Futures 154 (2023) 103265

Contents lists available at ScienceDirect

Futures

journal homepage: www.elsevier.com/locate/futures

Exploring potential futures: Evaluating the influence of deep uncertainties in urban planning through scenario planning: A case study in Rome, Italy

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ARTICLE INFO

Keywords:
Scenario planning
Deep uncertainties
Urban planning
Decision-making
Climate adaptation

ABSTRACT

Cities play a critical role in developing adaptable strategies to address the challenges posed by climate change. However, the inherent complexity of urban environments and their uncertain future conditions necessitate exploring innovative approaches and tools to assist the current planning practices. This paper presents a workflow rooted in model-based scenario planning for long-term adaptation planning given uncertain futures. To demonstrate the workflow's effectiveness, a pertinent case study was conducted in a flood-prone area of Rome. The study employed a land-use change model to examine potential urban growth patterns, considering the uncertain implementation of new poles of attraction. This interdisciplinary study constitutes an initial stride toward implementing uncertainty within urban planning frameworks. Future prospects encompass the integration of multiple models for cross-scale analysis, embracing further critical environmental and social aspects. This research contributes to advancing urban resilience strategies. It enhances the understanding of adapting to an uncertain future in the face of climate change, as urban areas must embrace comprehensive planning to ensure flexible adaptation when faced with climate-driven uncertainties in long-term planning. In conclusion, the study underscores that embracing uncertainty is a challenge and a pivotal opportunity to shape resilient and adaptable urban futures.

1. Introduction

The impact of climate-related developments on the built environment is a pivotal issue in the scientific debate (Mabrouk & Haoying, 2023). Climate change already affects the built environment through increasing urban flooding (Choi et al., 2021) and the Urban Heat Island effect (Falasca et al., 2019). Nevertheless, a comprehensive workflow to guide urban planners in developing flexible adaptation plans in the face of uncertainty is still lacking.

Conventionally, planning rests on the assumption of stationarity. However, anthropogenic and climatic changes have seriously affected the conditions underpinning historical time series used in forecasting. Therefore, "stationarity is dead" (Milly et al., 2008). For planning, this implies that if the actual future is different from the one assumed (e.g., with respect to population growth, economic

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https://doi.org/10.1016/j.futures.2023.103265
Received 31 May 2023; Received in revised form 2 September 2023; Accepted 6 October 2023
0016-3287/

development, economic activities, local demands, climate change), the plan is unlikely to achieve the stated objectives. True, ignoring uncertainties can simplify planning in the short-term, but with a higher risk of negative surprises in the long-term.

The problem of dealing with uncertainty is further amplified by the fact that cities are complex (self) adaptive systems (Cozzolino & Moroni, 2022; Moroni & Cozzolino, 2019). The inability to effectively comprehend and address uncertainties in decision-making processes carries significant costs. Urban planners often lack awareness of uncertainty or the knowledge to manage it effectively. The key to address this lies not in accurately predicting the future, but in being prepared to embrace the inherent uncertainty while still adhering to adequate planning practices (Moroni & Chiffi, 2021).

In response to uncertainty and complexity, in other disciplines that are planning for the future, alternative planning approaches emerged (Shepherd et al., 2018). Since the mid-20th century, scenario planning has continuously increased in popularity. As of today, an abundance of methods and techniques exists, and their application spans across a wide array of sectors in both public and private industries.

Scenario planning is a crucial support in addressing complex challenges and uncertainties in various domains requiring strategic decision-making, overcoming the limitations of human reasoning, identifying future trends, and adapting to changes. Scenario planning enables the identification of the pivotal factors that engender uncertainty, facilitating the comprehension of their interplay and weaving plausible alternative narratives of the future (Saliba, 2009). Several studies on the topic have investigated the origin of scenario planning and the typologies of scenarios highlighting the qualitative and quantitative methodologies and techniques employed (Amer et al., 2013; Bishop et al., 2007; Bradfield et al., 2005; Cordova-Pozo & Rouwette, 2023; Ducot & Lubben, 1980; Notten et al., 2003; Robinson, 1990; Walton et al., 2019).

Börjeson et al. (2006) provide a straightforward typology of scenarios according to three questions: "*What will happen?",* "*What can happen?",* and "*How can a specific target be reached?*". The first question refers to predictive scenarios (Makridakis et al., 1998), which aim to predict future outcomes based on probability and likelihood. These scenarios help plan, adapt to expected situations, and identify potential challenges. Predictions are usually made within a defined structure, relying on historical data and causal relationships. The second question, "*what can happen?*", is addressed by explorative scenarios (Avin & Goodspeed, 2020). Explorative scenarios are particularly beneficial when the underlying structure for scenario construction is uncertain, such as during periods of rapid and unpredictable changes or when the mechanisms leading to potentially challenging futures are not fully understood. Additionally, explorative scenarios prove useful when users possess a solid understanding of the current system but seek to explore the implications of alternative developments. The third question, "*How can a specific target be reached?*", is addressed by normative or prescriptive scenarios (Iverson Nassauer & Corry, 2004). This type of scenario incorporates normative considerations and values to assess how to reach or avoid a specific target.

Compared to predictive or normative approaches, the advantages of exploratory scenarios are rooted in their capacity to encompass a wider spectrum of potential futures, transcend the limitations of projections, and embrace the intricacies of systems characterized by deep uncertainty. This insight contributes to a more holistic and adaptable approach to strategic decision-making in the face of an uncertain and evolving future (Maier et al., 2016).

Scenario planning has evolved into distinct schools (Carvalho, 2021): (i) The Intuitive Logics School (Bradfield et al., 2005), also referred to as the Anglo-Saxon school, finds its roots in the work of Herman Kahn and is notably influenced by business perspectives. Royal Dutch/Shell serves as a pioneering reference in this approach. The method entails the identification of influential micro and macro forces, ranking uncertainties, and constructing scenarios. (ii) The Probabilistic Modified Trends School (Amer et al., 2013) is deeply influenced by methodologies like Trend Impact Analysis (TIA) and Cross-Impact Analysis (CIA). TIA involves adjusting extrapolations by incorporating historical data and accounting for unforeseen events, while CIA assesses the intricate interdependencies among variables. This school, seeks to generate multiple alternative futures rather than a single extrapolation. (iii) The French School - La Prospective (Godet, 1986) originates from Gaston Berger's emphasis on long-term planning. have paved the way a mathematical and systems analysis-oriented approach. This approach, informed by the "La Prospective" methodology, combines varied analytical tools to create scenarios.

The central question for this paper is: "How to evaluate long-term urban planning options under uncertain future conditions?". The study aims to address the research gap, specifically the absence of a workflow utilized by urban planners to address the uncertainty about cities' future and inherent complexity. To this end, we rely on exploratory modeling (Bankes, 1993; Moallemi, Kwakkel, de Haan, & Bryan, 2020) and scenario discovery (Bryant & Lempert, 2010; Kwakkel & Jaxa-Rozen, 2016), which are rooted in explorative scenario thinking and the scenario logic school, in order to create scenario narratives (Dawson & Moglia, 2019) that describe how uncertainties influence future vulnerabilities and what this implies for urban planning. We use District X in Rome as a case study and explore plausible futures up to 2050 in light of the uncertainties that influence urban development.

To structure the analyses, we used a land-use change model implemented in Metronamica (Van Delden and Hurkens, 2011), a generic integrated spatial decision support system to simulate land-use dynamics, widely used for scenario-based land-use modeling to explore adaptive strategies to climate change (Carter, 2018; Kazak, 2018; Mancosu et al., 2015), participatory policy approaches (Hewitt et al., 2014), and for investigating the land-use dynamics triggered by human decision-making (Lauf et al., 2012). We account for future uncertainties regarding land-use demands and the influences of infrastructure options. For this study, we performed five thousand computational *"what if"* experiments using exploratory modeling. The resulting land-use maps for 2050 are clustered to reveal archetypical land-use patterns. Next, the clusters are analysed to assess their relevance for decision-makers. Lastly, Scenario Discovery is performed for each decision-relevant cluster to reveal the combination of uncertain input parameters under which the cluster occurs.

The paper is structured accordingly. First, we provide a literature background to support the methodologies and tools applied. Secondly, we introduce the general workflow and present an applicative case based on the selected case study. Finally, we present the conclusions regarding the approach, addressing the limitations and future challenges.

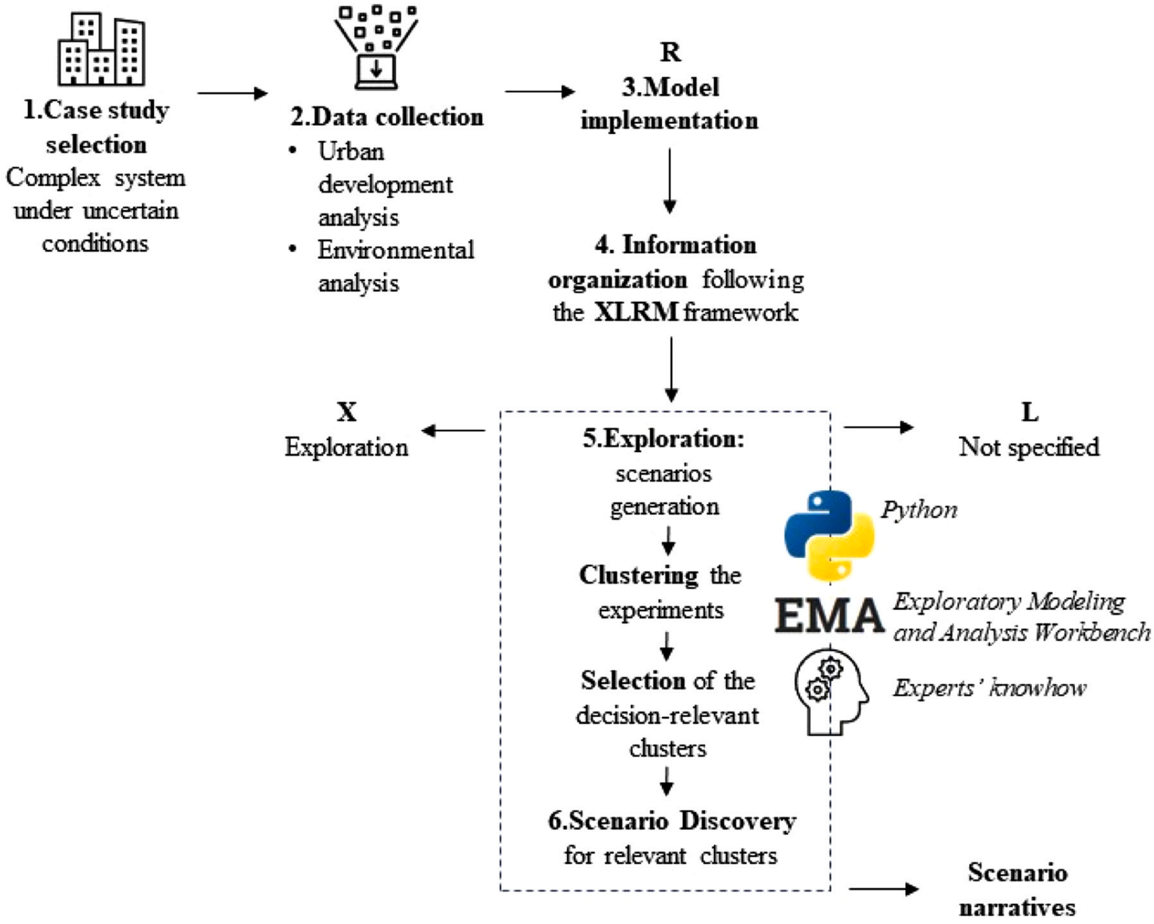
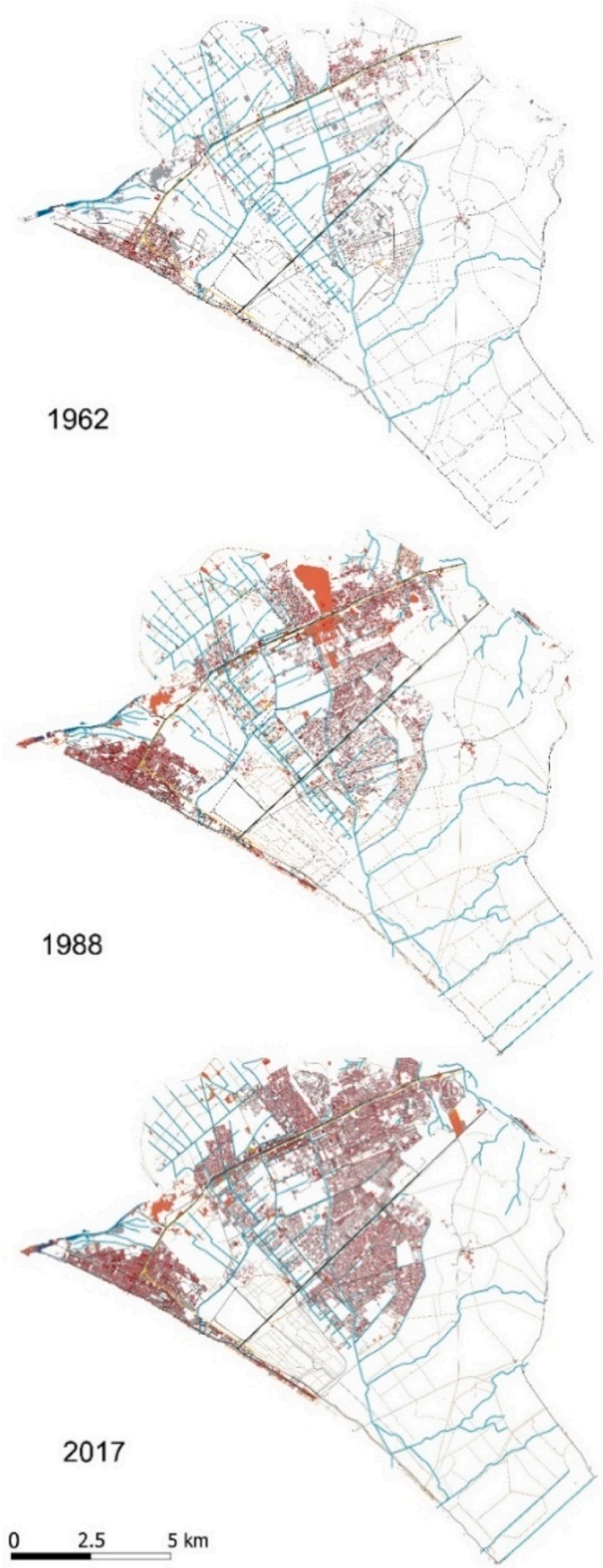
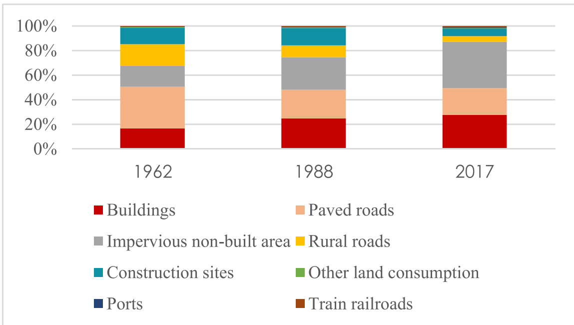


Fig. 1. The general workflow used for this study.

Fig. 2. Case study area. The X Municipality of Rome.



(a)



(b)

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Fig. 3. (a) Maps of the urban growth in the X Municipality of Rome. (b) Land cover per class of land use expressed in percentage for the analysed periods.

2. Literature Background

Decision-makers face various uncertain factors that might undermine their plans' success. Furthermore, communicating uncertainties is an ongoing effort between policy stakeholders and scientists from different fields (Schueller et al., 2020). Usually, urban planners rely on forecasts, but undesirable outcomes can occur if the future differs from the assumptions made in the forecast.

Uncertainty is a multidimensional concept defined as any departure from the unachievable ideal of determinism (Walker et al., 2003). In this study, we focus specifically on deep uncertainties. Deep uncertainty means that a set of alternative assumptions can be enumerated but not ranked in terms of their plausibility (Kwakkel, Walker, & Marchau, 2010). Various planning and decision-making approaches to support the design of robust and adaptive plans have emerged under the umbrella of Decision Making under Deep Uncertainty (DMDU) (Lempert et al., 2003; Walker et al., 2001, 2010). Each approach (Haasnoot, Kwakkel, Walker, & ter Maat, 2013; Kwakkel, Haasnoot, & Walker, 2016; Lempert, Groves, Popper, & Bankes, 2006) offers different analytical perspectives and uses different techniques. Given a specific context, it can be beneficial to combine different techniques drawn from these different approaches (Kwakkel & Haasnoot, 2019).

Supporting decision-making under deep uncertainty benefits greatly from using simulation models. When dealing with deep uncertainty, one typically faces a complex dynamic system. Consequently, it is difficult to understand how the system works and anticipate possible future outcomes (Diehl & Sterman, 1995; Sterman, 2002). Therefore, simulation models are valid support to instantiate the system of interest, investigate plausible futures, and test interventions in the system in light of the various uncertainties (Bankes, 2009; Bankes, Walker, & Kwakkel, 2013; Holtz et al., 2015).

To structure the problem and organize the available information, many DMDU methods start from the "XLRM" framework (Lempert et al., 2003), which stands for: (i) Exogenous uncertainties ("X"): Elements that planners cannot control but could affect the feasibility or success of the decided strategies. The uncertainties can be environmental, demographical, economic, etc. They can also be characterized by more gradual changes over time or be surprise events in the future. (ii) Policy levers ("L"): Short-term strategies applied to reach near-term objectives. (iii) Relationships ("R"): Element of connection describing the interactions among the other described groups over time. It is usually represented by the model that can be implemented according to the planners' aims. The system's complexity necessitates a computational approach in case of deep uncertainties. (iv) Measures ("M"): Elements used to evaluate the performance of the policy levers in the different scenarios generated. They are ranked according to the desirability of the outcome. Once the information is organized, the simulation model is iteratively used to test the proposed actions in many plausible futures, refine the actions, and develop a strategy with desirable performance least affected by the uncertainties.

2.1. Model-based support for designing adaptive strategies

Kwakkel and Haasnoot (2019) present a taxonomy of the available DMDU approaches and the key ideas underpinning DMDU:

- Exploratory Modelling: A computer-assisted research methodology used to explore complex systems that cannot be understood entirely with human reasoning.
- Decision support: Approaches and tools used to facilitate the comprehension of a problem and the course of action that could be implemented using a posteriori decision analysis.
- Adaptive Planning: An approach that allows designing plans to be adapted as the conditions change, which implies exploring a wide range of possible futures to build a plan with flexible, adaptive actions to respond to possible uncertain conditions that could undermine the plan's success.

For this study, we rely on Exploratory Modelling (Bankes, Walker, & Kwakkel, 2013; Moallemi, Kwakkel, de Haan, & Bryan, 2020), a research method based on computational experimentation to investigate large ensembles of "*what if*" scenarios. The aim is not to develop a single model that reproduces reality because the uncertainties make a single representation a non-reliable source of information for the outcomes of interest (Bankes, 1993). Instead, exploratory modelling uses large-scale computational experimentation to explore how the system would behave across alternative assumptions regarding the uncertainties. So, a set of models reveals the system's behaviour across the uncertainties and is used to reveal the conditions under which strategies fail.

In the DMDU literature, identifying the conditions under which plans fail is called as vulnerability analysis. The basic idea is to identify the subspaces in the uncertainty space under which candidate strategies fail to meet the stated objectives. Vulnerability analysis uses two complementary analysis techniques: global sensitivity analysis (Jaxa-Rozen & Kwakkel, 2018) and Scenario Discovery (Bryant & Lempert, 2010; Kwakkel, 2019). Global sensitivity analysis helps reduce the problem's dimensionality by identifying which uncertainties and/or policy levers significantly impact the outcomes of interest. Scenario Discovery focuses on finding subspaces in the multidimensional model input space that generate decision relevant types of outcomes (e.g., the combination of uncertain conditions where a candidate strategy fails to reach the objectives).

Broadly speaking, Scenario Discovery is a model-based technique to finding subregions in the model input space (i.e., the combined uncertainty and lever space) given classified results from computational experiments. These subregions can be communicated as scenarios and help to define and frame uncertainty, identify vulnerabilities of a chosen strategy, and aid the development of adaptive

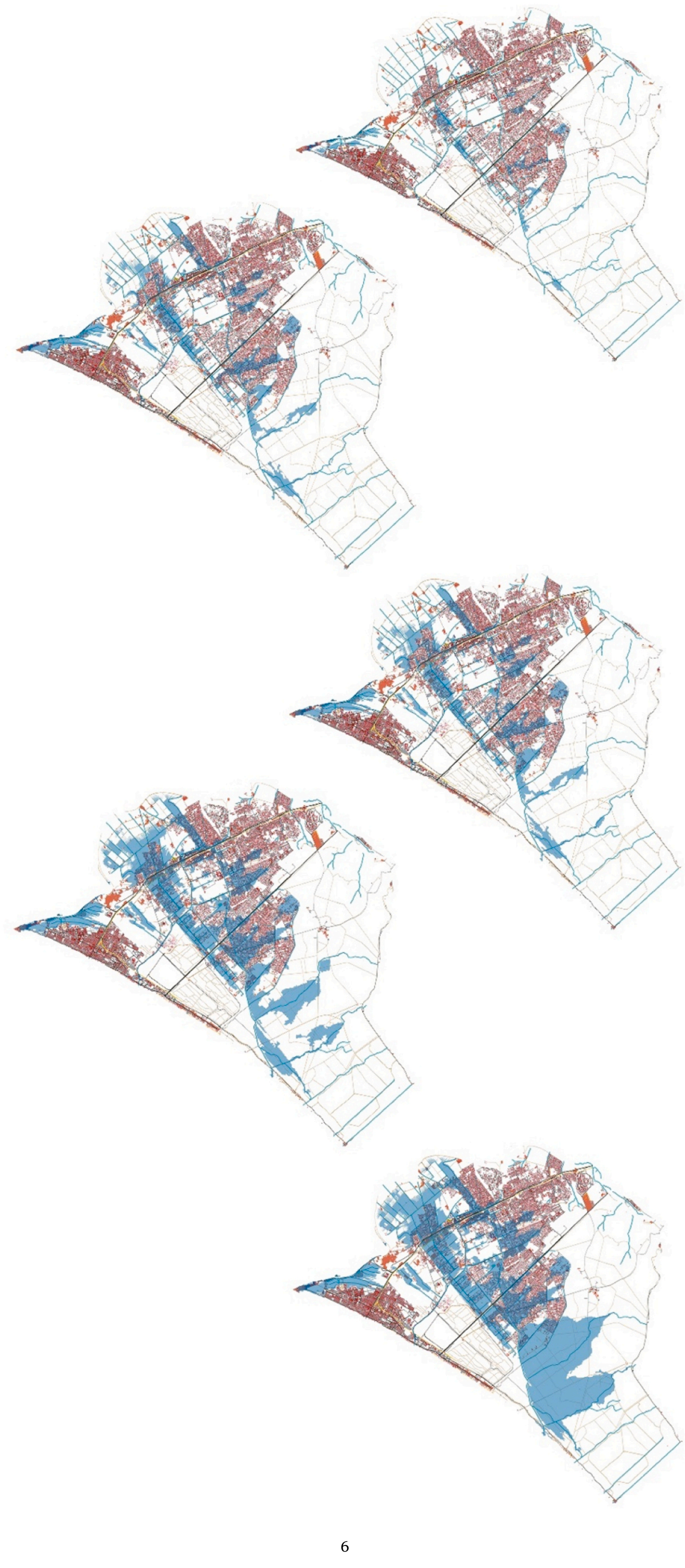

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Fig. 4. Inundations maps for different return periods (10, 30, 50, 200, 500 years).
Source: Authors' elaboration from the data provided by Consorzio di Bonifica Litorale Nord.

strategies. The most often used algorithm for Scenario discovery is the Patient Rule Induction Method (PRIM) (Friedman & Fisher, 1999). PRIM is a rule induction algorithm that has proven effective in producing lower-dimensional, orthogonal box-shaped regions in the model input space, which maximize coverage, density, and interpretability. These box-shaped regions can be interpreted as scenarios. Coverage measures how many cases of interest are included in the identified box-shaped region. Density measures the precision of box-shaped region by assessing how many cases are of interest out of all the cases within the box. This is important as the decision-makers would like their scenarios to have a good explanation for the cases of interest. Interpretability measures how easily the decision-makers can make sense of the box-shaped region. This is typically proxied by looking at the number of dimensions used to characterize the box. These three objectives compete, therefore, if one increases, it typically comes at the expanse of the others (Bryant & Lempert, 2010).

2.2. *RDM: approaches and applications*

The leading DMDU approach used in climate adaptation is Robust Decision-making (RDM) (Lempert et al., 2003), and its derived frameworks (Bartholomew & Kwakkel, 2020), which leverage the concepts of exploratory modeling, decision support, and adaptive planning to address complex environmental decision-making problems characterized by deep uncertainty. RDM and is variants rely on computational tools not to provide predictions about the future but to facilitate the reasoning about the impacts of uncertainty to aid decision making and planning in case of deep uncertainty. RDM, through Exploratory Modeling, combines Decision Analysis, Assumption-based planning, and Scenario Analysis with a bottom-up process: the process starts by considering one or multiple strategies. Models and data are then employed to evaluate these strategies across a diverse set of plausible future scenarios, providing valuable insights into the proposed strategies' vulnerabilities and identifying and assessing potential responses. The aim is to broaden the scope of futures and alternatives under consideration. Instead of offering fixed options, RDM focuses on shedding light on the trade-offs among reasonable choices.

Frameworks derived from RDM are: (i) Many Objective Robust Decision Making (MORDM) (Kasprzyk et al., 2013), which employs a many-objective evolutionary algorithm to manage diverse decision-maker perspectives and conflicting objectives. It generates a rich set of policy alternatives through many-objective evolutionary algorithms, allowing trade-offs among competing objectives. Uncertainty analysis, scenario discovery, and interactive visualizations aid in selecting preferred solutions from the generated set. Multiple scenarios representing deeply uncertain factors are used to stress-test candidate policies. The iterative process focuses on robustness assessment and refining alternatives by adjusting uncertainty parameters and decision levers. (ii) Multi-Scenario MORDM (Watson and Kasprzyk, 2017) built on MORDM by searching for candidate strategies across multiple reference scenarios. It addresses the limitation of single-scenario optimization by selecting additional scenarios based on where candidate solutions from the first scenario fail to meet objectives. The goal is to construct an optimized set of policy alternatives under different scenarios. (iii) Many Objective Robust Optimization (MORO) (Hamarat, Kwakkel, Pruyt, & Loonen, 2014; Kwakkel, Haasnoot, & Walker, 2015), an approach that integrates Many-Objective Robust Optimization into the RDM framework. MORO incorporates robustness considerations during the search phase by evaluating candidate solutions over an ensemble of scenarios. The family of RDM approaches offer a systematic way to explore and improve policy alternatives while considering a wide range of uncertain factors and scenarios.

An example of RDM is given by the long-term planning of the water resources for the Colorado River Basin (Groves et al., 2013, 2019). The primary goal was to assess the resilience of the Colorado River system over the following 50 years and to explore various strategies for managing the river's resources effectively. Key findings indicated that vulnerable conditions would likely arise in most scenarios characterized by lower-than-historical average streamflows and prolonged drought conditions. The analysis also highlighted important near-term, high-priority options that should be implemented, such as municipal, industrial, and agricultural conservation. The application of RDM and derived frameworks is growing rapidly to aid decision-making on complex environmental challenges marked by deep uncertainties and conflicting priorities, and many examples can be found in the literature (Beh et al., 2017, 2015; Ben-Tal et al., 2017; Daron, 2015; Dessai & Hulme, 2007; Gupta et al., 2020; Haasnoot et al., 2012; Iglesias & Garrote, 2015; Jäger et al., 2015; John et al., 2021; Lempert et al., 2013; Lempert & Groves, 2010; Lygoe et al., 2013; Shavazipour, Kwakkel, & Miettinen, 2021; Singh et al., 2015; Smith et al., 2022; Tolk, 2022; Trindade et al., 2017; Wang et al., 2023; Yan et al., 2017).

3. Workflow

Fig. 1 synthesizes the workflow, which guides the progression from initial case study selection to creating a comprehensive understanding of a complex system's behavior under uncertain circumstances. It emphasizes data-driven analysis, modeling, scenario generation, and scenario discovery, culminating in actionable insights for decision-making and understanding the potential implications of different courses of action. This section further explains each step, and an operative example is provided in the next sections.

1. *Case Study Selection:* This initial step identifies a complex system operating within uncertain conditions. This might involve choosing a real-world scenario or situation that exhibits intricate relationships and variables influenced by uncertainty. The aim is to set the foundation for a comprehensive analysis.

2. *Data Collection*: Once the case study is chosen, the process involves gathering relevant data related to urban development and environmental factors. This data collection phase helps comprehensively understand the chosen complex system's current state and potential dynamics.
3. *Model Implementation:* With the collected data, a model is constructed to simulate the interactions and behaviors of the analysed factors within the complex system.
4. *Information Organization:* In this step, the acquired information is structured and organized using the XLRM framework described in the literature background (Lempert et al., 2003). Based on the selection of the case study and the implemented model (R) are specified the uncertainties (X), the policy leavers (L), and the metrics (M).
5. *Exploration, clustering, and selection of decision-relevant clusters:* Various scenarios are generated to explore potential outcomes and responses within the complex system. The ensemble of experiments is generated using a space-filling experimental design over the entire space spanned by the set of uncertain factors. The generation, execution, and analysis of the computational experiments are done through the Modelling and Analysis Workbench (EMA) (Kwakkel, 2017). The EMA workbench structures the information using the XLRM framework. The model captures the relationships (R), but we still need to specify the uncertainties (X), the levers (L), and the outcomes (M). Before proceeding with the next step, the experiments are clustered because a binary classification is typically applied to the experiments when applying scenario discovery (Bryant & Lempert, 2010; Kwakkel & Jaxa-Rozen, 2016). However, in the case of complex models with rich outputs, directly imposing a binary classification on the results can produce a massive loss of decision-relevant information (Helgeson, 2020; Rozenberg et al., 2014; Gerst et al., 2013; Steinmann, Auping, & Kwakkel, 2020). Clustering is a process for dividing a set of objects into subsets with similar characteristics, which are different for each subset. Finding the best results for clustering is crucial since different algorithms can be used for this process. Once the scenarios have been generated and clustered, the next critical phase involves identifying and selecting the clusters of scenarios that hold particular importance for decision-making. This step acknowledges the role of domain-specific knowledge and expertise possessed by the decision maker. Drawing upon their deep understanding of the complex system, the decision maker employs their know-how to discern clusters with the most potential relevance and impact.
6. *Scenario Discovery and scenario narratives:* To analyse the experiments' results, Scenario Discovery (Bryant & Lempert, 2010; Kwakkel & Jaxa-Rozen, 2016) is applied to the identified relevant clusters with decision-making significance. The outcomes of Scenario Discovery serve as the foundation for constructing scenario narratives. These narratives holistically depict the plausible evolution of the complex system under distinct conditions. Each narrative paints a vivid picture of how variables interact. The scenario narratives generated through this process are indispensable tools for planners. They provide a nuanced understanding of the system's behavior, considering different futures and their associated uncertainties. Based on that information, planners can make informed decisions, develop adaptive strategies, and devise contingency plans that align with the system's inherent dynamics. By translating complex analytical results into accessible narratives, this step enhances communication between analysts and stakeholders.

4. Workflow application

This section presents the practical application of the methods and tools by adhering to the previously illustrated sequence of workflow steps. The initial selection of case studies through the subsequent stages encompassing data collection, model implementation, and information organization establishes the foundational underpinning for an exhaustive exploration of the intricate system under uncertainty. As the progression of the procedure unfolds, the generation of an ensemble of scenarios is followed by their subsequent clustering. At this stage, the planner's expertise is essential By actively selecting decision-relevant clusters relying on the analysis with a nuanced understanding of the system's intricacies that data alone might not capture. This convergence of data-derived insights and domain-specific proficiency ensures that the resultant narratives underpinning the scenarios are undergirded by both an empirical bedrock and a strategic understanding.

4.1. Case study selection and Data collection

The case study area is an urbanized flood-prone deltaic area in Rome, the X Municipality (Fig. 2), located between the Tiber River and the Tyrrhenian Sea. It is particularly suitable because the area is already highly vulnerable to flooding (Recanatesi & Petroselli, 2020), future urban development and climate change are likely to worsen the risk, urban development has been shaped by formal and informal settlements (Cellamare, 2010; Clough Marinaro & Solimene, 2020; Insolera, 1960), which is an interesting feature as former informal settlements are more vulnerable to climate change (Galdini & Nardis, 2023). The administration is considering several infrastructure investments and new poles of attraction for urban development that will shape the future urban fabric if implemented.

We diachronically analysed the urban development and used this to develop a land use change model. The analysis (Fig. 3) was carried out using a Geographical Information System (GIS) with a level III classification in the National Land Cover Map; the reference system is UTM (Universal Transverse Mercator) with WGS84 datum, and as software we used QGIS. ISPRA provided the base map from 2017, and other sources are satellite images from Digital Globe, geographic vector data (e.g., regional technical maps (CTR)), infrastructure networks from Open Street Map, and Urban Atlas-specific data regarding mining sites, dump sites, airports, and harbours. We relied on IGM (Geographical Military Institute) cartographies with an acquisition scale of 1:25000 for the historical mapping.

The data shows that soil sealing has constantly grown. In the 1950–1970 s, the rate was coherent with population growth, but from the 1970 s-2006, there was a decoupling (Munafò et al., 2010) where urban sprawl grew despite a decreasing demographic trend, which is consistent with the pattern of development of many areas in the Mediterranean (Salvati et al., 2012). The uncontrolled urban

Fig. 5. The X Municipality of Rome with the existing poles of attraction (International Airport and commercial hub) and the new infrastructures. A larger bridge to cope with the traffic towards the airport. A bridge to connect the commercial hub with the other side.

growth, environmental changes, outdated drainage systems that cannot cope with extreme events, and anthropic pressure make this area one of the most flood-affected municipalities in Rome (Fig. 4).

Fig. 5 shows the infrastructure options and new poles of attraction considered by the administration. The infrastructure options are two new bridges connecting the X Municipality to the other side of the Tiber. The Scafa bridge is to support the obsolete "Ponte della Scafa", which connects the X Municipality with the international airport. The Ostia Antica bridge would connect a commercial hub on the other side of the river with the main road and the adjacent agricultural area. Next to these two bridges, the idea of building a new football stadium with a business center is being discussed. The new football stadium had an assigned location just outside the boundaries of the X Municipality. However, since the project has repeatedly been called off, we are considering two potential locations here. The first location (Stadium hp1) is within the city of Rome limits, in the district of Tor di Valle. The second hypothetical football stadium location (Stadium hp2) is outside Rome's city limits.

4.2. Model implementation

The study explores how urban tissue might develop conditional on the various uncertainties and what this implies for the key vulnerabilities requiring planners' attention to reduce or monitor potential risk.

To explore the consequences of future urban developments due to the possible implementation of new infrastructure options and/or the new poles of attraction in the case study area, we implemented a land-use model using used Metronamica (RIKS, 2011). Two different time frames are considered for the calibration and validation of the model: 1962–1988 for calibration and 1988–2017 for validation. The land use map of 1962 was used as the initial conditions for simulating the land use patterns of 1988. We used "*manual calibration*" (Vliet et al., 2016), where the parameters are tweaked until a meaningful level of similarity is reached, indicating that the model is performing well enough. Next, we simulated the developments from 1988 to 2017 and used these for validation.

The Kappa statistic (Vliet, Bregt, & Hagen-zanker, 2011) and the Fuzzy Kappa (Hagen, 2010) are employed to evaluate the accuracy quantitatively through map comparison. The Kappa coefficients of agreements are widely used to assess if an acceptable level of accuracy is reached (Hagen-Zanker, 2009). In the calibration, the values obtained are 0.972 for Fuzzy Kappa and 0.98 for average similarity. The value obtained from the validation for Fuzzy Kappa is 0.94, and 0.96 for average similarity. Based on this, we consider the model fit for its purpose, which is the exploration of future urban fabric developments based on the past development pattern, given the possible implementation of new poles of attraction.

4.3. Information organization following the XLRM framework

The uncertainties are mainly about the demand for different land use classes and the influence of new infrastructures and new points of attraction (see Table 1). The range of values chosen is based on the analyses of the urban development, estimating the data

Table 1
Uncertainties considered and the associated ranges of values.

Exogenous Uncertainties (X)	Ranges	Ranges Motivation
Land demand Informal land use class	208 – 7051	Min value: 2017 n. of cells in the land use class; Max value: extrapolation of a value for the growth of the land use class expressed in n.of cells, based on the historical mapping.
Land demand residential land use class	38500 – 52000	"
Land demand residential + commercial land use class	4500 – 5500	"
Land demand commercial land use class	1200 – 1500	"
Land demand industrial land use class	1800 – 2300	"
Scafa bridge weight	[0, 0.1, 0.4]	Relative importance of the infrastructure ranging from 0 to 1. The ranges of parameters are based on the values used in calibration of the model for the weight of the accessibility parameters on the land use classes.
Ostia Antica bridge weight	[0, 0.1, 0.4]	"
Stadium weight	[0, 0.1, 0.4]	"

through extrapolation from the demand values for each land-use class. We relied on data from the past to simulate what would happen if similar conditions were in place in light of climate change, fostering new vulnerabilities within the built environment. This case study does not consider explicit policy interventions, so the levers are kept empty. The outcomes are the land use maps for 2050 generated in the exploration phase.

4.4. Exploration, clustering, and selection of the decision-relevant clusters

The model is employed to explore the evolution of the urban tissue in the X Municipality up to 2050 through computational experimentation performed with the EMA workbench that organized the information as described in 4.3.

To explore the 8-dimensional uncertainty space, we generated 5000 computational experiments using Latin Hyper Cube Sampling (Helton & Davis, 2002). This provides a space-filling design where all parts of the uncertainty space are explored equally. Before applying Scenario Discovery, the land use maps resulting from the 5000 experiments are clustered on spatial land-use patterns. In order to identify what specific algorithm performs better for the given data set, two different clustering algorithms are compared: agglomerative clustering (Theodoridis & Koutroumbas, 2009) and K-medoids (Jin & Han, 2010) (Table 2). Both clustering algorithms need a metric that specifies the similarity or inverse distance between data points. For this case, we used the kappa metric, which was also used for model calibration and validation.

Both clustering algorithms select the appropriate number of clusters based on high within-cluster similarity, high between-cluster dissimilarity, and interpretability (i.e., the total number of clusters). The average similarity, that is, the average Kappa value, is 0.96 amongst the 5000 experiments, which indicates that the resemblance is high. The relatively high similarity across the 5000 experiments is not unexpected because future developments are strongly environmentally constrained. According to the results, agglomerative clustering performs slightly better. Therefore, we used agglomerative clustering, obtaining five clusters based on the more balanced allocation of data points among the clusters and the within-cluster and between-cluster dissimilarity, suggesting a relatively low within-cluster dissimilarity and a meaningful separation between the clusters (Fig. 6).

Next, we visually inspected the maps in each cluster and derived quantitative data (Table 3, Table 4), to identify the decision-relevant clusters. We analysed the clusters to reveal the decision-relevant ones by quantifying the growth of each land use class, counting the pixels, and then comparing the results with the map from 2017 to assess the percentage increase. These are case-specific evaluations based on the context, where the recurring pattern of informal urbanization has led to an increased vulnerability of the built environment to climate-related phenomena and social disparities. Hence, the criteria to assess which cluster is decision-relevant should be tailored to the case under exam, relying on the experts' know-how to understand the overall picture emerging from the scenarios.In this case, the clusters representing the most undesirable outcome are clusters 4 and 5. In both clusters, informal settlements increase the most; in cluster 4, residential demand is higher than in the other clusters (Fig. 7).

Table 2
Results of the two candidate algorithms.

	Agglomerative clustering	K-medoids
No. of clusters	5	4
Members of each cluster	[1879; 608; 1131; 676; 706]	[1664; 1289; 1341; 706]
Distribution	Quite evenly distributed	Quite evenly distributed
Within-cluster dissimilarity	0.023036	0.037750
Between-cluster dissimilarity	0.025754	0.038639

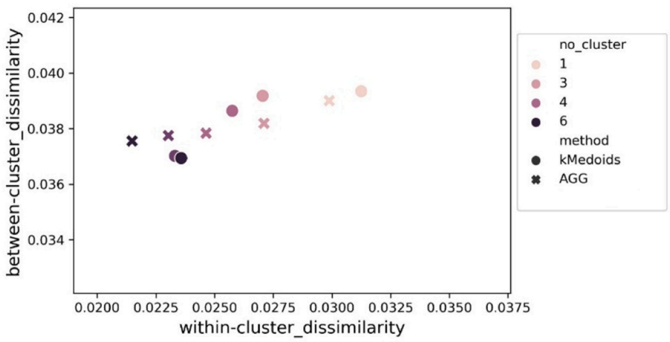

Fig. 6. Within-cluster and the between-cluster dissimilarity for the two candidate choices.

Table 3
Numbers of pixels for each land-use class in each cluster and in 2017.

Land use classes	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	2017
Non consumed	38381	39468	39572	36884	40424	33872
Agricultural	34255	34302	34281	34180	33862	43492
Informal	262	76	125	661	1178	208
Res/comm	5254	5216	5309	5402	4749	4566
Residential	42057	41121	41154	43515	40463	38752
Industrial	2272	2272	2081	1918	1822	1785
Commercial	1264	1308	1223	1201	1262	1211
Archaeological site	1489	1489	1489	1489	1489	1489
Pinewood	16094	16094	16094	16094	16094	16094
Reserve	96099	96099	96099	96099	96099	96099
Beach	4145	4145	4145	4145	4145	4145
Rural houses	268	268	268	268	268	268

Table 4
Percentage of land-use for each class in each cluster and in 2017.

Land use classes	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	2017
Non consumed	15.87%	16.31%	16.36%	15.25%	16.71%	14.01%
Agricultural	14.16%	14.18%	14.18%	14.13%	14.00%	17.99%
Informal	0.10%	0.03%	0.05%	0.27%	0.48%	0.08%
Res/comm	2.17%	2.15%	2.19%	2.23%	1.96%	1.88%
Residential	17.39%	17.00%	17.01%	17.99%	16.97%	15.92%
Industrial	0.93%	0.93%	0.86%	0.79%	0.75%	0.73%
Commercial	0.52%	0.54%	0.50%	0.49%	0.52%	0.50%
Archaeological site	0.65%	0.65%	0.65%	0.65%	0.65%	0.65%
Pinewood	6.65%	6.65%	6.65%	6.65%	6.65%	6.65%
Reserve	39.75%	39.75%	39.75%	39.75%	39.75%	39.75%
Beach	1.71%	1.71%	1.71%	1.71%	1.71%	1.71%
Rural houses	0.11%	0.11%	0.11%	0.11%	0.11%	0.11%

4.5. Scenario discovery and scenario narratives

From the Scenario Discovery results for cluster 4, we see that the land use pattern exhibited by this cluster arises when the football stadium is built in Fiumicino, on the other side of the river, and it strongly influences the development of the built environment. The land-use demand for the residential land-use class has the highest value, increasing by 2,07% from 2017 to 2050. Taken together, cluster 4 represents a situation where the X Municipality is an attractive area, the new poles of attraction generate new job opportunities, and the demand for housing is high. Urban growth is concentrated in the most vulnerable zone in terms of flooding. The narrative emerging from this depicts an area with increased imperviousness and, consequently, a worsened flood risk, specifically in zones already fragile as initially informal or built during the building speculation. Climate change will worsen urban heat island effects and make extreme rainfall more frequent in the future. This directly increases pluvial flood risk, but, since the surface drainage system has outlets in the sea and the river, climate change-induced sea-level rise could also become a significant issue in the future. The informal settlements increase by 0.19%, representing an undesirable outcome, as self-constructed houses are more vulnerable to environmental hazards, which exacerbate climate change. Moreover, the emergence of these new informal settlements is also a sign of the partial failure of the strategies in place because they are not fulfilling the housing demand, or the housing market is not attainable

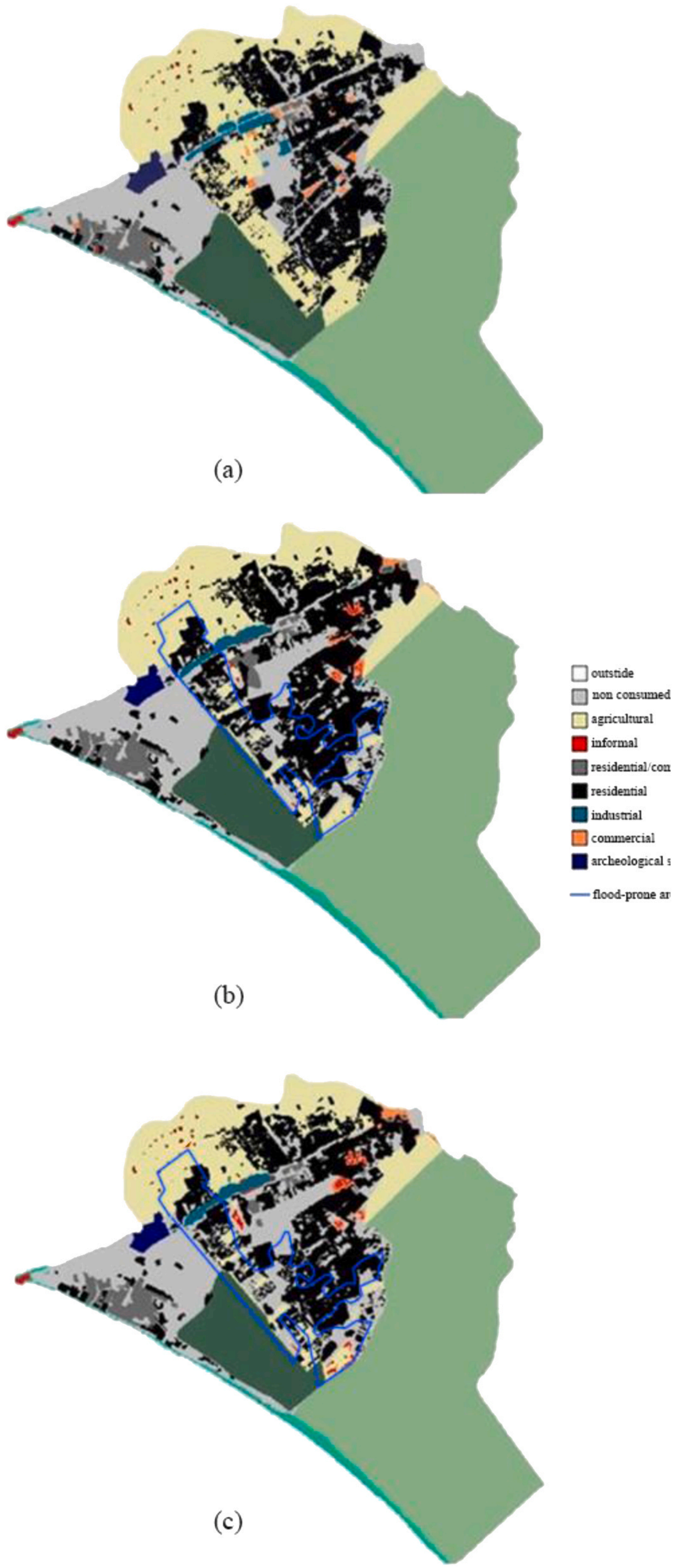

Fig. 7. (a) 2017 map. (b) Cluster 4.(c) Cluster 5. In both Clusters is overlayed a flooding map with a 50-year return period.

by lower-income inhabitants. Therefore, the new planned developments are insufficient for the demand, or some of the development should be implemented as social housing.

The land-use pattern of cluster 5 emerges if the stadium is built in Fiumicino and the new pole has high importance. The land use demand for the residential land-use class is in the middle of the considered range. In this case, urban growth compared to 2017 increases by 1,05%, the lowest value among the clusters. The narrative emerging from this is one where the importance of the new pole of attraction is high. Still, residential land use does not grow in line with local demand. This housing shortage results in the highest increase in informal settlements (i.e., 0.4%) across the clusters. This is reminiscent of historical developments in the area. The new stadium results in an increased attraction and, thus, higher demand for housing and potential new jobs for people with different social backgrounds. The residential development is inadequate to meet this demand, or the housing prices are not affordable for a portion of the population. Hence, informal settlements grow according to patterns seen in the past. This scenario shows several vulnerabilities. First, the new developments are concentrated in lower-lying areas so that floods will spread wider. In addition to an increase in soil sealing, we can assume that extreme rainfall events will be more frequent in the future. The overall picture illustrates a concerning situation, particularly regarding informal settlements.

5. Discussion

The built environment is complex and composed of many interrelated factors, which are, per se, a significant source of uncertainty. It is essential to account for uncertainties within the planning process to grasp better the overall changes that urban contexts may be undergoing (Borges et al., 2020).

Even though urban planning approaches have evolved in the last two decades, and flexible adaptation has been recognized as an essential feature, there is a need for a comprehensive workflow to guide urban planners in developing flexible adaptation plans in the face of uncertainty. This study presented a generic workflow and illustrated it using a relevant case study. Broadly speaking, the workflow can be divided into the following steps: (i) case study selection, (ii) data collection, (iii) model implementation, (iv) organization of the information, (v) exploration, clustering, and selection of decision-relevant clusters, and (vi) scenario discovery and scenario narratives.

In this case, the results could be utilized by planners and decision-makers to deliberate on the potential relocation of the stadium from the Fiumicino area due to the increasing vulnerabilities in the X Municipality that may arise. If the emerging points of attraction can contribute to the local economy, in response, possible measures can be implemented to mitigate future risks. However, the application of DMDU approaches in the built environment is still in its infancy and consequently requires further studies. The workflow presented in this study represents a first step toward such future investigations.

Computational scenario planning can help planners in architectural and urban fields to address uncertainties. However, most of the methods applied in the research are outside their expertise. Therefore, to structure a real cross-disciplinary plan to cope with unforeseen events, the first necessary step is to build common ground with other professionals and discuss further the best way to address uncertainties in the definition of adaptive plans for the built environment. Here we implemented a land-use model to simulate the land-use changes over time. The first limitation is that the uncertainties considered were just connected to the land-use demands and the impact of the possible implementation of infrastructures and poles of attractions. Consequently, the breadth of uncertainties considered can be improved, for example, by including social parameters to account for just urban planning in the face of climate change (Ciullo, Kwakkel, De Bruijn, Doorn, & Klijn, 2020). A second limitation concerns the modeling: a more accurate analysis of future floods requires a hydraulic model. In turn, this next requires considering how land-use change is affected by changing flood risk.

We used a case study to structure the analyses; therefore, the data and the uncertainties are case-specific. Given the complexity of the built environment and the characteristics that are necessarily related to context, this study cannot be interpreted as a one-size-fits-all solution. However, the workflow is generally applicable. A more comprehensive set of comparable cases would help develop general findings relevant to the urban environment. Nevertheless, the DMDU approaches and tools support building adaptive plans. Technical solutions are already oriented toward the implementation of resilient and adaptive strategies.

6. Conclusions and future outlooks

This work presents an interdisciplinary approach to include uncertainties in the urban planning process evaluating possible futures. We illustrated it through a case study in a flood-prone area in Rome. In this case, we implemented a land-use change model to assess the influence of uncertainties on future urban development, namely, land use demands for the different land use classes and the impact of possible infrastructures that could trigger an expansion of the urban fabric in the area. We generated five-thousand computational experiments that described the possible shape of the urban area through "*what if*" scenarios and described the narrative emerging from the decision-relevant cases. Although, as stated, the case study has limitations, the combination of methods shows the potential for further studies and applications toward the operative inclusion of uncertainties in the urban planning process.

Furthermore, additional analyses can be conducted to evaluate short-term and long-term options and structure several dynamic adaptive policy pathways (Haasnoot, Kwakkel, Walker, & ter Maat, 2013), addressing the vulnerabilities and emerging opportunities that may arise under changing conditions. A challenge for the future is integrating several models in the process, as cross scales analysis is necessary to increase adaptation to changing environmental conditions in the built environment.

Urban areas are expected to cope with many uncertainties in the future, namely climate change and the related environmental, economic, and social issues deriving from it. In this study, the identified vulnerabilities were related to the possible effect of different infrastructures on the built environment according to the pattern of urban development that emerged over time. However, as a future challenge, the implementation should be extended to a set of models that enables scenario planning under different "*what if*" conditions. Thus, the inclusion of more variables from Urban Physics and energetic factors for evaluating Urban Heat Island, combing the various environmental threats emerging from climate change.

In conclusion, the future is unknown, and anticipating this without addressing the uncertainties involved in delineating a long-term plan is no longer feasible. However, integrating uncertainties in the design process to pursue a flexible adaptation is still an open challenge for researchers and practitioners for field applications. In all the disciplines that require planning for the future, there should be particular attention to the exploration of unforeseen events that might undermine the objective of a plan. This kind of approach has already been proven beneficial in water management. However, it still lacks application in urban and architectural planning. Therefore, more case studies should be implemented to investigate how to move from theory to practice.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

References

Amer, M., Daim, T. U., & Jetter, A. (2013). A review of scenario planning. *Futures, 46*, 23–40. https://doi.org/10.1016/j.futures.2012.10.003
Avin, U., & Goodspeed, R. (2020). Using exploratory scenarios in planning practice: A spectrum of approaches. *Journal of the American Planning Association, 86*, 403–416. https://doi.org/10.1080/01944363.2020.1746688
Bankes, S. (1993). Exploratory modeling for policy analysis. *Operational Research, 41*, 435–449. https://doi.org/10.1287/opre.41.3.435
Bankes, S. (2009). Models as lab equipment: Science from computational experiments. *Computational and Mathematical Organization Theory, 15*, 8–10. https://doi.org/10.1007/s10588-008-9046-y
Bankes, S., Walker, W. E., & Kwakkel, J. H. (2013). Exploratory Modeling and Analysis. *Encycl. Oper. Res. Manag. Sci., 2*, 532–537. https://doi.org/10.1007/978-1-4419-1153-7_314
Bartholomew, E., Kwakkel, J.H., On considering robustness in the search phase of Robust Decision Making : A comparison of Many-Objective Robust Decision Making, multi-scenario Many-Objective Robust Decision Making, and Many Objective Robust Optimization 127 2020.
Beh, E. H. Y., Maier, H. R., & Dandy, G. C. (2015). Scenario driven optimal sequencing under deep uncertainty. *Environmental Modelling & Software, 68*, 181–195. https://doi.org/10.1016/j.envsoft.2015.02.006
Beh, E. H. Y., Zheng, F., Dandy, G. C., & Maier, H. R. (2017). Robust optimization of water infrastructure planning under deep uncertainty using metamodels Robust optimization of water infrastructure planning under deep uncertainty using metamodels. *Environmental Modelling & Software, 93*, 92–105. https://doi.org/10.1016/j.envsoft.2017.03.013
Ben-Tal, A., Brekelmans, R., Den Hertog, D., & Vial, J. P. (2017). Globalized robust optimization for nonlinear uncertain inequalities. *INFORMS Journal on Computing, 29*, 350–366. https://doi.org/10.1287/ijoc.2016.0735
Bishop, P., Hines, A., & Collins, T. (2007). The current state of scenario development: An overview of techniques. *Foresight, 9*, 5–25. https://doi.org/10.1108/14636680710727516
Borges, L., Hazin, M., Teixeira, A., & Almeida, D. (2020). Multidimensional flood risk management under climate changes: Bibliometric analysis, trends and strategic guidelines for decision-making in urban dynamics. *International Journal of Disaster Risk Reduction, 50*, Article 101865. https://doi.org/10.1016/j.ijdrr.2020.101865
Börjeson, L., Höjer, M., Dreborg, K. H., Ekvall, T., & Finnveden, G. (2006). Scenario types and techniques: Towards a user's guide. *Futures, 38*, 723–739. https://doi.org/10.1016/j.futures.2005.12.002
Bradfield, R., Wright, G., Burt, G., Cairns, G., & Van Der Heijden, K. (2005). The origins and evolution of scenario techniques in long range business planning. *Futures, 37*, 795–812. https://doi.org/10.1016/j.futures.2005.01.003
Bryant, B. P., & Lempert, R. J. (2010). Thinking inside the box: A participatory, computer-assisted approach to scenario discovery. *Technol Forecast Soc Change, 77*, 34–49. https://doi.org/10.1016/j.techfore.2009.08.002
Carter, J. G. (2018). Urban climate change adaptation: Exploring the implications of future land cover scenarios. *Cities, 77*, 73–80. https://doi.org/10.1016/j.cities.2018.01.014
Carvalho, P. (2021). Scenarios: Learning and acting from the future. *Insight & Foresight*.
Cellamare, C. (2010). Politiche e processi dell'abitare nella città abusiva/informale romana. *Arch di Stud Urbani e Reg Fr Angeli Ed*, 145–167. https://doi.org/10.3280/ASUR2010-097010
Choi, Y., Kang, J., & Kim, J. (2021). Urban flood adaptation planning for local governments: Hydrology analysis and optimization. *Int J Disaster Risk Reduction, 59*, Article 102213. https://doi.org/10.1016/j.ijdrr.2021.102213
Ciullo, A., Kwakkel, J. H., De Bruijn, K. M., Doorn, N., & Klijn, F. (2020). Efficient or Fair? Operationalizing Ethical Principles in Flood Risk Management: A Case Study on the Dutch-German Rhine. *Risk Anal, 40*. https://doi.org/10.1111/risa.13527
Clough Marinaro, I., & Solimene, M. (2020). Navigating the (in)formal city: Roma, urban life and governance in Rome. *Cities, 96*, Article 102402. https://doi.org/10.1016/j.cities.2019.102402
Cordova-Pozo, K., & Rouwette, E. A. J. A. (2023). Types of scenario planning and their effectiveness: A review of reviews. *Futures*, 149. https://doi.org/10.1016/j.futures.2023.103153
Cozzolino, S., & Moroni, S. (2022). Structural preconditions for adaptive urban areas: Framework rules, several property and the range of possible actions. *Cities, 130*, Article 103978. https://doi.org/10.1016/j.cities.2022.103978
Daron, J. (2015). Challenges in using a Robust decision making approach to guide climate change adaptation in South Africa. *Climate Change, 132*, 459–473. https://doi.org/10.1007/s10584-014-1242-9
Dawson, M., Moglia, M., 2019. Scenario Planning - Turning Scenario Narratives into an Active Planning Tool SCENARIO PLANNING - TURNING SCENARIO NARRATIVES INTO AN ACTIVE PLANNING TOOL.
Dessai, S., & Hulme, M. (2007). Assessing the robustness of adaptation decisions to climate change uncertainties: A case study on water resources management in the East of England. *Global Environmental Change, 17*, 59–72. https://doi.org/10.1016/j.gloenvcha.2006.11.005
Diehl, E., & Sterman, J. D. (1995). Effects of feedback complexity on dynamic decision making. *Organizational Behavior and Human Decision Processes*. https://doi.org/10.1006/obhd.1995.1043
Ducot, G., & Lubben, G. J. (1980). A typology for scenarios. *Futures, 12*, 51–57. https://doi.org/10.1016/S0016-3287(80)80007-3

Falasca, S., Ciancio, V., Salata, F., Golasi, I., Rosso, F., & Curci, G. (2019). High albedo materials to counteract heat waves in cities: An assessment of meteorology, buildings energy needs and pedestrian thermal comfort. *Building & Environmental, 163*, Article 106242. https://doi.org/10.1016/j.buildenv.2019.106242

Friedman, J. H., & Fisher, N. I. (1999). Bump hunting in high-dimensional data. *Statistics & Computing, 9*, 123–143. https://doi.org/10.1023/A:1008894516817

Galdini, R., & Nardis, S. De (2023). Urban informality and users-led social innovation: Challenges and opportunities for the future human centred city. *Futures, 150*, Article 103170. https://doi.org/10.1016/j.futures.2023.103170

Gerst, M. D., Wang, P., & Borsuk, M. E. (2013). Discovering plausible energy and economic futures under global change using multidimensional scenario discovery. *Environmental Modelling & Software, 44*, 76–86. https://doi.org/10.1016/j.envsoft.2012.09.001

Godet, M. (1986). Introduction to la prospective. *Futures, 18*, 134–157. https://doi.org/10.1016/0016-3287(86)90094-7

Groves, D., Bloom, E., Fischbach, J. ~R., & Knopman, D. (2013). Adapting to a changing Colorado River: Making future water deliveries more reliable through robust management strategies. *AGU Fall Meeting Abstracts*, H41K–H41407.

Groves, D. G., Molina-Perez, E., Bloom, E., & Fischbach, J. R. (2019). Robust decision making (RDM): Application to water planning and climate policy. In *Decision making under deep uncertainty: From theory to practice* (pp. 135–163). Springer International Publishing. https://doi.org/10.1007/978-3-030-05252-2.

Gupta, R. S., Hamilton, A. L., Reed, P. M., & Characklis, G. W. (2020). Can modern multi-objective evolutionary algorithms discover high-dimensional financial risk portfolio tradeoffs for snow-dominated water-energy systems? *Advances in Water Research, 145*. https://doi.org/10.1016/j.advwatres.2020.103718

Haasnoot, M., Kwakkel, J. H., Walker, W. E., & ter Maat, J. (2013). Dynamic adaptive policy pathways: A method for crafting robust decisions for a deeply uncertain world. *Glob. Environ. Chang., 23*, 485–498. https://doi.org/10.1016/j.gloenvcha.2012.12.006

Haasnoot, M., Middelkoop, H., Offermans, A., Van Beek, E., & Deursen, W. P. A. van (2012). Exploring pathways for sustainable water management in river deltas in a changing environment. *Climate Change, 115*, 795–819. https://doi.org/10.1007/s10584-012-0444-2

Hagen, A., 2010. Fuzzy set approach to assessing similarity of categorical maps 8816. https://doi.org/10.1080/13658810210157822.

Hagen-Zanker, A. (2009). An improved Fuzzy Kappa statistic that accounts for spatial autocorrelation. *International Journal of Geograhical Information Science, 23*, 61–73. https://doi.org/10.1080/13658810802570317

Hamarat, C., Kwakkel, J. H., Pruyt, E., & Loonen, E. T. (2014). An exploratory approach for adaptive policymaking by using multi-objective robust optimization. *Simul. Model. Pract. Theory, 46*, 25–39. https://doi.org/10.1016/j.simpat.2014.02.008

Helgeson, C. (2020). Structuring decisions under deep uncertainty. *Topoi, 39*, 257–269. https://doi.org/10.1007/s11245-018-9584-y

Helton, J. C., & Davis, F. J. (2002). Latin hypercube sampling and the propagation of uncertainty in analyses of complex systems. *Sandia Report*. https://doi.org/10.1007/3-540-54029-6_187

Hewitt, R., van Delden, H., & Escobar, F. (2014). Participatory land use modelling, pathways to an integrated approach. *Environmental Modelling & Software, 52*, 149–165. https://doi.org/10.1016/j.envsoft.2013.10.019

Holtz, G., Alkemade, F., De Haan, F., Köhler, J., Trutnevyte, E., Luthe, T., … Ruutu, S. (2015). Prospects of modelling societal transitions: Position paper of an emerging community. *Environ. Innov. Soc. Transitions, 17*, 41–58. https://doi.org/10.1016/j.eist.2015.05.006

Iglesias, A., & Garrote, L. (2015). Adaptation strategies for agricultural water management under climate change in Europe. *Agricultural Water Management, 155*, 113–124. https://doi.org/10.1016/j.agwat.2015.03.014

Insolera, I., 1960. Roma moderna: Un secolo di storia urbanistica. Torino.

Iverson Nassauer, J., & Corry, R. C. (2004). Using normative scenarios in landscape ecology. *Landscape Ecology, 19*, 343–356. https://doi.org/10.1023/B:LAND.0000030666.55372.ae

Jäger, J., Rounsevell, M. D. A., Harrison, P. A., Omann, I., Dunford, R., Kammerlander, M., & Pataki, G. (2015). Assessing policy robustness of climate change adaptation measures across sectors and scenarios. *Climate Change, 128*, 395–407. https://doi.org/10.1007/s10584-014-1240-y

Jaxa-Rozen, M., & Kwakkel, J. (2018). Tree-based ensemble methods for sensitivity analysis of environmental models: A performance comparison with Sobol and Morris techniques. *Environ. Model. Softw., 107*, 245–266. https://doi.org/10.1016/j.envsoft.2018.06.011

Jin, X., & Han, J. (2010). K-medoids clustering. In C. Sammut, & G. I. Webb (Eds.), *Encyclopedia of machine learning* (pp. 564–565). US, Boston, MA: Springer. https://doi.org/10.1007/978-0-387-30164-8_426.

John, A., Horne, A., Nathan, R., Fowler, K., Webb, J. A., & Stewardson, M. (2021). Robust Climate change adaptation for environmental flows in the Goulburn River, Australia. *Frontiers in Environmental Science, 9*, 1–18. https://doi.org/10.3389/fenvs.2021.789206

Kasprzyk, J. R., Nataraj, S., Reed, P. M., & Lempert, R. J. (2013). Many objective robust decision making for complex environmental systems undergoing change. *Environmental Modelling & Software, 42*, 55–71. https://doi.org/10.1016/j.envsoft.2012.12.007

Kazak, J.K., 2018. The Use of a Decision Support System for Sustainable Urbanization and Thermal Comfort in Adaptation to Climate Change Actions — The Case of the Wrocław Larger Urban Zone (Poland). https://doi.org/10.3390/su10041083.

Kwakkel, J. H. (2017). The Exploratory Modeling Workbench: An open source toolkit for exploratory modeling, scenario discovery, and (multi-objective) robust decision making. *Environ. Model. Softw., 96*, 239–250. https://doi.org/10.1016/j.envsoft.2017.06.054

Kwakkel, J. H. (2019). A generalized many-objective optimization approach for scenario discovery. *Futur. Foresight Sci., 1*, e8. https://doi.org/10.1002/ffo2.8

Kwakkel, J. H., & Jaxa-Rozen, M. (2016). Improving scenario discovery for handling heterogeneous uncertainties and multinomial classified outcomes. *Environ. Model. Softw., 79*, 311–321. https://doi.org/10.1016/j.envsoft.2015.11.020

Kwakkel, J. H., & Haasnoot, M. (2019). Supporting DMDU: A Taxonomy of Approaches and Tools. In V. A. W. J. Marchau, W. E. Walker, P. J. T. M. Bloemen, & S. W. Popper (Eds.), *Decision Making under Deep Uncertainty: From Theory to Practice* (pp. 355–374). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-05252-2_15.

Kwakkel, J. H., Walker, W. E., & Marchau, V. A. W. J. (2010). Classifying and communicating uncertainties in model-based policy analysis. *Int. J. Technol. Policy Manag., 10*, 299–315. https://doi.org/10.1504/IJTPM.2010.036918

Kwakkel, J. H., Haasnoot, M., & Walker, W. E. (2015). Developing dynamic adaptive policy pathways: a computer-assisted approach for developing adaptive strategies for a deeply uncertain world. *Clim. Change, 132*, 373–386. https://doi.org/10.1007/s10584-014-1210-4

Kwakkel, J. H., Haasnoot, M., & Walker, W. E. (2016). Comparing Robust Decision-Making and Dynamic Adaptive Policy Pathways for model-based decision support under deep uncertainty. *Environ. Model. Softw., 86*, 168–183. https://doi.org/10.1016/j.envsoft.2016.09.017

Lauf, S., Haase, D., Hostert, P., Lakes, T., & Kleinschmit, B. (2012). Uncovering land-use dynamics driven by human decision-making - A combined model approach using cellular automata and system dynamics. *Environmental Modelling & Software, 27–28*, 71–82. https://doi.org/10.1016/j.envsoft.2011.09.005

Lempert, R. J., & Groves, D. G. (2010). Identifying and evaluating robust adaptive policy responses to climate change for water management agencies in the American west. *Technol Forecasting and Social Change, 77*, 960–974. https://doi.org/10.1016/j.techfore.2010.04.007

Lempert, R. J., Popper, S. W., & Bankes, S. C. (2003). *Shaping the next one hundred years: New Methods for quantitative*. Santa Monica, CA: Long-Term Policy Analysis.

Lempert, R. J., Groves, D. G., Popper, S. W., & Bankes, S. C. (2006). A general, analytic method for generating robust strategies and narrative scenarios. *Management Science, 52*, 514–528. https://doi.org/10.1287/mnsc.1050.0472

Lempert, R. J., Kalra, N., Peyraud, S., Mao, Z., Tan, S. B., Cira, D., & Lotsch, A. (2013). *Ensuring robust flood risk management in Ho Chi Minh City* (pp. 1–63). World Bank. https://doi.org/10.1596/1813-9450-6465

Lygoe, R. J., Cary, M., & Fleming, P. J. (2013). A real-world application of a many-objective optimisation complexity reduction process. In R. C. Purshouse, P. J. Fleming, C. M. Fonseca, S. Greco, & J. Shaw (Eds.), *Evolutionary multi-criterion optimization* (pp. 641–655). Berlin, Heidelberg: Springer Berlin Heidelberg.

Mabrouk, M., & Haoying, H. (2023). Urban resilience assessment: A m ulticriteria approach for identifying urban flood-exposed risky districts using. *International Journal of Disaster Risk Reduction, 91*, Article 103684. https://doi.org/10.1016/j.ijdrr.2023.103684

Maier, H. R., Guillaume, J. H. A., van Delden, H., Riddell, G. A., Haasnoot, M., & Kwakkel, J. H. (2016). An uncertain future, deep uncertainty, scenarios, robustness and adaptation: How do they fit together? *Environ. Model. Softw., 81*, 154–164. https://doi.org/10.1016/j.envsoft.2016.03.014

Makridakis, S., Wheelwright, S. C., & Hyndman, R. J. (1998). *Forecasting: Methods and applications*. Wiley.

Mancosu, E., Gago-Silva, A., Barbosa, A., de Bono, A., Ivanov, E., Lehmann, A., & Fons, J. (2015). Future land-use change scenarios for the Black Sea catchment. *Environmental Science & Policy, 46*, 26–36. https://doi.org/10.1016/j.envsci.2014.02.008

Milly, A. P. C. D., Betancourt, J., Falkenmark, M., Hirsch, R. M., Zbigniew, W., Lettenmaier, D. P., Stouffer, R. J., & Milly, P. C. D. (2008). Stationarity Is Dead: Stationarity Whither Water Management ? *Science (80-), 319*, 573–574. https://doi.org/10.1126/science.1151915

Moallemi, E. A., Kwakkel, J., de Haan, F. J., & Bryan, B. A. (2020). Exploratory modeling for analyzing coupled human-natural systems under uncertainty. *Glob. Environ. Chang., 65*, 102186. https://doi.org/10.1016/j.gloenvcha.2020.102186

Moroni, S., & Cozzolino, S. (2019). Action and the city. *Emergence, Complexity, Planning Cities, 90*, 42–51. https://doi.org/10.1016/j.cities.2019.01.039

Moroni, S., & Chiffi, D. (2021). Complexity and uncertainty: Implications for urban planning. *Handb Cities Complex*, 319–330. https://doi.org/10.4337/9781789900125.00027

Munafò, M., Norero, C., Sabbi, A., & Salvati, L. (2010). Soil sealing in the growing city: A survey in Rome, Italy. *Scottish Geographical Journal, 126*, 153–161. https://doi.org/10.1080/14702541.2010.527855

Notten, P. W. F. Van, Rotmans, J., Asselt, M. B. A., Van, & Rothman, D. S. (2003). An updated scenario typology. *Futures, 35*, 423–443. https://doi.org/10.1016/S0016-3287(02)00090-3

Recanatesi, F., & Petroselli, A. (2020). Land cover change and flood risk in a peri-urban environment of the metropolitan area of Rome (Italy). *Water Resour Management*. https://doi.org/10.1007/s11269-020-02567-8

RIKS. (2011). *Metronamica - Model descriptions*. Maastricht, The Netherlands: RIKS. ⟨www.metronamica.nl⟩ ([WWW Document]. URL www.metronamica.nl).

Robinson, J. B. (1990). Futures under glass. A recipe for people who hate to predict. *Futures, 22*, 820–842. https://doi.org/10.1016/0016-3287(90)90018-D

Rozenberg, J., Guivarch, C., Lempert, R., & Hallegatte, S. (2014). Building SSPs for climate policy analysis: A scenario elicitation methodology to map the space of possible future challenges to mitigation and adaptation. *Climate Change, 122*, 509–522. https://doi.org/10.1007/s10584-013-0904-3

Saliba, G. (2009). Windows for the mind: The use of scenario planning for managing uncertainty. *Journla of Future Studies, 13*, 123–128.

Salvati, L., Munafo, M., Morelli, V. G., & Sabbi, A. (2012). Low-density settlements and land use changes in a Mediterranean urban region. *Landscape Urban Planning, 105*, 43–52. https://doi.org/10.1016/j.landurbplan.2011.11.020

Schueller, L., Booth, L., Fleming, K., & Abad, J. (2020). Using serious gaming to explore how uncertainty affects stakeholder decision-making across the science-policy divide during disasters. *International Journal of Disaster Risk Reduction, 51*, Article 101802. https://doi.org/10.1016/j.ijdrr.2020.101802

Shavazipour, B., Kwakkel, J. H., & Miettinen, K. (2021). Multi-scenario multi-objective robust optimization under deep uncertainty: A posteriori approach. *Environ. Model. Softw., 144*, 105134. https://doi.org/10.1016/j.envsoft.2021.105134

Shepherd, T. G., Boyd, E., Calel, R. A., Chapman, S. C., Dessai, S., Dima-West, I. M., Fowler, H. J., James, R., Maraun, D., Martius, O., Senior, C. A., Sobel, A. H., Stainforth, D. A., Tett, S. F. B., Trenberth, K. E., van den Hurk, B. J. J. M., Watkins, N. W., Wilby, R. L., & Zenghelis, D. A. (2018). Storylines: an alternative approach to representing uncertainty in physical aspects of climate change. *Climate Change, 151*, 555–571. https://doi.org/10.1007/s10584-018-2317-9

Singh, R., Reed, P. M., & Keller, K. (2015). Many-objective robust decision making for managing an ecosystem with a deeply uncertain threshold response. *Ecological Society, 20*. https://doi.org/10.5751/ES-07687-200312

Smith, R., Zagona, E., Kasprzyk, J., Bonham, N., Alexander, E., Butler, A., Prairie, J., & Jerla, C. (2022). Decision science can help address the challenges of long-term planning in the Colorado River Basin. *Journal of American Water Resources Association, 58*, 735–745. https://doi.org/10.1111/1752-1688.12985

Steinmann, P., Auping, W. L., & Kwakkel, J. H. (2020). Behavior-based scenario discovery using time series clustering. *Technol. Forecast. Soc. Change, 156*, 120052. https://doi.org/10.1016/j.techfore.2020.120052

Sterman, J. D. (2002). All models are wrong: Reflections on becoming a systems scientist. *System Dynamics Review, 18*, 501–531. https://doi.org/10.1002/sdr.261

Theodoridis, S., & Koutroumbas, K. (2009). Clustering algorithms II: Hierarchical algorithms. *Pattern Recognition*, 653–700. https://doi.org/10.1016/b978-1-59749-272-0.50015-3

Tolk, A. (2022). Simulation-based optimization: Implications of complex adaptive systems and deep uncertainty. *Information, 13*. https://doi.org/10.3390/info13100469

Trindade, B. C., Reed, P. M., Herman, J. D., Zeff, H. B., & Characklis, G. W. (2017). Reducing regional drought vulnerabilities and multi-city robustness conflicts using many-objective optimization under deep uncertainty. *Advances in Water Research, 104*, 195–209. https://doi.org/10.1016/j.advwatres.2017.03.023

Van Delden, H., Hurkens, J., 2011. A generic integrated spatial decision support system for urban and regional planning. MODSIM 2011 - 19th Int. Congr. Model. Simul. - Sustain. Our Futur. Underst. Living with Uncertain. 127–139.

Vliet, J. Van, Bregt, A. K., Brown, D. G., & Delden, H. Van (2016). A review of current calibration and validation practices in land-change modeling environmental modelling & software a review of current calibration and validation practices in land-change modeling. *Environmental Modelling & Software, 82*, 174–182. https://doi.org/10.1016/j.envsoft.2016.04.017

Vliet, J. Van, Bregt, A.K., Hagen-zanker, A., 2011. Revisiting Kappa to account for change in the accuracy assessment of land-use change models. Ecol. Modell. 222, 1367–1375. https://doi.org/10.1016/j.ecolmodel.2011.01.017.

Walker, W. E., Rahman, S. A., & Cave, J. (2001). Adaptive policies, policy analysis, and policy-making. *European Journal of Operational Research, 128*, 282–289. https://doi.org/10.1016/S0377-2217(00)00071-0

Walker, W. E., Marchau, V. A. W. J., & Swanson, D. (2010). Addressing deep uncertainty using adaptive policies: Introduction to Section 2. *Technological Forecasting and Social Change, 77*, 917–923. https://doi.org/10.1016/j.techfore.2010.04.004

Walker, W. E., Harremoës, P., Rotmans, J., van der Sluijs, J. P., van Asselt, M. B. A., Janssen, P., & Krayer von Krauss, M. P. (2003). Defining uncertainty: A conceptual basis for uncertainty management in model-based decision support. *Integrated Assessment, 4*, 5–17. https://doi.org/10.1076/iaij.4.1.5.16466

Walton, S., O'Kane, P., & Ruwhiu, D. (2019). Developing a theory of plausibility in scenario building: Designing plausible scenarios. *Futures, 111*, 42–56. https://doi.org/10.1016/j.futures.2019.03.002

Wang, H., Wanakule, N., Asefa, T., Erkyihun, S., Basdekas, L., & Hayslett, R. (2023). Application of multiobjective optimization to provide operational guidance for allocating supply among multiple sources. *Journal of Water Resources Planning & Management, 149*, 1–13. https://doi.org/10.1061/jwrmd5.wreng-5827

Watson, A. A., & Kasprzyk, J. R. (2017). Incorporating deeply uncertain factors into the many objective search process. *Environmental Modelling & Software, 89*, 159–171. https://doi.org/10.1016/j.envsoft.2016.12.001

Yan, D., Ludwig, F., Huang, H. Q., & Werners, S. E. (2017). Many-objective robust decision making for water allocation under climate change. *Science of the Total Environment, 607–608*, 294–303. https://doi.org/10.1016/j.scitotenv.2017.06.265