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The Use of Simulation to Reduce the Domain of "Black Swans" with Application to Hurricane Impacts to Power Systems

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Recently, the concept of black swans has gained increased attention in the fields of risk assessment and risk management. Different types of black swans have been suggested, distinguishing between unknown unknowns (nothing in the past can convincingly point to its occurrence), unknown knowns (known to some, but not to relevant analysts), or known knowns where the probability of occurrence is judged as negligible. Traditional risk assessments have been questioned, as their standard probabilistic methods may not be capable of predicting or even identifying these rare and extreme events, thus creating a source of possible black swans. In this article, we show how a simulation model can be used to identify previously unknown potentially extreme events that if not identified and treated could occur as black swans. We show that by manipulating a verified and validated model used to predict the impacts of hazards on a system of interest, we can identify hazard conditions not previously experienced that could lead to impacts much larger than any previous level of impact. This makes these potential black swan events known and allows risk managers to more fully consider them. We demonstrate this method using a model developed to evaluate the effect of hurricanes on energy systems in the United States; we identify hurricanes with potentially extreme impacts, storms well beyond what the historic record suggests is possible in terms of impacts.

KEY WORDS: "Black swans"; hurricanes; risk assessment; simulation model

1. INTRODUCTION

Surprising events with potential extreme consequences represent a challenge in a risk assessment setting. There is no doubt that they contribute to the risk a system faces, but if we cannot identify them, how can we then manage the risk that these surprising events introduce? Several authors have looked into the issue of surprising events with potentially extreme impacts, and our article can be seen as a contribution to this discussion.(1–5) The aim is to illustrate how simulations can be used to identify events with potential extreme impacts (the so-called black swans), and hence reduce the potential of being surprised by these events or their severity. In the present article, risk is defined as the consequences of the activity and associated uncertainties, which corresponds to definition (d) from the Society of Risk Analysis.(6)

As an example, we use the impact of hurricanes on the U.S. power system in terms of power outages from a single storm. The maximum peak number of customers without power in any hurricane in the United States was approximately 8–9 million during Hurricane Sandy, which impacted the mid-Atlantic coast in October 2012.(7,8) The impacts of Sandy were severe, and events such as this lead to a number of questions. How high could the total

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number of power outages reasonably be with physically plausible storms? Are there events that might lead to far greater outage numbers that would challenge emergency response? We show how simulations with a verified and validated hurricane performance prediction model can be used to identify extreme events, with impacts much larger than any previous level of impact. The simulation model considered has been trained and validated with the use of historical data.[9,10] In the present article, a hurricane scenario refers to a particular combination of a hurricane track and the peak wind speed of that hurricane. The hurricane track includes the location where the hurricane makes landfall and its trajectory across the United States. By the term "simulations," we mean the process of altering different inputs and combinations of inputs to estimate some output measure of interest. We are searching for inputs that might result in surprising outputs, and, in general, using models in a creative manner to increase our understanding of the modeled phenomena. In this article, simulations are only considered useful as long as the models used are verified and validated, meaning that they have been shown to provide good out-of-sample predictive accuracy.

The next subsection includes a short review of the concepts of surprising events, black swans, and perfect storms (which is another term often used to describe similar events). Section 2.1 presents existing methods, while Section 2.2 explains how our approach can be used as part of some of the existing methods, including why a simulation model might be useful to identify scenarios with potential extreme impacts. The subsequent section, Section 3, introduces the theory behind the use of models to identify extreme events. Section 4 presents the model that we will utilize in this article and the results of the case study. Before we conclude in Section 6, we present a discussion of our main findings in Section 5.

1.1. Classifying Surprising Extreme Events with Extreme Impact

Surprising events with extreme consequences are often referred to as either black swans or perfect storms. The distinction is not always clear, and might depend on how the different terms are defined. It is therefore important, in our opinion, to clarify the meaning of these terms, making sure that we know how they are related to our example and the use of a simulation model. The term "black swan" was popularized by Nasim Taleb in 2007,[1] when he published a book drawing an analogy between the story of the first discovery of a black swan and a surprising event. In the prologue, he defines a "black swan" as an event with the following three attributes:[1, p. xxii]

> *"First it is an outlier as it lies outside the realm of regular expectation, because nothing in the past can convincingly point to its possibility. Second, it carries an extreme impact (unlike the bird). Third, in spite of its outlier status, human nature makes us concoct explanations for its occurrence after the fact, making it explainable and predictable."*

Taleb's definition is not the only one of a "black swan." Aven[2] provides a discussion of a set of different definitions, where he concludes that "*a black swan has to be seen as a surprising extreme event relative to present knowledge/beliefs.*"[2, p. 49] This definition is elaborated in Aven and Krohn,[3, p. 9] and they divide black swans into three types:

(a) "Events that were completely unknown to the scientific environment (unknown unknowns)
(b) Events that were not on the list of known events from the perspective of those who carried out a risk analysis (or another stakeholder) (unknown knowns)
(c) Events on the list of known events in the risk analysis but judged to have negligible probability of occurrence, and thus not believed to occur."

We have chosen to use the definition by Aven[2] and the further subcategorizations of Aven and Krohn,[3] as we acknowledge that a surprise is relative to someone's knowledge and beliefs, and that black swans are more than unknown unknowns. A black swan is, as mentioned above, not the only analogy commonly used to describe a surprise. Some might also refer to a surprising event with extreme impacts as a "perfect storm." Patè-Cornell[4] distinguishes between black swans and perfect storms by referring to the different nature of the uncertainties related to these events. According to Patè-Cornell,[4] perfect storms can be seen as a conjunction of rare but known events, involving mostly aleatory uncertainty (randomness), while "black swans" are related to lack of knowledge, i.e., epistemic uncertainty.

2. EXISTING METHODS USED TO IDENTIFY EXTREME EVENTS WITH LARGE IMPACTS

According to Taleb,[1] almost all significant historical events, at the time of their occurrence, held the characteristics of a black swan. He uses the development of the Internet, the market crash of 1987, and the rise of Hitler and the subsequent war, as events that were difficult to predict, but that have had a large impact. It is not difficult to find more examples, and the importance of these events is clear. It is therefore not surprising that there exist a number of methods that can be used as tools when trying to identify and predict such events. The approach used in the present article has similarities to stress testing, reverse stress testing, sensitivity analysis, and vulnerability analysis, but carries some distinctions. In the following, we offer a short explanation of these methods and their relationship with our approach.

Stress testing is an approach commonly used in, for example, the nuclear and financial industries.(11–14) In the nuclear industry, stress testing has been implemented by the European Commission to carry out "comprehensive risk and safety assessments ('stress tests') of nuclear power plants in the European Union and related activities."(14, p. 1) In the financial industry, stress tests are used to test how banks perform if exposed to adverse economic developments. This is done to understand how resilient the banks are, and whether or not they can deal with unexpected extreme events.(13) In a stress test, the focus is on the system (e.g., the bank) and its ability to withstand both known and unknown hazards/"stresses" or scenarios. As pointed out by one of the reviewers of this article, a stress test is essentially performed by using a real-life system or a model and varying the inputs far beyond what is normal or expected. In our approach, the inputs are also varied, but they do not have to go beyond what is normal or expected, as we are looking for previously unseen combinations of inputs that carry a surprising extreme impact.

In reverse stress testing, the focus is on identifying ways in which failure of the system will result in a prespecified (typically negative and possibly extreme) outcome. Compared to stress testing, as the name implies, reverse stress testing works backward. The first step is to specify a significant negative outcome, and the second step is to identify different events or combinations of events that can lead to this outcome.(12) The main similarity between reverse stress testing and our approach is the focus on severe, unwanted, and maybe also previously unexperienced combinations of events that together result in an extreme outcome. The difference is that our approach searches for severe outcomes; i.e., a severe outcome is the result of the analysis, not the starting point.

Sensitivity analysis is commonly used in risk assessment. According to Saltelli,(15, p. 579) sensitivity analysis can be understood as "*the study of how the uncertainty in the output of a model (numerical or otherwise) can be apportioned to different sources of uncertainty in the model input.*" This method differs from our approach because the focus area is different. We are not trying to identify the most sensitive input parameter. We use the knowledge of the potential variation in input parameters to see how this might affect the model output. The aim is to create an understanding of combinations of model inputs (input parameters) that can create scenarios that we have not previously experienced and do not currently expect.

A vulnerability analysis, which in general "*aims at estimating the magnitude of the negative consequences that arise given that a strain is imposed on the system,*"(16, p. 29) can be used to identify failures with severe outcomes; see also Murray *et al.*(17) According to Haimes,(18 p. 293) "*vulnerability is the manifestation of the inherent states of the system that can be exploited to adversely affect that system,*" a definition similar to that of Johansson *et al.*(16) In these definitions of vulnerability, the focus is on the inherent components of the system and, as noted by Johansson *et al.*,(16, p. 28) not "*the environment in which the system is situated.*" In the present article, the system considered is the U.S. power system, and the hurricane scenarios are a combination of hurricane tracks combined with different hurricane peak wind speeds. The hurricane scenarios cannot be seen as an inherent part of the (power) system, but as an external hazard that potentially has an extreme impact on the (power) system, and is therefore somewhat different from a vulnerability analysis that focuses on the components within the system. The following section will explain how the use of a simulation model can be used as a tool when searching for severe outcomes.

3. HOW CAN A SIMULATION MODEL BE USED TO IDENTIFY EVENTS WITH POTENTIAL EXTREME IMPACTS?

In the present article, we consider the use of models only in situations where the model has been verified and validated, as in Guikema *et al.*(9) and Staid *et al.*(10) where repeated random holdout testing was used to assess out- of-sample predictive accuracy. The approach can formally be described as follows: the simulations will be performed using a verified and validated model G with parameter X used to predict the outcome of a quantity of interest Z. We establish distributions $F_i{}^*$ on the vector $X = (X_1, X_2, \ldots, X_n)$ of model parameters. We then perform a large number m of (Monte Carlo) samplings from these distributions, resulting in realizations $y_j = (y_{1j}, y_{2j}, \ldots, y_{nj}),\ j = 1, 2, \ldots, m$, which are then plugged into the model to obtain predictions $z_j{}^* = G(y_j)$ of Z; we keep the realizations that give us the worst predictions of Z. The sampled y_j then represents a potential future scenario that might lead to an outcome of Z (predicted by $G(y_j)$). In these situations, the simulation model can be used to create increased understanding related to interactions between different phenomena and systems, hence reducing the potential for surprises and black swans.

Because black swans can be divided into three types, as mentioned in Section 1.1, different approaches have to be used in order to deal with them.[19,20] If simulations (done by the use of a simulation model) are used to reduce the domain of black swans, they have to address the three types of black swans differently, as simulations might be useful in different ways for different settings. Let us here consider the use of simulation as a tool to reduce the domain of black swans types (a) through (c), in addition to perfect storms.

First, how can a simulation model be used to address or reduce the potential for surprises caused by unknown unknowns? Intuitively, this seems challenging, as simulations require a model, and a model is a representation of a known phenomenon. If the phenomenon is known, how can a potential surprising event be seen as an unknown unknown? It seems obvious that simulation models cannot be used to identify new phenomena. However, they can still be useful—if a simulation model and/or the simulations that are carried out manage to raise questions, identifying a need for more research, where the following research reveals a new phenomenon. For example, today, data mining or data analytics is used to create models and gather information from large amounts of data. Some of these models reveal relationships between input variables and/or the output that cannot be explained by today's phenomenological understandings. Occasionally, research on these relationships identifies a new phenomenon that has not previously been known. When this happens, more knowledge is gained and the domain of potential black swan events of type (a) caused by this phenomenon can be seen as reduced. Black swans type (a) have then, indirectly, been reduced by a simulation model.

For black swans of type (b), the unknown knowns, simulation models might be even more useful. Verified and validated models contain a lot of knowledge. This knowledge can be of importance when assessing risk, but if the model is treated like a "black box" this knowledge might be ignored. The knowledge is available (in the model), but is not known to the risk analyst. If a surprising extreme event takes place, it might be surprising because the relevant analyst did not properly understand the model. To avoid this, simulations can be used to create an understanding of the relationship between the input quantities and the predicted output. An example is the use of simulations based on a (verified and validated) model that is used to explain the movements of an oil spill on the sea surface. When running simulations with such a model, it is possible to create a picture of how a coastline can be affected by an oil spill. If the focus is on extreme impacts (which is a requirement to be classified as a black swan), we might use simulations to create a picture of where (and under which weather conditions) an oil spill has to occur in order to reach shore at a location where the impact can be considered as particularly severe.

Black swans of type (c) refer to an event that takes place even though the probability of its occurrence was judged as negligible. This probability is to be understood as subjective and the assessor might have assigned the probability based on weak background knowledge. For simulation models to be useful in this setting, they need to provide the analyst with information that will change (increase) the original probability of occurrence of this event. For example, if the assigned probability is based on weak knowledge, simulations can be used to increase this knowledge, creating a better understanding of conditions that might lead to that particular event. In this setting, simulations provide information that might increase the degree of belief related to the occurrence of that specific event. If the probability of an event is judged as extremely low or negligible, it means that the assessor has an extremely low or negligible degree of belief related to the occurrence of this event. For simulationsto be useful to reduce the domain of black swans type (c), they have to create an understanding and generate knowledge that can strengthen the background knowledge of the risk analyst (team) that assesses the (subjective) probability.

Simulation models can also be used to identify potential perfect storms. Potential perfect storms can be identified by altering the input quantities, picking extreme rare values of the input variables to see how these influence the output, like a sensitivity analysis. The challenge here is to pick the combination of unlikely (rare) input variables that will give an extreme impact/outcome. We also need to make sure that the combinations of input values actually are rare or unlikely, meaning that the estimation of an input value as unlikely/rare needs to be based on strong background knowledge. This means that the epistemic uncertainty related to the frequentist probability of a specific extreme input quantity has to be negligible. We need to know how much and with what frequency the input variable can vary. A simulation model can then be very useful for understanding how combinations might lead to extreme outputs. At the same time, it is unlikely that anything will be done to reduce the domain of these events, as the probability (relative frequency) of them occurring is extremely low (according to the definition of perfect storm), and the estimation of that probability (relative frequency) is built on strong knowledge.

The present article will use an example from the U.S. power system to show how a simulation model can be used to uncover scenarios that were unknown before the simulations were carried out. The example that we will use utilizes a verified and validated simulation model for predicting power outages caused by hurricanes in the United States; see Beck *et al.*,[7] Han *et al.*,[21,22] Nateghi *et al.*,[23] Guikema *et al.*,[9] and Quiring *et al.*[24] A power outage is defined as an event where one or more customers lose power.[21,22] The model is built on data from 12 previous hurricanes and uses factors such as gust wind speed, the duration of winds above 20 m/s, and population density in a validated statistical model to predict power outages. We will use simulations to identify potential combinations of hurricane tracks and wind speeds that have not been experienced yet and have potentially extreme (surprising) consequences in terms of power outages.

4. EXAMPLE: MODELING THE NUMBER OF POWER OUTAGES CAUSED BY A HURRICANE IN THE UNITED STATES

In order to get a good understanding of how a simulation model might be useful, we performed a case study. We wanted to see if a simulation model can provide information or create scenarios that, if they occur, would be considered a surprise. This does not mean that we are trying to create the worst hurricane scenario, with an extreme number of power outages. Our focus is on surprises, e.g., finding scenarios where a relatively low wind speed results in a surprisingly large number of power outages as well as scenarios with extreme numbers of power outages.

4.1. How Does the Model Work?

The power outage forecasting model used in this article is that of Guikema *et al.*[9] This model is the result of working with a large electric power utility for a number of years to develop a power outage forecasting model for its service area[21–23] and then generalizing this model to be used in other locations.[9] The model is a random forest, a form of an ensemble statistical learning theory model, trained and validated with past outage data. The model in the form of Guikema *et al.*[9] takes as input 3-second gust wind speed and the length of time for which wind speeds were above 20 m/s estimated from a hurricane wind field model, as well as population density, with all inputs being at the census-tract level. The wind field model takes as input a forecast track and the central pressure over time for a hurricane. The model predicts the number of people who will not have power, again at the census-tract level, for the entire potentially impacted area. A key aspect of the model development is the validation testing of the model. In developing the model, the authors used repeated random holdout testing to examine many different types of models and to choose the model that gave the best out-of-sample predictive accuracy. This model predicts outages for a single hurricane given a forecast track and intensity.

4.2. Simulation Method

The simulation model generates virtual tropical cyclones and estimates the power outages from each one. Because of the built-in randomness in the storm generation process, we run the simulation a large number of times in order to identify the high-impact storm scenarios (hurricane peak wind speed and trajectory). We run the simulation for a set of initial wind speeds (defined as the maximum 1-minute sustained wind of the storm) to evaluate the impact of storms of different strengths. We evaluate the impacts for storms with maximum intensity of 170 knots, 150 knots, 125 knots, 100 knots, 75 knots, 50 knots, and 34 knots, corresponding to 88 m/s, 77 m/s, 64 m/s, 51 m/s, 39 m/s, 26 m/s, and 17 m/s, respectively. The maximum peak wind speed of 170 knots was chosen as this is close to the peak wind speed experienced during Typhoon Haiyan in the Philippines in 2013, arguably the strongest tropical cyclone on record. The lowest peak wind speed of 34 knots was used as we were interested in potential surprising events, and a large number of power outages given a peak wind speed of 34 knots would definitely be seen as a surprise. To compare, the peak wind speed (1-minute sustained) for Hurricane Katrina was approximately 150 knots, while Sandy had a peak wind speed of approximately 100 knots.

The simulation structure is the same for each initial wind speed. For each iteration of the simulation, we generate a virtual storm using the following steps. First, we sample a starting location for the storm. This can either be a landfall location along the U.S. coastline or a point offshore but still within impact-range of the U.S. coastline. We generate the movement of the storm using a random forest statistical model. This model is trained on data from historical storm tracks in the same region of the coastline at which the storm is located. This allows us to generate storms that behave similarly, but are not identical, to past tropical cyclones. In this way, we create storm tracks that have not previously occurred, but that still can be seen as realistic and within the realm of possibility. As we generate each new track point for the storm movement, we simultaneously keep track of the 1-minute sustained wind speeds at each point along the storm's path. If the storm is over land, we decay the wind speeds with each time step according to the decay model of Kaplan and DeMaria.[25] We continue to generate storm movement until the wind speeds fall below the threshold for a tropical depression.

The storm track and intensity (central pressure over time) are then used as inputs to a wind field model. This calculates the wind field along the storm's path for the entire area of impact. We evaluate it at the census-tract level, and the wind field estimates the 3-second gust wind speed and the duration of wind speeds above 20 m/s for each census tract within reach of the storm. These two wind parameters, along with the population of each census tract, are then used as inputs for the power outage prediction model. For each storm, we predict the fraction of the population expected to lose power in each census tract.

In order to evaluate the results, the coastline was divided into four impact zones. Storms behave differently in the Gulf of Mexico and the North Atlantic, for example, and the impacts have the potential to be very different because of the locations of major cities, areas of high population density, and storm movement. Thus, we looked at each zone separately when assessing the impact. The first zone stretches along the Gulf of Mexico from the Texas-Mexico border to the edge of the Florida peninsula. The second zone covers the western side of the Florida peninsula. The third zone covers the eastern side of Florida up to the Florida-Georgia border. The fourth zone stretches from Georgia to Maine, covering the rest of the U.S. Atlantic coast. Table I gives an overview of the average annual number of historical hurricanes in each of the different zones. The hurricanes simulated in zones 3 and 4 were initiated both onshore and offshore, but still within impact range of the U.S. coastline. The hurricanes in zones 1 and 2 were initiated at landfall (onshore) because in these zones, hurricanes are unlikely to move parallel to the coast, staying offshore and causing damage.

Table I. Historical Hurricanes in Period from 1948 to 2012, Divided by Zone

Location	Number of Hurricanes from 1948 to 2012	Average Number of Hurricanes per Year	Maximum Wind Speed on Record
Zone 1	103	1.6	165 knots (85 m/s) (Camille, 1969)
Zone 2	43	1.7	111 knots (57 m/s) (Isabell, 1964)
Zone 3	57	0.9	128 knots (66 m/s) (Andrew, 1992)
Zone 4	49	0.8	113 knots (58 m/s) (Helene, 1958)

For each wind speed evaluated, we simulated a total of approximately 5,000 virtual storms for hurricanes with onshore landfall locations and a total of 20,000 virtual storms for the offshore locations; see process 1 in Fig. 1. The difference is because we found it more challenging to achieve convergence for offshore tracks. This resulted in a different number of hurricane scenarios in the different zones, as shown in Table II. In addition, the tracks identified as the "top 10" tracks in each zone were rerun for all peak wind speeds; see processes 2 and 3 in Fig. 1. The "top 10" tracks are the 10 hurricanes

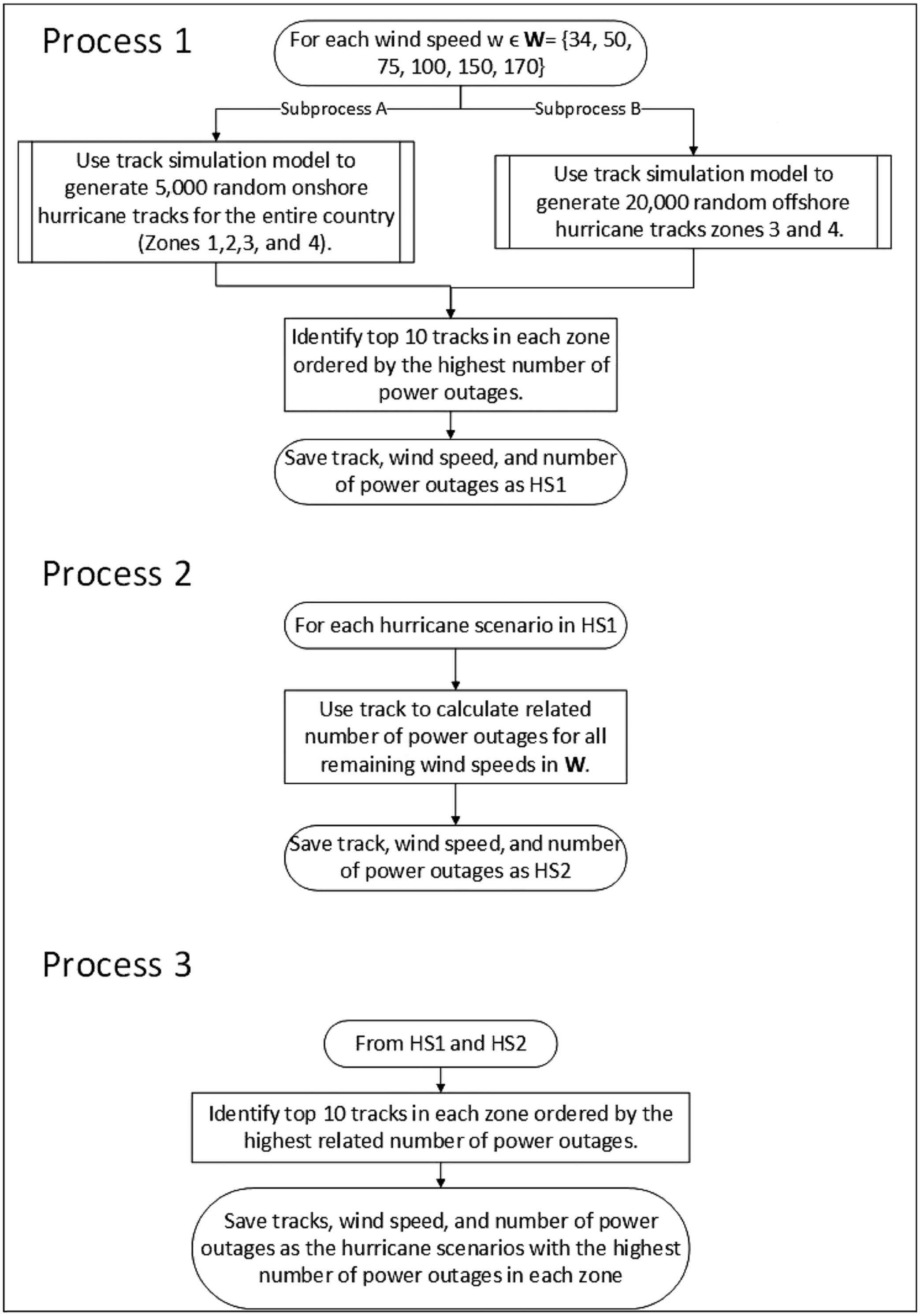

Fig. 1. Summarization of simulation methodology.

Table II. Number of Simulations for Peak Wind 170 Knots and 150 Knots

Peak Wind Speed	Zone	Replications
170 knots/88 m/s	1	3,506
	2	1,016
	3	4,930
	4	15,070
150 knots/77 m/s	1	3,529
	2	1,004
	3	4,848
	4	15,152

with the highest related number of power outages identified in process 1 in Fig. 1. This resulted in 60 additional storms for each peak wind speed, when including the original "top 10" storms for each peak wind speed; we refer to these as the "top 70" tracks (10 tracks for each of the 7 peak wind speeds).

4.3. Simulation Results

The methodology described in Section 4.2 resulted in an evaluation of 1,960 different hurricane scenarios. These 1,960 hurricane scenarios include 70 tracks for each of the 7 peak wind speeds, in each of the 4 zones ($70 \times 7 \times 4 = 1960$). Fig. 2 illustrates a subset of tracks from these 1,960 hurricane scenarios. The subset includes the tracks with the highest predicted number of power outages (from process 1) for a peak wind speed of 34 knots and 125 knots (17 m/s and 64 m/s), with the different colors illustrating the different zones where the hurricanes make landfall (colors visible in on-line version).

The maximum number of power outages was, based on process 1, found for a hurricane in zone 4 with a peak wind speed of 150 knots (77 m/s), and not 170 knots (88 m/s), which would have been expected. Consequently, we decided to run processes 2 and 3. The purpose was to see how an altered peak wind speed would influence the predicted number of power outages, given that the hurricane track was kept constant. When we, in process 3, increased the peak wind speed from 150 knots to 170 knots, keeping the hurricane track constant, the predicted number of power outages increased from 51 million to 54 million power outages. This shows that while stronger storms are estimated to have more outages, as expected, at these high wind speeds, there is significant sensitivity to the storm track.

Processes 2 and 3 resulted in additional hurricane scenarios, created based on the "top 70" tracks. However, the difference between the maximum predicted number of power outages found among the "top 10" tracks from process 1 and the new "top 70" tracks was small. This is not surprising, as the CDF and convergence plots, presented in Figs. 3 and 4, suggest that there are sufficient replications to reach the tail of the different distributions. The maximum number of power outages found for each peak wind speed, from processes 1 to 3, is presented in Fig. 5.

For zone 2 (the west coast of Florida), we can see, based on the CDF functions presented in Fig. 3(b), that the maximum number of power outages stabilizes for peak wind speeds of 100–125 knots (51–64 m/s). This means that most people in this area are without power when the peak wind speed reaches approximately 100–125 knots. The same stabilizing trend can be seen for zone 4; this is also supported by the CDF and convergence plots presented in Fig. 3(d) and Fig. 4(d). For the hurricanes making landfall in zone 1 (the Gulf of Mexico) and in zone 3 (the east coast of Florida), the peak wind speed and the number of power outages appear to have a more linear relationship. For zone 1, however, there seems to be some stabilization after the peak wind speed reaches 150 knots (77 m/s). Fig. 6 shows the two hurricanes from zone 1 with the same track but with different peak wind speeds. The hurricane presented in Fig. 6(a) has a peak wind speed of 170 knots (88 m/s) and an estimated number of power outages of 10.9 million. Fig. 6(b) shows the same hurricane track, but with a peak wind speed of 150 knots (77 m/s). The related number of power outages is 10.5 million, which is not very different from the predicted number of outages related to the same track but with an increased wind speed (170 knots). The hurricane tracks related to the highest number of power outages in zone 3 (generated by process 1) can be seen in Appendix A.

The highest numbers of power outages are, not surprisingly, related to the strongest peak wind speeds, and occur in the highest populated areas (zone 4). Fig. 7(a) shows the hurricane scenario with the largest number of power outages, 54 million. This hurricane scenario has a peak wind speed of 170 knots (88 m/s) and occurs in zone 4 (the East Coast of the United States north of Florida). When the peak wind speed of the hurricane presented in Fig. 7(b) is reduced to 150 knots (77 m/s), the related number of power outages is 3 million less than that of the hurricane presented in Fig. 7(a). The gradient

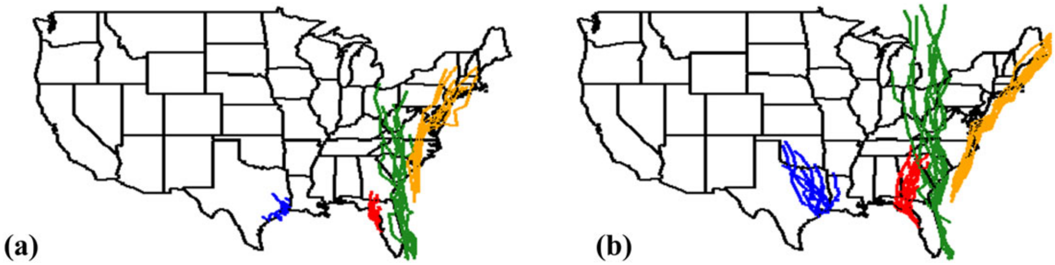

Fig. 2. (a) Top 10 tracks in each zone with maximum peak wind speed of 34 knots (17 m/s) and (b) top 10 tracks in each zone with maximum peak wind speed of 125 knots (64 m/s).

range from red to light yellow indicates the gradual decrease from a high to low fraction of power outages. Red illustrates that approximately 100% of the population has lost power.

Fig. 8 illustrates the probability related to the different predicted number of power outages given a hurricane scenario with a specific peak wind speed making landfall in a specific zone. Fig. 8 shows the tail of the cumulative distribution for the number of power outages given four different scenarios. These four scenarios are considered as surprising either because the total number of power outages is extremely large, or because the total number of power outages is surprisingly large given a relatively weak hurricane. We can see that the tails of these cumulative distribution functions are heavier than what is typically seen in F-N curves, meaning that there is not a very rapid decrease in probability when the number of power outages increases. Qualitatively, this suggests that it would be easy to understate the probability of the very bad outcomes without a model to estimate their conditional likelihood.

4.4. Interpretation and Discussion of Results

The highest number of power outages predicted for any of the hurricane scenarios generated was 54 million; see Fig. 7(a). This is more than five times the highest number of power outages ever recorded in the United States during Hurricane Sandy. Hurricane Sandy had a severe impact, but even though the peak wind speed of 100 knots (51 m/s) was high, it is not extreme. Some might therefore have been surprised by the impact caused by this hurricane. According to our results, a hurricane with the same peak wind speed as Hurricane Sandy making landfall in zones 3 or 4 could potentially lead to an even higher number of power outages. Our simulations identify a scenario with approximately 35 million power outages in zone 4 for a storm with 100 knots (51 m/s) wind speed. The red line in Fig. 5 indicates the number of power outages from Hurricane Sandy.

With the red line in Fig. 5 as a reference, our simulations show that 10 million power outages are possible for all wind speeds in zone 4, except 34 knots (17 m/s). That a peak wind speed of 50 knots (26 m/s) potentially results in approximately 10 million power outages is a surprising result. This wind speed is substantially weaker than for Hurricane Sandy. According to the Saffir-Simpson Hurricane Wind Scale, this is not even a hurricane category 1 (NOAA).[27] The National Weather Service Forecast Office[28] writes that a category 1 hurricane has:

> *Winds 74–95 mph (64-82 kt or 119–153 km/hr). Storm surge generally 4–5 ft above normal. No real damage to building structures. Damage primarily to unanchored mobile homes, shrubbery, and trees. Some damage to poorly constructed signs. Also, some coastal road flooding and minor pier damage.*

That a hurricane scenario with a maximum wind speed less than a hurricane category 1 potentially can result in 10 million power outages is arguably even more surprising than the 54 million power outages related to the scenarios where the maximum wind speed is 170 knots (88 m/s). As mentioned in the above section, for each peak wind speed, we kept the 10 scenarios with the highest number of related power outages. For the scenarios with a peak wind speed of 50 knots (26 m/s), the related number of power outages, from process ranged from 8.2 million to 10.6 million in zone 4. This illustrates the deviation between the different tracks that a hurricane might have, all with a severe impact. The aim of our simulations has been to provide an overview of potential future hurricane scenarios that could be considered surprising. These hurricane scenarios clearly demonstrate that it is not only extreme and

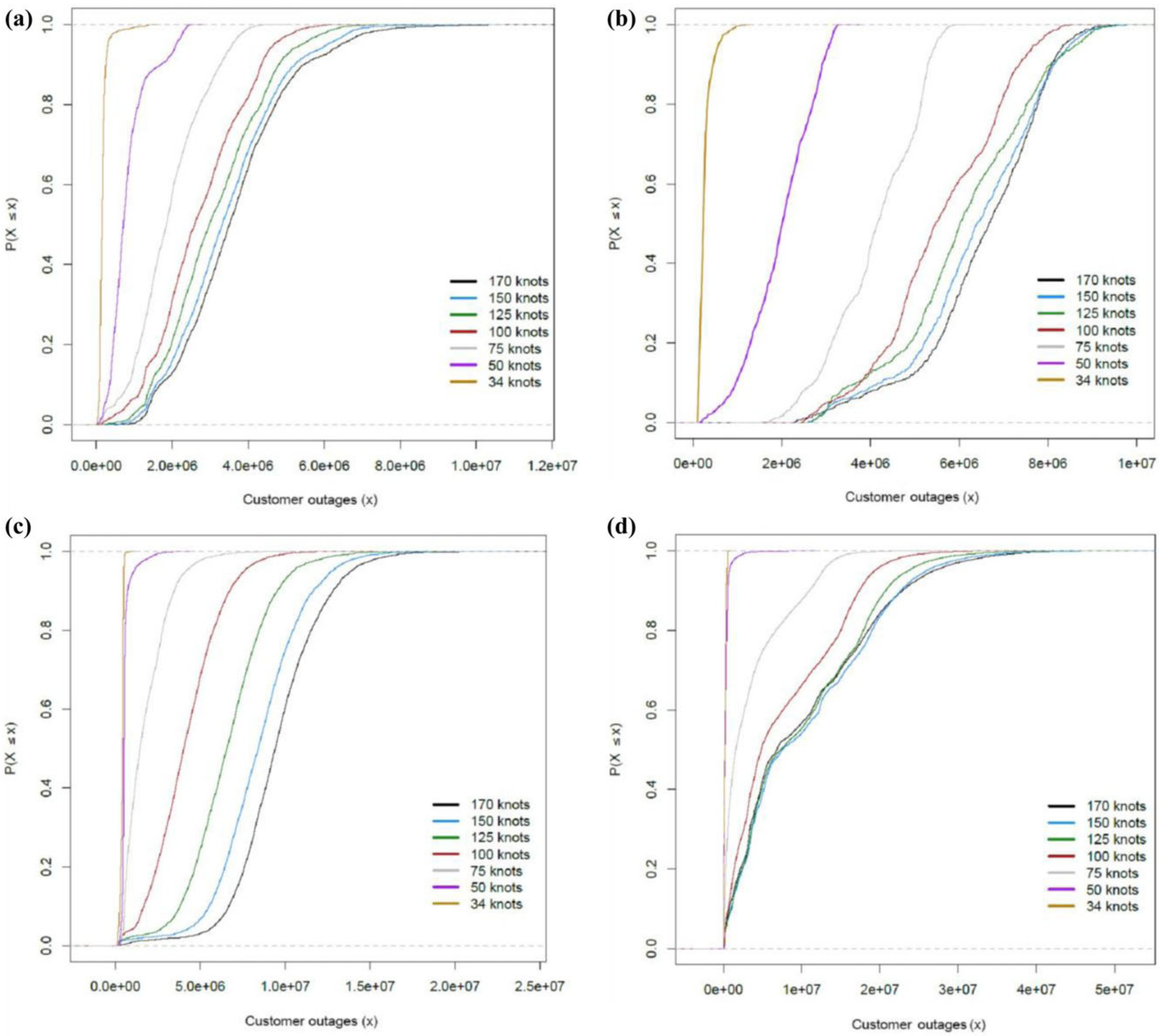

Fig. 3. (a) CDF for all peak wind speeds in zone 1, (b) CDF for all peak wind speeds in zone 2, (c) CDF for all peak wind speeds in zone 3, and (d) CDF for all peak wind speeds in zone 4.

unlikely wind speeds that potentially result in large number of power outages. Furthermore, this knowledge might be relevant when considering the need for upgrades of the power system.

For the highest peak wind speeds, we can see that how the hurricane moves, where it makes landfall, and its trajectory have the largest influence on the predicted number of power outages, not the peak wind speed. This is especially relevant in zones 2 and 4 (and to some degree zone 1), where we can see that the maximum number of power outages seems to stabilize when the peak wind speed is around 125–150 knots (64–77 m/s); see Figs. 3 and 4. For zone 4, we can see that the CDF functions for peak wind speeds above 125 knots (64 m/s) are very similar, which will be further addressed in Section 5.3. For zone 3, we can see a more linear relationship between an increase in peak wind speed and the related number of power outages. A possible explanation is the trajectory of the hurricanes in zone 3.

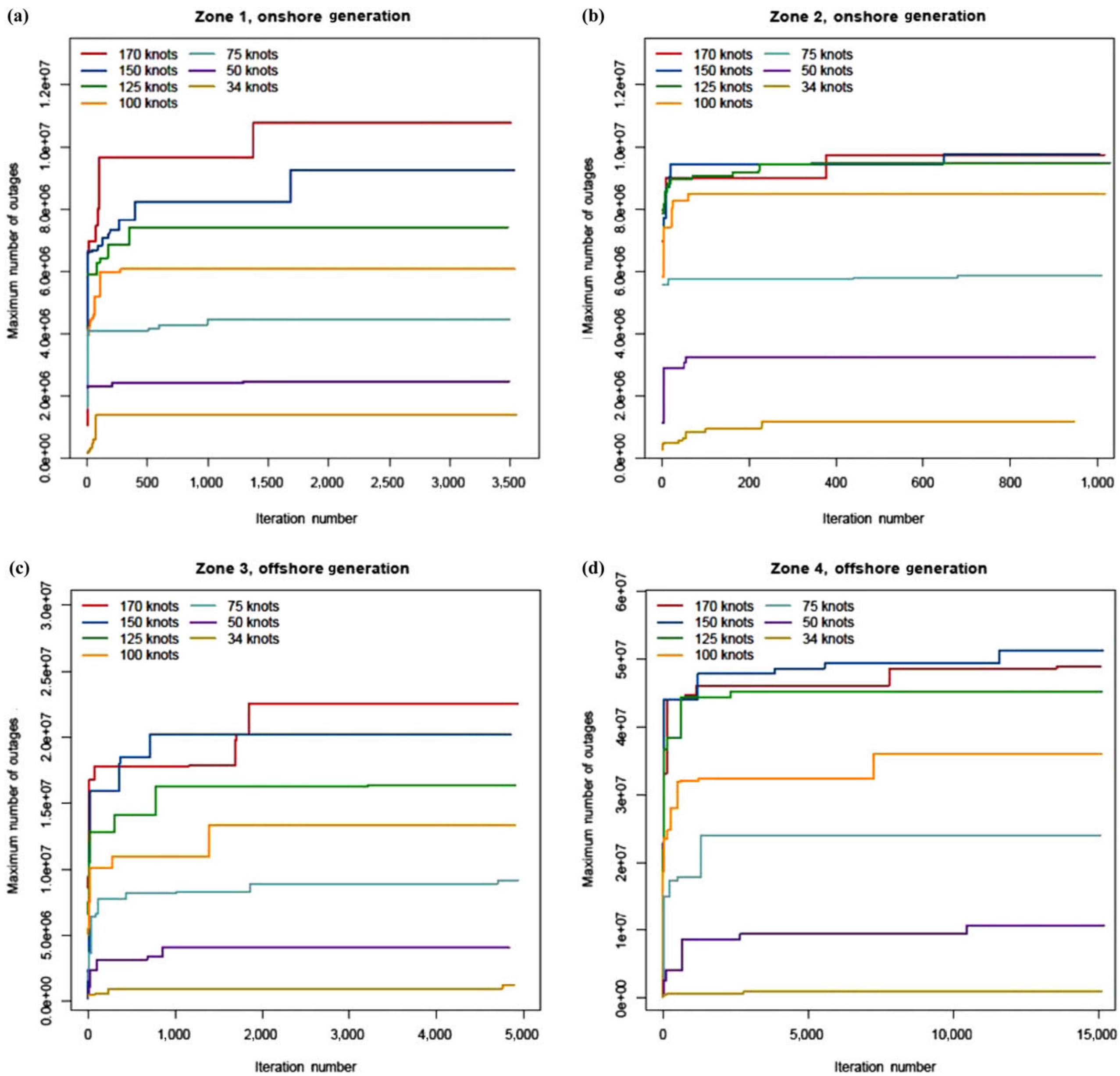

Fig. 4. (a) Convergence plot for zone 1, (b) convergence plot for zone 2, (c) convergence plot for zone 3, and (d) convergence plot for zone 4.

As the wind speed in this zone increases, the hurricane reaches further inland, increasing the impacted area of these hurricanes. In zone 4, on the other hand, most damage is caused if the hurricane follows the east coast, and an increase in wind speed will not lead the hurricane further inland or cover (much) more of the coast. If the hurricane should change direction and move further inland, it will not necessarily increase the number of power outages, as the highest population density is close to the coast.

Prior to our simulations, most people would likely have expected that the largest number of power outages would be related to a hurricane moving along the east coast of the United States because this is the highest population density area. That a strong hurricane hitting the east coast of the United States potentially leads to large numbers of power

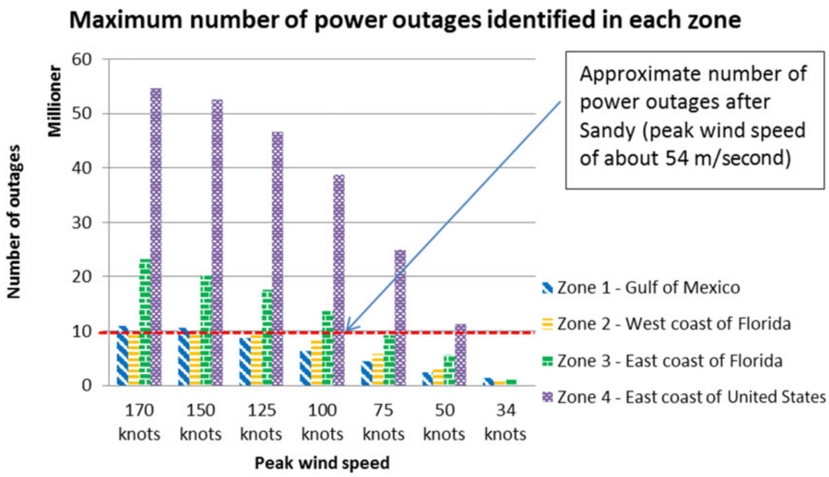

Fig. 5. Maximum number of power outages for each peak wind speed, compared with Hurricane Sandy.

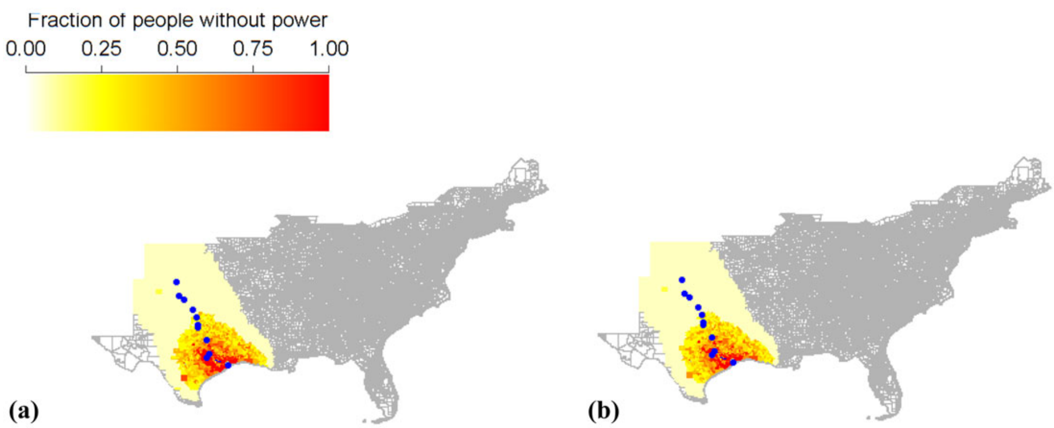

Fig. 6. (a) Fraction of people without power in zone 1 for the worst storm found for 170 knots (88 m/s) wind speed. The predicted number of power outages is 10.9 million. (b) Fraction of people without power in zone 1 for the worst storm found for 150 knots (77 m/s) wind speed. The predicted number of power outages is 10.5 million.

outages has been highlighted in other studies also. The National Infrastructure Simulation and Analysis Center[28] has performed a study looking at the impact of a category 3 hurricane in the New England area. It has used a maximum wind speed of 49 m/s (110 mph), and predicted that 21.5 million people could lose power if the simulated hurricane should occur.[28]

This is close to the present simulations that run with a peak wind speed of 100 knots (51 m/s). Fig. 9 presents the fraction of people without power for two different hurricane scenarios that are quantitatively similar to the NISAC scenario, with a peak wind speed of 100 knots. As we can see, our hurricane scenarios include a larger impacted area, and the related number of power outages is 36 million (Fig. 9(a)) or 30 million (Fig. 9(b)). Both of these scenarios provide a higher prediction than NISAC, which makes sense as the impact area considered is larger. However, both studies produce results where the potential number of outages is higher than previously experienced. The study performed by NISAC can also be seen as an argument of why extreme numbers of power outages might not be a surprise at least for the scientific community, after they have seen the results of simulated storms.

The results from the present simulations show a substantial gap between the number of power outages experienced in the United States and the identified potential. We argue that this is an important finding, as this information can be used to evaluate the need for measures to potentially reduce the number of power outages caused by strong winds as well as measures to respond to much larger loss

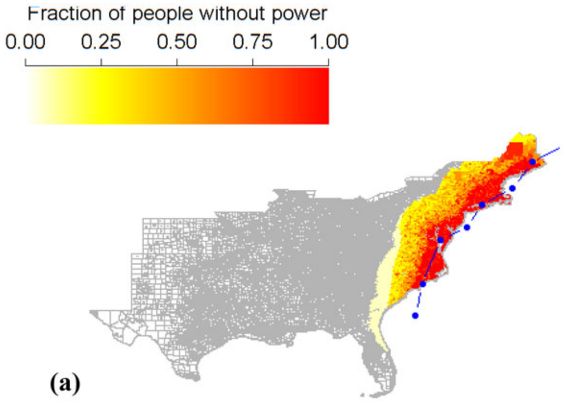

Fig. 7. (a) Fraction of people without power in zone 4 for the worst storm found for 170 knots (88 m/s) wind speed. The predicted number of power outages is 54.7 million. (b) Fraction of people without power in zone 4 for the worst storm found for 150 knots (77 m/s) wind speed. The predicted number of power outages is 52.7 million.

of power events than previously experienced. These measures can be implemented in the days before a hurricane hits. These simulation results can also provide guidance to support longer-term system hardening planning.

Evaluating risk reducing measures is, however, challenging without addressing the likelihood of the different hurricane scenarios. Table I provides an overview of the number and strength of historical hurricanes registered between 1948 and 2012. We can see that most hurricanes make landfall in zone 1. For zone 4, where our simulations lead to the highest number of power outages, the number of storms is approximately half of what is seen in zone 1. During the 64 years from 1948 to 2012, there was an average of 0.77 storms each year in zone 4. If we assume that the occurrence and strength of the historical hurricanes is representative for the future hurricanes in the United States, we can say that it is likely that we will experience a hurricane in this area during the next couple of years. However, the relevance of these historical data is debated.(10) This discussion is influenced by the potential impact that climate warming might have on future hurricane scenarios, with regard to location, intensity, and the number of expected hurricanes per year (frequency). According to Staid *et al.*,(10) researchers seem to agree that the hurricanes will intensify, while changes in both the location and frequency are seen as more uncertain. Predicting these parameters is therefore challenging, especially when considering potential hurricane scenarios 20 years from now. When making predictions related to next year's hurricane scenarios, it is easier to consider historical data as relevant and the uncertainty related to the intensity, fraction, and location of next year's hurricanes can be considered as low. However, in order to perform long-term planning and evaluate different measures that can improve the U.S. power system, long-term predictions are necessary. The lack of knowledge related to the future hurricane scenarios (epistemic uncertainty, due to potential future consequences of climate change) reduces the relevance of the historic hurricane fraction, location, and intensity. This uncertainty is important to keep in mind when discussing potential future hurricane scenarios and evaluating the need for risk reducing measures.

5. DISCUSSION OF SIMULATION RESULTS IN A RISK ANALYSIS CONTEXT

The simulations presented in Section 4 were carried out to get a better understanding of whether and, if so, how a simulation model can be used to reduce the domain of surprising extreme events. For the hurricane example used in this article, the phenomenon is to a large degree known. There is strong knowledge related to how hurricanes affect the power system. The uncertainties related to the number of power outages given a specific hurricane scenario are mostly caused by random variation (randomness). That is, if the detailed hurricane scenario (hurricane track and peak wind speed) is known, the related number of power outages can be considered as subject to random variation. However, our outage model is fully deterministic *given the full set of model inputs*. The randomness in outages is randomness in what is realized in practice for a given hurricane. There is strong

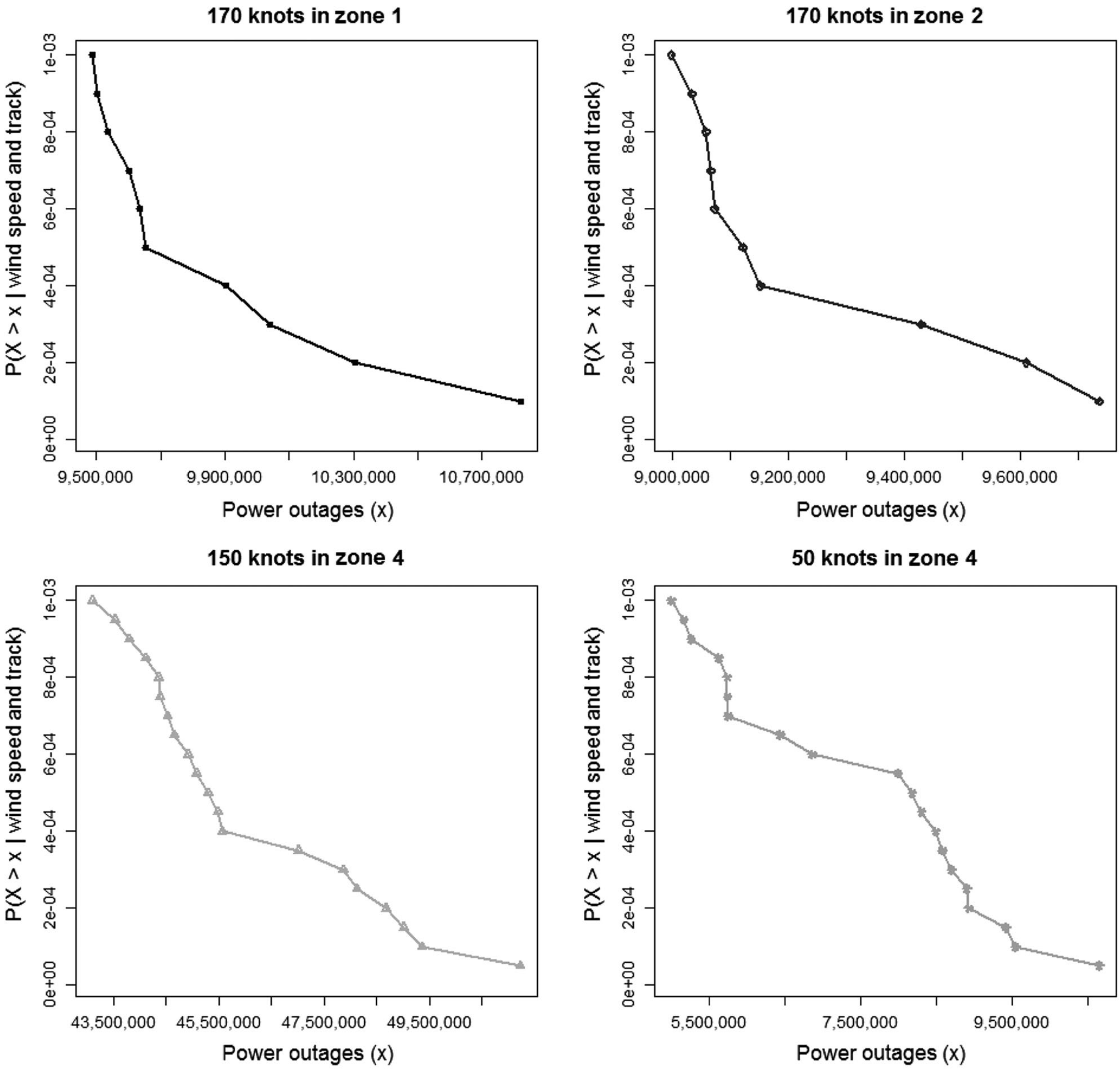

Fig. 8. Tail of cumulative distribution function for number of power outages, X, for four different scenarios.

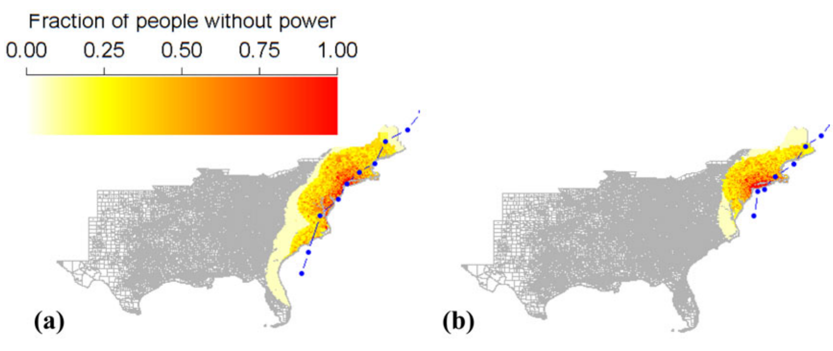

Fig. 9. (a) Fraction without power, given a hurricane with a peak wind speed of 100 knots (51 m/s). Predicted number of power outages is approximately 36 million. (b) Fraction without power, given a hurricane with a peak wind speed of 100 knots (51 m/s). Predicted number of power outages is approximately 30 million.

knowledge related to the number of power outages given a specific hurricane scenario (a relationship modeled by the power outages model). However, there is lack of knowledge related to the future hurricane scenarios, especially their future tracks and intensity. We do not know the details of how hurricane frequency, intensity, and landfall location will change in response to climate change.[10] This uncertainty is epistemic. In addition, the model is built on historical data and there is epistemic uncertainty related to whether or not the model will be representative for the future. For example, one source of epistemic uncertainty is related to the population: Will large groups of the population move, so that there are more (less) people living in other areas than assumed in the model? Also, if major revisions and updates are done on the power system, this can influence the prediction accuracy of the model used, and is not accounted for in the simulations performed in the present article. Uncertainties related to future hurricane scenarios therefore include both aleatory and epistemic uncertainty. This is in accordance with Patè-Cornell's[4] observation; in real-life situations, most surprises occur when we have a combination of both aleatory and epistemic uncertainty. Making a clear distinction between "perfect storms" and "black swans" in real life is therefore, in our opinion, difficult. By elimination, we can conclude that, as future hurricane scenarios are influenced by more than aleatory uncertainty, they cannot be addressed as perfect storms. We are therefore considering black swans as the most appropriate term in this article.

5.1. Reducing the Domain of Black Swans and Perfect Storms

Section 3 presented a set of arguments related to what a simulation model and its simulations would have to provide in order to reduce the domain of different types of black swans. Based on our simulations, we see that the simulation model is useful in different ways in order to reduce the domain of black swans. However, in some situations, they are more useful than others. In the following, we will use the hurricane example to see how these simulations have provided information that can be used to reduce the domain of the different types of black swans. Our thinking follows the same lines as Kaplan and Garrick,[29, p. 12] namely, that *"[i]f we know there is a hole in the road around the corner, it poses less risk to us than if we zip around not knowing about it."* Their argument being that awareness on its own can be enough to reduce risk. However, we believe that the information (knowledge) has to be used in order to reduce risk. In our situation that means that the information has to be used either to reduce the probability of a hurricane occurring (not generally possible), or the impact should a hurricane occur. We argue that our simulations provide information that can be used to emphasize the importance of investing in measures that can be used to reduce the impact of a hurricane.

The main advantages of the simulations are, in our opinion, related to black swans of types (b) and (c). Distinguishing between (b) and (c) is challenging as it depends on the original belief of the different stakeholders (utility companies, politicians, laypeople, etc.). Let us consider two groups of relevant stakeholders that are asked to assign a probability to the event, "a hurricane result in more than 30 million power outages." Some do not even consider the event that an hurricane might result in more than 30 million power outages; let us call them group 1. The other group thinks that it can happen, but that the probability of its occurrence is so low that it can be ignored, group 2. If a hurricane resulting in more than 30 million power outages occurs, it will, for both groups 1 and 2, be seen as a surprise with extreme consequences—a black swan. For group 1, it was a black swan type (b), while for group 2 it was a black swan type (c). The aim of our simulations has been to provide information that can change the original belief of these groups by illustrating the possibility for extreme number of power outages.

One of the reviewers of an earlier version of the present article wanted to know if our results could actually be seen as surprising should they occur. To respond to this question, we sent an informal email to a set of relevant stakeholders to create an understanding of their perceptions related to potential hurricane scenarios. These individuals included both leading experts on hurricane-induced power outages and members of the general public. None of them had seen the result of this article. The question raised was: "What would a particularly bad hurricane look like in the US in terms of number of outages?" We got a range of different answers, but the similarity between them was that they were far from the scenarios that we have identified. The highest number suggested was 30 million, and that was suggested as a "worst case scenario."

Our results indicate that there is a potential for hurricanes with almost two times as many power outages as predicted by the experts, and more than five times the number of power outages experienced during Hurricane Sandy. Even for relatively low peak wind speeds (50 knots [26 m/s]), a hurricane moving along the East Coast (north of Florida) can result in more power outages than Hurricane Sandy. This is the information that will influence the original beliefs in groups 1 and 2 (and also those replying to our informal survey). For group 1, this knowledge means that a larger number of power outages need to be considered, and included in the risk assessment. Group 2 can use this insight to reevaluate the probability of experiencing more power outages than seen so far, potentially concluding that the event can no longer be ignored due to negligible probability. That way, the risk analysts (and relevant stakeholders) in groups 1 and 2 will not be that surprised if a hurricane results in more than 30 million power outages. This insight should be used to evaluate the need for risk reducing measures,[30] and potentially reduces the domain of black swans types (b) or/and (c).

For black swans of type (a), it is more challenging to see how our simulations can be useful. However, they are not completely irrelevant for black swans type (a), and in our example we can see that the simulations identify a question: "Why does the number of power outages stabilize when the peak wind speed reaches 125 knots (64 m/s) in zones 2 and 4 and not in Zone 3?" Investigating questions like this can reveal new information (or potential areas for model improvements). For our example, this is relatively unlikely, but in general, simulations can raise interesting and important questions that can be used to direct and prioritize research. In this way, research can generate new knowledge and identify new phenomenon, potentially reducing the domain of black swans type (a).

5.2. Benefits and Challenges when Using Simulation Models to Identify Potentially Surprising Scenarios

Simulations can provide useful insight when evaluating the costs related to the implementation of risk reducing measures. For the situation considered in this article, the simulations provide insight that should be used when considering the future costs of power outages in the United States. These costs are relevant inputs when evaluating the need for upgraded power systems. A report from the Economic Development Research Group[31] argues that the best way to estimate the magnitude of future costs (caused by power outages) is to consider the scale of historical costs. When only considering historical costs, a tacit assumption is made; namely, that the historical cost related to power outages is representative for the future. This assumption ignores important uncertainties related to future costs as our simulations show that there is a potential for (significantly) higher numbers of power outages than seen so far. In addition, some researchers argue that climate change will influence future hurricanes. However, the effect of climate change on future hurricanes is not that clear.[10] Updates to the power system can be considered as a risk reducing measure, where the aim is to reduce the number or/and duration of power outages. In addition, simulation models are useful when performing emergency planning and preparation. How can and should we prepare for extreme hurricane scenarios? What can be done in order to reduce the consequences as much as possible? These questions are important, and very difficult to answer without insight about potential future hurricane scenarios and their severity. Insights about potential future scenarios are also valuable during design. In this phase, simulations can create useful inputs when evaluating the need for robust and/or resilient solutions.

Another benefit of using simulations is related to early warning signals. Simulations do not directly create early warning signals, but simulations can identify extreme impact scenarios. Knowing what these scenarios look like can be used to recognize relevant information, signals, and interactions quicker than if these scenarios were unknown.[32] Van der Merwe[32, p. xxi] illustrates how scenario thinking can create awareness by referring to last time you purchased a car; "What did you notice when you drove your [new] car onto the streets? You probably noticed how many people were driving the same car!" This makes it seem like there were many more of these cars than before your purchase. This is a good example of how background knowledge influences the details or signals to which attention is given. Before buying a new car, that car did not have any special meaning; there was no reason to look for a car of that particular type. By the use of simulations, we can create awareness related to potential future scenarios, making it easier to know what to look for and recognize the early warning signals.

The challenges related to the use of simulations are to a large degree dependent on the verification and validation of the simulation model used and relevance of the data that the model is based on. Simulations based on a model that cannot be justified can create scenarios that are not only imprecise, but also misleading. The importance of using a verified and validated model cannot be underestimated. In addition, simulations might in some situations be very resource demanding.

6. CONCLUSIONS

In the present article, we have seen how simulations, through increased insight, can reduce the domain of black swans. Here, we concluded that the use of simulations was most useful when reducing the domain of black swans of types (b) and (c), the unknown knowns and the known events where the probability is judged as negligible. For black swans type (a), the unknown unknowns, we concluded that it was difficult to see how simulations directly could be used to identify new phenomenon, which would have been necessary to reduce the domain of black swans caused by an unknown phenomena. However, we argue that, in some situations, simulations can be used to identify areas where more research potentially leads to understanding and identification of a new phenomenon, creating new knowledge that indirectly might reduce the domain of the unknown unknowns.

By using a simulation model to predict the potential future number of power outages, we have increased the understanding of the potential impact a hurricane might have on the U.S. power system. We have seen that the number of power outages experienced so far (in the United States) is low compared to the potential, and that relatively low peak wind speeds can result in large number of power outages. The most surprising simulation result is related to a relatively weak hurricane with a track along the east coast of the United States (north of Florida). The 1-minute maximum wind speed is 26 m/s and the predicted number of power outages is above 10 million, larger than previously experienced anywhere in the United States. The largest predicted number of power outages is also related to a hurricane with a track along the east coast of the United States, with a maximum wind speed of 77 m/s. The predicted number of 54 million power outages is five times higher than the highest experienced number of power outages in the United States. This is important information that should be included when evaluating the need for risk reducing measures.

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REFERENCES

1. Taleb NN. The Black Swan: The Impact of the Highly Improbable Fragility, 2nd ed. rev. ed. United Kingdom: Penguin Group, 2007.
2. Aven T. On the meaning of a black swan in a risk context. Safety Science, 2013; 57:44–51.
3. Aven T, Krohn BS. A new perspective on how to understand, assess and manage risk and the unforeseen. Reliability Engineering and System Safety, 2014; 121:1–10.
4. Patè-Cornell E. On "black swans" and "perfect stormsdä: Risk analysis and management when statistics are not enough. Risk Analysis, 2012; 32(11):1823–1833.
5. Murphy JF, Conner J. Beware of the black swan: The limitation of risk analysis for predicting the extreme impact of rare process safety incidents. Wiley Online Library, 2012; 31(4):330–333.
6. Society of Risk Analysis. SRA Glossary, 2015. Available at: http://www.sra.org/sites/default/files/pdf/SRA-glossary-approved22june2015-x.pdf, Accessed on January 14, 2016.
7. Beck M, Guikema S, Buckstaff K, Quiring S. Modeling storm outages: New tools for enhancing utility preparedness and response. public utilities fortnightly, 2013 October. Available at: https://app.box.com/s/2gkpg73w0sgkm29vbvpv, Accessed on February 23, 2015.
8. Webley K. Hurricane Sandy by the numbers: A superstorm's statistics, one month later. Time, 2012 November 26. Available at: http://nation.time.com/2012/11/26/hurricane-sandy-one-month-later/, Accessed on January 1, 2015.
9. Guikema SD, Nateghi R, Quiring SM, Staid A, Reilly A, Gao M. Predicting hurricane power outages to support storm response planning. IEEE Access, 2014; 2:1364–1373. OPEN ACCESS. doi: 10.1109/ACCESS.2014.2365716
10. Staid A, Guikema SD, Nateghi R, Quiring SM, Gao MZ. Simulation of tropical cyclone impacts to the US power system

under climate change scenarios. Climatic Change, 2014; 127(3–4):535–546.
11. Bank for International Settlements. Principles for Sound Stress Testing Practices and Supervision. Bank for International Settlements, 2009 May. Available at: http://www.bis.org/publ/bcbs155.pdf, Accessed on October 7, 2014.
12. Committee of European Banking Supervisors. CEBS Guidelines on Stress Testing (GL32). Committee of European Banking Supervisors, 2010 August 26. Available at: http://www.eba.europa.eu/documents/10180/16094/ST_Guidelines.pdf, Accessed on October 7, 2014.
13. European Banking Authority. The EBA's Role in the EU-Wide Stress Test. European Banking Authority, 2014. Available at: http://www.eba.europa.eu/risk-analysis-and-data/eu-wide-stress-testing/2014/the-eba-s-role-in-the-eu-wide-stress-test, Accessed on October 31, 2014.
14. European Commission. Technical Summary on the Implementation of Comprehensive Risk and Safety Assessment of Nuclear Power Plants in the European Union, 2013. Available at: http://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52012SC0287R(01)&from=EN), Accessed on January 1, 2016.
15. Saltelli A. Sensitivity analysis for importance assessment. Risk Analysis, 2002; 22(3):579–590.
16. Johansson J, Hassel H, Zio E. Reliability and vulnerability analyses of critical infrastructures: Comparing two approaches in the context of power systems. Reliability Engineering & System Safety, 2013; 120:27–38.
17. Murray AT, Matisziw TC, Grubesic THA. Methodological overview of network vulnerability analysis. Growth and Change, 2008; 39(4):573–592.
18. Haimes YY. On the definition of vulnerabilities in measuring risks to infrastructures. Risk Analysis, 2006; 26(2):293–296.
19. Aven T. Implications of black swans to the foundations and practice of risk assessment and management. Reliability Engineering & System Safety, 2015; 134:83–91.
20. Haugen S, Vinnem JE. Perspectives on risk and the unforeseen. Reliability Engineering & System Safety, 2014; 137: 1–5.
21. Han SR, Guikema SD, Quiring SM, Lee KH, Rosowsky D, Davidson RA. Estimating the spatial distribution of power outages during hurricanes in the Gulf Coast region. Reliability Engineering & System Safety, 2009; 94(2):199–210.
22. Han SR, Guikema SD, Quiring SM. Improving the predictive accuracy of hurricane power outage forecasts using generalized additive models. Risk Analysis, 2009; 29(10):1443–1453.
23. Nateghi R, Guikema SD, Quiring SD. Comparison and validation of statistical methods for predicting power outage durations in the event of hurricanes. Risk Analysis, 2011; 31(12):1897–1906.
24. Quiring SM, Schumacher AB, Guikema SD. Incorporating hurricane forecast uncertainty into a decision-support application for power outage modelling. Bulletin of the American Meteorological Society, 2014; 95(1):47–58.
25. Kaplan J, Demaria M. A simple empirical model for predicting the decay of tropical cyclone winds after landfall. Journal of Applied Meteorology, 1995; 34(11):2499–2512.
26. National Hurricane Center. Saffir-Simpson Hurricane Wind Scale. NOAA, 2013. Available at: http://www.nhc.noaa.gov/aboutsshws.php, Accessed on December 12, 2014.
27. National Weather Service Weather Forecast Office. Saffir-Simpson Hurricane Scale. NOAA, 2008. Available at: http://www.srh.noaa.gov/mfl/?n=saffirsimpson, Accessed on December 14, 2014.
28. U.S. Department of Homeland Security (DHS). National Protection and Programs Directorate Office of Cyber and Infrastructure Analysis U.S. Department of Homeland Security. New England Hurricane Scenario Analysis Report. 2014 October.
29. Kaplan S, Garrick BJ. On the quantitative definition of risk. Risk Analysis, 1981; 1(1):11–27.
30. Campbell RJ. Weather-Related Power Outages and Electric System Resiliency. Congressional Research Service, Library of Congress, 2012 August 28. Available at: http://digital.library.unt.edu/ark:/67531/metadc122249/m1/1/high_res_d/R42696_2012Aug28.pdf, Accessed on February 17, 2015.
31. Economic Development Research Group. Failure to Act: The Economic Impact of Current Investment Trends in Electricity Infrastructure. American Society of Civil Engineers, 2011. Available at: http://www.google.no/url?sa=t&rct=j&q=&esrc=s&source=web&cd=3&ved=0ahUKEwjHpOmkivjPAhUCBywKHcjhCBIQFggxMAI&url=http%3A%2F%2Fwww.asce.org%2FuploadedFiles%2FIssues_and_Advocacy%2FOur_Initiatives%2FInfrastructure%2FContent_Pieces%2Ffailure-to-act-electricity-report.pdf&usg=AFQjCNHQa4kp-dZe7Kzhazp44w5UW6GAvw&bvm=bv.136593572,d.bGg, Accessed on October 26, 2016.
32. Van der Merwe L. Foreword. Pp. xi–xiv in Chermack TJ (ed). Scenario Planning in Organizations: How to Create, Use, and Assess Scenarios. Berrett-Koehler Publishers, 2011.

SUPPORTING INFORMATION

Additional supporting information may be found in the online version of this article at the publisher's website:

Figure A.1 Simulated hurricane track with peak wind speed of 150 knots (77 m/s), zone 1. Related number of power outages is 9.2 million.
Figure A.2 Simulated hurricane track with peak wind speed of 125 knots (64 m/s), zone 1. Related number of power outages is 7.4 million.
Figure A.3 Simulated hurricane track with peak wind speed of 100 knots (51 m/s), zone 1. Related number of power outages is 6.0 million.
Figure A.4 Simulated hurricane track with peak wind speed of 170 knots (88 m/s), zone 3. Related number of power outages is 22.5 million.
Figure A.5 Simulated hurricane track with peak wind speed of 150 knots (77 m/s), zone 3. Related number of power outages is 20.2 million.
Figure A.6 Simulated hurricane track with peak wind speed of 125 knots (64 m/s), zone 3. Related number of power outages is 16.3 million.
Figure A.7 Simulated hurricane track with peak wind speed of 100 knots (51 m/s), zone 3. Related number of power outages is 13.3 million.
Figure A.8 Simulated hurricane track with peak wind speed of 50 knots (26 m/s), zone 4. Related number of power outages is 10.6 million.

Figure A.9 Simulated hurricane track with peak wind speed of 170 knots (88 m/s), zone 2. Predicted number of power outages is 9.7 million.

Figure A.10 Simulated hurricane track with peak wind speed of 150 knots (77 m/s), zone 2. Predicted number of power outages is 9.5 million.

Figure A.11 Simulated hurricane track with peak wind speed of 125 knots (64 m/s), zone 2. Predicted number of power outages is 9.5 million.

Figure A.12 Simulated hurricane track with peak wind speed of 100 knots (51 m/s), zone 2. Predicted number of power outages is 8.5 million.