Structuring uncertainty to improve climate change management success

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Abstract.

There is a growing concern about the unforeseen negative consequences of climate change. In response, important scholarly efforts have produced valuable frameworks to help decisionmakers construct adaptation plans. Drawing on the success and failures of current adaptation plans, these frameworks have been developed to prevent maladaptations, meaning the unforeseen negative consequences of adaptation plans. We argue that while current frameworks focusing on planning and risk management are crucial, the inherent uncertainty of climate change requires a more nuanced approach. We propose a novel "adaptation grid" that aligns existing frameworks with Decision Making under Deep Uncertainty (DMDU). This grid leverages insights from current frameworks to structure different kinds of uncertainty and how they impact adaptation planning. Our approach recognizes that adaptation strategies lie on a continuum of success and failure. We advocate for indicators that go beyond success measurement, instead focusing on acceptable degrees of failure, learning from past actions, and identifying early warning signals. By incorporating a richer understanding of uncertainty, DMDU offers a comprehensive cognitive, methodological and theoretical framework for constructing qualitative observations into measurable indicators, imagining alternative futures, and implementing a management-learning system to help us better navigate climate change uncertainties.

Introduction

The year 2023 will likely be remembered as a pivotal moment setting the stage for future climate scenarios that we have never witnessed before. It brought record-breaking sea and land temperatures, marked by the hottest summer in the Northern Hemisphere and the lowest extent of Antarctic Sea ice in 45 years of satellite tracking (Esper et.al. 2024; McCulloch et.al. 2024; Purich & Doddridge 2023). It is estimated that the carbon budget remaining to keep warming below 1.5°C is equivalent to approximately six years of current CO2 emissions (Lamboll et al., 2023). We came dangerously close to surpassing some of Earth's tipping points, posing severe risks to human life (Wunderling et.al. 2024). As expressed in the 2023 state of the climate report, we ventured into uncharted territory (Ripple et al., 2023).

The socio-environmental trends that emerged in 2023 persisted through 2024 (Copernicus 2024; Ripple et al. 2024; Romanello et al. 2024; World Meteorological Organization 2024), reinforcing the view that we have already entered an era of increasingly unpredictable and challenging climate scenarios in the short and medium term. If this is the case, the need for robust adaptation plans becomes more urgent than ever to ensure societies are prepared for future climate challenges. According to the Adaptation Gap Report (UN Environment Programme, 2024), 87% of countries worldwide have developed adaptation plans. However, despite their widespread adoption, progress remains contentious. Many of these plans have led to unintended negative consequences, as reflected in the growing body of research on maladaptation. Maladaptation occurs when adaptation measures inadvertently worsen climate impacts rather than mitigating them (Magnan et al. 2016; Schipper 2020; Reckien et al. 2023), underscoring the need for more effective, context-specific, and forward-thinking adaptation strategies.

In response to the incoming data on the success and failure of adaptation plans, significant scholarly effort has been dedicated to developing frameworks to minimize the risk of adaptation going wrong. To date, most of these frameworks are termed "ex ante" because their goal is to identify maladaptations before they happen (Boutroue et.al. 2022; Reckien et.al. 2023; Magnan et.al. 2014). Consequently, maladaptation has been predominantly framed as a problem of planning and risk management. For instance, the IPCC's Sixth Assessment Report (AR6) states: "successful adaptation and maladaptation need to be considered as the two ends of a continuum of risk management strategies" (section 17.5.1). Accordingly, many of these studies have focused on how planning and management practices have led to maladaptation. For example, due to short-termism (Piggot-McKellar 2020), inadequate planning and execution of infrastructures (Barnett & O'Neill 2010; Hallegatte 2009), lack of coordination among stakeholders, donors, public servants, and experts participating in different steps of the adaptation process planning (Bertana et.al. 2022), or political decisions where allocation of risk and resources are linked to problems of equity and injustice (Martinez-Allier 2023; Eakin et.al. 2021).

Cases of maladaptation are likely to increase in the short and medium-term even if planning processes run flawlessly. Maladaptation is an integral part of management strategies. This happens because the success of risk management strategies is limited by different degrees of uncertainty. In the context of climate change, uncertainty stems from an incomplete understanding of how political, economic, social, and natural systems interact (Incropera 2016; Hasnoot et.al. 2024). As a result, all management strategies lie on a continuum of outcomes where successful and failed adaptation strategies represent its ends (AR6, Reckien 2023). In recent years uncertainty and its effects on climate change have been subject to intense scrutiny (Scoones & Stirling 2023). It is well-established that uncertainty is an inherent aspect of socio-ecological systems, as these involve complex, non-linear dynamics resulting in positive and negative unforeseen consequences (Steffen et.al. 2020). Furthermore, uncertainty inversely correlates with climate change efforts, the higher the degree of uncertainty the less likely projects are to be successful. In AR6, for example, its authors claim that the limits of adaptation are not fully known, especially for higher degrees of climate change, and that uncertainty about the magnitude and timing of climate change impacts makes it difficult to design robust adaptation strategies.

From this perspective the best adaptive management strategies are not those that guarantee success, an impossible expectation, but those that can delineate pathways towards adaptation, establish acceptable risk thresholds, and create early warning systems for decision-makers and stakeholders to take the actions necessary to pivot projects trending towards the maladaptive side of the continuum.

Building on the theoretical discussions outlined, this study aims to strengthen and refine existing maladaptation frameworks. We propose contributing to the development of an adaptation management grid that integrates these frameworks with Decision Management under Deep Uncertainty (DMDU), bridging methodological and theoretical gaps in current approaches. Our goal is to leverage insights from maladaptation research to construct robust future scenarios, enabling a deeper understanding of potential climate outcomes while identifying trends and uncertainties across different levels. This structured approach will help design strategies for navigating an increasingly unpredictable future. Central to this effort is the recognition that effective adaptation hinges on a clear understanding of how different types of uncertainty shape risk management strategies, ensuring that adaptation plans are both flexible and robust in the face of deep uncertainty.

In what follows, we will introduce the field of Decision Making under Deep Uncertainty (DMDU) and illustrate its application with a case study. Our intention is not to assert that these are the only methods to be used, but rather to introduce DMDU and showcase its strengths as a comprehensive methodological, epistemic, and cognitive framework for addressing adaptation efforts. Our argument is developed as follows: first we will discuss uncertainty as a category to motivate that maladaptation frameworks should incorporate a richer sense in which talk about uncertainty. Next, we will introduce the fundamentals of DMDU and exemplify them with a case study of our own on water management in Mexico City. Finally, we will discuss how uncertainty analysis can enhance adaptation planning.

Adaptation-Maladaptation frameworks.

The term maladaptation in the context of climate change studies refers to adaptation actions that fail to reduce vulnerability to climate impacts or that inadvertently increase vulnerability. The concept has its origins in the late 1990s and has evolved through various academic discussions and publications. The term maladaptation"began to appear in climate change literature in the late 1990s. It was first referenced indirectly by Scheraga and Grambsch in 1998 in their work related to climate adaptation strategies, although a specific definition was not established at that time (Magnan 2014). The earliest formal definitions emerged in the early 2000s, particularly through the work of Barnett and O'Neill (2010), who provided a clear definition of maladaptation as actions taken to avoid or reduce vulnerability to climate change that inadvertently increase vulnerability in other systems, sectors, or social groups. Since, the term has gained attention and has been reconceptualized to suit different theoretical and methodological interests, for example, emphasizing anticipatory planning (Magnan et.al. 2016), justice-sensitive approaches (Glover & Granberg 2021), or dynamic, iterative methods

(Chi et.al. 2021). However, empirical validation of these frameworks and operational metrics for real-time adaptive monitoring remain key research gaps (Reckien 2023) (table 1).

In the context of maladaptation frameworks, uncertainty has been addressed explicitly in the Precautionary Framework (PF) (Hallegatte, 2009). PF helped popularize the notions of “no regret” or “future-proof” strategies, emphasizing the need to construct robust strategies that could work across different future scenarios. However, PF did not incorporate an analysis of uncertainty or provided ways to understand how uncertainty is structured and how this structure might impact negatively on adaptation management. When Hallegatte introduced PF in 2009, he assumed that climate scientists would need to investigate further how to understand, identify, and assess uncertainty. This has happened in climate studies (the transition from AR5 to AR6 being a clear case), but uncertainty analysis has not been explicitly integrated into adaptation-maladaptation frameworks.

Framework	How to tackle maladaptation	When is it implemented?	Is it quantified?	Is uncertainty dealt with explicitly?
Barnett & O'Neill (2010) Pathway framework	Ex ante. Decision-makers ask pertinent questions at the planning stage based on five proposed pathways.	Planning stage	No	No
Bertana et.al. (2022). Process Framework	Ex ante by identifying structural problems in the planning stage.	Planning stage	No	No
Boutroue et.al. (2022) Governance framework	Ex ante. Ensuring equitable representation of diverse interests, facilitating reasoned debates, and maximizing the flexibility of adaptation decisions to accommodate changing circumstances.	Planning stage/M&E	No. Explicitly moving away from quantitative estimators	No
Chi et.al (2021) Spatial framework	Ex ante. Explores spatial analysis for evaluating maladaptation in adaptation planning. Systematic review of land-use and spatial change impacts. Ex post could be used to assess adaptation outcomes.	Planning stage/M&E	Yes	Yes
Fünfgeld & Schmid (2020) Justice framework	Ex ante. Justice-sensitive framework proposes integrating distributional, procedural, and recognition justice into maladaptation planning.	Planning stage	No	No
Hallegatte (2009) Precautionary Framework	Ex ante, coming up with future proof/no regret decisions.	Planning stage	No	No
Juhola et.al (2016)	Ex ante by understanding different sources of vulnerability, or ex post by	Planning stage/M&E	No	No

Feedback framework	studying in what sense projects increased vulnerability.			
Magnan (2014) Assessment Framework	Ex ante. Decision-makers follow 11 practical guidelines to minimize the risk of maladaptation.	Planning stage	No	No
Reckien et.al. (2023) Navigating the Adaptation-Maladaptation continuum (NAM).	Ex ante by evaluating the maladaptive potential of some proposals. Ex post by assessing risks at the M&E stage.	Planning stage/M&E	Yes	No
Tubi & Williams (2020) Multiple dimensions framework	Ex ante. Develops a conceptual framework to assess trade-off dynamics inherent in adaptation actions. Explicitly studies adaptation-maladaptation jointly.	Planning stage	No	No

Table 1. A selection of maladaptation frameworks. Feedback, NAM and Spatial methods could in principle be used at the M&E stage. However, as far as we know, they have not been implemented that way. Feedback framework has been used as an ex post evaluation framework. M&E stands for Monitoring and evaluation.

Following a similar motivation to Hallegatte, Magnan (2014) developed the Assessment framework (AF), with a focus on uncertainty. Magnan asks, “How do we adapt to changes that cannot yet be precisely defined?” (p.2). AF advocates for flexibility in planning to address both current and future climate-related extreme events and gradual changes, emphasizing their multi-temporal nature. PF guidelines are based upon the pathway framework (Barnet & O’Neill, 2010) and Hallegatte’s PF, aiming to reduce potential future risks by focusing on present initiatives following the principle “first, do no harm”. Like Hallegatte, Magnan acknowledged the uncertainty problem and expected future studies would operationalize his insights.

Recently, Reckien et al. (2023) introduced the NAM (Navigating the Adaptation-Maladaptation Continuum) framework, developed to evaluate adaptation projects. NAM is built around six outcome criteria that focus on either equity-related issues or system-level factors. Although not explicitly labeled as such, these criteria align with six distinct types of uncertainty related to interactions within socio-environmental systems and the effects of policies on vulnerable populations. NAM provides a risk indicator to position projects on the maladaptation-adaptation continuum. Risk is calculated based on known factors that either facilitate or constrain adaptability. Crucially, the uncertainty addressed in NAM pertains to "unknown knowns”, this is, the framework identifies known strategies likely to enhance or reduce adaptability, even if their effectiveness in specific contexts remains uncertain.

While NAM, AF, and PF represent valuable approaches to understanding and addressing the adaptation-maladaptation continuum, particularly given their emphasis on the evolving nature of adaptation projects and the non-absolute nature of success, there is room for improvement. Specifically, linking their proposed guidelines more directly to the associated uncertainties could give decision-makers and stakeholders clearer insights into which projects are at greater risk of maladaptation and, crucially, why. This insight could enhance the overall planning process by addressing uncertainties more effectively and promoting better adaptive strategies.

Uncertainty in climate change adaptation decision making.

Uncertainty is a multifaceted concept that intersects epistemology, materiality, experience, and practice (Scoones & Stirling 2020). Uncertainty involves not only the absence of knowledge about phenomena but also the consequences of unpredictable events that unfold over time. In climate change adaptation studies, uncertainty is often framed in terms of known unknowns (KUs) and unknown unknowns (UUs) (Nisbet 2022, Fulvi & -Wodak 2024). KUs include gaps in information, such as the relative importance of key climate drivers, underlying variables, parameters, and their associated probability distributions. In contrast, UUs refer to events that cannot be captured probabilistically due to a lack of historical precedent or their extreme rarity, making it impossible to construct meaningful probabilistic models. In general, unknowns encompass a wide range of uncertainties arising from the material (e.g., policies and practices), relational (e.g., power dynamics), and cognitive (e.g., values and preferences) dimensions of human-environment systems. However, these dimensions of uncertainty have been less thoroughly explored in the context of climate change adaptation decision-making.

For example, Bojórquez-Tapia et al. (2022) highlight the critical role of uncertainty in the development of large-scale infrastructure projects, particularly in politically charged and contested contexts. They argue that effective decision-making in such projects requires acknowledging and addressing diverse forms of uncertainty. Similar challenges arise in the context of climate change adaptation. Adaptation management strategies are often shaped by conflicting stakeholder interests and differing problem framings, which can lead to disagreements over problem definitions and viable adaptation pathways. Moreover, climate change adaptation is embedded in political, social, and institutional structures that influence how different actors interact within formal and informal networks, relationships, and norms. As a result, uncertainty in adaptation decision-making is not solely a technical issue but is also deeply intertwined with the political, social, economic, and cultural contexts that shape which forms of knowledge are deemed valid and actionable. Consequently, different kinds of uncertainty require distinct approaches for understanding and addressing them.

From general uncertainty to structuring the unknown

As we enter a world of deep uncertainty, merely acknowledging uncertainty may not be enough to develop sound adaptive plans and strategies. There are two major reasons: First, uncertainty is a multifaceted concept. It includes epistemic uncertainties related to knowledge gaps in our understanding of socioenvironmental systems (Beven et.al. 2018), but also encompasses the numerous ways people perceive, understand and cope with uncertainty, especially those already experiencing the impacts of climate change (Mehta 2019; Nightingale et.al. 2019). Consequently, there are different kinds of uncertainty requiring distinct approaches for understanding and addressing them (table 2).

Second, KUs and UUs involve events that cannot be anticipated probabilistically even if we have access to probability distributions (Taleb 2010). Thus, it is not possible to develop robust ex ante risk management strategies. At best, we can have a rough idea of potential outcomes. This rough idea is the motivation for regret-safe strategies but note that climate change studies operate in a state of deep uncertainty. In socioenvironmental systems, deep uncertainty arises from the complex interactions between human and natural variables, which often lead to outcomes that exceed expectations. Examples include emergent phenomena such as the increase of lightning-induced wildfires due to climate change (Pérez-Invernón et.al. 2023), situations where heterogenous groups of people bring to the table different ways of understanding and dealing with uncertainty (Sarkar et.al. 2024), or in the disconnect between scientific advances and policy processes (Kotamäki et.al. 2024). This suggests that simply recognizing uncertainty's role in risk-management success is not enough. What is needed is a deep understanding of how different kinds of uncertainty impact the complex process of planning adaptation pathways.

Kind	**Source of uncertainty**	**How is it tackled?**	**Kind of unknowns involved**
Aleatoric	Inherent randomness in a system	Can't be tackled.	known unknowns/ unknown unknowns
Complex	Inherent complexity in systems	Can't be tackled.	known unknowns/ unknown unknowns
Contextual	How people from different cultural backgrounds understands and copes with uncertainty	Participatory frameworks. Embracing uncertainty Promoting equity and justice	known unknowns
Data	Lack of data, measurement errors, noise.	Modelling	known unknowns/ unknown unknowns
Deep	Different kinds of uncertainty affecting a system	DMDU frameworks	unknown unknowns
Epistemic	Lack of empirical knowledge	More research, data, statistical modelling	known unknowns/ unknown unknowns
Intrinsic	Inherent limitations of decision-maker's perceptual or cognitive abilities	Paticipatory frameworks	known unknowns/ unknown unknowns

Management	Lack of complete information necessary to make decisions and achieve certain outcomes	DMDU frameworks	unknown unknowns
Modelling	Assumptions built into models	Making explicit abstractions and idealizations	known unknowns/ unknown unknowns
Moral	Not knowing how one ought to act	Can't be tackled.	known unknowns/ unknown unknowns
Ontologic	Lack of knowledge about how the world actually is	More research (but it can be argued that we will never know the world is).	unknown unknowns
Political	Fluctuations in political, economic, and social conditions.	Future-proof; no regret strategies	known unknowns/ unknown unknowns
Polysemic	Use of open-ended terms that may be interpreted in different ways by the people participating in the same process	Paticipatory frameworks	known unknowns
Prospective	Impossibility of knowing the future	DMDU frameworks	unknown unknowns
Sociopolitical	Potentially unanticipated outcomes resulting from sociopolitical processes	Participatory frameworks. Embracing uncertainty promoting equity and justice	known unknowns/ unknown unknowns
Underdetermination	Incapacity of telling apart, through objective means, a theoretical, normative, or experimental framework	Can't be tackled.	unknown unknowns
Utility	it is not possible to assign precise utilities to consequences	Can't be tackled.	unknown unknowns

Table 2. Different types of uncertainties affecting adaptation management plans. References: Bojorquez-Tapia (2022), Mehta (2019), Marchau (2019), Aston (2023), Bradley (2014), Dequech (2011), Taebi (2020).

In our view, a critical area for improvement in current adaptation-maladaptation frameworks is the explicit diagnosis of how different kinds of uncertainty affect the risk management process. Uncertainty must be treated as a complex issue affecting nature, people, and the things that are possible to know. Acknowledging the different sources of uncertainty turns uncertainty into something meaningful: it is not a vague term that fosters fear and doubt, but a category that sheds light on unknowns in particular contexts. Understanding these contexts directs attention to areas that might otherwise be neglected, helping adaptation plans to develop more effective strategies.

The Proposal: DMDU Approach

Many of the challenges associated with maladaptation align with the principles of Decision Making Under Deep Uncertainty (DMDU), a group of methodological, epistemic, and cognitive frameworks (Marchau et al., 2019). DMDU represents a multidisciplinary approach aimed at designing and implementing policies and plans in environments characterized by deep uncertainty. Maladaptation can emerge, for example, from incomplete knowledge during the planning stage due to limited understanding of complex phenomena, the inherent risks of planning with unclear future trajectories, conflicting information hindering consensus among stakeholders, or unforeseeable events such as extraordinary natural phenomena. DMDU shares many of the motivations behind adaptation-maladaptation studies, making it a natural source of insights for informing the design, implementation, and monitoring of adaptation plans. As a broad framework for understanding, investigating, and addressing uncertainty, it has been implemented in various forms in climate change studies (Lempert et.al. 2024; Haasnoot et.al. 2024; Hallegatte et.al. 2020). Recent literature reflects growing efforts to enhance and operationalize robust decision-making methods such as Robust Decision-Making (RDM), Dynamic Adaptive Policy Pathways (DAPP), and Multi-Objective Robust Optimization (MORO). These studies underscore the importance of planning for diverse uncertainties, including those arising from climate variability, socio-economic shifts, and systemic interactions. Key DMDU methods such as DAPP and RDM are increasingly applied in climate change contexts, for example, to stormwater management (Habib et.al. 2024), wastewater systems (Allison et.al. 2024) and has been pivotal in the IPCC's understanding of how uncertainty impacts climate change adaptation and risk assessments (Lempert et.al. 2024) (table 3).

Framework	Focus	Method	Insights/outcomes	Explicitly Deals with different types of uncertainty?
Kanyama et.al. 2024	Municipal sea-level rise	RDM	Municipalities shifted from traditional planning perspectives; suggested changes in planning regulations	No
Habib et.al. 2024	Stormwater systems	DAPP	Early action facilitated by real-time monitoring and proactive execution	No
Allison et.al. 2024	Wastewater systems	DAPP, ROA	Quantified adaptation thresholds and critical trigger points	No
Lawrence et.al. 2019	Coastal adaptation	DAPP	Collaborative stakeholder planning enabled adaptive strategies for long-term coastal risks	No

Lempert et.al. 2024	IPCC	DMDU principles	Highlights DMDU role in strengthening IPCC adaptation/risk assessments	Yes
Webber & Samaras 2022	Transportation networks	RDM	Provides framework for decision-makers to justify resilience investments	No

Table 3. A selection of recent DMDU applications to climate change adaptation plans.

DMDU approaches deal with both unpredictability and deep uncertainty. Unpredictability refers to situations where constructing probabilistic future projections is not feasible due to insufficient data, lack of understanding of underlying causes, or disagreement among decision-makers on the best course of action. Deep uncertainty describes systems featuring multiple forms of uncertainty, requiring the creation of a catalog of “what-if” scenarios based on possible states of the world. Once a comprehensive set of what-if scenarios is developed, these alternatives can be quantified and processed using computationally intensive methods to uncover inconspicuous alternatives and gain a thorough understanding of the system under study. DMDU serves as a tool for studying complex systems, integrating qualitative and quantitative information from diverse sources, such as adaptation studies. Importantly, scenarios are not intended to predict the actual state of the world, as probabilistic models do. Instead, they serve as guiding principles for making robust decisions that remain effective across different possible futures. Additionally, they facilitate flexible decision-making, enabling stakeholders to be proactive by anticipating events rather than merely reacting to them.

Drawing on the DMDU literature, we propose that constructing effective management plans in contexts of deep uncertainty requires a comprehensive approach that integrates cognitive, mathematical, informatic, and methodological tools. This includes mathematical methods to translate qualitative observations into measurable indicators, cognitive tools to process and generate diverse future scenarios, and cognitive techniques for imagining alternative futures. Effective communication and strategy formulation also depend on representation tools that clearly convey knowledge and codify plans. To evaluate the effectiveness of different strategies and their potential pitfalls, tools are needed to assess why certain approaches outperform others and to identify circumstances where previously successful strategies may become ineffective. Additionally, methodological tools are essential for translating information into indicators that can set acceptable thresholds for navigating maladaptive outcomes and act as early warning signals for risk factors. Finally, methods for learning from implemented actions are crucial for improving strategies and adapting to changing circumstances.

In the following section we present an example to show how the DMDU framework is used and how it can accomplish the goals we ideally look for to navigate the adaptation-maladaptation continuum successfully.

Case study: Identification of water scarcity vulnerability patterns

The basin of Mexico has undergone profound transformations over more than seven centuries of water management (Benson-Lira et.al. 2016; Eakin et.al. 2017; Tellman et.al. 2018). As Mexico City has expanded, water demand surged, leading to unsustainable groundwater extraction and aquifer depletion, which was worsened by industrial and urban pollution, causing a decline in water quality. Numerous efforts have been made to improve water management in the basin of Mexico. However, water scarcity is expected to worsen in the coming years due to multiple sources of uncertainty, such as ongoing urbanization and climate change, as well as intangible factors such as inadequate governance (Eakin et al. 2017; Knieper and Pahl-Wostl, 2016).

Addressing the need for adaptation plans to tackle water scarcity requires adopting analytical approaches able to account for the full spectrum of uncertainty. This includes not only biophysical drivers of water scarcity vulnerability but also the social and political norms, rules and relationships under which water management operates. By explicitly incorporating the sources of uncertainty involved in tangible and intangible water scarcity drivers into analytical frameworks, decision-makers can develop robust adaptation interventions that can be effectively monitored using meaningful context-specific indicators.

In this paper, we draw on concepts and approaches from Robust Decision Making (RDM) framework (Weaver et.al. 2013; Marchau et.al. 2019; Stanton et.al. 2021) to uncover vulnerability patterns related to water scarcity in Mexico City. RDM, developed within the DMDU framework, is particularly well-suited for developing adaptation pathways that effectively account for both biophysical and water governance related uncertainties in water management decision-making, thereby increasing the likelihood of achieving robust outcomes for adapting to water scarcity.

RDM refers to a family of decision management models used to analyze adaptation strategies under multiple future scenarios. Central to RDM is the XLRM matrix where ('X') represents key exogenous forces encountered by decision-makers and other stakeholders; ('L') signifies policy levers, comprising actions constituting the strategies decisionmakers want to explore; ('M') denotes performance metrics used to rank the desirability of various scenarios, and ('R') describes the relationships between factors and how the future may evolve over time based on the decision-makers' choices of levers and the manifestation of uncertainties. Table 3 shows the XLRM matrix for our case study.

Exogenous drivers of water scarcity explored in this study were conceptualized to represent the governance challenges that policymakers face in managing the complex water system within Mexico City. Uncertainties included: variations in water supply from both external (specifically the Cutzamala Reservoir System) and internal sources (local underground aquifers, wells and springs), influenced by climate change and groundwater overexploitation; urban sprawl regularization in peri-urban conservation areas; and increased pressure on water systems due to investments aimed at maintaining or building hard infrastructure leading to improve water distribution efficiency (table 4).

Uncertainty (X)	**Strategy (L)**
• Water supply from external sources	• Build infrastructure
• Water supply from internal sources	• Maintain infrastructure
• Urban sprawl	• Budget
• Water distribution	• Protests
Relationship (R)	**Metric (M)**
• MEGADAPT	• Vulnerability to water scarcity

Table 4. XLMR matrix showing the uncertainty drivers (X), the policy levers or strategies (L), the relationship model (R) and the metric (M).

We used MEGADAPT (Bojórquez-Tapia et al. 2019), a spatially explicit hybrid model for coupled socioecological systems that simulates trajectories and spatial patterns of socio-hydrological vulnerability. Trajectories emerge from interactions between elements of the socio-institutional subsystem (e.g., actions and decisions) and the biophysical subsystem (e.g., hydrological responses). In MEGADAPT, socio-institutional actions are operationalized as decisionmakers' policy levers (L) that can modify attributes of the water infrastructure system in each spatial unit at each annual time step. Input data for simulations were collected through focus group interviews and participatory workshops, with all relevant actors represented (i.e. water managers, authorities, residents; see Bojorquez-Tapia et.al. 2019; Bojorquez-Tapia et.al. 2021).

In this study, we used budget allocation as the primary policy lever to represent the varying financial capacities of stakeholders in addressing water scarcity through infrastructure maintenance or development. This choice was driven by the need to explore the widely held view that water scarcity is linked to poor management, specifically, how and under what conditions this connection manifests. Additionally, most maladaptation frameworks are applied at the planning stage, where stakeholder perceptions of future actions play a crucial role. Budget allocation serves as a proxy for the complex web of relationships that shape how actions are perceived and prioritized. We implemented three levels of budget allocation, each corresponding to the number of spatial units influenced by stakeholder decisions: Low = 50; Medium = 1000, High = 2000 (budget units). At the end of each step, we calculated water scarcity vulnerability for each spatial unit using a nonlinear combination of exposure, sensitivity, and adaptive capacity (EQ1). The resulting vulnerability scores ranged from 0 (lowest vulnerability) to 1 (highest vulnerability).

$$V_{et}^{k} = V_{st}^{k} = 1 - \sum_{1}^{n} w_{it}\, x_{it}^{k} \qquad (1)$$

Where exposure V_e and sensitivity V_s were computed as the sum of the weight w and the standardized score x given by participants to different actions related to water scarcity. i, k and t refer respectively to actions, spatial units, and time (for further details see Eakin & Bojórquez-Tapia, 2008).

We conducted a set of 12 simulation experiments by combining one of six exogenous uncertainties (table 4) with each of the three budget allocation levels (L). We ran the model under each scenario and projected simulations to the year 2060. A regression tree analysis (RTA; R package "party" (Zeileis et.al. 2012) was used to classify simulation experiments into groups of similar water scarcity vulnerability outcomes. RTA is a non-parametric method that recursively partitions the data into subsets, called nodes, which are relatively homogeneous in response. Partitions or splits are determined by a threshold value of a single covariate, selected to maximize dissimilarity between the two new nodes. Nodes that cannot be further split are called terminal nodes (Miquelajauregui et al., 2016). For each terminal node, we calculated the mean water scarcity vulnerability. We then mapped the spatial distribution of water scarcity outcomes for each resulting tree node (Figure 1).

Uncertainty scenario	**Description**
reduc_agua	Reduction in water supply from wells
asentamientos	Regularization of informal settlements in periurban conservation areas
base	Baseline scenario
increm_cutza	Increases in water supply from Cutzamala system
reduc_cutza	Reductions in water supply from Cutzamala system
mejora_efi	Increases in water distribution pressure

Table 5. Description of uncertainty scenarios implemented to simulate water scarcity vulnerability.

We used QGIS version 2.18.18 to categorize water scarcity vulnerability outcomes in each node using the natural breaks method (Bearman 2021). Vulnerability levels were classified as very low (VL), low (L), medium (M), high (H), and very high (VH) levels. The categories were assigned according to the following vulnerability values with corresponding values: 0.008-0.2525 (VL), 0.2525-0.5081 (L), 0.5081-0.6813 (M), 0.6813-0.8615 (H), and 0.8615-1.0 (VH) (Figure 2).

Results and discussion

We developed a framework to introduce uncertainty analysis into understanding water scarcity in Mexico City. The goal was to gain insights that could help decision-makers in enhancing adaptation strategies. Drawing on input from different stakeholders, future simulations identified critical areas requiring revised management approaches. In particular, results show that northern and southeastern regions of Mexico City are highly vulnerable both now and in the future, even in the best-case scenario (Fig. 2C). Conversely, traditional downtown areas exhibit low degrees of vulnerability even in the worst-case scenario, but the overall risk of water scarcity is high for the city given the model's assumptions (Fig. 2B). However, assuming that a single strategy will address the issue across the entire city is incorrect, as our analysis reveals that water scarcity stems from different causes across different spatial units.

Co-production of future scenarios and vulnerability.

A key challenge in participatory processes is transforming qualitative insights informed by participants into quantitative indicators. This challenge arises from the difficulty of translating rich concepts provided by stakeholders into mathematical indicators that may not fully capture their intended meaning. In our case study, we addressed this challenge by relying heavily on knowledge coproduction through stakeholder interviews and analyses to understand diverse perspectives and interests on water scarcity issues in Mexico City. Interview narratives were coded and aggregated into "meta narratives" that represented common themes and perspectives. The core idea is that narratives form a network of relationships between concepts and ideas. By analyzing individual narratives, a meta narrative emerges, composed of the most prominent concepts and ideas (nodes) and their relations (Eakin et.al. 2019). In this study, three major narratives emerged: 1) irregular and informal urban growth as a driver of water insecurity; 2) infrastructure and management failures, from limited budget and poor maintenance; and 3) inequitable water distribution and insufficient monitoring as a driver of poor water quality. Each meta narrative was mapped onto specific geographic landscapes to create spatio-temporal representations of actors' values, actions, influence, and responsibilities represented as levers in the XRLM matrix (table 3). Multicriteria Decision Analysis (MCDA) was then used to disaggregate actors' decisions into rules. The MCDA results informed software agents representing actors' behavior within the MEGADAPT model (see Bojórquez-Tapia et.al. 2019, 2021 for further details).

Observe how vulnerability to water scarcity was modelled as a result of actors' decisions. This is important because as mentioned earlier, most adaptation-maladaptation frameworks are ex ante and look for ways to minimize risk at the planning stage. Therefore, problems are associated to management practices and the ways in which decision-makers anticipate future events and minimize risks (Hallegatte et.al. 2020). Water scarcity is influenced by a series of biophysical elements and socio-economic-political factors. Ultimately, however, decisions are made based on how different stakeholders perceive and respond to challenges. Perceptions are shaped by known and unknown uncertainties related to future climate change impacts, social dynamics emerging throughout the planning stage, or to the positive and negative feedback resulting from decisions taken by people and the subsequent responses by socio-natural systems.

Once decision rules were incorporated into the MEGADAPT model, we generated multiple future scenarios depicting all possible developments based on the system's rules. Future scenarios were codified into the RTA. RTA produced a tree with four resulting nodes (Figure 1). The highest vulnerability levels (mean = 0.79) were associated with terminal node 1 (G1) driven by reductions in water supply from the Cutzamala system (reduc_cutza), regardless of budget allocation levels. A split at the right side of the tree root, terminal node 2 (G2), was determined by budget allocation levels, with lower levels of budget allocation (<500) linked to a mean vulnerability of 0.65 (G2). Higher budget allocation levels (>1000) resulted in lower vulnerability outcomes (terminal nodes G3 and G4), with G4 showing particularly low vulnerability (mean = 0.51) under scenarios that included improvements in water distribution efficiency (mejora_efi).

Figure 1. Regression tree for simulated water scarcity vulnerability projected to 2060. The first split in the tree, or root, is defined by the covariate with the strongest relationship with vulnerability outcomes. For example, in G1 the strongest relationship has to do with water supply reduction. Mean estimates are shown within each box.

Future scenarios are not predictions but rather explorations of potential positive and negative outcomes, helping decision-makers come up with solutions that account for a wide range of future possibilities. As shown in figure 1, node G1 linked water supply to high levels of vulnerability. However, simulations revealed that, in certain areas of the city, the root cause of the problem was not hard infrastructure itself, but rather soft infrastructures, meaning sociopolitical norms, rules, and values shared by the community. This is an important result because water scarcity is often assumed to be solvable by the construction of ever larger distributions systems. This result is in line with recent literature on adaptation strategies where hard infrastructures have been singled out as one of the main contributors to maladaptation (Piggot-McKellar et.al. 2020, Pörtner & Roberts 2022). For instance, in AR6 it is explicitly assumed that representative key risks have to do with "critical physical infrastructure" even though biases during the planning stage are acknowledged. Typical issues with physical infrastructures involve vices found at the planning stage such as short-termism and inadequate budget allocation (Bertana et.al. 2022). However, in our case study, the challenge does not stem from management or budget deficiencies, but from social and political uncertainties which persist in historically disadvantaged areas of the city. These uncertainties reflect unresolved historical injustices that contribute today to negative feedback loops exacerbating water scarcity. This becomes more evident when compared to outcomes in downtown areas comprising high-end neighborhoods. These areas remain under low levels of vulnerability even in the worst-case scenario. This insight is crucial for adaptation-maladaptation frameworks because it suggests that root causes may not be linked to faulty management practices but to different uncertainties having to do with incomplete knowledge, but also, to not addressing the elephants in the room in terms of social, cultural, economic, political injustices, to not fully understanding how complex-dynamic systems operate, or to been unable to understand how high impact low probability events could develop in the future, to name some examples.

Spatial distribution of water vulnerability present and future

The spatial distribution of initial (2021) and projected (2060) water scarcity vulnerability outcomes for each tree node is shown in Figure 2. In 2021, 35% of Mexico City's spatial units were highly vulnerable to water scarcity, 21% were moderately vulnerable, and the remaining 43% had lower vulnerability (Figure 2A). The boroughs located in the eastern part of Mexico City exhibited very high vulnerability in the worst-case scenario for the year 2060 (Fig. 2B) while the western areas showed very low and low vulnerability in the best-case scenarios for the year 2060 (Fig. 2C).

Figure 2. Distribution patterns of water scarcity vulnerability for (a) initial conditions (2021), and projected outcomes for (b) terminal node 1 (G1), and (c) terminal node 4 (G4) representing the worst- (budgetary constrictions) and best-case scenarios (ample budget in 2060) respectively.

By 2060, significant increases in VH and H water scarcity vulnerability were observed in group G1, especially in the boroughs of Tlalpan and Magdalena Contreras to the southeast (Figure 2b). Group G2 had more spatial units with L and VL vulnerability (n=617) compared to G1 (n=303); these are boroughs to the west. Group G3 showed moderate increases in H and VL vulnerability, while group G4 experienced decreases in VH and H vulnerability but increases in L and VL vulnerability (Figure 2c).

Structuring uncertainty

As can be seen in the maps, north and southeastern parts of Mexico City have reached a steady equilibrium involving high vulnerability. According to our simulations, no amount of budget allocation changes these areas' vulnerability. To better understand this result let us take a closer look at the uncertainties involved. From the XLRM matrix we know that four different kinds of uncertainties were modelled: water supply from external sources, water supply from internal sources, urban sprawl, and water distribution. However, note that these uncertainties are in themselves riddled with uncertainty having to do with the root causes of say, limited water supply from the Cutzamala system: is it because of biophysical factors having to do with precipitation? Or is it because of sociopolitical factors having to do with water distribution? These two sources of uncertainty are not simply lack of knowledge as they form a web of related uncertainties that ultimately affect management decisions. From meta narratives we know that stakeholders recognized three major narratives behind water scarcity dynamics: 1) irregular and informal urban growth as a driver of water insecurity; 2) infrastructure and management failures, from limited budget and poor maintenance; and 3) inequitable water distribution and insufficient monitoring as a driver of poor water quality. These narratives can help us structure the different sources of uncertainty as seen in table 6.

Uncertainty Dimension	**Irregular Urban Growth**	**Infrastructure & Management Failures**	**Poor Water Distribution**
Data & Information	- Limited and unreliable data on informal settlements and unplanned urban expansion - Difficulties forecasting settlement patterns and urban sprawl	- Incomplete records on infrastructure age, performance, and maintenance histories - Uncertainty regarding repair and replacement timelines	- Inaccurate measurement of water consumption and losses - Incomplete mapping of distribution networks and monitoring of illegal connections
Policy & Regulatory	- Ambiguous urban planning and land use regulations - Inconsistent enforcement of zoning laws and development standards	- Uncertain political commitment to infrastructure investment - Evolving regulatory frameworks that affect maintenance priorities and	- Unclear oversight of water allocation protocols - Shifting policies regarding water rights and distribution equity

		management practices	
Economic & Financial	- Unpredictable economic drivers of migration and informal settlement growth - Uncertain funding for urban planning and service provision	- Budget constraints that lead to deferred maintenance and limited infrastructure upgrades - Uncertainty in cost-benefit assessments for long-term investments	- Economic disparities influencing water pricing and access - Unpredictable allocation of financial resources for distribution network improvements
Environmental & Climate	- Uncertain impacts of climate change on local hydrology and urban water demand - Variability in precipitation patterns affecting groundwater recharge and surface water availability	- Exposure to climate-induced stresses (e.g., extreme weather events) that further compromise aging infrastructure - Uncertainty in predicting how environmental changes will impact system resilience	- Climate variability that affects overall water availability - Unpredictable environmental stressors that can compromise the stability of distribution networks
Social & Cultural	- Diverse stakeholder perceptions of informal growth and urban expansion - Unpredictable community responses to planning initiatives	- Variability in public trust and support for water management policies - Divergent stakeholder priorities that complicate consensus on infrastructure improvements	- Social inequities that result in uneven access to water resources - Uncertain community engagement and political pressures influencing distribution decisions
Epistemic & Ontologic	-Knowledge gaps in our understanding of population growth & migration patterns making it difficult to forecast water demand accurately.	-Uncertainty in infrastructure risks due to limited monitoring. -Unknown Water Loss from Illegal Taps & Leakages: Non-	-Uncertainty in supply-demand Gaps due to unreliable consumption and availability data. -Impact of political & economic decisions.

	-Unclear impact on groundwater recharge. -Lack of comprehensive water usage data because informal areas often lack metering, leading to uncertainty in estimating water consumption. -Effectiveness of rainwater harvesting & other local solutions.	revenue water loss is difficult to quantify in areas with weak enforcement. -Effectiveness of future infrastructure investments. -Unpredictable climate resilience of infrastructure because systems may fail under extreme climate conditions, but exact points of failure are difficult to predict.	-Hydrological variability due to missing or incomplete data. -Efficiency of emergency water supply measures: Tanker water distribution and rationing plans have unknown long-term sustainability and effectiveness.

Table 6. Different sources of uncertainty drive water scarcity. This table illustrates that water scarcity is a multifaceted problem where each uncertainty dimension plays a distinct role in driving challenges across different spatial and operational scales.

Information in table 6 further allows stakeholders to consider different scenarios to use for decision-making, For example, brainstorming table 6 provided some of the following insights (table 7).

Irregular Urban Growth	**Infrastructure & Management Failures**	**Poor Water Distribution**
Unplanned urban expansion overwhelming water infrastructure capacity.	Aging, leak-prone infrastructure causing significant water loss.	Inequitable allocation policies prioritizing certain regions/sectors over others.
Encroachment on water recharge zones (e.g., wetlands, forests) reducing groundwater replenishment.	Inconsistent funding for maintenance/upgrades, leading to systemic failures.	Geographical disparities (e.g., elevation, remoteness) limiting access to water networks.
Rapid, unpredictable population growth	Corruption/bureaucratic inefficiencies delaying critical repairs or innovations.	Economic inequality excluding marginalized

outpacing water resource planning.		groups from affordable water access.
Climate variability exacerbating strain on water resources in rapidly urbanizing areas.	Lack of adaptive management to address climate shocks (e.g., droughts, floods).	Political conflicts over shared resources (e.g., transboundary rivers, aquifers).
Land-use changes (e.g., concretization) disrupting natural hydrological cycles.	Technological obsolescence failing to meet modern demand or efficiency standards.	Underpricing or subsidies encouraging waste in privileged sectors (e.g., agriculture, alcoholic and non-alcoholic beverages).

Table 7. Proposed causes leading to water scarcity. This table translates insights coming from uncertainties and metanarratives into specific causes. The idea is to show how structuring uncertainty helps decision-makers visualize the web of problems behind water scarcity. Some of these problems are the elephant in the room that often passes unnoticed in adaptation planning programs.

Most current adaptive-maladaptive frameworks rely on heuristic processes, where a set of relevant questions is posed to help decision-makers assess potential risks. For instance, REGILIENCE, a European project promoting climate resilience pathways across regions and cities in the European Union, offers a self-assessment tool to identify maladaptation risk factors during the development of adaptation plans or strategies (Regilience, 2024). Questions cover issues like whether all potential risks were considered, whether the best available data and modelling were used, or whether objectives are feasible, measurable and time bound. REGILIENCE does not explicitly incorporate uncertainty into the analysis, though it can be inferred from the questionnaire. For example, when asking about considering the "full range of current and future climate risks" (Question 1) or whether the plan ensures that it does not burden any social groups (Question C10). However, without the proper tools, these questions can be misleading. You cannot consider the "full range" of current and future climate risks without a cognitive tool to help envision all possible futures. Similarly, you cannot "ensure" your plan will avoid affecting vulnerable groups unless you have simulated a wide set of potential responses to the actions being considered.

In this context, coupling a framework like REGILIENCE (or any other framework) with our case study or similar DMDU methods, allows participants in the planning stage to answer questions based on experience but also through insights generated by simulations. In this sense, DMDU provides cognitive tools that enable researchers, stakeholders, and decision makers to truly consider a broader sense of potential futures affecting their actions.

To envision the set of possible futures, computational assistance is essential. Incorporating computational power into the decision-making process allows us to generate a multitude of potential scenarios, moving beyond reliance on imagination alone. This presents both advantages and challenges. On the positive side, machines can help us simulate various trajectories and condense the vast array of options into a manageable set to assist in decision making processes. A challenge though, is that navigating may require substantial computational power, which may not be accessible to all, particularly when dealing with large, heterogenous regions such as Mexico City. However, this challenge might not apply when focusing on smaller-scale settings, such as local communities.

DMDU methods can be implemented in different ways. In this study, we used Robust Decision Making (RDM) in conjunction with MEGADAPT. Regardless of the specific approach, mathematical tools are essential because they allow us to model a wide set of possible futures to fully understand the potential consequences of the actions being considered. Based on that understanding, quantification helps establish monitor and evaluation methods that establish acceptable thresholds to create early warning signals crucial for navigating the adaptation-maladaptation continuum. Remember that the goal is not aiming at absolute success, but to identify when a successful project has run its course and needs to be adapted or replaced.

We propose the use of mathematical tools to construct indicators, emphasizing that it's not about assigning arbitrary numbers to propositions but about establishing a system to translate insights into actions and measure their outcomes numerically. These actions must achieve measurable outcomes, which can then be ordered, prioritized and assessed. By representing actions through numbers, we can delineate a spectrum of potential futures. Rather than relying solely on imagination, leveraging computational power allows us to generate a multitude of potential scenarios.

A potential critique of DMDU methods relates to their association with data-intensive and quantitative frameworks. DMDU methods have also been accused of ignoring the particular contexts in which they are applied (Stanton & Roelich 2023). We believe that DMDU can help bridge existing gaps facilitating the integration of diverse knowledge systems. The challenge is constructing the right tools to translate rich concepts envisioned by communities into formal representations that truly represent their meaning. We believe this task becomes more manageable when different sources of uncertainty are explicitly acknowledged, as it is often within these areas that social and equity injustices persist, obscured by generalized discussions of “uncertainty” and influenced by political, social, and economic biases.

Many challenges facing maladaptation frameworks are addressed within the DMDU framework, including the concept of navigating the continuum. Navigating the continuum acknowledges that all strategies, no matter how effective at first, may eventually become ineffective. By using DMDU tools, decision-makers can better understand the underlying causes of this transition and adapt plans as necessary. In this context, monitoring and evaluation (M&E) processes become crucial for understanding the effectiveness of adaptation strategies over time. Despite their importance, there is a perception that M&E processes are difficult to implement. For example, Juhola & Käyhkö 2023 suggest that setting up such systems at the national level may be impractical due to the complexity and scope required. This view is valid, given the vast range of resources, variables and stakeholders involved at that scale. However, at smaller scales, the implementation of M&E systems is not only feasible but also more practical. Many contemporary adaptation plans already include specific indicators to track the success of strategies, even though these are often limited in scope. The key challenge lies in selecting the right indicators: those that can provide meaningful insights into why systems behave the way they do, particularly in relation to the social-environmental interactions and the uncertainties inherent in adaptive management. This is where DMDU can play a pivotal role. DMDU frameworks provide the tools to identify and select relevant indicators that capture the critical variables affecting system dynamics. By focusing on these indicators, decision-makers can ensure that adaptive options have a low probability of becoming maladaptive, allowing for proactive adjustments before significant problems arise.

Proactive planning lies at the heart of successful adaptation. While not all events can be predicted, acknowledging the possibility of low-probability, high-impact events allows decision-makers to prepare for them. DMDU-enriched frameworks provide a means of generating "if-then" scenarios, enabling a proactive approach to planning for uncertainty. If certain thresholds are crossed, or if specific events occur, pre-defined actions can be taken, ensuring that adaptation strategies remain flexible and responsive. This proactive stance is crucial as we enter an era of unforeseen climate scenarios. DMDU offers cost-efficient solutions that can be implemented on standard devices, making them accessible even in resource-constrained settings. By focusing on manageable, localized interventions, DMDU frameworks can support adaptation efforts in contexts where traditional large-scale infrastructures may not be feasible.

Conclusion

In this paper, we discuss DMDU as a mathematical, cognitive, and representational system to complement adaptation-maladaptation frameworks. We propose DMDU as a tool to help transform the qualitative guidelines provided by maladaptation frameworks into quantitative indicators, enhancing modeling and decision-making by enabling a deeper understanding of the uncertainties and complexities that surround adaptation efforts (table 4).

The general proposal is to use the guidelines provided by different maladaptation frameworks as inputs to DMDU processes. Guidelines in all maladaptation frameworks consist of a series of questions that assist decision-makers and stakeholders alike in considering possibilities. These possibilities relate to the aspects they should be focusing on. However, while these questions stimulate thought and imagination, they fall short in terms of providing the means to translate insights into actionable and measurable information.

DMDU addresses this gap by offering mathematical and computational tools that allow stakeholders to model possible futures, transforming qualitative insights into quantitative indicators. These indicators enable ordering, prioritizing, and assessing adaptation actions.

The key is not to arbitrarily assign numbers but to create a system that systematically translates qualitative insights into quantifiable, actionable data.

In conclusion, while the problem of adaptation-maladaptation management remains challenging, integrating DMDU into maladaptation frameworks offers a powerful tool for improving the preparedness of adaptation strategies. As climate change presents increasingly unpredictable challenges, implementing DMDU-enhanced frameworks will be essential for ensuring that adaptation strategies remain flexible and responsive, avoiding falling into the maladaptive side of the continuum.

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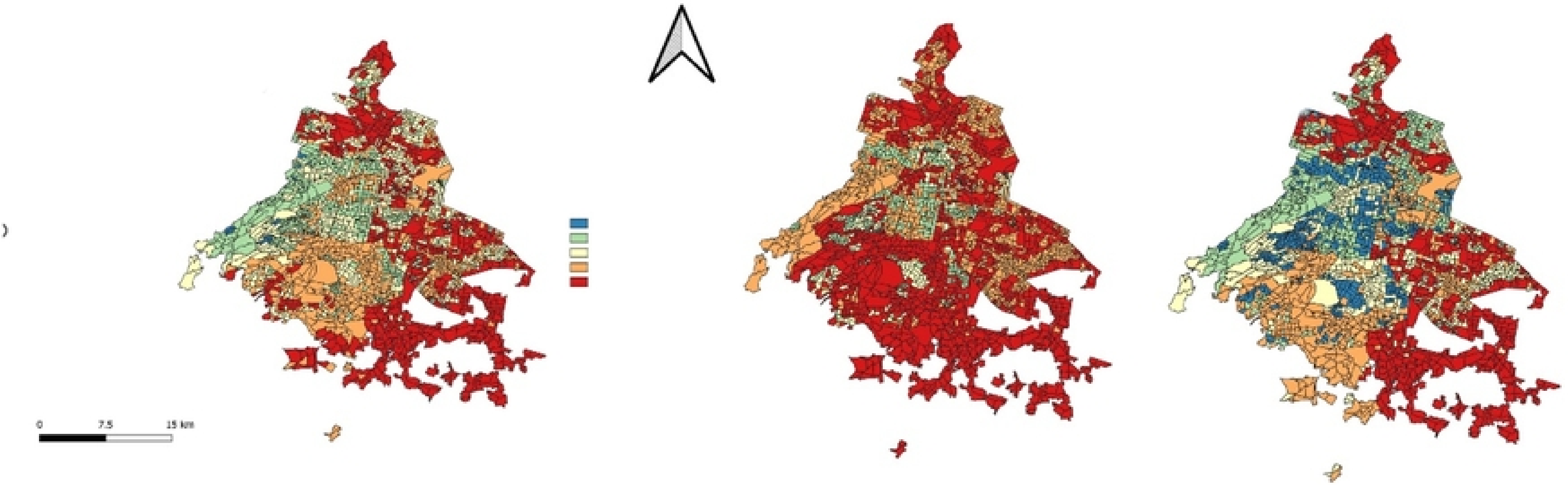
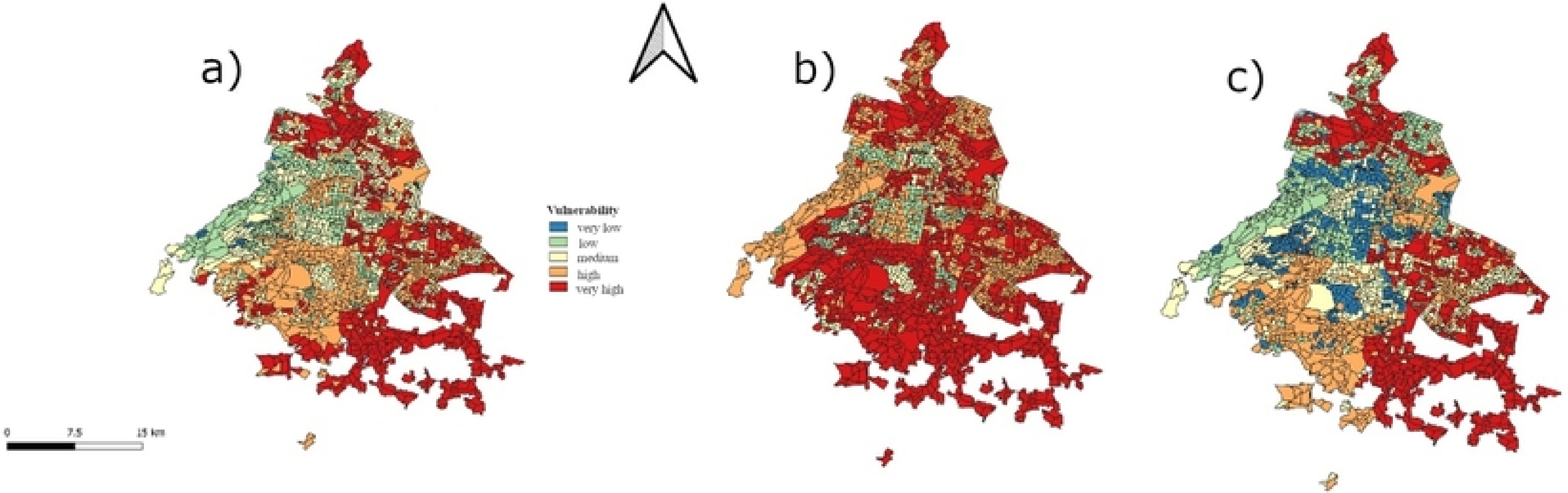


Figure



a)
b)
c)
Vulnerability
very low
low
medium
high
very high
0
7.5
15 km

Figure