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Bayesian Network and Monte Carlo Simulation Augmented External Flood Probabilistic Risk Assessments for Nuclear Power Plants

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ABSTRACT

Probabilistic risk assessments (PRAs) quantitatively and qualitatively assess risk insights at nuclear power plants (NPPs) using conventional tools (i.e., event trees and fault trees). These assessments are guided by answering the risk triplet principle: (1) what can go wrong? (2) how likely is it? (3) what are the consequences? The nuclear industry has extensive experience in employing PRAs, particularly for internal events risk-informed applications. However, due to the modeling complexities, there is comparatively limited experience in external event PRAs, including flood risks. Furthermore, conventional PRA tools have limitations such as the binary state assumption, component failure independence assumption, and the static treatment of logic when applied to external floods. Furthermore, the spatial variations due to the site's topology can significantly impact the probabilistic flood hazard assessment. This paper proposes a hybrid framework that strategically integrates the external flood PRA framework with the novel tools of a Bayesian network and Monte Carlo simulation to address these limitations. This hybrid framework accounts for the spatial variations from site-level and location-specific hazards by modeling relevant random variables, addressing the varying impacts of external flood demand across the nuclear power plant's site.

INTRODUCTION

Probabilistic risk assessments quantify the risks and highlight the risk contributors associated with an NPP. Traditionally, the PRAs use conventional risk tools of event trees (ETs) and fault trees (FTs). PRAs have supported risk-informed decision-making in the United States' nuclear industry since the 1990's. This support has resulted in extensive experience and knowledge for probabilistically assessing risks in NPPs, especially for internal events. There is comparatively limited experience in performing external event risk in nuclear power plants, including external floods, due to substantial variations in site-specific geography, meteorology, hydrology, and hazard data availability, as discussed by Ferrante (2015).

Furthermore, there are limitations in conventional PRA tools that are highlighted when applied to external floods, such as the static treatment of time, component failure independence assumption, and binary component state assumption. Traditionally, risks due to external floods have been screened out from consideration. Accordingly, the current practice has been assessing flood hazard safety using the traditional design-bases approach. The design basis approach deterministically compares select elevations to a probable maximum phenomenon such as local intense precipitation (LIP), storm surges, or seiches. Concerns over climate-induced floods, and as Vaishanav et al. (2020) describe, there has been an increasing interest in employing external hazard PRAs. However, there are few examples of comprehensive external flood PRAs due to the previously mentioned modeling challenges.

External flood PRAs consist of three technical elements: (1) probabilistic flood hazard assessment (PFHA), (2) flood fragility evaluation, and (3) flood plant response model. PFHAs characterize and quantify the external flood probabilistically (e.g., their frequency and severity) at a given site. The results of a PFHA are typically presented in a hazard curve, which provides the annual exceedance frequency (AEF) at a flood demand variable (e.g., flood height, duration, velocity). External flood hazards are traditionally analyzed assuming a site is spatially homogeneous, meaning the flood hazard has the same probability of exceedance within the site. The spatial homogeneity assumption can challenge the model's accuracy when the hazard is assessed within the site, as described by Quinn et al. (2019) and Nguyen et al. (2020). This limitation impacts the PFHA regarding hazard within the NPP site, producing inaccurate assumptions on the flood's impact on flood protection features. The flood fragility evaluation assesses a flood protection feature's capacity to withstand the flood's demand. Fragility is the conditional probability that a flood protection feature reaches or exceeds a damage state, given the flood demand. Structure, System, and Components (SSCs) are conventionally assumed as either functional or failed when the flood reaches the SSC's elevation, resulting in a cliff-edge effect. This binary SSC state assumption is also seen in the conventional risk tools, as previously mentioned, which are used to depict the plant response model. The plant response models the accident sequence and component failure combinations, informed by the PFHA and fragility evaluation results. These limitations in the conventional PRA framework contribute to the challenges in developing comprehensive external flood PRAs.

This paper proposes a hybrid risk framework to leverage the extensive knowledge and experience in the conventional PRA framework with a Monte Carlo (MC) simulation augmented Bayesian network (BN) to address limitations in flood risk modeling, focusing on the challenges in the homogeneity hazard assumption. BNs are a convenient tool to model a diverse set of random variables, such as PFHA and fragility evaluation results, as well as the conditional dependencies between them. These modeling abilities allow the BN to differentiate the external flood depth probability distributions between site-level and flood protection features, as well as model the causal relationship between them. However, BNs can become large and complex, requiring a large memory demand. Additionally, BNs typically discretize continuous variables, resulting in a discretization error. These limitations in BNs are addressed by integrating relevant nodes out of the BN by leveraging physical relationships through MC simulations. This is further discussed in the next section.

PROPOSED HYBRID PRA FRAMEWORK

This work proposes a hybrid framework in which the PFHA, flood fragility evaluation, and flood-relevant random variables are modeled in the MC-augmented BN. The results of the BN are then linked to the conventional framework in the plant response model, as seen in Figure 1 below.

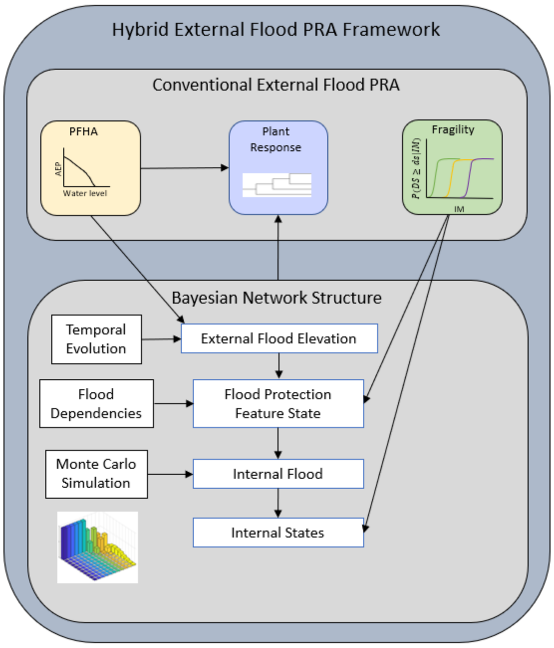


Figure 1. Overview of Proposed Hybrid External Flood PRA Framework

The hybrid framework provides a more realistic model for assessing external flood risks. The BN is developed based on the causal relationships of the flood pathway, incorporating temporal and SSC dependencies.

Representative EDG Building Case Study

This paper applies the framework to an external flood impacting a representative emergency diesel generator (EDG) building envelope, as seen in Figure 2.

The representative building envelope consists of five flood protection features: three identical penetration seals (PS) and a door (D) protected by a floodgate (FG). Note that the floodgate and door are located at the same location and are assumed to have the same location-specific external flood height.

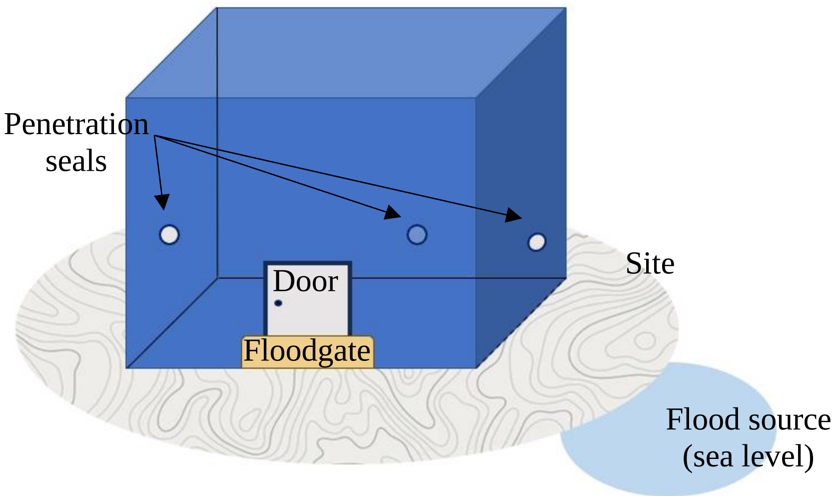


Figure 2. Representative Building Envelope of an EDG Building

This work assumes that the external flood is a storm surge originating at sea level from a nearby ocean or sea, in which sea level serves as the reference elevation measured from the mean sea level (MSL) datum. The site reference elevation is arbitrarily assumed to be at six feet relative to MSL. The EDG building is located on a spatially variable site.

Monte Carlo augmented Bayesian Network

This paper demonstrates the MC augmented BN by probabilistically mapping external to internal flood, accounting for relevant variables. As previously mentioned, the framework proposes to incorporate the PFHA and flood fragility evaluation results in the BN, along with other random variables relevant to the problem context. This paper focuses on providing the PFHA spatial modeling development. However, the BN accounts for fragility by adapting high-confidence-low-probability of failure (HCLPF) capacities to obtain flood fragility curve parameters, pre-existing degradation by adapting plant walk-down reports, and developed best-estimate damage flow area assumptions by employing thorough literature surveys. Shen et al. (2023) discuss these methods in greater detail.

The random variables are categorized and outlined into five classifications and colors: external flood nodes (green), pre-existing degradation nodes (light blue), component state nodes (dark blue), internal flood nodes (purple), and nodes integrated through the MC simulation (dashed purple).

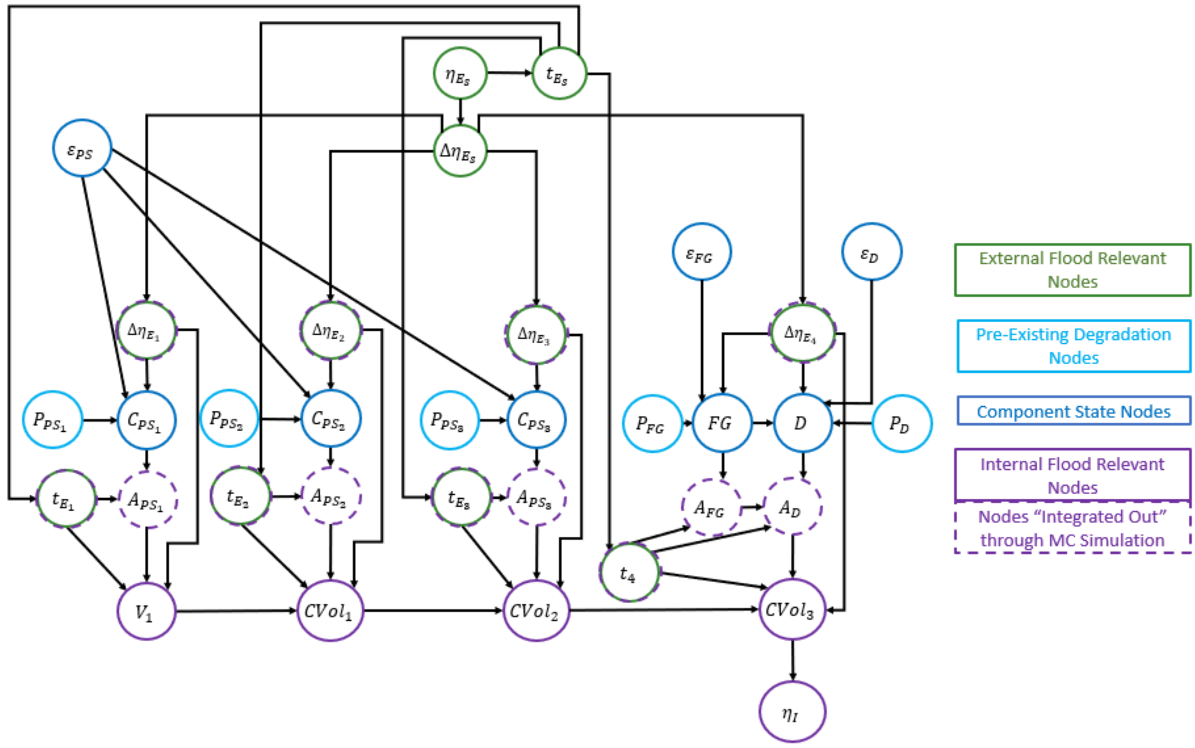


Figure 2. Proposed External Flood BN

The MC simulation augments the BN to integrate relevant nodes out of the BN into other nodes through physical relationships. This work leverages the Bernoulli equation to model flow volumes V_1 and $CVol_n$ as functions of random variables: location-specific external flood depth $\Delta\eta_{E_i}$, flood duration t_{E_i} and flow area A_{j_i} where j indicates the feature and i indicates the feature number for multiple identical features. This augmentation reduces memory demands and discretization errors. These relevant nodes outlined in dashed purple are integrated into the flow volume or cumulative flow volume nodes, and the function of random variables is evaluated through an MC simulation. This integration transforms the BN from Figure 2 to Figure 3.

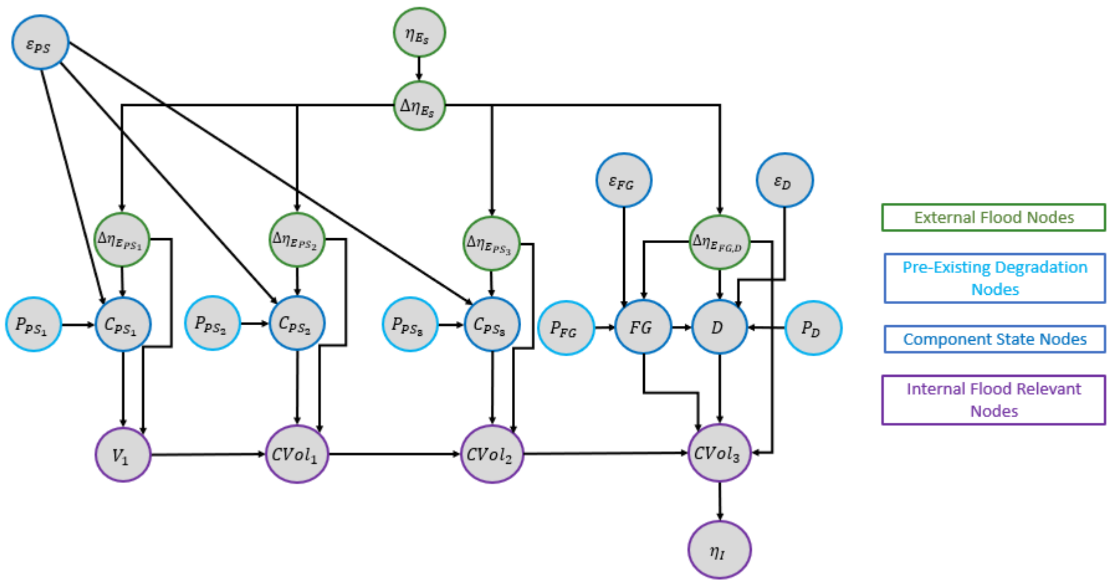


Figure 3. Simplified Proposed External Flood BN

EXTERNAL FLOOD SPATIAL VARIATION

This work incorporates the spatial variability assumption by incorporating the probabilistic effects of topography between flood source, the site, and the site's topography. The BN models three "layers" of external flood nodes, established through causal relationships: (1) external flood site elevation (η_{E_S}), (2) external flood site depth ($\Delta\eta_{E_S}$), and (3) external flood feature location depth ($\Delta\eta_{E_{j_i}}$).

The first node layer, external flood site elevation node η_{E_S}, models the flood elevation that impacts the site, measured from MSL. The probabilities of this node can be obtained from the results of a PFHA, which is generally provided in terms of AEF rather than probability. This work adapts a relationship from "Seismic Hazard and Risk Analysis" by Baker et al. (2021), as seen in equation (1).

$$P\left(n_{low} < \eta_{E_s} \leq n_{high} \middle| \eta_{E_s} > n_{min}\right) = \frac{\lambda_{\eta_E \geq n_{low}} - \lambda_{\eta_E > n_{high}}}{\lambda_{\eta_E > n_{min}}} \tag{1}$$

Where $P\left(n_{low} < \eta_{E_s} \leq n_{high} \middle| \eta_{E_s} > n_{min}\right)$ is the conditional probability that the external flood elevation is between flood heights n_{low} and n_{high}, which defines the node discretization, given that the external flood elevation exceeds the minimum threshold n_{min}. $\lambda_{\eta_E \geq n_{low}}$ and $\lambda_{\eta_E \geq n_{high}}$ are the AEFs of external flood elevations greater than n_{low} and n_{high}, the difference is normalized by $\lambda_{\eta_E > n_{min}}$, or the AEF of the external flood elevation greater than the minimum threshold height. This work leverages a representative hazard curve in an arbitrary location from the Costal Hazard System (CHS) (2023). The hazard curve is extrapolated to zero feet, which is also assumed to be n_{min}.

This work assumes that the η_{E_S} node is discretized from zero to sixteen feet and above in bin widths of 0.5 feet. The last bin is an infinite state that captures the entire hazard domain. This node discretization results in 34 states. The representative hazard curve scale is on the left y-axis in blue, and the discretized conditional probability is plotted on the right y-axis in black in Figure 4.

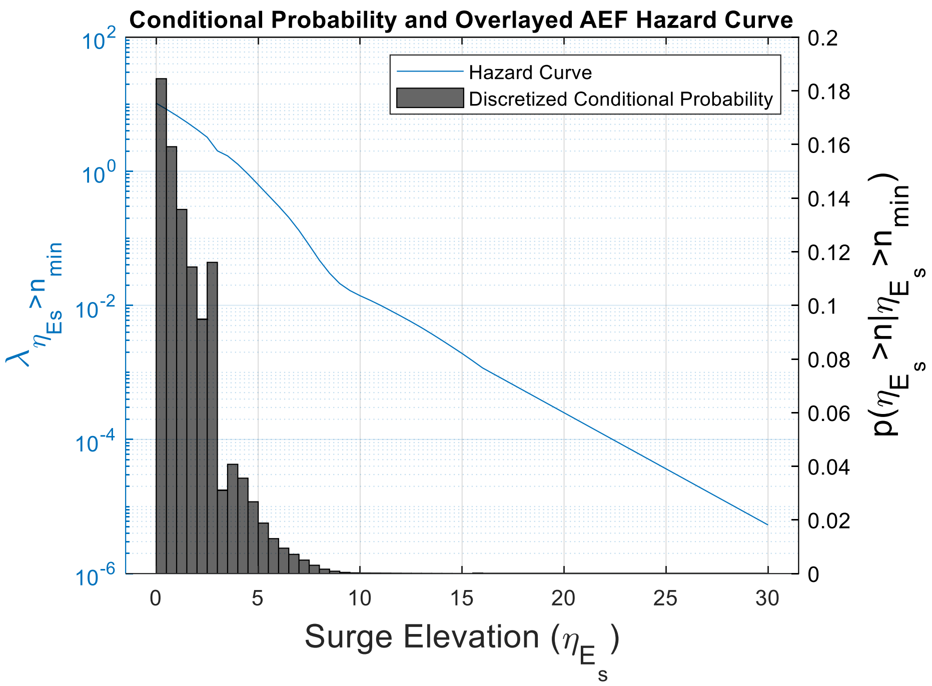


Figure 4. Representative Hazard Curve, Overlayed with Discretized Conditional Probability

The second node layer, external flood site depth $\Delta\eta_{E_S}$, models the external flood depth that is normalized by the plant elevation, which recall is arbitrarily assumed to be six feet above MSL. The probabilities are obtained as the direct probabilistic mapping from the difference between η_{E_S} and plant elevation.

The third node layer of $\Delta\eta_{E_{j_i}}$ differentiates the flood site depth from the flood protection feature location-specific depth. This node depicts the site flood depth above the flood protection feature, accounting for differences in depths that arise due to the site topography. This node is a direct probabilistic mapping from the difference between $\Delta\eta_{E_S}$ and flood protection feature location's elevation in relation to the reference plant elevation and installation height.

This paper assumes representative flood protection feature installation's height and variable inter-site elevation at the feature, which are provided in Table 1. For example, the site's elevation at PS_1 due to topographic effects is two feet less than the reference plant elevation. Furthermore, the seal's installation height is three feet above the reference plant elevation. Therefore, the external flood must overcome a total of five feet. The CPT for the third node layer is also obtained as a direct probabilistic mapping of external flood site depth to external flood feature-specific depth.

Table 1. Flood protection feature representative installation heights and location-specific elevations regarding the plant elevation.

Flood Protection Feature	Installation Height [ft]	Feature Specific Elevation [ft]
PS_1	$+3$	-2
PS_2	$+3$	$+0$
PS_3	$+3$	$+2$
FG	$+1$	$+1$
D		

Comparison of Spatial Homogeneity and Spatial Variability Assumptions

Incorporating spatial variability in the model better accounts for the site's topography effects on the location-specific hazard. The spatial variability effects in this model can be shown through inference by the insertion of evidence. Inference is an advantageous characteristic of BNs that allows the model to propagate the probabilistic effects on the CPTs throughout the model. There are two major types of inference: forward and backward. Forward inference is predictive, propagating evidence in the direction of the causal relationships. Backward inference is diagnostic, which propagates evidence in the opposite direction of the causal relationships.

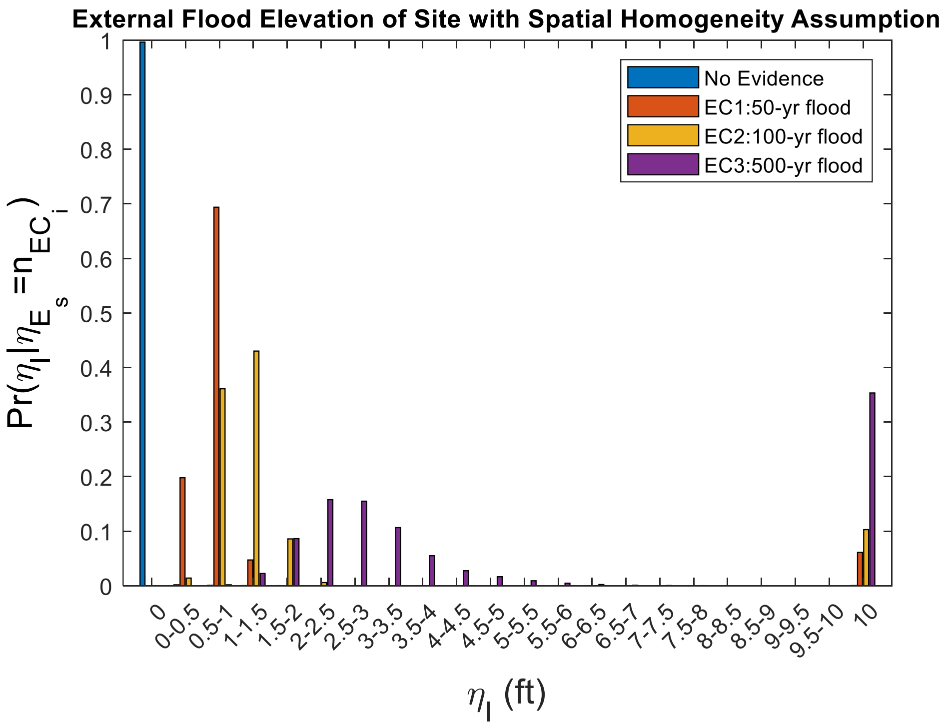
This paper implements forward inference by leveraging three representative evidence cases (ECs) on the external flood site elevation to demonstrate the effects of spatial homogeneity and spatial variability assumptions on the probability distribution of internal flood height. Recall the structure of this BN is based on the flood pathway of an external flood impacting an EDG building envelope fragility, resulting in an internal flood depth. The ECs propagate through this structure, updating the probability distributions from the child nodes between the external flood site elevation and internal flood depth. The Bayesian updated probability distributions of internal flood depth are plotted against each EC for both homogeneous and varying assumptions in Figure 5(a) and Figure 5(b)

The ECs are 50-year, 100-year, and 500-year floods at the representative site extracted from the hazard curve. Note that the external flood elevation for each EC is associated with an increasing site hazard, resulting in a shift to the right in internal flood depths, reflecting an increase in demand on the flood protection features.

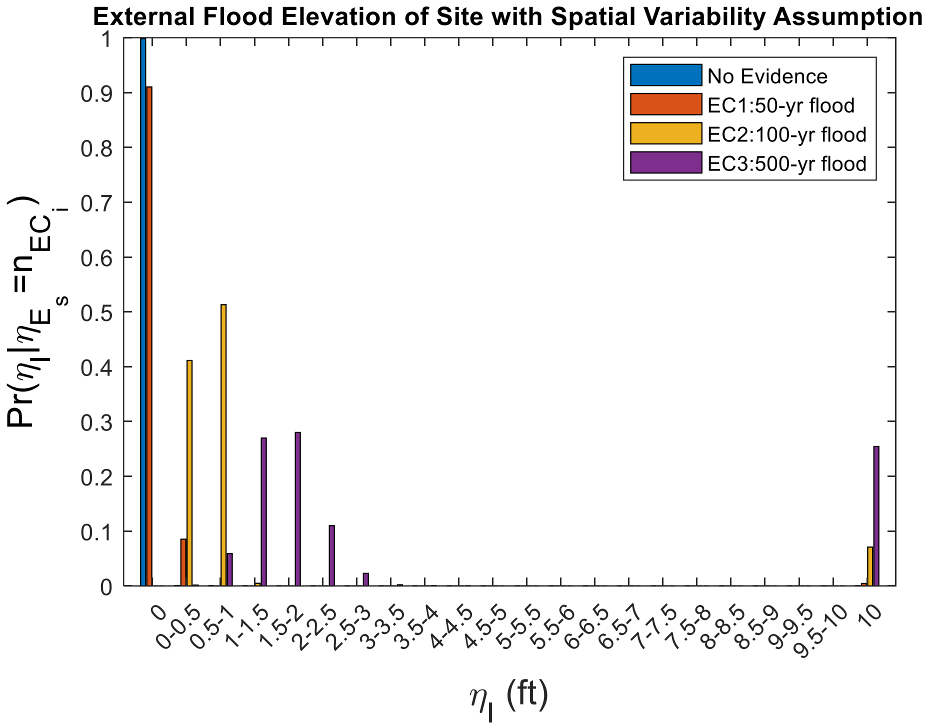
This results in the following external flood site elevations:

- No Evidence: No observed evidence is propagated in the model.
- EC1: A 50-yr flood event resulting in an external flood site elevation of $\eta_{E_S} = 9.14$ ft.
- EC2: A 100-yr food event resulting in an external flood site elevation $\eta_{E_S} = 11.02$ ft.
- EC3: A 500-yr flood event resulting in an external flood site elevation $\eta_{E_S} = 14.77$ ft.

A comparison of the spatial homogeneity and spatial variability effects for each evidence case is provided below, where Figure 5(a) is the spatially homogenous assumption and Figure 5(b) is the spatially variable assumption.



(a) Spatial Homogeneity Assumption



(b) Spatial Variability Assumption

Figure 5. Observed Evidence Effect on Internal Flood Height Node

The homogeneity assumption in this example provides a more conservative result than the variability assumption, which is consistent with the provided assumptions in Table 1 and the site hazard data set. Therefore, the homogeneity assumption for this representative case study models a larger contribution of external flood height to internal flood height through the flood protection features, assuming the only elevation of the flood above the plant elevation of six feet. Meanwhile, the spatial variability assumption in this demonstrative study allows the BN to account for the variable elevations at each flood protection accurately, which features the external flood that must account for. The differentiation between the spatial homogeneity and variability model can provide more robust information on the configurations of flood protection features to risk-informed decision-makers to predict and diagnose system behavior during a flood.

CONCLUSION

There is limited experience in external flood risk analyses due to the complexity of phenomena and modeling challenges in conventional risk tools. BNs have inherent characteristics that expand the binary state assumption to multiple states model diverse random variables to incorporate temporal dependencies and spatial variabilities through causal dependencies.

This work proposes an external flood hybrid PRA framework that links the conventional PRA framework with a novel tool of an MC-augmented BN to address these challenges. The paper focuses on the development and impact of incorporating spatial variability in the BN, applying representative assumptions.

The paper provides an example of an MC-augmented BN that probabilistically models external flood site elevation to internal flood depth with relevant random variables. The model accounts for spatially variable hazards within a site, which is demonstrated through Bayesian inference, providing site-specific information of the representative site and building envelope. This model offers a framework that integrates more site-specific information for practitioners to model a more accurate representation of an external flood impacting an NPP. Furthermore, this model enables practitioners to transparently identify vulnerabilities in the system, better understanding the likeliest configurations that may lead to a certain amount of internal flood.

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