Urban Growth in Metropolitan Regions Using Dynamic Modeling by Cellular Automata: A Comparative Analysis Between Brazil and Portugal

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Abstract: This study synthesizes the outcomes of land use changes obtained through the implementation of dynamic modeling by cellular automata across two metropolitan regions in Portugal and Brazil. The purpose is to analyze the primary findings acquired, considering the particularities of each nation and evaluate the potentialities of the used data. The study examined the metropolitan regions of MRRJ (Rio de Janeiro, Brazil) and AMP (Porto, Portugal). Modifications were implemented in the DinamicaEgo software to the fundamental data representing static and dynamic variables for each context. The findings revealed a substantial increase of urban areas in the MRRJ, and the modeling demonstrated its applicability across the two contexts, considering the requisite modifications for the data accessible in each country.

1 INTRODUCTION

Cellular models in urban modelling became implicit in early computer models of the 1960s, e.g., the work of Chapin and Weiss for North Carolina (Chapin and Weiss,1968) Waldo Tobler's model for Detroit in 1970 (Tobler, 1970), and the model developed by Couclelis for Los Angeles in 1989 (Couclelis,1989).

Cellular automata (CA) have emerged as the prevailing architectural design employed in spatial simulation models. Cellular automata, as defined by Stephen Wolfram, are mathematical representations of physical systems in which time and space are discrete (Wolfram, 1983). These representations take the form of a regular uniform grid, where each location contains a discrete variable. In accordance with a predetermined set of local rules and the values of the variables in their immediate vicinity at the previous time increment, the variables in each cell are updated simultaneously. CA models have the capability to emulate various concerns associated with land use changes. They can be used to create self-modifiable models for high-resolution urban land use dynamics, prototypes to simulate land conversion via integrated Geographic Information Systems (GIS) (Clarke, *et al* 1997; White *et al*, 1997; Wu, 1998) and have numerous applications for simulating scenarios involving urban dynamics (Barredo et al, 2003; White, and Engelen, 1993). The use of dynamic models can support the definition of environmental public policies that involve the assessment of land use and land cover as a fundamental component to understand changes that may result from combined biophysical and socioeconomic factors, with both short-term and long-term impacts (Meyer and Turner, 1992).

In this context, the research aimed to identify potential scenarios of land use and land cover change until the year 2050 in the Metropolitan Area of Porto (AMP) and the Metropolitan Region of Rio de Janeiro (MRRJ), specifically within the boundaries of urbanized territories, while observing changes between classes and specificities.

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2 STUDY AREA

The study area encompasses two Metropolitan Regions: Metropolitan Area of Porto (AMP) and the Metropolitan Region of Rio de Janeiro (MRRJ - Figure 1). Although referred to by different acronyms—AMP for the Metropolitan Area of Porto in Portugal and MRRJ for the Metropolitan Region of Rio de Janeiro in Brazil—both regions fulfil analogous roles within their respective national contexts. In 2021, the Porto Metropolitan Area (AMP), composed of 17 municipalities, had a population of approximately 1,7 million inhabitants distributed across an area of 2,040 km². Meanwhile, the Rio de Janeiro Metropolitan Region (RMRJ), consisting of 22 municipalities, was home to around 12 million inhabitants in an area of 6,700 km², with significantly higher population density due to the concentration of people in municipalities like Rio de Janeiro, São Gonçalo, and Duque de Caxias. These regions represent important urban hubs in their respective countries, facing distinct challenges in terms of planning and urban development.

Each area functions as a logistical hub for regional planning, economic development, and the coordination of urban services. Both regions represent densely populated areas that support integrated infrastructure alongside public policy frameworks. This functional alignment underscores the significance of metropolitan regions as foundational elements in urban planning and governance in each country.

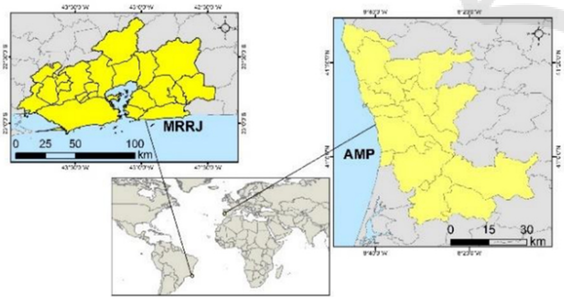

Figure 1: Study area - Areas considered in the study for comparison purposes

Situated in southeastern Brazil, the Metropolitan Region of Rio de Janeiro (MRRJ) is an extremely urbanized, multifaceted, and diverse region. This region, which includes the capital city, Rio de Janeiro, and significant neighbouring municipalities including São Goncalo, Duque de Caxias, and Niterói, is renowned for its geographical, historical, and economic importance. Based on a survey carried out in 2022 by the Brazilian Institute of Geography and Statistics (IBGE, 2022), the Metropolitan Region of Rio de Janeiro is the second most populous metropolitan area in Brazil, comprising 74% of the total population of the state of Rio de Janeiro, with an estimated 12 million inhabitants.

The Metropolitan Area of Porto is the second largest in Portugal, encompassing 17 municipalities around the city of Porto. According to data from the Land Use and Occupation Map - COS2022 (Instituto Nacional de Estatística, 2022).

The AMP has emerged as a strategic area for advancing mobility and sustainability projects, essential for the region's future.

3 MATERIALS AND METHODS

The CA model used in this work is implemented in the Dinamica EGO (Environment for Geoprocessing Objects) platform 7.4, a software developed by researchers from Federal University of Minas Gerais (UFMG). The methodology used is presented according to the scheme shown in Figure 2.

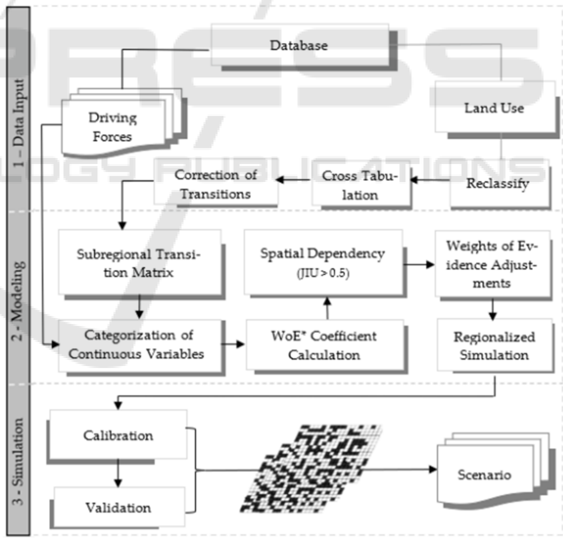

Figure 2: Workflow *(*WoE – Weights of Evidence).*

Simulation models utilize two types of explanatory variables, divided between Static and Dynamic. The former remains unchanged at each temporal step of the model, while the latter changes with each iteration based on the distance from the central axis being analyzed.

The first step in the modeling process is parameterization using the Weight of Evidence method, following the Bayesian approach. This involves assigning weights to different input variables based on their relevance to the specific problem.

Historical transition matrices are calculated. The transition matrix describes a system that changes in discrete increments of time. In the Dinamica EGO platform, matrices are calculated using a Markovian model, which combines the Markov Chains technique with Cellular Automata. Dinamica EGO also employs Markov chains to determine the amount of change, as well as cellular automata to reproduce patterns of these changes from probability maps, which are calculated using the Weight of Evidence statistical method (Soares Filho *et al*, 2002). Cellular automata (CA)-based models have been widely used due to their ability to simulate dynamic spatial patterns. The choice of the CA-Markov model in this study is justified by its integration of Markov transition matrices with dynamic spatial modeling, enabling the capture of land use changes with high temporal and spatial granularity.

For the desired period—a range of years—two types of matrices are generated: a global matrix, representing the transition rates for the entire training period, and a multistep matrix, which reflects annual changes. The global matrix aggregates all transitions across the specified period, while the multistep matrix allows for more granular modeling by representing changes on an annual basis.

It is important to clarify which transitions are being modeled, as this directly influences the simulation outcomes. In DINAMICA, transitions are managed through two Cellular Automata (CA) algorithms: the Patcher, which simulates the aggregation of land patches, and the Expander, which models the expansion of existing areas. These mechanisms ensure that spatial patterns align with the observed dynamics, providing a robust framework for projecting future scenarios.

In Dinamica EGO, a set of sub-regional functors is used to process the data separately in each sub-region. In this model, transitions are simulated annually for each of the subdivisions, dividing a map into parts for separate data processing and then combining the results. This allows the modeler to define operations that should be applied only to specific sub-regions or different parameters and coefficients. The result is a model that respects the regional context. In both cases, the transitions of interest focus on changes to urban, vegetation, and cultivated areas.

The dynamic variables considered in this study are exclusively related to land use and land cover in the years specified for each region: AMP and MRRJ. These variables reflect temporal changes that directly influence the projected scenarios and are updated in each iteration of the model. The static variables, on the other hand, remain constant throughout the modeling process and represent potential factors influencing the observed and projected land use changes. These variables include hydrography, transportation systems, and topography, which play a fundamental role in defining spatial patterns of urban expansion and enable the simulation of future scenarios. The dynamic variables include distances from existing urban areas, which are updated at each iteration of the model, while static variables, such as elevation and the hydrographic network, remain unchanged. Dinamica EGO uses Markov matrices to determine transition rates and spatial patterns based on weights of evidence calculated using the Bayesian method.

In summary, the calibration was conducted using the Expander and Patcher functions, which simulate, respectively, the expansion of existing patches and the formation of new urban patches. To address the specificities of the study area, the model was regionalized, dividing the territory into subareas with distinct characteristics and adjusting parameters for each region. This process allowed for greater accuracy in annual simulations, respecting regional contexts and producing results tailored to the geographic complexity of each studied area. Validation was based on spatial similarity between simulated and observed maps from 2021 (RMRJ) and 2019 (AMP), using fuzzy methods and moving windows. The simulation was regionalized to account for local characteristics of the territory, such as differences between rugged terrain areas and lowlands. The model annually simulates transitions, adjusting parameters to reflect local dynamics and generate accurate predictions of urban expansion.

3.1 Metropolitan Area Porto – Portugal - Model

The Metropolitan Area of Porto (AMP) was modeled utilizing the subsequent variables: land use and occupation, roads and railways, hydrography, elevation and slope.

The elevation and slope values were derived using the USGS-provided NASADEM Digital Elevation Model (30m spatial resolution).

At a 1:10,000 scale, the road network is an integral component of the National Motorway Network, while the railway network is an extension of the National Railway Network.

The hydrographic network is a 1:200,000 scale representation of the principal channels and rivers extracted from the Hydrography Network of Continental Portugal. Only the main rivers and channels were considered. While pertinent to the simulation process, this class is regarded as limiting in the modeling process for the expansion of the urbanized class.

In the study, the Land Use and Occupation Map (COS) for 2015 and 2018 was considered for the preliminary analysis, focusing on the base period 2015–2018. The primary categories analyzed were vegetated cover, agricultural regions, and urbanized areas. To project future scenarios, the model incorporated simulations for specific years: 2030, 2040, and 2050. A cross-tabulation analysis was conducted using the converted matrix dataset, maintaining the same spatial resolution to assess changes over time and validate the model's outputs.

3.2 Metropolitan Region in Rio De Janeiro/Brasil - Model

In MRRJ, the initial and final maps come from the time series provided by Mapbiomas (collection 7.1), including the years 2016 and 2021, that is, a period of 05 years, con-sidered sufficient to identify areas of urban expansion.

The MapBiomas 7.1 collection includes annual land use and land cover data for the period 1985 to 2021. The secondary data taken from the platform have some spatial inconsistencies in the thematic classifications, often due to noise and main-ly in classes and transversal themes, e.g., agriculture and pasture. Currently, there are 30 classes available, from macro-classes 1 - Forest; 2 - Non-Forest Natural Formation; 3 - Farming; 4. Non vegetated area; 5 – Water. The static variables were obtained from official Brazilian agencies (hydrography, road system, and topography).

The first stage of adjusting the Mapbiomas data consists of correcting incorrect transitions that normally occur in the form of isolat-ed pixels and have no correspondence in the real world, for example, a pixel classified as urban infrastructure should not transition to the water class.

The established rule was that no pixel originally classified as urban infrastructure (class 24) - Areas with significant density of buildings and roads - should transition to other classes. After the correc-tion, the other subclasses other than urban infrastructure were converted to the “Others” class, maintaining binary use maps.

Finally, the last phase involves data calibration, validation, and scenario observation. The maximum value of the Fuzzy similarity index is considered, using exponential decay for window sizes of 3x3, 5x5, 7x7, 9x9, and 11x11 as a validation method. The index varies from 0 to 1, where 1 indicates perfect spatial agreement.

Kernel Density Estimation was applied in the study to enhance the identification of change-prone areas.

4 RESULTS

Regarding the parameterization of the transition algorithms, Expander and Patcher, the model achieved better validation results with a higher percentage assigned to the Expander algorithm: 0.92% (RMRJ) and 0.87% (AMRJ).

Considering the threshold mentioned in (Soares Filho *et al*, 2002), where values close to 0.6 in the similarity index with exponential decay indicate adequate spatial congruence between simulated and real maps, it is reasonable to conclude that, in terms of suitable similarity, the period from 2015 to 2018 (AMP) and from 2016 to 2021 (MRRJ) showed satisfactory adjustments, especially in the 3x3 window.

4.1 Metropolitan Region in Rio De Janeiro/Brasil

To Metropolitan Region of Rio de Janeiro Based on the model, the following areas are identified as particularly promising for urban expansion in 2050: Situated west of the Capital, on the boundary between the Santa Cruz and Guaratiba communities. Additional noteworthy localities within the Capital comprise Campo Grande, Vila Militar, Campo dos Afonsos, Vargem Grande, and Recreio dos Bandeirantes. These are areas with available spaces for urban occupation and increased construction. Furthermore, the Baixada Fluminense encompasses municipalities Duque de Caxias, Magé, Nova Iguacu, and Seropedica, all of which exhibit substantial prospects for development.

In the East Fluminense, Maricá, Niterói, and São Goncalo are the municipalities that are undergoing the most significant urban development. In the Mountain subregion, Petrópolis municipality observes noteworthy urban expansion in the vicinity of the central area, which encompasses the Vila Militar and Valparaíso neighborhoods. In the southern region, notable residential areas include

Independência and Quitandinha. Notable are the regions of Mosela to the west and Bonsucesso and Itaipava to the north. The aforementioned regions symbolize the anticipated epicenters of urban growth as predicted by the model for the year 2050 (Figure 3).

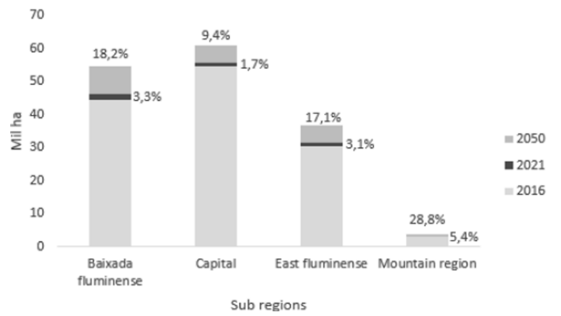

Figure 3: Urbanization by subregion through 2050, represented graphically by absolute and relative values.

Kernel density estimation (Figure 4) was employed to depict urban expansion in 2050. This interpolator enables the determination of the magnitude of a particular occurrence throughout an entire region (Freire, 2015). Druck *et al*, (2004) describe how the Kernel density estimator creates a surface whose value is proportional to the sample intensity per unit area and fits a two-dimensional function to the considered events in order to estimate the point intensity of the process across the entire study region. Kernel Density estimates the intensity of events (in this case, urbanization) per unit of area, generating a continuous surface that highlights regions with higher concentrations of change. This technique complemented the analysis based on transition matrices, enabling the mapping of regions with significant urban change. The use of this methodology was essential due to the high variability in land use in the MRRJ, providing a more detailed view of urbanization hotspots and enhancing future scenarios for urban planning and environmental management.

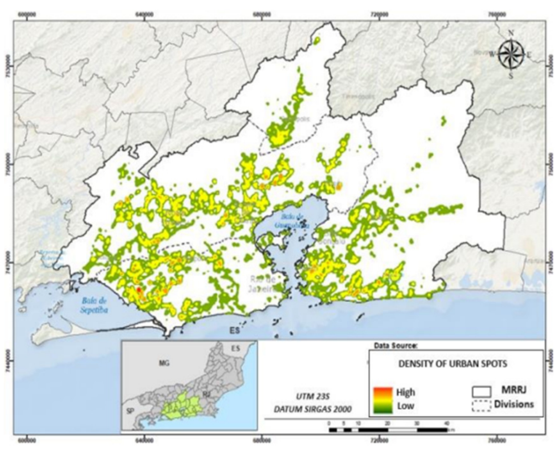

Figure 4: Urban Expansion Scenario for 2050 in MRRJ.

Municipalities outside the capital (Rio de Janeiro) highlight a current trend of urban expansion and demand for housing and new developments.

4.2 Metropolitan Area Porto - Portugal

The Figure 5 highlights the results obtained after modeling for the years 2030, 2040, and 2050 with a detailed analysis of the evolution.

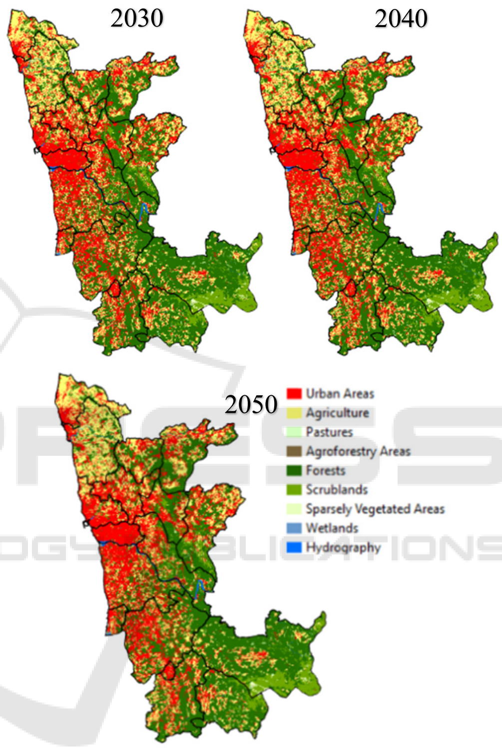

Figure 5: Future Landuse Scenarios for AMP in 2030, 2040, and 2050.

A 2.66 percent increase in urbanized territories is observed across the entire study area from 2030 to 2040, and a 2.55 percent increase from 2040 to 2050. The projected increases for agricultural regions are 1.13% and 1.08%, correspondingly. On the contrary, a decline in forested regions is noted, fluctuating by approximately 1.8% during both time periods.

The Figure 6 delineates the regions where anticipated alterations occur during the examined time frames. There is a total of 2274 polygons. From 2023 to 2040, there is a projected total of 1097 regions undergoing changes, namely involving the conversion of brush areas into urbanized zones and the transformation of brush areas into agricultural land.

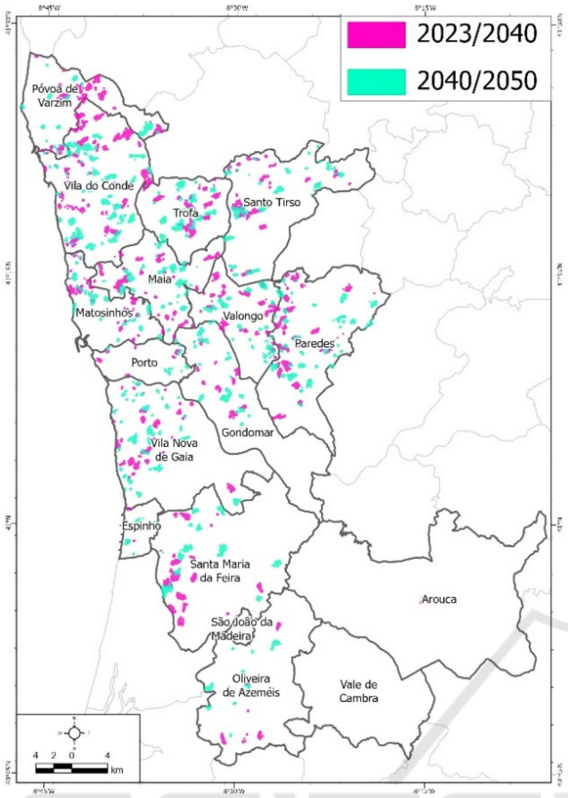

Figure 6: Regions with alterations in landuse during 2023 – 2040 and 2040 and 2050.

There is a significant concentration of expansion near the cities of Vila Nova de Gaia, Matosinhos, and Gondomar, which are already densely urbanized areas close to the metropolitan center of Porto. This growth suggests a continuous trend of urbanization in peri-urban areas and an expansion into zones with existing infrastructure.

In the period from 2040 to 2050, growth appears more dispersed, with new urbanization points emerging in regions such as Paredes, Santo Tirso, and Oliveira de Azeméis, indicating a possible gradual decentralization of the observed expansion. This pattern suggests a potential saturation of central areas and a search for new development zones on the periphery of the AMP, leading to a more balanced growth between municipalities in the northern and southern parts of the Metropolitan Area. These data highlight the need for integrated urban planning to meet the growing demands for infrastructure and services in these emerging regions.

Figure 7 highlights the projection for the Serra do Monte area (Northern Region of the AMP), with three representations: the 2050 projection showing urbanized area growth; a 2023 GE image as a reference; and a combination of both, indicating urban area densification and anticipated changes.

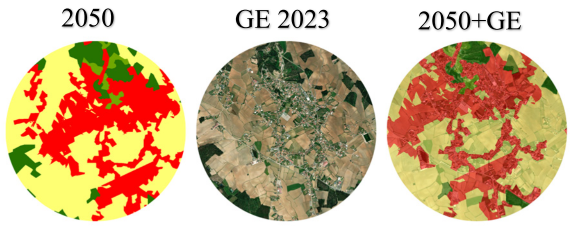

Figure 7: Changes in 2050 for Serra do Monte, Northern Region of the AMP.

Figure 8 demonstrates the predominant vegetation scenario near the A28 highway, which may be impacted by increased urban construction by 2050. The imagem also highlights an on-site view of the area. The red arrow indicates the direction of the photo's viewpoint.

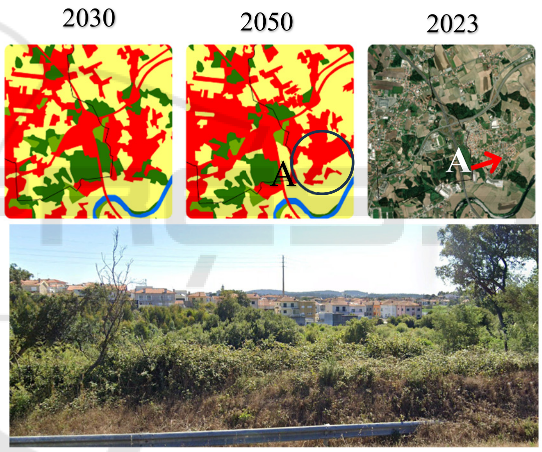

Figure 8: Changes in 2050 for Póvoa de Varzim.

Vila Nova de Gaia, located south of Porto, is expected to expand residential growth in areas with exposed soil and available land, as highlighted in Figure 9.

The results presented for the Metropolitan Regions of Rio de Janeiro (RMRJ) and the Metropolitan Area of Porto offer distinct perspectives regarding urban expansion projections. In the RMRJ, there is a notable focus on specific expansion areas, particularly in sub-regions with significant growth, such as the Baixada Fluminense and the East Fluminense. In the case of the Metropolitan Area of Porto, direct changes in land use stand out, detailing transformations in agriculture and urbanized territories. The conversion of areas from scrubland and agriculture into urbanized territories is emphasized. In both contexts, the results converge by

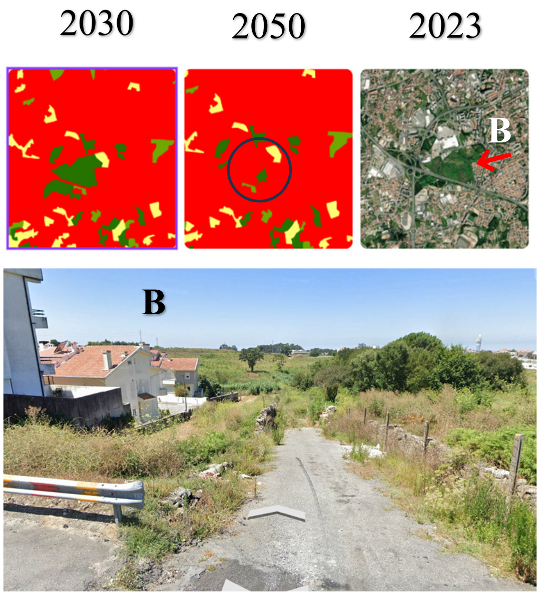

Figure 9: Changes in 2050 for Vila Nova de Gaia.

highlighting challenges related to urban growth, such as inadequate infrastructure and environmental impacts, underscoring the need for sustainable public policies and careful urban planning in both regions.

5 CONCLUSIONS

This study presents a synthesis of the outcomes achieved by employing cellular automata to perform dynamic modeling in multiple metropolitan regions of Portugal and Brazil. The research centers on the primary discoveries, taking into account the specific characteristics of each nation and the data utilized, while analyzing the metropolitan areas of Rio de Janeiro (RMRJ) and Porto (AMP). The DinamicaEgo software was modified with respect to the fundamental data that represented static and dynamic variables in each respective context. The findings unveiled a significant rise in RMRJ, thereby illustrating the model's versatility in different settings, contingent upon the data requirements of each country.

The findings pertaining to urban expansion projections for the Metropolitan Region of Rio de Janeiro (RMRJ) and the Metropolitan Area of Porto (AMP) present unique and discernible viewpoints. RMRJ places considerable emphasis on particular expansion zones, particularly in rapidly developing subregions like Baixada Fluminense and East Fluminense. Particular attention is paid to explicit alterations in land use within AMP, which pertain to agricultural and urbanized regions. Both contexts emphasis the transformation of agricultural and scrubland regions into urbanized ones. The findings converge in that they emphasize the environmental impacts and insufficient infrastructure associated with urban expansion, thereby emphasizing the necessity for sustainable public policies and meticulous urban planning in both areas.

In future stages of the research, new variables are intended to be included in the modeling process. The boundaries of protected areas in the AMP may improve the delineation of urban areas for future decades.

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REFERENCES

Barredo, J.; Kasanko, M.; McCormick, N.; Lavalle, C. (2003) *Modelling dynamic spatial processes: simulation of urban future scenar-ios through cellular automata.* Landscape and Urban Planning, 64, 145–160.

Chapin, J.R.; Weiss, S.F. (1968). *A probabilistic model for residential growth*. Transportation Research, v.2 p 375-390.

Clarke, K.; Hoppen, S.; Gaydos, L. (1997) *A self-modifying cellular automaton model of historical urbanization in the San Francisco Bay area*. Environment and Planning B, 24, 247–261.

Couclelis, H. (1989) *Macrostructure and Microbehavior in a Metropolitan Area*. Environment and Planning B, v.16, p.141-154.

Druck, S., Carvalho, M. S., Câmara, G., & Monteiro, A. V. M. (2004). *Análise Espacial de Dados Geográficos*. Brasília: Embrapa.

Freire, F. H. M. A. (2015). *Introdução à Estatística Espacial*. Recuperado de http://www.observatoriodas metropoles.ufrj.br/download/aulasanalise-espacial.pdf/

Instituto Brasileiro de Geografia e Estatística (IBGE). (2022). *Censo results 2022*. Acesso https://censo20 22.ibge.gov.br/panorama/

Instituto Nacional de Estatística (INE). (2022). *Land Use and Occupation Map (COS2022)*. Lisboa: INE.

Meyer, W. B., & Turner, B. L. (1992). *Human population growth and global land-use/cover change.* Annual review of ecology and systematics, 23(1), 39-61.

Soares-Filho, B. S., Cerqueira, G. C., & Pennachin, C. L. (2002). *DINAMICA—a stochastic cellular automata model designed to simulate the landscape dynamics in an Amazonian colonization frontier. Ecological Modelling, 154*(3), 217-235.

Tobler, W. R. (1970). *A computer movie simulating urban growth in the Detroit region*. Economic Geography, 46(2), 234–240.

White, R.; Engelen, G.; Uljee, I. (1997) *The use of constrained cellular automata for high-resolution modeling of urban land use dy-namics.* Environment and Planning B, 24, 323–343.

White, R.; Engelen, G. (1993). *Cellular automata and fractal urban form: a cellular modelling approach to the evolution of land use patterns*. Environment and Planning A, 25, 1175–1199.

Wolfram, S. (1983) *Statistical mechanics of cellular automata.* Review of modern physics, v. 55, p.601-643.

Wu, F. (1998) *SimLand: A prototype to simulate land conversion through the integrated GIS and CA with AHP-derived transition rules.* International Journal of Geographical Information Systems, 12(1), 63–82.