

# Resilience by design: A deep uncertainty approach for water systems in a changing world

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## ABSTRACT

Current water infrastructure designs and design processes are ill-suited to address deep uncertainties related to climate variability and change. Water systems increasingly exhibit fragility to extreme weather events and changing climate conditions. The concept of resilience offers a framework to improve water system design for uncertain futures by incorporating capabilities such as persistence, adaptability and transformability. Existing formalizations of resilience in engineering design, however, are dependent on assumptions of climate and hydrologic stationarity and of well-characterized uncertainty, rendering them obsolete relative to our current understanding of the uncertainties we face. In this paper, we use methods based on decision making under deep uncertainty to establish a methodology to design for the resilience of water systems. The formulation generates water system design options that provide resilience capabilities at least cost and specify the optimal choices for persistence, adaptability and transformability for performance over a wide range of possible futures. As it was developed for application beyond water systems, the Resilience by Design is a generalizable approach offering important new methods of planning and managing for the resilience of critical infrastructure.

## 1. Introduction

Recent and repeated incidence of extreme weather resulting in major disasters to cities, and to agricultural systems, with countless human victims plainly reveals that society is not prepared for the climate risks we now face. These events and their often catastrophic consequences are increasing in frequency relative to historic norms [47] and overwhelming infrastructure designed according to that history. The infrastructure underpinning our vital water systems is particularly vulnerable. Why are water infrastructure systems unable to handle these shocks? The primary reason is a failure of planning and design to accommodate these events. Water systems and the infrastructure and operational rules that undergird them have been designed using static assumptions of climate and deterministic assumptions of other key design variables. Consequently, our water systems are not designed to handle climate surprises [40], and as a society we are exposed to more risk than intended in our infrastructure design and often much greater vulnerability than we realize. In short, we have been overconfident in our ability to anticipate and design for an uncertain future and thus, too often, our support systems fail in the face of surprise.

Climate changes are expected to cause an increase in the frequency and magnitude of extreme weather events, subsequently increasing the

risk to infrastructure systems and to the communities that depend on them. Empirical studies have provided evidence of increasing trends in climate extremes [11] while also indicating that some trends may be occurring that we have yet to detect, like flood risk [48]. Yet, the complexity of the earth's climate, including the chaotic manifestations of natural variability, defy immediate progress in the accurate prediction of weather-related design variables [19,25,32,45,10,26]. Despite the expectation that, on average, extreme weather events will increase, we currently lack the technical ability to estimate changes at specific locations at the temporal and spatial scales required for infrastructure design [49].

The lack of precise estimates of essential design variables, including knowledge of the direction of change in the case of precipitation for many regions [22], has troubling implications for water infrastructure system design and operations. Typical infrastructure design processes use deterministic methods that depend on single estimates of future design variables. More advanced approaches use probabilistic estimates of design variables that are represented with probability distribution functions. Now, ample evidence suggests that the probability distributions themselves are changing over time, in ways we can only partially anticipate [e.g., [44,2,5]]. Without a reliable replacement for historical probabilities, however, current design methods are caught between dependence on potentially unreliable estimates based on the historical

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record and projections from models that do not reliably simulate the variables of concern. Compounding current challenges, our design approaches depend on risk-based benefit cost analysis that rely upon the estimation of weather risks that we cannot accurately predict. As a result, we face valid and urgent concerns for the future performance of our infrastructure systems amidst increasing evidence of their fragility.

There is growing public recognition that these are critical design challenges given our limited ability to anticipate the trends and shocks of the future. Indeed, society's desire to build the resilience of critical systems is a response to heightened awareness of the fragile nature of infrastructure. While climate research may eventually improve our ability to predict climate futures, society must make decisions now on infrastructure design. Our current design approach will have lasting consequences for future preparedness. While we have little control over the weather and our ability to accurately predict future climates, the methods we choose to design infrastructure systems for resilience to future stressors are within our control. Recent advances in decision making under uncertainty and high-performance computing enable new design methods that are capable of meeting this challenge [31]. Here, we endeavor to take up that challenge through advances in methods for systems analysis and resilience design.

Applied systems analysis and resilience science aim to address the challenge of designing critical systems, such as water infrastructure, for future uncertainties and related risks. Our conception of resilience couples the engineering design standard of robustness with the ecological concepts of persistence, adaptation, and transformation (cf, [14,6]). We define a resilient infrastructure system as one that can maintain its function and services over a wide range of future conditions, adapting and transforming to accommodate change, while managing failure in a systematic manner that limits damages and costs during extreme events. Resilience is rarely applied quantitatively in the design of infrastructure systems (e.g., [1] and, in those rare cases, only probabilistic approaches have been applied (e.g., [20,50]). Examples include logistic networks, such as electric motor supply chains [21], runway use scheduling [51] and transportation networks (e.g., [41,23]). Where uncertainties can be confidently characterized in probabilistic terms, these resilience design methods may be adequate. However, the design of long lived infrastructure systems demands methods that can address uncertainties that defy confident assignment of probability distributions to outcomes. Such uncertainties have been described as "severe," "Knightian" and most recently as "deep uncertainty" and include uncertainties associated with climate change, population growth and demand transitions, among others [42]. Knight [24] proposed the original distinction between "risk", which was characterized by unknowns that could be described probabilistically, and "uncertainty" which could not be described probabilistically due to lack of adequate knowledge. To build resilience in the face of deep uncertainty requires a more robust, quantitative approach to designing infrastructure systems.

In this paper we propose a new methodology to incorporate decision making under deep uncertainty within resilience design processes. This is possible through the application of decision making under deep uncertainty (DMDU) theory to a formulation built upon optimal control theory. The resilience design literature provides a probabilistic basis for the mathematical formulation, which is updated for the case where assigning a single probability distribution to uncertain variables is not advisable. In Section 2 we describe in more detail the sources of shortcomings in current infrastructure design approaches and the guidance that the resilience literature offers for addressing them. In Section 3, we suggest a solution in the form of an optimal control model addressing the key principles derived in Section 2. In Section 4, we describe the implementation of the model within a DMDU framework. The paper closes with final considerations for further development and application of this new framework, which we call "Resilience by Design".

## 2. Designing infrastructure for a deeply uncertain future

Infrastructure investments entail large capital costs, affect large areas, are long to construct and long-lived, and are unique by nature of their social-ecological setting. Many infrastructure systems design efforts commonly require tradeoffs among diverse interests with differing preferences, with effects that are realized over long time periods and large spatial areas. The design process for new projects and systems can be lengthy and highly complex, as they often have the potential for significant societal and environmental impacts, both positive and negative, that go well beyond the lifetime of the investment [52,53]. To these complexities we must add uncertainty related to future climate, societal and Earth system conditions, as we reckon with evidence of our limited ability to accurately anticipate the future (e.g., [38]). Recognition of these concerns has motivated growing interest in resilience design for infrastructure, understanding that these critical systems must perform well in the face of uncertainty and surprise [54].

Conventional infrastructure design and evaluation methods are based on assumptions of well-defined uncertainties using fixed probability distributions in the cases where uncertainty is quantitatively addressed. Unwarranted confidence in our ability to describe uncertainty can exacerbate system vulnerability and undermine resilience [28]. Both Cost Benefit Analysis (CBA) and our application of Cost Effectiveness Analysis (CEA) as standard design and decision criteria demonstrate how resilience can be undermined by overconfidence in probabilities. Cost Benefit Analysis and related methods (e.g., CEA) often guide infrastructure design and are typically authoritative when evaluating infrastructure alternatives. Since at least the U.S. Flood Control Act of 1928, CBA has been the basis for evaluating alternative water infrastructure designs [55].

The inability to accurately estimate the probabilities of climate-related design values in the future undermines CBA because of its dependence on such probabilities. For example, the typical design approach for a flood control system requires estimation of the probability of occurrence of flood magnitude, which is used to estimate the expected benefits of flood risk reduction. In a context of perfect information, risk-based CBA leads to the efficient use of financial resources. The efficient level of flood protection is the level at which the expected benefits of the flood protection system (avoided damages) meet or exceed the expected cost of providing that protection. Events that exceed that magnitude are expected to happen so rarely that they do not warrant design consideration. In this context, CBA informs the design process by assuring that resources are used efficiently in an economic sense. However, the effect of climate change on hydrologic variability and extremes defies our ability to estimate the required probabilities. Consequently, this standard design approach breaks down. Use of historical observations to estimate flood probabilities may underestimate (or overestimate) the risk as yet there are no credible predictions of what the future probabilities are likely to be.

The evidence suggests that a wide range of uncertainties cause unreliable estimates of costs and benefits in infrastructure design. Flyvbjerg [56] is particularly critical of infrastructure design approaches, citing CBA as "strongly misleading" and a cause of misplaced overconfidence in design certainty (cited in [57]). Dams in particular have been identified as problematic from a financial, environmental and social perspective [58]. Key issues include the difficulty of discounting future costs and benefits, underestimation of the value of losses (common given the loss averse nature of human value judgments), and the difficulty of estimating effects within complex systems [16]. This challenge is increased when ecosystem services are involved, as they present additional non-market valuation and benefit aggregation concerns [43].

In addition, conventional design approaches do not adequately consider the performance of the system in failure. Instead, the typical approach is to satisfy a specified level of reliability (meaning non-failure) for providing desired services. With the design level of

reliability met, the ultimate consequences of cases that end in failure are typically disregarded. Lack of consideration of the consequences of failure is especially problematic given the well-established human nature of risk aversion. Empirical studies demonstrate that people prefer to avoid a loss of a given magnitude over a gain of the same magnitude and the difference in preferences may be quite large [16], [59]. Brown and Gregory [60] found the preference for avoiding losses over equivalent gains to be on the order of 2:1 to 5:1 in experimental tests (cited in [16]). Insurance markets exist to enable people to avoid large private financial losses, demonstrating their willingness to pay to do so. However, there is no equivalent real (versus financial) mechanism for humans to avoid losses from infrastructure failure. Faced with deep uncertainty relative to future conditions of the Earth system and to complex human societal change, conventional project evaluation frameworks that are dependent on probabilities that we cannot reliably estimate and that also disregard the consequences of failure are not merely obsolete; they are arguably a critical liability and source of fragility for critical infrastructure systems.

### 3. Resilience by design

Resilience offers the conceptual framework for updating infrastructure design methods to prepare for the future. Advances in resilience science (cf. [61,62,14]) suggest that resilience refers to the ability of a system both to remain in its current equilibrium, persisting under and adapting to change, as well as its ability to shift or transform to a new equilibrium, thriving in a changed configuration. Resilience derives from the system's "identity" – its components, their configuration and interactions – which enables it, under disturbance, to maintain coherent "function" within an expected range of variation [6]. System "functions" include the provision of specific services, or more broadly, the societal services produced by natural systems and economic and social capital from human systems (*ibid*). This conceptualization of resilience addresses the need to recognize that under extreme change, systems cannot merely persist without change but must adapt and transform to novel conditions and stressors. Under changing climate and water futures, this approach to resilience enables design to sustain system function and services for the long term under whatever range of stressors may be projected. Following the framing proposed in related work [14,6] we suggest that three capabilities characterize a resilient system:

- **Persistence:** its ability to maintain coherent function in response to disruption and changing conditions without altering its identity;
- **Adaptability:** its ability to maintain coherent function by modifying its identity to accommodate change;
- **Transformability:** its ability to change identity and to establish a new, stable function when pushed beyond tipping points that preclude maintaining its prior state

The Resilience by Design framework thus focuses on identifying and evaluating the performance of a given system design or "identity" in terms of its persistence, adaptability and transformability in the face of future hazards and to incremental change (see Fig. 1). The proposed framework provides an analytical approach to the design of systems that perform coherently under the stresses of gradual change and of rapid onset shocks that would otherwise preclude its function and provision of services. For instance, a resilient water infrastructure system would be able to sustain its water provisioning, water quality regulation, and waste- and storm-water management services under both low frequency changes and trends in precipitation regimes as well as extreme flooding or drought events.

The resilience literature implicitly acknowledges the difficulty of foreseeing future conditions and the effects they yield in a complex system (c.f., [63]). Meanwhile, the resilience *design* literature is largely based on probabilistic approaches that rely on an assumption of

prescribed future probabilities. The result is resilience design approaches that address uncertainty and capabilities such as persistence and recovery, but only when probabilities can be well defined. Uncertainties that must be considered for our future system and infrastructure designs are not so easily predicted. Climate change, for instance, defies our accurate prediction.

The prevailing approach in the resilience design literature formulates the design challenge as an optimal control problem. The methods integrate the design of a system with the monitoring and control functions that enable adjustment to changing conditions. Hosseini et al. [21] summarizes this literature, which typically examine network systems, especially transportation and logistics. A large number of studies use optimization models to prescribe optimal recovery strategies (see [64,65,1]). Uncertainty is generally modeled probabilistically, for example, assigning probability density functions to network outage occurrence and location [21,46,34] or not explicitly considered [28]. Furthermore, there is no recognition of the dependence of built infrastructure systems on the resilience of ecosystems and the services they provide.

Youn et al. [46] provides an instructive probabilistic formulation. The model consists of "resilience-driven system design" featuring a design objective that is the sum of "reliability," which is satisfactory performance for assumed conditions and "restoration" which is recovery from a problematic condition or state. This model provides a useful basis for resilience design by integrating the design of the system with the ability to recover from failure as well as predictive functions to proactively adapt to changing conditions when and if they are detected. However, the Youn et al. [46] model is developed for cases of well-characterized uncertainty and short operational periods, such as an aircraft control actuator. Consequently, there is no consideration of the effects when the system enters failure mode, as infrastructure systems sometimes do, but aircraft must never. There is also no acknowledgment of changing probabilities over time and uncertainty in probability distributions due to the short time horizon considered. These are not tenable assumptions for infrastructure design. Achieving resilience in infrastructure systems requires planning for the long term and for the uncertainties and surprises the future may hold. In particular it requires accommodation for the need to transform when the current system configuration can no longer provide the required services.

Recent advances in decision making under deep uncertainty provide an opportunity to advance the probabilistically-based resilience design approach presented by Youn et al. [46] for applicability to the design of infrastructure systems. This growing subfield hails from the discipline of decision analysis. Marchau et al. [31] provides a recent review and sampling of these methods. The core of the framework focuses on using multi-dimensional sensitivity analysis to assess the performance of alternative strategies over a wide range of possible futures (e.g., [4,12,27]). In this literature, providing acceptable performance over a wide range of futures is referred to as robustness. Some methods use single or multiple probability distributions to characterize the weight of evidence for the robustness of a strategy, for example, by quantifying the probability assigned to the futures to which a strategy is robust [9,39]. This approach has been widely applied to assess the robustness of infrastructure systems to climate change, especially in the case of water infrastructure. However, it has not been previously applied to the challenge of designing for infrastructure resilience by incorporating the capabilities of persistence, adaptability and transformability.

### 4. Resilience by design methodology

Resilience by Design is a performance-based conceptualization of resilience, which means that the resilience of a particular system design is evaluated based on how it performs under a set of specified test conditions, and as measured based on specified resilience metrics. This approach is common in engineering resilience studies but contrasts with prescriptions for resilience that focus on the presence or absence (or

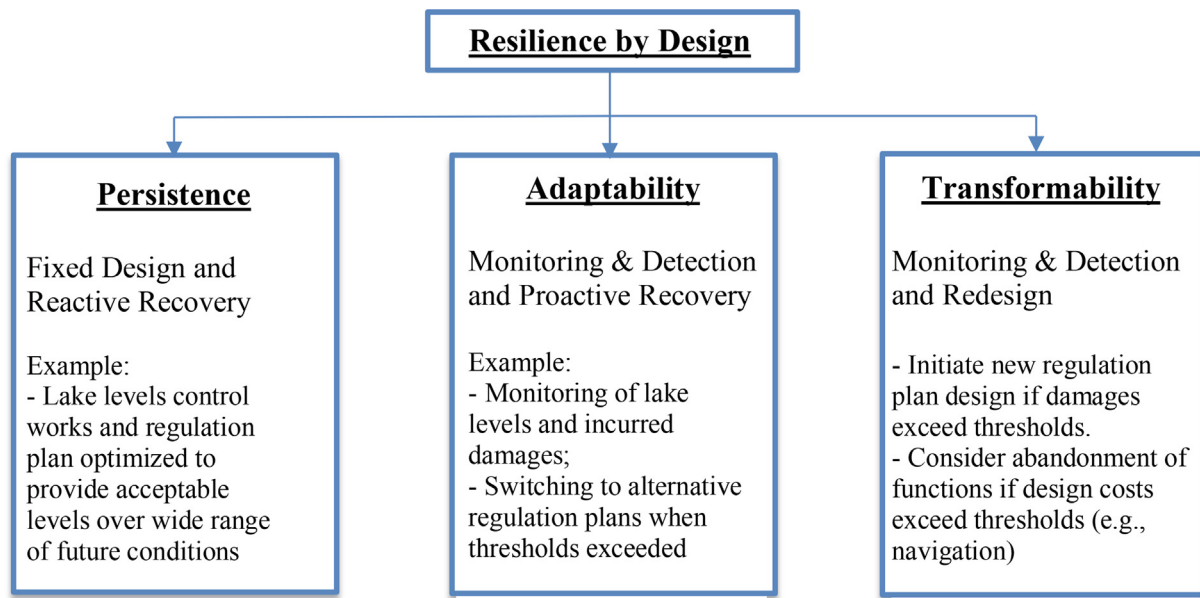


Fig. 1. Resilience is defined here as consisting of three components. Examples provided based on hypothetical water infrastructure systems, such as the management of lake levels via operating of control works or construction of new control works (see [8]).

degree) of particular resilience traits (e.g., [62,66,3,67,68,69]). Cataloging the traits of resilient systems serves as a useful reference in the design of a resilient system but provides little guidance on which traits are needed and in what proportion or combination for a particular design. While options such as creating redundancy through multiples of critical facilities may enhance resilience, design should seek efficiency in the use of financial and physical resources. By evaluating alternative designs based on performance, the relative contribution to total system resilience of different design aspects may be observed. In this way, the most efficient design for achieving system resilience may be identified.

Following the optimal control literature, Resilience by Design approaches the evaluation of alternative designs via optimization, which is an efficient and systematic way to evaluate multiple possible designs. The optimization process is embedded within a decision making under deep uncertainty framework. The overarching objective is resilient performance of the system that enables it to persist in its function under disturbance, adapt to changing conditions as they develop, and identify the need to transform to a new system via initiating a redesign process when conditions warrant.

The mathematical formulation described below implements a resilience design objective suited for long-lived infrastructure systems subject to a large number of uncertain, external factors. In most cases, such factors are associated with poorly characterized uncertainty. The design objective solves for resilience capabilities of persistence, adaptability and transformability, formulated as a fixed system design that is directly integrated with reactive recovery from changing conditions and proactive responses to anticipated change. It also quantifies damages that are not mitigated by the design, called residual risk [7], to signal when transformation is required. Decision variables are the design parameters of the system, the choices that are to be made. Constraints include immutable physical aspects of the system and performance aspects that must be met. Here we present the optimization as a formal mathematical model, while we note that Resilience by Design may be applied as conceptual or logical framework for design and may be used to rank alternative design options. The approach may be applied to design new infrastructure and to renovate existing systems, as well as planning efforts. The process begins with an initial step of assessing vulnerability to future conditions as described, for example, in Brown et al. [9] and Ray and Brown [70]. The result is a system designed for the long term, limited by our ability to predict the outcomes

of external forces, but not beyond our ability to design systems that can respond to them.

#### 4.1. General formulation of resilience by design

Resilience by Design requires an alternative mindset for the designer; one in which the aspiration is to create a design that effectively lasts forever, rather than providing only the next increment of service – or more accurately, *while* providing the next increment of service. In other words, the designer should consider what is required for the system to continue without end. This is the essence of resilience. While this does not preclude discounting future costs and benefits, full consideration of the long term future generally implies a low discount rate and may require hyperbolic discounting to ensure the future is not inappropriately undervalued. For simplicity, we omit discounting in the derivation that follows below.

Given the centrality of cost benefit analysis (CBA) to infrastructure design processes, the Resilience by Design formulation begins by enhancing CBA to address uncertainty. Following a probabilistic formulation (deep uncertainty will be addressed in Section 4.2), the CBA design problem can be described as:

$$\begin{aligned} \max [\text{Expected Net Benefit}] \\ = [\text{Total Expected Benefit}] - [\text{Total Expected Cost}] \end{aligned} \quad (1)$$

where the goal is to identify the system design that maximizes the Expected Net Benefit. Here we focus on costs for the purpose of clarity and conciseness, although uncertainty in benefits can be addressed as well using the method presented in Section 4.2. The total expected cost of a design, including the losses that are incurred due to failures or damages can be stated as:

$$\begin{aligned} [\text{Total Expected Costs}] \\ = [\text{Fixed Design Cost}] + [\text{Expected Cost of Reactive Recovery}] + \\ [\text{Expected Cost of Proactive Recovery}] + [\text{Cost of Monitoring and Detection}] + [\text{Utility of Expected Losses}] \end{aligned} \quad (2)$$

Here there is a distinction between values known at the time of design, which include fixed costs of the system, operation and maintenance and of monitoring and detection (M&D), and unknown values, including the costs of reactive and proactive recovery and of losses,



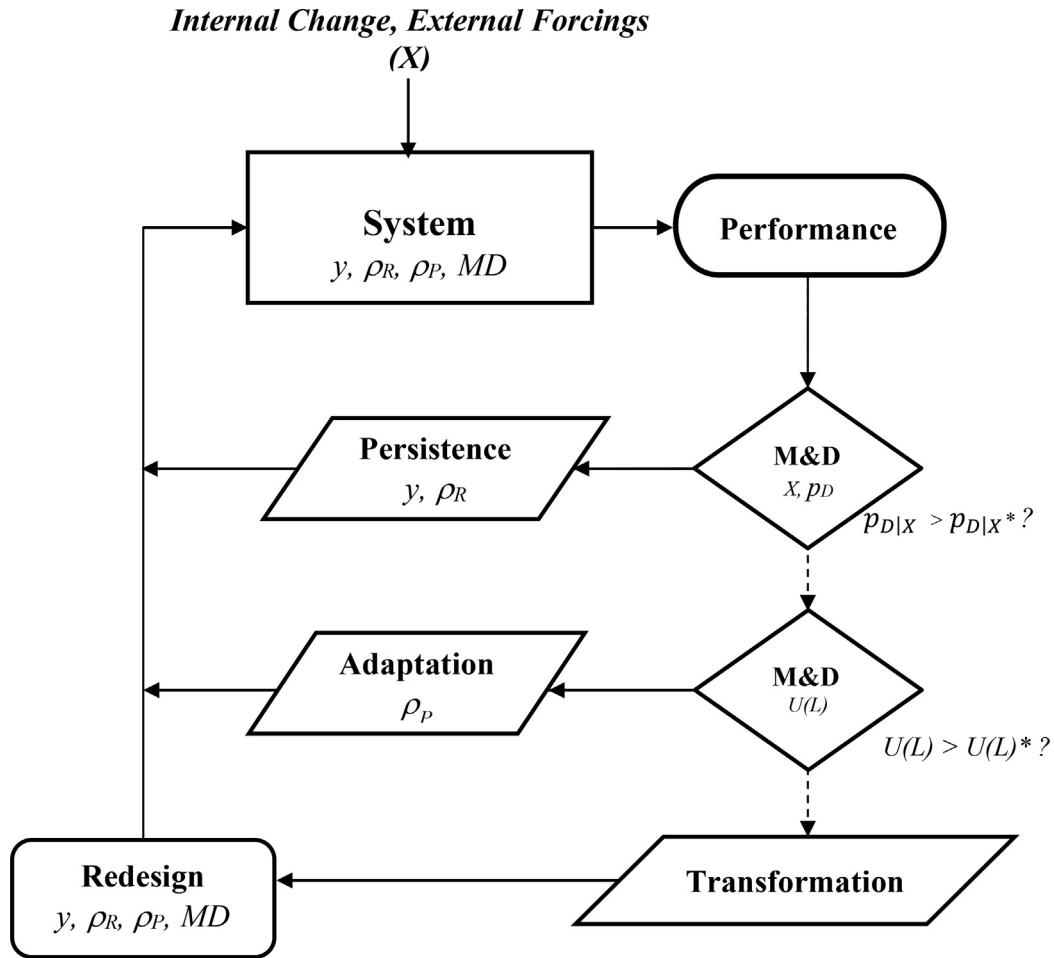


Fig. 2. Schematic of information flow in a resilient design consisting of persistence, adaptation and transformation. Symbols as defined in the text. Normal operation of a resilient system is based on resistance. When the probability of problematic conditions exceeds a designated threshold ( $p_{D|X} > p_{D|X}^*$ ), the system executes adaptation. When the utility of losses exceeds an acceptability threshold, transformation is initiated leading to a new system design.

which are expected values conditioned on random variables that represent external factors unknown at the time of the design. In addition, we distinguish between *reactive* recovery, which is the recovery from a failure state when it occurs and *proactive* recovery, which is the corrective action implemented to prevent or mitigate a failure when it is likely. Proactive recovery depends on monitoring and detection of the conditions that increase the probability of failure and the initiation of appropriate actions. Finally, we introduce a utility function for losses to reflect the well-established human preference for avoiding large losses [16]. Finally, the design approach applies equally to structural components as well as the policies for management of water systems that determine their operations (see [9] for an example of adaptive management of an infrastructure operating policy).

This Resilience by Design approach considers the three capabilities of a resilient system described above [6], as illustrated in Fig. 2. Designs for persistence incur the fixed design costs of providing a desired level of service reliability and the reactive recovery costs to return the system to normal after failure. Fixed design costs include both capital costs and routine operations and maintenance costs. Implicit in this formulation is the optimization of operations with selection of the fixed design (e.g., [17]. Reactive recovery actions are determined partially by the fixed design (and limited to operations of that fixed design) and/or by components specifically related to recovery actions. For example, Lund [71] incorporates sandbagging activities and evacuations as recovery activities with a floodplain management design optimization. Adaptability of the system corresponds to its ability to proactively recover when conditions warrant. This involves both detecting conditions that

are problematic for the system's current configuration and detection of deterioration in system performance. In either case, proactive recovery activities can be initiated to select operations, policies or system configurations that better suit prevailing conditions. Finally, transformation of the system is incorporated into the design process through inclusion of the utility of losses. The utility of expected losses triggers transformation of the system when they exceed a threshold of acceptability. For example, a design option with an unacceptably large utility of losses indicates that the system requires transformation. In such cases, performance objectives for the system and constraints must be re-evaluated or an entirely new system design process initiated. It is conceivable that in extreme cases, transformation may include abandonment of the proposed infrastructure for a location in which the utility of losses is consistently too great.

The design challenge can be described as an optimization seeking to minimize the total cost of the design (we focus on costs solely for clarity). Let  $Z$  equal the total cost of a given resilience design:

$$Z = \sum_i C_i y_i + \left[ \sum_k C_k (\rho_R) (1 - p_D) + \sum_l C_l (\rho_P) p_D + U[L(y_i, \rho_R, \rho_P, p_D, X)] \right] \quad (3)$$

where  $C_i$  represents the cost of alternative fixed design variables,  $y_i$ ,  $C_j$  is the cost of monitoring and detection components  $MD_j$ ,  $C_k$  is the cost of

reactive recovery activities,  $\rho_R$ ,  $p_{D|X}$  is the probability of detection of problematic performance based on the monitoring and modeling function (this probability is conditional on the values of  $X$  and defined for a given probability distribution on  $X$ ; see below), and  $C_l$  is the cost of proactive recovery activities  $p_p$ . In addition to the direct costs of the system design our formulation includes the losses  $L(-)$  that are incurred by a given design due to poor performance under ‘extreme’ circumstances. The losses are a function of the fixed design, the recovery activities, detection of the problematic conditions, and the value of the external uncertain variable(s) that cause those conditions. A utility function,  $U(L)$  is used to value losses proportionally to societal preferences for the avoidance of large losses.

Let a particular system design be represented by  $D_R$ , representing a particular set of  $y_b$ ,  $MD_j$ ,  $\rho_R$ , and  $p_p$ . The planner’s objective is to minimize total expected cost,  $Z$ , of a given design,  $D_R$ , by selecting the combination of fixed design variables, reactive recovery capabilities, monitoring and detection capabilities, and proactive recovery capabilities:

$$\min_{D_R} E_X [Z] = E([Total\ Cost\ (D_R)]) \quad (4)$$

The expectation is calculated by integrating over the probability distributions of external random variables,  $X$ , yielding:

$$\begin{aligned} \min_{D_R} E_X [Z] &= \int p(X) Z_X dX = \sum_i C_i y_i + \sum_j C_j MD_j \\ &+ \int p(X) \left[ \sum_k C_k (\rho_R) (1 - p_{DX}) + \sum_l C_l (\rho_p) p_{DX} + U \right. \\ &\left. [L(y_i, \rho_R, p_p, p_{DX}, X)] \right] dx \end{aligned} \quad (5)$$

This formulation seeks the combination of fixed design values and adaptive design values that minimize the expected cost of the design, including the utility of losses when failure occurs. The utility function must return values in the same units as costs. The decision variables chosen by the optimization also determine the relative proportion of persistence and adaptability capabilities and the necessity of transformation. The decision variables  $y_i$  and  $MD_j$  represent the fixed design values of the system that, combined with the decision variables for reactive recovery,  $\rho_R$  and their costs,  $C_k$ , represent the persistence of the system following Eq. (2). Similarly, the level of adaptability is set by the optimal values of the monitoring and detection costs,  $C_j$  and  $C_b$ , the cost of proactive recovery actions  $p_p$ . The occurrence of hazards in the future is uncertain, so terms affected by hazards are modified by the probability  $p(X)$  of the random vector  $X$  representing uncertain external factors, such as temperature, precipitation, demand, costs, etc. This includes all variable costs and losses. Note that at this point we define expectations for a single  $p(X)$ , however  $p(X)$  itself is uncertain; the robustness evaluation for multiple probability distributions on  $X$  is described in Section 4.2.

Finally the utility of losses,  $U[L]$ , provides an indication of when transformation is necessary. The utility function represents losses that may be both financial and nonfinancial and incurred by different parts of society. As such, preferences must be representative of the society or stakeholders impacted, for example, as described in Brown et al. [8] and Moody and Brown [33]. When the value of the utility of losses reaches an unacceptably high level relative to decision-maker preferences, the fixed system design with reactive and proactive recovery costs, is unable to provide the necessary level of service. This condition necessitates design for transformability. The result is a design optimization that yields system resilience to uncertainties through persisting and recovery, forecasting and adapting, and transforming based on projected future conditions.

#### 4.2. Addressing deep uncertainty

A particular challenge for assessing resilience is the dependence of the evaluation on assumptions about future conditions, for example, the future probabilities of external factors,  $p(X)$ . The term “deep uncertainty” has been used to describe cases where a single probability distribution cannot be specified to describe future conditions with confidence. A variety of methods have been developed to address deep uncertainty (see [31]). In general, these methods emphasize sensitivity analysis of designs over many possible futures, rather than the use of expected values based on a probabilistically described future or a single best guess future. Moody and Brown [72] introduced a climate robustness index to quantify the ability of alternative designs to provide acceptable performance over many possible futures. This is one of several alternatives for quantifying robustness depending on the preference of the analyst [18]. The method evaluates designs over a range of possible future outcomes, and defines “ex post” scenarios according to a given design’s ability to provide acceptable performance across this range. While this requires that a threshold of acceptable performance be specified, the threshold can be varied in evaluating alternatives, or subject to sensitivity analysis. Incorporating the ability to provide acceptable performance over a deeply uncertain future renders the optimization decision one of maximizing the performance *robustness* ( $Rb_S$ ) of a given alternative design,  $D_R$  over the possible values of external factors,  $X$ , for a set of possible probability distributions on  $X$ :

$$\max_{D_R} Rb_S [\min_{D_R} E_X [Z]] \quad (6)$$

where  $S$  is the set of probability distributions on  $X$ . Seeking optimal alternatives over a set of probability distributions has been called belief dominance [3], reflecting the non-dominated performance across uncertainty in future probabilities of  $X$  (which the authors describe as beliefs). Belief dominance is similar to preference dominance, the basis of Pareto optimality, where an alternative is non-dominated if one objective cannot be improved without reducing the performance of another objective. In practical terms, belief dominance can be implemented by evaluating alternatives over different sets of probabilities assigned to possible future outcomes. That is, the future is described not by a single probability distribution but rather by a set of distributions. Options that perform best across all the distributions are non-dominated in terms of the uncertainty of future outcomes. This can also be combined with Pareto optimality in the case of a multi-objective decision problem, for example, if  $Z$  is a vector of objectives including financial costs, environmental costs and social costs. In this paper, with no loss of generality, we present only the single financial cost objective.

#### 5. Conclusion

The potentially devastating implications of climate change and the deeply uncertain trends of its magnitude and direction raise concerns that current infrastructure systems are not prepared for the future. Since design processes have not adapted to the implications of a non-stationary climate, there is further concern that new and retrofit infrastructure development designs will be similarly ill-conceived. To provide the resilience that people desire, infrastructure design must address the uncertainty of the future, including uncertainties that cannot confidently be modeled probabilistically, and those that manifest as trends or low frequency variability. Infrastructure design must also account for losses and the disproportionate value they hold in human decision-making. Finally, infrastructure systems designs must acknowledge and preserve ecosystems that provide many of the underpinning functions and services that infrastructure intends to harness and sustain.

A resilience approach provides the conceptual basis for this urgently needed advance in the design of critical infrastructure. Here we introduce the Resilience by Design methodology for infrastructure design

to incorporate both the ability to manage short term shocks and surprises and to accommodate long term trends. The methodology follows a decision making under deep uncertainty framework that addresses the implications of our limited ability to correctly predict future conditions. While the approach is a significant advance for the resilience design literature, perhaps our more significant contribution is the expression of an objective to achieve acceptable and enduring performance over previously untenable time frames. Our belief is the Resilience by Design approach may help to fundamentally change the design of infrastructure to address urgent challenges of navigating uncertain climate and Earth system futures. Mathematical and empirical experimentation will be required to test and refine this hypothesis, some of which we have undertaken in related work [13]. It is the authors' hope that this contribution will inspire further applications to design for a resilient future.

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