Structuring uncertainty to improve climate change management success

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Abstract.

This paper advances the field of climate adaptation by addressing two persistent challenges: navigating multiple forms of uncertainty and enabling the construction of actionable future scenarios. Using a methodology grounded in Decision Making under Deep Uncertainty (DMDU), we combine computational modeling with stakeholder-informed metanarratives to connect abstract analysis with grounded, context-specific knowledge. Our study introduces a novel simulation approach to water scarcity vulnerability in Mexico City, revealing that no amount of budget allocation alone can solve the persistent vulnerability of areas like Iztapalapa. This counterintuitive finding, generated through model-based scenarios, was contextualized and explained by community-derived metanarratives that surfaced deep social, political, and historical uncertainties. In doing so, we highlight how simulations and narratives together offer a more robust means of identifying adaptation pathways than either can alone. Our vulnerability model integrates exposure, sensitivity, and adaptive capacity, drawing from both quantitative service indicators and community knowledge. We argue that addressing climate challenges requires cognitive and methodological tools capable of holding plural uncertainties, enabling diverse futures to be imagined and evaluated.

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 was estimated that the carbon budget remaining to keep warming below 1.5°C was equivalent to approximately six years of current CO_2 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 and continue undeterred in 2025 (Copernicus 2024; Ripple et al. 2024; Romanello et al. 2024; World Meteorological Organization 2024, 2025), 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. Despite their widespread adoption, success of adaptation plans remains contentious. A growing body of literature on maladaptation highlights that many such plans have resulted in unintended negative consequences. Maladaptation occurs when adaptation measures inadvertently exacerbate climate impacts rather than mitigating them underscoring the need for more effective, context-specific, and forward-thinking adaptation strategies (Magnan et al. 2016; Schipper 2020; Reckien et al. 2023, Higuera Roa et.al. 2025).

Cases of maladaptation are likely to increase in the short and medium-term even if planning processes run flawlessly. Maladaptation should be understood as an inherent component of risk management strategies as their effectiveness is constrained by different forms of uncertainty (Reckien et.al. 2023; Pörtner & Roberts 2022). In the context of climate change, uncertainty arises from the limited and contested knowledge among stakeholders regarding appropriate models to represent the dynamics of socioenvironmental systems, the probability distributions about key variables and parameters, and the relative importance of alternative outcomes (Steffen et.al. 2020). According to Scoones and Stirling (2023), uncertainty also arises from human interactions shaped by socio-political complexity, institutional arrangements, conflicting interests, and unequal capacities. These factors influence how actors interact through formal and informal rules, relationships, and norms, ultimately shaping how risks, resources, and responsibilities are negotiated within socially differentiated contexts (Incropera 2016; Hasnoot et.al. 2024).

Climate change adaptation planning often takes place in contexts marked by divergent stakeholder interests and conflicting problem framings. These differences hinder the development of shared understandings around critical elements such as problem definitions, the selection of appropriate performance metrics, and the evaluation of strategies under uncertain future conditions. Given this complexity, the objective of adaptation planning should not be to guarantee success, an unrealistic expectation under deep uncertainty, but to help chart multiple plausible pathways toward adaptability, set clear thresholds for acceptable risk, and establish early-warning systems that enable decision-makers and communities to course-correct before initiatives slide into the maladaptive side of the continuum. Addressing these challenges requires decision-support approaches entailing decision analytics, stakeholder engagement/deliberation, and interactive modeling and evaluation. Combining robust decision-making approaches with collaborative research and co-production processes can be constructive in clarifying the decision-rule systems that shape stakeholder actions. Such an inclusive, scenario-based approach not only enriches our understanding of uncertainty but also ensures that adaptation plans remain flexible, culturally relevant, and grounded in the realities of those they are designed to protect (Mehta et.al. 2019).

Despite important advances in adaptation studies, many existing approaches still fail to grapple with the full complexity of socio-political, economic, and ecological dynamics, particularly as they unfold across multiple temporal, spatial and material scales (Mehta et.al. 2025). We believe that a crucial oversight hampering the success of these studies is that they treat uncertainty as a single, unified concept and develop tools as if all uncertainties could be addressed in the same way. This is a critical oversight.

Our work addresses this oversight by unpacking the multiple sources and types of uncertainty that shape socioecological vulnerability. Rather than aiming for predictive accuracy, we focus on building tools that help actors navigate uncertainty and imagine a broader range of possible futures. In this context, the field of Decision Making Under Deep Uncertainty (DMDU) has emerged as a promising framework for informing and supporting climate change adaptation planning in the face of profound uncertainty (Moallemi et al. 2020; Haasnoot et al., 2024). DMDU encompasses a suite of approaches that shift the focus from classical "predict-then-act" models to exploratory and adaptive decision-making. These approaches are particularly valuable for bridging "uncertainty from above," conceptualized by climate modelers and policymakers, and "uncertainty from below," grounded in the lived experiences of communities facing climate impacts (Mehta et.al. 2019). By unpacking the multiple dimensions and sources of uncertainty, DMDU frameworks enable the exploration of a wider range of plausible futures and support the design of adaptation strategies that anticipate change rather than pursue unique certain solutions We use a case study approach based on DMDU not to claim it is the only valid framework, but to showcase its potential as a flexible, epistemically pluralistic toolkit. We argue that DMDU methods, when combined with narrative insights and place-based knowledge, offer a powerful way to engage with multiple uncertainties simultaneously.

The core contribution of this study is showing how multiple forms of uncertainty can be effectively integrated into adaptation planning to understand the root causes of current vulnerabilities and improve our ability to anticipate and prepare for a range of future conditions. using a methodology that helps bridge abstract modeling with grounded, contextual realities. By recognizing how different uncertainties have shaped present conditions, imaginable and unforeseen future conditions can be explored, moving toward a model of adaptation planning that is not just robust and flexible, but also deeply informed by both technical and lived ways of knowing. This is essential for designing strategies that remain effective across diverse, unpredictable, and rapidly changing futures. Such an inclusive, scenario-based approach not only enriches our understanding of uncertainty but also ensures that adaptation plans remain flexible, culturally relevant, and grounded in the realities of those they are designed to protect.

Our argument unfolds in three parts. First, we examine uncertainty as a conceptual category to highlight the need for adaptation frameworks to engage with a more nuanced and multidimensional understanding of uncertainty. Second, we introduce the core principles of DMDU and illustrate their application through a case study on water management in Mexico City, focusing on the municipality of Iztapalapa. Finally, we reflect on how systematic uncertainty analysis can enhance adaptation planning by supporting the development of strategies that are more robust, flexible, and context responsive.

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). This vocabulary seeks to bridge different ways of understanding the uncertainties affecting adaptation planning. In this context, uncertainty arises not only from inherently unpredictable variables, but also from limitations in modeling capabilities, data gaps, not really knowing how socio-ecological systems interact, or to different subjective interpretations of future risks and appropriate responses. 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 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 (Mehta et.al. 2025; Scoones & Stirling 2020).

For example, Bojórquez-Tapia et al. (2022) propose a comprehensive typology of uncertainty that is particularly relevant for large-scale infrastructure planning under complex and dynamic conditions 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 planning is often highly controversial since it usually entails the participation of multiple stakeholders with asymmetric power and competing knowledge. Thus, climate change adaptation must explicitly address the historical power struggles and imbalances, the goals and mindsets of powerful actors, and the structure and rules-in-use that shape system dynamics. 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 (Miquelajauregui & Madariaga-Fregoso 2022). As we understand it, this is the divide expressed between uncertainties from above and below. Consequently, these different kinds of uncertainty require distinct approaches for understanding and addressing them, and tools to bring them together to act collectively.

From general uncertainty to structuring the unknown

As we enter a world of deep uncertainty, merely acknowledging uncertainty falls short on what is required to develop sound adaptive plans and strategies. There are two main reasons: First, uncertainty is a multifaceted concept. It includes epistemic uncertainty, which refers to knowledge gaps in our understanding of socioenvironmental systems (Beven et.al. 2018). It also encompasses socially constructed dimensions of uncertainty, including how diverse stakeholders perceive, interpret, and respond to it. These perspectives are particularly important for communities already experiencing the impacts of climate change (Nightingale et al., 2019). Addressing such complexity requires inclusive, impact-oriented processes of knowledge coproduction that generate information that is credible, legitimate, and salient across different contexts. Consequently, distinct types of uncertainty demand tailored approaches for their identification, interpretation, and management (Table 1). A key limitation of many existing adaptation frameworks is their tendency to treat uncertainty as a singular, knowledge-based problem, rather than as a complex, systemic issue that manifests across multiple domains of decision-making and social experience. The second problem is that, operationalizing a rich concept called uncertainty impacts the methodologies used to describe it, define it, and understand it. Typically, in climate change studies uncertainty is studied using probabilistic methods (see for example Pörtner & Roberts 2022), but probability theory is not *expressive* enough to cover everything we want to convey when talking about uncertainty. To see why let us understand the difference between low probability and low possibility events.

In this context we will talk about low probability events as Black Swans after Nicholas Taleb (Taleb 2010). Black swans are events falling on the tails of probability distributions. Because they fall on the tails of distributions their probability of occurrence is very low. However, should they happen, their impact would be very high. Crucially, black swans are events that cannot be anticipated, even if after the fact, we can trace the chain of events leading to them. A classic example is the 2008 financial crisis. At the time, most financial experts failed to predict it even if today it is possible to explain it and to pinpoint the numerous causes leading to it (Taleb & Martin 2012). Different sources of uncertainty are intertwined explaining why, despite there being available data, it is not possible to tie them up to anticipate upcoming high impact events.

There exists another major category of uncertainty that cannot be captured probabilistically due to its contingent nature. Contingency implies uncertainty regarding whether a particular event is possible. Considering what kind of events are likely is influenced not only by the body of knowledge available at a given time and place but also by political, social, economic, and cultural conditions shaping which knowledge items are considered possible. This distinction is crucial because we are not referring to rare events dismissed due to their low probability of occurrence; rather, we are addressing events that are dismissed because they are not considered feasible. These events are unknown unknowns. UUs represent a broad category of uncertainty rooted in various causes.

The key point from our discussion is that we have two large sets of events categorized under the name uncertainty. These events cannot be anticipated probabilistically even if we have access to probability distributions. Therefore, it is not possible to develop robust *ex ante* management strategies, exactly the goal of most adaptation plans as they seek to understand how to better anticipate, be prepared, and cope with, future climate events. Climate change studies live 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 black swans 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), plans that overlook major risks by failing to understand the nested events that give rise to unknown unknowns or by failing to identify specific risks (Rising, 2022), or in the disconnect between scientific advances and policy processes (Kotamäki et.al. 2024). This suggests that simply recognizing uncertainty's role in adaptation 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 and developing powerful tools to help imagine what the future might be like from different worldviews.

In our view, 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.

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 1. Different types of uncertainties affecting adaptation management plans. Note that uncertainty in this context deals with low probability events and low possibility events. References: Bojorquez-Tapia (2022), Mehta (2019), Marchau (2019), Aston (2023), Bradley (2014), Dequech (2011), Taebi (2020).

The Proposal: DMDU Approach

Many of the challenges associated with adaptation 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. DMDU shares many of the motivations behind adaptation 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).

DMDU approaches deal with both low probability and low possibility events. In DMDU lingo deep uncertainty refers to systems featuring multiple forms of uncertainty. Assessing deep uncertainty requires 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. 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.

As introduced, DMDU aligns well with the general expectations of adaptation plans. Adaptation plans in general look to anticipate climate change impacts on communities and to promote actions to minimize the strength of impacts, cope with changing conditions, reduce vulnerability of populations (Pörtner & Roberts 2022). We propose that constructing effective adaptation 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, computer tools to process and generate diverse future scenarios, and cognitive techniques for imagining alternative futures. 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.

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

Background

Mexico City is located in the Basin of Mexico, a region that was once covered by a lacustrine system spanning approximately 1,500 km2 of the basin floor. Over more than seven centuries, the basin has experienced profound socio-environmental transformations driven by extensive water management efforts (Benson-Lira et.al. 2016; Tellman et.al., 2018). These transformations have largely stemmed from infrastructure decision-making aimed at managing water supply and mitigating flood risk management (Tellman et al., 2018). As Mexico City expanded and underwent industrialization, water demand surged, leading to intensive groundwater extraction and increase sewage outflow. Major public water infrastructure projects were implemented, including the Lerma-Cutzamala system, to alleviate water demand. Despite efforts, water scarcity remains a persistent and critical challenge for the city.

Water scarcity risks are expected to worsen due to climate change, urban growth and institutional challenges such as inadequate or poorly coordinated governance structures (Eakin et al. 2017; Knieper and Pahl-Wostl, 2016). In addition, uncertainty in decision-making driven by limited data, information, and competing stakeholder priorities further complicates effective water management and long-term planning in the city.

Currently, Mexico City's water supply is sourced from three main systems. Approximately 67% is drawn from groundwater aquifers located in watersheds to the south and east of the city. The Lerma-Cutzamala system, which transports water from the neighboring State of Mexico, contributes around 28% of the total supply. The remaining 5% comes from local springs and the last free-flowing river, the Magdalena (González Villareal et al. 2024). Despite this diverse supply network, uneven water access reveals pronounced inequalities in water supply. Half of residents receive continuous, 24-hour access to tap water. An additional 27% receive water daily, but only during designated hours; these households rely on rooftop or yard tanks to meet their needs between deliveries. Another 21% of the population receives water only two or three days per week on a rotating delivery schedule known locally as *tandeo* (SEDEMA 2020). The remaining 2% is not connected to the formal distribution network and must purchase water from private tanker vendors (INEGI 2025).

These patterns reflect deep uncertainties tied to irregular urban growth, aging infrastructure, inequitable distribution, and overreliance on external sources. These uncertainties are not standalone phenomena: they are intimately tied to a range of structural and systemic causes that underpin water management challenges. For example, unplanned settlements often encroach on recharge zones, reducing natural aquifer replenishment. Explosive population growth outpaces planning, and climate variability adds further strain. Infrastructure and management failures are rooted in aging, leak-prone systems and compounded by inconsistent funding and corruption or bureaucratic inefficiencies that delay repairs and technological upgrades. The failure to adopt adaptive management approaches in response to climatic shocks, floods and droughts as paradoxical examples in Mexico City, leaves systems vulnerable to future stresses.

Distribution inequities arise not only from technical breakdowns but also from policy choices. Water allocation rules frequently favor wealthier districts or industrial users, while low-income neighborhoods face intermittent or costly private supplies. Elevation and remoteness further limit access. Consider that in Mexico City water costs from the network are subsidized, yet half the city lacks daily service. Those unable to store enough water must pay premium prices to tankers. Political disputes over shared aquifers and subsidies for water-intensive industries, such as soft drinks and breweries, encourage waste and deepen social divides (Talledos Sánchez et al. 2020).

Below this macroscopic layer there are other major sources of uncertainty. One of the core dimensions of uncertainty stems from limitations in data and information. Rapid, informal urban expansion often occurs beyond the reach of formal data collection mechanisms, resulting in unreliable or incomplete information about settlement patterns. This data gap complicates the ability to anticipate future growth and understand its implications for water demand. In unmetered areas, consumption is estimated rather than measured, making it hard to evaluate the impact of proposed solutions, such as rainwater harvesting or emergency tanker supplies. Similarly, infrastructure systems lack detailed records on age, performance, and maintenance history, complicating efforts to assess system vulnerability or to prioritize repairs. The distribution network is further plagued by uncertainty due to the absence of accurate consumption data, poor monitoring of illegal connections, and incomplete mapping of supply routes all of which obscure the real patterns of water usage and loss. Just to give an idea of the problem, consider that in 2022, Mexico City's water authority, SACMEX, reported that 52.2 percent of water in the network qualified as "non-revenue". Non revenue is a metric to determine the proportion of the volume of water running through the system that is lost due to leakage, measurement errors, intakes not recorded in the user registry, and clandestine tapping (IPDP 2025).

Economic and financial uncertainties further complicate the picture. Migration driven by economic hardship is difficult to forecast, leaving planners scrambling to provide basic services that are perpetually underfunded. Pricing inequalities and unpredictable budget allocations deepen disparities in who receives water and how reliably it flows. Layered on top of these human factors are environmental and climate uncertainties: shifting precipitation patterns, erratic groundwater recharge, and extreme weather events make it almost impossible to design static infrastructure that remains robust across all possible futures.

Social perceptions and cultural dynamics introduce yet another layer of uncertainty. Trust in water authorities varies across neighborhoods, and only 54.2 percent of residents express satisfaction with service quality (IPDP 2025). Also, given the complexities of the city, the notion of water scarcity itself is problematic. It can refer to different degrees of water availability. For example, for users of the Cutzamala system scarcity is understood as not enough supply to fill up tankers everyday, whereas in southeastern regions scarcity means not having water for days. Or it can refer to not having clean water, a historical problem in the city. Uncertainties in the use of terms especially when political discourse on water scarcity conflates different meanings, makes it harder to come up with useful solutions.

Effective adaptation decision-making in Mexico City must account for major uncertainties stemming from both exogenous factors, such as climate change, altered precipitation or infiltration capacity, and endogenous risk, such as fragmented water governance. These uncertainties are not isolated, rather, they are deeply embedded in the structural and systemic drivers that shape water management in Mexico City. This interconnectedness highlights that water management is not merely a technical problem, but a complex interplay of environmental conditions, social dynamics, and institutional limitations. Recognizing and addressing these overlapping uncertainties is essential for developing adaptation strategies that are both resilient and equitable in the face of ongoing change.

Methodological aspects.

Many adaptation frameworks such as those developed by the IPCC and incorporated into national climate plans, emphasize the importance of anticipating risks, avoiding maladaptive outcomes, and ensuring that adaptation measures do not inadvertently harm vulnerable populations. While these frameworks provide valuable conceptual guidance, they often lack actionable tools or practical methodologies for navigating deep uncertainty and tailoring strategies to specific socio-environmental contexts. To address this gap, this paper demonstrates how the Decision Making under Deep Uncertainty (DMDU) approach can be applied to systematically explore a range of plausible futures and generate insights that enhance our understanding of present and future vulnerabilities to water-related risks. By leveraging DMDU, we aim to contribute to the development of more adaptive, resilient, and equitable water management strategies in the face of complexity and uncertainty.

In this paper we aimed at identifying vulnerability patterns related to water scarcity in Mexico City. Specifically, we address two research questions: (1) Which areas within Mexico City are projected to be most vulnerable to future water scarcity? and (2) What biophysical and decision-making drivers contribute to greater water scarcity vulnerability? From a methodological perspective we wanted to explore how multiple forms of uncertainty be effectively integrated into adaptation planning to understand the root causes of current vulnerabilities and improve our ability to anticipate and prepare for a range of future conditions. To explore these questions, we draw on concepts and techniques from the Robust Decision Making (RDM) framework developed within the broader DMDU paradigm (Weaver et.al. 2013; Marchau et.al. 2019; Stanton et.al. 2021). RDM follows a structured learning process known as deliberation with analysis, which facilitates stakeholder engagement, mutual learning, and consensus-building around complex decision challenges (Lempert et al., 2003).

In the context of climate change adaptation, this process begins with the extraction of stakeholders' priorities, preferences, and underlying assumptions that shape adaptation planning. A central strength of RDM is its explicit focus on deep uncertainty, conditions under which stakeholders lack clear knowledge, or consensus, about the probabilities of future outcomes or the causal relationships among key system drivers. This information is systematically organized using a four-component framework known as XLRM. In this framework: X represents key exogenous and endogenous uncertainties (e.g., rainfall variability, groundwater recharge rates, climate change effects); L denotes policy levers—actions or interventions that decision-makers wish to evaluate; R captures the relationships or system models that describe how the world may evolve under different assumptions and policy choices; and M stands for performance metrics used to evaluate the success or desirability of various strategies across multiple scenarios. This structure supports the identification of robust strategies that perform well across a wide range of plausible futures.

Exogenous and endogenous drivers of water scarcity explored in this study included variations in water supply from both external (specifically the Cutzamala 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 2).

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

Table 2. XLMR matrix showing the uncertainty drivers (X), the policy levers or strategies (L), the relationship model (R) and the metric (M).

Future simulations were implemented using MEGADAPT (Bojórquez-Tapia et al. 2019, Bojorquez-Tapia et.al. 2021), 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 in XLMR matrix) 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 that brought together water managers, authorities, and residents from three water-stressed municipalities: Iztapalapa, Xochimilco, and Magdalena Contreras. A key challenge in participatory processes is transforming qualitative insights informed by participants into quantitative indicators. This challenge arises from the difficulty of honoring the nuance of stakeholder perspectives while creating meaningful, mathematical metrics. We met this challenge through an iterative co-production process coding interview narratives into “meta-narratives” or “storylines” that capture shared themes and future visions, and then representing them as concept networks (Eakin et al. 2019; Shepherd et al. 2018). Meta-narratives and storylines turn the usual modeling approach, relying on probabilistic reliability, into a heuristic machine to investigate the future: “rather than asking what will happen (...) storylines allow us to ask what would be the effect of particular interventions across a range of plausible futures” (Shepherd 2019, p. 6-7).

From this analysis, three dominant narratives emerged: informal urban growth driving insecurity, infrastructure and management failures caused by underinvestment, and inequitable distribution compounded by inadequate monitoring. Next, a multicriteria decision analysis (MCDA) translated stakeholders’ priorities into decision rules, which informed software agents in the MEGADAPT model (Bojórquez-Tapia et al. 2019, 2021).

In our simulations, we used budget allocation as a proxy for stakeholder uncertainties and financial capacities in addressing water scarcity through infrastructure maintenance and development. By varying the budget lever, we could test the common assumption that water scarcity stems from poor management and examine the conditions under which this link becomes significant. We defined three budget levels: Low (50 units), Medium (1,000 units), and High (2,000 units), each determining how many spatial units water managers could affect with infrastructure investments. After each allocation step, we computed vulnerability to water scarcity in each unit as a nonlinear function of exposure, sensitivity, and adaptive capacity. The resulting vulnerability scores ranged from 0 (lowest vulnerability) to 1 (highest vulnerability).

To operationalize our modeling approach, we calculated water scarcity vulnerability (V_w) as a function of exposure (V_e), sensitivity (V_s), and adaptive capacity (V_a).

V_e was modeled using indicators related to water service quality, including intermittent supply (tandeo), scheduled water deliveries, days without service, known infrastructure deficiencies, or low hydraulic pressure. V_s captured social vulnerability, including total population and income levels.

Both V_e and V_s were computed using the following formula:

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

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.

These weights and scores were derived from stakeholder assessments to ensure relevance and contextual grounding.

V_a was modeled as households' ability to implement coping strategies. Since many community strategies are difficult to quantify, we represented V_a as a combination of known institutional and personal capacities, particularly the construction of water storage systems, and a parameter for community-based adaptation efficiency (e), which is an unknown capturing locally devised strategies. The evolution of V_a over time was given by:

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$$V_{at+1}^{k} = \begin{cases} V_{at}^{k} + \frac{e}{10} & y_a = 1 \\ 0 & y_a = 0 \end{cases}$$

Where *k* represents spatial units and *t* time. Function returns 1 for successful adaptive capacity building and 0 otherwise.

Finally, overall vulnerability to water scarcity V_w,. was calculated in two nonlinear steps:

$$V_{lt}^{k} = V_{et}^{(1-Vst)}$$

Where V_l accounts for the relation between V_e exposure and V_s sensitivity.

$$V_{wt}^{k} = V_{lt}^{k(1+V_{at}^{k})}$$

Where V_w is vulnerability to water scarcity, V_a adaptive capacity, *k* spatial units and *t* time.

This structure reflects the interaction between exposure and sensitivity, and the moderating effect of adaptive capacity. By integrating both quantitative indicators and stakeholder knowledge, our model provides a structured yet flexible framework for analyzing water vulnerability under deep uncertainty. (see Bojorquez-Tapia & Eakin 2018, and Bojorquez Tapia et.al. 2021 for more details).

We conducted a set of 12 simulation experiments by combining one of six exogenous uncertainties (Table 3) 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 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 Cutz system
reduc_cutza	Reductions in water supply from Cutz system
mejora_efi	Increases in water distribution pressure

Table 3. Description of uncertainty scenarios implemented to simulate water scarcity vulnerability.

Finally, 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: 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). The spatial distribution of initial (2021) and projected (2060) water scarcity vulnerability outcomes for each tree node is shown in Figure 2.

Results

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 and stakeholders imagine future scenarios and extract lessons to be used in adaptation plans. We asked two main questions: (1) Which areas within Mexico City are projected to be most vulnerable to future water scarcity? and (2) What biophysical and decision-making drivers contribute to greater water scarcity vulnerability?

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 (Figure 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 (Figure 2B). However, assuming that a single grand 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.

Future scenarios and vulnerability.

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 forecasts but rather explorations of potential positive and negative outcomes, helping decision-makers and stakeholders 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 infrastructures. Typical issues with physical infrastructures involve vices found at the planning stage such as short-termism and inadequate budget allocation (Bertana et.al. 2022, Piggot-McKellar et.al. 2020, Pörtner & Roberts 2022).

In our case study, historically marginalized areas remained vulnerable under all scenarios, while affluent districts held low vulnerability even in worst-case simulations (figure 2C). Large budgets only reduced risk where soft infrastructure was strong. This highlights that root causes lie not in engineering or funding gaps alone but in unresolved social, economic, and political injustices that perpetuate negative feedback loops, meaning that decision-making drivers contribute to greater water scarcity vulnerability far more, than biophysical dynamics. This is important evidence exposing that water inequalities have everything to do with invisibilized historical power differences, problems that will not be solved by allocating more money through larger infrastructures or via privatization schemes (Mehta 2025).

Spatial distribution of water vulnerability present and future

As can be seen in the maps in figure 2, 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.

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 (Figure 2B) while the western areas showed very low and low vulnerability in the best-case scenarios for the year 2060 (Figure 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).

To better understand these results we examined the four key uncertainties from the XLRM matrix: water from external sources, water from internal sources, urban sprawl, and water distribution. Each of these uncertainties are in themselves riddled with further uncertainties 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? From meta narratives we know that stakeholders recognized three major storylines 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 helped us structure the various sources of uncertainty to clarify what is at stake. To illustrate, consider the municipality of Iztapalapa (the large red zone in southeast Mexico City visible in Figure 2C). Simulations identified this entire municipality as a locality where no amount of budget allocation meaningfully reduces water vulnerability. Understanding why requires delving into Iztapalapa's deep historical problems.

Iztapalapa occupies a former peninsula of the ancient Lake Texcoco, on which the Mexica (Aztecs) originally built Tenochtitlan. Following the Spanish conquest in the early sixteenth century, colonial authorities undertook a gradual but relentless drainage of Lake Texcoco. As a result, local surface and groundwater systems were severely disrupted, and the area transitioned from a naturally buffered lacustrine environment to exposed, subsiding land (Alcocer and Williams 1996). Historically, Iztapalapa's residents were farmers using the Chinampas system to produce food. This system was destroyed continuously for centuries. On that last surviving chinampa in the 20th century now sits the Central de Abastos, Mexico City's main wholesale food market inaugurated in 1982 (Reid 1985). During much of the twentieth century, federal and local authorities directed marginalized rural-to-urban migrants to Iztapalapa from southern states such as Oaxaca and Chiapas, regions historically underinvested in national development projects. This inward flow accelerated in the late 1980s and 1990s as economic crises prompted evictions from other parts of the city and informal settlement grew, swelling Iztapalapa's population to over 1.8 million by 2000 (INEGI 2025). Compounding these socio-political pressures, Iztapalapa has been historically the city's urban hinterland hosting the city's five prisons and principal landfill areas all located here, reflecting a persistent neglect in urban planning.

Future scenarios become valuable here not because they predict outcomes, but because they force difficult questions triggered by the stark finding that no budget scenario helps Iztapalapa. This striking result prompted us to turn to meta-narratives to understand the underlying causes. What we found were layers of social, political, and economic uncertainties rooted in centuries of historical marginalization, institutional neglect, and environmental degradation.

Discussion

The integration of simulations and meta-narratives was crucial in illuminating Iztapalapa's persistent vulnerability. While infrastructure investments remain a common remedy, more pipes, larger rainwater collectors, our simulations reveal that more budget allocated to infrastructures cannot solve the deeper power imbalances and historical marginalization that perpetuate scarcity. This is important because our second research question asked about the biophysical and decision-making drivers contribute to greater water scarcity vulnerability. Scenarios prompt stakeholders to think geographically and historically. In this sense, scenarios help fulfill a major goal of adaptation *ex ante* strategies: to identify circumstances where previously successful strategies may become ineffective. Iztapalapa is a case in point: even if we believed larger infrastructures could help, now we know that option has run its course. This demonstrates the strength of our DMDU approach understood as a cognitive framework that enables people to truly consider a broader sense of potential futures affecting their actions. In this case, simulations uncover counterintuitive patterns or signals, while meta-narratives provide the contextual grounding needed to interpret those signals.

In this work uncertainty was tackled simulating different scenarios affecting internal and external water supplies and budget allocation to different spatial units. Future simulations highlighted a stark finding when it was discovered that large areas of the city remain vulnerable regardless of budget allocation. Note that computer simulations do not represent actual states of the world. They are useful fictions in the sense that while not being accurate descriptions of the world, help uncover trends, insights, correlations that are not easy to come by. There is a second step where model results have to be contextualized to help people connect the dots when planning real-life actions. This context comes from qualitative information. Centuries of lake drainage, land subsidence, volcanic terrain, rapid informal settlement, and institutional neglect have intertwined to create uncertainties far deeper than pipe leaks or reservoir levels. Only by recognizing how these root causes shape today's water uncertainties can we begin to imagine adaptive pathways that truly address Iztapalapa's vulnerabilities.

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. One of the main strengths of simulations is their ability to process vast amounts of quantitative and qualitative information and reveal insights that may not be immediately obvious: our finding that Iztapalapa remains in high vulnerability regardless of budget allocation, is an insight that would likely have remained hidden using conventional approaches. However, simulations come with limitations. As the complexity and scale of problems grow, so does the difficulty of making the system tractable. Ensuring that the rules embedded in a model accurately reflect reality is another major challenge. In our case, we used metanarratives, derived from stakeholder engagement, to build those rules, grounding our models in real-world knowledge. Still, reliance on computational tools requires significant resources which may not be accessible to all, particularly when dealing with large, heterogenous regions such as Mexico City. However, this challenge may be less constraining at smaller-scale settings, such as local communities, as has been done for example, in storyline analyses (Shepherd 2019).

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 people think and imagine new scenarios. Remember that the goal is not aiming at absolute success, but to identify plausible futures to develop robust strategies. We want to understand when a successful project might run its course and needs to be adapted or replaced. Mathematical tools are not about assigning arbitrary numbers to propositions but about establishing a system to translate insights into actions to help us order, prioritize and assess multiple futures.

Relying on math and computer power *alone* has important pitfalls. DMDU methods have been accused of ignoring the particular contexts in which they are applied (Stanton & Roelich 2023). In the climate change literature, quantitative methods have sometimes been associated to *positivist science*, meaning an over-reliance on traditional scientific knowledge at the expense of other forms of knowing (Garcia-del-Amo et.al. 2020; Schipper et.al 2021). Critics argue that climate change studies have privileged western, technical solutions at the expense of nature-based or community-driven knowledge, particularly from Global South countries. Positivist critiques are not about formal methods *per se* but about a vision of the world where only a subset of all knowledge is considered valid. Navigating the future requires a plurality of ways of knowing to really understand the root causes driving vulnerability at specific times and places. It's about re-imagining human's place in the world (Ghosh 2016; Nightingale et.al. 2019). The challenge is constructing the right tools to use this plurality of ways of knowing. The challenge is twofold: on one hand, finding ways to translate rich concepts envisioned by communities into formal representations that truly represent their meaning. That's what we tackled in this paper via mega-narratives. On the other, perfecting pluralistic tools where quantitative and qualitative information work together giving us cognitive access to insights that are not easy to come by, especially when many different points of view are in dispute. We believe this task is easier if different sources of uncertainty are acknowledged as it is there where social, political, and economic injustices lag hidden under a general label of "uncertainty".

Conclusion

In this paper, we aimed at identifying vulnerability patterns related to water scarcity in Mexico City. Specifically, we address two research questions: (1) Which areas within Mexico City are projected to be most vulnerable to future water scarcity? and (2) What biophysical and decision-making drivers contribute to greater water scarcity vulnerability? Methodologically, we propose DMDU as a tool to enhance modeling and decision-making by enabling a deeper understanding of the uncertainties and complexities that surround adaptation efforts.

The general proposal is to use the guidelines provided by different adaptation- maladaptation frameworks as inputs to DMDU processes. Guidelines in all adaptation 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. These indicators enable ordering, prioritizing, and assessing adaptation actions. The key is not to arbitrarily assign numbers but to create a system that systematically works with qualitative and quantitative insights to construct actionable data.

Based on our findings, a clear policy recommendation emerges: to expand adaptation planning beyond infrastructure investment. This is easier said than done, Mexico City as a clear example where discourse is based on reducing inequalities but actions are mainly targeted at allocating more money to infrastructures. To help stakeholders and decision-makers alike, it is essential to incorporate uncertainty mapping into planning processes: people has to recognize the multiple forms of uncertainty at stake , social, political, ecological, political, aleatoric, deep, and use tools that can model and reveal them. Clearly, co-developing scenarios with communities is key. Most adaptation efforts already recognize this but fail at providing the cognitive tools to truly imagine alternative futures. Support hybrid methodologies integrating qualitative narratives with quantitative simulations to better capture the complexity of climate vulnerability. Again, easier said that done as, in our experience, there is a clear divide between quantitative and qualitative methods where some are preferred over the other, instead of being seen as two faces of the same methodological toolkit that will help answer the questions. Finally, focus should be on systemic inequalities targeting adaptation strategies that explicitly address historical marginalization and socio-political power imbalances.

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.

References.

1. Alcocer J. & Williams W.D. 1996. Historical and recent changes in Lake Texcoco, a saline lake in Mexico. International Journal of Salt Lake research 5: 45-61. DOI: 10.1007/BF01996035
2. Allison, A.E.F., Lawrence, J.H., Stephens, S.A., Kwakkel, J.H., Singh, S.K., Blackett, P. Stroombergen, A. 2024. Planning for wastewater infrastructure adaptation under deep uncertainty. Front. Clim. 6:1355446. doi: 10.3389/fclim.2024.1355446
3. Aston, S., Nardini, M., Beierholm, U., 2023. Different types of uncertainty in multisensory perceptual decision making. Philosophical Transactions of the Royal Society B Biological Sciences, 25;378(1886), 20220349. doi: 10.1098/rstb.2022.0349.
4. Bearman N., 2021. GIS: Research Methods. Bloomsbury Academic, UK.
5. Benson-Lira, V., Georgescu, M., Kaplan, S., Vivoni, E., 2016. Loss of a lake system in a megacity: The impact of urban expansion on seasonal meteorology in Mexico City. Journal of Geophysical Research: Atmospheres, 121(7), 3079–3099. https://doi.org/10.1002/2015JD024102. D.,
6. Bertana, A., Clark, B., Benney, T.M., Quackenbush, C., 2022. Beyond maladaptation: structural barriers to successful adaptation, Environmental Sociology, 8(4), 448-458, DOI: 10.1080/23251042.2022.2068224.
7. Beven, K. J., Almeida, S., Aspinall, W. P., Bates, P. D., Blazkova, S., Borgomeo, E., Freer, J., Goda, K., Hall, J. W., Phillips, J. C., Simpson, M., Smith, P. J., Stephenson, D. B., Wagener, T., Watson, M., and Wilkins, K. L., 2018. Epistemic uncertainties and natural hazard risk assessment – Part 1: A review of different natural hazard areas, Nat. Hazards Earth Syst. Sci., 18, 2741–2768, https://doi.org/10.5194/nhess-18-2741-2018.
8. Bojórquez-Tapia, L. A., Eakin, H., Reed, P. M., Miquelajauregui, Y., Grave, I., Merino-Benítez, T., Molina-Pérez, E., 2022. Unveiling uncertainties to enhance sustainability transformations in infrastructure decision-making. In Current Opinion in Environmental Sustainability (Vol. 55). https://doi.org/10.1016/j.cosust.2022.101172.
9. Bojórquez-Tapia, L. A., Janssen, M., Eakin, H., Baeza, A., Serrano-Candela, F., Gomez-Priego, P., Miquelajauregui, Y., 2019. Spatially-explicit simulation of two-way coupling of complex socio-environmental systems: Socio-hydrological risk and decision making in Mexico City. Socio-Environmental Systems Modelling, 1, 16129. https://doi.org/10.18174/sesmo.2019a16129.
10. Bojórquez-Tapia, L.A., Eakin, H., Hernández-Aguilar, B., Shelton, R., 2021.Addressing complex, political and intransient sustainability challenges of transdisciplinarity: The

case of the MEGADAPT project in Mexico City, Environmental Development, 38, 100604, https://doi.org/10.1016/j.envdev.2020.100604.
11. Copernicus, 2024. The 2024 Annual Climate Summary. Global Climate Highlights. Copernicus. https://climate.copernicus.eu/global-climate-highlights-2024.
12. Dequech, D., 2011. Uncertainty: a typology and refinements of existing concepts. Journal of economic issues, 45(3), 621-640. doi 10.2753/jei0021-3624450306.
13. Eakin H, Bojorquez-Tapia LA. 2008. Insights into the composition of household vulnerability from multicriteria decision analysis. Global Environmental Change 18(1):112- 127. https://doi.org/10.1016/j.gloenvcha.2007.09.001
14. Eakin, H., Bojórquez-Tapia, L.A., Janssen, M.A., Georgescu, M., Manuel-Navarrete, D., Vivoni, E.E., Escalante, A.E., Baeza-Castro, A., Mazari-Hiriart, M., Lerner, A.M., 2017. Opinion: Urban resilience efforts must consider social and political forces, Proceedings of the National Academy of Science USA, 114:186–189, 10.1073/pnas.1620081114.
15. Eakin, H., Siqueiros-García, J.M., Hernández-Aguilar, B., Shelton, R., Bojórquez-Tapia, L.A., 2019. Mental Models, Meta-Narratives, and Solution Pathways Associated With Socio-Hydrological Risk and Response in Mexico City. Frontiers in Sustainable Cities, 1. DOI:10.3389/frsc.2019.00004.
16. Esper, J., Torbenson, E.J. & Büntgen, M.U, 2024. 2023 summer warmth unparalleled over the past 2,000 years, Nature. https://10.1038/s41586-024-07512-y.
17. Fulvi, D., & Wodak, J., 2024. Gambling on unknown unknowns: Risk ethics for a climate change technofix. The Anthropocene Review, 11(2), 285-301. https://doi.org/10.1177/20530196231204324.
18. García-del-Amo, D., Mortyn, P.G., Reyes-García, V., 2020. Including indigenous and local knowledge in climate research: an assessment of the opinion of Spanish climate change researchers. Climate Change 160, 67–88. https://doi.org/10.1007/s10584-019-02628-x.
19. Ghosh, A., 2016. The great derangement. Climate change and the unthinkable. The University of Chicago Press, Chicago.
20. González-Villareal, F.J., Vázquez Herrera, E., Arriaga Medina, J.A. 2024. Perspectivas del agua en el Valle de México. Propuestas hacia la seguridad hídrica. Agua Capital. Red del Agua, UNAM, CERSHI, UNESCO.
21. Haasnoot, M., Di Fant, V., Kwakkel, J., Lawrence, J., 2024. Lessons from a decade of adaptive pathways studies for climate adaptation, Global Environmental Change. 88102907. https://doi.org/10.1016/j.gloenvcha.2024.102907.
22. Habib, A., Akyuz, D., Nasher, N., Musleh, F. 2024. Resilient Stormwater Management of a Coastal Catchment. Journal of Water Management Modeling. https://doi.org/10.14796/JWMM.C514
23. Hallegatte, S., Rentschler, R., Rozenberg, J., 2020. The Adaptation Principles. A Guide for Designing Strategies for Climate Change Adaptation and Resilience. The World Bank, Washington DC, USA.
24. Higuera Roa, O., Walz, Y. & Nehren, U. 2025. How to avoid the risk of maladaptation? From a conceptual understanding to a systematic approach for analyzing potential

adverse effects in adaptation actions. Mitig Adapt Strateg Glob Change 30, 27. https://doi.org/10.1007/s11027-025-10217-w
25. Incropera F.P., 2016. Climate change: a wicked problem. Cambridge University Press, NY.
26. INEGI (2025). https://www.inegi.org.mx/temas/agua/ Retrieved on May 4th, 2025.
27. INEGI (2000). Perfil sociodemográfico del Distrito Federal. XII Censo General de Población y Vivienda 2000.
28. IPDP (2025). https://indicadores.cdmx.gob.mx/group/06-agua-limpia-y-saneamiento. Retrieved on May 4th, 2025.
29. Knieper, C., Pahl-Wostl, C.A, 2016. A comparative analysis of water governance, water management, and environmental performance in river basins. Water Resources Management, 30, 2161-2177. https://doi.org/10.1007/s11269-016-1276-z.
30. Kotamäki, N., Arhonditsis, G., Hjerppe, T., Hyytiäinen, K., Malve, O., Ovaskainen, O., Paloniitty, T., Similä, J., Soininen, N., Weigel, B., Heiskanen, A-S., 2024. Strategies for integrating scientific evidence in water policy and law in the face of uncertainty, Science of The Total Environment, 931,172855, https://doi.org/10.1016/j.scitotenv.2024.172855.
31. Lamboll, R.D., Nicholls, Z.R.J., Smith, C.J. Kikstra, J.S., Byers, E., Rogelj, J., 2023. Assessing the size and uncertainty of remaining carbon budgets. Nat. Clim. Chang. 13, 1360–1367. https://doi.org/10.1038/s41558-023-01848-5.
32. Lempert R.J., Lawrence, J., Kopp R.E., Haasnoot, M., Reisinger, A., GrubbM., Pasqualino, R., 2024. The use of decision making under deep uncertainty in the IPCC. Frontiers in Climate, 6, URL=https://www.frontiersin.org/journals/climate/articles/10.3389/fclim.2024.1380054
33. Magnan, AK., Schipper, E.L.F., Burkett, M., Bharwani, S., Burton, I., Eriksen, S., Gemenne, F., Schaar, J., Ziervogel, G., 2016. Addressing the risk of maladaptation to climate change. WIRE's Climate change. 7(5), 646-665. doi.org/10.1002/wcc.409.
34. Marchau, V., A. W. J., Walker, W.E., Bloemen, P. J. T. M., Popper, S.W. (Eds)., 2019. Decision Making under Deep Uncertainty: From Theory to Practice. Springer, Switzerland. https://doi.org/10.1007/978-3-030-05252-2
35. McCulloch, M.T., Winter, A., Sherman, C.E., Trotter, J.A., 2024. 300 years of sclerosponge thermometry shows global warming has exceeded 1.5 °C. Nat. Clim. Chang. 14, 171–177. https://doi.org/10.1038/s41558-023-01919-7.
36. Mehta, L. (2025). Why invisible power and structural violence persist in the water domain. IDS bulletin, 56(1A). https://doi.org/10.19088/1968-2025.111.
37. Mehta, L., Adam, H.N. & Srivastava, S., 2019. Unpacking uncertainty and climate change from 'above' and 'below'. Reg Environ Change 19, 1529–1532. https://doi.org/10.1007/s10113-019-01539-y.
38. Mehta, L., Leach, M., & Scoones, I. (2025). Environmental governance in an uncertain world. *IDS bulletin*, *56*(1A). https://doi.org/10.19088/1968-2025.110.
39. Miquelajauregui, Y., & Madariaga-Fregoso, A. (2022). Knowledge Coproduction for Transformative Climate Adaptation: Building Robust Strategies. IntechOpen. doi: 10.5772/intechopen.107849

40. Miquelajauregui, Y., Cumming, S.G., Gauthier, S., 2016. Modelling variable fire severity in boreal forests: effects of fire intensity and stand structure. PLOS One 11(2), https://doi.org/10.1371/journal.pone.0150073.
41. Moallemi, E. A., Kwakkel, J., de Haan, F. J., & Bryan, B. A. (2020). Exploratory modeling for analyzing coupled human-natural systems under uncertainty. *Global Environmental Change*, *65*, 102186.
42. Nightingale, A. J., Eriksen, S., Taylor, M., Forsyth, T., Pelling, M., Newsham, A., Boyd, E., Brown, K., Harvey, B., Jones, L., Bezner Kerr, R., Mehta, L., Naess, L.O., Ockwell, D., Scoones, I., Tanner, T., Whitfield, S., 2019. Beyond Technical Fixes: climate solutions and the great derangement. Climate and Development, 12(4), 343–352. https://doi.org/10.1080/17565529.2019.1624495.
43. Nisbet, E.G. Methane's unknowns better known. Nat. Geosci. 15, 861–862 (2022). https://doi.org/10.1038/s41561-022-01049-3.
44. Pérez-Invernón, F.J., Gordillo-Vázquez, F.J., Huntrieser, H., Jöckel, P., 2023. Variation of lightning-ignited wildfire patterns under climate change. Nature Communications 14, 739. https://doi.org/10.1038/s41467-023-36500-5.
45. Piggott-McKellar, A.E., Nunn, P.D., McNamara, K.E., Sekinini, S.T., 2020. Dam(n) Seawalls: A Case of Climate Change Maladaptation in Fiji. Managing Climate Change Adaptation in the Pacific Region. In: Filho, W.L. (Ed.)., Climate Change Management (CCM), Springer Nature, Switzerland, pp.69-84. https://doi.org/10.1007/978-3-030-40552-6_4.
46. Pörtner, H.-O. & Roberts, D.C. (Eds)., 2023. "Technical Summary". In Climate Change 2022 – Impacts, Adaptation and Vulnerability (pp. 37–118). Intergovernmental Panel on Climate Change. Cambridge: Cambridge University Press. https://doi.org/10.1017/9781009325844.002.
47. Purich, A., & Doddridge, E. W., 2023. "Record low Antarctic sea ice coverage indicates a new sea ice state". Communications Earth and Environment 4(1). https://doi.org/10.1038/s43247-023-00961-9.
48. Reckien, D., Magnan. A. K., Singh, C., Lukas-Sithole, M., Orlove, B., Schipper, E.L.F., Coughlan de Perez, E., 2023. Navigating the continuum between adaptation and maladaptation. Nature Climate Change 13(9): 907–918). https://doi.org/10.1038/s41558-023-01774-6.
49. Reid, A. (1985). Las chinampas de Iztapalapa: su tecnología, historia y desaparición.2089 *Revista A: De la metropoli mexicana, VI (15)*, 183-192
50. Ripple, W. J., Wolf, C., Gregg, J. W., Rockström, J., Newsome, T. M., Law, B. E., Marques, L., Lenton, T. M., Xu, C., Huq, S., Simons, L., & King, S. D. A., 2023. "The 2023 state of the climate report: Entering uncharted territory". BioScience, 73(12), 841–850. https://doi.org/10.1093/biosci/biad080.
51. Ripple, W.J., Wolf, C., Gregg, J. W., Rockström, J., Mann, M.E., Oreskes, N., Timothy M Lenton, T.M., Rahmstorf, S., Newsome, T.M., Xu, Ch., Svenning, J-C., Cardoso Pereira, C., Law, B.E., Crowther, T.W. 2024. "The 2024 state of the climate report: Perilous times on planet Earth". BioScience, biae087. https://doi.org/10.1093/biosci/biae087.

52. Rising, J., Tedesco, M., Piontek, F., & Stainforth, D. A. (2022). The missing risks of climate change. Nature, 610(7933), 643-651. https://doi.org/10.1038/s41586-022-05243-6.
53. Romanello, M., Walawender, M., Hsu, S-C., Moskeland, A., Palmeiro-Silva, Y.,..., Costello, A. 2024. The 2024 report of the Lancet Countdown on health and climate change: facing record-breaking threats from delayed action. The Lancet 400(10465), 1847-1896.
54. Sarkar, A., Bandyopadhyay, N., Singh, S., Sachan, R., (Eds)., 2024. Risk, Uncertainty and Maladaptation to Climate Change Policy, Practice and Case Studies. Springer Nature, Singapore.
55. Schipper, E.L.F., 2020. Maladaptation: When Adaptation to Climate Change Goes Very Wrong. One Earth (Volw. 3, Issue 4, pp. 409–414). Cell Press. https://doi.org/10.1016/j.oneear.2020.09.014.
56. Schipper, E.L.F., Dubash, N.K. & Mulugetta, Y., 2021. Climate change research and the search for solutions: rethinking interdisciplinarity. Climatic Change 168, 18. https://doi.org/10.1007/s10584-021-03237-3.
57. Shepherd, T. G. (2019). Storyline approach to the construction of regional climate change information. Proceedings of the Royal Society A, 475(2225), 20190013. http://dx.doi.org/10.1098/rspa.2019.0013.
58. Scoones I., & Stirling.A. (Eds)., 2020. The politics of uncertainty: challenges of transformation. Routledge, UK.
59. SEDEMA (2020). Evaluación interna del programa: Sistemas de captación de agua de lluvia en viviendas de la Ciudad de México. Informe anual 2020. Secretaría del Medio Ambiente de la Ciudad de México. https://www.sedema.cdmx.gob.mx/storage/app/media/CosechaDeLluvia/evaluacion-interna-cdll-2020.pdf
60. Shepherd, T. G., Boyd, E., Calel, R. A., Chapman, S. C., Dessai, S., Dima-West, I. M., ... & Zenghelis, D. A. (2018). Storylines: an alternative approach to representing uncertainty in physical aspects of climate change. Climatic change, 151, 555-571. https://doi.org/10.1007/s10584-018-2317-9.
61. Stanton, M.C.B. & Roelich, K., 2021. Decision making under deep uncertainties: A review of the applicability of methods in practice. Technological Forecasting and Social Change, 171, 120939. https://doi.org/10.1016/j.techfore.2021.120939.
62. Steffen, W., Richardson, K., Rockström, J., Schellnuber, H.J., Dube, O. P., Dutreuil, S., Lenton, L.M., Lubchenco, J., 2020. The emergence and evolution of Earth System Science. Nature Reviews Earth & Environment. 1, 54–63. https://doi.org/10.1038/s43017-019-0005-6
63. Taebi, B., Kwakkel, J.H., Kermisch, C., 2020. Governing climate risks in the face of normative uncertainties. WIREs Climate Change, 11, e666. https://doi.org/10.1002/wcc.666
64. Taleb, N. N., 2010. The Black Swan. The impact of the highly improbable. Random House, NY.
65. Taleb, N.N., & Martin, G.A. (2012). How to Prevent Other Financial Crises. *SAIS Review of International Affairs 32*(1), 49-60. https://dx.doi.org/10.1353/sais.2012.0010.

66. Talledos Sánchez, E., Álvarez Becerril, B., Hatch Kuri, G., Antonio, R. S., & Velázquez Zapata, J. A. (2020). Captura política, grandes concentraciones y control de agua en México: Informe agua. Colegio de Geografía UNAM-OXFAM.
67. Tellman, B., Bausch, J.C., Eakin, H., Anderies, J. M., Mazari-Hiriart, M., Manuel-Navarrete, Redman, C.L., 2018. Adaptive pathways and coupled infrastructure: seven centuries of adaptation to water risk and the production of vulnerability in Mexico City. Ecology and Society, 23(1),1. https://doi.org/10.5751/ES-09712-230101.
68. United Nations Environment Programme (2024). Adaptation Gap Report 2024: Come hell and high water. As fires and floods hit the poor hardest, it is time for the world to step up adaptation actions. Nairobi. https://doi.org/10.59117/20.500.11822/46497.
69. Weaver, C. P., Lempert, R. J., Brown, C., Hall, J. A., Revell, D., Sarewitz, D., 2013. Improving the contribution of climate model information to decision making: the value and demands of robust decision frameworks., 4(1), 39-60. https://doi.org/10.1007/s11269-016-1276-z.
70. World Meteorological Organization. 2024. State of the Climate Report 2024. Update for COP 29. WMO, Geneva.
71. World Meteorological Organization.2025. WMO Global Annual to decadal Climate Update 2025-2029, WMO. Geneva.
72. Wunderling, N., von der Heydt, A. S., Aksenov, Y., Barker, S., Bastiaansen, R., Brovkin, V., Brunetti, M., Couplet, V., Kleinen, T., Lear, C. H., Lohmann, J., Roman-Cuesta, R. M., Sinet, S., Swingedouw, D., Winkelmann, R., Anand, P., Barichivich, J., Bathiany, S., Baudena, M., Bruun, J. T., Chiessi, C. M., Coxall, H. K., Docquier, D., Donges, J. F., Falkena, S. K. J., Klose, A. K., Obura, D., Rocha, J., Rynders, S., Steinert, N. J., Willeit, M., 2024. Climate tipping point interactions and cascades: a review, Earth Syst. Dynam., 15, 41–74, https://doi.org/10.5194/esd-15-41-2024.
73. Zeileis, A., Hothorn, T., Hornik, K., 2008. Model-Based Recursive Partitioning. Journal of Computational and Graphical Statistics, 17(2), 492–514. https://doi.org/10.1198/106186008X319331