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A human-environmental network model for assessing coastal mitigation decisions informed by imperfect climate studies

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ABSTRACT

A Bayesian network model is developed to explore the interaction between physical and social processes that influence mitigation decisions and outcomes for extreme events. The network includes statistical relationships for event occurrence and magnitude; uncertainty in the parameters of these models; a high degree of variability in the sequence of events that occurs in any given time interval, and the possibility of long-term trends in the frequency, magnitude and impact of events. The model is applied to coastal storm surge events in the New York City (NYC) area. A 50 cm increase in sea level is predicted to approximately double the expected cumulative damage over a 40-year period. A 20% increment in storm frequency yields a further predicted increase of about 18% in the cumulative damage. The uncertainties in long-term trends associated with climate change may be reduced by scientific studies. However the value of this information is affected both by study accuracy and the extent of its trust, acceptance and utilization by decision makers. Implications of this are assessed in the model, showing that the probability of regret is notably reduced when climate study results are used to support mitigation decisions. This is demonstrated even when the studies have relatively low accuracy, moreso when they exhibit good or perfect accuracy. Based on model insights and limitations, further research needs are identified to better understand extreme event risk perception and management in coupled human-environmental systems.

1. Introduction

In many cases the capacity to understand and manage long-term natural and anthropogenic risks is found to improve with time (Brody, 2003; Brody et al., 2009; Albright and Crow, 2015; Reyers et al., 2015; Jongman et al., 2015; Bouwer and Jonkman, 2018). However, the path to greater scientific knowledge, social learning, and improved capacity for risk management is often indirect, and rarely rapid. As noted in the literature, risk knowledge may be subject to “negative learning” (Oppenheimer et al., 2008) in which natural variability or biased study and appraisal cause scientific beliefs regarding risks to diverge from their true values. This may also be accompanied by misguided perceptions of reduced uncertainty in risk model predictions, referred to as “false precision.” (Small and Fischbeck, 1999; Bistline, 2015) A third case occurs when new information results in “disconcerting learning “(Hannart et al., 2013), where uncertainty about the science increases as a result of new or improved knowledge. As new scientific findings emerge experts may apply different weights to the conflicting studies. Even absent motivational bias (Montibeller and Winterfeldt, 2015), different inferences and policy recommendations can result (Stiber et al., 1999). Among conflicting experts, decision makers, or other interested parties, additional studies and knowledge can help to build consensus for management plans, but not in all cases (Xian et al., 2018a). Depending on how these studies are perceived, they may have little or no effect on stakeholder preferences for management options, and may even increase conflict (Small et al., 2014).

Modern statistics provides a quantitative framework for assessing the extent to which inferences from limited samples might misrepresent both an underlying population and the distribution of a future sample of observations from that population (Cox and Hinkley, 1979; Geisser, 1993; Gelman et al., 2014). This problem is especially relevant when characterizing infrequent events, such as severe hurricanes or earthquakes, since their rarity dictates that many historical records, even those of long duration, include only a small number of events for model selection and fitting (Bier et al., 2004; Embrechts et al., 2013). Estimation is made more problematic when methods for recording and characterizing events change over the period of observation, and when the underlying random processes exhibit uncertain trends or other

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nonstationary behavior (Katz et al., 2002; Tokdar et al., 2011). In addition, various biases affect how people view and perceive rare event occurrences (Tversky and Kahneman, 1975; Wachinger et al., 2013). To what degree might estimates based on either formal statistical methods or empirical heuristics result in misleading inferences, with the potential to support or encourage decisions that are later subject to regret?

Hurricane induced storm surge events (e.g. Hurricanes Katrina in 2005, Sandy in 2012 and Irma in 2017) have caused significant recent damage to coastal regions (Pistrika and Jonkman, 2010; Xian et al., 2015; Hatzikyriakou et al., 2015; Xian et al., 2018b). Concurrently, scientific advances have improved our understanding of the physical and human processes affecting event occurrence and damage, as well as methods for deciding among alternative mitigation options. Examples include: an improved capability to detect changes in storm surge distributions (Resio et al., 2017; Rogers et al., 2018; Lin and Emanuel, 2016; Lin et al., 2016); advances in the ability to predict changes in mean sea level (Slangen et al., 2017; Hulbe, 2017; Oppenheimer and Alley, 2016); and new methods for multiobjective robust decision making with uncertain future outcomes and learning (Schneider et al., 2000; Mochizuki et al., 2017; Kim et al., 2017; Kwakkel et al., 2016).

Many probabilistic risk assessment models have been developed and applied to coastal storm surge flooding (e.g. Purvis et al., 2008; Aerts et al., 2013, 2014; Lickley et al., 2014; Zwaneveld and Verweij, 2014; Oddo et al., 2017). For the most part these models focus on normative decision support, advancing methods for optimization of coastal mitigation projects. Examples include solutions that address uncertain storm damage and dike performance (Slijkhuis et al., 1997) and the use of dynamic programming with uncertain future sea level rise (Brekelmans et al., 2012; van der Pol et al., 2014). In contrast, this study incorporates behavioral elements of decision making that are “positive,” seeking to understand how people *do* behave, rather than how they *should* behave under limited normative criteria. These elements have been considered in an increasing number of recent studies, for example, searching for compromise solutions among multiple stakeholders with different preferences and conflicting objectives (Oddo et al., 2017; Wong-Parodi et al., 2018) and consideration of behavioral responses by coastal decision makers confronted with alternative future climate change outcomes and events (Kwadijk et al., 2010; Haasnoot et al., 2013). Like a number of recent studies addressing coastal or inland flood protection, we adopt the avoidance of post-hoc regret from either insufficient or unnecessary funds devoted to mitigation as a central measure of outcome utility (Aissi et al., 2009; Rosner et al., 2014; Butler et al., 2016; van der Pol et al., 2016; Casal-Campos et al., 2018).

2. Bayesian networks

The coupled human-environmental systems model developed in this study is implemented in a Bayesian network. A Bayesian network is a directed acyclic graph that connects a set of random variables (nodes), indicates the direction and magnitude of causal influence between these nodes, and allows derivation of joint and conditional probability distributions for them. Direct relationships between “parent” nodes and their “child” nodes are captured by the conditional probability table (CPT) for the latter. The CPT gives the probability of each possible state in the child node for each possible combination of states in its parent nodes. Indirect influences between nodes are subsequently inferred through numerical propagation of Bayes Rule through the network. Bayes Rule is the fundamental equation of conditional probability by which prior probabilities of events are updated to posterior probabilities given new observations or evidence (Lee, 2012; Stone, 2013)

Bayesian networks have been used to characterize system uncertainty and compare risk management options in a wide range of technology, risk, safety, health, and climate applications (e.g., Borsuk et al., 2004; Landuyt et al., 2013; Richards et al., 2013). Parameter (CPT) estimation may be approached using a number of qualitative or quantitative methods, including expert elicitation (Stiber et al., 1999; Catenacci and Giupponi, 2013; O'Hagan et al., 2006) and statistical analysis of observed data or mechanistic models for event relationships (Barton et al., 2008; Xu et al., 2010; Yang et al., 2012). Various software packages are available for building and implementing Bayesian networks (Korb and Nicholson, 2003) and we utilize one such program, Netica, in this study (Norsys, 2016). The executable version of the NYC storm damage network model is available from the authors (execution will require downloading Netica from Norsys Software, most recent price: $285 academic / $785 commercial).

The Bayesian network model developed in this study includes many of the physical and engineering science elements found in previous studies of coastal storm surge, but adds new dimensions to account for information potentially gained from (imperfect) climatic risk studies and projections; the extent of dissemination of study results; and the distribution of perceived risks across decision makers. Physical risk and probability models are available for some of the model elements. For other parts, especially involving information flow and human behavior, predictive models are not yet available. For these elements we perform scenario and sensitivity analysis with the network to determine the effect of different assumptions on predicted model outcomes.

2.1. Bayesian network model for New York City hurricane surge damage and protection options

The Bayesian network model for New York City (NYC) coastal protection decisions is summarized in Fig. 1. The model incorporates information on historic hurricane frequency, simulated surge elevation, resulting economic damage, and an uncertain range of future sea level and storm outcomes following a mitigation decision. Fig. 1 includes inputs and summary results for variables with historic data (on the left portion of the network) while results for nodes reflecting uncertain decisions and outcomes are shown in the middle and right side of the network, including alternative outcomes that could occur. A graph of the full Netica network, including all computational nodes and variable states, is shown in Figure A1.1 in Appendix A1 of the Supplementary Material.

The major information sources and analyses underlying the network model include:

A A coupled hurricane-hydrodynamic-inundation model that simulates Atlantic tropical storms and specifies their storm surge elevations and inundation areas and depths across the NYC study area (Aerts et al., 2014).

B An economic damage model that calculates the damage to coastal housing and infrastructure for each storm simulated in part A.

C A damage function fitted to the results of Part A and B that predicts the fraction of potentially impacted housing and infrastructure that is damaged by an event, as a function of its peak storm surge elevation.

D A probabilistic representation of the number of events that occur during a baseline assessment period (conditioned on the estimated baseline Poisson rate) and the associated cumulative damage from these events (dependent on the storm surge heights and the damage function).

E Sensitivity analyses for the effects of future climate change on event frequency and reference elevation (sea level rise), the implications for storm damage, and the accuracy of scientific studies conducted to predict these changes.

F A probabilistic model of stakeholder and decision makers' perceived risks and selected levels of coastal protection (dependent on the observation period outcome in D and the results of the scientific studies in E).

G A probabilistic characterization of the potential cumulative damage during the future outcome period, determining the likelihood of regret based on the probability that protection levels chosen in part