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Publication date
2022

Document Version
Final published version

Published in
Proceedings of the 32ND EUROPEAN SAFETY AND RELIABILITY CONFERENCE (ESREL 2022)

Citation (APA)
Aydin, N. Y., Krishnan, S., Yu, H., & Comes, M. (2022). An Integrated Framework for Incorporating Climate Risk into Urban Land-Use Change Modeling. In M. Chiara Leva, E. Patelli, L. Podofillini, & S. Wilson (Eds.), *Proceedings of the 32ND EUROPEAN SAFETY AND RELIABILITY CONFERENCE (ESREL 2022)* Article R25-01-258 (Proceedings of the 32nd European Safety and Reliability Conference). ESREL. https://www.rpsonline.com.sg/proceedings/esrel2022/html/R25-01-258.xml

Proceedings of the 32nd European Safety and Reliability Conference (ESREL 2022)
Edited by Maria Chiara Leva, Edoardo Patelli, Luca Podofillini, and Simon Wilson
 Published by Research Publishing, Singapore.
doi: 10.3850/978-981-18-5183-4_R25-01-258-cd

An integrated framework for incorporating climate risk into urban land-use change modeling

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Cities are complex socio-technical systems (STSs) under tremendous stress due to climate change. To incorporate resilience into urban plans and move towards evidence-based long-term decision-making, we must unravel complex land-use dynamics and the effect of climate uncertainties on cities. Currently, land-use dynamics are explored through Cellular Automata models to investigate the impacts of urban planning scenarios. What is, however, missing to support resilience decisions, is a systematic analysis of long-term climate uncertainties on land-use change. This study addresses this gap by analysing the effects of flood uncertainties on land-use patterns. While conventionally, urban planning decisions for climate uncertainty are based on a few scenarios, we use exploratory modeling to sample and combine uncertain climate variables to scenarios and understand the implications of the climate scenarios on land use via computational experiments. Specifically, we integrate flood probability maps into land-use maps to assess land suitability. Agglomerative clustering allows us to analyze the resulting land-use maps based on their similarity. Finally, we select representative maps from each cluster and compare them with the baseline map. We apply our integrated modeling approach in the Metropolitan Region of Amsterdam (MRA). Our results show spatially explicit alternatives for high-density residential development that is climate-resilient. The proposed framework can be applied to other cities to investigate the long-term impacts of climate uncertainties and adopt resilience-informed decision-making.

Keywords: simulation modeling, decision support, uncertainty, urban resilience, land-use modeling, cellular automata, exploratory modeling.

1. Introduction

The recent impacts of climate-induced disasters have proven the need to shift away from conventional urban planning and introduce resilient and long-term evidence-based decisions relying on data analytics to account for interactions and rippling effects between complex urban systems. However, as urban decision impacts reach far into the future, short-term responses typically made in the aftermath of a disaster, need to be complemented by adaptive decision-making to account for the long-term uncertainties (Krishnan et al. 2021). To achieve this ambition, we need to understand the complex land-use dynamics in cities. Urban land-use change models allow decision-makers to analyze complex relationships between driving forces of urban growth and explore alternative futures by simulating hundreds of scenarios.

Cellular Automata (CA)-based models enable spatially explicit exploration of future urban growth by integrating drivers and processes relevant to land-use dynamics (White et al. 1997). Built with in-depth expert knowledge and extensive qualitative and quantitative data, CA models can capture the non-linearity and self-organization of urban systems to produce a realistic representation of how a complex urban system evolves and spatial patterns change in the long term (Kim and Batty n.d., 2011).

While CA models are promising, the main limitation is that they can only integrate a few scenarios via the 'Story and Simulation' (SaS) approach. This limits exhaustive consideration of possible (climate) futures (van Delden and Hagen-Zanker 2009). Hence, climate-related uncertainties, particularly the consequences of extreme events, have a limited representation within CA models. Structural approaches and frameworks to integrate climate uncertainties into CA-based land-use change models are still missing (Maier et al., 2016).

This research aims to address this gap by developing an integrated framework that combines CA and exploratory modeling to investigate the impacts of climate uncertainties on long-term land-use changes. We selected Metronamica, a CA-based modeling framework to model the land-use change, allowing for simulations over a wide range of urban land-use functions (van Delden and Vanhout 2018). We focus on the long-term uncertainty of flooding impacts on land-use patterns by integrating flood probability maps into the physical suitability of land-use categories in Metronamica.

To systematically investigate the thereby defined uncertainty space, we connect Metronamica with exploratory modeling. The combination of Metronamica and exploratory modeling allows us to translate the uncertainties pertaining to multiple flooding probabilities into multiple spatial outcomes.

2. Methods & Materials

2.1 Land-use change modeling

CA-based land-use change models have gained popularity due to their ability to integrate multiple factors that contribute to urban growth processes over time in spatially explicit ways (Wagner 1997; Stanilov and Batty 2011). Metronamica is a popular CA modeling tool that offers an integrated approach to consider changing demographic and economic trends, and zoning policies instead of focusing on a single aspect like economy and or ecology. Its graphical user interface makes it possible to update model inputs interactively and explore the model behavior visually in a short amount of time (RIKS n.d., 2014). Metronamica works on a land-use allocation component where different land-use classes (LUC) compete to occupy specific locations within the model boundary. The factors that influence allocation are:

- Local accessibility (roads, rails, stations)
- Physical suitability (elevation, slope, soil characteristics)
- Zoning regulations (nature reservations, airport-area restrictions),
- Attraction and repulsion between LUCs.

2.2 Spatially explicit exploratory modeling

Exploratory modeling (EM) supports decision-making under deep uncertainty, allowing decision-makers to assemble, simulate and analyze the consequences of hundreds of scenarios (Kwakkel 2017). Since there is no need to define the plausible scenarios before model simulation runs, the bias from modelers and planners is reduced (Cox 2020). Conventionally, the Exploratory Modeling & Analysis (EMA) is applied to explore deep uncertainties and complex decision problems that require considering multiple objectives. However, EMA is not commonly applied to spatial datasets to explore the uncertainty space spatially explicitly.

Therefore, in this study, we expand the conventional EMA methods to make the investigation spatially explicit by connecting the EMA workbench with Metronamica. To this end, we used the EMA workbench (Kwakkel 2017) as a tool for sampling and combining uncertain climate variables. We sample exhaustive combinations of flood suitability ranges to generate thousands of experimental runs to represent the impact of flood uncertainty in our case study. These simulations result in many maps that are clustered based on their similarity. Finally, we select representative maps from each cluster and compare them with the baseline map.

2.3 Integrating flood probability

We use suitability values to determine the appropriateness of a LUC to occupy a specific position under a specific probability of flooding. A standard Metronamica simulation requires a fixed suitability value for each simulation. However, we argue that the impacts of flood probability categories and damages cannot be accurately translated into a single set of suitability values. Instead, we assign a range of values for each LUC to model the impact of climate uncertainties.

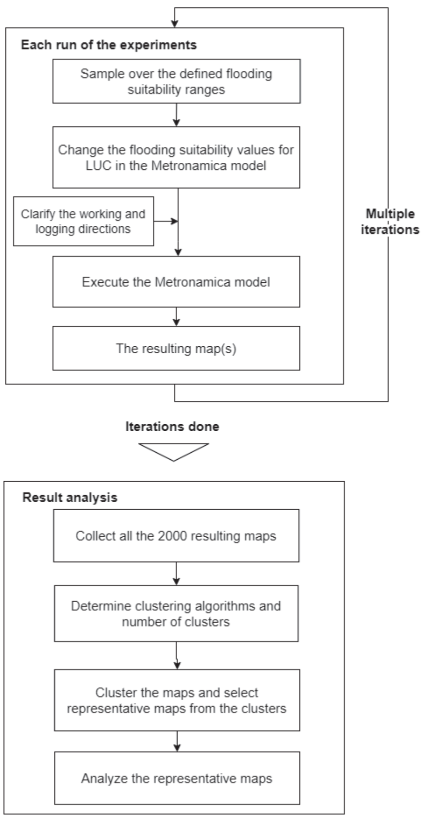

Fig 1: The overall workflow using the integrated modeling framework of "Metronamica-EMA" and assessing its outcomes

We use the EMA workbench to define the upper and lower bounds of the flood suitability ranges that influence the land-use allocation module in Metronamica. EMA samples values between the lower and upper bounds of the uncertain parameters. Metronamica uses these samples to generate outcome maps that indicate how land-use changes under different flooding probabilities. Fig. 1 demonstrates the overall workflow of the integrated modeling framework between Metronamica and EMA workbench[1].

2.4 Case study & data: Metropolitan Region of Amsterdam

The study area modeled is the Metropolitan Region of Amsterdam (MRA) in the Netherlands. The MRA is an agglomeration of 32 municipalities and houses 2.5 million people, 14% of the country's total population. MRA's economic attractiveness has led to high inward migration, housing shortage, and pressure on existing infrastructure systems. The region faces accelerated climate threats from rainfall and sea-level rise, making it an ideal case to study the impacts of climate change on long-term urban planning.

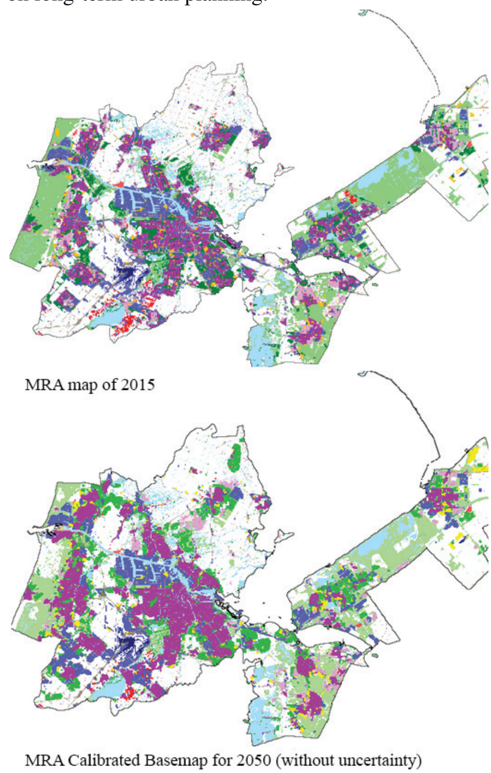

Fig 2: Land use of the MRA (2015- top) calibrated using historic data and simulated land-use of MRA (2050) using projected space demands

This study focuses on (1) simulating future land-use changes in the MRA for the year 2050; and (2) assessing the long-term impacts of flood risk on the land-use changes. The objective is to provide spatially explicit evidence to inform urban planning and infrastructure decisions.

We use Metronamica to model the changes in 12 major land-use classes (LUCs), including *Residential low (L), medium (M), and high (H) densities, Public Amenities, Recreation, Commercial, Mineral/Industry, Airport, Transport, Nature, Agriculture,* and *Water*. The data for the model was acquired from open-source databases, namely the Dutch Central Bureau of Statistics (CBS), Publieke Dienstverlening Op de Kaart (PDOK), Netherlands Environmental

[1] The full codebook may be accessed at https://github.com/feifeiyuzhuzhu/Master_thesis.

Agency (PBL), and OpenStreetMap (transport data). All maps were input as raster maps at a resolution of 100 by 100 meters to capture a suitable level of detail for urban functions.

The base Metronamica model was calibrated using a historical series of land-use maps between 1996 and 2015. The calibration involves adjusting spatial interaction rules between different LUCs that determine how much space they can occupy around each other (for instance, *Commercial* and *Public Amenities*often attract each other and are represented by a positive curve). In addition, the model integrates factors like Elevation maps, Soil quality data, Transport networks (roads, railways, stations), and significant soft and hard zoning policies that influenced land-use changes in the MRA (refer to Section 2.1).

To simulate land use for 2050, we use projected space demands for *Residential* and *Commercial* LUCs from CBS (see Fig. 2). The demands for other LUCs, such as *Public Amenities* and *Recreation*, were extrapolated based on their historical growth and in proportion to residential growth. Data for flood risks were obtained from the national climate database: *KlimaatEffectAtlas* Netherlands, presenting spatial projections for 2050 (https://klimaateffectatlas.nl/). We use data for the location-specific probability of flooding which indicates the total probability of flood depths ranging from 0 to 200 cms from the combined primary and regional water systems. From that data, we select the probability of areas to experience a flooding event of more than 50cms - a depth threshold beyond which floods cause significant damage to LUCs and infrastructure systems (Huizinga et al. 2017). The probability of flooding above 50cms ranges from 1 in 30 years to 1 in 30,000 years, also known as the return period of a flooding event.

3 Setting up the baseline scenario

3.1 Suitability values

We first determine suitability values for the baseline scenario, which does not consider uncertainty. The suitability value for each LUC is determined by the flood risk, which is the product of flood probability and the estimated economic damages for that LUC. The higher the flooding risk, the lower the suitability of this LUC for future growth in that area. The flooding probability is grouped into five categories. In Table 1, the columns from left to right indicate incrementally increased flooding probability, and the rows indicate the severity of economic damages of each LUC. The hierarchy of economic damages were identified from a Dutch inundation risk study that calculates the amount of damage for different inundation depths (Koks et al. 2012).

We assign suitability values that between 0 (unsuitable) and 1 (extremely suitable) for each LUC under the five flooding probability categories:

- All LUCs are deemed extremely suitable for allocation in areas with an extremely small flood probability. Therefore, 1 is given for all the values under *ESP*.
- *Nature* has the highest suitability value as it can sustain itself under all flood probabilities due to its capacity to absorb risk. All suitability values associated with *Nature* are equal to 1.
- *Residential (H)* has the lowest suitability value of 0 in the high probability (*HP*) area, as it will be impacted severely by flooding as it also has commercial, public, and recreational functions concentrated around it.For all the other LUCs, as the probability increases, the suitability value decreases by increments between 0 and 0.3. The LUCs facing potentially severe flooding damages are less suitable to be shifted to areas with higher probabilities, as compared to those having relatively lower damages. This is why *Residential (H)* has an increment of 0.3, whereas *Agriculture* has the smallest increment.

Table 1: Suitability values for the baseline scenario. ESP, VSP, SP, MP, HP correspond to *extremely small probability, very small probability, small probability, middle probability* and *high probability,* respectively.

Suitability values (baseline scenario)	**ESP**	**VSP**	**SP**	**MP**	**HP**
Nature	1	1	1	1	1
Agriculture	1	1	0.9	0.9	0.8
Recreation	1	0.9	0.9	0.8	0.7
Industry	1	0.9	0.9	0.8	0.7
Greenhouses	1	0.9	0.8	0.7	0.6
Residential (L) / Public amenities	1	0.8	0.6	0.4	0.2
Commercial/ Residential (M)	1	0.8	0.5	0.3	0.1
Residential (H)	1	0.7	0.4	0.2	0

The allocation of a LUC also depends on other factors in Metronamica (discussed in Section 2.2), which remain unchanged for the entire simulation process.

3.2 Uncertainty ranges

To explore the impact of flood risk on land-use changes, we grouped the flood probability categories into "high," "middle," and "low.", as this helped produce better result variability, and reduced the number of uncertain parameters, which limits the load on computational resources. Then, we adapted the *HP*, *SP* and *ESP* values from the baseline scenario (Table 1) as the boundaries of uncertainty ranges for each category. Since the main objective of uncertainty analysis in this study is to explore the unexpected conditions and the impacts of extreme flooding events, we designed the experiments to provide insights into the worse scenarios and increasing flood probabilities. Therefore, *HP* values are used as the lower bound for the "medium" probability category, as we assume in the worst unexpected case, the consequence of a flood event in this category may evolve into that in the "high" category. The same applies to the "small" category. No uncertainty range is considered for the "high" probability category as the *HP* values already imply the worst scenarios. The specific intervals that provide the range of each parameter are specified in Table 2. From there, EMA samples the suitability ranges for the scenarios that are used as input for the Metronamica model. Thereby, we represent the flood uncertainty due to climate change in a spatially explicit manner.

Table 2: Uncertainty ranges for the suitability of each land-use class.

Suitability ranges	**Low probability**	**Medium probability**	**High probability**
Values in baseline scenario	**(ESP, SP)**	**(SP, HP)**	**HP**
Nature	1	1	1
Agriculture	(0.9,1)	(0.8,0.9)	0.8
Recreation/ Industry	(0.9,1)	(0.7,0.9)	0.7
Greenhouses	(0.8,1)	(0.6,0.8)	0.6
Residential (L) /Public amenities	(0.6,1)	(0.2,0.6)	0.2
Commercial / Residential (M)	(0.5,1)	(0.1,0.5)	0.1
Residential (H)	(0.4,1)	(0,0.4)	0

3.3 Clustering algorithms

We ran 2,000 experiments simulating different flood suitability values resulting in 2,000 land-use maps. The number of simulations is determined considering the available computational resources. These maps are clustered into groups to further investigate the spatial impacts of flood uncertainty.

We tested multiple clustering algorithms, including agglomerative, agglomerative combined with multidimensional scaling (MDS), k-means, and k-medoids. Each algorithm was tested with 2-10 clusters. The best-performing clustering algorithm is selected based on the performance to achieve a high similarity within each cluster, a high dissimilarity between the clusters, and an even distribution of maps in the cluster.

The similarity of land-use maps is evaluated using the Kappa index, which presents the percentage of the consistent cells in the two compared maps (i.e., base and simulated maps) (Visser and de Nijs 2006). In our case, the inter-and intra-cluster similarities of maps are calculated by pairwise comparison of kappa values. This approach resulted in the following settings for each algorithm:

Clustering Algorithm 1: Agglomerative clustering with a "complete" linkage method (3 clusters)
Clustering Algorithm 2: Agglomerative clustering with the "average" linkage method (3 clusters)
Clustering Algorithm 3: Agglomerative clustering combined with an MDS of 4 (4 clusters)
Clustering Algorithm 4: Agglomerative clustering combined with an MDS of 9 (4 clusters)

Hence, we arrive at a total of 14 clusters.

3.4 Selection of the representative maps

We start with a single algorithm that presents maximum variations between clusters and allows us to select a representative map from each cluster. However, selecting representative maps to summarize the land-use change patterns for every cluster proved to be challenging as the inter-and intra-cluster similarity is low. Therefore, we selected multiple maps from each cluster to capture the plausible variations of land-use patterns. A total of 34 maps are selected that represent:

1. **Maps with the highest and lowest variation in each cluster:** within each cluster, we calculate the closeness of the map to the other by summing up the pairwise Kappa indices. A total of 18 maps are selected.
2. **Randomly selected maps from the clusters: S**ome clusters share the same highest and lowest variation of representative maps. In such cases, we randomly selected a map to replace the representative map that had already been included in Step 1. A total of 8 random maps are selected.
3. **Outliers**: While initially excluded from the clustering process to obtain an even distribution, outliers are included to account for variability, providing insights into potential land-use changes. A total of 8 maps were selected**.**

4 Results

In all simulations, the total allocation of LUCs is met and the space demands for all scenarios are satisfied. In other words, flood exposure does not have an impact on the volume of growth. To investigate the influence of flood uncertainty, the 34 maps are visually compared (i.e., a cell-by-cell comparison for amount and location) with the simulated baseline map of 2050, which does not take into account the uncertainty ranges for flood risk for suitability.

4.1 Land-use changes from 2015 to 2050

The 34 representative maps demonstrate overall land-use changes from 2015 to 2050 under a flooding probability of above 50 cm which are compared with the baseline map. In this paper, for illustration purposes, we discuss representative maps from three different clustering algorithms (see Section 3.3) in Fig 3. Overall we observe that *Residential* areas become more prominent, connected, and compact. Low and medium-density residential classes change to high-density to accommodate the rising population in 2050.

In the baseline map, there is a significant increase in *Residential (H)* in Location 1. However, Location 1 is characterized by high flooding probability, therefore, this increase is not recommended considering the flood uncertainty, as the suitability value for *Residential(H)* is relatively low (0.4 to 0.7). Instead, in the representative map, the footprint of *Residential(H)* decreases significantly and the majority of the location is allocated to a combination of *Residential(M)* and *Recreation*, which is relatively more suitable to absorb floods.

Overall, the uncertainty associated with the suitability value for *Residential(H)* makes a significant difference to the land-use changes between the baseline and representative maps. In Location 2, *Residential(M)* footprint is projected to increase in northeast MRA in the baseline scenario. This location is classified as a low flood risk area, therefore, we observe that the region sees growth of *Residential(H)* in the representative map when the flood risk is integrated. As compared to the baseline map, more *Nature* and *Public Amenities* appear in Location 2, presumably because to support the rising residential areas and they are also more suitable for the low flood probability.

In the baseline map for 2050, southwest MRA (Location 3) is projected to see an immense expansion of *Commercial* areas presumably due to the proximity and expansion of the *Airport.* Location 3 is characterized by a medium probability of flooding. Hence, with the integration of flood risk, we notice a change in the spatial distribution of *Commercial* cells as they become dispersed around the Airport and move towards the west, in the representative map. This could be because *Commercial* demands could not be met in other locations of the MRA as they have a higher probability of flooding. Instead, the model chooses to allocate new *Commercial* areas in the medium flood-risk zone as it is moderately suitable and damages can be minimized. From an attraction point of view, the southwest region has a number of train stations and the airport is located in this area, which is lucrative for *Commercial areas.* Furthermore, *Mineral* and *Industry* areas shrink as the demand for this land type is expected to drop from 2015 to 2050.

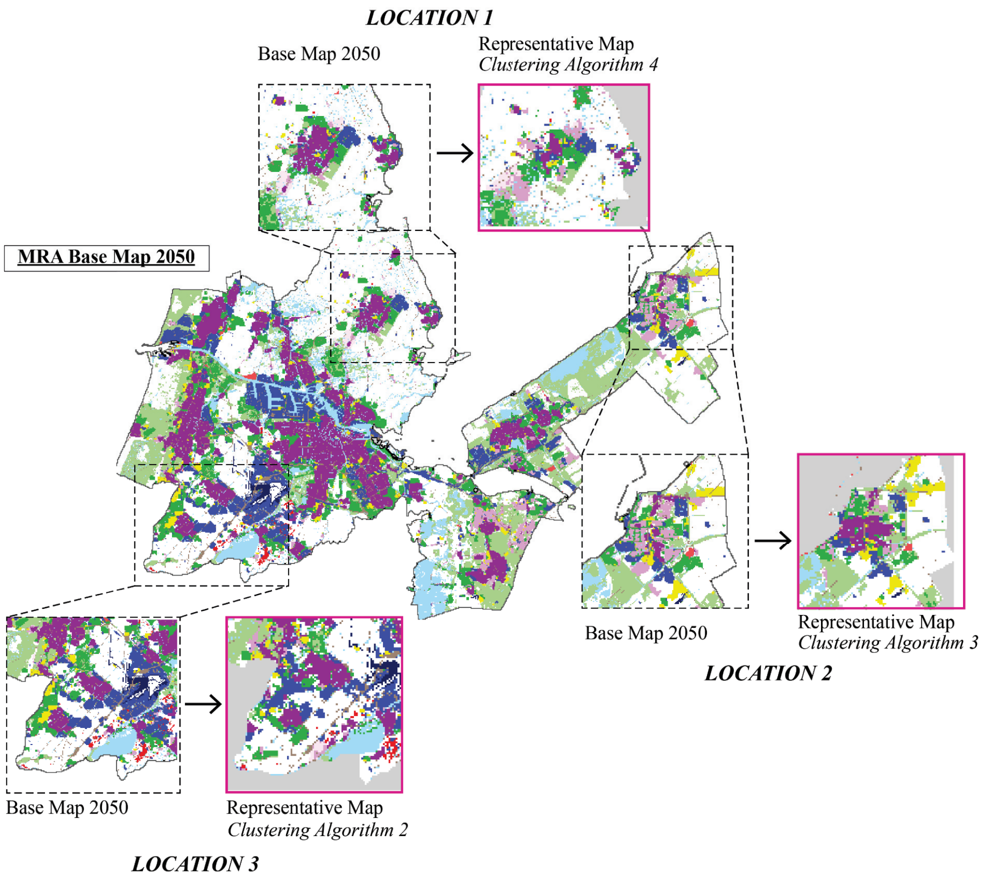

*Fig. 3: Comparison of land-use distribution between the **Baseline Map of 2050 v/s Representative Map using different clustering algorithms** under flood uncertainty. It highlights changes in Residential(H) (purple), Residential (M) (dark pink), Residential (L) (light pink), Agriculture (white), Nature (light green), Commercial (blue), Public Amenities (yellow) and Recreation (green) areas. **Location1:** High flooding probability; **Location2**: Low Flooding probability; **Location3**: Medium Flooding Probability.*

5 Conclusion

Climate change is a pressing issue for cities, and becoming resilient against climate-induced shocks is a priority for decision-makers worldwide. The success of urban resilience strategies relies on the spatial decisions taken today because the built environment changes slowly. However, most urban resilience strategies stay at the conceptual level and are not spatially explicit.

This paper addresses the need for spatial and systematic exploration of urban climate uncertainty to limit exposure to climate-induced disruptions. It presents an integrated modeling framework to assess the impact of flood uncertainties on land-use dynamics for the MRA between 2015 and 2050.

The proposed framework presents a way to quantitatively link climate uncertainty with the driving factors of land-use change. It includes climate change variables in a spatially explicit way and incorporates future urban growth trends. Outcomes of the framework can help in decision-making processes for developing evidence-based urban planning strategies and developing resilience-enhancing interventions for multiple infrastructure systems.

The methodological novelty of this study relies on the connection between the CA-based land-use model and the Exploratory Modeling Workbench to systematically explore the uncertain factors. Therefore, the proposed framework is a step forward in considering climate uncertainties for resilience-informed decision-making processes. Furthermore, the framework presented here overcomes the limitation of the traditional SaS approach when accounting for the uncertainties.

We demonstrated our framework in the Metropolitan Region of Amsterdam (MRA) by integrating land-use characteristics and climate change influences. However, this framework can be applied to other cities to systematically investigate the impacts of climate uncertainties on urban development.

6 Future work

We observe that not all representative maps fit well with the long-term visions set out by decision-makers in the MRA. While this framework integrates the climate uncertainty (i.e., flood uncertainty) as the physical suitability factor in the CA model, the uncertainty in zoning or neighborhood interactions was not integrated into the framework. We aim to integrate uncertainty in zoning parameters using exploratory modeling when simulating a land-use change in future research.

Furthermore, future work will involve refining the development of scenarios and the selection of representative maps in close consultation with decision-makers at the MRA. The most relevant outcomes for decision-making can be examined. Due to the data availability, we could simulate for a time horizon until 2050, and there may be more insights by extending the simulation time. Flooding probability data beyond 2050 can be extrapolated using spatio-temporal rainfall data and collaboration with some climate experts. More complex versions of this model can integrate socio-economic indicators and spatial impacts.

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