

Hybrid Urban Model (CA + Agents) for the Simulation of Real Estate Market Dynamics and Sea-Level Rise Impacts

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Abstract. The paper presents a proposal for a hybrid model - based on cellular automata and agents - that simulates the spatial distribution of population and built area according to real estate market's dynamics and the risk of flooding due to sea-level rise. Its main differential is the integration of network analysis metrics to the functioning of the cellular automata. This proposal was motivated by the interest in analysing future development scenarios for the coast of Rio Grande do Sul, a state located in southern Brazil. Its demographic dynamics have been generating pressure for urban growth to the detriment of the surrounding natural environment, making cities in the region more susceptible to natural phenomena such as the sea-level rise. The proposed model is presented through the ODD + D description protocol and the results of simulations executed for Imbé and Tramandaí, two municipalities located on the coast of Rio Grande do Sul. The results show that the model represents the effect of current planning policies on long-term urban development. However, some urban dynamics are not yet precisely represented by the proposal at its current stage of development.

Keywords: Urban modelling · Cellular automata · Agents

1 Introduction

The north coast of Rio Grande do Sul - a state located in southern Brazil - has been presenting the highest demographic growth in the state, contrasting with the population decrease that occurs in its neighbouring regions [1]. In addition, during the summer, the region's population increase up to 250% in relation to the winter period due to the touristic attractiveness of local beaches [2]. These dynamics cause an intense real estate market that generates pressure for more urban growth [3], creating challenges for urban management and affecting the surrounding natural environment [1]. In this sense, the suppression of dunes and vegetation makes the region's urban areas more susceptible to natural disasters such as storms or even the sea level rise due to climate changes, expected to impact the region by the end of the century [4].

In the literature, no analyses are found on how these issues will affect cities on the north coast of Rio Grande do Sul, although studies that apply modelling and simulation techniques to speculate on the development of cities have become commonplace in

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other regions of the world in order to anticipate possible urban trends according to different scenarios [5–8]. Aiming to contribute to this set of studies by adapting existing modelling techniques to the specific context of the coast of Rio Grande do Sul, the authors' ongoing research seeks to analyse development scenarios of municipalities in the mentioned region using cellular automata and agents.

This work presents a hybrid model - based on cellular automata and agents - to assist the analysis of the study area and whose main objective is the representation of: i) locational preferences of the population groups; ii) land value variation; and iii) the impact of sea-level rise on the region's urban configuration. The differential of this proposal is the use of network analysis metrics as attributes of the cellular automata, enabling the direct communication of non-adjacent cells. Experimental simulations show that the model is able to represent the effect of planning policies on long-term urban development.

2 Research Background

Complex systems are systems whose components are other complex systems and in which the interaction between such components originates endogenous and decentralized processes of organization that influence the system's behaviour at all scales [9]. Cities are classified as complex self-organizing systems since they consist of numerous individuals with complex behaviour interacting with each other and the environment on the micro-level and influencing the patterns that emerge in the city's macro-level [10]. Because cities are complex self-organizing systems, their operation presents the specific characteristics of such systems: emergence [11], non-linearity and far-from-equilibrium functioning [12], path dependence [9] and robustness [13].

To model cities as complex self-organizing systems, it is necessary to treat them as processes, incorporating time in the model and assuming an algorithmic approach, in which the behaviour of the system's components is disaggregated into actions performed iteratively step by step [14]. Two specific model types are commonly applied to implement such an approach: cellular automata (CA) and multi-agent models (MAM). CA consists of the division into cells of the represented territory, each representing a fraction of it. These cells present: i) a state, which assumes a value from a pre-defined list of possibilities; ii) a set of transition rules indicating how states change over time; and iii) attributes which describe the characteristics of the territory and are also used to define transition rules [15]. States and attributes generally provide a geographical description of the territory - land cover, occupation, use - while transition rules tend to incorporate theoretical spatial or economic statements referring to dynamics of cities [16]. In this sense, CA's general objective in urban modelling is to capture the rules that determine how the state of cells changes according to what happens in its neighbourhood and how these changes produce patterns representing future possibilities for the system [17].

The agents of a MAM are able to move within the limits of the model, and each also has its own attributes and states, as well as transition rules; however, due to their mobility, it is not required for them to have an immutable neighbourhood [16], and interactions between agents usually occur between those who are close enough during simulation or between those connected by means of communication, such as social networks [18, 19].

Agents enable the simulation of a heterogeneous system in which the specificities of different population groups are considered [18]. They also can interact with the territory when CAs and MAMs are used in a hybrid model, enabling the territory's cells to be modified according to the interaction with agents and also to modify them [16].

However, for such models of complex systems, the validation process presents dilemmas regarding the difficulty of testing all the assumptions that are present in the model [20] and the lack of consensus on how to demonstrate the reliability of future predictions, considering that past or present empirical observations do not necessarily indicate how the system will develop into the future [14]. It is commonly accepted that such models serve to inform the debate about specific urban issues and not to provide completely accurate forecasts [21]. Given that cities are path-dependent, one way to demonstrate the model's reliability is to show that simulated results correspond to possible behaviours of cities and that, therefore, they could be one of the many future possibilities for the analysed urban system [14]. One can accomplish this by using: i) map comparison metrics that define the goodness-of-fit between reality and simulation, showing if simulations represent specific aspects of the study area [22]; and ii) fractal metrics for which the literature has already defined values that typically represent cities, showing that simulation represents general behaviours of cities [14].

3 Model Description

The proposal is composed of a CA model representing the analysed environment and a MAM representing the population's locational preferences. It is described in the following subsections with the use of the ODD + D protocol for ABMs [23].

3.1 Overview

Purpose. The proposed model aims to provide a methodological platform to integrate land value variation dynamics and the impact of natural phenomena into the analysis of urban environments. The main question that the model seeks to answer is: how the referred factors influence urban growth and the population's spatial distribution? In this paper, the only represented natural phenomenon is the sea level rise, but other factors could also be included in future studies.

Entities, State Variables, and Scales. The model is composed of agents, cells, and real estate developers (REDs). Cells correspond to hexagonal fractions of the territory with 50-m-long edges. Their state represents its urbanization capacity and reachability, dividing them into: i) cells that can be urbanized; ii) those that cannot be urbanized but are reachable, such as beaches; and iii) cells that cannot be urbanized and are unreachable, such as lakes or the sea. The attributes that influence the cells' state are presented in Table 1. Empirical GIS data is uploaded at initialization to define the cell's initial state and attributes.

Agents represent individuals who settle in cells to perform residential or commercial activities. Their state variables are: i) their income; ii) the cell's minimum attractiveness for the agent to settle in it; and iii) the maximum number of iterations that the agent may remain in the same cell.

REDs are implemented as a computational function that looks for cells where they could build more units to increase their capacity and profit from such operation. They do not have state variables and are not physically represented in simulations.

Table 1. Attributes of CA's cells.

Attribute	Description
Occupancy	The number of agents inhabiting the cell
Capacity	The maximum number of agents that can simultaneously inhabit the cell
Load	An estimate of the agent attractors in the cell. It is divided into natural (such as beaches) and urban load (active residences and commerce). It weighs the results of the spatial opportunity and convergence metrics
Spatial opportunity	A network analysis metric which estimates the accessibility to commercial use and services from the point of view of residences [24]. In this study, it represents the cells' attractiveness to residential agents
Spatial convergence	A network analysis metric which measures the locational privileges of commercial activities [25]. In this study, it represents the cell's attractiveness to commercial agents
Land value	An estimate of the cell's sale value

Process Overview and Scheduling. The simulation process works according to the following steps: i) agents are inserted in the model and seek, among the cells compatible with their income, the most attractive ones; ii) as agents settle in or leave, cells update their attributes; iii) agents check if their current cells still meet their attractiveness and cost requirements and, if this does not happen, they search for another one; and iv) the most sought cells become more expensive, attracting REDs who expand these cells' capacity to profit with the sale of the created units. During this process, some cells are affected by sea-level rise.

Since spatial opportunity and convergence metrics are based on the analysis of the territory as a network, the shortest paths between all pairs of cells are computed using a graph representation as described in Sect. 3.3.

3.2 Design Concepts

Theoretical and Empirical Background. Real estate market dynamics follow the modelling of microeconomic supply and demand as proposed by Filatova [26], where the land value is defined endogenously in the model as agents decide which cells they find attractive. Agents' locational preferences and the behaviour of REDs are based on Krafta [24, 25], who proposed metrics to characterize the territory according to the preferences of residences or commerce and models of urban development based on such metrics. The logic of allocating different land uses according to their own preferences was loosely based on the proposals of White, Engelen and Uljee [14].

Individual Decision-Making and Learning. Agents decide where to settle in by analysing, for a randomly selected set of cells, if its land value is lower than the agent's income and if it is more attractive than the agent's requirement. After settling in, an agent decides to leave the cell if: i) its land value becomes higher than the agent's income; ii) it becomes less attractive than the agent's requirement; and iii) the agent's maximum number of iterations in the same cell is reached.

RED's decision to expand a cell is based on the developer's equation as proposed by Krafta [25]: if the cost of buying a cell and constructing in it is lower than the expected gains for selling the additional units, which is computed based on the neighbouring cells' land value, than REDs decide to perform such operation.

Individual Sensing and Predictions, Heterogeneity, and Collectives. Agents can perceive a cell's attractiveness and land value, and they use such information when settling in a cell or deciding whether to leave it. REDs also perceive a cell's land value, and they make predictions about its future price by analysing the neighbours' land value and considering their average as the value that the cell will probably have in the future.

Agents are distinct from one another because they have different incomes and attractiveness requirements. However, although such attributes are the same for some agents, they do not form any kind of collectives.

Stochasticity. When agents and REDs analyse cells, their search is performed considering a randomly selected set of cells with random size. Such randomness represents the fact that one cannot gather information about the whole system when deciding for a place to live in or when considering where to insert a building.

Observation. The main objective of simulations is to observe the spatial distribution of population and buildings, identifying the main factors that caused the appearance of the densest urban areas and analysing how the restriction of cells due to sea-level rise affect the population locational choices. Besides, the cells' land value and the agents' income may also indicate the appearance of economic spatial segregation.

3.3 Details

Implementation Details, Input Data and Initialization. The model is being developed in Gama Platform [27]. As input, it uses data on territory and roads from OpenStreetMap [28] and sea-level rise from Climate Central's Coastal Risk Screening Tool [4]. Currently, the model is initialized with an unoccupied territory.

Submodels. To enable the use of network analysis metrics as attributes of CA's cells, a graph representation was added as an auxiliary layer of the CA. In such representation, cells' centroids are nodes - weighted according to their load attribute - and their connections are represented as edges whose impedances are defined according to the hierarchy of the roads they intersect - it increases as the road's hierarchy increases. Based on these, the shortest paths (i.e., the ones with the lowest sum of impedances) between all nodes are computed, and they are used for computing the spatial opportunity and convergence metrics as described by Krafta [24, 25].

Validation. The authors expect to validate such results using the comparison between simulated results for the period 2010 to 2020 and the existing situation in 2020 through the measure of the goodness-of-fit for multiple spatial resolutions [22], and, for future scenarios simulations, metrics whose typical values for cities are described in the literature, such as the radial dimension and the cluster-size frequency distribution [14].

4 Results

To demonstrate the feasibility of the proposed model, an experimental simulation was performed for the municipalities of Imbé and Tramandaí, which compose a conurbation on the coast of Rio Grande do Sul, using a CA containing 16,000 cells. Since it was an experiment to test the model in its initial development stage, the territory was considered as initially unoccupied, and a fixed number of random agents was added per iteration of the simulation. Besides, the sea-level rise was updated in the 100th, 150th and 200th iterations with forecasts' data of, respectively, 2040, 2060 and 2080.

Figure 1 shows how the spatial distribution of agents evolved during simulation. High agent concentrations can be seen in areas close to the seashore, especially those close to several important roads, with areas further inland only being occupied when free cells next to the beaches become scarce. Figure 2 shows the variation of cells' land value and how the most sought areas become more expensive, making lower-income agents look for cheaper cells elsewhere.

Such observations indicate that current planning legislation – represented as an attribute of the CA - creates a tendency for spatial concentration in areas whose building restrictions are permissible, and the increase of sea-level rise reinforces such concentration. Therefore, one could consider modifying such building restrictions, aiming at a more homogeneous distribution of the population that needs to relocate due to sea-level rise, making the urban changes caused by it less drastic.

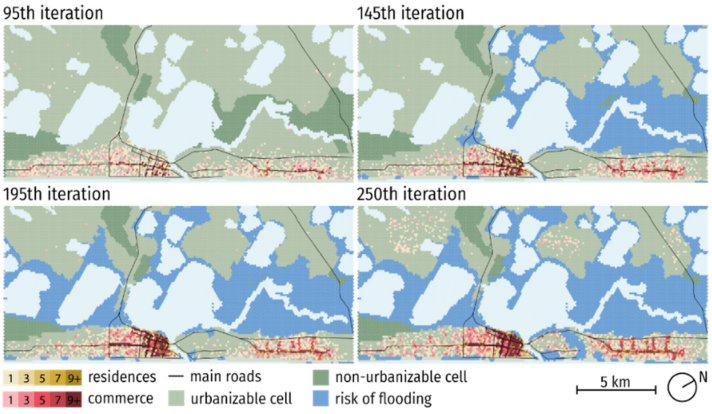

Fig. 1. Evolution of the spatial distribution of population during the performed simulation.

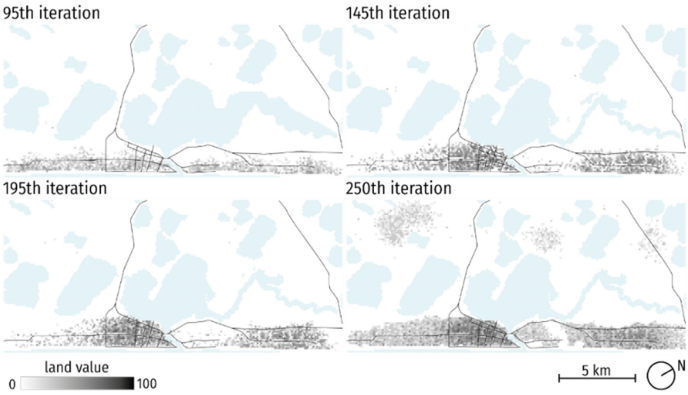

Fig. 2. Evolution of the cells' land value during the performed simulation.

The simulations also indicate that the model tends to overestimate forces of urban agglomeration to the detriment of those responsible for urban dispersion. This can be seen in the 145th and 195th iterations, where there is a concentration of agents in reduced areas of the territory which expands elsewhere only when available cells in central areas become scarce. This is probably due to the absence of factors that contribute to dense areas becoming less attractive, such as congestion.

5 Final Remarks

This study aimed to propose a predictive model of the urban configuration of municipalities on the north coast of Rio Grande do Sul. The presented simulation seems to be coherent with the theoretical bases used to support the study and demonstrate the relevance of simulating the impacts of sea-level rise and land market dynamics to inform discussions about planning policies. However, the results also show that the model overemphasizes agglomeration forces since it does not consider some of the sprawl forces existing in actual urban development.

Other improvements planned to be introduced in the following stages of development are: i) the implementation of validation metrics; ii) the introduction of the seasonal agents that repeatedly inhabit the municipalities for short periods; iii) the introduction of institutional equipment - such as parks, schools and hospitals - that affect the attractiveness of specific regions in particular ways since commonly their location is the result of top-down planning. Despite these considerations, the proposed approach still has the potential to provide more accurate results and, therefore, could be a relevant tool for urban modelling.

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