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A System-of-Systems Framework for Exploratory Analysis of Climate Change Impacts on Civil Infrastructure Resilience

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Abstract

Climate change has various chronic and acute impacts on civil infrastructure systems (CIS). A long-term assessment of resilience in CIS requires understanding the transformation of CIS caused by climate change stressors and adaptation decision-making behaviors of institutional agencies. In addition, resilience assessment for CIS includes significant uncertainty regarding future climate change scenarios and subsequent impacts. Thus, resilience analysis in CIS under climate change impacts need to capture complex adaptive behaviors and uncertainty in order to enable robust planning and decision making. This study presented a system-of-systems (SoS) framework for abstraction and integrated modeling of climate change stressors, physical infrastructure performance, and institutional actors' decision making. The application of the proposed SoS framework was shown in an illustrative case study related to the impacts of sea level rise and subsequent saltwater intrusion on a water system. Through the use of the proposed SoS framework, various attributes, processes, and interactions related to physical infrastructure and actor's decision making were abstracted and used in the creation of a computational simulation model. Then, the computational model was used to simulate various scenarios composed of sea level rise and adaptation approaches. Through an exploratory analysis approach, the simulated scenario landscape was used to identify robust adaptation pathways that lead to a greater system resilience under future uncertain sea level rise. The results of the illustrative case study highlight the various novel capabilities of the SoS framework: (i) abstraction of various attributes and processes that affect the long-term resilience of infrastructure under climate change; (ii) integrated modeling of CIS transformation based on simulating the adaptive decision-making processes, physical infrastructure performance, and climate change impacts; and (iii) exploratory analysis and identification of robust pathways for adaptation to climate change impacts.

Introduction

Climate change is one of the major challenges of the 21st century. For example, hurricanes and storm surge events have become stronger and longer-lasting over the past 30 years as a result of climate change impacts. These phenomena can have catastrophic impacts on coastal communities and result in coastal erosion, destruction of civil infrastructure systems (CIS), and catastrophic saltwater contamination of the water supply. Given the significance of CIS in economic growth, human well-being, and protection of communities against natural disasters, enhancing the resilience of CIS is one of the grand challenges facing engineers and policy-makers in the 21st century (Heller 2001; O'Rourke 2007). CIS closely interacts with the social and environment systems; hence, the resilience of CIS is contingent upon its transformation and adaptation to evolving conditions in socio-environmental systems (Xu et al. 2012). In particular, climate change is a major driver of changes in the socio-environmental conditions surrounding CIS. Climate change affects the resilience of CIS in various ways: (i) changes in temperature and precipitation affecting the erosion of networks, (ii) population displacement affecting the demand on networks,

(iii) changes in the priorities of agencies affecting the allocation of limited resources, and (iv) increased frequency and magnitude of extreme events (e.g., floods) leading to a greater exposure of networks to risks (Koetse and Rietveld 2009; Chappin and Lei 2014). Climate change, directly and indirectly, affects the performance of physical assets. For instance, the physical condition of a pavement network may be directly affected by the increased number of freeze-thaw cycles induced by climate change. On the other hand, climate change may stimulate changes in behaviors of infrastructure users and institutional agencies which in turn affect the physical condition of assets. In addition, institutional agencies adapt their decision making and behaviors as they learn about the impacts of climate change on physical networks. This includes changes in policy objectives (e.g. putting more emphasis on mitigation and adaptation) or resource allocation. Also, user behaviors change both as a direct result of climate change impacts (e.g. the user is forced to choose a new route due to inundation of a previously used road), or in response to changes in the above-mentioned factors (i.e. conditions of physical assets and decisions of the infrastructure agency). A review of the existing literature shows that the steady-state analysis approaches are unable to provide a thorough understanding of the transformation of CIS under climate change due to lack of consideration of (Fiksel 2006): (i) the dynamic behaviors and interactions between infrastructure networks, institutional agencies, and users; (ii) future uncertainty related to climate change impact scenarios.

Capturing Complex Adaptive Behaviors

The key to addressing these gaps is adopting a complex systems perspective in the assessment of CIS resilience to climate change impacts (Ostrom 2007; Fiksel 2006). In a complex system perspective, the resilience of CIS is emergent properties as a result of complex interactions among physical infrastructure assets and multiple institutional actors and institutions. In fact, a complex systems framework was successfully adopted in the past for a better understanding of the dynamic interactions and adaptation of ecological systems to the impacts of climate change (Alley et al. 2003; Parmesan 2006).

The literature related to ecological science has made significant advancements in adopting a Complex Adaptive Systems (CAS) perspective for understanding the dynamic interactions affecting the resilience of ecological systems. Evidence suggests that analogies to ecological systems and adopting a CAS approach may reveal new ways to analyze and provide design and decision guidelines for resilient CIS networks (Xu et al. 2012; Bollinger and Dijkema 2012). Recently, the complex adaptive nature of CIS has been recognized and a number of studies have started to model sustainability and resilience of CIS based on the principles of complex adaptive systems modeling. Several studies (e.g., Rinaldi et al. 2001; Amin 2002; Thomas et al. 2003; Brown et al. 2004; Mostafavi et al. 2012) proposed the use of a CAS framework for integrated modeling, robust analysis, and a better understanding of resilience and interdependencies in CIS. However, despite the growing literature in the areas of resilience and infrastructure interdependencies, conceptualization of CIS as CAS has been hindered by two major limitations: (i) lack of a theoretical framework for better understanding of resilience in CIS as a CAS; and (ii) lack of a methodological framework for modeling the adaptive behaviors, dynamic processes, and uncertain perturbations in ICI as a CAS.

To address this gap, this study proposed a system-of-systems framework for abstraction of complex adaptive behaviors and interactions among institutional actors and physical infrastructure

(Figure 1). Accordingly, CIS are analyzed as systems-of-systems composed of multiple physical infrastructure systems as well as social systems consisting of government regulation agencies, service providers, and consumers. These systems are open (with a changing environment and a dynamic number of participants), heterogeneous, temporally and geographically decentralized, and functionally, operationally, and managerially interdependent. A SoS framework for the assessment of CIS would enable capturing the activities of and interactions among the various institutional actors and physical infrastructure, and thus facilitates examining the transformation of CIS under climate change impacts.

FIGURE 1 HERE

Exploratory Analysis under Uncertainty

In addition to complex adaptive behaviors, planning, and decision-making of CIS for climate change adaptation involves significant uncertainty. Hence, conventional ex-post analysis and optimization approaches are not capable of capturing these complex adaptive behaviors and uncertainty (Mostafavi et al. 2011). A new approach has recently emerged in order to deal with adaptive behaviors and uncertainty in complex systems. This analysis approach, so called Exploratory Analysis (Bankes, 1993; Kwakkel and Pruyt 2013), uses computational models and simulation experiments to conduct scenario analysis and evaluate the behavior of complex and uncertain systems (Bankes 2003; Agusdinata 2008; Mostafavi et al. 2013). Exploratory analysis has been utilized in different studies (e.g., Mohor et al. 2015; Hristove 2015; and Lampert et al. 2004) for evaluation of climate change. However, the use exploratory analysis in the context of CIS resilience under climate change impacts is rather limited. In this context, exploratory analysis can provide novel insights regarding how CIS performance will evolve under different scenarios of climate change impacts and adaptation actions. Unlike the existing approaches for assessment of CIS resilience, the exploratory analysis does not aim to predict the behavior of a system and does not intend to optimize a system. Instead, exploratory analysis focuses primarily on considering different resilience and adaptation scenarios based on changes in system behavior and future uncertainty. To this end, an appropriate framework for exploratory analysis of CIS resilience under climate change should enable: (i) a bottom-up assessment of the behaviors and interaction between physical infrastructure and actors; and (2) long-term assessment of resilience based on capturing and integrating various climate change stressors, actors' decision-making processes, and physical infrastructure performance. To this end, this study proposes a system-of-systems (SoS) framework for the assessment of CIS resilience under climate change impacts. In the following sections, first, the components of the proposed SoS framework are explained. Then, the application of the proposed framework is explained in an illustrative example pertaining to assessment of a water supply system under sea level rise impacts. In the illustrative case study, the proposed SoS framework was used in the creation of a computation model in order to simulate various scenarios and explore adaptation pathways.

System-of-Systems Framework

The proposed SoS framework for the analysis of CIS resilience under climate change impacts includes three phase: Definition, Abstraction, and Implementation. Each phase includes a number of tasks which will be described in detail in the following sub-sections.

Definition Phase

The first phase of the analysis is definition. The outcomes of the definition phase will inform the relevant stressors, actor and infrastructure attributes, and metrics to be considered in the abstraction and implementation phases. Definition phase includes two tasks: (i) defining the levels of analysis, the context of analysis, and limitations and (ii) defining the metrics for evaluation of SoS performance and resilience at different levels of analysis. First, the levels of analysis include base, system, and SoS levels. The resilience outcomes at each level are obtained as a result of the interactions between the components at the lower level. For example, the attributes and interactions of institutional actors and physical infrastructure affect the resilience outcomes at the system level. The context of the analysis should define the infrastructure sector, mode, and function, as well as the climate change impacts for which the analysis is performed. The context of analysis determines the type of climate change stressors to be included in the analysis, the impact of stressors on physical infrastructure, and the action space of the institutional actors for responding to climate change stressors. For example, assessment of water infrastructure systems under sea level rise impacts would involve different climate change stressors, physical infrastructure impacts, and action space compared to examining road networks performance under the impacts temperature variation. The second task in the definition phase is to define the metrics for evaluation of resilience and performance across different levels. Consideration of different resilience metrics at different levels would depend on the study objective and context. For example, Batouli and Mostafavi (2016) used a network-level life cycle cost as a metric for evaluation of the impacts of flooding on road infrastructure in order to determine the value of adaptation actions. Other studies (e.g., Dehghani et al. 2013) have used measures of network vulnerability for assessment infrastructure resilience under disruptions caused by natural disasters. Another important consideration is the relationship between different metrics at different levels. Due to the non-linear behaviors in CIS, the resilience metrics at each level cannot simply be determined by aggregating the metrics at the levels below. In other words, resilience performance at the SoS level is an emergent property as a result of the interactions between different systems components at the level below. The aggregation of individual systems resilience may not be an indicator of CIS at the SoS level.

Abstraction Phase

The second phase of the proposed SoS framework is abstraction. In the abstraction phase, relevant institutional actors and physical infrastructure assets and their attributes and interactions at the base level are captured. There are various attributes and behaviors that affect the internal feedback processes between institutional actors and physical infrastructure assets. For institutional actors, the decision-making behaviors such as information processing, resource allocation, project prioritization, and retrofit/capacity expansion are examples of behaviors that may be abstracted. For physical infrastructure assets, attributes such as Level of Service (LOS), functional capacity, condition, operability, and fragility are examples of traits that need to be modeled. These traits will be used for modeling the behaviors of infrastructure agents. For example, the LOS of an infrastructure component depends on its functional capacity, condition, and operability. The condition of an infrastructure agent depends on its decay rate and condition improvement due to maintenance/rehabilitation. Operability is the ability of the physical entity to perform its intended function. Operability decreases due to perturbations (e.g., disasters). The operability of an infrastructure agent depends on its condition and fragility. Fragility determines the likelihood of function loss in a physical entity given a certain level of disturbance. The level of fragility could be determined using fragility curves. At the system and system-of-system level, the main traits are performance and LOS. In addition , an important aspect of SoS analysis of CIS resilience is the ability to integrate asset condition degradation, level of service, and vulnerability with the decision-making processes and adaptation actions of institutional actors and enable dynamic analysis over time (Koetse and Rietveld 2009; Lambert et al. 2012; and Dehghani et al. 2013).

Infrastructure Assets: The dynamic behavior of infrastructure assets can be represented using two state variables: (1) Exposure state ($Exp_{ijt} = Exposure\ of\ asset\ i\ to\ stressor\ j\ at\ time\ t$); and (2) Condition state ($C_{it} = Condition\ of\ asset\ i\ at\ time\ t$). Exposure state determines the exposure of an infrastructure asset to climate change stressors. The value of Exposure state variable would be 0 or 1. For example, if a bridge is exposed to flooding, the Exposure state variable for the bridge would be equal to 1. The value of Exposure state variable can be determined based on location of an asset and the hazard models. For example, flood maps can be used for determining the temporal and spatial distribution of flood events. Details about considering stressors in the SoS framework is provided later in this paper. Another element for representing the behavior of physical infrastructure assets is Condition state variable. Condition state variable determines the physical condition of an asset. For different types of infrastructure, different measures can be used to present their condition states. For example, for road pavements, pavement serviceability rating (PSR) index can be used. For bridge superstructure, structural serviceability can be used as the Condition state variable. An important element is determining the Condition state variable is the use of appropriate condition deterioration equations to model the decay rate of physical infrastructure. The Condition state variable can then be used in determining the Service Limit state variables. Service Limit state variables are twofold: (i) the level of service ($LOS_{it} =$

$Level\ of\ Servie\ of\ asset\ i\ at\ time\ t$) of an infrastructure asset based on its condition; and (ii) the fragility ($F_{it} = Prob(failure|Exp_{ijt})$= Fragility of asset *i* to stressor exposure *j* based on its condition at time *t*). Determination LOS and Fragility variables based on the Service Limit state variable vary for different types of infrastructure. For example, for water main infrastructure, if pipelines are in good condition, the system will have small amount of water leakage, and thus, the level of service would be high. In the same example, the probability of water main breaks due to a stressor (e.g., earthquake) would be lower if pipes are in good condition. The mathematical representation of Service Limit state variables for different types of infrastructure assets is limited due to lack of theory. A substitute for mathematical representation would be the use of truth tables to determine the relationships between Condition State variable and Service Limit state variables. Table 1 depicts a numerical example of a truth table for water main assets. Such truth tables can be determined based on analysis of historical data or expert opinions.

TABLE 1 HERE

The variable explained above for representation of dynamic behaviors of infrastructure as assets are affected by the decision-making processes of institutional agencies. For example, building salinity barriers for water wellfields would be an action that reduces the exposure of water infrastructure to salt water intrusion to aquifers. In addition, the condition of infrastructure assets is improved if the agency implement maintenance and rehabilitation activities. In the following sections, the elements for capturing the adaptive decision-making behaviors of institutional actors are discussed.

<u>*Institutional Actors:*</u> Given the complexity of civil infrastructure systems, a proper assessment of resilience hinges on an understanding of the decision-making behaviors in social systems exposed

to climate change impacts (Patt and Siebenhüner 2006; Chappin and van der lei 2014; Lambert et al. 2012). In the context of resilience decision making, the existing evidence confirms that certain behavioral and social phenomena affect the decision rules related to adaptation actions (Patt and Siebenhüner 2006; Berger and Troost 2013). In order to capture the decision-making processes of institutional actors in response to climate change impacts, different elements of decision theory can be used. The three main elements of decision-making processes of institutional actors in response to climate change impacts include: (1) identifying exposed infrastructure assets to different stressors under uncertainty; (2) selecting appropriate adaptation actions to reduce exposure or mitigate impacts for the exposed assets given resource constraint; and (3) learning from past decisions and actions and actions of others to improve future decisions (Kunreuther and Weber 2012). These three elements of adaptation decision-making processes of institutional actors can be captured using different elements of decision theory as explained below:

The first element is related to identifying exposed infrastructure assets to different stressors under uncertainty. This element of decision making can be captured based on assessing the perception of institutional actors of future climate change impacts. The perception of institutional actors is based on their current available information and may be different from the actual future impacts of stressors. For example, in identifying the exposed infrastructure assets to future flood events, an institutional actor utilizes the available information related to the future flood event exposure to determine what infrastructure assets (e.g., roads and bridges) will be exposed. Since the identification of exposed assets is done based on the information about future stressors and not the actual future stressors, the institutional actors uses the perceived state of nature rather than the actual state of nature to make its decision. If the actual state of nature for stressor *i* at time *t* is S_t^i, the perceived state of nature (S_t') would be based on the available information or observation of actual state of nature in the previous period. Accordingly, this element of decision-making processes can be captured using stressors data and conditional decision rules $\left(Exp_{ijt} \middle| S_t'\right)$. For example, if Bridge A is located in an area that will be flooded if a fast sea level rise projection occurs, and the institutional actor perceives the occurrence of a fast sea level rise projection in the following period, Bridge A will be identified as exposed by the agency.

After the exposed assets are identified, the next element of decision making is to select appropriate adaptation actions to mitigate the impacts of climate change stressors. The impacts of climate change stressors and corresponding adaptation alternatives can be realized at two levels: network and asset levels. For example, coastal flooding is an impact affecting a network of infrastructure for which different adaptation alternatives (e.g., installing storm water pump stations, constructing breakwater barriers, and population relocation) may be considered. At the asset level, the impacts of climate change stressors on different types of infrastructure varies. For example, salt water intrusion into fresh water wells is one of the major impacts of SLR on water supply infrastructure. Possible adaptation action alternatives for coping with salt water intrusion include exploitation of aquifers in non-affected areas, building desalination capacity in treatment plants, and building additional reclaimed water production facilities (Berry 2012). These adaptation actions may be implemented by different actors for the identified exposed assets at different points in time and in response to the perceived state of nature related to different stressors. Hence, the adaptation action space can be defined as $A_m^k\left(S_i^j\right) = \{A_1^k, A_2^k, \ldots\ldots, A_n^k\}$, where $A_m^k\left(S_i^j\right)$ is the action *m* by Actor *k* in response to perceived state S_t'. The selection of most appropriate action for an exposed asset can be captured based on decision-theoretic approaches such as Utility, Prospect, Option, and Regret Minimizing Theories depending on the costs and utilities of different adaption actions. The selection of appropriate decision-theoretic approaches depends on the context and objective of the analysis. The available evidence confirms that the decision-making behaviors of institutional actors is not purely rational and hence does not justify the use of conventional decision theory models to explain the actors' decision-making behaviors (Patt and Siebenhüner 2006; Berger and Troost 2013). Hence, additional behavioral and social phenomena need to be investigated for a better understanding of the decision-making behaviors of institutional actors. For example, an important element that need to be considered is the risk attitude of institutional actors. Since the resilience decision-making processes are made under uncertainty, accounting for the risk attitude of the actors is an important consideration. For example, Expected Utility Theory can be adopted to examine different Risk Attitudes ($R_t = Risk\ Attitude\ of\ an\ Actor\ at\ time\ t$) such as risk seeking, risk averse, and risk neutral attitudes. The risk attitude of institutional actors can be change based learning from past decisions. For example, if an actor had selected Salinity Barrier as the best adaptation action for an exposed wellfield of a water supply system based on a risk neutral attitude, and the selected adaptation action was not effective in mitigating the impacts, the actor's risk attitude may change to risk averse for decision making in the next decision point.

The third element of decision-making processes of institutional actors is learning. Institutional actors respond to SLR impacts based on their learning from the historical impacts and actions of others. In addition, individual actions and risk perception of institutional actors may be in response to the choices and risk perceptions of others (Kasperson and Kasperson 1996). As a result, actors respond not to a climate stressor itself, but to the other actors' responses to the stressor (Patt and Siebenhüner 2006). Indeed, climate change adaptation is a collection of actors' responses motivated by local concerns. It does not need a central authority to guide the adaptation process because the adaptation is in the community's own interest (Patt and Siebenhüner 2006). However, coordination between actors' actions is an essential aspect towards more effective adaptation. The coordination behaviors of social actors can be captured based on game-theoretic approaches.

In addition to the adaptation decision-making behaviors, the decision-making processes related to regular maintenance and rehabilitation (M&R) of infrastructure assets should be captured in the SoS framework. The M&R decision-making processes of institutional actors affect the condition of physical assets. Different elements such as the availability of funding, condition of assets, and prioritization policy of institutional agencies can affect the M&R decisions. These decision-making elements can be captured using appropriate decision-theoretic approaches as discussed by Batouli and Mostafavi (2015) and Batouli and Mostafavi 2016.

<u>*Climate Change Stressors:*</u> Various scientists have investigated the impacts of climate change from physical, biological, and hazards aspects. However, the translation of the results of climate change impacts studies into stressors in the SoS framework require certain considerations. Depending on the context of an analysis, climate change stressors on physical infrastructure can vary from flood and storm surge impacts to salt water intrusion and bridge scours. In the SoS framework, these impacts can be captured based on their temporal and spatial distribution as well as their magnitude. As mentioned before, the actual state of nature for stressor *i* at time *t* is S_t^i. A stressor impacts an asset in the spatial distribution of the hazard covers the location of an asset and the magnitude of the stressor is greater than the service limit state (i.e., fragility) of the asset. As discussed earlier, fragility of infrastructure assets is captured in the physical infrastructure component of the framework. The fragility of an infrastructure asset depends on its condition as well as the magnitude of the stressor. Hence, in order to capture climate change stressors, the results of climate change hazard and impact studies should be translated into data tables of asset exposures

(Exp_{ijt}) that include information about temporal and spatial distribution for different magnitudes of a stressor. An example of such data table is shown in Figure 2.

Another featureof capturing climate change stressors in the SoS framework is the probabilistic occurrence of these stressors. In order to capture the actual state of nature for a stressor at time t (S_t^i), the occurrence of the stressor should be examined probabilistically through the use of the existing data and adoption of suitable random process modeling approaches as will be explained in the Implementation Phase section of the SoS framework.

FIGURE 2 HERE

<u>*Infrastructure Systems:*</u> The coupled effects of infrastructure assets performance and institutional agencies' decision-making processes need to be aggregated in determining system level performance and resilience. In capturing system level performance, it is critical to properly abstract the dependencies between different physical assets. For example, capturing the dependency between pump stations and water main lines is important in determining the system level performance of water infrastructure. The condition of pipelines and pipe breaks affect the energy consumption of pump stations and hence influence the system level energy performance. Consideration of different types of dependencies between infrastructure assets would depend on the context and objective of the analysis. Rinaldi et al. (2001) identified different types of system dependencies (e.g., physical, logical, and cyber). One or multiple dependencies may be relevant for a specific study. For example, in consideration of the dependencies between pump stations and water main lines, one study may only focus on capturing physical dependency (i.e., output of water main lines depends on whether pump stations are functional); while another study may consider

dependencies such as changes in the energy usage of pump stations based on the condition of pipelines.

After the dependencies between infrastructure systems are captured, different system-level performance measures can be investigated. For example, vulnerability is a widely used measure for assessment of system level performance. Vulnerability is defined as the susceptibility of infrastructure networks to climate change impacts that can significantly affect the functionality of infrastructure. The vulnerability of infrastructure can be evaluated using a network analysis approach (e.g., Jenelius et al. 2006; Arianos et al. 2009; Winkler et al. 2010; Yazdani and Jeffrey 2012; Christodoulou and Fragiadakis 2014). In a network analysis approach, each asset in a system is considered as a node and the dependencies between different infrastructure assets is captured based on links between the nodes. Accordingly, disruptions in infrastructure assets can be captured based on the removal of links between the nodes in the network. Then, through the use of graph-theoretic measures (e.g., connectivity and efficiency), the vulnerability of infrastructure networks can be determined. Another system level measure that can be assessed is system reliability. System reliability can simply be defined as the level of service produced to supply the demand. The level of service supplied can be captured based on the capacity of infrastructure assets in the system. For example, the capacity of a treatment plant, pump stations, reservoirs, and water mains would determine the amount of water that can be supplied by a water supply system. In this example, if a water main breaks or a groundwater source is salinated by salt water intrusion, the capacity of the water supply system decreases. Furthermore, various other system level performance measures can be considered. For example, Batouli et al. (2015) and Batouli and Mostafavi (2016) used a system level life cycle cost and Batouli and Mostafavi (2015) considered a system level life cycle impact measure in the evaluation of system performance. Depending on the context and objective of a study, various resilience and sustainability measures may be used. However, the required measure should be defined at the definition phase of the SoS since the measures influence the abstraction of various infrastructure attributes and dependencies that need to be captured.

Implementation Phase

The third phase of the SoS framework is implementation in which computational representation of abstracted system components are created for conducting simulation experiments and exploratory analysis. An important step in the implementation phase is the selection of appropriate modeling and simulation methods. The selected modeling techniques should be consistent with the characteristics of the system. In the assessment of the impacts of climate change on infrastructure systems, an appropriate modeling technique should capture the dynamic, stochastic, and adaptive nature of system attributes. To this end, different modeling methods can be used for a different system component and integrated into a multi-method model.

<u>*Modeling Methods:*</u> For modeling the performance of infrastructure assets, system dynamics, Markov chain, and mathematical modeling are examples of modeling techniques that can be used. For example, Rehan et al. (2011) and Rashedi and Hegazy (2015) utilized system dynamics for modeling the performance of water distribution infrastructure assets. Ortiz Garcia et al. (2006) used dynamic mathematical approaches to model the condition and deterioration of road pavements. For implementing the decision making and behaviors of institutional actors, agent-based modeling (ABM) can be used. ABM is an effective simulation approach for analyzing decision-making processes of actors in infrastructure systems (Pahl-Wostl 2002; Bernhardt and McNeil 2008; Mostafavi et al. 2013; Batouli and Mostafavi 2014; Bhamadipati et al. 2015;

Mostafavi et al. 2015; Batouli et al. 2015; Batouli and Mostafavi 2015). The use of ABM will enable: (1) discovering what decision rules, micro-behaviors, and preferences result in adaptation decisions; and (2) juxtaposing the preferences of various decision makers with the range of adaptation alternatives to determine the distribution of expected outcomes. ABM enables building the computational representations of adaptation decision settings based on the abstracted decision and behavioral rules and conduct virtual experiments to generate a theoretical space that will include a wide range of community profiles in terms of climate change adaptation decision-making factors. Finally, climate change stressors can be implemented through the use of appropriate mathematical elements and models. For example, the rate of saltwater intrusion into ground water can be represented using a mathematical function in a SoS model. Stochastic climate change stressors, such as flooding and storm surge events, can be implemented using stochastic models such as random processes. For example, the occurrence of storm surge can modeled using a Poisson Process model with appropriate parameter values. The selection of appropriate modeling approach for implementation of each component is affected by the ability to an integrated the modeling techniques into a multi-method simulation platform. A robust multi-method simulation platform should be able to cope with the complexity of calculating dynamic variables and uncertainties from different sources at different levels of multiple subsystems and modeling methods.

<ins>*Exploratory Analysis:*</ins> The ability to conduct exploratory analysis is the most important advantage of the proposed SoS framework. The ultimate goal of resilience analysis in infrastructure systems is to simulate future possible landscapes rather than produce point predictions. Analysis of complex systems will not be effective if simulation models are used to produce point predictions (Bankes 2002). Exploratory analysis and modeling have been utilized in the study of climate

change impacts in previous studies (e.g. Lempert, Schlesinger, and Bankes, 1996; Lempert and Schlesinger, 2000). The use of the proposed SoS framework enables conducting exploratory analysis to help decision makers or planners access to pattern or patterns of a complex system's behavior under deep uncertainties that accurate prediction or optimization is not possible or feasible. An exploratory analysis does not intend to predict the behavior of a system or is not concentrated on optimization of a system to achieve a specific aim; however, it takes different scenarios in the system into account and then looks at the output of each scenario. So there has been a methodological shift in researchers from the approach to construct such models to make the best estimation in systems toward methods that uses models which explore different possibilities in both the structure of system behavior and the outputs of a system (Agusdinata 2008). Through an exploratory analysis, a study can investigate for uncertain scenarios in the system of interest that can occur in order to examine the behavior of the system in each scenario and identify scenarios that lead to desirable outcomes. Hence, an exploratory analysis provides scientists and decision-makers with a robust tool to study system components and structures under which a specific scenario outcome would be generated.

FIGURE 3 HERE

In SoS analysis of infrastructure systems resilience, the results of simulation models should be processed to generate different possibilities and to identify the decision factors affecting resilience. To this end, exploratory analysis of infrastructure resilience explores the outputs of different scenarios by conducting hundreds or thousands of computational experiments that help to analyze the system behavior. The process of exploratory analysis includes different steps (Figure 3). The data obtained from simulated data can be analyzed through various statistical approaches to conduct meta-modeling. To this end, meta-modeling of simulated data can provide insights about the significance of various elements affecting the resilience of infrastructure under climate change impacts. Meta-modeling enables identifying robust pathways across multiple scenarios, assumptions that lead to a certain output, and key trade-offs across pathways. The steps of exploratory analysis will be explained in the next section in the context of an illustrative case.

Illustrative Case Study

In order to demonstrate the application of the proposed framework, an illustrative case was used to assess the impacts of sea level rise on water supply infrastructure. In this illustrative case, the water supply system is composed on one treatment plant and three groundwater well fields. Sea level rise causes salt water intrusion in groundwater wells, and thus affect the long-term performance and resilience of the system. Through the use of the proposed SoS framework, different components of the water supply system were abstracted and modeled in order to assess the resilience of the system.

Sea Level Rise Stressors

Sea level rise stressors considered in the illustrative case study were twofold: (1) chronic saltwater intrusion due to sea level rise; and (2) acute salt water intrusion due to storm surge events. A key consideration is accounting for the uncertainty of future sea level rise projections. Despite several studies, there is no consensus among scientists regarding the rate and projections of future sea level rise. Based on a study by the International Panel of Climate Change (IPCC), three sea level rise scenarios are likely: slow (1.6 ft), moderate (3.3 ft), and fast (4.9 ft) by 2100. Hence, in the illustrative case, the State of Nature variable for future sea-level rise projections is represented using Equation 1:

$$S = \{S_{slow}, S_{Moderate}, S_{Fast}\} (1)$$

Based on the state of nature, the rate of saltwater intrusion into groundwater wells can be determined based on the findings of groundwater models. For example, in the illustrative case, the results of the groundwater modeling conducted in Southeast Florida was used to determine the rate of saltwater intrusion into the well fields: (1) 8.8 mm/year for slow sea level rise scenario; (2) 10.7 mm/year for moderate scenario; and (3)17.3 mm/year for the fast scenario. The rate of saltwater intrusion was used to determine the year in which each well field gets exposed under different sea level rise scenarios.

The second stressor on the water supply system of the illustrative case is acute saltwater intrusion caused by storm surge. Hurricane and storm events can cause storm surges that lead to wash-over saltwater intrusion into the well fields. The exposure of well fields to salt water intrusion depends on the occurrence of storm surges and its magnitude. The magnitude of storm surge events varies based on the state of future sea level rise. In the illustrative case, the occurrence of storm surge events was modeled through the use of a Poisson Process Model as shown in Equation 2:

$$Pr(Storm\ Surge|Sea\ Level\ Rise\ State) = \lambda \times e^{\lambda} \qquad (2)$$

Where λ is the likelihood of having one storm surge event at each year. In the illustrative case λ values of 3%, 3.5%, and 4% were used for slow, moderate, and fast seal level rise scenarios respectively. Accordingly, the exposure of each wellfield to saltwater intrusion caused by storm surge was determined using Equation 3:

$$Pr(Saltwater\ intrusion\ in\ well\ i|Storm\ surge) = Well\ Exposure\ Threshold \quad (3)$$

Where, well exposure threshold is contingent on the location of the well and magnitude of storm surge events. In this illustrative case, well exposure threshold values between 30%-50% were used for different well fields in the system. The elements discussed above were used to model sea level rise stressors in the illustrative case.

Institutional Actor Decision Making

In the illustrative case, the institutional actor operates and manages the treatment plant and groundwater fields. The adaptation decision-making behavior of the institutional actors is captured using the steps shown in Figure 4. The decision-making process for adaptation occurs at certain time intervals and certain decision points (every five years in this illustrative case). The adaptation decision-making process includes two steps. The first step of adaptation decision making is to identify wells that will get exposed during the next decision horizon (e.g., 5 years in the illustrative case). The exposure of the wells is determined based on the perceived scenario of sea level rise and the associated salt-water intrusion rate for each scenario. Because of the uncertainty in projecting sea level rise, the perceived sea level rise of the actor may be different from the actual state of nature. Accordingly, the exposure of each well based on the perceived sea level rise scenario is determined using Equations 4-5:

$$Exp_{it} = 1; If\ Well\ Distance\ from\ Salinity\ Line < (Rate\ of\ Saltwater\ Intrusion\ \times\ Decision\ Horizon\ Duration)\ (4)$$

$Exp_{it} = 0; If\ Well\ Distance\ from\ Salinity\ Line > (Rate\ of\ Saltwater\ Intrusion\ \times$
$Decision\ Horizon\ Duration)$ (5)

Where, Exp_{it} is the exposure of well *i* during decision period *t*, and Decision Horizon Duration is the number of years during which the exposure of wells are analyzed (i.e. 5 years in the illustrative case). The rate of salt water instruction is obtained based on the perceived sea level rise scenario at decision point *t*.

Another element affecting the exposure of well fields is the occurrence of storm surge. As mentioned earlier, the occurrence of storm surge is modeled through the use of a Poisson Process. Accordingly, the actor will evaluate the probability that one storm surge event occurs during the next decision horizon. Based on the perceived scenario of sea level rise and likelihood of storm surge during the next horizon, exposed wells are identified using Equations 6-8:

$Likelihood\ of\ at\ least\ one\ storm\ surge\ during\ the\ next\ period = \lambda \times e^{-\lambda}$ (6)

$Exp_{it} = 1; If\ WLikelihood\ of\ at\ least\ one\ storm\ surge\ during\ the\ next\ period <$
$Risk\ Tolerance$ (7)

$Exp_{it} = 1; If\ WLikelihood\ of\ at\ least\ one\ storm\ surge\ during\ the\ next\ period <$
$Risk\ Tolerance$ (8)

Where, λ is the probability of storm surge related to a sea level rise scenario, Exp_{it} is the exposure of well *i* during decision period *t*, Risk Tolerance is the acceptable level of risk by the actor. The Risk Tolerance threshold values vary based on the risk attitude of the actor. In the illustrative case, the following values were used: 10% for risk averse, 20% for risk neutral, and 30% for risk seeking.

Based on the consideration of wells exposure to sea level rise and storm surge, if no wells are identified to get exposed to salt water intrusion, the agency does not implement any adaptation actions and proceeds to the next decision point. If one or more wells are identified to potentially get exposed to salt water intrusion, the next step of adaptation decision making is to select appropriate adaptation actions. In the illustrative case, the adaptation action space considered the following adaptation actions: (1) adding desalination capacity to the treatment plant; (2) building salinity barriers to protect the well fields; (3) implement deep well injection to control ground water levels; (4) adding storage capacity; and (5) closing a wellfield and exploiting new well fields farther from the salt water line. Each adaptation action has different cost and effect on the water supply system. Adding desalination capacity will increase the ability of the system to desalinate sea water. Building salinity barriers and deep well injection reduce the rate of saltwater intrusion into groundwater wells. Adding storage capacity increases the redundancy of the system during service disruptions caused by storm surge events. Table 2 summarize the cost information for each adaptation action. The effectiveness of each adaptation action was determined based its influence on the performance of water supply (explained later in this section).

FIGURE 4 HERE

TABLE 2 HERE

In the selection of adaptation actions, the risk attitude of the institutional actors affects what decision-theoretic rules are used. If the actor has a risk-averse attitude, the actions are selected in order to minimize the impacts of saltwater intrusion (based on regret minimization theory). If the actor has risk-seeking attitude, the actions are taken in order to minimize costs. If the actor has a risk neutral attitude, decision-making process include a benefit-cost analysis (i.e., an action with above average adaptation effectiveness and costs). Based on the available adaptation funding, risk attitude of the actor, and corresponding decision rules, adaptation actions are selected for each exposed well.

Prior to the next decision point, the actor evaluates the decisions and actions in the previous decision point and adapts the perceived sea level rise and risk attitude. If the actor did not identify the exposure of wells properly, the perceived sea level rise scenario is updated. For example, if the actor identified a well experienced saltwater intrusion while it had not been identified as exposed in the previous step, the actor updates the perceived sea level rise state accordingly (e.g., from slow to moderate or from moderate to fast). Similarly, if the actor selected an adaptation action that was not effective in mitigating salt water intrusion, the risk attitude of the actor is updated (e.g., from risk neutral to risk averse). Through this process, the adaptive decision-making behaviors of the institutional actor was captured during a 20-year analysis horizon with decision points every five years.

Water System Performance

The water system in this illustrative case is composed of three components: (1) treatment plant, (2) reservoir, and (3) wells. The attributes of each component of the water system is summarized in Table 3.

TABLE 3 HERE

The performance of water supply system in this illustrative case was evaluated based on the level of service, which is the amount of water that the system can supply, using Equation 9:

$$Annual\ Water\ Supply = \sum(Extraction\ from\ wells) + Desalination\ Capacity + Storage\ Capacity \quad (9)$$

Without any storage capacity, the annual water supply of the system is equal to the amount of water extracted and treated from wells. Desalination capacity enables the treatment plant to perform desalination in case a well experiences salt water intrusion. In the case of no saltwater intrusion, desalination capacity is not utilized. Storage capacity is used in cases of storm surge salt water intrusion. Saltwater intrusions caused by storm surge are temporary. If a well is disrupted due to storm surge, the storage capacity can be utilized as a backup. At the beginning of the simulation, the system does not have any storage or desalination capacity. These capacities are added to the system based on the adaptation actions of the actor.

The resilience of the water supply system is determined based on a measure called Service Reliability Index (SRI), which captures the reliability of water supply to meet the demand. SRI is calculated using Equation 10:

$$Service\ relaibility\ Index = \frac{\sum_{t=1}^{n} Annual\ Water\ Supply}{\sum_{t=1}^{n} Annual\ Demand} \quad (10)$$

If SRI is less than 1, it shows a disruption in a system. If SRI is greater than one, it shows a redundancy in the system.

Model Verification

Since the illustrative case was based on a hypothetical example, validation of results was not relevant. Internal verification of the simulation model was conducted to ensure the completeness, correctness, consistency and coherence of the computational simulation models. In addition, the components of the model and their relationships were evaluated by three subject matter experts (SMEs) involved in planning and adaptation of water systems in order to conduct a face verification. Through the process of face verification, the SMEs evaluated whether the model captures significant system components, attributes, and relationships. Due to the illustrative nature of the case study, no further verification and validation were conducted.

Simulation and Exploratory Analysis

The computation simulation model for the illustrative case was created in Anylogic 7.0. Figure 5 depicts the UML class diagram of the computational simulation model. The model developed for the illustrative case includes an animation component which helps in visualizing the effects of different inputs on the performance of the water system under different scenarios of sea-level rise. The inputs for each scenario include the actual sea level rise scenario, the perceived sea level rise scenario, and actor's risk attitude at the beginning of the simulation, and the funding available for adaptation actions at each decision point. Figure 6 depicts snapshots from the animation component in which salt water intrusion and impacts on wells and water supply system are visualized. The animation and visualization interface includes different components such as Service Reliability Index dashboard, storm surge log, adaptation action log, and adaptation action visualization. These elements enable examining various dynamic factors during scenario analysis and evaluation.

FIGURE 5 HERE

FIGURE 6 HERE

In addition to evaluation of individual scenarios and evaluation of different dynamic behaviors in each scenario, the simulation model can be used for exploratory analysis in order to create the resilience landscape of the system. In fact, the ultimate goal of exploratory analysis is to simulate the adaptation landscape and identify the factors that are most effective in reaching the desired outcomes (Bankes 2002). Hence, the results of simulation models should be processed to generate the analysis landscape and to identify the decision factors affecting the outcomes (Kleijnen et al. 2005). Exploratory analysis includes the following steps:

Simulate various scenarios: First, meta-modeling was used for exploring the variation of output variables as functions of different input variables in the simulation model (Staum 2009). Through scenario analysis, 1000 scenarios composed of different combinations of input factors (e.g., actual sea level rise, initial budget, adaptation funding, and actor's risk attitude) were implemented.

Examine different likelihood of uncertain scenarios: Figure 7 shows the simulation results related to the probability distributions of Service Reliability Index (SRI) values under different actual sea level rise scenarios. As shown in Figure 7, the probability of achieving greater SRI in the system varies in different sea level rise scenarios. Under slow sea level rise scenario, the likelihood of achieving SRI values of greater than 95% is about 70%. There is only 10% likelihood that under slow sea-level rise the SRI of the system will be less than 90%. These likelihoods are different in moderate and fast sea level rise scenarios. Under moderate sea level rise, there is about 50% likelihood that the system SRI is less than 90% and the likelihood of having very high SRI values (i.e., greater than 95%) is about 30%. This likelihood is even smaller under fast sea level rise scenario, in which there is less than 12% likelihood that the system SRI is greater than 90%.

FIGURE 7 HERE

FIGURE 8 HERE

<u>*Create and examine the scenario landscape*</u>: The next step of the exploratory analysis is to identify scenarios leading to different system SRI values. Different data-mining methodologies, such as regression, clustering, classification model, and neural networks, could be used for creation of the meta-model. Regression and neural network models are useful for developing meta-models to be used for prediction purposes. Clustering and classification models are beneficial for creation of meta-models to be used for explaining the attributes pertaining to certain policy outcomes. Some data mining methods, such as Classification and Regression Tree (CART), can be used both for explaining the impact of different system attributes as well as generating various scenarios and pathways. CART is a nonparametric technique that can select, from among a large number of variables, the most important variables in determining the outcome variable to be explained and their interactions (Breiman et al. 1984). A regression tree is a tree-structured representation in which a regression model is fitted to the data in each partition. An advantage of CART analysis is that it facilitates identification of significant factors affecting the policy outcomes as well as the scenarios leading to the desired resilience outcomes. Hence, in this illustrative case, the simulated data were used for meta-modeling using CART analysis. The simulated scenario landscape was investigated to explore the scenarios which could lead to a greater reliability in the water system. In a scenario landscape, each path (consisting of a number of branches) leads to a terminal node. Each path represents an adaptation scenario, and each terminal node represents an outcome. Each

branch of a scenario represents specific values of model parameters. Model parameters that are located in higher branches of the landscape are of more significance in affecting the outcome. Figure 8, shows CART diagram that shows different scenarios leading to different SRI values. The CART diagram provides two insights. First, the factors located in the higher branch of the diagram have more significant effects on the system outcome. In this illustrative case, the most significant factor affecting the system outcome is the actual sea level rise scenario. This implies that, regardless of the actor's and infrastructure system attributes, the future performance of the system is sensitive to the actual sea level rise scenario.

The second insight obtained from the CART diagram is identification scenarios that lead to desired outcomes under each actual sea-level rise scenario. To this end, the SRI values were divided and color-coded into four categories: (1) Very high (SRI > 95% - color-coded with green); (2) High (95%>SRI > 90% - color-coded with blue); (3) Moderate (90%>SRI > 80% - color-coded with yellow); and (4) Low (80%>SRI > 90% - color-coded with red). Accordingly, different scenarios were examined to identify pathways towards greater system performance under each sea level rise scenario. Under slow sea level rise scenario and with a risk-seeking attitude in decision making, high values of SRI can be obtained if the adaptation funding at each decision step is greater than $400M; otherwise, with adaptation funding less than $400M the SRI values will be in the high category range. If risk attitude is risk averse or risk neutral under slow sea level rise scenario, a lower adaptation funding can lead to higher SRI values. Under this scenario, if adaptation funding is greater than $200M, SRI values will be very high. Under this scenario, very high SRI values can be obtained with a funding of less than $200M as long as the actor has a correct perception about sea level rise (i.e., perceived sea level rise is also slow). If the actor has an incorrect perception about sea level rise scenario, SRI values will be in the high category. Under moderate sea level rise scenario, achieving very high SRI values would not be possible regardless of the risk attitude and adaptation funding levels. Under moderate sea level rise scenario, if adaptation funding is greater than 400M, the SRI values will be in the high category. If adaptation funding is between \$200M and \$400M, the SRI values will be in the low category if the agency underestimates the sea level rise scenario (i.e., perceived sea level rise is slow while actual sea level rise is moderate). Under the same funding range, if the agency has correct perception about the sea level rise scenario, SRI values will be in the moderate category. Under the fast sea level rise scenario, high SRI values can only be obtained if the adaptation funding level is greater than \$400M. If adaptation funding is between \$200M and \$400M, the SRI values will be in the low category in most of the scenario. Only if the agency has a correct perception and the risk attitude is neutral, moderate SRI values can be obtained with adaptation funding ranging between \$200M and \$400M.

Evaluate different pathways: This exploration of scenarios helped in identification of different pathways towards a greater performance in the system as shown in Table 4. Each pathway is composed of uncertain scenario (i.e., sea-level rise scenario) as well as decision and behavioral factors leading to a certain system outcome (i.e., SRI). In decision making under uncertainty, the objective is to identify robust decisions that can lead to the desired outcomes under different uncertain scenarios. The desired outcome in this illustrative case was to have high SRI values.

Explore robust pathways: Through the investigation of different pathways, five pathways (1,2, 3,4, and 7) were identified that lead to very high or high SRI values. Three of these five pathways are related to the slow sea level rise scenario. Only one pathway lead to high SRI values under moderate sea level rise scenario and one for fast sea level rise scenario. A common attribute of these pathways is an adaptation funding level of greater than \$400M at each decision point. Hence, for this illustrative case, a robust pathway for adaptation to future uncertain sea level rise scenario will include an adaptation funding of greater than $400M. While this level of funding would lead to high SRI values, with any risk attitude, under slow and moderate sea level rise, it requires a risk neutral attitude in decision-making under fast sea level rise scenario. This implies that, under the uncertainty of future sea level rise scenarios, having a risk neutral attitude would enable achieving high SRI values under all sea level rise possibilities.

TABLE 4 HERE

Discussion and Concluding Remarks

Due to the hypothetical nature of the illustrative example, the results do not have any particular theoretical significance. Nevertheless, the results of the illustrative example show the novel capabilities of the proposed SoS framework for resilience analysis of CIS under climate change impacts. First, the application of the SoS framework show its capability in capturing both chronic and acute climate change impacts. In the illustrative case, chronic salt water intrusion due to sea level rise was captured along with the acute wash over salt water intrusion due to storm surge events. The impacts of chronic and acute climate change stressors differ. Chronic stressors accelerate the degradation of physical infrastructure which make them more vulnerable to acute stressors. Unlike the majority of resilience analysis methodologies proposed in the literature which focus mainly on acute stressors and disruptions, the SoS framework enables capturing the combined effects of these stressors. Second, the SoS framework enable capturing the long-term transformation of CIS for a better resilience analysis. Current approaches for resilience analysis assume that physical infrastructure possess some inherent adaptive capacity and resilience, while in reality adaptation and resilience of infrastructure are derived from the decisions and collective behaviors of institutional actors and users. This assumption has inhibited the creation of an integrated theory of infrastructure adaptation and resilience and long-term planning and policy formulation. The proposed SoS framework addresses this limitation by capturing the adaptive decision-making behaviors of actors in response to climate change stressors and in interaction with physical infrastructure. Capturing these adaptive behaviors and complex interactions is essential in understanding the long-term transformation of CIS. The SoS framework enables integration of various decision-theoretic, stochastic, and physical infrastructure models needed to simulate the long-term evolution and uncertainty in CIS for resilience analysis to climate change impacts. Integration of various models into an integrated framework provide opportunities for exploring new dimensions of resilience.

Finally, the implementation of the SoS framework enable conducting exploratory analysis in order to make robust decisions under uncertainty. Exploratory analysis and modeling has emerged recently in order to provide an approach for robust decision making under uncertainty. Unlike conventional modeling approaches that are intended for prediction and optimization purposes, exploratory analysis aims to capture adaptive behaviors and dynamic interactions in complex systems and uncertainty and examine the probability of various possibilities. Through exploratory analysis, various scenario landscapes are simulated and evaluated in order to identify robust pathways that lead to the desired outcomes in a system. While exploratory analysis has been successfully adopted in assessment of climate change uncertainty in other contexts, its use in the context of CIS has been very limited due to the lack of appropriate theoretical and methodological frameworks. The SoS framework proposed in this study addresses this gap in order to implement further exploratory analysis studies in the context of CIS. In particular, assessment of CIS resilience to climate change impacts is a domain in which traditional optimization and analytical approaches have failed to provide meaningful insights for robust planning and decision making. The illustrative case results demonstrated the utilization of the SoS framework for identifying robust adaptation pathways under sea level rise uncertainty. The application of the proposed SoS framework in future studies can advance the use of exploratory analysis in the context of CIS, and thus lead to better understanding of resilience and sustainability, development of more effective solution concepts, and formulation of robust strategies and policies.

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