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Sources of uncertainty in interdependent infrastructure and their implications

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ABSTRACT

While significant modeling advances have unpacked the complexities of interdependent infrastructure, post-disaster reconnaissance consistently demonstrates a wide variability of outcomes and how much is still to be learned. With that in mind, one might expect the treatment of uncertainty to be quite advanced in interdependent infrastructure models, but we find that to not be the case. In this work, we identify, define, and describe two key classes of uncertainty: system uncertainty and modeling uncertainty. System uncertainty is inherent in all complex infrastructure systems and possesses several subclasses (e.g., physical uncertainty and operational uncertainty). Modeling uncertainty occurs when researchers downscale a complex system to a mathematical or other symbolic representation. It too has several subclasses (e.g., parameter uncertainty and completeness uncertainty). We then identify how the literature to date treats uncertainty with respect to each type of uncertainty. While some work has investigated the implications of physical and temporal uncertainty, by and large, most types of uncertainty have had minimal exploration, suggesting significant knowledge gaps. Finally, we suggest a path forward for treatment and discussion of uncertainty, including what can be learned from other fields involving complex interdependent systems.

1. Introduction

Since the release of Presidential Decision Directive 63 twenty years ago, US doctrine on critical infrastructure has placed significant emphasis on improving our understanding of interdependencies (e.g., PDD-21 1998, EO13231 2001, NIPP 2013) [20,112,113]. The rationale is, if we know the sources and the strengths of dependencies, we can proactively intervene and prevent cascading failures from one sector to the next. Researchers and scientists, in collaboration with public and private infrastructure organizations, have heeded the call; without doubt, significant contributions have been made. Reconnaissance of cascading failures of infrastructure following 9/11 and Hurricane Sandy, among other post-disaster investigations, have provided detailed case studies on the causes of these failures and what later transpired [53, 74,96]. Plenty more studies have used real system data to identify potentially fragile or critical nodes [71,92] and to propose enhanced recovery strategies [42,79,107]. The research has also significantly pushed the boundaries of mathematical modeling [30,101]. However, as many *ex post*-disaster studies reveal, what we know about dependencies might be quite limited. Further, the existence and strengths of dependencies do not always comport with what is expected. That is, significant uncertainty exists.

With that in mind, one might expect the treatment of uncertainty to be quite advanced when discussing and modeling interdependent infrastructure. In sum, we find that not to be true. Moreover, while credence has been given to aleatory uncertainty, particularly when modeling hazard scenarios and component failures, the discussion of the sources and magnitude of uncertainty in interdependent infrastructure is extremely limited. This implies that little is understood of the influence that these uncertainties have on coupled system performance. While most articles assume dependencies to be fixed and binary (e.g., [27, 122]), the reality is that some dependencies are far more spatially and temporally fluid. This is especially true when the source of a dependency is less physical and more a function of individual or societal decisions [60]. Operational and organizational changes within an infrastructure sector can alter more mundane aspects such as repair sequences, and

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more strategic aspects, such as investment prioritization, which in total, changes system resilience. Socio-economic disruptions have complex interactions with infrastructure with respect to the availability of parts, labor, and capital, among other aspects, and are usually discounted in infrastructure models [32]. The degree to which human behavior and bureaucratic frameworks influence complex infrastructure systems is just as influential as the reliability of system components – as is unfortunately illustrated in the 2021 Texas Winter Storms – though is not often considered in the interdependent infrastructure literature. This paper provides the language and a framework for the field to discuss these important aspects.

Dependencies need not be stationary connections nor deterministic. Some connections may be ephemeral and exist only in periods of extremes, such as peaks in customer demand, while others are constant, such as the dependences of water pumps on electric-power. Dependencies also possess varying degrees of strength, with some dependencies being strong, such as how a generation unit requires water for its cooling towers, and other dependencies having loose associations, such as how the transportation and energy sector are intertwined via tariffs [94].

A significant portion of interdependent infrastructure models do not discuss or mathematically capture system uncertainty. While it would be wholly impossible for a single model to capture and quantify all uncertainties affecting the coupled system, ignoring uncertainty in its entirety is similarly dubious. It suggests that results and the models themselves may possess significant uncertainty. This, we argue, could create ramifications for decision-makers who are not informed of the limits of understanding.

The purpose of this paper is three-fold. The first is to isolate and categorize the root sources of uncertainty in the field of interdependent infrastructure. This is completed in Section 3. A methodology for how the divisions were created is provided in Section 2. Broadly, we divide this into two groups: system uncertainty and modeling uncertainty. System uncertainty deals more with internal properties of infrastructure and how external factors (e.g., operators and the environment) influence the operability of interdependent networks. The discussion leverages much of the taxonomy used to describe dependencies (e.g., physical and geographic dependence, as defined by [89]), but also incorporates mention of how significant epistemic uncertainty exists within these systems – a discussion that is often eschewed. Further, we explore how policy decisions and decisions made by operators and other infrastructure decision-makers contribute to system uncertainty. Modeling uncertainty, on the other hand, focuses on the uncertainty that results when researchers downscale a complex system to a mathematical or other symbolic representation. This uncertainty is inherent with all models. Inaccurate and incomplete data, computational constraints placed on models, and assumptions due to lack of knowledge all contribute to modeling uncertainty.

The second purpose of this work is to evaluate how the current state of the science handles uncertainty. This is provided to some degree in Section 3, and Section 4 is devoted to this. To be clear, our work is by no means a comprehensive review of the current literature. Ouyang [77] performs this task quite well. Rather, we identify works that have driven the scholarship in the area of uncertainty and interdependent infrastructure (which is relatively few) and discuss the types of uncertainty contained in these papers. By having first identified the root sources of uncertainty in Section 3, we can then discuss the types of uncertainty that are present and missing in this space.

The third purpose is to provide a path forward when discussing and handling uncertainty in interdependent infrastructure. In Section 5, we discuss the importance of presenting uncertainty when conveying research results to decision-makers and the need to expand beyond physical "hard" systems to include the interactions with "soft" infrastructure systems (e.g., financial systems) and humans. We also identify current best practices for handling uncertainty that are used presently in other fields involving complex interdependent systems (e.g., the climate and global change literature).

The foundational work on uncertainty by Der Kiureghian and Ditlevsen [21] poses a provocative question about whether taxonomies (aleatory and epistemic, in their case) actually matter, especially once modeling begins and aleatory and epistemic uncertainty can begin to merge. We argue that they do matter. First, the field of interdependent infrastructure is relatively nascent, and our observation is that lexical gaps are leading to modeling gaps, especially when it comes to incorporating the impacts of human and societal decisions. The second is more practical. Knowing what causes the uncertainties allows decision makers and funders (e.g., federal agencies) to decide how to expend resources to reduce uncertainty (and thus often times, risk). For example, epistemic uncertainty can be resolved (or at least reduced) through more research. Aleatory uncertainty can be resolved (or at least reduced) through better equipment, improved protocols, and general system investments. This influences investment decisions, but on the flip side, decisions-makers need to be informed about the types of uncertainties and their sources.

This work builds from and is complementary to other work in the space that explores the dimensions of interdependent infrastructure [51,89,97,119]. Early work in this space tends to focus on how to decompose coupled systems into discrete functional dimensions. It has not placed much emphasis on the role of human decisions, institutions, and bureaucracies (e.g., Rinaldi et al. [89] uses the catchall "logical"). Recent work by Sharma et al. [97] is similar to our work in the methodological approach for developing taxonomies (see Section 2). They decompose their classification of interdependent infrastructure into orthogonal dimensions ("ontology" and "epistemology") as we do in our classification of sources of uncertainty ("systems" and "modeling"). However, our classification structure is unique and we link our dimensions to how it is treated in the literature whereas existing work has not linked the dimensions of interdependencies to uncertainty nor describe how uncertainty is present in interdependent infrastructure models.

As this work demonstrates, insufficient consideration has been given to uncertainty. This could make researchers over-confident of their results and also provide too little information to decision-makers. This work makes progress at overcoming this shortfall by systematically categorizing the types of uncertainty that are present in interdependent infrastructure systems and identifying gaps in the literature. We believe this to be timely and critically important as the field advances into more complicated interdependent networks, such as socio-technical networks [60].

2. Methodology

Our study uses taxonomy methods to delineate types of uncertainty encountered in modeling interdependent infrastructure. Taxonomies, also known as classifications, frameworks, and typologies, occur in many areas of science [3,23]. Some authors use the terms interchangeably while others provide precise definitions for each term [72]; we chose the former. At the most basic level, taxonomies and their related terms seek to group similar types of concepts or objects and distinguish them from those that are less similar. Grouping occurs across one or more dimensions, which are composed of any number of characteristics.

In our study we follow the general taxonomy method of Nickerson et al. [72]. The first step in taxonomy creation is deciding on its purpose. For this study, the purpose is to categorize types of uncertainties so that model creators and users can better understand the implication of each uncertainty type in model use and interpretation.

The next step is to decide to choose criteria that will be used to judge the usefulness of the taxonomy. Popular criteria that we adopt are two subjective measures, conciseness and robustness, and four objective measures, uniqueness of dimensions, uniqueness of characteristics within a dimension, whether cases are uniquely classified, and no null cells. The subjective measures are chosen to ensure the taxonomy is usable. It should not have too many dimensions and characteristics as to be unwieldy and not too few as to lack meaningful distinctions among cases. The objective measures ensure that dimensions and characteristics are not duplicative, that the taxonomy makes precise categorizations, and that there are no 'empty' spots in the taxonomy with no cases or unlikely combinations of characteristics.

After the taxonomy purpose and criteria are set, the main methodological process is an iterative loop between empirical-to-conceptual and conceptual-to-empirical subprocesses, where the loop is repeated until the usefulness criteria are met. The primary distinction between the two subprocesses are their starting points. Empirical-to-conceptual begins with a set of objects or concepts. Based on inspection of the objects and background knowledge, researchers create characteristics that are relevant to the purpose of the taxonomy. Once the candidate characteristics have been identified, then the objects are grouped into dimensions by some type of cluster analysis or informally by graphical or some other manual technique.

In contrast, the conceptual-to-empirical subprocess begins with researchers using their background knowledge of existing theory to deduce relevant dimensions and characteristics. Once created the researchers examine objects for fit with the deduced characteristics. At the end of either sub-process is an initial taxonomy that may be further modified by another subprocess. The choice of which subprocess to use in the first loop is usually a function of a sufficiently large sample of objects and the richness of background theory. For example, big data applications have large sample sizes but often poor theory. As a result, a natural first choice for sub-process is empirical-to-conceptual. For analyses such as ours, where background theory is relatively rich but only a few cases are available, a conceptual-to-empirical approach is more appropriate.

After the initial taxonomy is created, further loops may be entered if the taxonomy criteria are not met. If new objects are found, or if some objects were reserved for out-of-sample testing, then another empirical-to-conceptual loop might be helpful. Otherwise, conceptual-to-empirical analysis may be used to further refine the taxonomy. With either subprocess, dimensions may be added or eliminated if needed. The literature on taxonomy creation emphasizes that finding an 'optimal' taxonomy structure is unlikely, and that focus should be put on constructing a taxonomy that best fits the purpose laid out in the first step. This design philosophy is similar to that described in other synthesis techniques, such as the 'best fit' framework synthesis methodology used for systematic reviews.

3. Sources of uncertainty in interdependent infrastructure

This section focuses on the types of uncertainty that are inherent in infrastructure dependencies, inherent with our current understanding of interdependent infrastructure, and inherent to modeling efforts. The former two relate to system uncertainty and the latter relates to modeling uncertainty. System uncertainty possesses both aleatory and epistemic uncertainty, while modeling uncertainty is largely epistemic. These concepts, including formal definitions, are expanded upon in the sections that follow.

As discussed in Nickerson et al. [72] and Sharma et al. [97], for taxonomies to be useful for modeling, their dimensions must be orthogonal. As such, our two key dimensions – systems uncertainty and modeling uncertainty – are orthogonal. However, in any instance when modeling interdependent infrastructure occurs, (at least) one type of system uncertainty exists and (at least) one type of modeling uncertainty exists. Likely, multiple types exist, and further, there are no rules that preclude the co-existence of a specific type of system uncertainty and a type of modeling uncertainty; thus, the types of uncertainty within each dimension should not be considered unique branches but rather matrixed. More specifically, each type of uncertainty contained within system uncertainty could intersect with each type of uncertainty contained within modeling uncertainty and vice versa.

3.1. System uncertainty

We define system uncertainty for interdependent infrastructure networks as uncertainty concerning the events, states, quantities, or phenomena (including system shocks and external hazards) that influence and connect infrastructure networks. System uncertainty both reflects uncertainty intrinsic to coupled systems (largely aleatory uncertainty, though we identify one instance where epistemic uncertainty could play a role) and reflects a limited understanding of the phenomena that connects coupled systems (epistemic uncertainty). Understanding which uncertainties are reducible and which are not provides important context for decision-makers in terms of when and where to allocate research funds (for knowledge discovery) and when to alter properties or components of the system (to enhance system reliability).

For simplicity, the forms of system uncertainty described in this section largely stem from Rinaldi et al. [89] – e.g., physical, geographic (or spatial), and cyber. While we broadly consider logical dependencies and uncertainties, this has historically been a "catchall" for dependencies that are not one of the other three described in Rinaldi et al. [89]. As such, we divide logical dependencies into multiple additional orthogonal categories. Furthermore, we identify additional forms of uncertainties (e.g., temporal uncertainty) that we feel are not appropriate in the four original divisions discussed in the originating work. The sources of uncertainty are presented in Table 1 and a short discussion of each follows.

To illustrate how the different sources of system uncertainty can be measured, consider a set of systems, S, subject to some phenomenon, A, and with their performance characterized by a (possibly time-dependent) vector, X (e.g., the state of or flow between the systems). For simplicity, and without loss of generality, we consider two systems, System 1 and System 2. In Table 1, some examples of uncertainty metrics for the different uncertainty sources are given using the aforementioned notation.

Before proceeding, we add brief notes on the work's scope. First, we limit the discussion to only uncertainties related to dependencies and do not discuss uncertainties that are inherent to a single infrastructure system (e.g., the reliability of a transformer at an electrical substation). Second, the types of uncertainty below refer to a one-way dependence for both simplicity and because the reciprocating forms of dependency may not be identical to the one discussed. That being said, multiple forms of system uncertainty – if not all the forms discussed below – are likely to exist in any coupled system. This is discussed with more depth in Section 5. Third, this may not be a collectively exhaustive list, and rather reflects the current understanding of interdependent infrastructure. More research and discussion in this field may highlight additional sources of uncertainty.

3.1.1. Physical uncertainty

Definition: Uncertainty about the quantities characterizing the flow between the systems.

Example: A water pumping station (or a pumphouse) requires electric-power for operations. The flow of electric-power can be uncertain, especially in times of extremes. The flow can depend on the state of the parent system (i.e., how much electric-power can be provided) and the state of the child system (i.e., how much power is required). Alternatively, the flow can depend on the state of the electric cable that connects the systems.

Discussion: Physical dependencies assume a flow of some commodity (e.g., water, power, widgets) from one system to another. This flow requires something physical over which the commodity is transported. Because these physical connections are forged by individuals and organizations, knowledge of these connections exists (i.e., the existence and mechanism of these links is established). Thus, the phenomenon surrounding physical uncertainty is well characterized and it lacks epistemic uncertainty. (This is not to say that everyone with operational

Table 1
Sources of system uncertainty and their definition

Source of System Uncertainty	Definition	Example uncertainty metrics	Main type of uncertainty
Physical uncertainty	Uncertainty about the quantities characterizing the flow between the systems	$P(X \leq x) = P(X_1 \leq x_1)$, where X_1 characterizes the flow from System 1 to System 2	Aleatory
Spatial uncertainty	Uncertainty about how phenomena (e.g., hazardous events) affect collocated systems and how phenomena behind the spatial distribution of collocated systems influences system states	$P(X \leq x \mid A)$, where X characterizes the performance/state of the systems and A is a spatial phenomenon, such as a hazardous event	Aleatory
Temporal uncertainty	Uncertainty about how dependencies and phenomena that link systems (e.g., consumer demand shifts) depends on and changes over time	$P(X(t) \mid A)$, $t > T$, and $P(T \leq t \mid A)$, where $X(t)$ characterizes the performance of the systems at time t and T is the time between the occurrence of a phenomenon A and dependency effects starting to express themselves	Aleatory
Governance uncertainty	Uncertainty about possible future regulations, policies, or norms and how they could impact system performance or the operational environment	$P(X \leq x \mid A)$ and $P(A)$, where X characterizes the performance/ state of the systems and A is a governance phenomenon (top-down decisions) that may affect the system (e.g., new regulations)	Epistemic (A) Aleatory (X)
Socio-economic uncertainty	Uncertainty about decisions made by consumers and other end-users in response to a disruption or other external stimuli	$P(X \leq x \mid A)$ and $P(A)$, where X characterizes the performance/ state of the systems and A is a socio-economic phenomenon (bottom-up decisions) that may affect the system (e.g., changes in supply chains, demand, or consumer/market behavior)	Epistemic or aleatory (A), depending on the phenomenon Aleatory (X)
Operational uncertainty	Uncertainty about the phenomena that dictate operational decisions or procedures	$P(A)$, where A is a phenomenon that - if it occurs - dictates operational decisions or procedures	Aleatory or epistemic, depending on the phenomenon
Informational uncertainty	Uncertainty by the child network about the state of or the phenomena affecting a parent network due to a lack of knowledge	From the point of view of System 2: $P(X_1 \leq x_1)$ or $P(A_1)$, where X_1 characterizes the state of System 1 and A_1 is a phenomenon affecting System 1	Epistemic
Cyber uncertainty	Uncertainty about the state of the cyber infrastructure enables the flow of information between systems and uncertainty about the quantities that reflect the flow of information using cyber infrastructure	Special case of informational uncertainty, where X characterizes the states of the cyber subsystems and/or Analogous to physical uncertainty, where X characterizes the flow of information between the systems	Aleatory

responsibilities *knows* of these physical connections – a form of informational uncertainty).

With this in mind, physical uncertainty possesses aleatory uncertainty and is inherent to the system. The uncertainty resides in the *quantity* of flow being provided. Flow uncertainty can originate in the parent system based on the level of service it is able to provide (i.e., its state), originate in the child system based on what it demands, or originate in the reliability of the component that connects the systems. The literature largely assumes that flow from the parent to the child system depends on the operability of the parent network and its ability to provide the service (e.g., [121]). We cannot find an example in the literature where the reliability of the component(s) that physically connects the systems is considered.

Of the uncertainties discussed in this paper, physical uncertainty is the most prevalent in the literature – likely coinciding with physical dependencies being so ubiquitous. Zio and Sansavini [121] imbed a Monte Carlo simulation that represents probabilistic failure scenarios for a single network within an interdependent network model to quantify how internal failures propagate to external systems along with its uncertainty. This method is similar to Wu and Dueñas-Osorio [114] which uses established seismic fragility curves to model the damage of components in the water sector and how these failures could propagate. Zhang et al. [118] simplify this approach by assigning conditional failure probabilities to those links that connect networks. In this instance, the conditional probabilities reflect more the state of the parent network than the state of the actual component connecting the systems.

3.1.2. Spatial uncertainty

Definition: Uncertainty about how phenomena (e.g., hazardous events) affect collocated systems and how the spatial distribution of collocated systems influences system states.

Example 1: Roads that are impassable due to debris after a windstorm are likely to have downed power lines and thus intersections with signal outages. Electrical and road networks are linked by the wind and their spatial proximity. The hazardous event (the wind) initiates the failure sequence in this instance.

Example 2: Internet cables are often collocated with water distribution infrastructure underneath roadways. A water main break can flood these cables if not properly protected, and lead to wide-spread Internet outages. The water main break initiates the failure in this instance, but the impacts are magnified by the close spatial proximity of the systems.

Discussion: This type of uncertainty is unique in that there are two underlying phenomena – one extrinsic and one intrinsic – which spatially connect infrastructure systems. The first relates to how hazards or other external spatial shocks probabilistically connect two systems. The closer two assets from different systems are, the more likely one is to be damaged if the other is damaged when spatially-distributed hazards occur. They are also likely to sustain similar degrees of damage; however distinct systems have different vulnerabilities to hazards for a variety of reasons. There is inherent and thus aleatory uncertainty to this process. A windstorm could cause debris to make a roadway impassable, but there remains a possibility that electric lines remain intact. Significant research is underway exploring the epistemic uncertainty that remains in our knowledge about hazards (e.g., [9]), but this uncertainty is not a property of the infrastructure system.

A second type of spatial uncertainty does not concern external hazards, but rather is a function of collocation and an event that occurs in one of the systems. A component failure in one system (an intrinsic event) could damage components in systems that are close, and thus affect their operational states as well. As with hazards, this is a form of aleatory uncertainty, as the likelihood of a component failure is a property of the system. There has been discussion about how infrastructure operators and researchers do not understand spatial dependencies well (e.g., O'Rourke [74] discusses the previously unknown spatial dependencies between the US Stock Exchange and the water in New York City following 9/11). While these spatial dependencies were unknown, we argue that this is a type of informational uncertainty (and thus a form of epistemic uncertainty).

3.1.3. Temporal uncertainty

Definition: Uncertainty about how dependencies and phenomena that link systems (e.g., consumer demand shifts) depends on and changes over time.

Example: Many cellular towers (like other critical infrastructures) have backup generators for the case where they lose electric-power. There are instances where generators were low on fuel at the start of the outage or simply ran out at some point in time, possibly stymying electric-power restoration due to an inability to effectively communicate.

Discussion: This class of uncertainty focuses on how dependencies and the phenomena that affect dependencies both depend on time and change over time. This could be seen as an extension of the other types of uncertainty discussed in this paper; it acknowledges that random events all have a time component. A pipe breaks at some point in time. Information that could change restoration plans becomes known at a certain point in time. When these random events will be realized is uncertain. There could be a significant lag time between the initiating event and effects on downstream systems. Rinaldi et al. [89] described in detail how the California energy crisis in the late 1990's contributed to agricultural losses and ultimately to problems within the banking and finance sector. This was witnessed over years, and was not a quick system "shock."

We argue that there is another aspect to this dimension of uncertainty. That is, temporal uncertainty also considers how dependencies between systems change over time. We could envision scenarios whereby systems are independent, but are sporadically linked during times of extremes. For example, a water system could operate without relying on natural gas, but could become critical and large consumers of natural gas during electric-power outages to operate key pumps. This is an example of significant changes in end-user demands.

This type of uncertainty likely contains both aleatory and epistemic uncertainty. There is an inherent randomness to *when* components fail. However, how dependencies evolve over time - especially in socio-technical systems - is more complex than a coin flip. It is arguably the basis of emerging research on dynamic dependencies (e.g., [37]) and could itself be a new frontier in interdependent infrastructure research [60,67]. While consideration of temporal aspect is common in interdependent literature, especially when it comes to staging restoration sequences (e.g., [45,47]), the uncertainties associated with it are generally less acknowledged. However, the body of work that examines correlation among recovery curves contradicts this statement [25,123].

3.1.4. Governance uncertainty

Definition: Uncertainty about possible future regulations, policies, or norms and how they could impact system performance or the operational environment (e.g., trade agreements and how they affect infrastructure development). This can also be viewed as uncertainty stemming from top-down decisions.

Example 1: Governing entities overseeing public-private partnerships (PPP) for infrastructure development or expansion can impact system performance and its ability to respond to disruptions. The dynamics of a PPP framework can determine specific performance requirements or safety standards, which can drastically alter operations [19].

Example 2: Government policies can influence the level of infrastructure protection employed, and thus modify operations. Policy changes in the US have led to a focus on infrastructure resilience by requiring infrastructure operators and owners to include resilience and protection indices in their risk assessments [69].

Discussion: Governance uncertainty results from a lack of knowledge about how governing bodies, organizations, and stakeholders may constrain, dictate, or guide the development, operations, and maintenance of infrastructure systems and the ways in which this will impact system performance. Anticipation of policies and inter-agency agreements and their effect on the system can help characterize and reduce uncertainty through modeling [68]. Generally, governance uncertainty is epistemic because governance phenomena are hard to predict. Many regulatory reforms result from system disruption. For instance, the 2003 Northeast Blackout led to the formation of EPACT 2005, a regulatory organization tasked with ensuring US grid reliability and developing reliability standards [41]. This added operational and investment costs to electric utilities, but also, in theory, could have disincentivized dependent sectors in investing in backup power. However, in certain cases governance uncertainty is aleatory as it results from dynamics across governing bodies and potential unintended consequences of policies (e.g., moral hazard resulting from insurance policies).

Prior studies have focused on the implication of governance in infrastructure management and the role of infrastructure networks in policy development. Examples include policy frameworks for infrastructure development [15], policy implications on reconstruction after disasters [80], the role of governance in infrastructure risk management [109], and the need for policymakers to understand and learn from infrastructure networks before making decisions of infrastructure investment and regulation ([110]). However, minimal work has been done to quantify and characterize the uncertainty that stems from how regulatory or policy uncertainty affects the operations or system performance of interdependent infrastructure. Taneja et al. [103] explored how to design adaptive and flexible port infrastructure systems to manage international trade unpredictability and globalization. Hiteva and Watson [40] explore the future of how interdependent infrastructure may be governed. They make compelling arguments including investment in joint infrastructure projects in targeted areas and rethinking how government agencies oversee systems.

3.1.5. Socio-economic uncertainty

Definition: Uncertainty about decisions made by consumers and other end-users in response to a disruption or other external stimuli. These, in aggregate, alter demand for infrastructure and affect other market-forces (e.g., interest rates). This can also be viewed as uncertainty stemming from bottom-up decisions.

Example: Response by humans and markets to disruption can result in demand shifts for infrastructure systems. In a city with multi-modal transit systems, extreme precipitation can drive demand from the roads (e.g., bus, biking, scooter) to underground transit systems (e.g., subways, metro, train) which can lead to system disruption (e.g., delays) and amplify the impact of a disaster (e.g., more rescues due to delayed track/station flooding).

Discussion: Uncertainties from socio-economic interdependencies are a result of how people - individually and collectively - respond to disrupted infrastructure, and how this in turn, impacts infrastructure performance, community functioning, and multiple sectors of the economy. For simplicity, we divide this classification into economic uncertainty and socio-uncertainty.

The uncertainties in economic interdependencies results from (i) the lack of information about the different economic sectors and their interdependent relations (epistemic uncertainty), (ii) the inherent randomness in economic loss estimation (aleatory uncertainty). To address epistemic uncertainty, input-output tables have been used to inform production and demand levels for each economic sector and derive interdependent relations [35]. Aleatory uncertainty is described using probabilistic models and Bayesian variations to existing methods of loss estimation which is less studied [115].

One way in which economic uncertainty manifests is in supply chains. While the speed of infrastructure recovery directly influences economic losses, so do the dynamics of supply chains and how supply chains react to the failures. This leads to a third layer of uncertainty for economic interdependencies, which is the dynamic behavior of supply chains and combines both types of uncertainty. Links within the supply chain network are not only uncertain but also dynamic over time. Depending on the spatial and temporal distribution of demand and supply across economic sectors, dependencies between supply chain nodes and edges can appear, disappear, or change in magnitude of importance. Changes in the demand can be the result of uncertainty in social interdependencies which may or may not be predictable. For example, a shortage of desk furniture during a pandemic could have been predicted whereas an increase in demand for toilet paper was not anticipated.

In addition to economic impact and loss estimation, uncertainty in social interdependencies is the result of human and organizational behavior in human-infrastructure interactions. Conceptual and simulation-based frameworks have been developed to model the human layer within infrastructure interdependencies [49,61] such as agent-based models that capture interdependencies between infrastructure and human agents [16,100]. Consideration of socio-economic perspectives in infrastructure modeling has recently gained attention Karakoc et al. [46] where planning and restoration is informed by socio-economic indicators. Uncertainty from short-term disruptions (e.g., natural hazards) and long-term changes (e.g., development) propagates differently through socio-economic and infrastructure systems, leading to a dynamic reconfiguration of interdependencies and an intersection with temporal uncertainty.

3.1.6. Operational uncertainty

Definition: Uncertainty about the phenomena that dictate operational decisions or procedures.

Example: The US Army Corps of Engineers operates 29 locks on the Mississippi River that allow for the transport of bulk commodities. Changes to operations, including lock closures, have ripple effects on bulk commodity transport and commodity markets.

Discussion: While infrastructure operations are increasingly digitally monitored, owners and operators still make the bulk of the operational and repair decisions. These decisions heuristics may be (and usually are) informed by data derived from system monitoring and operational protocols. Protocols are put into place to maintain reliability and to prevent catastrophic failures (e.g., nuclear power plants). Despite protocols, operators use judgement and experience to make decisions, especially during unforeseen situations [64]. Biases, lack of training, inexperience, and risk tolerances all affect which decision operators make [99], and thus, these decisions lack certainty. When these operability decisions affect child systems – such as could be the case when an electric-power utility decides a repair sequence following a major wind storm – it creates uncertainty as to when services will function again or as to how reliable some components are, and presumably, could cause the child system to make more conservative decisions.

Whether this is a form of aleatory or epistemic uncertainty is debatable. To be a form of aleatory uncertainty, we would need to assume that decisions are probabilistic acts made in proportion to how decision-makers value one alternative relative to other alternatives (e.g., as described in [57]), and that these preference weights are quantifiable. Known decision biases makes this proposition somewhat dubious. Regardless of the types of uncertainty that is present, minimal research has explored how operational decisions propagate in highly networked coupled systems. Ouyang and Wang [79] and González et al. [33] explore the impacts of decisions related to repair sequences of coupled systems, but their objectives are to be prescriptive and what repair sequences *should* resemble. Reilly et al. [87] make hypotheses regarding decisions that strategic operators from interdependent networks would make, though the framework is conceptual and abstract. We are unable to find literature related to operational and decision uncertainty in interdependent infrastructure and how these decisions propagate into operability.

3.1.7. Informational uncertainty

Definition: Uncertainty by the child network about the state of or the phenomena affecting a parent network due to a lack of knowledge.

Example: Water management utilities often need to repair pumps after major hurricanes. Assuming that many of the pump stations are without power, repair sequencing could be done more effectively if the water utility knew when power would be restored to each station.

Discussion: Infrastructure operators and owners make frequent tactical and strategic decisions, including when and how to invest resources, how to conduct system repairs, and often how much supply they should generate. While through sensors and other technology, they have increasing situational awareness about the state and the phenomena affecting their own system, it is uncommon for them to have complete operational information about the systems on which they depend. We can envision this being relevant in numerous circumstances, and some jurisdictions are trying to reduce this lack of knowledge. For example, in one city with which an author spoke, when a utility applies for a permit to conduct underground maintenance or repair, other utilities with equipment in the area are notified. This is to encourage collocated utilities to simultaneously conduct maintenance and to notify them about possible outages. That being said, an author has spoken with many utilities in the aftermath of outages caused by minor weather events or component failures to major weather events, and a frequent grievance is that they tend to know little about when systems on which they depend will be operational again. This, they say, slows recovery in that they are unable to sequence their repair strategy to align with when that of other utilities.

Contrary to reality, the bulk of the interdependent infrastructure literature on network decision-making makes assumptions that all parties have complete and perfect knowledge about other systems. For example, Cavdaroglu et al. [13] and González et al. [33] formulate prescriptive interventions for sequencing repairs following disasters and Reilly et al. [87] discuss how interdependent infrastructure may gain a competitive advantage by exploiting their (assumed to be universally-known) interdependencies. While mathematically convenient, this assumption is dubious at best. Sharkey et al. [95] is an exception to this assessment. While it did not examine informational uncertainty per se, it did explore how better coordination via information sharing among sectors could speed restoration processes using an optimization framework. More recently, Talebiyan and Dueñas-Osorio [101] modeled operational decisions under uncertainty in an interdependent context using a Bayesian Hierarchical Model and demonstrated model improvements when less uncertainty is present (e.g., through communication).

We argue that informational uncertainty is likely the only form of system uncertainty to be solely composed of epistemic uncertainty. This uncertainty results from a lack of knowledge about another system by decision-makers. Withholding information, could, in theory, be strategically advantageous [87], though it also could slow repair and restoration of services, and contribute to redundant investments. The NIPP (2013) has called for additional information sharing among sectors to help reduce informational uncertainties [20]. No guidance has been offered, however, on what types of information are useful, and when or how that information should be shared.

3.1.8. Cyber uncertainty

Definition: Uncertainty about the state of the cyber infrastructure enables the flow of information between systems and uncertainty about the quantities that reflect the flow of information using cyber infrastructure.

Example: Electric generation units are highly integrated with complex SCADA systems for system monitoring and control. Some of this information is transmitted to grid operators via cyber infrastructure. A lapse in security protocols exposes the unit to intrusion and which, in theory, could cause massive outages.

Discussion: In many ways, this class of uncertainty is similar to physical uncertainty. Many sectors rely on a consistent flow of information, usually over the Internet or other telecommunication networks, about the status of other sectors in a manner similar to how water pumps rely on a steady flow of electric-power. Increasingly, this communication facilitates both automated controls (e.g., part of the concept behind "Smart Cities," see: [117]) and data and knowledge transfer (e.g., using email or a Cloud service provider). What makes this concept slightly unique from physical uncertainty is that (a) it strictly relates to an information flow and (b) the physical pathway that facilitates the information flow is often neither owned nor operated by the system generating the information nor the system consuming the information.

Numerous infrastructure sectors, including water and railroads, now rely on highly integrated SCADA systems, and other types of Industrial Control Systems (ICS) for operations. These systems tend to be *internal*, and the properties of uncertainty surrounding them are considered outside the scope of this paper. However, sectors are increasingly dependent on another for digital communication. Telecommunications and electric-power are obvious examples.

Similar to physical uncertainty, cyber uncertainty, we contend, consists mainly of aleatory uncertainty. Cyber connections are physical connections (e.g., wires, wireless signals) forged by individuals and their existence lacks uncertainty, which is not to say all operators are aware of their existence (informational uncertainty). However, the level of service that a cyber connection can provide depends on the reliability system components (aleatory uncertainty), e.g., routers and Ethernet cables, and how the system is operated (operational uncertainty).

This is not to say that epistemic uncertainty does not exist *within* cyber systems. Scala et al. [93] identifies five sources of epistemic uncertainty within cyber systems (e.g., system scalability and human behavior). Cherdantseva et al. [14] reviewed methods for evaluating the risk of cyber systems, though these methods generally assumed that uncertainty is characterized. While research increasingly considers cyber dependencies [6], little research explicitly considers cyber uncertainties in interdependent infrastructure. Tian and Sansavini [105] begin this work by conducting a simulation to see how grid spitting – the separating of electric networks into islands due to imminent instability – is governed by reliable communication and cyber infrastructure.

3.2. Modeling uncertainty

We define modeling uncertainty for interdependent infrastructure systems as uncertainty that stems from downscaling complex interdependent systems into a conceptual or mathematical model, or some other symbolic representation. Modeling uncertainty arises within all models [73]. In this section, we describe four generic types of modeling uncertainty and then give examples of sources of each. Unlike system uncertainty, modeling uncertainty is largely composed of epistemic uncertainty.

The generic types of modeling uncertainty that we describe follow from Aven and Zio [2]. We additionally include completeness uncertainty, which is also known as ontological uncertainty [62]. This is consistent with recent arguments made by Bjerga et al. [10] that completeness uncertainty - defined by the degree to which sources of uncertainty are included in the model - is not implicitly contained within other types of uncertainty but rather is a form of modeling uncertainty itself. Table 2 lists the generic types of modeling uncertainty and provides examples of some of their sources.

Interdependent infrastructure models, f, link two or more systems using parameters, Z, to represent performance characteristics, Y. These performance characteristics are uncertain and can be system-wide quantities of interest (e.g., the number of people losing water supply) or more focused quantities (e.g., the flow of electricity in a line). The values of Y and Z may be influenced by external phenomena or events, A (e.g., wind gusts, operational changes).

3.2.1. Parameter uncertainty

Definition: Uncertainty about the values of parameters, Z, used in model f.

Example: Consider a codependent and collocated electric-power utility and water utility which reside in a hurricane-prone region. A model, $f(Z_1, Z_2, Z_A)$, is created to forecast the number of customers, Y, that lose water supply as a result of a hurricane. Parameters Z_1, Z_2 and Z_A may include features related to the water system (e.g., the pressure at different nodes in the systems), features related to the power system (e.g., the reliability utility poles), as well as features related to hurricane, A (e.g., wind speed), respectively. Parameters Z_1 and Z_2 along with the parameters that represent the event A usually possess uncertainty.

Discussion: This type of uncertainty addresses uncertainty about parameters used within models. This type of uncertainty is usually in the class of epistemic uncertainty and often results from inaccurate and incomplete data. For example, it is impossible to collect all system state data for massive infrastructure systems due to their complexity and the cost. Further, instrumentation error can lead to additional knowledge gaps. Parameter uncertainty is typically managed by assigning probability distribution to the parameters, such as the rate parameter in a Poisson probability model used to model the occurrences of hurricanes (e.g., [98]). This type of uncertainty can be in the class of aleatory uncertainty when the parameter is an observable but random quantity, such as a hurricane wind speed when used to forecast electric-power outages (e.g., [34]).

Of the types of modeling uncertainty discussed in this paper, parameter uncertainty appears to be the type most commonly addressed in the interdependent infrastructure literature, albeit it is still uncommon. For example, Barker and Haimes [4] describe a multi-objective approach to evaluate the uncertainty in the “parameters of interdependency” using an inoperability input-output model (IIM). Moreover, [5] quantifies implications of uncertainty from expert-elicited probability distributions using IIM for an interdependent set of economic and infrastructure sectors.

3.2.2. Model output uncertainty and model structural uncertainty

Definition (model output uncertainty): Uncertainty about the difference between the model output, $f(Z)$, and the actual outcome, Y, for parameters, Z. This difference is also called the model error, $f(Z) - Y$.

Definition (model structural uncertainty): The difference between

Table 2
Types and sources of modeling uncertainty

Type of Modeling Uncertainty	Definition	Example Uncertainty Metrics	Possible Sources of Uncertainty	Type of Uncertainty
Parameter uncertainty	Uncertainty about the values of the parameters, Z, of a model f	$P(Z \leq z)$	Inaccurate and incomplete data	Epistemic (aleatory if the parameter is subject to random variation)
Model output uncertainty	Uncertainty about the difference between the model output, $f(Z)$ and the actual outcome, Y	$P(f(Z) - Y \leq d)$	Incomplete knowledge about the values of the model parameters that permeate through the model; assumptions, simplifications, approximations introduced in the model	Epistemic
Model structural uncertainty	Uncertainty about the difference between the model output $f(Z_{true})$ given the true parameter Z_{true} and the actual outcome, Y	$\int P(f(Z) - Y \leq d \mid Z = z)\, dH(z)$, where $H(z) = P(Z \leq z)$	Assumptions, simplifications, approximations introduced in the model	Epistemic
Completeness uncertainty	Uncertainty about the completeness of the parameter vector Z	Not commonly quantified	Incomplete knowledge of the system, phenomena and/or processes involved	Epistemic

the model output $f(Z_{true})$ given the true parameters, Z_{true}, and the actual outcome Y. This difference is also called the conditional model error $f(Z_{true})$ - Y.

Example: Consider again the interconnected water and power system subject to hurricanes described above. The model, $f(Z_1, Z_2 \mid Z_A)$, could predict the number of customers who will lose water supply given a wind speed, Z_A. If this is done in advance of a storm, wind speed, Z_A, is an estimate. However, Y can later be observed. It is likely that $|f(Z_1, Z_2 \mid Z_A) - Y| \geq 0$ due to the uncertainty in the parameter vector $Z = (Z_1, Z_2, Z_A)$, but the magnitude of this difference is uncertain before event A occurs.

Model structural uncertainty is slightly different. Even if the parameter values, including the true wind speed, Z_{Atrue}, were known *a priori*, it is likely that $|f(Z_{1true}, Z_{2true} \mid Z_{Atrue}) - Y| \geq 0$ due to structural inaccuracies in the model. That is the model, which is a simplified representation of the system, possesses errors. This could be due to erroneous or limiting assumptions made by the modeler or computational limits. This is akin "metadoxastic uncertainty" in Murphy et al. [70] and, in principle, should influence the level of confidence we have in our models.

Discussion: The adage by George Box "All models are wrong, but some are useful," describe these uncertainties well. Both model output uncertainty and model structural uncertainty are influenced by assumptions and judgments made by the researcher that may not be true, and by simplifications and approximations introduced in the model. That is, the structure of the model and the complex process it represents is not perfectly accurate. This could be due to human error and the modeler being unaware of how to appropriately compose the model, or potentially due to volitional uncertainty and the modeler bringing their own judgements and assumption about alternatives into the process [70]. Additionally, parameter uncertainty due to incomplete knowledge contributes to model output uncertainty when these parameter uncertainties permeate through the model. Because all models have structural deficiencies, both model output uncertainty and model structural uncertainty are types of epistemic uncertainty. These types of uncertainty are handled in different ways. The researcher could leverage different modeling techniques to answer the same question, or the researcher could relax some assumptions and identify their influence of the assumption on outcomes. Similarly, the researcher could potentially gain access to more computational resources, which would allow them to run more granular models.

Note that model output uncertainty and model structural uncertainty are evaluated before observing the outcome Y. Thus, when the risk assessment is carried out and $f(Z)$ is used to predict Y, the outcome of Y is uncertain.

Still, there are no articles in the interdependence infrastructure modeling literature that directly address model output or model structural uncertainty. However, there are a myriad of articles that accomplish this indirectly. Take the entire body of work that uses Shelby County, TN - a county in the United States that is especially prone to floods and earthquake - as a case study (e.g., [24,33,43,46,116]). All of these models examine network robustness and recovery strategies for different modeling assumptions and approaches. They thus acknowledge that no one model accurately predicts all outcomes.

3.2.3. Completeness uncertainty

Definition: Uncertainty about the completeness of the parameter vector Z.

Example: Consider again the interconnected water and power system in a hurricane-prone region. An operator or researcher may be interested in developing a model, $f(Z)$, to predict the performance of the water system, Y, given a hurricane. The parameter vector Z reflects relevant sources of risk, such as the age of the water system, the exposure of the power system, and the intensity of the hurricane. However, the vector Z is incomplete. There will always be aspects that are excluded (e.g., squirrels chewing through an electrical line [66]). This is in part due to modeling limitations, and in part because of knowledge gaps or ignorance regarding key phenomena [11]. Completeness uncertainty reflects the uncertainty about both the number of factors that are missing in the model and the contribution those missing factors have on the outcome.

Discussion: Completeness uncertainty is a type of epistemic uncertainty. It results from incomplete knowledge about the system, phenomena, and/or random processes and their contribution to the outcomes. It is common to distinguish between known and unknown completeness uncertainty. There are often reasons to exclude some known events, interactions, or other factors in a model. These reasons could include limited resources, a lack of tradition for including, etc. [10]. This is an instance of known completeness uncertainty. On the other hand, there may be unaccounted factors because they are unknown to the risk analyst. For obvious reasons, these elements are excluded from modeling efforts and results in unknown completeness uncertainty. The interdependent literature largely avoids this topic. Liu and Song [56], a literature review on urban critical infrastructure networks, discuss how both coupled networks and instances of "unknown unknowns" are pressing challenges in the field. They argue that resilience-based design approaches - ones that emphasize adaptation over redundancy - may help to ameliorate some of these problems.

3.3. The relationship between system uncertainty and modeling uncertainty

System uncertainty and modeling uncertainty are separate concepts, though the fact that they both exist likely influences how we understand and report on the other. The former is inherent with all complex systems while the latter reflects how the researcher understands, interprets, and then mathematically downscales the complex system. They are, however, interdependent themselves (see Figure 1). System uncertainty (should) influence model design and thus model uncertainty. Der Kiureghian and Ditlevsen (2009) offers rich reflection and insight on how aleatory uncertainty in complex systems (e.g., material properties in their case) quickly becomes a form of epistemic uncertainty once measured and modeled [21]. They argue that the lines between aleatory and epistemic uncertainty can become muddled during the modeling process (see Section 3.1 in Der Kiureghian and Ditlevsen (2009) for a longer exposition of this idea). Linking model uncertainty to system uncertainty, if the purpose of models is to learn from them and to ultimately make enhancements to the system, then the decisions that are made using models will influence system uncertainty. Exactly how system and modeling uncertainty are related in practice is an open question, and is to some extent related to broader philosophical questions about the role models play in science [28].

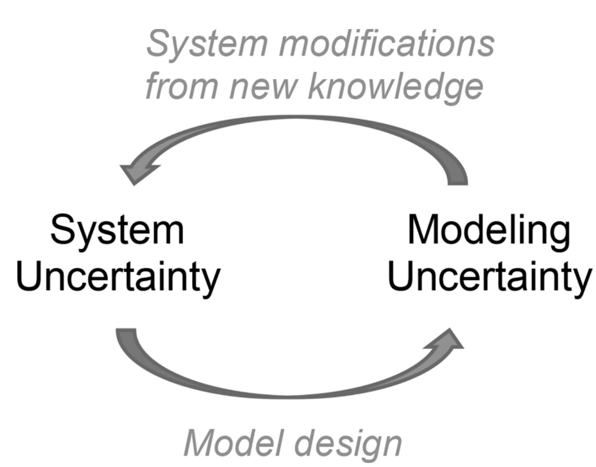

Figure 1. Conceptual relationship between system uncertainty and modeling uncertainty

4. Treatment of uncertainty in the literature

Various methods have been developed to model interdependencies of infrastructure networks facing disruptions, including empirical approaches (e.g., [92]), network-based approaches (e.g., [1,27,31,36]), simulation and agent-based approaches (e.g., [8,26,104]) and Leontief input-output approaches (e.g., [4,35,115]), among many others [77]. In this section, we briefly review the body work in each of these categories and discuss if and how they incorporate uncertainty.

4.1. Empirical approaches

Empirical approaches use observed data sto make inferences about underlying phenomena. Thus, in a way, empirical approaches either implicitly or explicitly acknowledge the presence of uncertainty because they use data to make a best guess at the "true" values of the underlying process. These methods regularly rely on observations following extreme disruptions (e.g., an earthquake) because doing so otherwise requires an often-infeasible detangling of functioning components and interactions [50]. However, as discussed in Dueñas-Osorio and Kwasinski [25], a major drawback to date of these approaches is the "lack of measured coupling strengths under diverse operating conditions." Essentially, by only taking one snapshot of the system, it is impossible to understand the magnitude of uncertainty within the system and the diversity of system responses.

The body of literature that leverages operational data remains relatively small compared with the larger body of research devoted to network modeling [48,92]. While the datasets are often challenging to obtain, when combined with emerging data science techniques (e.g., [116]), they hold tremendous potential for exposing previously unknown complex interactions [96]. McDaniels et al. [63] develops an archetypical framework for empirical observations; continuing and expanding work in this vain may facilitate modern data exploratory approaches and reveal more about the range of outcome possibilities. However, additional consideration should be given to expanding the set of dependency archetypes to include the roles that individuals, institutions, and governance systems have in shaping dependences and how the dependencies evolve over time.

4.2. Network models

In network-based approaches, components of the infrastructure are mathematically represented by nodes that are connected by directed edges (i.e., links with a specific direction). Edges can be within one network or between different networks to represent interdependencies. Within these approaches, topology-based methods provide tangible insights on the performance of an infrastructure, they are computationally efficient and they require less data on system characteristics in comparison to flow-based methods which require more information and provide more realistic descriptions of network operations [51,83]. Both methods, however, present limitations in assessing the uncertainty of interdependencies due to computational and modeling constraints [39,76]. A few studies consider probabilistic methods to overcome these limitations. Probabilistic extensions include conditional probabilities used to measure the strength of an interdependency and model cascading failures [38] and Bayesian network approaches combined with minimum link set to model interdependencies based on the access to repair resources [43,89]. While these extensions model uncertainty at the system level, the topology of the network in these studies is predefined and assumed to be the same, thus adding additional modeling uncertainty. Recent work considers dynamic network models to capture uncertain and dynamic interdependencies [116].

4.3. Simulation and agent-based models

A logical extension to network models is to imbed them within a simulation model to explore how the model performs over a range of parameters. This class of models are among the more relevant models for quantifying the implications of uncertainty. The approach can focus on uncertainty stemming from the hazard or operational environment exclusively (e.g., [26,90]), and can additionally include the actions of individuals or organizations, for example in repair sequences (e.g., [8,42]). The latter approach is often composed of agent-based models (ABMs). Interdependent Markov-chains have also been used more recently with success to probabilistically relate two or networks (e.g., [85]).

Simulation models have especially explored the effects of physical, spatial, and temporal uncertainty (e.g., [12,106]). To some extent, via ABMs, they have been extended to consider the actions of individuals (e.g., [88]). This somewhat limited body of work focuses mostly on operational and governance uncertainties (e.g., [78,104]), and informational and socio-economic uncertainty have had minimal exploration in these platforms (e.g., [44]). Similarly, these models generally view the source of uncertainty to stem from parameters - either the true value of a deterministic parameter is unknown or the parameter itself is uncertain (e.g., [42]). While useful, the modeling approaches should be expanded more often to consider whether the structure of the model possesses inaccuracies and the impact this could have (e.g., [59]).

4.4. Inoperability Input-Output Models

The original input-output (I-O) model [52,65] has been transformed to assess how decreased functionality, or inoperability, in an infrastructure can propagate to a number of other interconnected industry sectors [91]. Further extensions of the inoperability input-output model (IIM) include a discrete-time dynamic version, dynamic inoperability input-output model (DIIM), to quantify the temporal propagation of the disruption and the recovery process [54] and the multiregional IIM (MRIIM) to capture spatial characteristics of a cascading disruption [17]. The approach has been extensively used to model the cascading effect of disruptions in multiple sectors. Applications include transportation systems (e.g., [81]), inventory management (e.g., [29]), power grid (e.g., [58]), and others (e.g., [102]). The method has also been adapted to model cascading failure across civil infrastructure systems [36].

Considerations of uncertainty have been addressed by using a probabilistic formulation of DIIM Leontief input-output [75], combining IIM with an extreme event uncertainty model [5], and applying an uncertain demand-driven approach [115]. These extensions make the implicit assumption that inoperability propagation is governed by the uncertainty of the parameter characterizing the function linking both systems. Another approach is adapting IIM to model cascading failures across civil infrastructure systems [36] or modeling the uncertainty of the interdependency matrix as a function of infrastructure stochastic recovery process [7], accounting for multiple sources of uncertainty.

5. Discussion, steps forward, and conclusions

Significant evidence points to uncertainty being vastly understudied in interdependent infrastructure. This is potentially concerning for decision-makers who are likely to be uninformed to the degree of variability inherent within models. It also makes it impossible for them to decide whether more resources should be spent on improving system reliability or improving our knowledge about the system. In this section, we finalize the discussion though next steps and other considerations for the field, including how the field can learn from other disciplines to incorporate uncertainty.

5.1. Reconceptualization of infrastructure

The significant majority of the interdependent infrastructure literature focuses on hard infrastructure (e.g., electric-power systems, transportation systems) and less on soft infrastructure (e.g., hospitals, governance systems) and the people these systems serve. Among the next frontiers for interdependent infrastructure models will be how physical infrastructure interacts with less tangible, but no less important, soft systems to support societal functioning. This will require a highly interdisciplinary approach with scientists from many fields (e.g., [60]). The field of disaster science has laid the foundation to enable convergence research, and put forth recommendations including (1) setting a research agenda that is problem-focused and solutions-based, (2) embracing multidisciplinary perspectives and interdisciplinary problems, (3) identifying useful boundary objects [84,86].

5.2. The human dimension

A major source of uncertainty in infrastructure stems from humans. Everything from individual demand to how groups govern adds uncertainty. Until recently, individuals have been treated as a monolithic body seeking a collectively "optimal" solution, with the perspective usually being that of utility owner or a regulator (e.g., [51]). Recent studies have shown that a more nuanced approach with a broader set of objectives is warranted, both within the field of interdependent infrastructure systems, and more broadly [18,60]. After extreme events, for example, user demand can drastically change especially as individuals briefly adapt to disruptions [22]. Restoration strategies could account for the ability of sub-populations to adapt, and prioritize repairs according to local need. Policy and regulations similarly should account for the impact that humans have on (and the vulnerability that some subpopulations possess) when creating system guidelines and other regulatory procedures.

5.3. Intersection of types of uncertainty

While this paper makes mention of it, an underexplored concept is that in any given situation, there are multiple types of uncertainty that interact. The mechanisms through which this occurs and the implications of this (e.g., the degree to which this amplifies uncertainty) is worthy of its own investigation. This may be especially important when there are interaction effects that could result in unexpected emergent behavior. Take, for instance, the intersectionality of socio-economic uncertainty and governance uncertainty. The uncertainty of economic interdependencies lies, in part, in the dynamic behavior of supply chains. Each actor in the systems may respond differently to external shocks and stimuli, and could result in emergent behavior. Ultimately, supply chains are governed in part by trade agreements - a top-down global force that potentially constrains the actions of each actor. Knowledge of such agreements and economic sectors can reduce uncertainty; however, there is also inherent uncertainty in factors that influence trade agreements and their cascading effect on supply chains and economic sectors.

This concept is additionally important because the interaction effects may mask the root source of the uncertainty. For example, a researcher may attribute uncertainty to the passage of time, but the true cause of the uncertainty is changes to how the system is being governed and how this forces operations to evolve over time.

5.4. Learning from other fields

The field of interdependent infrastructure is not the only field to explore interacting elements and to consider the role of uncertainty. In the climate and global change literatures, models used to gain insight into the interdependence of natural and social systems have greatly increased in complexity. This is because many relevant questions require investigating dynamics across multiple spatial levels over long-time scales. As a result, modeling uncertainty has been a topic of interest, in particular model output and structural model uncertainty [82,108]. One methodology that has been developed that might have applicability to interdependent infrastructure modeling is model intercomparison [111]. In an intercomparison exercise, multiple modeling groups use their models to answer the same question with parameters Z set to be as similar as possible. As a result, variation in model output can be isolated to structural differences among models, some of which are artifacts of practical modeling assumptions and some of which are due to differences in expert knowledge and judgment as embedded in modeling choices. Once model outputs are produced, guided desliberative processes are undertaken to identify output differences, discuss possible sources of uncertainty, and design further experiments to refine estimates of and sources of uncertainty. In the arena of interdependent infrastructure, number case studies have focused on Shelby County, Tennessee to evaluate variants of similar problems (e.g., [24,43,46,116]). In principle, the field could leverage this array of models to address a particular risk question to isolate the role and sources of model output and structure model uncertainty, and possibly other forms of uncertainty.

5.5. Unraveling and communicating uncertainty

Zio and Aven [120] highlight the challenges related to the representation and communication of uncertainty through a discussion on smart grids. To help demystify uncertainty, they strongly encourage researchers to make a simplistic representation or an "architecture" through which to describe the relationship among elements that each possess uncertainty, even if quantification of the uncertainty is imprecise. This architecture, they argue, is both useful for decision-makers to understand how uncertainty propagates, but also for researchers to understand relationships and to decide how to structure the models. This should be conceptually straightforward for interdependent infrastructure when the components of the architecture are known, along with the relationship among the components. However, complications could emerge when some forms of uncertainty, such as informational uncertainty or operational uncertainty or other forms of epistemic uncertainty, are present. It is possible that the researcher does not have a clear sense of how uncertainty in ones system propagates to other systems, though possible and mostly likely linkages should be conveyed.

6. Conclusion

As evidenced by the ever-increasing body of literature, significant advances have been made in the modeling space for interdependent infrastructure. Further, governments have made investments in understanding how systems interact and are taking steps to fortify these linkages - oftentimes for national security reasons (e.g., NIPP 2013 [20]; the proposal of The European Programme for Critical Infrastructure Protection [55]). Interestingly, while this body of knowledge goes into significant depth in some areas (e.g., optimization), the treatment of uncertainty lacks a thoughtful and cohesive approach. To address this, we identify and provide the language to discuss the types of uncertainty that are present in the field of interdependent infrastructure and reflect on how the research has addressed this uncertainty to date. Our study suggests that the analysis has mostly been conducted in an ad hoc manner. By discussing uncertainty through a structured framework, it both enables researchers to simply identify the types of uncertainty present in their system and provides them with the motivation to address it. When researchers present findings that include sources of uncertainty, it informs decision-makers with the limits of system understanding, and potentially guides them to whether more resources are needed to better understand the system (i.e., reduce epistemic uncertainty) or to improve system reliability (i.e., reduce aleatory uncertainty).

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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