

MR POTATOHEAD: Real Estate Market Edition — Development of a common description template for agent-based residential real estate market models

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Abstract

In recent years, a wide range of agent-based real-estate market models (ABM-REMMs) have been developed to incorporate actor and environmental heterogeneity and feedbacks between scales, features not possible in traditional real-estate market models. Despite close communication and collaboration between scholars, independent research groups have developed customized model codes, often in different programming languages. To synthesize this knowledge, we present a new meta-model template “MR POTATOHEAD: Real Estate Market Edition” (MP-REME), developed collaboratively by the authors, to describe and compare six independently developed ABM-REMMs. We demonstrate that the six models are special cases of a generalized meta-model, which is suitable for a wide range of agent-based exploration of real-estate market dynamics. The MP-REME templates can serve as a design pattern to catalyze development of a community ABM-REMM code base, facilitating faster model development, model transparency and replicability, and model comparison. Residential real estate (land and housing) markets impact a wide variety of critical socio-ecological outcomes at local, national, and international scales, and scientifically robust and transparent real-estate market models are needed to explore the impacts of these markets on socio-ecological outcomes. Given the range of differences between models, development of such a standard model is critical to increase confidence in the application of ABM-REMMs to policy analysis of issues such as urban flooding, carbon sequestration, heat island mitigation, and biodiversity preservation.

Keywords

agent-based modeling; real-estate markets; design pattern; model replication; reusable building blocks

Code availability

The “MR POTATOHEAD: Real Estate Market Edition” (MP-REME) templates are available at <https://github.com/dawncassandra/MR-POTATOHEAD-Real-Estate-Market-Edition>.

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1. Introduction

Residential real-estate (land-and-housing) markets shape urban form, function and value. Locally, land markets impact urban phenomena such as segregation, gentrification, housing affordability, accessibility, the efficiency of the transport systems, urban sprawl, and positive and negative externalities. Land markets are also playing an increasingly prominent role on the international stage, as both individual and institutional investors direct capital towards real-estate investments in the face of high securities market volatility and lower prevailing bond rates. International trade patterns and policies, as well as national fiscal policies, create cross-scale linkages between global drivers and local land markets. Housing markets impact household well-being through multiple channels. They shape the availability and quality of dwellings, the development place-and-neighborhood urban amenities, the home/work commute, and dynamics of household wealth through the homes' asset value. Lastly, how residential real estate actors manage their properties defines CO₂ emission footprints as well as damages from climate-induced hazards, like floods or wildfires, affecting both climate change mitigation and adaptation.

1.1 Real-estate market interactions through a complex systems lens

Researchers are increasingly applying a complex-systems lens and related methodologies to understand urban systems in general, and land and housing markets specifically. Complex systems are characterized by heterogeneous actors (differing by type, resources, beliefs, and capabilities) who interact with each other and their environment. Actor decisions may adaptively evolve in response to new information from their own experience, other actors, or the environment. Decisions are often shaped and co-evolve through interactions with higher-level actors and institutions (Wyman et al., 2013; Verburg and Overmars, 2009).

Real-estate markets are a clear example of a complex system. On the land-market side, long-term owners, speculators, and government entities supply land for new housing development. Developers, who can include non-profit and municipal home providers, assess the potential profitability of housing that might be developed on that land, applying boundedly rational models of cost and end-user demand (Valaei Sharif et al., 2023). Their assessments of what can be built are constrained by planning and zoning systems, influenced by developers' expectations of what planning/zoning changes might be allowed. Developers supply homes for purchase and rental, which may be purchased, rented, and occupied by institutional investors, individual investors, and directly by households. All of these owners/occupants may also supply homes back to the market, for sale or rental. Over the course of their life cycle, households may move from renting, to owning, to investing, and back to renting. Because information on land and housing characteristics, assessments, and sales prices may be private or only available at high cost in many locations, market actors may have differential access to information. Further, housing market trends tend to be volatile and cyclical, and their transitions can be difficult to predict. Thus, all housing market actors can be characterized as boundedly rational; however, those with better access to information have a market advantage.

Why are agent-based models of real-estate markets needed? As discussed in detail by Parker and Filatova (2008) and Anas et al. (1998), traditional microeconomic approaches to understanding land value, grounded in the seminal theories of Von Thünen, have produced robust insights into the evolution of urban land-use distribution, land-value gradients, and land-use transportation interactions. However, housing markets have unique features: their products are highly spatially differentiated, creating almost unique goods; buyers participate in few or no repeated transactions, limiting opportunities for learning; markets are highly information-scarce; and goods are allocated through bilateral or small-numbers-bidding transactions. In such conditions, traditional models may produce incorrect answers, for instance, predicting too-low prices and too-small urban footprints (Sun et al. 2014; Filatova et al., 2009). To address these limitations, agent-based models (ABM) can represent the decentralized interactions of heterogeneous market actors and their responses to policies, while embedding housing markets in the macro economy (Farmer & Foley, 2009; Gatti et al., 2010; Geanakoplos et al., 2012; Huang et al., 2014; Parker & Filatova, 2008).

ABMs are simulation models that can directly represent the decentralized interactions of diverse market actors, across a spatially explicit landscape. Models do not impose and solve for a set of equilibrium conditions, and thus highly restrictive simplifying model assumptions need not be imposed, allowing for detailed exploration of

how diverse actors' decisions shape market outcomes. Agent-based real estate market models (ABM-REMMs) can represent important phenomena that traditional real estate market models have not been able to capture. At the local level, ABM-REMMs can incorporate key sources of actor and environmental heterogeneity, as well as modeling interactions between the two. ABM-REMMs can also model top-down effects of global cross-scale linkages, providing a more nuanced, and perhaps more accurate, understanding of global economic drivers and (supra)national fiscal policies on land market economic, social and environmental outcomes.

1.2 Goals and outline

This paper presents the MR POTATOHEAD: Real Estate Market Edition conceptual meta-model (MP-REME) ontology and corresponding description templates, which nest a representative group of research-based agent-based models of real-estate (land and housing) markets. In short, the paper strives to demonstrate that all of these research-based ABM-REMMs can be viewed as a special case of one larger, comprehensive model. Our paper walks the reader through the structure of MP-REME, focusing on the research questions that can be asked and answered by different model representations, making reference to the reported models and other selected representative works. Rather than reviewing all of the details and definitions of the ontology, we discuss how representative papers have modeled particular aspects of the housing market and how these representations facilitate market or policy experiments. The paper is organized as follows: Section 2 gives a broad overview of previous agent-based land and housing market models and of model comparison methods. Section 3 describes our methods to create the MP-REME templates. Section 4 describes the new templates, and section 5 reviews uses of their elements in existing research outputs of the authors. Section 6 summarizes contributions, highlights areas where comparative research and enhancements to the modeling framework are needed, notes limitations, and suggests future research directions to which ABM-REMMs can be applied, including modeling of socio-ecological systems.

2. Background and context

2.1 How has the field of ABM-REMMs developed to date?

ABM-REMMs have seen significant development over the past two decades, evolving from conceptual prototypes to empirically grounded models capable of capturing complex behavioral, spatial, and institutional dynamics (Liu et al., 2023; Crooks et al., 2021). A full literature review of all ABM-REMMs developed to date is beyond the scope of this review; rather we cite selected work and highlights. Early foundational work laid out key design challenges in modeling land markets (Parker & Filatova, 2008). Further progress was reviewed by Huang et al. (2014), with a focus on representation of four key market elements (preferences, budget constraints, competitive bidding, and endogenous relocation). A wave of research that integrated individual preferences, budget constraints, relocation decisions, and spatial context followed (Filatova, 2015; Magliocca et al., 2011; Ge, 2017; Ge et al., 2018). Recent studies have expanded the analytical scope of ABMs to examine how market dynamics are shaped by the regulatory environment, infrastructure investments, and speculative behavior. Examples include exploring the effect of price expectations and zoning regulations on urban sprawl (Magliocca et al., 2015), the influence of macro-prudential policies on housing market trends (Carro et al., 2023), the impacts of light-rail transit on land use patterns and housing outcomes (Parker et al., 2016), green gentrification dynamics (Caprioli et al., 2023), the effect of touristic rental market on housing prices (Overwater & Yorke-Smith, 2022; Innocenti et al., 2023; Prunetti et al., 2025), the effects of new public housing on market dynamics (Zhu et al., 2018), the role of bounded rationality in explaining the oversupply of uniform, "feasible" developments (Dragičević & Hatch, 2018), the effects of sudden changes in mortgage interest rates on the UK housing market (Gamal et al., 2024), and the disproportionate advantages gained by wealthier developers, who can afford greater risks, from up-zoning policies (Almagor et al., 2018b).

At the same time, microsimulation models – closely related to ABMs – have advanced the integration of land-use, transportation, and demographic systems, particularly through discrete choice-based approaches (Waddell, 2007; Miller, 2018; Zhu et al., 2018). Although traditionally lacking in land market representation, these models are increasingly incorporating spatial bidding and housing supply mechanisms (Zhong et al., 2022; Huang et al., 2013).

On a broader scale, several macroeconomic agent-based models have been developed to study systemic housing market behavior (Axtell & Farmer, 2025; Carro, 2023). These include models of urban housing markets calibrated to micro-data (Geanakoplos et al., 2012) and macro-financial models that explore the role of credit access and banking regulations on housing prices and business cycles (Glavatskiy et al., 2021; Erlingsson et al., 2014; Ozel et al., 2019). Together, recent advancements hold substantial promise for future efforts to model land and housing markets. However, a critical frontier for ABM-REMMs remains in integrating detailed household-and-developer-level behaviors within broader macroeconomic and institutional contexts.

2.2 What is the state-of-the art in model code sharing and replication?

In spite of the healthy growth of both theoretical and applied ABMs of urban land markets, the vast majority of models have developed their own model code, with minimal model sharing (Filatova et al., 2025; Parker et al., 2019). Some coordination has taken place, for instance, the Land Use in an eXurban Environment (LUXE) model (Sun et al., 2014) replicates the Artificial Land Market (ALMA) model (Filatova, et al., 2009) exactly as a special case. However, even groups that remained in close communication throughout their research have developed separate codes based on (sometimes multiple) different programming languages. While each group has generally published their model code, few have reused the code of others. One consequence of this independent code development is that we lack detailed knowledge of the specific mechanisms of each other's models. The corollary result is that we do not know how these different assumptions are affecting the results of our models, or how robust the results are to these small differences.

3. Methods

In 2018, we convened a group of researchers who have all developed agent-based real estate market models, through two workshops. The workshop goals were to develop a set of common templates, through which the individual model assumptions and rules could be illustrated. The templates are modifications of the MR POTATOHEAD conceptual design pattern (Parker et al., 2008), which describes key components of agent-based land-use models via a common template. The templates outline the detailed assumptions of each model, allow comparisons between models, and suggest new model configurations that might combine elements.

Six research groups participated in the effort, representing separately developed ABM-REMMs, developed to ask and answer different research questions. Authors from four model groups have been in close communication from the inception of their model development. Filatova and Parker pioneered early conceptual and practical development of ABM-REMMs (Filatova et al., 2009; Parker & Filatova, 2008). Both have maintained close communications with other authors (Magliocca and Prunetti) building fine-scale ABM-REMMs. Models of Ge and Carro's group, both representing coarser-scale, equilibrium-price based models, were developed independently. The work of the six groups represents a large portion of the current scholarship on ABM-REMMs. Two additional researcher groups were invited to participate in the workshops but were unable to do so (Rosenfield et al. 2013; Almagor et al., 2018a); these authors were suggested as reviewers for this paper. All of these research groups build models where housing and/or land are allocated competitively between potential buyers, per the Level 2 models of Sun et al. (2014). Three additional researchers who at that point had less developed MR-REMES also participated in the workshops, but not this publication: A. Crooks, A. Heppenstall, and N. Schwartz. Work of the paper's authors plus workshop participants represents around one third (42/145) of articles returned on Scopus using the query (TITLE-ABS-KEY ("agent-based" OR "agent based") AND TITLE-ABS-KEY (land OR housing) AND TITLE-ABS-KEY (market) AND TITLE-ABS-KEY (urban ,OR city OR cities)) AND PUBYEAR (> 2004).

The group modified three of the class diagrams from the original MR POTATOHEAD conceptual design pattern (Parker et al., 2008) to reflect the details of land-market actors and processes. The Demographic class is modified to include household buyers, sellers, and renters, real estate agents, developers, investors, and finance agents. The Agent Decision class now includes representation of multiple types of buyers and sellers (households, developers, and investors). The Land Exchange class is modified to represent detailed market interactions, drawing on the questions outlined in Parker & Filatova (2008), including specifying the market actors, identifying the spatial structure and attributes of the properties being sold, identifying how information about ask and bid prices is distributed, specifying rules for determining what units will be sold and to whom, and what rules govern when and how market activity takes place. Each research group participating in the exercise drafted responses

to the template for their individual projects. Further, the templates were used to develop the Corsica model (Innocenti et al. 2020) and to guide expansion of the WARM model (Valaei Sharif et al., 2025), and, more recently, development of a new MP-REME comprehensive structure, which includes components from more recent models of D. Prunetti, A. Heppenstal, and T. Filatova.

Below, we briefly summarize the work of each group represented in this paper, with key citations. Section 4 compares the specific assumptions and model mechanisms of each project.

- Magliocca et al. (2011) developed CHALMS (Coupled Housing and Land Markets) to investigate location decision of residential housing consumers (housing markets), conversion of agricultural land to residential housing (land markets), and how feedbacks between the two markets influenced the dynamics of the development process (Magliocca et al. 2011). CHALMS models interactions between owners of developable land, developers who buy land and build and sell homes, and home buyers. The CHALMS model was initially used to investigate the mechanisms of urban sprawl land-use patterns, and subsequent model applications investigated the influence of zoning policies of development patterns, finding that the effectiveness of zoning policies to control urban sprawl hinged on the distribution of residential consumer preference (Magliocca et al., 2012). Using survey data from a collaborative project, the psychological biases of housing developers towards particular types of houses were found to drive the timing and overall amount of ecological housing types offered to consumers (Magliocca et al., 2014). A final application of the original CHALMS model analyzed the relative influence of individual and spatial economic factors, such as lot size preferences and travel costs, on urban sprawl patterns (Magliocca et al., 2015). Recent work has adapted the CHALMS model to investigate mode sensitivities and location and adaptation decisions in coastal settings (Magliocca & Walls, 2018; Walls et al., 2018)
- Filatova (2015) developed the Risks and Hedonics in Empirical Agent-based land market (RHEA) model to provide a methodological platform to simulate the aggregated impact of households' residential location choice and dynamic risk perceptions in response to flooding on urban home markets. RHEA models interactions between home buyers and sellers, mediated by an information-providing real estate agent. The RHEA model relies on detailed empirical housing transaction data and hedonic analysis to initialize the urban landscape and the Realtor agent pricing module correspondingly, with detailed modeling of adaptive price expectations as the simulation unfolds (Filatova, 2015). RHEA also utilizes microdata from surveys among buyers and sellers (de Koning et al., 2019), capturing the shift in location choices over time (de Koning & Filatova, 2020). It integrates adaptive behavior into the spatial landscape using behavioral theories and empirical data sources. The platform can be used to assess: how changes in households' preferences or risk perceptions capitalize in property values, how price dynamics in the housing market affect spatial demographics in hazard-prone urban areas, how structural non-marginal shifts in land markets emerge from the bottom up, and how economic land use systems react to climate change (de Koning et al., 2019; Filatova, 2015).
- Ge (2017) developed an agent-based model to strive to replicate the dynamics behind housing bubbles, in the absence of major external shocks. The model includes interactions between a developer assumed to own all land, who develops and sells homes, households who sell and buy homes, and investors who sell and buy homes. Ge (2017) demonstrates that housing bubbles can form and dissipate endogenously, under the combination of lax lending policies and a sufficiently high proportion of housing investors.
- Carro et al. (2023) developed an agent-based model of the United Kingdom housing and mortgage markets, geared towards the study of macroprudential regulation and its heterogeneous effects across the various segments of the household sector. They represent interactions between a home developer, who supplies homes to the housing market, investors who buy and rent homes, and household sellers, buyers, and renters. Preliminary results from Baptista et al. (2016) indicated that an increase in the rental investment sector may increase housing market cycles and their volatility, but loan-to-income mortgage restrictions can dampen these cycles. Carro et al. (2023) reconfirm these results, further exploring how spillovers from the investor rental market impact the resident owner market. Carro (2023) expands this model to Spain, seeking to explain Spain's more volatile housing market cycles. They explore loan-to-loan-to-value, loan-to-income and debt-service-to-income ratios, finding that

both loan-to-value and soft loan-to-income limits can dampen housing cycle volatility, but also both cause a shift away from residential buyers and towards the rental investment sector.

- Prunetti et al. (2025) model interactions between land sellers, developers who buy land and develop and sell homes, resident home buyers, and investor home buyers, who purchase to rent to tourists. Their model is used to assess policies designed to decrease home price pressure in coastal areas and protect ecologically sensitive zones: business as usual, a blanket ban on tourist-rental investments, a tax on tourist-rental income, coastal setbacks for tourist-rental investments, and no-tourist-rental-investment central business district buffer zones. They find that the tax and coastal zoning are most effective, whereas the blanket ban causes residential expansion into ecologically sensitive zones and harms tax revenues.
- Parker et al. (2016) developed the Waterloo Area Regional Model (WARM) to explore interactions between home purchase decisions, transportation mode choices, and transit usage. WARM models only interactions between resident home sellers and buyers. Valaei Sharif et al. (2025) adapt WARM to analyze the value added from the development of a buyer bid model that reflects household's heterogeneous valuations for structural and neighborhood characteristics, based on household typologies developed using survey data. The model is used to demonstrate housing market sorting around household typology and income.

4. Template structure overview of MR POTATOHEAD: Real Estate Market Edition

Figure 1 provides a conceptual overview of the market processes being modeled by various researchers. (Note, individual models may not contain all of these processes and features. Note also, our market representation does not include all actors who might be active in real estate markets, such as lenders, Central Banks, municipalities, institutions, or non-profits.) Describing from the upper left, land parcels available for purchase are supplied by a variety of actors, including owners of undeveloped land (such as farms or forest owners), resident owners, speculative investors, and developers. Diverse actors compete to purchase land, including speculative investors, developers, and households. On the supply side, sellers make a decision to put a parcel up for sale, and buyers choose to bid on that parcel. Through varying institutional mechanisms, if agreement to purchase is reached between a buyer and a seller, a land transaction occurs.

Following the bottom of Figure 1, the parcel may be developed into housing units by a developer (with a time lag for construction), or existing housing units may be placed for sale in the housing market (if, for instance, a rental property is converted to condominiums) or for rent. Residential properties can take many forms, from a group of residential buildings, a single building housing multiple residential units of varying types, down to a single building housing one residence (a single-family home). From a housing market perspective, we assume that the housing market operates at the scale of a group of residences that have identical characteristics at a particular point in space. For instance, a developer may be pre-selling virtually identical 1 bedroom apartments in a particular building and also selling identical 2-bedroom units in the same building. Or, a resident may be selling a single-family home. Each of these cases (labeled a "container") participates in one market transaction. Each housing container can be offered for sale by various suppliers, including investors, developers, or existing households. Buyers can equivalently include investors, developers (for instance, who seek to convert existing residential properties), or residents. Sellers make their properties available on the market at particular prices (ask prices), buyers submit bids, and local institutional details determine which properties transactions ultimately occur.

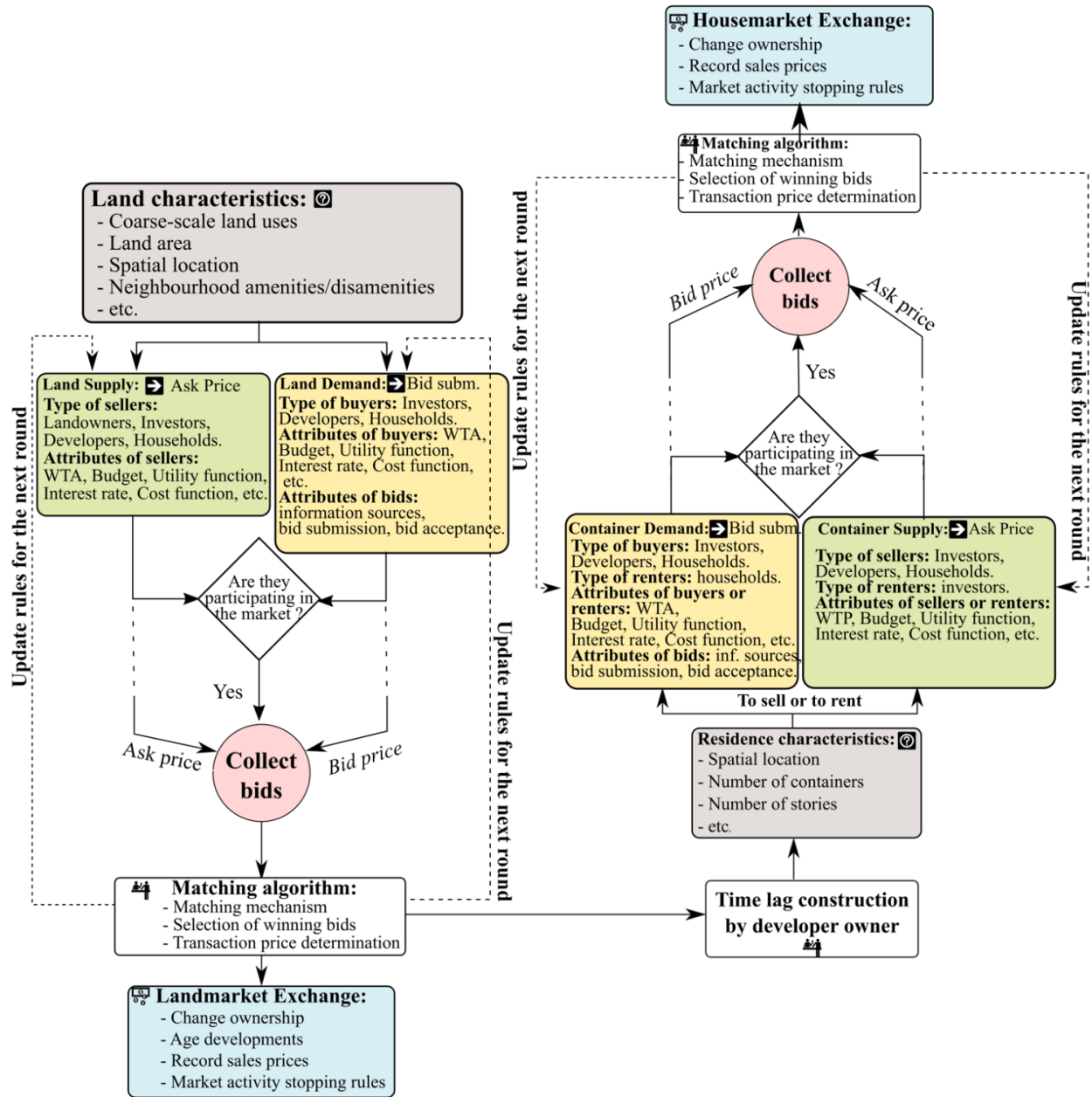


Figure 1: Conceptual overview of the real estate market.

5. Description of individual class templates

This section has two goals. First, we present and illustrate the class components of the new template, as illustrated in Figure 2. Second, for each component, we discuss and compare the assumptions and algorithms of different models, focusing on different choices made for the construction of the component by different research projects and on what research questions can be asked and answered by incorporating these components. The specific template responses for each model are presented in comparison tables in the Supplementary Materials A and in full details for each model in Supplementary Materials B.

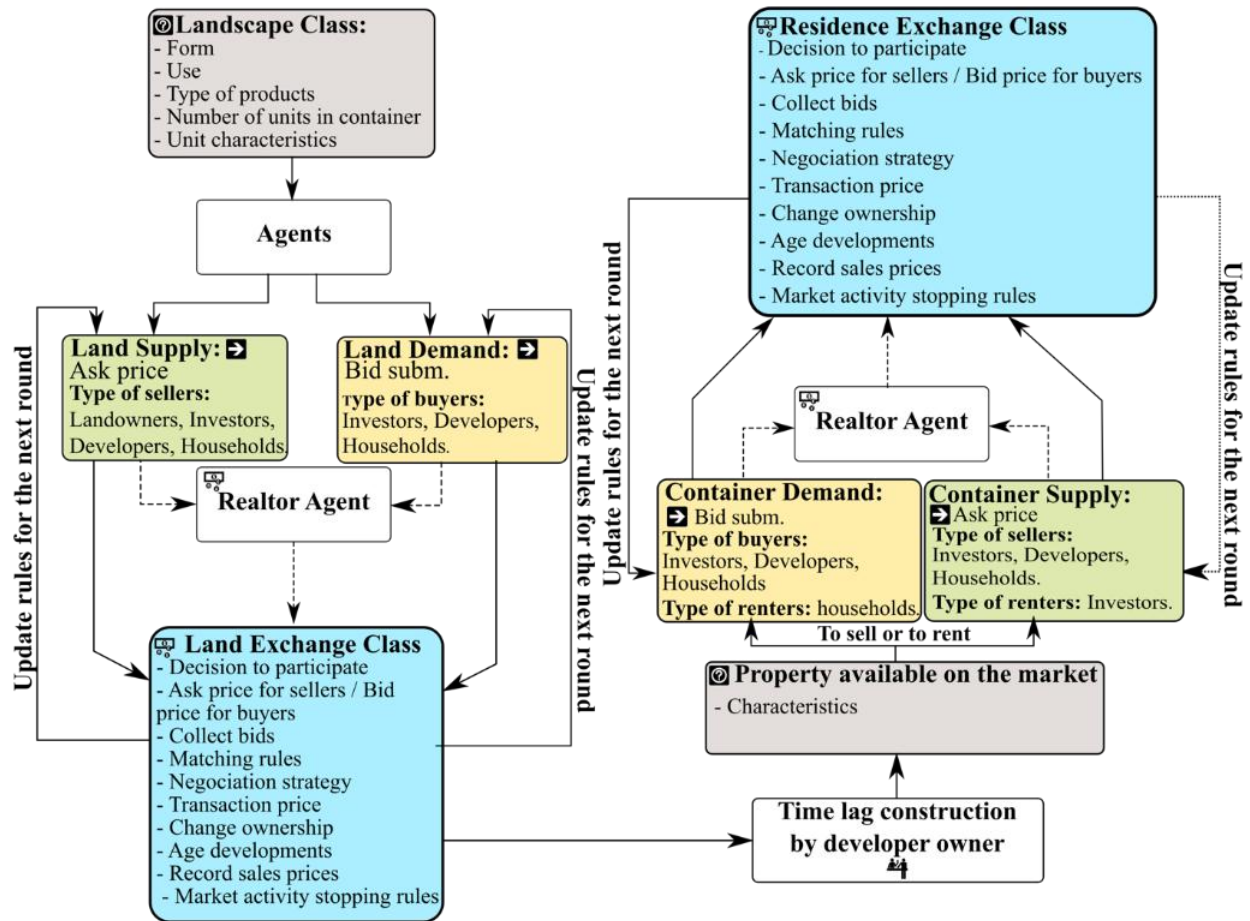


Figure 2: ABM-REM class diagram overview.

5.1 Landscape class

The *Landscape* class is designed to represent the characteristics of land cover, land use, and the built environment that are relevant to ABM-REMMs. It contains fields that describe the intended role and technical features of the model's landscape representation, answering the question "What is the form and resolution of the model's spatial representation?" Specific responses for each model are summarized in Table S1 (Landscape Class Template). The landscape class also describes the spatial data inputs into the model. Note, often data for these models comes in different spatial structures and resolutions, requiring separate geographic information systems (GIS) analysis to create spatial data inputs for the model. Creation of input data is thus its own model effort, often complex and requiring assumptions and compromises. We are assuming that documentation for GIS data creation should be part of the metadata for the GIS layers; thus, we do not ask for this information in the templates.

The first section of the template answers the question "What is the form of the base landscape?" Users can identify their models as abstract or empirical. As discussed in Parker et al. (2002), abstract and empirical agent-based models of land-use and land-cover change often (although not universally) play different roles, with abstract models often used to demonstrate hypotheses and seek generalizable insights, and empirical models more often used to seek scientific and policy insights from real-world case studies (Parker et al., 2002; Robinson et al., 2007; Dai et al., 2020).

Both the intent of the model and available data can impact how the landscape is represented. Real estate market models can be completely a-spatial, for example, those coupled with national-scale macroeconomic models (Carro et al., 2023). Such models are developed when higher-scale outcomes (such as general levels of housing prices or household indebtedness) are of primary interest, or where computational complexity or data availability prevent the development of spatially explicit models.

Cell-based landscapes are often used for theoretical models, where an assumption of a uniformly tessellated landscape is supported. For instance, cells might represent city blocks hosting large high-rise buildings (Almagor et al., 2018a), or single-family homes that develop around a new transit station as a “new town” (Filatova et al., 2009; Parker & Meretsky, 2004). Such models can be expanded to have endogenously varying density within uniform cells and to include spatial fields of contiguous groups of cells, representing a farm for sale, or a zoned area. For example, in a coupled land and housing market model, CHALMS (Magliocca & Walls, 2018) models developer’s endogenous decisions to offer homes that vary in home and lot size on the residential market. Multi-cell farms are sold in the housing market and then developed into housing of varying sizes and densities.

Cell-based models can also be developed using real-world raster data, in cases where remotely sensed (i.e. land cover) data are available, but cadastral land-use data, such as parcel boundaries and zoning polygons, may not be available.

As higher-fidelity empirical models are developed to represent and seek insight on real-world case studies, researchers often develop vector-based models that operate over real-world parcel boundaries. For instance, Filatova (2015) developed the vector-based housing market RHEA ABM to understand flood risk exposure and property price impacts, as buyers and sellers with biased risk perceptions negotiate prices and update their price expectations. Parker et al. (2016) develop a vector-based ABM that integrates with network transportation models to understand linkages between housing market activity and transportation mode choice. (Prunetti et al., 2025) develop a parcel-level, vector-based land-and-housing-market ABM that examines how demand for touristic amenities shapes land-use change and property prices; building on this same framework, they empirically calibrate additional tourist-rental, tax, and coastal/CBD-zoning policy levers to quantify their combined effects on urban growth, land competition, and housing affordability across Corsica. All of these vector-based models rely on detailed GIS data about transportation accessibility, amenities, and disamenities. These data are used to create regression models (hedonic models) that estimate the impacts of these factors on development probabilities, price expectations, and buyer and seller values (see agent decision model sections).

Whether landscape representations are a-spatial, cell based, or vector, modelers define or categorize data into coarse-scale land uses, generally divided into developable and undevelopable categories. Again, these categories are generally matched to the research questions of the model. Many models (Filatova et al., 2009; Filatova, 2015; Magliocca et al., 2011; Prunetti et al., 2014) focus on when and how previously rural land may be converted into urban use, so include developable or urban lands. Models may also focus on densification and thus include a gradient of residential densities (Magliocca et al., 2011), low-rise apartments (Prunetti et al., 2025), and high-rise builds (Almagor et al., 2018a).

In ABM-REMMs, the number of residences at a single location can vary, to represent all the housing in a country or town, a development containing a mix of housing types, or an apartment building with many virtually identical units. To represent this phenomenon, we develop the concept of a “container” that represents the collection of unique housing products being bought and sold in the marketplace at a given location. This container approach simplifies model construction by avoiding the challenge of modeling parcel subdivision and agglomeration, which would require models of both land markets and the planning process.

In its simplest form, a single parcel with a single residence is represented by a single container type on a single patch (Filatova et al., 2009). The container approach can also be used to represent increasing density at a particular location. For instance, (Magliocca et al., 2011) implement 18 potential housing types based on combinations of small, medium, and large homes on lot sizes ranging from 0.25 acre to 10 acres, using a cell size of 1 acre (0.4047 hectares). Thus, the model can represent four 0.25 acre homes on one spatial entity (one container with four identical units), or a compound spatial entity of 10 acres that contains one home (one container on one compound spatial entity). CHALM’s capacity to represent density is used to replicate empirically and theoretically supported patterns of decreasing density and increasing lot size in suburbs.

Containers can also represent multi-family residential units. In these cases, the building footprint, number of stories, and patch/polygon area can be combined to calculate the floor space ratio (FSR, which reflects the building height if building mass were uniformly distributed across the parcel). FSR is a frequently used zoning metric, so these fields allow easy assessment of whether a proposed housing type is feasible under zoning regulations. Building height influences view-sheds, and important amenity in many regions, and can be used to

calculate view-sheds of simulated landscapes (Rød & van der Meer, 2009). Building height and footprint may also influence wind patterns, heat island impacts, and pervious surface to absorb storm-water runoff, facilitating linkages with model of the environmental impacts of urban development (Ying et al., 2016).

Keeping with the example of the multi-unit residential building, modelers can define multiple different unit types within a single container. For instance, an apartment building may have 1 and 2 bedroom units, or a row house block with interior and end units. The user can describe all of the unit characteristics included in the model, which may be minimal or uniform for simple theoretical models, or may use detailed property characteristic data with fields selected through statistical analysis (Parker et al., 2016; Prunetti et al., 2025). Such detailed data allows modeling of developer decisions of what to build, as well as housing market activity of individual unit types.

While one of the main advantages of ABM-REMMs is their ability to represent spatially explicit landscapes, the container approach allows the models to be implemented as completely a-spatial (Glavatskiy et al., 2021; Carro et al., 2023), incorporate proxies for space through the characteristics of the spatial entities (for example, urban, suburban, or ex-urban housing markets; Ge, 2017), or represent spatial location at the scale most relevant for housing markets, such as a single apartment building (Prunetti et al., 2025). Ideally the degree of spatial representation should be justified and matched to the research question of interest, but often such coarse representations of space are required for computational tractability or data availability constraints.

5.2 Property exchange class

Following Figure 2, we create specialized versions of the MR POTATOHEAD (Parker et al. 2008) *Land Exchange* class to represent market exchange. Two *Property Exchange* classes are created: *Land* and *Residences*, to represent each market. Specific responses for each model are listed in Table S2 (Land market), S3 (Residence market) and S4 (rental market) in the Supplementary Materials.

Focusing on the “residence” exchange mechanisms, and comparing models that use the “container” approach (less spatial and more aggregate) to models that focus on the exchange of individual properties, we note differences in how the prices of individual units are determined. The more aggregate models use “market clearing” algorithms, closer to the mechanisms of aggregate supply-and-demand analytical models. For example, Ge (2017) ensure matching of supply and demand of houses and identification of an ‘equilibrium’ price by estimating the intersection of an endogenous downward sloped demand curve upward sloped supply curve, calculated by a “real estate agent”. In Carro et al. (2023), home buyers are matched to the highest quality house they can afford, and to the cheapest possible house in this band. House investors, on the contrary, are matched to the highest yield house they can afford, and to the cheapest possible house within a given yield. If multiple bids are received, buyers who are able probabilistically increase their prices. Bidding proceeds through multiple rounds until no more transactions occur. Magliocca et al. (2011) employ an iterative process whereby the utility of the bidder with the highest bid is re-calculated using that bid price, then the house buyer is potentially matched with a different affordable home that produces the highest utility, ensuring that 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. In contrast, Filatova (2015), Parker et al. (2016), and Prunetti et al. (2025) model direct price formation, where buyers who have a fixed willingness to pay bid and potentially negotiate for specific properties. These strategies show an interesting spectrum from adherence to traditional neoclassical economics models to direct modeling of how home purchase markets operate in the real world.

Property exchange models also employ various models of bargaining. In the simple case where one bid is received, and that bid is higher than the seller’s willingness to accept, most models set the transaction price to the bid price (Prunetti et al., 2025; Parker et al., 2016). Bargaining is relevant in several contexts. Even for bilateral transactions, Magliocca et al. (2011) set the transaction price between the two based on relative market power, following Filatova et al. (2009). If the highest bid is still below the seller’s willingness to accept, both Filatova (2015) and Prunetti et al. (2025) model a bargaining process. Prunetti et al. (2025) similarly model negotiation between sellers and buyers, only if the buyer’s willingness to pay (private knowledge) exceeds the seller’s willingness to accept (also private knowledge). In this case, a transaction price is determined based relative market power, measured by the number of other bidders on the house. Filatova (2015) model a complex bargaining process, where the seller queries the buyers with the highest bid, and that buyer compares the price

difference proposed by the seller to the opportunity cost of renting for a half year. Filatova (2015) assumes that public information about prices is also available, through a real estate agent who estimates price changes. Both prevailing prices and relative market power (proportion of buyers to sellers, or sales-to-listings ratios) can be viewed as “emergent properties” of real estate markets. Through expectations and bargaining strategies, they shape, and are shaped by, pricing and negotiation strategies. These cross-scale feedbacks highlight the advantage of ABM-REMMs over static, single-scale modeling approaches.

Models deal differently with unsold units. Ge (2017) precludes the possibility of unsold units through their market clearing algorithm. In Carro et al. (2023), unsold houses enter the rental market. Filatova (2015) and Carro et al. (2023), model incremental price reductions for unsold homes.

5.3 Agent decision model templates

MP-REME implements descriptions of a wide range of land-and-housing-market actors, starting from a generic agent decision model template, which can be modified to represent a diverse set of buyers and sellers. Additionally, modeled agents can assume multiple roles. For instance, a developer can be a land buyer then, once the property is developed, a home seller. A household can be a buyer of both their own residence and an investment property. Further, coupled with noting that ask prices are private information in the Property Exchange template, each agent type can have access to different information, facilitating representation of information asymmetry.

This template builds from the agent decision model template developed by Parker et al. (2008), describing the actor type, the actor’s attributes, including budget, preferences, time horizon/discount rate, risk perceptions, price expectations, preferences, utility, costs, demographic characteristics, and more. The templates also implement the real-estate market features outlined by Parker & Filatova (2008). Buyer-specific templates describe the buyer’s willingness to pay and bid price strategy, and seller-specific templates describe expected returns, willingness-to-accept, and ask price algorithms. Each template outlines when and how these actors decide to participate in markets and decide which properties to rent, buy, or sell. Buyer and renter templates specify how many properties they can place bids on, and seller/landlord templates describe how many bids they accept on each property, how those bids are evaluated, and how the sellers might strategically respond to multiple bids. Investor templates describe how investors decide to bid on properties, how much they bid, how they determine rents, and whether/how they sell their assets. Each individual actor template describes that actor’s negotiation strategy, if applicable. Both buyers and sellers may be able to adjust bid or ask prices, in response to an unsuccessful transaction. Each actor may also decide whether to remain on the market or leave it.

5.4 Land supply

Two models represent land supply. Their model choices are listed in Table S5 (Landowner land seller). In Prunetti et al. (2025), household land-owners offer parcels for sale, and the willingness-to-accept for each parcel is based on prices from recent transactions of similar parcels, estimated through a spatial regression of the sales data. Land supply is deliberately scarce – only 2500 parcels are classified as buildable, while extensive coastal, mountainous, and agricultural protection regulations render most of the island off-limits – so developers compete for the limited inventory, driving up prices and motivating the explicit modeling of a dedicated land market. Similarly, in Magliocca et al. (2011), farmer land owners develop price expectations based on recent land sales, but using multiple estimation algorithms. However, they also must receive more than the opportunity cost of maintaining the land in agriculture, with ask prices dynamically adjusted based on the amount of land developers demand. The inclusion of returns to agriculture allows Magliocca et al. (2011) to run scenarios on how changes in returns to agriculture can stall or trigger land conversion, a critical issue worldwide. However, detailed price data on both current urban land prices and agricultural returns are not universally available, creating challenges for researchers who seek to represent the critical dynamics of land supply and land-value change.

5.5 Land demand

5.5.1 Developer land buyers

Two models directly represent developer land buyers. Their model choices are listed in Table S6 (Developer Land Buyer). As in the real world, their developer land buyers must estimate the potential profits they can make from housing constructed on a potential parcel. These boundedly rational expectations directly influence developers' bid prices for land. In Prunetti et al. (2025), developer agents – each specialized in a single housing type (e.g., cottage, villa) – scrutinize every parcel offered for sale. For each site, they form an expected sale price for the house they intend to build by matching the parcel's locational attributes with recent transaction prices of comparable houses, an expectation generated through a spatial regression of empirical sales data. After accounting for construction costs and their target profit margin, this value becomes the developer's maximum willingness-to-pay for the land. The bid they actually submit is a fixed fraction of that amount that incorporates a developer-specific leeway value, leaving room for negotiation with the household land-owner. Capacity constraints further limit how many plots each developer can pursue in a period, sustaining competition without enabling unlimited land acquisition. This approach, with more statistical sophistication, most closely resembles the “pro-forma” approach that developers use in real life (Valaei Sharif et al., 2023). Magliocca et al. (2011) alternatively choose from 20 different prediction algorithms, comparing estimates using a loss aversion algorithm consistent with prospect theory, and from there also bid based on expected net returns. Developers in both models consider relative bargaining power in the market (adapted from Filatova et al., 2009), and both model bilateral negotiations, using different algorithms.

5.5.2 Investor land buyers

In the models reviewed in this paper, investor land buyers are not present. However, other important ABM-REMMs represent these important market actors, addressing, for example, how ABM-REMMs can illustrate the dynamics of land acquisition and property decay behind Smith's “rent-gap hypotheses” (Jackson et al. 2008; Diappi and Bolchi 2008).

5.6 Home sellers

5.6.1 Developer home sellers

Models use different strategies to represent housing supply, as detailed in Table S7 (Developer residence seller). Carro et al. (2023) model a simplified land developer, who supplies sufficient new homes to the market to meet a parametric target ratio of new homes per population, supplied at a random quality level. Ge (2017) assumes that a representative developer owns and can develop all land, and then supplies identical housing to the point where the marginal construction cost equals the expected sales price, thus bringing more construction to regions with higher home prices. In Prunetti et al. (2025), developer agents transition to *home sellers* once a house is completed. Magliocca et al. (2011) model detailed home supply costs, including construction loan finance costs and terms. Similarly to how they model land price expectations, developers use multiple price expectation mechanisms to estimate future housing prices, using these estimates to determine home construction. Developers in Magliocca et al. (2011) can hold land before developing homes; carrying costs are explicitly modeled.

Strategies for setting the ask price for new housing differ between models. Again, the more aggregate, a-spatial models have simpler ask-price-setting strategies, while the more spatially detailed, empirical models employ greater detail. Carro et al. (2023) set ask prices empirically, based on the real-world current distribution of house prices for the quality level constructed by the developer. This strategy implies that they could not explore recent housing market challenges, such as rising construction costs and interest rates, using their models. Ge (2017) set the ask price equal to the marginal construction costs, which increases with more home construction. However, marginal costs are modeled as a quadratic function of quantity, again missing the opportunity to run scenarios around changes in construction costs, interest rates, and other cost factors. In contrast, Prunetti et al. (2025) set an ask price equal to the land purchase price plus construction cost, augmented by a target profit margin and a developer-specific leeway factor that leaves room for bargaining. Magliocca et al. (2011) form an ask price by estimating expected rents using hedonic regression algorithms, for house types that have yet to be constructed. For housing types that have been built, the developer uses a simple spatially weighted extrapolation. Their willingness-to-accept is based on a minimum profit percentage.

Models differ in how they determine accepted bids. Carro et al. (2023) collect bids at an aggregated market level, in advance of the market clearing rule described in section 5.2. In the case of multiple bids, the developer increases ask prices by an increment and then selects randomly among the bidders who can still afford the house. Ge (2017) also applied the market-clearing mechanism described in section 5.2, applied at the neighborhood scale to model heterogeneous demand by neighborhood. Magliocca et al. (2011) accept the highest bid, as long as it exceeds their willingness to accept. In Prunetti et al. (2025), if at least one household or investor bid meets the developer's ask price, the unit sells immediately; otherwise a single-round negotiation splits the surplus between the highest bid and the developer's reservation value, with the final price rising when demand pressure is high. In sellers' markets, the ability to model negotiation and "bidding up" is key to understanding price dynamics.

Models deal similarly with unsold homes. Carro et al. (2023) and Ge (2017) decrease the price of unsold houses by a set percentage in every time period, with no lower bound. Ge (2017) takes units off the market if they have not sold for 24 time periods, potentially resulting in loan default. In Prunetti et al. (2025), a house that remains unsold for two consecutive quarters loses its profit premium, and if it fails to sell in a third quarter the developer is declared bankrupt and replaced, explicitly tying sales performance to firm turnover and preserving competitive supply dynamics over the 40-quarter horizon.

5.6.2 Investor home sellers

Mirroring real-world trends, as rental units become vacant, investor owners may decide to sell their investment property, as detailed in Table S8 (Investor residence seller) (Carro et al. 2023, Ge 2017). This possibility, however, is not yet modeled by Prunetti et al. (2025), but is an important extension for future work, in order to understand the long-run impacts of their proposed policies to contain investor activity.

5.6.3 Household sellers

Model choices for household sellers are detailed in Table S9 (Household residence seller).

Decision to sell

Several models represent household sellers, with varying degrees of detail. These details are seen first in the household's decision to sell a home they currently own. Ge (2017) randomly assign a percentage of residents to relocate, who list their homes for sale. Valaei Sharif et al. (2025) randomly sample a percentage of local residents, equal to the estimated out-migration of the region, to determine homes for sale. Their households are drawn from demographic distributions from the Canadian census. Carro et al. (2023) offer the richest models of household demographics, modeling household age, income, wealth, and propensity to save, although they also have a simple monthly probability of selling their home. Once their home is sold, they are assumed to return to rental housing. Filatova (2015) model endogenous relocation based on subjective "fear of flooding," which updates based on personal flood experience, news of flooding, flood insurance costs, and moving costs.

WTA/Ask price

Ge (2017) form price expectations simply through the last period's price in their neighborhood, with their WTA based on this price plus a time-on-market adjustment. Valaei Sharif et al. (2025) set the seller's willingness to accept and ask price based on a hedonic assessment price estimate, essentially their price expectation mechanism. This estimate remains static as the model runs, potentially dampening the modeling of price appreciation in WARM. Filatova (2015) model adaptive price expectations through hedonic functions, which are updated by a real-estate agent, and available to all actors in the model (realistic for the US, considering the availability of estimated prices through companies like Zillow). Sellers set their ask price according to this function, adjusting by time on market, flood history, and changes in demand in their local neighborhood. Sellers' WTAs are set by the payoff costs to their mortgage.

Bid acceptance

Ge (2017) and Carro et al. (2023) employ the market-clearing algorithms described in 5.2. Valaei Sharif et al. (2025) collect multiple bids and accept the highest bid, if it is above the seller's WTA. Filatova (2015) models sellers as accepting the highest bid if above their WTP, but engaging in negotiations with the highest bidder as described in 5.2. However, the seller also compares accepting the bid to their opportunity cost of waiting another 6 months to sell the home (one half year of mortgage payments).

Unsold residences

Sellers in Valaei Sharif et al. (2025) keep unsold residences on the market, until they are sold or the simulation ends. Sellers in Filatova (2015) will reduce their ask prices after a flood event, in proportion to the flood risk zone. Sellers in (Ge 2017) adjust their unsold home prices according to time on market, and will take unsold homes off the market after the maximum time set by the model. However, they also have the option to default on their mortgage if the market sales price is lower than the mortgage owed. In contrast, Carro et al. (2023) also adjust prices downward for unsold homes, but if this decrease would leave the household in a loss position if the house were sold, they take the house off the market.

5.7 Home buyers

5.7.1 Residence home buyers

The majority of models described in this paper have buyer households, who decide to enter the housing market, place bids on homes, and purchase homes, as detailed in Table S10 (Household residence buyer). Household's participation in the market, housing budget, and subsequent willingness-to-pay for homes is based on their household preferences for a specific location, own wealth and income.

Decision to buy

In Ge (2017), a fixed number of household buyers are activated in each round. In Filatova (2015), a portion of residents are assigned to be home buyers. As the model runs, some successful home sellers then become local home buyers. Magliocca et al. (2011) model households as having a stochastic residence time, and when activated, they enter the house market. Buyers can also endogenously decide to relocate, triggered by a change in utility following a storm event, provided utility can be increased by the move, accounting for moving costs. Valaei Sharif et al. (2025) model incoming buyers as new in-migrants to the region, drawn from Canadian census households, based on historical migration data. These diverse household profiles provide the data required to customize household willingness-to-pay functions to household size and income. Carro et al. (2023) also utilize their detailed household demographic profiles to drive important policy experiments, described below. In particular, household wealth evolves through the model runs, dependent on income and endogenous essential and non-essential household consumption. Household housing budgets also depend on maximum possible mortgage approval. From this distribution, households who do not have a home decide whether to enter the buying market by comparing the longer-term costs of renting vs. buying, including a psychological cost of being a renter.

Household budgets

Filatova (2015) set household budgets through an empirically estimated distribution, with lower-income households spending a higher percentage of their income on housing. Magliocca et al. (2011) take a similar approach, varying the proportion of income spent on housing by income level. Housing budgets are the residual of consumption goods expenditures, cost of flood damage and flood insurance, and travel costs to the house. Valaei Sharif et al. (2025) set housing budgets so that mortgage payments are no more than a fixed percentage of income. In Prunetti et al. (2025), resident household buyers are drawn from three income brackets (low, middle, high), each allowed to purchase at most one home per quarter.

Direct modeling of household finances allowed Carro et al. (2023) to explore the housing market impacts of policies such as limits on loan-to-value (LTV) and debt-to-income (DTI) ratios in the UK owner-occupier mortgage market. Their models allow households to make either mortgage or cash purchases, dependent on household wealth. Their policy experiments assessed the impact of different loan-to-value (LTV) strategies on housing mortgage approvals, transactions, and prices. Like Ge (2017), they find that LTV restrictions can dampen housing market cycles, but causes shifts from owner-occupant to investor home purchases. They found that the ability of their model to represent heterogeneous household incomes was key to its ability to replicate housing market cycles. Ge (2017) require that buyers' wealth and incomes cover both a cash down payment and a monthly payment, with an income-dependent maximum. Prunetti et al. (2025) also model a housing budget that depends on a fixed share of monthly income, an annual increment of wealth, and travel costs from the home.

Price expectations

Carro et al. (2023) model buyer price expectations for particular quality homes through a simple trend-with-intercept regression. In Prunetti et al. (2025), for every house-parcel on the market, the agent forms a class-specific expected price via a hedonic model. Valaei Sharif et al. (2025) also model buyer price expectations

through iterative hedonic model runs based on transaction data from the last 4 time periods. These expected prices are used to identify properties that are affordable under the household's budget constraint.

WTP / Bid price

Carro et al. (2023) model willingness to pay (WTP) for a home as a simple stochastic non-linear function of household income. Households then bid on the highest quality house that they can afford. Ge (2017) use an abstract utility function and random, uniformly distributed parameterization to estimate buyer's utility from neighborhood quality, location quality, and consumption of non-housing goods. Magliocca et al. (2011) define WTP as the housing budget, described as a money-metric indirect utility function, with parameters randomly assigned across households. As described in 5.2, a secondary market-clearing mechanism allows households to calculate bid prices that reflect the relative utility difference between that option and the one that produces the maximum utility; thus, households do not necessarily bid the maximum of their budget. These highly abstract representations of household buyers' preferences mean that these models can't be used to examine how household preferences lead to real-world market sorting, or how evolving household preferences shift markets.

The remaining models develop detailed empirical housing preference and utility functions, to better model market segmentation and market sorting. To calculate bid prices, Prunetti et al. (2025) subtract commuting costs from their estimate of the market value of the home, and assesses net benefit through a quasi-linear indirect utility function, whose parameters are estimated through hedonic regression. Their WTP function is derived from a modified form of the bid function in Filatova et al. (2009). The household bids on the home with the highest utility, and the bid submitted equals a fixed fraction of the agent's maximum WTP, leaving room for negotiation. By combining income, commuting costs to the CBD, amenity preferences, and bargaining behavior, the module tracks how policy shocks reshape affordability and spatial sorting in Corsica's supply-constrained housing market. Filatova (2015) models buyers as forming preferences for homes based on house age, lot size, land size, and neighborhood quality, using these estimated coefficients as weights in a multi-criteria money-metric indirect utility function. Bid prices are not based on this utility, but instead are anchored to the seller's ask prices, bidding above or below this price stochastically. Note this strategy differs from previous models of strategic bidding by Filatova et al. (2009) and adapted by Magliocca et al. (2011), which increase or decrease bids based on the proportion of buyers to sellers in the market. Buyers bid on a subset of the most expensive houses they can afford – with the implicit assumption that these provide the highest money-metric utility. When in a negotiation, buyers compare the difference in asking price to their opportunity cost of remaining in the home search market for another half a year. Valaei Sharif et al. (2025) compare two strategies to form willingness-to-pay/bid price. In the first, WTP is derived from a first-stage regression model, which includes only property and neighborhood attributes. In the second, the WTP of the first-stage regression is shifted by household-specific marginal WTP for property and neighborhood attributes, derived from a second-stage regression model that employs buyer survey data. In both cases, similar to Carro et al. (2023), the WTP is truncated by the household's budget. The second approach facilitates exploration of market sorting by household type, revealing the household types and income levels who are most likely to lose out in bidding wars, and thus not be able to achieve single-family housing ownership.

Unsuccessful buyers

Valaei Sharif et al. (2025) model unsuccessful buyers as leaving the market. In reality, these buyers might enter the condo or rental markets; if data are available, future models will include these options to fully address research questions related to market sorting. In Magliocca et al. (2011), buyers leave the market after 3 unsuccessful time steps. In Carro et al. (2023), unsuccessful buyers are assumed to return to social housing, from where they can re-enter the sales or rental markets. In Ge (2017), unsuccessful buyers increase their bid prices each round they fail to purchase a home, until they reach their time-on-market threshold, at which point they leave the market. In Prunetti et al. (2025), unsuccessful buyers stay on the market.

5.7.2 Investor home buyers

ABM-REMMs are making important contributions to current debates on housing financialization (housing as a human right vs. housing as an investment) by including investor home buyers, who acquire homes for speculative and/or rental income purposes. For example, Carro et al. (2023) demonstrate that restrictions on household mortgages can advantage investors by increasing their share of housing ownership, the number of properties they own, and the rent they receive, and their net returns (due also to lower home prices). Prunetti et al. (2025) show that restrictions on investor housing purchases can temper speculative price premiums – by

roughly €40/m² – and reallocate prime coastal plots to resident households, thereby easing affordability pressures without depleting the overall housing supply. Ge (2017) demonstrates that even a small proportion of investors, combined with lax lending restrictions, can trigger housing bubbles. These model choices are detailed in Table S11 (Investor residence buyer).

Forward-looking financial estimations of expected rental income return and salvage value are modeled by both Carro et al. (2023) and Prunetti et al. (2025). Carro et al. (2023) include mortgage payments in their net return calculation, facilitating exploration of lending policies for investment homes. Such price expectation mechanisms lead to housing market cycles, as rising markets increase profit expectations, and then contribute to upward investment trends, until no more wealthy households are available to buy, leading to a downward trend in markets. Prunetti et al. (2025) use this mechanism to explore how taxes on rental incomes will impact the market share of investors, other housing submarkets, and prevailing housing development and prices.

5.8 Rental markets

5.8.1 Investor landlords (renting out homes)

In our group of models, only Carro et al. (2023) model investor landlords. These model choices are detailed in Table S12 (Investor residence lessor).

Price expectations play a key role for investors who rent out units (landlords). Carro et al. (2023) use an exponential moving average of previous rents (assumed to be open knowledge) to set rental rates, but reduce this rate if units remain vacant. They note that the existence of a rental market in their model provides a cushion that might dampen housing market cycles, as households always have a rental option (and also a no-cost social housing option). Since Prunetti et al. (2025) already develop empirical models of expected rents to support home purchase decisions, the creation of investor landlord agents is a natural next step.

5.8.2 Household renters

In our group of models, only Carro et al. (2023) model household renters, detailed in Table S13 (Household residence renter). They demonstrate that their loan-to-value experiments increase the proportion of household renters, as those households are squeezed out of the home purchase market by more highly capitalized investors. However, the rent-to-income ratio for these renters is higher, as their incomes are on the higher margin that would allow them to purchase homes in the absence of the policy.

6. Discussion, conclusions, and future work

6.1 Reflections on the ontology-building exercise

This process has revealed, for every case, that important details of models are not sufficiently described in our publications. It has also been very helpful in revealing differences in model assumptions for models that, at first glance, seem almost identical. While their conceptual bases are very similar, their practical implementations differ. Therefore, we hope that these standard templates will create an effective documentation protocol for ABM-REMMs, facilitating better model communication and comparisons. Parker's team has recently used the templates to describe another model (Gamal et al., 2024b) and to design an expanded model, which includes components from several other models. We are refining the template to identify reusable building blocks (Filatova et al., 2025), paving the way for code sharing and model comparison. To support this effort, we've implemented our MP-REME templates in Obsidian (Obsidian 2026), an object-oriented note tool that allows us to cross-reference one template item through many templates.

6.2 Suggestions for structured comparisons

There are some clear areas where structured comparisons, within the same code base, are needed. Models include assumptions with two purposes in mind: to represent real estate markets with sufficient accuracy, and to represent the mechanisms needed to answer specific research questions. The first purpose is where coordination between our modeling communities is most needed. Reflecting, for example on the agent decision templates alone (Section 5.3), comparison of the specific mechanisms used in each model to determine which buyers are active in the market, what budgets they have available for housing, how they form price expectations, how they form bid prices, and what they do if their bids don't succeed presents a cacophony of approaches –

each potentially having some theoretical and some empirical justification. Yet, we really don't know which of these approaches are most justified, nor do we know how these approaches impact the ultimate model results and thus the answers obtained to the paper's main research questions. How robust are those answers to the specific mechanisms chosen in each model? These disparate approaches highlight the need for cross-model comparisons, across multiple case studies, in order to build standardized models that are sufficiently robust for policy analysis. Based on the comparisons from this paper, we suggest the following as priorities for model comparison:

1. **Price formation:** As noted, models use very different mechanisms for determining sales prices for land and housing units, from competitive bidding to algorithmic price adjustments to facilitate market clearing. Direct comparison of alternative mechanisms for price formation (5.2) within the same empirical models, with the opportunity for extensive verification and out-of-sample validation, is an important challenge for future work. Structured comparisons between models that represent individual properties, allocated through bilateral transactions, and models that pool properties and use market-clearing algorithms would also be very helpful, especially as the community works towards the development of multi-scale national models used by central banks (Borsos et al., 2025). When are aggregate models sufficient? Where do they fail? What questions can they not address? Can results of finer spatial scale models be generalized or aggregated to provide regional inputs to national housing market models?

In this comparison, other tradeoffs should be evaluated, such as computational efficiency vs. realism, and data limitations that prevent the development of fully spatial models. If simpler, less data intensive "container" models are sufficient for research questions such as macro-characteristics of housing markets, fiscal, tax, and central bank policy, widespread housing market models can be developed and deployed more quickly, at lower cost. In contrast, addressing many questions related to how markets sort residents spatially, and how that spatial sorting impacts climate change vulnerability, spatial segregation, access to environmental quality, flood risk, or heat island impacts requires spatially explicit models that clearly link new residents to a geographic location. Development of such models may remain more data and resource intensive, but the results may well justify the efforts. Regardless, we echo the call in Carro et al. (2023) to develop spatially disaggregated housing market ABMs, which also contain levers to test national-level economic policies.

2. **Bargaining and negotiation:** Within those that model decentralized bidding and price formation, models also use different mechanisms to represent bargaining and negotiation. In addition to comparing these mechanisms directly in the same model, future mixed-methods research could engage with experimental economists and real-estate market professionals to better understand which of these models have strongest empirical support. What is the simplest empirically robust method to model market competition and bargaining? Should upwards-and-downward responses in bid and ask prices be modeled explicitly for each market actor? Or is it sufficient to implement an algorithm that splits gains from trade, depending on the state of the market?
3. **Unsold units:** Models also use various assumptions to represent the fate of unsold units, from keeping the properties on the market, price reductions, sale of the unit, to bankruptcy. Again, ideally the assumption used should have empirical support from the local case study, based on real-world research that sheds light on how home sellers behave in falling markets. How many keep their homes off the market to avoid a loss? How many are forced into default because they can't cover mortgage payments? Minimally, sensitivity of model outputs to this assumption should be systematically undertaken. How should price adjustments by sellers and buyers, when each does not succeed in the market, be modeled? To answer these questions, research need detailed data on list, bid, and final sales prices – data often out of reach for researchers, due to cost or access rights.
4. **Price expectation:** Comparison of different models of price expectations applied to the same case study (for all buyers and sellers) would be a natural next step. What algorithms for estimating price expectations have the most empirical validity? Does the answer differ between real estate professionals (land speculators, developers, and lending officials) and households, who participate in market transactions with different frequency?

5. **WTA, Ask prices, WTP, and Bid prices:** Related, researchers should compare the impacts of different algorithms to determine WTP and bids, such as undertaken in (Valaei Sharif et al. 2025), but on a broader scale, and inclusive of sellers' algorithms as well. Again, researchers often have differential access to real-estate data, meaning that they need to rely on different algorithms to determine these metrics. Comparative research on the impact of these choices would help frame the implications of choices made due to data scarcity.
6. **Household budgets:** Models differ in their approach to modeling household housing budgets, from a simple percent-of-income approach to modeling detailed intertemporal tradeoffs between housing, consumption, and alternative investments. Direct comparison of these strategies is an important area for future work, provided data on housing expenditures as a percent of income, and how these change in buyers-and-sellers-markets and interest rate changes, are available. Budget should of course reflect local institutional rules that link income and credit to loan availability.
7. **Unsuccessful buyers** Models take diverse approaches to modeling the next steps for unsuccessful buyers, from remaining on the market for a fixed period of time, to moving to the rental market, to out-migration. These diverse approaches to a seemingly simple assumption highlight the need to identify appropriate rules for unsuccessful buyers, ideally through site-specific data analysis and real estate professional interviews. Here, demographic data on the percent of households in ownership vs. rental tenure and migration are often available for model calibration or rule validation.

6.3 Next steps—building a shared code base

The next project goal is to build a common code base – likely focusing first on household buyer and seller interactions – which will nest each model as a special case, by calling particular functions and/or modules. We hope this code base will facilitate formal cross-model comparisons, extending preliminary efforts in our community, such as comparison of the impacts of market representation on economic and spatial outcomes (Huang et al., 2013; Shipeng Sun et al., 2014) or the testing of new methods for global sensitivity analysis in ABM-REMMs (Magliocca & Walls, 2018). We currently plan to build this code base in Netlogo. In short, we think a NetLogo code base is more likely to be used by others, and contributed to, than a code base in another language. NetLogo is used for labs and illustrative examples for two textbooks that teach agent-based modeling (Railsback & Grimm, 2019; Wilensky & Rand, 2015). It also has relatively low barriers to entry, compared to other languages. A NetLogo code base is more likely to be seen as an easy entry point for new scholars, especially those lacking prior computer science training. Further, it is likely to be used for teaching. We look forward to the social science community's feedback on this ambitious, but hopefully practical, project.

One potentially promising approach to developing the modules needed to populate the full MP-REME models is the "Reusable Building Blocks" (RBB) initiative (Berger et al., 2024), supported by an open access platform to host, review, improve, and reuse such building blocks: <https://www.agentblocks.org/>. It provides programming-language-neutral metadata on potential components of agent-based models, together with working code implementations. These clearly documented, context-specific, and reusable building blocks enhance transparency and comparability across different ABMs. MP-REME modules could be linked directly to building blocks, and might have alternative implementations of the same processes in different contexts, scales, or programming languages (Filatova et al., 2025). Noting Berger et al. (2024) points distinguishing lower-level RBBs from what they call 'modules' representing entire subsystems, should RBBs be widely adopted, higher-level work could collect RBBs together, providing guidance on implementation options for different parts of such subsystems, guided by the MP-REME templates. Filatova et al. (2025) provide a set of criteria for what constitutes an RBB, to help decide which part of the full ABM could be useful as an RBB. Similarly, Innocenti et al. (2024; 2025) provides further support by introducing the structured 5-SSIMP method, explicitly defining conceptual, computational, and executable Reusable Building Blocks to improve modularity and interdisciplinary collaboration. In combination, the MP-REME templates, the code for each described model, the meta-data for the RBBs, and the RBB code could provide data for a "small language model" designed to provide programming support for ABM-REMM.

6.4 Next steps— MP-REMM community review

Efforts have been underway to develop standard model description protocols for over two decades. The most successful of these efforts, fairly widely adopted, is the ODD (Overview, Description, Details) framework first proposed by Grimm et al. (2006), and since adapted by many authors (Grimm et al. 2020; Szangolies et al. 2024; Polhill et al., 2008; Müller et al., 2013; Müller et al., 2014). The first MR POTATOHEAD model was originally proposed as an adjunct to the ODD protocol. Interested readers can see a side-by-side comparison of the two protocols applied to the same models by comparing Parker et al. (2008) (the first applications of MR POTATOHEAD) to Polhill et al. (2008) (descriptions and comparisons of the same models using ODD).

Since that time, both ODD and MR POTATOHEAD have evolved. We now propose that MP-REME serve as the “details” template as part of ODD, as implemented by Valaei Sharif et al. (2025). Building a community standard is a step-wise process, but again, we propose to follow the ODD model by offering a structured “details” section for ABM-REMMs.

Here, we have demonstrated how the templates can be applied to multiple models. We now invite other members of the ABM-REMM community, including authors, editors, and teachers, to try the MP-REME templates, available through the “Model Code” weblink, and provide feedback. How might users learn and use these protocols? In order of technical depth, they may first use this paper to understand how real-estate markets are structured, by reviewing the overview diagram and class structure. By then reviewing the individual class templates, they can gain a deeper understanding of how the individual components are structured, learning what questions you need to ask and answer to understand real-estate market components, including how real-estate actors make decisions. Second, they may use the template to assist in reviewing a new article or study (perhaps in the context of a class), by using the template to identify the features represented in an ABM-REMM. Third, they can use the templates to design their own model, as have the authors (Innocenti et al., 2020; Valaei Sharif et al., 2025). While they may not choose to model all components, or all elements within a class, the templates can support conversations and deliberate decisions about what to include and what to leave out, given the team’s research goals and resource constraints. Finally, as our work moves forward, readers should look for, reuse, adapt, and contribute novel MP-REMM reusable building blocks.

We did not ask authors to complete the “Demographic Dynamics” template from the original MR POTATOHEAD templates. “Demographic Dynamics” describes the global rules by which agents enter and leave the model (Immigration and out-migration, Reproduction, Birth/Death, and Household Division/Agglomeration), and make transitions through their life cycles (Aging, Marriage, and Succession)” (Parker et al., 2008, page 7). However, we encourage all users of MP-REME to additionally fill out this template as part of their extended ODD description.

The lead author of this paper, while searching for information in co-authors publications, found themselves thinking the very thoughts commonly expressed by Volker Grimm, (2006) that a common template minimally allows the reader to know where to look for particular information, and to know that all needed details are provided. Beyond that minimal requirement, template adequacy could be tested through efforts to replicate a given model only by using the templates. Ideally our community will be able to undertake these tests through workshops and additional collaborative research, again ideally conducted with Central Banks, other government partners, and real estate professionals. These efforts will contribute to more general global efforts to make scientific models FAIR and transparent (Barton, Lee, et al., 2022; Barton, Ames, et al., 2022).

6.5 Next steps— Model extensions and policy applications

Several new class templates need to be added to MP-REME to represent the full suite of market actors, including finance/lenders, institutional real-estate investors, and central banks. We invite other scholars to contribute to this effort. Potential modifications of an expanded model include:

- Several of the models described here could easily be modified to examine current policy responses to rising rental and home cost and precarity, as for instance are now being implemented in B.C. Canada (Ministry of Attorney General, BC, 2026). On the investor side, these include vacant unit taxes, investment home taxes, and rental replacement laws. On the land development side, policies include inclusionary zoning (requirements for a percent of affordable units in new developments), increased

residential density such as allowing 4 units on any residential parcel, or upzoning to mid-rise around transit, non-profit housing finance, and streamlined development approvals.

- None of our models represent project cancellations, an important recent real-world phenomenon, but they could be easily modified to do so, using algorithms from Valaei Sharif et al. (2023). Cancellation of large high-rise projects can have ripple effects on real-estate markets, not only through reduced housing supply, but also through impacts on price expectations and land values.
- None of our models represent large-scale real-estate speculation –whether by home developers who assemble land for current development or by land speculators who bank land to be sold later. Such speculative behavior is a major component of housing financialization (Aalbers, 2017; August, 2022); thus, models can better inform current debates on housing as a human right vs. housing as a commodity (Farha & Schwan, 2021) by representing these speculative actors.
- Note that the models reviewed in this paper do not model “renoviction” decisions (a circumstance that mirrors Smith’s rent gap hypothesis at a smaller scale, where landlords evict current tenants, renovate units, and rent units at higher rents to a different demographic) (August & St-Hilaire, 2025). Our models could easily be modified to model landlord renoviction decisions by incorporating renovation costs and expected rent increases.
- As rental markets are crucial for understanding equity impacts of policies, and modeling housing market sorting in general, the addition of rental markets is a crucial next step for the models applied to Waterloo and Corsica. In Waterloo, such models can help to understand how transit-induced gentrification and renoviction push vulnerable households not only to unsuitable rentals, but also to homelessness (Doucet, 2021). In Corsica, modeling of rental markets can help to understand how the presence of touristic investors impacts full-time renters, including those who work in the tourist industry.
- Demographic shifts/transitions can cause linked changes to residential sales and rental markets. For example, aging populations in many countries could lead to many single-family homes coming to market as retirees downsize into condos or rental apartments – provided those apartments are available (Cortinelli & Jasim-Tucci, 2023). Further, sudden changes in immigration can lead to or reduce pressure on both rental and sales markets, potentially through complex pathways (Gunderson & Cukier, 2024). ABM-REMMs are ideal tools to model such impacts, as they can link housing demographics to housing changes, provided they are coupled with demographic transition and household formation models.
- On the macroeconomic side, models can be used to examine linkages between economic downturns induced by trade wars, radical changes in tax policy, and supports like universal basic income and housing markets. To remain able to respond to current internationally triggered macroeconomic shocks, model mechanisms must include levers to model tariff-sensitive construction costs, changes in household transportation costs due to oil and gas price shocks, international supply disruptions, and emerging technologies such as pre-approvable typologies and modular construction.

6.6 Potential contributions of MP-REME to modeling socioecological systems

We conclude by highlighting how MP-REME can contribute to modeling of socioecological systems, the focus of this journal. Such systems are classic examples of coupled human-natural systems (Liu et al., 2007; Seto et al., 2010; Rosenzweig et al., 2018). Agent-based models, due to their fine-scale spatial structure and ability to model cross-scale, non-equilibrium processes, are ideal for modeling human-environment interactions (Parker et al., 2002; Parker et al., 2003). ABM’s contributions to modeling spatial socio-ecological systems are now well recognized (Filatova et al., 2013).

We argue that urban real estate markets have specific, and significant connections within urban socio-ecological systems, particularly with respect to urban climate. With nearly 70 percent of world population projected to live in cities by 2050 (Kundu & Pandey, 2020), urban areas become the epicenter of the social, economic and climate crisis nexus, as well as the starting point for action, as signified by the new IPCC Special Report on Cities (IPCC,

2025). Within this context, urban housing markets link directly to global environmental change, either as an amplifier of existing challenges or as solutions. For example, with the acceleration of losses due to climate-induced hazards, housing markets capture the signal shifting individual demand for safer locations, resulting in climate gentrification when the poor are priced out of safety or are trapped in high risk locations (Thompson et al., 2023). Despite recognition of urban housing and climate change as urgent issues, they are often viewed as conflicting priorities, with public rhetoric discussing tradeoffs between addressing safe and affordable homes as a human right and funding of climate change action in cities. This rhetoric can detract attention from the significant ways that they interact and are co-determined. Land and housing markets shape urban form and function, which are major contributors to climate challenges in cities (Monkkonen et al., 2024; Egerer et al., 2021). This paper illustrates how ABM-REMMs can be applied to understand interactions between flood risk and housing markets. ABM-REMMs are being, and can further be applied to understand interactions between real-estate markets and transit contributions to climate, pollution exposure, heat island impacts, residential yard climate contributions, and many other urban socio-ecological systems. As such, ABM-REMMs increasingly combine economic (e.g. preferences for location, income and affordability), financial (e.g. mortgages), environmental (e.g. flood risks and nature-based solution adaptations) as well as social (e.g. inequity and gentrification) dimensions (Mutlu & Filatova, 2026), opening new horizons for policy-oriented analysis.

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Supplementary Material

The Supplementary Material for this article can be found online at <https://sesmo.org/article/view/18913/18471>.

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