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Predicting support for flood mitigation based on flood insurance purchase behavior

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Abstract

What is the decision-making mechanism people rely upon to mitigate flood risk? Applying Bayesian Network modeling to a comprehensive survey dataset for the US Gulf Coast, we find that the overall support for flood mitigation can be inferred from flood insurance purchase behavior (i.e. without insurance versus with insurance purchased mandatorily, voluntarily, or both). Therefore, we propose a theoretical decision-making mechanism composed of two dimensions including informed flood risk and sense of insecurity. The informed flood risk is the primary determinant on one’s overall support for flood mitigation. Risk mitigation decisions are largely contingent on the level of risk that is effectively conveyed to individuals. Additionally, sense of insecurity plays a moderate role in determining individuals’ overall support for flood mitigation. The sense of insecurity can move people toward overall support for mitigation, but the effect is not as large as the informed risk. Results of this study have fundamental policy implications. The flood risk informed by Federal Emergency Management Agency’s flood maps not only provides the compulsory basis for flood insurance purchase but also determines individuals’ overall support for flood mitigation. Flood map inaccuracy can immensely mislead individuals’ overall risk mitigation decision. Meanwhile, this flood risk mitigation decision-making mechanism inferred from a survey data in the US Gulf Coast needs to be tested and validated elsewhere.

Introduction

A recent Intergovernmental Panel on Climate Change special report states that human-induced ‘global warming is likely to reach 1.5 °C between 2030–2052’ [1]. The projected temperature rise will pose widespread and serious risk to society, ranging from more frequent extreme weather events to sea level rise. Among all climate-related hazards, flood has incurred the most economic damages and affected the most people [2]. The coastal region, due to the coupling effects of climate change and rapid population growth [3], is especially prone to flooding. Recent hurricanes serve as vivid reminders of how devastating hurricane-induced flooding can be to coastal communities [4–6]. In a changing climate, hurricane-induced coastal flooding is projected to become more often and intensive in decades to come [7–9].

Increasing flood risk renders it imperative for coastal residents to take adequate mitigation measures. Purchasing flood insurance would be a sensible option for residents who are vulnerable to flooding. Abundant evidence suggests that many individuals do not have flood insurance [2]. Other flood mitigation measures include but are not limited to home elevation, house modification for flood-proofing, construction of sea walls, installation of flood warning

4 Mitigation means differently in different contexts. Mitigation in the context of climate change refers to attempts to curb carbon emission to limit climate change. Mitigation in this study means lowering flood impacts or flood risk reduction.
system, and relocation [10–12]. Despite the effectiveness of flood mitigation measures, few adopt these measures voluntarily [13, 14]. Fundamentally, what is the decision-making mechanism people rely upon to mitigate flood risk? Furthermore, given various mitigation measures, do they have the proclivity to forgo the others because the adoption of one such as purchasing flood insurance has provided sufficient sense of security?

This speculation is based on the concept of moral hazard, referring to the idea that purchasing insurance lowers the incentive for the policyholders to seek self-protection measures that would increase actual probabilities of hazardous events [15]. Two previous studies have provided a theoretical base for the use of insurance purchase behavior to predict self-protection behavior [16, 17]. Moral hazards have been observed in a broad range of insurance markets such as automobile, long-term care, and health [18]. A limited number of empirical studies that have been conducted in the domain of natural disaster insurance market however find little evidence for the presence of moral hazards [19]. Instead, they find that insurance purchases can increase the tendency towards self-protection against flooding across insured individuals [19–22]. These findings prompt the second speculation: do individuals who have adopted one tend to adopt the others for more security? The drive behind such decisions is risk aversion. A study conducted in flood-prone areas in Germany indicates insurance policyholders adopt more private flood mitigation measures [21]. Another study which was done among Florida households finds a positive correlation between insurance coverage and private mitigation measures [22]. Similarly, a recent study that uses an experiment among Dutch homeowners finds that individuals who buy insurance are more likely to self-protect against flooding [23].

In this study, by using a comprehensive climate survey among coastal residents in the US Gulf Coast region, we aim to test which tendency is more dominant among flood insurance policy holders. Particularly, we classify flood insurance purchase behavior into four categories including non-purchase behavior and purchase for mandatory, voluntary, and both mandatory and voluntary reasons. The significance of this study is two-fold. First, by classifying insurance purchase behaviors into four categories as opposed to two (with versus without insurance), we attempt to gain deeper insight into individuals’ flood mitigation decision-making. Inferring from the results, we propose a theoretical decision-making mechanism, which can be further tested and validated in future studies.

Second, the US.

Gulf Coast displays great vulnerability to climate change impacts in general and flooding in particular [24]. Over the past three decades (1980–2018), this region has suffered the greatest amount of economic damages caused by weather and climate disasters in the US [25]. In addition to its exposure to climate change [24], this region’s population embodies more ethnic diversity, larger income gap, higher poverty rates, lower income, higher percentages of racial minority and old residents and all suggest greater social vulnerability [26, 27]. This region presents an ideal natural laboratory to study risk reduction decisions. Meanwhile, results of the present study are believed to assist policy makers to reach informed decision.

Data and method

To investigate how flood insurance purchase behavior influences individuals’ mitigation policy support among the US Gulf Coast residents, we use a comprehensive climate change survey for all coastal counties in the Gulf Coast in 2012 (SM 1). In addition to flood insurance purchase behaviors, the survey includes various questions related to socio-demographic characteristics, perceptions of local climate change, and perceptions of flood-related hazards that may affect mitigation behavior/intention [28–32]. We construct an interconnected Bayesian Network (BN) model to study how these variables jointly affect the support for flood mitigation.

Our model uses a BN [33], which is a statistical model to describe probabilistic relationships among a set of variables using a directed acyclic graph (DAG). The DAG structure of BN enables the Joint probability distribution) of all the modeled parameters to be expressed in terms of a product of conditional probability distributions (CPD), describing each variable in terms of its parents, i.e. those variables it depends upon. We employ BN here for its ability to propagate uncertainty, perform inference and calculate conditional probabilities. BN has better capabilities of handling nonlinear discrete dataset than other regression-based relationship model such as Structural Equation Model [34]. Also, BN shows superiority over other statistical methods when dealing with incomplete data by flexible marginalization methods [35]. The sample size of this data (~3800 observations) falls short of the significant criteria for modern machine learning tools (e.g. deep neural network) while BN works well [46]. BNs have been applied in previous studies on risk communication [36], coastal risk analysis and decision making [37, 38], and community resilience to coastal hazards [39–41]. The output in a probabilistic form is well suited to address decision-support needs.

A BN established the relationships between parameters through directed links (hypothesical causal relationships) which represent conditional probabilities trained on observations, probabilistic or deterministic equations or expert opinion. Here we apply the Correlation Networks Method (with a

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5 Marginalizing means considering all possible values the unknown variables may take and averaging over them.
threshold of 0.4 [42]) to initiate and MCMC method based on accuracy [43] to search for the optimal network structure. Then based on common knowledge we slightly refined the network and train the BN model parameters based on the EM algorithm [44] under maximum-likelihood principle. Uncertainties in the relationships derived from the observational training and uncertainties in the input parameters are propagated through the BN to provide a predicted probability for each discrete outcome. The \( n - 1 \) accuracy test is applied to the trained network and a 10% Monte-Carlo Cross Validation is applied to the optimized network to avoid the over-fitting risk (SM2). The overall model accuracy is \( \approx 80\% \) (90% confidence interval: 73.7%–84.3%). Our BN stores conditional probabilities to make predictions using combinations of statistical inference and joint probability calculations.

For the known BN structure and a CPD for each node (modeling factor interactions), given evidence of one factor, inferences about the likely values or probability distributions of other factors can be made. For example, the value of Education may be inferred from the values of the other factors, i.e. \( p\text{(Education | Age, Race, Gender)} \). More generally, inferences of the ability distributions of other factors can be made. For one factor, inferences about the likely values or probabilities to make predictions using combinations of statistical inference and joint probability calculations.

Figure 1. Bayesian network model constructed and trained for the Gulf Coast dataset. The three layers of the BN are socio-demographic background and geographic context (top layer), perceptual factors and behavioral manifestations (middle), and support for flood mitigation (bottom). The arrow links represent conditional probabilities estimated based on the data (for further details see SM1 and interactive model interface available: https://kelvinfkr.github.io/Gulf_Coast/).

A bootstrap method is applied underline to capture the confidence level of the inferred results [45] (SM3).

Figure 1 shows the variables and graphic structure of the BN model. The obtained BN can be considered as being composed of three layers. The first layer includes socio-demographic variables, which are considered as explanatory factors in hazard mitigation behavior models because they indicate individuals’ social vulnerability to hazards [46], as well as different risk perceptions [30, 47] and knowledge possessed by different socio-demographic groups [48]. We also consider the geographic context represented by the percentage of land area of the Special Flood Hazard Area (SFHA)\(^6\) per county. The SFHA is designated by the Federal Emergency Management Agency’s (FEMA’s) flood map, and it is found to be positively related to perceptions of changing flood amount [32] and voluntary flood insurance purchase behavior [31]. Tenure—the length of residence in the coastal region —indicates exposure to coastal hazards and experience with hazards. Longer tenure increases the likelihood to buy flood insurance [28].

The second layer considers perceptions of local climate change and of flood-related hazards, which may translate into unwillingness to take more actions to protect themselves from flood risks [49–51]. Informedness about climate change increases perceptions of local climate change, which positively affect belief in

\(^6\)SFHA also known as the 100 year flood zone, referring to areas that would be inundated by a flood event with the chance of one percent in any given year.
and concern for global climate change [52]. We posit that belief in negative impact of climate change on local communities and immediate families are more likely to adopt and support flood mitigation. All the flood mitigation support measures involve the local government. One’s trust in local government has positive effects on flood insurance purchase behavior [31] and is hypothesized to affect overall flood mitigation support.

Moreover, we place the key predictor—flood insurance purchase behavior in the second layer. We consider flood insurance purchase behavior as an important manifestation of risk reduction decision. The first category of flood insurance purchase behavior refers to no flood insurance. The other categories include purchase behaviors for three different reasons. One uniqueness of this survey is that it asked coastal residents with insurance about the reason to buy, including ‘it is required,’ ‘to feel safer,’ and ‘both.’ Homeowners who reside in SFHA are required to buy flood insurance if receiving mortgages from a federally backed or regulated lender. The decision to purchase flood insurance under this condition is mandatory. Some residents purchase flood insurance to feel safer. This decision implies voluntary nature. The last category is purchasing flood insurance because it is required and doing so makes them feel safer, which render its nature partially mandatory and partially voluntary. The questions about purchasing flood insurance are the only survey items representing flood mitigation behavior in this survey.

The third layer contains measures of public support for flood mitigation. The end node in this structure is public support for flood mitigation, indicated by a combined score of 12 measures. The 12 measures are derived from 12 survey items related to support for flood mitigation. A complete list of the 12 survey items is shown in SM4. We divide all the 12 measures into two categories: private and public. When the benefit of adopting a particular flood mitigation measure is more applicable to certain individuals, we classify this support measure as private. One example is ‘do you support or oppose providing incentives for property owners to relocate threatened houses, buildings, and other structures?’ When the benefit is more applicable to the community as a whole, we classify it as public. One example is ‘do you support or oppose increasing funding for sea-level monitoring?’ Each of the 12 items is measured as −1 (‘oppose’), 0 (‘don’t know’), and 1 (‘support’). We first calculate two scores to represent support for private and public measures, respectively. We then combine these two to create the overall scores of support for flood mitigation. The overall scores are then converted to three categories—‘support,’ (score 7–12) ‘neutral,’ (3–7) and ‘oppose’ (0–3). These criteria are selected based on the percentages of respondents by partisanship (Democrats: 32.43%; Independent: 44.87%; Republican: 22.70%) given that public support for policies has strong political connotations and climate change related hazards have become increasingly politicized in the American public discourse.

Results

The BN structure is constructed based on both prior knowledge as discussed above and data driven structure training. The overall prediction accuracy of the model is approximately 80% (90% confidence interval: 73.7%–84.3%). The baseline percentage of people who support overall flood mitigation is 31.8%. There are 55 possible paths to influence overall public support for flood mitigation by single variables. Figure 2 shows the effect size of each category of each variable on the final outcome. Five single influencers are significant. The most effective factor we discovered here is the flood insurance purchase for both mandatory and voluntary reasons. Under the condition that all individuals purchase flood insurance for both mandatory and voluntary reasons, the percentage of supporters for overall flood mitigation would increase to as high as 51% (confidence interval: 47%–54%). If everyone decides to purchase flood insurance because it is required, the percentage of supporters for flood mitigation would rise to 39% (confidence interval: 35%–43%). The decision not to buy flood insurance will lead to a decrease in percentage of supporters to 28% (confidence interval: 26%–29%). The view that climate change impact on immediate family is somewhat negative will increase support to 36% (confidence interval: 34%–39%). The view that climate change impact on immediate family is somewhat positive will lead to decrease in support to 29% (confidence interval: 25%–33%).

The BN model differs from conventional regression models in the regard that BN is based on interdependent relationships among variables. It is thus not advisable to interpret the insignificant effects of individual variables (figure 2) as no effects given that all variables are interconnected in the network. For example, the dominant influence of political partisanship in affecting perceptions of climate change [39] and behavior intention to address this issue [37] has been well-documented. We visualize the flow of conditional probabilities from partisanship through perception of risk to support for flood mitigation with a Sankey diagram7 (figure 3). Most Democrats (44.8%) perceive the local climate to be somewhat different while most Republicans (49.8%) think it has been pretty much the same. A majority (60.1%) of people who think the

7 Sankey diagram is a standard diagram developed in recent year. According to Wikipedia: Sankey diagrams are a specific type of flow diagram, in which the width of the arrows is shown proportionally to the flow quantity... Sankey diagrams put a visual emphasis on the major transfers or flows within a system. They are useful in locating dominant contributions to an overall flow. Often, Sankey diagrams show conserved quantities within defined system boundaries.' (https://en.wikipedia.org/wiki/Sankey_diagram).
local climate has been very different or somewhat different feel the impact of climate change on immediate family are somewhat negative (56.3%). However, half of those who feel moderately negative about climate change impact on immediate family do not have insurance, and half of those who feel neutral about climate change impact on immediate family have insurance. Interestingly, many fully mandatory insurance buyers (40.1%) have neutral view about the impact of climate change on immediate family, and yet a substantial percentage of them (39.9%) support flood mitigation.

The BN analysis indicates that the flood insurance purchase behavior has a central role and serves as if a ‘bridge’ connecting socio-demographic background and geographic context and other perceptual factors

| Sample | Percentage | Effect Size (95% CI) |
|--------|------------|---------------------|
| Partisanship | | |
| Republican | 24% | 0.31(0.28,0.33) |
| Independent | 43% | 0.32(0.30,0.34) |
| Democrat | 33% | 0.32(0.30,0.35) |
| Informedness about Climate Change | | |
| A lot of information | 19% | 0.32(0.29,0.35) |
| Some information | 22% | 0.32(0.29,0.34) |
| A little information | 35% | 0.32(0.30,0.34) |
| Don’t need information | 26% | 0.31(0.29,0.36) |
| Race | | |
| Others | 23% | 0.32(0.29,0.35) |
| Black | 20% | 0.32(0.29,0.35) |
| White | 57% | 0.32(0.30,0.33) |
| Education | | |
| Less than High School | 13% | 0.32(0.28,0.33) |
| Over Highschool Degree | 53% | 0.32(0.30,0.33) |
| College Degree | 34% | 0.32(0.30,0.34) |
| Length of Residence | | |
| One Year or Less | 2% | 0.32(0.24,0.41) |
| 2-10 years | 21% | 0.32(0.29,0.34) |
| 11-20 Years | 27% | 0.32(0.30,0.35) |
| More than 20 Years | 50% | 0.32(0.30,0.33) |
| Age | | |
| 18-24 | 12% | 0.32(0.28,0.35) |
| 25-34 | 17% | 0.32(0.29,0.35) |
| 35-44 | 18% | 0.32(0.29,0.35) |
| 45-54 | 18% | 0.32(0.29,0.34) |
| 55-64 | 15% | 0.32(0.28,0.35) |
| 65 and over | 20% | 0.32(0.29,0.34) |
| Gender | | |
| Male | 48% | 0.32(0.30,0.33) |
| Female | 52% | 0.32(0.30,0.34) |
| Perception of Local Climate | | |
| Pretty Much the Same | 40% | 0.28(0.26,0.36) |
| Somewhat Different | 40% | 0.35(0.33,0.37) |
| Very Different | 20% | 0.32(0.29,0.35) |
| Perception of Flood Related Hazards | | |
| Increased | 40% | 0.27(0.29,0.33) |
| About the Same | 54% | 0.32(0.30,0.34) |
| Decreased | 7% | 0.33(0.28,0.38) |
| Climate Impact on Local Community | | |
| Very Positive | 3% | 0.35(0.28,0.42) |
| Somewhat Positive | 10% | 0.32(0.28,0.36) |
| Neither Positive nor Negative | 36% | 0.32(0.30,0.34) |
| Somewhat Negative | 43% | 0.31(0.29,0.33) |
| Very Negative | 8% | 0.32(0.28,0.38) |
| Climate Impact on Immediate Family | | |
| Very Positive | 3% | 0.30(0.23,0.38) |
| Somewhat Positive | 8% | 0.29(0.25,0.33) |
| Neither Positive nor Negative | 50% | 0.29(0.28,0.31) |
| Somewhat Negative | 34% | 0.36(0.34,0.39) |
| Very Negative | 6% | 0.31(0.26,0.37) |
| Trust in Local Government’s Preparedness | | |
| Not Prepared at All | 23% | 0.32(0.30,0.35) |
| Not Very Prepared | 42% | 0.32(0.30,0.34) |
| Somewhat Prepared | 42% | 0.32(0.30,0.34) |
| Very Prepared | 13% | 0.32(0.28,0.35) |
| Purchase Status of Insurance (Yes or No) | | |
| No | 54% | 0.28(0.25,0.29) |
| Yes | 46% | 0.36(0.35,0.38) |
| Flood Insurance Purchase Behavior (Why) | | |
| Required | 10% | 0.39(0.35,0.43) |
| Satisfied | 24% | 0.28(0.26,0.31) |
| Both | 13% | 0.81(0.47,0.54) |
| Flood Zone | | |
| Few Parts in Flood Zone | 76% | 0.32(0.30,0.33) |
| Some Parts in Flood Zone | 15% | 0.30(0.27,0.33) |
| Over Half Parts in Flood Zone | 2% | 0.34(0.25,0.44) |
| Most Parts in Flood Zone | 8% | 0.34(0.30,0.39) |

**Figure 2.** Effect of different conditions on support of climate policy in the Gulf Coast.
with public support for flood mitigation. Specifically, for individuals who do not buy flood insurance or buy insurance voluntarily (reside outside the SFHA), their most likely attitude toward overall flood mitigation measures is neutral. For individuals who buy insurance mandatorily or both mandatorily and voluntarily (reside inside the SFHA), their most likely attitude is support although the probability to support vary substantially between individuals who buy fully mandatorily and those who buy partially mandatorily.
and voluntarily. Informed by these results, we propose a theoretical decision-making mechanism composed of two dimensions including informed flood risk and sense of insecurity, as illustrated in figure 4. The level of informed risk is the primary driver of the decision to support overall flood mitigation. The informed flood risk is not objective risk per se in the following two regards: (1) The informed flood risk is manifested in flood maps created by FEMA. (2) Through legal requirement—those who reside within the SFHA are required to buy flood insurance to qualify for federally regulated or federally-guaranteed loans, and the flood risk is theoretically conveyed to those who are at high risk estimated by FEMA.

This result has fundamental policy implications. FEMA, through designation of flood hazard zones and legal requirement for residents to purchase flood insurance within SFHA, successfully conveys flood risks to those who need to be aware of flood risk. While the flood map has become a powerful risk communication tool, numerous studies have shown the flaws and inaccuracies of the maps [53, 54], and these inaccuracies would lead to misleading decision on an entire set of mitigation measures. To incentivize coastal residents to adopt flood mitigation measures that are proportional to the actual risk, it is essentially important to ensure the accuracy of flood hazard zone designation in flood maps. A big barrier to effectively updating flood maps is the concern over costs that tends to dominate local discussions [55]. The challenge of frequently updating flood maps on FEMA’s end thus puts the risk communication task on the shoulders of local governments.

Furthermore, as figure 4 shows, the variation that exists between groups within the same level of informed flood risks reveals the second dimension on the decision mechanism. Within the same level of informed risk, the sense of insecurity increases the probability to support and decreases the probability to oppose. For people who are not required to buy flood insurance but still decide to do so, their decision reflects their innate sense of insecurity 8. The sense of insecurity also propels those who are required to buy to consider increasing security in doing so. For the other two groups, their behaviors and motives indicate low sense of insecurity 9.

In summary, support for flood mitigation is primarily conditioned on the informed risk. The sense of insecurity nevertheless tilts one further to support flood mitigation given the same informed risk. Individuals who have adopted one measure tend to support more. Two major propositions can be made: (1) the increase of informed risk can lead to more support for flood mitigation; (2) the increase of sense of insecurity can cause more support for flood mitigation.

Conclusion

Overall, this paper represents a pilot study on flood mitigation behavior intention, resulting from using one mitigation behavior (i.e. flood insurance purchase) to predict overall support of flood mitigation, based on a comprehensive survey for the US Gulf Coast region. Although there is a long line of literature that considers the presence/absence of moral hazards in insurance markets, the novelty of this study is the further classification of insurance purchase behavior into voluntary and mandatory categories both of which along with non-purchase behavior predict varying levels of support for other flood mitigation measures. Our results indicate the absence of moral hazards. Flood insurance policy holders are more likely to support other mitigation measures than individuals without flood insurance. We further infer from the results that the informed risk represented by the FEMA’s flood hazard zone provides the fundamental condition under which individuals make risk mitigation decisions. People do not make flood mitigation decisions that are deemed inappropriate for the level of risk they confront. Sense of insecurity can certainly facilitate support within the same informed risk. In all, individuals who have adopted one measure (flood insurance) tend to support more.

The primary policy implication in the US flood insurance market is the fundamental role flood hazard zone plays in determining flood mitigation actions. Further, FEMA’s flood maps serve as a powerful risk communication tool influencing decisions to purchase flood insurance and overall support for flood mitigation. Our results imply the importance of risk information in overall flood mitigation decisions. Although the flood premiums do not reflect real risks due to discounts [56], flood hazard zones have effectively conveyed the risk to homeowners. Risk signals can thus be delivered to homeowners through various means. We are well aware that this inferred decision-making mechanism may be significantly influenced by the US flood insurance market structure. Meanwhile, this study is based on one survey in the US Gulf Coast region. The proposed decision-making mechanism thus needs to be tested and validated elsewhere, especially in regions/countries with different flood insurance market structures.

Further, more methodological efforts need to be exerted to further test the proposed decision-making mechanism by investigating the dynamics of informed

8 It should be noted that the sense of insecurity only applies to flood risks in this study.
9 It should be noted that there is possibility that some individuals in ‘No insurance’ group are required to buy or would like to buy but cannot afford to buy. For those individuals, it is arguably reasonable to place them in the ‘low risk and low sense of insecurity’ group. According to Maslow’s hierarchy of human needs (1943), human beings tend to satisfy basic physiological needs such as food, water, sleep, and shelter before they turn their attention to other needs such as safety. We contend that these people who cannot afford flood insurance are preoccupied with paying day-to-day bills and do not necessarily feel particularly insecure about flood risks.
risk, sense of insecurity, and mitigation behaviors/intentions. The approximation of informed flood risk is crude in this study. Future studies can consider creating more precise measurement of informed flood risk by eliciting responses about the premiums of flood insurance or deriving information about the specific flood hazard zone they reside in. The sense of insecurity for flood risk needs to be measured in a more nuanced way. A gradient of informed risk combined with a spectrum of sense of insecurity can provide deeper insights into individuals’ risk mitigation decisions.

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