Agent sensing

During the competitive house bidding process (see *Interactions*), residential housing consumers observe the number of other consumers bidding on the same set of housing on which they are bidding. Based on the ratio of houses on which they are bidding to competing consumers, consumer agents can adjust their bids to be more competitive or maximize their utility by bidding less than the asking price.

The developer can observe spatially explicit neighborhood characteristics in the housing market. Within each extended von Neumann neighborhood (8x8 cells), the developer knows how many consumers bid on each housing type, the average consumer incomes and housing and amenity preferences of residents, and average housing prices for each housing type.

Finally, landowners can observe the number and location of other landowners, which influences their bargaining power (see *Interactions*) with the developer.

2.5. Agent prediction

2.5.1. Financial Prediction Models

Developers and landowners make pricing decisions informed by expectations of future housing and land prices, respectively. Adapted from price expectation models used in agent-based financial literature (e.g. Arthur, 1994, 2006; Axtell, 2005), agents try to predict next period's price based on current and past price information. An agent is given a set of twenty prediction models. Each prediction model may use one of six different prediction methods, and there may be more than one model applying the same prediction method in the agent's set of twenty models. Some of these prediction methods map past and present prices (P) into the next period using various extrapolation methods.

1. *Mean model*: predicts that P(t+1) will be the mean price of the last *x* periods.

(19) $$P(t+1) = \frac{\sum_{i=t-x:t} P(t_i)}{x}$$

2. *Cycle model*: predicts that P(t+1) will be the same as *x* periods ago (cycle detector).

(20) $$P(t+1) = P(t-x)$$

3. *Projection model*: predicts that P(t+1) will be the least-squares, non-linear trend over the last *x* periods.

(21) $$P(t+1) = aP(t_s)^2 + bP(t_s) + c\ ;$$

where t_s is the time span of *t*-*x* to *t*, and *a*, *b*, and *c* are coefficients of fit.

Other methods translate changes from only last period's price to next period's price.

4. *Mirror model*: predicts that P(t+1) will be a given fraction ξ of the difference in this period's price, P(t), from last period's price, P(t-1), from the mirror image around half of P(t).

(22) $$P(t+1) = 0.5P(t) + [0.5P(t) - (1-\xi)(P(t) - P(t-1))]$$

5. *Re-scale model*: predicts that P(t+1) will be a given factor ζ of this period's price bounded by [0,2].

(23) $$P(t+1) = \zeta P(t)$$

6. *Regional model*: predicts that P(t+1) is influenced by regional price information coming from neighboring agents.

For landowners, land prices are a function land scarcity as measured by the number of remaining landowners, N_f, in the region at time t.

(24) $$P(t+1) = P(t)\left(1 + \frac{1}{N_f}\right)$$

For developers, the expected price of house types with size, h, on lot size, l, in a given neighborhood, N_b, is the mean of prices of house and lots of the same sizes in adjacent neighborhoods, N_{nei}. N_{nei} are neighbors in the cardinal directions.

(25) $$P(N_{b|hl}, t+1) = mean\left\{P(N_{nei|hl}, t)\right\}$$

All models in the agent's set of prediction models are used to predict the price in the next time period (*P(t+1)*). In time t+1, the actual price is known and the performance of each model is determined by squaring the difference between the predicted price and the actual price. The prediction model with the least error is used to make the agent's pricing decisions in the current period. This same process of prediction and evaluation is used every period so that the most successful prediction model is used every time. However, prediction model error is cumulative such that the most successful model may not continue to be over time.

2.5.2. Developer's 'New Consumers' Prediction Models and Demand for Land

Adapted from Arthur's (1994) "El Farol Problem", the developer attempts to predict the population at time t using past population information from the last ten years. Population information for time t is not known until new consumers bid for houses on the housing market (section A.4). Just as agents are allocated twenty financial prediction models, developers are allocated twenty population prediction models. However, instead of receiving six different predictions methods, developers receive only the first five prediction methods listed above in Section A.1.1. For trends in population from time t-x to t -1 (where x ranges from two to ten years in the past), developers attempt to predict how many new consumers will enter the market in time t.

The developer uses this prediction as the number of new consumers in time t, which corresponds to the number of new houses that need to be supplied in time t for new consumers, N_{new}. In addition, the developer observes the number of consumers who bid on houses but were not the highest bidder on any house in t-1 and therefore did not locate in the region, N_{old}. By combining the number of houses needed for new consumers (N_{new}) and consumers from last period that did not locate (N_{old}), the number of new houses that need to be constructed in the current period (H_{new}) is calculated.

(26) $$H_{new}(t) = N_{new}(t) + N_{old}(t-1)$$

Based on the developer's rent projections (section A.2.2), the H_{new} most profitable houses are chosen for construction later in the period. Given this housing set and the associated land required to build each, the developer calculates how much land will be needed in the current period. The developer's demand for land is then the difference between the amount of land needed for new construction and the amount of vacant land already owned by the developer from previous land purchases (if any). For example, if the developer calculates ten new houses are needed in time *t* and the ten most profitable houses require two acres each, but the developer already owns five acres that are vacant, the developer's demand for land in the current period will be fifteen acres.

2.5.3. Landowner's Spatial Discounting Models

Land is an immobile good with spatially heterogeneous attributes, thus land prices vary in space and time. Landowners observe the price and location of one or more land transactions through time. A landowner then attempts to discount the observed transaction price(s) based on the distance from his location. The spatially discounted price(s) accounts for spatially variable land values and enables an adjustment of land prices based solely on trends in the market land price.

A coefficient of spatial discounting is predicted using a genetic algorithm that enables the landowner to 'learn' the best coefficient over time (see *Agent Learning*). Initially, each landowner is allocated a 'population' of 100 random coefficients bounded by [-200, 200]. After the transaction price(s) is observed, it is discounted using each coefficient in the landowner's 'population' of the coefficients and compared to the landowner's current asking price to evaluate the 'fitness' of each coefficient.

(27)
$$\chi_i(t) = \chi_i(t-1) + \left| \left(\frac{P_{ask|F}(t) - P_{L|F}(t)}{\bar{D}_F} \right) - \beta_i \right|;$$

where the fitness, χ_i, of coefficient β_i is the absolute value of the difference between the current asking price of landowner *F*, $P_{ask|F}$, and the average of the transaction price(s), $\bar{P}_L$, divided by the average distance, $\bar{D}_F$, of the observed transaction price(s) from landowner *F*. 'Fitness' is measured as such so that the 'most fit' coefficient will be the one with the least error. The 'most fit' coefficient is designated as 'active' and is used as β_L in Equation 24 to spatially discount observed transaction prices.

The landowner spatially discounts the observed transaction price(s) by predicting the coefficient of spatial discounting in a linear extrapolation to give the spatially discounted price, $P_{L|F}$, faced by landowner *F*.

(28)
$$P_{L|F}(t) = \beta_L \bar{D}_F + \bar{P}_L(t);$$

The coefficient of spatial discounting, β_L, represents the marginal discount of the observed transaction price(s) per cell away from landowner *F*. The spatially discounted price, $P_{L|F}$, is then given as an input into the landowner's financial prediction models (see *Agent Prediction*).

2.6. Interactions

2.6.1. Housing market competition

Residential housing consumers competitively bid with other consumers to maximize their objective functions given asking prices of houses, personal budget constraints, location, perceived risk of storm damage, and competition from other consumers. Consumers place bids on all houses that generate positive utility or salience value (depending on objective function) and are thus within their budget constraints given asking prices. Each consumer observes the number of other consumers placing bids on their set of prospective houses and adjusts their bid according to competition levels. If there are more bids than there are houses being bid on, then bid prices are adjusted upwards. If there are fewer bids than there are houses being bid on, then bid prices are adjusted downwards. Bid adjustments are designed to reflect the relative supply of and demand for housing and quantify competition with the housing market. While the design choice of allowing any agent to simultaneously bid on multiple houses is not necessarily how it happens in the real world, it does capture effects of competition information communicated by real estate agents. Even if real estate agents do not know the amounts of competing bids at the time a client's bid is placed, they often communicate the level of interest from other consumers. Thus, a housing consumer's bid is based on the number of other bidders, rather than the amount of competing bids. This feature, combined with the one round, sealed-bid auction style of the algorithm used to calculate the transaction price, has minimal inflationary effects on prices (i.e., 'bidding wars') that would stem from allowing simultaneous bids on multiple houses.

A given consumer will bid on the set of houses for which their WTP is greater than or equal to the developer's asking price. The housing-market competition factor, *HMC,* describes the competition for housing each consumer faces in the housing market:

(29) $$HMC_c = \frac{N_C - N_H}{N_C + N_H}$$

where N_H is the number of houses the consumer bids on and N_C is the number of other consumers bidding on those same houses. Consumer *c* then sets a bid price for each house in response to market conditions. Competition is high for a given consumer if there are more bidders for the houses he/she is bidding on than there are houses, and the bid will be increased. Competition is relatively low if there are more houses he/she is bidding on than total bidders for those houses, and the bid is adjusted downward. The adjustment of consumers' bid prices in response to market conditions allows consumers to attempt to maximize their gains from trade and the likelihood that they will be the highest bidder.

Houses are assigned to consumers with the highest bids for each house. If a consumer has the winning bid on multiple houses, then the consumer chooses the house that generates the highest utility given the winning bid prices. Consumers that locate in a house are assigned a residence time drawn randomly from a normal distribution (μ=12.5, σ=11 time steps). When residence time is exceeded, the consumer moves-out, re-enters the consumer pool, and the newly vacant house is put back on the market. This ensures regular turnover in the housing market due to unobservable events (e.g., relocation due to change in employment). Consumers that do not locate after three consecutive time steps are removed from the consumer pool. New housing consumers are introduced into the 'consumer pool' of existing consumers at the start of each time step at a rate of ten percent a year.

2.6.2. Bargaining power in the land market

If the developer's WTP for a given landowner's holding is greater than the landowner's WTA for land, then the two enter into bilateral negotiation to determine the final transaction price. Bargaining power in the land market, ε, is adapted from Parker and Filatova (2008) and captures differences in the developer's demand for, and the landowners' supply of, land at the initial WTP of the developer.

(30) $$\varepsilon = \frac{d_{Land} - A_{F^*}}{d_{Land} + A_{F^*}}$$

where d_{Land} is the acreage demanded by the developer and A_{F^*} is the acreage supplied by participating landowners. F^* is the subset of all landowners for which the condition WTP > WTA is true. If the developer demands more land than landowners supply, ε is positive and landowners ask a price above their WTA. If landowners supply more land than is demanded by the developer, ε is negative and the developer will bid below the initial WTP. The amount of land supplied by landowners in any given period depends on the initial WTP of the developer for each landowner's holdings, which depends on rent expectations in the housing market. Thus, the housing and land markets are explicitly linked.

2.7. Collectives

No collectives are represented in this model.

2.8. Stochasticity

Each model execution uses a different random number seed to generate stochasticity in model outcomes. Both developer and landowner agents are allocated a set of prediction models (see *Agent Prediction*) during model initialization that differ in time horizon and prediction method. Each initialization entails a random allocation of prediction models to each agent. Also, in the case of ties during competitive bidding in the housing and/or land markets, among residential housing consumers and landowners, respectively, the winner is randomly chosen. Finally, as described in *Environment* (section 1.2.2), storms are randomly generated each time step with a probability equal to the historical average of the storm climate of interest.

2.9. Observation

The primary metrics extracted from model results are descriptive statistics of development extent; number and location of all housing types; land and housing prices; timing and location of land sales and housing construction; vacancy rates; located (i.e., resident) consumer incomes and preferences; rate of relocations; consumer characteristics of relocations; income and housing and land price distributions; and consumer utilities relative to optimum housing option. All of these metrics are associated with emergent patterns. All of these metrics are capable of being both spatially- and temporally-explicit, stored as maps for each time step (i.e., 'data bricks'), but can also be aggregated to average values over time and/or final state measures.

Data is also extracted and summarized relative to the occurrence of storms. The time step of each storm in every model execution is identified and indexed. Using this index, all relevant metrics are gathered and classified by time steps before and after each storm event. These metric are then summarized (e.g., median or average values) for each time step before/after a storm across model executions. This procedure is repeated for all storms even if multiple storms occur per model execution.

3. Details

3.1. Implementation details

The model code is implemented in Matlab and is written to leverage Matlab's Parallel Processing Toolbox to execute model runs in parallel (i.e., across implementations rather than within each implementation). The code if freely available on OpenABM.org.

3.2. Initialization

Each model execution is initialized with a developed central business district (CBD) and other existing residential development around the CBD and along the coastline. The initial development pattern is the average result of thirty 'spin-up' simulation runs. This was calculated by observing the average percent developed area for the entire region across the spin-up runs, and selecting the most frequently developed cells across spin-up runs until the total developed area equaled the observed average percent of developed area. To initialize housing prices, the first ten time steps of experimental simulation runs are used to find stable levels given consumer demand for housing in the initial landscape development pattern. Initial housing asking prices are set equal to their land and construction costs (i.e., zero profit), and residential housing consumers with randomly allocated incomes and housing preferences, and equal in number to available houses, competitively bid on housing. When all winning bidders have been assigned to houses or no positive bids remain, the bidding process stops. Housing sale prices are observed and set as new asking prices, all houses are set to vacant, and the same consumers repeat the bidding process. The initialization period finishes when the average difference between asking and sale prices is less than one percent. Housing prices in the initialization period provide a price history used for the developer's rent prediction models during dynamic simulation.

Developer and landowner agents are also randomly allocated price prediction models at the start of each model execution (see *Agent Prediction* and *Stochasticity*).

3.3. Input data

The baseline storm probability, or 'storm climate', is calculated from annual probabilities (Costanza et al., 2008) from the Mid-Atlantic region consisting of Maryland, Virginia, Delaware, Pennsylvania, and New Jersey. Alternative scenarios with higher probabilities of storm occurrence are implemented using the storm climates of North Carolina, Texas, and Florida. Spatially explicit expected damages in the event of a storm are calculated via a three-step approach. First, the coastal flood module of the Hazus-MH model (FEMA, 2012; Scawthron et al., 2006) is run for the coastal areas of Maryland to obtain flood depths in a 100-year storm event at a 30-meter resolution. Second, percent property value loss as a function of flood depth is calculated based on US. Army Corps of Engineers (USACE, 2006) damage functions and using residential property values from the MDProperty View dataset (MDP). Finally, percent property value losses are regressed against distance to the coast to estimate a spatially explicit damage gradient.

Land values in uses other than residential development (e.g., agriculture) are aggregated and averaged by counties in Maryland from the U.S. Department of Agriculture's Agricultural Census (NASS, 2012). Infrastructure and square footage construction costs are estimated from Frank (1989) and Fodor (1997). Transportation costs are estimated in terms of travel time and out of pocket expenses (BTS, 2007). Time costs are assumed to be a function of average road speed (30 mph), average number of workers per house (2), average wage per person ($30/h), value of time as a percent of wage (50%), and the road network indirectness coefficient (0.3) (this is the ratio of network distance to the Euclidian distance). Calculations in that study based on U.S. Bureau of Labor Statistics' Consumer Expenditure Survey Safirova et al. (2006).

3.4. Submodels

3.4.1. Residential Consumer Bid Formation

With a limited number of houses available at any given point in time, consumers may not always be able to locate in the house that provides the highest utility. Thus, we compute a bid, R* (c, n), for each housing option available for each consumer that reflects the relative utility difference between that option and the one that produces the maximum utility, U*:

(31) $$R^*(c,n) = P_{ask|n}\frac{U(c,n)}{U^*}$$

The consumer's bid for any particular house is then the minimum of their constant share of income for housing as shown in Equation 3 (i.e., *WTP*) or the bid price calculated here. The degree to which the bid differs from *WTP* depends on the relative utility of each housing option, the consumer's income, and idiosyncratic preferences, as well as the developer's asking prices.

3.4.2. Rules for Matching Consumers with Houses

After the bidding process is completed, the highest bidder for each house is identified. For each consumer in the set of winning bidders, the set of houses for which the consumer owns the highest bid is identified. The consumer's utility is recalculated for each of these houses using the winning bid instead of the initial asking price. Given these new levels of utility, the consumer is matched with the house that produces the highest utility. Once a consumer is matched with a house, both the consumer and house are removed from the market. The matching process is reiterated with the remaining bids, which are kept constant, until all consumers are matched, all houses are occupied, or all positive bids are exhausted. This process ensures consumers are matched to houses that generate their maximum possible utility levels given competitive bids from other consumers and discrete housing options provided by the developer.

3.4.3. Developer Rent Projections

Rent projections are calculated as the weighted combination of local and regional (suburb-wide) expected rents for existing houses (Magliocca et al, 2011). The method of rent projection depends on the level of uncertainty in rent expectations. If a given housing type has been built, a spatially weighted extrapolation is made based on distance and price trends. If the given housing type has not yet been built within the region, the developer relies on a hedonic regression model based on existing housing characteristics. The hedonic regression uses median consumer income (x_1) from similar housing types, lot size of the given housing type, h (x_2), and travel costs (x_3) to and amenity level (x_4) in the given location, i, to project an expected rent:

(32) $$R_{proj}(i,h) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4$$

3.4.4. Dynamic Subjective Risk Perception

A common Bayesian learning model (Viscusi, 1991) provides a formalization of dynamic, subjective risk perception in which individual housing consumer agents observe the occurrence of a storm event and update their expected probability of future storms (Davis, 2004; DeGroot, 1970). However, additional empirical evidence demonstrates that not only does risk perception diverge from objective levels over time, but also the rate at which it diverges varies in relation to time since a hazard event (e.g., Atreya and Ferreira, 2012; Bin and Landry, 2013; Gallagher, 2014). This is modeled by modifying the Bayesian updating model with a weighting parameter that discounts past information (Camerer and Ho 1999; Malmendier and Nagel 2011).

Following the formalization of Gallagher (2014), the expected annual probability of a storm *E(p)*, or subjective risk perception, at time *t* is formalized as:

(33) $$E(p|S'_t, t') = \frac{S'_t + \alpha}{t' + \alpha + \beta}$$

where α and β are parameters of a beta distribution, $S'_t = \sum_{s=1}^{t} y_s \delta^{t-s}$ are weighted storm observations, and $t' = \sum_{s=1}^{t} \delta^{t-s}$ is the number of yearly observation ‘equivalents with time-weighting parameter $\delta = 0.91$ following the findings of Gallagher (2014).

3.4.5. Adaptive Responses

In the absence of storm events, location decisions by incoming residential housing consumers are made on an annual basis (same as the scheduling for developer and landowner decisions). When a storm event occurs, existing, located housing consumers (i.e., residents) undertake a re-evaluation of their current location and decision to purchase (or not) insurance given updated storm risk information (see *Dynamic Subjective Risk Perception*). Specifically, residents evaluate the value of remaining in place, remaining in place and purchasing insurance, or relocating to another available house within or outside the region. The user-specified objective function is used to value alternative options (see *Objective Functions*).

Relocation decisions are based on the stress-resistance model (Benenson, 1998). The decision to relocate occurs in two steps. The first step is an evaluation of 'stress' by comparing the current satisfaction (i.e., utility or salience value) of the housing location to past satisfaction level at the time of move-in. Following Robinson et al. (2010), a resident is considered 'stressed' if satisfaction level decreases by 15%. All housing consumer attributes remain fixed throughout the simulation, so the only variable factors influencing this decision updated risk perception and asking prices of available housing. The second step involves 'stressed' residents evaluating whether the gain in satisfaction from available housing options is positive net of moving costs. Moving costs are heterogeneous among consumers (Table 1) and equal to 10% of annual income. Residents considering relocation observe asking prices, locations, and amenity values of available houses within the region. A housing option external to the region has an asking price estimated with the developer's regional rent expectation model (Eq. 28) assuming zero amenity value (i.e., inland). For evaluation of housing options within the region, the resident compares current satisfaction to the average level that could be achieved in available housing options, because a relocating consumer is not guaranteed to move into an available house (due to competitive bidding). Consumer choosing to relocate within the region must re-enter the consumer pool to competitively bid for available housing, and consumers choosing the external option are removed from the simulation.

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