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**Key Points:**
- This review characterizes the flood management literature addressing green infrastructure and decision making under deep uncertainty (DMDU).
- Case studies in the literature span five continents, and use various adaptation strategies, modeling techniques, and sources of climate data.
- Continued and transparent research to develop open source methods for DMDU can improve resilience planning.

**Supporting Information:**
Supporting Information may be found in the online version of this article.

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**A Review of Decision Making Under Deep Uncertainty Applications Using Green Infrastructure for Flood Management**

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**Abstract**

Decision making under deep uncertainty (DMDU) approaches are well-suited for making decisions about infrastructure to manage flooding exacerbated by climate change. One important system for climate resilience and flood management is green infrastructure, which refers to a network of natural and semi-engineered areas that provides ecosystem functions. Green infrastructure is often characterized as a low-regret strategy with multiple co-benefits under uncertainty. These attributes enable green infrastructure to be an important adaptation strategy under DMDU frameworks for flood management. However, DMDU analyses that include green infrastructure are still relatively limited, perhaps due to computational or modeling complexity and other barriers. This paper identifies and reviews publications in the flood management literature that use DMDU frameworks and refer to green infrastructure adaptation strategies, in order to identify trends and inform future research. The reviewed publications are categorized according to a variety of performance metrics, climate change scenarios, DMDU metrics, and hydrologic modeling techniques, and represent several adaptation strategies applied to case studies on five continents using a range of data sources and assumptions. This paper highlights a number of solutions that can be employed to facilitate additional research at the intersection of these fields. Primary among these is the transparent documentation and use of open source models, methods, and data. Future research should also focus on communication among different stakeholders, particularly in ensuring definitions, assumptions, and data requirements are clear. These partnerships can facilitate effective application of robust strategies such as green infrastructure for urban adaptation to the effects of climate change.

**Plain Language Summary**

Our review characterizes the state of the literature at the intersection of three interconnected fields: flood management, Decision Making under Deep Uncertainty, and green infrastructure. We highlight publicly available modeling and statistical packages that are commonly used in the literature, and draw attention to methods, trends, potential solutions, and challenges we observed. Given that most of the literature reviewed was published in the last four to eight years, we believe that this article provides novel and timely information that will lead to and guide further research to successfully plan for and adapt to flooding exacerbated by climate change. Our paper also provides useful information to communities of researchers and academics seeking to use existing tools and develop new tools for decision making under deep uncertainty.

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1. **Introduction**

Uncertainties are inherent to any attempts to make decisions about the future. Model outputs, like those from climate model projections, are subject to several types of uncertainty, including model uncertainty, data uncertainty, and scenario uncertainty. The authors of (Marchau et al., 2019) characterize different levels of uncertainty, and describe the condition of deep uncertainty. Problems are deeply uncertain when impacts analysts cannot agree on the conceptual models that could be used to represent probable futures, the probability distributions representing uncertainty of parameters in the future, and/or how to value the different outcomes. As a result, decisions made using human intuition or conclusions drawn from historical trends are likely to be disrupted by surprising and unpredictable events (Lempert et al., 2003; Marchau et al., 2019).

Decisions under climate change, especially regarding infrastructure resilience, are emblematic of deep uncertainty (Chester et al., 2020; Hallegatte et al., 2012). The timing and magnitude of specific future changes are difficult to anticipate, and stakeholders cannot wait until future projections are less uncertain or until effects are observed or experienced to enact adaptation or mitigation measures (Murphy et al., 2011; Pollitt, 2015). For example,
a number of researchers have developed probabilistic frameworks or projections to estimate the effects of the melting of the West Antarctic and other influential ice sheets on high-end scenarios for sea level rise (Bakker et al., 2017; DeConto & Pollard, 2016; Haasnoot, Kwadijk, et al., 2020; Hinkel et al., 2019; Kopp et al., 2017). A sensitivity analysis or prediction-based analysis would only be able to capture some of these uncertainties (Marchau et al., 2019), and experts remain undecided about the range or probability of different outcomes that would be required for a sensitivity analysis (Bakker et al., 2017; Kopp et al., 2017). In spite of this deep uncertainty, along with achieving net-zero emissions, the consequences of climate impacts require decision-makers to plan for the future and take some form of adaptive action (including no action or deferred action).

Instead of relying on prediction-oriented, top-down decision making techniques for solutions to deeply uncertain problems like localized climate change impacts, stakeholders can apply resilience-oriented, bottom-up approaches often characterized as decision making under deep uncertainty (DMDU) (Dessai & van de Sluijs, 2007; Marchau et al., 2019). Researchers associated with organizations such as the Society for DMDU, the RAND Corporation, and other institutions have made considerable contributions to formalizing these approaches, and have edited a book outlining commonly used methods and tools, and their application (Marchau et al., 2019).

These DMDU approaches have been applied to decision making for many different types of infrastructure, including conservation and forest management (Kingsborough et al., 2017; Radke et al., 2010; Singh et al., 2015; Tingstad et al., 2017), renewable energy (François et al., 2017; Popper et al., 2009), agriculture (Maru et al., 2017; Tanaka et al., 2015), flood management (Kalra et al., 2015; Lempert, Kalra, et al., 2013; Reed & Kollat, 2013; Steinschneider et al., 2015), transportation planning (Lempert et al., 2020), and other applications (Halim et al., 2016; Slepchenko et al., 2019). These approaches are useful for problems categorized as long-term decisions, “shaping the next one hundred years”, where solutions or actions are large, permanent, or long-lived investments with large capital costs (Lempert et al., 2003). Considering these criteria and the devastating trend and nature of recent flooding events in the United States (U.S.) and elsewhere (Mallakpour & Villarini, 2015; NOAA National Centers for Environmental Information [NCEI], 2020; Razavi et al., 2020; Slater & Villarini, 2016), in this literature review we focus on DMDU frameworks and methods used for flood management, particularly flood management plans using green infrastructure. Flood estimation guidance must account for climate change (Wasko et al., 2021), and DMDU approaches could prove particularly useful in ensuring this guidance satisfies all stakeholders and is robust under deep uncertainty.

Green infrastructure can be defined as a network of natural or semi-engineered areas and other open spaces that conserves natural ecosystem conditions, values, and functions, and provides a wide array of benefits to people and wildlife, such as managing flooding impacts and creating healthier urban and suburban environments (Benedict & McMahon, 2006; Caparrós-Martínez et al., 2020; Naumann et al., 2011; U.S. Environmental Protection Agency [EPA], 2020). While green infrastructure has become known as a low-impact and low-regret strategy for urban storm water and flood management (Barah et al., 2020; Depietri & McPhearson, 2017), researchers publishing at the forefront of these fields have noted that there are relatively few publications applying DMDU to urban storm water management utilizing green infrastructure, likely due to challenges in modeling and simulation (Fischbach et al., 2020).

In this review, we identify and summarize trends in the flood management literature using DMDU frameworks and referring to green infrastructure as an adaptation strategy. A critical assessment of this literature can identify prominent trends and lead to improved resilience planning and more effective and robust urban adaptation to climate change. After this introduction (Section 1), we provide a brief overview of common DMDU approaches (Section 2) and of green infrastructure (Section 3). We provide a detailed account of our review methodology in Section 4. In Section 5, we review DMDU approaches as applied to flood management in 122 case studies from the literature. In Section 6, we present further review and analysis for 64 of these 122 case studies, each of which spans all three fields: green infrastructure, DMDU, and flood management. Finally, in Section 7, we discuss the trends identified in these reviews, suggest future pathways for research, and present conclusions.

2. DMDU Approaches

Instead of trying to predict the future by choosing a single future state or waiting for the future to play out in order to make decisions and act accordingly (a “predict-then-act” approach), DMDU focuses on vulnerability and adaptation, identifying a large number of future states and then working backward to determine which steps
should be taken so that the chosen solution is successful over more than one future state (an “agree on decisions” approach; Lempert, 2019; Lempert, Popper, et al., 2013). Discussion among a diverse group of stakeholders can ensure that actions are taken after systematic, well-informed decisions are made (Lempert et al., 2003). It is important to note that the goal is not to make better predictions, but to make better decisions under deep uncertainty (Lempert, 2019).

Three prominent bottom-up approaches can be identified from comprehensive reviews of DMDU approaches and metrics: Robust Decision Making (RDM), Adaptive or Adaptation Pathways, and Decision Scaling (Dittrich et al., 2016; Giuliani & Castelletti, 2016; Johnson & Geldner, 2019; Marchau et al., 2019; Moallemi et al., 2020). The reader is referred to these reviews for a more detailed overview of these approaches, all of which share similar elements and underlying objectives.

2.1. Overview of Decision Support Frameworks

RDM is commonly defined as a framework allowing decision makers to look into a range of plausible futures and select strategies which perform reasonably well and minimize regret across a wide range of futures (Marchau et al., 2019). This framework is particularly well suited to problems with deep uncertainty by combining four key concepts: Decision Analysis, Assumption-Based Planning, Scenario Analysis, and Exploratory Modeling. Developed primarily by researchers at the U.S.-based RAND Corporation, the framework is iterative, which can be distilled into five steps (Lempert, 2019).

First is the generation and framing of decisions, strategies, or alternatives, based on stakeholder preferences and definitions of key factors. Different scenarios or states of the world are generated, sometimes using exploratory modeling or expert opinion. The metrics used to measure performance are outlined and used in the second step to evaluate decisions across scenarios. In the case where multiple objectives are important for performance, many-objective robust decision making (MORDM) can be employed to evaluate decisions. In this second step, the decision makers can determine which scenarios are failures, that is, the scenarios for which the decisions or alternatives do not meet pre-determined performance or threshold levels. The performance metrics are used to isolate the successful decisions within scenarios, and perform vulnerability analysis and tradeoff analysis to further compare successful decisions across scenarios. Based on these analyses in Steps 3 and 4, the decision makers can change the alternatives so that more scenarios are successful, and return to the first step, repeating the analysis to select those strategies that meet objectives over many plausible future states of the world. The most robust scenarios can also be used to generate adaptive strategies (Hallegatte, 2014; Lempert, 2019; Moallemi et al., 2020).

The Adaptive or Adaptation Pathways approach, hereafter referred to as Adaptation Pathways, is complementary to the RDM approach, and ensures RDM by explicitly including decision making over time (Kwakkel et al., 2016). The Dynamic Adaptive Policy Pathways (DAPP) approach combines Adaptive Policymaking and Adaptation Pathways into a single framework (Haasnoot et al., 2013). These approaches, developed primarily by European-based researchers at Delft University of Technology, Deltares, and the World Bank, allow the decision makers to evaluate a number of sequences of decisions (or pathways) over a number of futures, choosing the most promising alternative now, while allowing for flexibility in making future decisions. For this reason, the DAPP approach is often combined with a real options analysis or engineering options analysis framework, where flexibility (de Neufville & Scholtes, 2011) is explicitly valued (Haasnoot et al., 2013).

DAPP can be used as a framework to guide future actions. Decisions can be postponed until further information becomes available for assessing performance and robustness of alternatives. Pathways are valued based on their ability to meet certain objectives, monitored as signals related to impacts or driving forces within the system (Haasnoot et al., 2013, 2019). For example, some adaptation pathways are developed primarily through conversation with stakeholders, in order to protect against particular sea level rise projections (Aerts et al., 2018) while others are combinations and permutations of adaptation strategies put forward in existing plans and documents in order to meet pollution reduction targets (Tariq et al., 2017). Switching from one pathway or alternative to another is governed by adaptation tipping points. At each adaptation tipping point, the current strategy can no longer meet the system’s objectives, and other alternatives are considered. The pathways and scenarios must be monitored over time to identify these signals (Haasnoot et al., 2019).
Decision Scaling is another framework used to ensure robust decisions are made under climate change. Developed and used primarily by researchers at the University of Massachusetts-Amherst and the World Bank, this framework combines bottom-up vulnerability assessments of strategies with plausible future states of the world informed by climate projections for use in a decision-analytic framework (Brown et al., 2011, 2012). Like RDM and Adaptation Pathways/DAPP, this method accepts the large uncertainties associated with the future and emphasizes robustness over a wide range of plausible futures (Brown et al., 2011).

First, stakeholders decide on suitable performance metrics and decision thresholds, which are similar to adaptation tipping points under the Adaptation Pathways/DAPP framework. The framework uses decision analysis to characterize the future climate in terms of position relative to this threshold (Brown et al., 2012). In the second step, different scenarios are explicitly or formally modeled to develop a climate response function. This function is used to calculate the values of the performance metrics under different scenarios. The last step of the decision-scaling process is the creation of subjective probabilities representing the climatic futures (Brown, 2011). These probabilities represent a weighting of the pertinent hazards, and therefore an estimate of risks. Rather than provide an optimal solution, the final portfolio of plans will be robust over a range of scenarios (Brown et al., 2011; Moody & Brown, 2013).

RDM, Adaptation Pathways/DAPP, and Decision Scaling approaches can readily take advantage of the widely different global climate models used to project future states of the global climate and inform regional and down-scaled models. Under these frameworks, the range of scenarios should be as diverse as possible to develop adaptive strategies and represent all possible and plausible futures (Lempert et al., 2003). In addition, depending on the metrics used and assumptions made, analyses can lead to different and mutually contradicting solutions (Giuliani & Castelletti, 2016; McPhail et al., 2018). As a result, these frameworks can be very data and resource intensive, and analysis requires clear definitions of models, metrics, risks, and scenarios in order to be useful for decision makers (Dittrich et al., 2016; Giuliani & Castelletti, 2016).

### 2.2. DMDU Metrics for Performance

Various metrics can be used to assess performance of strategies under plausible scenarios with unknown or undecided probabilities. Non-probabilistic criteria are commonly evaluated based on three main decision criteria: satisficing, regret, and descriptive statistics such as expected value or variance (McPhail et al., 2018; Moallemi et al., 2020). While RDM tends to make use of all three criteria, Decision Scaling and Adaptation Pathways/DAPP primarily make use of descriptive statistics and satisficing concepts (Kwakkel & Haasnoot, 2019).

Using descriptive statistics, adaptation strategies are assessed based on the expected value of the metric of choice, such as cost, net present value (NPV), or the results of a benefit-cost analysis. For example, stakeholders in Florida deciding on the optimal coastal protection for urban settlements may choose the strategy with the lowest cost across all scenarios (Genovese & Green, 2015). While this is a dominant metric to interpret and communicate risk and resilience, the system must be well understood and uncertainties must be well characterized to represent robustness using this concept (Johnson & Geldner, 2019). Multi-objective analyses, such as those used in MORDM, commonly use a weighting scheme or use Pareto optimization to evaluate over competing objectives. Pareto optimization does not lead to a single solution, but to a collection of solutions that are all optimal or non-dominated by other solutions in the set, known as the Pareto front (Pareto, 1896).

Regret-based approaches select strategies that minimize an expected value of a metric of choice, but also ensure that actions taken have low regret, regardless of the future. Regret can be defined by relative performance, for instance, the difference between optimal performance and performance of the current scenario under one particular state of the world. For example, in analyzing the future of nuclear reactors in France, one researcher chose to use the regret criteria developed by Savage (1950) to minimize regret for 27 strategies (Perrier, 2018).

Under the Adaptation Pathways/DAPP framework, stakeholders are effectively choosing the pathway with the least regret, using criteria such as minimax, which maximizes the minimum regret for all scenarios (Giuliani & Castelletti, 2016; Johnson & Geldner, 2019; Kunreuther et al., 2013; Lempert, 2019).

Lastly, satisficing approaches select as acceptable all scenarios that meet some pre-determined quality standards or threshold (e.g., maintain reliability above some value). First introduced by Starr (1963) and further developed by Simon (1996), satisficing is similar to the domain criteria, where the most robust strategy is selected as the one which meets some performance threshold over the largest fraction of domain space or number of scenarios.
(Kwakkel & Haasnoot, 2019; Schneller IV & Sphicas, 1983). Scenario discovery is one subspace partitioning method often used to understand performance across all scenarios (Bryant, 2015; Bryant & Lempert, 2010). In the case of domain criteria, some optimal performance can be sacrificed for increased robustness, that is, less sensitivity to assumptions (Lempert, 2019; Lempert & Collins, 2007). For example, a number of collaborators analyze water availability in the research triangle of North Carolina, U.S., using a criteria defined as the fraction of states or scenarios in which a solution meets the performance requirements outlined by stakeholders (Herman et al., 2015).

2.3. DMDU for Flood Management

DMDU approaches are well-suited for making decisions regarding urban infrastructure to manage flooding under climate change because there are multiple facets of deep uncertainty associated with the future of flood management and urban infrastructure (Johnson & Geldner, 2019). Despite advances in modeling techniques, projections of precipitation and resulting pluvial flooding are deeply uncertain (Dittes et al., 2018; Lopez-Cantu et al., 2020; Rözer et al., 2019). Future population trends, land cover, and income rates are among other non-climate related uncertainties that decision makers have to take into account. In addition, water and wastewater infrastructure are typically long lived (30–200 years) and capital intensive investments, and are highly exposed to climate change risks (Hallegatte et al., 2012). The high initial investment and long payback period of water-related infrastructure leads stakeholders to seek solutions with low regret when making decisions about replacing, updating, or maintaining this infrastructure. Using historical trends instead of potential projections, as well as conducting analyses that do not take uncertainties into account, could lead to undersized infrastructure and significant future costs and damages, or oversized infrastructure and overspending (Cook et al., 2020; Wobus et al., 2014, 2019).

A number of literature reviews have identified DMDU approaches used to make decisions about flood and water management infrastructure (Dittrich et al., 2016; Johnson & Geldner, 2019; Marchau et al., 2019). Applications span a number of different infrastructural adaptations, including reservoirs or water management (e.g., Culley et al., 2016; Lempert & Groves, 2010; Tingstad et al., 2014), dikes or levees (e.g., Ceres et al., 2019; Ciullo et al., 2019; Raso, Jan, & Timmermans, 2019), dams or barrages (e.g., Fu et al., 2015; Shortridge & Guikema, 2016), infrastructure retrofits (e.g., Lempert, Kalra, et al., 2013; Radhakrishnan, Nguyen, et al., 2018; van Veelen et al., 2015) and land use change or green infrastructure (e.g., Fischbach et al., 2017, 2020; Tariq et al., 2017). A high level review with brief examples of these applications is provided in the Supplemental Information. The concept of green infrastructure is examined in further detail in Section 3.

3. Green Infrastructure

3.1. Overview of Definition and Terms

There are many concurrent definitions of green infrastructure, but most definitions describe a network of natural or semi-engineered areas and other open spaces, both terrestrial and aquatic, that conserves natural ecosystem conditions, values, and functions, and provides a wide array of benefits to people and wildlife (Benedict & McMahon, 2006; Caparrós-Martínez et al., 2020; Naumann et al., 2011; U.S. Environmental Protection Agency [EPA], 2020). The natural areas and open spaces of green infrastructure installations can lead to many co-benefits, including increased permeability or water storage upstream of central water treatment or collection systems, reduction in flooding, improved air and water quality, and temperature control (Ahiablame et al., 2012; Bell et al., 2019; Choi et al., 2021; Eckart et al., 2017; Gonzalez-Meler et al., 2013; J. Wang & Banzhaf, 2018; J. Wang et al., 2020). For systemic reviews of green infrastructure, the reader is referred to (Caparrós-Martínez et al., 2020; Choi et al., 2021; Parker & Zingoni de Baro, 2019; J. Wang & Banzhaf, 2018; Ying et al., 2021) for bibliometric reviews, and to (Bartesaghi Koc et al., 2017; Fletcher et al., 2015; Matsler et al., 2021; Mell, 2017) for discussions about terminology and typology. The reader is also referred to the International Storm water Best Management Practices (BMPs) database, which provides annually updated data summarizing performance of urban storm water BMPs to improve their design, selection, and performance (The Water Research Foundation, Environmental and Water Resources Institute of ASCE, and Federal Highway Administration 2022, available at https://bmpdatabase.org/about). This review focuses on application of green infrastructure strategies for flood management and mitigation under deep uncertainty.
Common examples of green infrastructure strategies for flood management include green roofs, permeable or porous pavements, rain gardens, bioretention cells or infiltration trenches that serve to recharge underground water sources, vegetated swales or bioswales to facilitate water flow away from important infrastructure, as well as urban tree canopy and disconnected downspouts or rainwater harvesting (Fischbach et al., 2020; U.S. Environmental Protection Agency [EPA], 2020). Coastal strategies such as wetlands, marshes, dunes, berms, and living shorelines that are installed to manage flooding due to storm surge and sea level rise are also considered green infrastructure, but are often referred to as nature-based solutions (Webb et al., 2018). These “green” strategies that facilitate infiltration, evapotranspiration, and detention of flood waters are contrasted against traditional “gray” infrastructure primarily made out of concrete and designed to detain or redirect flood waters. While there is no consensus for green infrastructure classification, various researchers have defined typologies or continua based on the purpose, configuration, and hydrologic processes of green infrastructure installations (Bartesaghi Koc et al., 2017; Bell et al., 2019; Fletcher et al., 2015; Matsler et al., 2021; J. Wang & Banzhaf, 2018).

The concept of green infrastructure emerged as early as the 1970s, although the focus and purpose of green infrastructure has expanded significantly over the decades (Fletcher et al., 2015). The evolution of terms used to refer to this concept or similar concepts is summarized in Table 1. This is not meant to be an exhaustive list, but is organized chronologically to highlight the evolution of the field into one that embraces numerous co-benefits (Fletcher et al., 2015; Huang et al., 2020; J. Wang & Banzhaf, 2018). For instance, the most recent terms “sponge city” or “nature-based solutions” are more applicable to systems with multiple functions and benefits, beyond water quantity management and water quality improvement. The evolution of terms also highlights the multi-disciplinary nature of green infrastructure: the terms in Table 1 below span the fields of landscape architecture and planning, urban engineering, human and ecosystem health, among others. Throughout this review, “green infrastructure” is the term most often used to encapsulate any and all of these terms.

Mell (2017) argued that the field of green infrastructure has had three eras in its history: exploration (1998–2000), expansion (2005–2010), and consolidation (2010 to present). Only in the last few years has the literature grown

| Term                                      | Year developed | Location                     | Comments                                                                                       |
|-------------------------------------------|----------------|------------------------------|------------------------------------------------------------------------------------------------|
| Best management practices                 | 1972           | North America                | Related to Clean Water Act, includes other pollution prevention interventions                   |
| Alternative techniques/compensatory       | 1980s          | France                       | Term refers to measures designed for urban drainage solutions and improving quality of life     |
| techniques                                |                |                              | Originally used to refer to on-site systems as opposed to larger downstream measures; now used to refer to small-scale practices |
| Source control                            | 1980s          | North America                | Origin in Prince George's County MD                                                            |
| Low impact development                    | 1990s          | North America, New Zealand   | Origin in landscape architecture, now mostly synonymous with LID                                |
| Green infrastructure/green storm water    | 1990s          | USA                          | Origin in landscape architecture, now mostly synonymous with LID                                |
| infrastructure                             |                |                              | Broad principle of design, focus on supplementing water supply and reducing flooding            |
| Water sensitive urban design              | 1990s          | Australia                    | Broad principle of design, linked to/similar to WSUD                                           |
| Integrated urban water management         | 1990s          | International                | Broad principle of design, linked to/similar to WSUD                                           |
| Sustainable Urban Drainage Systems (SUDS,| 1997           | UK                           | Refers to concept or specific techniques, focus on storm water, similar to LID                 |
| SuDS)                                     |                |                              |                                                                                                 |
| Storm water quality improvement devices    | 1998           | Australia                    | Use of this term has declined with increasing multifunctionality of systems                     |
| Storm water control measures              | 2008           | USA                          | This term replaced BMP, used to refer to structural and non-structural measures                  |
| Sponge city                               | 2014           | China                        | Focus on systems functionality of the city as a whole (Chan et al., 2018)                       |
| Nature-based solutions                    | 2015           | International                | A broader term focus on biodiversity and ecosystem services (Escobedo et al., 2019)             |

*Note. Information compiled from (Fletcher et al., 2015; Huang et al., 2020).*
beyond establishing how or where to implement green infrastructure, in order to provide more succinct evidence to support its use and various benefits. For example (Berndtsson, 2010), conducted a review of the laboratory and field experiments seeking to quantify the performance of green roofs, adding specificity to the general statements about co-benefits. Ahiablame et al. (2012) conducted a similar review for bioretention systems, evaluating runoff reduction and pollutant removal of the laboratory and field experiments. Eckart et al. (2017) and Gonzalez-Meler et al. (2013) reviewed the literature for a range of green infrastructure strategies, summarizing and comparing hydrological performance in terms of runoff reduction, peak flow reduction, and mitigation of pollutant loads.

3.2. Green Infrastructure Purpose and Metrics for Performance

Often the metric of performance depends on the goal of the green infrastructure installation. Traditionally, in the U.S., green infrastructure has been installed to ensure that cities meet the requirements of the Clean Water Act as stipulated by the Environmental Protection Agency (EPA; McPhillips et al., 2020). Cities with combined sewer systems can use green infrastructure to reduce runoff before the water is treated at a central treatment plant, and prevent overloading of the systems during period of wet weather, thus reducing combined sewer overflows (Bell et al., 2019; Fischbach et al., 2017). Green infrastructure has therefore been employed as a means for urban water or urban flood management, and achieves many other co-benefits that could be measured with their own performance metrics (Choi et al., 2021; McPhillips et al., 2020; Sussams et al., 2015).

Regardless of the goals that a particular green infrastructure installation is expected to achieve, green infrastructure installations are primarily designed at the municipal or local scale. This is largely due to differences in climate, soil types, and state or municipal laws, design guidelines, and other requirements (McCurdy & Travis, 2018; McPhillips et al., 2020). Reviews of the literature have identified a number of metrics used to design green infrastructure that is installed to manage flooding, for example, green infrastructure can be designed to capture the “first flush” of rainfall with its high contaminant load or to capture a certain amount (inches or mm) of rainfall. This threshold depth is often defined using some percentile of the 24 hr storm event defined for the location (Levitan, 2013; Struck et al., 2011; U.S. Environmental Protection Agency [EPA], 2010). As the field continues to evolve, and new practices and goals are established, it is important that design guidelines for green infrastructure are correlated with municipal and wider goals for climate change adaptation (McPhillips et al., 2020).

Various models can be used to understand the flood management performance of green infrastructure strategies before they are installed. Most models make use of differential equations in one or multiple dimensions in order to predict peak runoff volume, runoff rate, and pollutant loading, mostly at the parcel or sub-catchment scale. A review of modeling tools for green infrastructure hydrologic performance and economics reveals that most models simulate runoff generated by rainfall to assess performance, and use complex pricing methods or databases to conduct cost benefit analyses or life cycle cost calculations (Jayasooriya & Ng, 2014). Hydrologic and Hydraulic (H&H) models can be one-, two- or three-dimensional. One-dimensional (1D) models used to simulate runoff or water depth tend to be sufficient for some non-coastal applications protecting from pluvial (rainfall-induced and independent of nearby waterbodies) flooding, but two- and three-dimensional (2D, 3D) models may be necessary when modeling complex flows or coastal hydrology (Chau, 2010; Knapp et al., 1991).

Most models discussed in the aforementioned 2014 review are suitable for planning level analyses, due to the data requirements and potential for variation in input parameters (Jayasooriya & Ng, 2014). Publicly available models can be as simple as a spreadsheet tool with a number of assumptions, or complex enough to capture the geospatial impervious area and model equations of fluid motion (U.S. Environmental Protection Agency [EPA], 2021). More complex models require more user input and technical expertise to interpret results, and some researchers have extended existing tools or created their own model to improve simulation accuracy or capture larger catchment areas (e.g., Abi Aad et al., 2010; Feng & Burian, 2016; Golden & Hoghooghi, 2018; Korgaonkar et al., 2018).

3.3. DMDU for Green Infrastructure for Flood Management

Multiple features of green infrastructure contribute to its suitability as a flood management and climate adaptation strategy. Green infrastructure is a low-regret strategy, meaning that it is a valuable course of action regardless of the future scenario (Kirshen et al., 2015; Pyke et al., 2011). As such, low-regret near-term options are
particularly of interest to decision makers and planners (Fischbach et al., 2017; Helberg et al., 2009). Planning for optimal placement and sizing of green infrastructure installations requires a number of inputs, such as soil type, plant type, and future demographics, land use change, and climatic conditions such as expected precipitation and temperature. Some of these factors are deterministic, but given the deep uncertainty of future scenarios, DMDU frameworks like those discussed in Section 2 have proven helpful in characterizing potential performance of green infrastructure installations (Fischbach et al., 2020).

Green infrastructure is generally decentralized, that is, this strategy can be applied close to the “source” of flooding as compared to the centralized collection system or wastewater treatment plant that serves an entire city. The decentralized nature of green infrastructure solutions allow for flexible, adaptive, cost effective flood management even at the catchment scale (Jarden et al., 2016; B. R. Rosenzweig et al., 2018; Spatari et al., 2011). This reduces the risk associated with large, long-lived, and capital-intensive centralized systems, contributing to low regret nature of the strategy.

Lastly, green infrastructure and urban green spaces provide multiple co-benefits over their lifetime. These can include the moderation of temperature, reducing noise and air pollution, reducing energy consumption of buildings by reducing heat flux, urban food production, increasing soil infiltration, sequestering carbon dioxide, providing wildlife habitats, and beautification of urban environments, thus contributing to sustainable development of urban areas (Alves et al., 2019, 2020; Choi et al., 2021; Hansen & Pauléit, 2014; Lovell & Taylor, 2013). Green infrastructure also offers a number of social benefits during and after construction, such as higher employment to capital ratio and a shorter and potentially incremental implementation period than “gray” infrastructure (Lilauwala & Gubert, 2019). Various literature continue to bridge the gaps in understanding and valuation of the range of possible co-benefits and ecosystem services by reviewing existing literature (Barton et al., 2015; Choi et al., 2021; Parker & Zingoni de Baro, 2019; Tudorie et al., 2019) or developing frameworks or indicators for performance over multiple co-benefits (Pakzad & Osmond, 2016; Pataki et al., 2011; Wise et al., 2010). For example (Fischbach et al., 2020), used a benefit transfer approach to represent the benefits of combined sewer overflow and as well as recreation benefits, benefits from tree planting, and amenity values, that is, resident’s willingness to pay for aesthetic improvement due to green infrastructure. The authors note that these co-benefits can difficult to monetize due to lack of data, and are likely an underestimate of real world co-benefits. However, for green roofs for example, structural and maintenance constraints may reduce some achievable co-benefits, and performance-based design and stakeholder engagement is needed to help maximize co-benefits across design tradeoffs (Cook & Larsen, 2021).

4. Methodology

We reviewed relevant publications through January 2022 from the Web of Science and Google Scholar databases, supplemented by the database of RAND publications. The following search parameters were entered into the publicly available software Publish or Perish (Harzing, 2007) and the RAND database of reports and journal articles: flood OR flood management OR storm water/storm water AND (“robust decision making” OR “adapt* pathway*” OR “decision scaling”).

Because of the large number of references identified through Google Scholar (in some cases, more than 1,000 references were organized by relevance), we found the average number of citations for all references for each search term, and only included publications in the final assessment if they were among the top 30 relevant publications and had more than the average number of citations for each search term. While this method is imperfect, it provides a first screening approach to identifying the relevant literature.

After removing duplicate entries, 237 unique publications were identified (Webber & Samaras, 2022). A screening and selection process identified 120 unique publications that presented 122 unique case studies for assessment (Webber & Samaras, 2022). While a number of excellent working papers and book chapters have been published analyzing strategies for adaptation and mitigation, the publications for review in this manuscript were limited to peer-reviewed journal publications and conference papers. Reviews of existing literature (e.g., Dittrich et al., 2017; Hill, 2012; Jones et al., 2020; Sala & Bocchi, 2014; Wreford et al., 2020), and publications deemed irrelevant to flood management (e.g., A. F. Bennett & Hughes, 2009; Subbiah, 2003; Tschakert et al., 2016) were also excluded.
Of the 122 case studies, the subset that implemented green infrastructure as an adaptation measure was identified by searching abstracts and full texts for any of the terms shown in Table 1, as well as reading the full texts to ascertain if examples of green infrastructure (such as rainwater harvesting or living shorelines) were used, without explicit mention of any of the terms in Table 1. Sixty four publications analyzing flood management using DMDU approaches were identified for review and assessed to identify further trends and patterns (Webber & Samaras, 2022). Figure 1 details this methodology and directs readers to the relevant sections discussing the trends that were identified through this search.

5. DMDU Approaches for Flood Management Under Climate Change: Trends and Patterns

Figure 2 summarizes trends from these 122 case studies regarding flood management under deep uncertainty, whether or not green infrastructure was used as an adaptation strategy. RDM and Adaptation Pathways/DAPP were much more popular search terms among the 120 publications than Decision Scaling, and the three frameworks were sometimes used in combination or comparison. The vast majority of the literature (112 of 120) was published relatively recently, during or after 2014. The distribution of case studies also reflected the research groups and institutions that developed and use each framework: case studies using Adaptation Pathways/DAPP are primarily European, but those using Decision Scaling and RDM are primarily North American (see Figure 2). The case studies represented a wide range of different locations across five continents. In 2010–2013, the literature was dominated by use of the RDM framework for case studies from North America, but among 2018–2022 publications the Adaptation Pathways/DAPP framework was more prevalent.

As shown in Figure 2, almost all case studies referred to some structural adaptation; less than half also used non-structural adaptation. For this literature review, we adopt the nomenclature used by the U.S. Army Corps of Engineers and National Research Council, and refer to non-structural adaptations as those that aim to reduce exposure of vulnerability to flooding without architectural or construction-based techniques (National Research Council, 2014). For example, construction of a reservoir or sea wall, raising or elevation of existing structures, and other infrastructural retrofits are considered structural adaptation measures for the purposes of this review. Managed retreat, water management strategies (e.g., reservoir operation guidelines), and other policy interventions are considered non-structural. Thirteen case studies referred only to non-structural adaptation for flood management. Sixty four of the 122 case studies included green infrastructure as a structural adaptation measure; this subset will be more fully explored in Section 6.

5.1. Performance Metrics

A range of performance metrics were used to assess the adaptation measures in the literature. Most case studies used multiple metrics in assessing performance of adaptation strategies, but a single cost metric, a single physical metric, or qualitative metrics were also used.

5.1.1. Physical Performance Metrics

Fourteen of the 122 case studies used a single performance metric. The most widely used was a measure of flood depth or flood level (7 of 14 case studies; Brown et al., 2011; Cheng et al., 2017; Radhakrishnan, Nguyen, et al., 2018; Roy et al., 2020; Smallegan et al., 2017; Yin et al., 2017; Zevenbergen et al., 2020). Other physical metrics used included discharge volume of a dike or reservoir (Raso, Kwakkel, Timmermans, Panthou, 2019; Van Vuren et al., 2015) and pollutant reduction metrics, such as the total maximum daily load (Jiang et al., 2017; Tariq et al., 2017).

5.1.2. Monetary Performance Metrics

Thirty one of 122 case studies used a single monetary metric. In most cases, costs were estimated using Net Present Value (NPV) for adaptation costs and benefits, such as expected annual damages or damage functions (e.g., Ceres et al., 2019; de Ruig et al., 2019; Genovese & Green, 2015; Haasnoot, van Aalst, et al., 2020; Löwe et al., 2017; Moore et al., 2016; Radhakrishnan, Islam, et al., 2018; Sriver et al., 2018; Wong et al., 2017). Cost effectiveness, such as cost per gallon of reduced combined sewer overflow, was also a common metric (e.g., Mei et al., 2018; van Veelen et al., 2015; Xie et al., 2017; Xu et al., 2019).
Whether cost was used as a single metric or one of many metrics, different researchers considered different types of costs for cost benefit analyses. Costs could be estimated based on market prices (e.g., Mobley et al., 2020), investment or installation costs (e.g., Ceres et al., 2019; Sriver et al., 2018), or replacement costs (e.g., Hérivaux et al., 2018). In some cases, researchers specified that operational and maintenance costs were not included (e.g., Hall et al., 2019) while others specified that these costs were included (e.g., Tingstad et al., 2014; M. Wang et al., 2017). Some researchers estimated costs based on past research or existing literature (e.g., Aerts

![Flow chart depicting methodology. Numbers within circles represent number of publications, unless specifically labeled as case studies. Bold numbers refer to subsections in this review where these trends are discussed (e.g., [§5]).](chart.png)
et al., 2018; Ashley et al., 2018; Cabral et al., 2019; Ciullo et al., 2019; Mei et al., 2018; M. Wang et al., 2017). Of the case studies that included green infrastructure as an adaptation strategy, most did not discuss or try to monetize the co-benefits of green infrastructure, in fact a few went so far as to avoid monetizing co-benefits because of the difficulty of estimating costs for various ecosystem services, as discussed briefly in Section 3.3 (e.g., Hall et al., 2019; Moore et al., 2016).

5.1.3. Multiple Performance Metrics

Sixty-five of 122 case studies used more than one metric to assess and compare adaptation strategies. Each publication assessing performance using multiple metrics referred to between two and 10 metrics, most which (41 of 65 case studies) included some form of monetary metric (e.g., Groves & Sharon, 2013; Kapetas & Fenner, 2020; Kasprzyk et al., 2013; Lawrence & Haasnoot, 2017; Manocha & Babovic, 2018; Poff et al., 2016; Ramm et al., 2018a, 2018b). Of these 65 case studies, 12 used Pareto optimization techniques to evaluate conflicting objectives. These conflicts were usually between the expected cost and the expected level of service, performance, or benefits, such as a reduction in greenhouse gas emissions, reduction in levels of pollutant in a lake, or improvement in volumetric reliability (e.g., Beh et al., 2015b; Giuliani & Castelletti, 2016; Hadka et al., 2015; Singh et al., 2015). Most of these publications used the Multiobjective Optimization Evolutionary Algorithm (MOEA), the Nondominated Sorting Genetic Algorithm II (NSGA-II) or a variant of these algorithms to illustrate important tradeoffs (e.g., Borgomeo et al., 2016; Hadka et al., 2015; Kasprzyk et al., 2013; Quinn et al., 2018).

5.1.4. Qualitative Performance Metrics

Twelve of 122 case studies used qualitative performance metrics, that is, they evaluated performance through conversations with stakeholders or other methods estimating non-quantitative metrics such as political risk of retreat (e.g., Gibbs, 2016) or societal perception of flooding (e.g., Radhakrishnan et al., 2017). All of these case studies except one used the adaptation pathways framework, where tipping points can be identified through interviews or other participatory processes.

5.2. Climate Change Representation and Data Sources

Some case studies (32 of 122) evaluated flood risks without explicitly modeling climate change, but most used scenarios (71 of 122 case studies) or change factors (13 of 122 case studies) to represent future projections compared to base case scenario or present day (see Table 2). These scenarios and multiplicative or additive change factors were primarily informed by downscaled climate projections from the Coupled Model Intercomparison Project Phases 3 and/or Phase 5 (CMIP3 and/or CMIP5) as represented by the downscaled projections category shown in Table 3. Existing literature or expert elicitation was sometimes used to estimate change factors (e.g., Buurman & Babovic, 2016; Wu et al., 2017) and scenarios (e.g., Aerts et al., 2018; Casal-Campos et al., 2015; Löwe et al., 2017; Ramm et al., 2018a).
In order to represent climate change, case studies also referred to global scenarios such as those found in the Fourth and Fifth Climate Assessments Reports from the Intergovernmental Panel on Climate Change (IPCC), local scenarios such as those developed by the Royal Netherlands Meteorological Institute and the UK Climate Projections to inform climate uncertainty (Institution of Civil Engineers, 2019; IPCC et al., 2014; KNMI et al., 2014), and other scenarios with simple metrics (e.g., 1 m of SLR; e.g., Hérivaux et al., 2018) or scenarios unique to the application (e.g., Fu et al., 2015; Singh et al., 2015).

Case studies that used probabilistic estimates in Tables 2 and 3 primarily used generalized extreme value distributions (e.g., Ceres et al., 2019; Raso, Kwakkel, & Timmermans, 2019; Sriver et al., 2018) or annual exceedance probabilities (Groves et al., 2014; Hall et al., 2019; Johnson et al., 2013; van Veelen et al., 2015) to represent climate change uncertainty. These probabilities were extracted from historical information (Ceres et al., 2019; Raso, Kwakkel, & Timmermans, 2019; Sriver et al., 2018).

6. Green Infrastructure Adaptation Strategies Within DMDU Approaches for Flood Management Under Climate Change: Trends and Patterns

This subset of case studies using green infrastructure as an adaptation strategy showed similar trends to the publications outlined in Figure 2. “Green infrastructure” was the most common search term among the publications and the absence of other terms such as “compensatory techniques” or “storm water quality improvement devices” aligns with the trends identified by (Fletcher et al., 2015; see Figure S1 in Supporting Information S1). The use of different green infrastructure terms used based on continent or location also generally aligned with trends in Table 1. For example, the term “water sensitive urban design” was used in case studies from Oceania.
while “sponge city” was used exclusively in case studies from Asia (see Figure S2 in Supporting Information S1). Among the 64 case studies, 25 did not use any of the terms in Table 1, but still referred to green infrastructure strategies for adaptation. Eighteen of these 25 publications were focused on adaptation to coastal flooding.

### 6.1. Green Infrastructure Strategies

The 64 case studies incorporated a range of 24 different green infrastructure strategies, the most popular of which were porous pavements, green roofs, and bioretention cells. This is shown by the value of the cells along the diagonal in the heatmap in Figure 3. Most case studies (40 of 64) assessed more than one type of green infrastructure strategy. Cells on the off-diagonals represent the number of publications in which these two strategies were used together. The strongest cluster of green infrastructure strategies included green roofs, permeable pavements and bioretention cells, with a second cluster among detention tanks or ponds and rainwater or stormwater harvesting as shown in the value of the non-diagonal cells in the heatmap in Figure 3 (Fischbach et al., 2017; Kirshen et al., 2015; Mei et al., 2018; M. Wang et al., 2017; Xie et al., 2017; Xu et al., 2019). Clusters observed among the 24 green infrastructure strategies for all 64 case studies can be found in the Supplemental Figures (see Figure S3 in Supporting Information S1).

![Figure 3. Heat map showing correlations among the strongest cluster of green infrastructure strategies employed among the 64 case studies reviewed. Cells along the diagonal represent the number of publications in which that strategy was used. Cells on the off-diagonals represent the number of publications in which these two strategies were used together.](image)

### 6.2. Hydrologic and Hydraulic (H&H) Modeling

Many of the case studies (31 of 64) used the simpler 1D or 1D/2D modeling to understand performance of green infrastructure and impact of flooding (e.g., Casal-Campos et al., 2015; Ghodsi et al., 2016; Kim et al., 2017; Kirshen et al., 2015; Mei et al., 2018; Moore et al., 2016; Ramm et al., 2018a; M. Wang et al., 2017, 2019). The most popular among these models was the Storm Water Management Model (SWMM), an open source model developed and maintained by U.S. EPA scientists (Niazi et al., 2017). SWMM is adequate for hydrologic applications in sub-catchments or neighborhoods, and therefore is often used for urban and municipal settings. Other researchers developed their own hydrologic models, or used locally developed models for analysis (e.g., Fu et al., 2015; Manocha & Babovic, 2018), Additional modeling options included 2D and/or 3D models (e.g., Aerts...
et al., 2018; de Ruig et al., 2019; Fischbach et al., 2020; Genovese & Green, 2015; Haasnoot, Kwadijk, et al., 2020; Smallegan et al., 2017) such as MIKE (DHI, 2017), CoSMoS (Barnard et al., 2014; Erikson et al., 2018; O’Neill et al., 2018) and SLOSH (NOAA, 2022); water balance models (e.g., Beh et al., 2015a, 2015b; Fischbach et al., 2015; Wu et al., 2017); and various conceptual or other frameworks (e.g., Haasnoot, van Aalst, et al., 2020; C. Rosenzweig & Solecki, 2014; Smith et al., 2013; Thorn et al., 2015). Each of these additional modeling categories represented 14 or fewer case studies.

Many of the models were used to characterize water quantity: specifically the depth or location of urban flooding (e.g., Fischbach et al., 2020; Kapetas & Fenner, 2020; Kim et al., 2017; Kirshen et al., 2015), total flood or runoff volumes (e.g., Fischbach et al., 2017; Xie et al., 2017), peak flows (e.g., Babovic & Mijic, 2019; Dittrich et al., 2019; Mei et al., 2018), or an aggregated flood or resilience index (e.g., Cheng et al., 2017; M. Wang et al., 2017). Water balance models especially were used to quantify available water supply for a catchment or study area (e.g., Beh et al., 2015a; Manocha & Babovic, 2018; Wu et al., 2017). Coastal case studies typically used H&H models to characterize the depth or extent of storm surge (e.g., Genovese & Green, 2015; Peyronnin et al., 2013; Smallegan et al., 2017), or sea level rise (e.g., de Ruig et al., 2019; Haasnoot, Kwadijk, et al., 2020; Kool et al., 2020; Kwakkel et al., 2016). Some models were used to characterize water quality (i.e., pollutant loading; e.g., Fischbach et al., 2015; Tariq et al., 2017; Xu et al., 2019), or a combination of water quantity and quality metrics (e.g., Casal-Campos et al., 2015; Di Matteo et al., 2019; Ghodsi et al., 2016; Kim & Chung, 2014; Liang et al., 2020; Zhang et al., 2019).

6.3. DMDU Metrics

Similarly to H&H models, many case studies used the simpler DMDU metrics for evaluation of alternative strategies. Descriptive statistics such as maximizing NPV or minimizing costs were most popular (42 of 64 case studies; e.g., Aerts et al., 2018; Kirshen et al., 2015; Löwe et al., 2017; Moore et al., 2016; Xie et al., 2017). A similar finding was revealed in the 2019 review by Johnson & Geldner, 2019. In most cases, researchers compared a number of strategies and solutions to find the one with the minimum value (costs) or a maximum value (benefits). Some case studies also used multi-criteria optimization strategies such as Multi-Criteria Decision Analysis, Technique of Order Preference Similarity to the Ideal Solution, or Nondominated Sorting Genetic Algorithm II to evaluate adaptation strategies (e.g., Kim et al., 2017; Manocha & Babovic, 2018; M. Wang et al., 2017; Wu et al., 2017). Only four used Pareto optimization (Beh et al., 2015a, 2015b; Manocha & Babovic, 2018; Di Matteo et al., 2019).

Satisficing approaches were also found in the literature (8 of 64 case studies), most of which used scenario discovery or similar models (e.g., Babovic & Mijic, 2019; Fischbach et al., 2017, 2020; Radhakrishnan et al., 2019; Ramm et al., 2018a; Tariq et al., 2017). More complex regret-based approaches (Casal-Campos et al., 2015; Kim & Chung, 2014; van der Pol et al., 2021) were less popular. Other frameworks included real options analyses (Buurman & Babovic, 2016; Dittrich et al., 2019; Manocha & Babovic, 2016, 2018) and game theory (Ghodsi et al., 2016). Of the case studies that used the more rigorous scenario discovery or stress testing criteria, four explicitly used publicly available toolkits or algorithms such as the Patient Rule Induction Method (PRIM; Fischbach et al., 2017, 2020; Ramm et al., 2018b; Tariq et al., 2017).

7. Discussion and Conclusions

7.1. Discussion and Suggestions for Future Work

7.1.1. Green Infrastructure Terms and Strategies

It is difficult to compare practices and results among green infrastructure installations in different disciplines or continents, partly because of the use of many different green infrastructure terms and types. This is particularly prominent when considering riverine/inland and coastal applications using green infrastructure strategies. Other reviews of the green infrastructure literature have found that the overlapping terminology and conceptualizations can hinder communication, collaboration, and research discovery (Kotze et al., 2020; Matsler et al., 2021; Osaka et al., 2021; Prudencio & Null, 2018). The range of terms and strategies outlined in this review highlight the fact that researchers need to clearly convey the strategies used as well as the methodologies and assumptions made to facilitate future research around green infrastructure applications.
7.1.2. Performance Metrics

A wide range of performance metrics and assumptions associated with monetary metrics presents the same sort of difficulties as the wide range of green infrastructure terms. Future research elucidating the co-benefits of green infrastructure projects and developing methods extending and building on benefit-cost analysis (e.g., Haasnot, van Aalst et al., 2020; Woodruff et al., 2018) could greatly inform feasibility and costs and benefits of robust strategies for DMDU. Estimating individual or community willingness to pay is one common way to monetize benefits, but can be difficult to derive (Banfi et al., 2008; Breidert et al., 2006; Daziano & Achtnicht, 2014). In addition, this metric represents the benefit for an “average” individual, therefore excluding those individuals in low income communities who are likely to be more vulnerable to the effects of climate change (Levy & Patz, 2015; Reckien et al., 2017; USGCRP, 2018). These factors tend not to be deeply uncertain, and so uncertainty could be represented using a sensitivity analysis or standard errors (Daziano & Achtnicht, 2014). However, this kind of analysis tends not to take risk preferences into account, and costs and benefits are likely to be different for different subsections of the population (Fischbach et al., 2020). Future cost benefits methods should consider co-benefits of green infrastructure without neglecting the effects of adaptation strategies on equity among different stakeholder groups.

7.1.3. Climate Change Uncertainty

It is computationally challenging to represent uncertainty due to climate change and/or represent the many plausible future scenarios of the world (Flato et al., 2013). In addition, statistical or empirical downscaling requires significant data and computational inputs as well as technical expertise (Diaz-Nieto & Wilby, 2005; Farjad & Gupta, 2017). Many of the publications assessed in this review refer to downscaled climate projections in assessing climate change uncertainty. Some downscaled projections are publicly available for download, but these data sets are more likely to be available for developed countries. If the data are available, the small spatial scale of green infrastructure projects (parcel scale, m to km) is smaller than the spatial scale of publicly available downscaled climate data (~10 km; Brekke et al., 2013; Lopez-Cantu et al., 2020). Lastly, methodological decisions such as the type or number of climate models, downscaling techniques, data sets used, and time period of study can strongly influence the future projections and therefore change the adaptation decision made based on these projections (Cook et al., 2020; Ekström et al., 2016; Lutz et al., 2016). These compounding factors may discourage or limit the representation of climate change uncertainty in decision making.

The timing and magnitude of local climate impact will likely remain deeply uncertain, but future work expanding open source downscaled climate data to represent more geographical regions could encourage the use of DMDU frameworks to plan for flood management under climate change. Further research identifying the effects of methodological choices for decision making could also guide understanding about relative importance of decisions, and therefore which decisions should be the focus on discussions among all stakeholders.

These methodological choices can be difficult to communicate to non-expert stakeholders. A climate change factor, one of the more common representations used in the literature (Wasko et al., 2021), is a relatively simple way to represent future scenarios (Casal-Campos et al., 2015; Cook et al., 2017; Fischbach et al., 2017; Kapetas & Fenner, 2020). This factor representing the ratio between some statistic in the future and the same statistic in the past or present may be also easier to explain to policy makers and non-experts (Ruiter, 2012). However, despite their prevalence, there are no clear guidelines on how climate change factors should be developed or used (Anandhi et al., 2011; Wasko et al., 2021) and there is no consensus on how climate change should be represented for flood management or how to design for non-stationarity in floods (François et al., 2019; Serinaldi & Kilsby, 2015). For instance, change factors can be additive or multiplicative, and can be calculated for all values of the variable or for particular percentiles (Anandhi et al., 2011). In a recent peer-reviewed report, Miro et al. (2021) transparently reported the development and use of change factors to update intensity-duration-frequency curves: multiplicative changes between historic and future values were calculated for individual quantiles for the 24 hr rainfall depth. This method, the quantile delta method, is one of many equally viable methods, and this gap should be addressed in future research.

7.1.4. Modeling and Computational Complexity

Within this review, modeling and computation complexity can be represented by the hydrologic models and DMDU methods and metrics used in the literature. The relatively large number of publications using descriptive statistics rather than satisficing or regret highlights the computational complexity of DMDU approaches. Formal
models and techniques can be expensive and time consuming as well as data intensive, requiring hundreds of thousands of dollars and thousands of CPU-hours for simulation (Fischbach et al., 2017; Hallegatte et al., 2012). Pursuing green infrastructure studies using DMDU approaches that are anchored in the criterion of regret and satisfying requires significant processing and/or calculations that may be outside of some organizations’ capabilities or expertise (Fischbach et al., 2020).

Existing DMDU methods and guidance in the form of GitHub repositories, R packages, Python notebooks, and blogs should be more widely used to guide modeling endeavors and methods for satisficing and regret. Examples include the R package for scenario discovery (sdtoolkit; Bryant, 2015; Bryant & Lempert, 2010), the Exploratory Modeling and Analysis workbench developed by researchers at Delft University of Technology (Kwakkel & Pruyt, 2013), Open MORDM for multi-objective optimization (Hadka et al., 2015), PRIM (Duong, 2021), and other packages such as the R package foresight (B. Bennett et al., 2019).

It is important to continue to develop new tools and maintain existing open source tools. Packages and programs should be supported by experts within the field and be frequently updated (Niazi et al., 2017). For example, more recent versions of SWMM (beginning with 5.1.010) have a built-in modeling capacity for low impact development, encouraging further analysis of green infrastructure for flood management. Development of new open source software and expansion of existing modeling tools and packages for hydrological and hydraulic modeling and DMDU approaches can support further research at the intersection of these three fields. If researchers prefer to use tools developed by their own groups rather than than previously developed tools and frameworks developed by peer groups (Moallemi et al., 2020), care should be taken to avoid unnecessary redundancy in modeling tools and frameworks.

Using these methods still leads to increased computational needs compared to the simpler robustness criteria, and data requirements can be significant. Future work could expand on the possibility to analyze DMDU for green infrastructure without formal models, for example, with increased use of expert analyses or stakeholder expertise (Popper, 2019). Expert elicitation is an increasingly popular way to assess the deep uncertainty associated with climate change decision making, for example, for precipitation patterns (Dessai et al., 2018), energy (Usher & Strachan, 2013), and sea level rise (Garner et al., 2018). Expert elicitation can sometimes be perceived as a low-effort alternative to computationally intensive analysis, but it is also time consuming, requires careful consideration of the questions being asked, and is, by definition, subjective and influenced by human bias (Morgan, 2014). Finally, using rainfall measures as a proxy to track or predict the hydrologic performance of green infrastructure, may provide a less data and computationally intensive method under uncertainty than hydrologic simulation and on-site sensors (Cook et al., 2021).

### 7.2. Conclusions

This review characterizes the state of the literature at the intersection of three interconnected fields: flood management, DMDU, and green infrastructure. The publications reviewed represent a range of locations, adaptation strategies, modeling techniques, data sources, and assumptions. Future research could focus on the co-benefits of green infrastructure and development of metrics to evaluate these co-benefits, as well as further understanding of green infrastructure types to improve communication among stakeholders and encourage future research.

Despite attributes of green infrastructure suggesting it would be a useful and robust strategy for DMDU analyses, trends toward simpler hydrologic models and DMDU metrics support the notion that there are potential computational and modeling barriers to using DMDU and green infrastructure in planning for flooding and flood management under climate change (Fischbach et al., 2020). Publications in the literature have used some publicly available methods and statistical packages, but the data requirements necessary for accurate analyses can be high. Significant data and computing requirements could be one factor inhibiting more formal DMDU studies for green infrastructure strategies. It is likely that the open source tools, frameworks, and solutions already being used in the literature will be further employed to grow the body of literature at the intersection of the three fields included in this review. Maintenance and improvement of existing tools, development of new tools, and continued transparent research demonstrating their use can further facilitate the use of DMDU frameworks in future research.

We acknowledge the limitations of the search parameters within this review. These trends are identified from a relatively small sample of publications in English from three databases through January 2022. We acknowledge that this field is quickly growing, as evidenced by 36 of 237 publications that were identified using our search.
parameters between December 2020 and January 2022. A number of expanded terms (see Table 1) were used to broaden the search beyond the predominant term used in this review (“green infrastructure”), but these terms were also closely related to urban drainage, and did not include other green infrastructure terms identified in the literature, such as urban forestry or ecological infrastructure (Matsler et al., 2021). Further review including “resilience” or “water management” as search terms would expand the number of publications for review and could lead to identification other important trends for future research. Similarly, further review could include a wider range of terms related to decision making under uncertainty than the three (“robust decision making”, “adapt* pathway*”, and “decision scaling”) considered in this review.

Throughout this review, discussions about uncertainty and deep uncertainty have focused on uncertainty surrounding climate change impacts. However, there are many other potential sources of uncertainty, such as trends in land use and land cover and urbanization, the changing intensity of precipitation that leads to flooding, and the performance of different types of green infrastructure installations over time. For example, authors have identified and analyzed significant uncertainties in land use and land cover projections on global and continental scales, attributed to multiple components of uncertainty (Alexander et al., 2017; Prestele et al., 2016). Depending on the type of flooding being experienced and the geographical location of a particular green infrastructure installation, different types of green infrastructure may be more effective or more cost effective. In addition, the effectiveness of aging green infrastructure remains an active field of research. Focusing only on one type of green infrastructure, green roofs, authors have used lab scale experiments and modeling approaches to draw opposing conclusions about the potential storm water retention of aging green roofs (Bouzouidja et al., 2018; De-Ville et al., 2017, 2018). Future work could highlight these and other potential sources of uncertainty, perhaps quantifying them in comparison to climate uncertainty, and further developing these active areas of research.

DMDU and green infrastructure are both remarkably interdisciplinary approaches by which stakeholders can successfully plan for and adapt to flooding exacerbated by climate change. Future research incorporating these complementary fields should focus on communication among different stakeholders and experts, particularly in defining definitions, assumptions, and data requirements are clear. These transparent partnerships can then facilitate effective application of robust strategies such as green infrastructure for urban adaptation to the effects of climate change.

Conflict of Interest
The authors declare no conflicts of interest relevant to this study.

Data Availability Statement
The data set detailing the unique publications and case studies identified in this review is accessible at (Webber & Samaras, 2022).

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