Roads or Radar: Investing in Infrastructure or Improved Forecasting in the Face of Hurricane Risk

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ABSTRACT Given limited funding, should we invest in infrastructure to speed evacuation in an emergency, or in forecasting technology to better predict the timing and intensity of the event? For example, should we build additional evacuation routes along the Gulf Coast of the United States to speed hurricane evacuations or should we improve our ability to forecast the path and intensity of an approaching storm?

In this research, we use dynamic programming to model the evacuation and information-gathering decision of an official responsible for public safety. We assume that at each stage, an evacuation can be ordered that will take several stages to complete, or a decision can be made to wait and gather additional information regarding the approaching storm. Early evacuation mitigates loss, but may ultimately not have been necessary. On the other hand, waiting too long to evacuate could produce tragic consequences.

By investing in infrastructure to speed the evacuation process, we are able to wait longer and thereby act with greater information.
Keywords: dynamic programming, investment decision, hurricane forecast, evacuation speed, value of information

1 Introduction

Suppose that a tropical depression has formed in the Gulf of Mexico. Whether this depression will develop into a hurricane and where (if) it will make landfall are uncertain. To reduce this uncertainty, meteorologists gather data about the storm and produce track and intensity forecasts. Meanwhile, along the Gulf Coast, communities ponder whether the probability of a storm is high enough to warrant action, such as the fortification of buildings, taking shelter, or even full-scale evacuation.

Many parties, including the weather service, government or city officials, and private individuals, may be concerned about this situation. However, few of them can make the decision to mitigate the loss in the vulnerable area.

The emergency-response command structure differs in every state. By law, governors in most states have the ultimate authority to order evacuations even though some governors delegate this authority to local officials such as mayors, county judges, or county presidents (Wolshon et al. 2005). The identity of the individual is not important for our research. Therefore, we simply assume that some governmental body issues an evacuation request, which need not be mandatory.

Under perfect forecasting, individuals would immediately know whether the storm warrants action. Given ample warning, the ability to take these actions quickly is not as important as it is in the real world of imperfect forecasts, where the storm's path and intensity may not be clear until the last few hours before landfall. Most storms form far enough away, roughly five days before landfall (NOAA 2006, National Hurricane Center 2006), that we could take advantage of a perfect forecast. Thus, improved forecasting accuracy could save lives, mitigate damage, and avoid false alarms.

On the other hand, if we had the ability of instantaneous mitigation or evacuation, the accuracy of the forecast would not be important because we could always take action "at the last minute." Such an infrastructure system would be akin to having perfect information on the storm, since we are always able to act once the storm's path and intensity become clear.

Thus, we face a tradeoff. We can invest in improving our forecasting ability (e.g., improved models, more real-time data) to provide accurate warnings earlier or invest in mitigation and infrastructure (roads, shelters, etc.) that can be used quickly, perhaps in the final hours before the storm arrives. Which of these areas is the better investment? What is the optimal mix of these two alternatives? The interplay between the emergency response system (ERS) and the emergency forecasting system (EFS) is depicted in Figure 1. Both are affected by natural (e.g., a hurricane) or manmade (e.g., terrorist attack) events. The ERS and EFS are coupled at many different levels. However, we are primarily focused on their coupling through investment. What do improvements to one system imply about the value of investments in the other system?

In this paper, we develop a dynamic programming model to represent a dynamic multi-stage decision (e.g., evacuation) in the face of oncoming risk. We also provide preliminary results from the dynamic programming regarding the value of increased evacuation speed. The value of improved forecasting will be presented elsewhere.

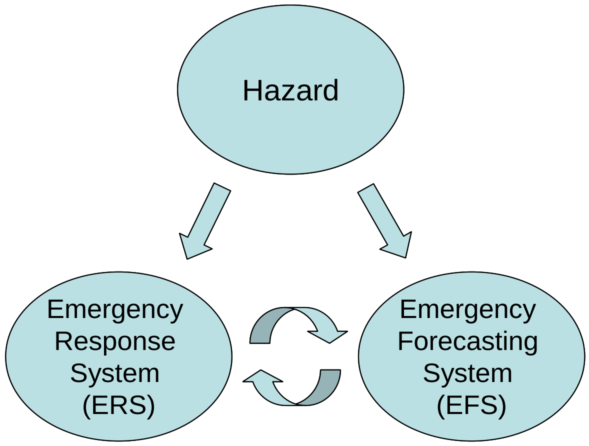

FIGURE 1. Risk response and forecasting system

2 Literature Review

This work has connections to several areas including dynamic programming, dynamic decision-making, Bayesian updating, and cost-loss ratio. Among these, dynamic programming is the primary tool used to address decision problems that evolve over time.[1]

If the decision situation is not only a selection among the alternatives but also a determination of timing, a static decision model is inadequate. McCardle (1985) helped motivate our research by developing a dynamic programming model to analyze an action-timing decision problem regarding technology adoption and information gathering. The decision maker (DM) is a firm that considers the adoption of an innovation and wants to reduce the level of uncertainty associated with its profitability by sequentially gathering information, updating its prior estimate of profitability in a Bayesian manner. This model was formulated in a different setting from ours, but the structure of the decision problem is analogous.

Ahn and Kim (1998) considered the problem of deciding the best action time when observations are made sequentially. To handle this type of problem, they formulated an action-timing problem with sequential Bayesian revision and derived a decision rule based on the observation or information. They performed a simulation to assess the value of the Bayesian strategy. In their generic problem, the decision-making process starts with observation x_k $(k = 1)$ being generated from an exponential distribution. Using the observation x_k, prior belief on a state is revised to get the posterior belief on the state. Then $d^*(n)$, the optimal strategy with n re-

[1] For an introduction to dynamic programming, see Howard (1966).

maining decision stages, is calculated. If the value is greater than or equal to $d^*(n)$ at decision stage n, the DM accepts the observed value x_k and the decision-making process ends. If x_k is less than $d^*(n)$ at decision stage n, the DM rejects it for another observation. Their work is relevant to our problem even though they provide a decision rule based on the information or observation at each stage, rather than on the revised belief on the state of an event. In addition, they consider only two alternatives: "accept" the current observation or "reject" for another observation.

The concept of cost-loss ratio is one of the most important for this research.[2] Here, "cost" means that of preventive action and "loss" means the loss or damage from an adverse event. Many people analyze the hostile-weather or natural-disaster problem using this concept. Zhu et al. (2002) used an expense matrix that includes two kinds of loss. They assumed that loss is comprised of protectable loss (L_P) and unprotectable loss (L_U). Their expense matrix shows that the expense is $C + L_U$ if the action is taken and the event occurs, C if the action is taken but the event does not occur, $L_P + L_U$ if the action is not taken but the event does occur, or 0 if the action is not taken and the event does not occur. Thus, their decision is to take action if $P > C/L_P$, a clear and simple decision rule. They assumed that there was at most one relevant decision timing. They also assumed that cost of preventive action and loss from the hostile event do not depend on the timing of the decision or action. If the cost and the loss depend on the timing, as in hurricane evacuation, the simple cost-loss ratio policy no longer works. However, even in the variable cost and loss structure, it is still useful to recognize that the decision policy depends on the protectable part of loss rather than the unprotectable part.

Einstein and Sousa (2007) compared the warning systems for natural threats like tsunami, flood, hurricane, and pandemic. They also suggested a tool to evaluate the warning systems as a decision tree. They compared the maximum expected values of the alternatives "perfect/imperfect warning device," "take active/passive measure," and "no action," based on the cost of the measure, effectiveness of the measure, and probability of threat.

Wolson et al. (2005) recognized that a critical issue in hurricane evacuations is timing. They showed that the time required to evacuate is estimated from a combination of clearance times and the pre-landfall hazard time. Clearance time is the time required to configure all traffic control elements on the evacuation routes, initiate the evacuation, and clear the routes of vehicles once deteriorating conditions warrant its end. Prelandfall hazard time is the time during which hazardous conditions exist prior to actual hurricane landfall. Due to these factors, preplanned evacuation times vary widely by location. They estimated the ideal minimum advanced-notification times that some states prefer to have before issuing

[2]For more details about cost-loss ratio, see Thompson (1952).

the evacuation, depending on the hurricane category.

Katz and Murphy (1990) showed the relationship between the scientific quality and economic value of imperfect weather forecasts in a multistage decision-making model. They considered a prototype multistage decision-making model involving two possible actions and two possible stages of weather. They defined a quality parameter q that measures the relative distance of p_1 between p_θ and 1, making $0 \leq q \leq 1$, with $q = 0$ for climatological information and $q = 1$ for perfect information. Here, p_1 is the conditional probability of adverse weather given a forecast of such weather and p_θ is the long-run relative frequency of adverse weather. They also defined a relative economic value V_F/L, where the value of imperfect weather forecast V_F is defined as expected expense associated with climatological information minus expected expense associated with imperfect weather forecasts and L is loss. They analyzed the relative economic value as a function of quality q of imperfect weather forecasts for the multistage cost-loss ratio model with a discount factor. The results showed that the economic value is zero for forecasts whose quality falls below a threshold. Above this threshold, economic value rises at an increasing rate as forecast quality in-creases toward that of perfect information. The results imply that the current long-range forecasts, which are of relatively low quality, are apparently ignored by many DMs due to the existence of a quality threshold.

Buizza (2001) discussed the accuracy and the potential economic value of categorical and probabilistic forecasts of discrete events. Accuracy is assessed using known measures of forecast accuracy, and potential economic value is measured by a weighted difference between the probability of true detection and the probability of false detection, with the weights a function of the cost-loss ratio, the observed ratio, and the observed relative frequency of the event. The result shows that forecast skill cannot be defined objectively but depends on the measure used to assess it. In other words, forecasts judged to be skillful according to one measure can show no skill according to another measure.

Considine et al. (2004) estimated the value of both existing and more accurate hurricane forecast information for resource producers in the Gulf of Mexico. A probabilistic cost-loss model was used to estimate the incremental value of hurricane forecast information for oil and gas leases in the Gulf of Mexico over the past two decades. Detailed computations of hurricane forecasting accuracy were performed using records from the National Hurricane Center and Marine Forecast/Advisory from 1980 to 2000. Evacuation costs and potential losses were estimated using data from the Minerals Management Service and oil company drilling records. Estimates indicated that the value of existing 48-hour hurricane forecast information to oil and gas producers averaged roughly $8 million per year during the 1990s, which substantially exceeds the operating budget of the National Hurricane Center. From an industry perspective, however, these values are a small fraction of drilling and production costs. Moreover, although recent hurricane-forecast accuracy is improving, it has not been sufficient to create significant value to this industry. On the other hand, forecast value dramatically increases with improvement in accuracy, rising by more than \$15 million per year with a 50% improvement in 48-hour forecast accuracy.

Regnier and Harr (2006) used a discrete Markov model of hurricane travel to model the decision to prepare for an oncoming hurricane. Their model was derived from historical tropical cyclone tracks and was combined with the dynamic decision model to estimate the additional value that can be extracted from existing forecasts by anticipating updated forecasts. They used variable hurricane-preparation cost, which is defined as a fraction of the maximum loss, increasing linearly or exponentially after a critical lead time. They used a discrete Markov model to represent the path of a hurricane and the strike probability for multi-period decision making with respect to a sequence of forecasts with improving accuracy for a single event, but they didn't use Bayesian revision. Simulation was used to compare the expense in different cases. Their results indicate that a DM who has the flexibility to wait for updated hurricane forecasts can extract a substantial value from adopting a dynamic decision approach.

3 The Model

While there are many conceivable risks and mitigating actions, we will use hurricane to represent a risk or other hazard, and evacuation to represent the protective action or countermeasure. Taking action immediately upon receiving information of an approaching hurricane can mitigate the damage or loss, but at some cost. If action is taken and the hazard strikes, then this cost was not "wasted." If, however, the event does not occur, then the preventive expenditure was on a false alarm.

Fortunately, we have another choice. We can defer the decision and collect more in-formation about the upcoming event, in order to reduce the likelihood of a wrong decision. However, information gathering can be costly and any delay in taking action could result in greater loss. Therefore, we must carefully weigh the benefit of gathering additional information against its potential cost.

We use dynamic programming to model this problem structure. Let $V_j(p_j)$ be the anticipated expense from following an optimal policy at stage j, when the current probability of hurricane strike is p_j. We assume either that the detected hurricane will hit the vulnerable area at stage N or that it will not. This assumption will be relaxed in future research. p_j is the stage j estimate of the probability that the hurricane will strike, which is estimated using the information collected up to stage j. L_j is the loss if evacuation is begun at stage j; therefore L_N represents the loss if evacuation is not completed before the hurricane strikes.

If the DM ignores the oncoming hurricane without further information gathering, the loss will be L_N with probability p_j. We refer to this as the "Ignore" alternative. If the DM takes action ("Act") at stage j, there will be an evacuation cost C_j and loss L_j with probability p_j. If the DM defers the decision ("Wait") and collects additional information at cost γ, the anticipated expense from the deferred decision depends on the additional information. This leads to the following dynamic programming functional equation:

$$V_j(p_j) = \min\{p_j L_N, C_j + p_j \cdot L_j, \gamma + \overline{V}_{j+1}(p_j)\}, \quad for \;\; p_j \in (0,1) \qquad (3.1)$$

3

$$\overline{V}_{j+1}(p_j) \equiv (1-p_j)V_{j+1}\left(\frac{(\alpha+\beta+j)p_j}{\alpha+\beta+j+1}\right) + p_j V_{j+1}\left(\frac{(\alpha+\beta+j)p_j+1}{\alpha+\beta+j+1}\right) \qquad (3.2)$$

$$\overline{V}_N(p_{N-1}) = p_{N-1}L_N \qquad (3.3)$$

$\overline{V}_{j+1}(p_j)$ is the expected value from following an optimal policy at stage $j+1$, given the current posterior probability p_j at stage j. $\overline{V}_N(p_{N-1})$ is the terminal value of $\overline{V}_{j+1}(p_j)$. This is equivalent to the value of decision "Ignore" at stage $N-1$ because the DM's only choice at the terminal stage is to face the risk if he or she didn't take action previously.

We assume that the information structure is represented by the conjugate pair Beta-Bernoulli.[4] According to this information structure, the DM's prior distribution on the probability of hurricane strike is a Beta with parameters (α, β) and the information comes from a Bernoulli distribution with parameter p^*. We denote the information at stage j as binary random variable X_j, where $X_j = 1$ is a forecast that the hurricane will strike and $X_j = 0$ is a miss forecast. The probability of receiving information that the hurricane will strike is $P(X_j = 1) = p^* = 1 - P(X_j = 0)$. The prior probability of a strike p_0 is the mean of this distribution, which is equal to $\alpha/(\alpha+\beta)$.

Upon the arrival of information, the DM updates his/her prior distribution in the standard Bayesian fashion. Under the Beta(α,β) prior and Bernoulli information, the posterior distribution of P, given the j observed pieces of information $X_1, X_2, \ldots, X_j$, is Beta $(\alpha + S_j, \beta + j - S_j)$, where $S_j = X_1, X_2, \ldots, X_j$. This distribution has a mean of $(\alpha+S_j)/(\alpha+\beta+j)$. As the X_i's are either 0 or 1, S_j is just the number of positive signals,

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[3]The range of p_j does not include 0 or 1, since we assume that the prior probability is between 0 and 1 and posterior probability never reaches 0 or 1.

[4]For background about conjugate pairs, see Raiffa and Schlaifer (1961).

which mean "Hurricane will hit," from the first j pieces of information, and $j - S_j$ is the number of negative signals, which mean "Hurricane will miss." Here, the range of S_j is 0 to j. This model structure is clearly limited because hurricane forecasts are richer than "hit" or "miss." We plan to relax this assumption in future work.

Since we assume that the DM can collect only one piece of information at each stage, we consider the DM to be at stage j when he or she has collected exactly j pieces of information. If the DM is at stage j with prior probability p_j, then with probability $1-p_j$ the next piece of information is a 0 (miss) and the point estimate decreases to $(\alpha+\beta+j)p_j/(\alpha+\beta+j+1)$; while with probability p_j, the next piece of information is a 1 (hit) and the point estimate increases to $((\alpha+\beta+j)p_j+1)/(\alpha+\beta+j+1)$.

We suppose that the expense for the DM is the summation of evacuation cost C_j and loss L_j and that it depends on the timing of evacuation. The expense is summarized in the following table.

Table 1. Expense of evacuation decision

	Hit	Miss
Evacuate at j	$C_j + L_j$	C_j
Do not evacuate	L_N	0

$L_j \leq L_N$ for all $j < N$

The table shows that the loss from the hurricane depends on when the evacuation decision is made and that the evacuation cost does not depend on whether the hurricane hits the area. The loss from acting is less than from waiting $(j < N)$, because the earlier the DM starts evacuation, the more will be protected and the less will be lost. L_j can be interpreted as a measure that is proportional to the percentage of population and property still remain-ing in the vulnerable area when the hurricane strikes.

4 Analysis

4.1 Loss profiles

Illustration: Linear Loss

For convenience, we assume a risk-neutral DM. Let's start with a simple linear loss structure described by the following equations.

$$L_j = L_N - \frac{N-j}{N} L_N \quad for\ j \leq N \tag{4.1}$$

L_j is the loss from hurricane if the evacuation decision is made at stage j and the hurricane strikes eventually. L_j can be interpreted as proportional to the percentage of population and property still remaining in the vulnerable area when the hurricane strikes, if evacuation is begun at stage j.

So, $L_N - L_j$ can be interpreted as the protectable part of loss by starting evacuation at stage j.

Assume the cost of evacuation C_j is constant at 1 and does not depend on the decision timing. Loss increases linearly from 0 to 5, depending on the timing of evacuation decision. Stage 0 is the only timing of evacuation decision that can prevent all loss from the hurricane because $L_0 = 0$ and $L_j > 0$ for all $j > 0$ in Equation (4.1). The protectable part of the loss is strictly decreasing in j. Therefore, the later the evacuation decision, the greater the loss in the event of a hit. We assume γ is 0.001 and the prior probability on the hurricane strike is Beta(0.2, 1).

In this example, we assume the final stage is 30, which means the DM can gather up to 30 pieces of information before the hurricane either hits or misses. According to the historical hurricane tracks (NOAA 2006) and tropical cyclone reports (National Hurricane Center 2006), initial detection of a hurricane is made roughly 3 to 7 days before its landfall as a tropical depression, depending on the location of storm creation and its direction of movement. Since the forecast is updated every 6 hours, lead time of initial forecast of a hurricane is roughly 20 to 30 stages.

The calculation of the dynamic programming starts from the final stage. Because the DM doesn't have a choice at stage 30, $\overline{V}_{29}(p_{29})$ is calculated as $\min\{p_{29}L_{30}, C_{29} + p_{29} \cdot L_{29}, \gamma + \overline{V}p_{29}\}$. If p_28 is 0.863, p_{29} is $(\alpha+\beta+28)p_{28}/(\alpha+\beta+29) = (0.2+1+28)0.863/(0.2+1+29) = 0.834$ or $((\alpha+\beta+28)p_{28}+1)/(\alpha+\beta+29) = ((0.2+1+28)0.863+1)/(0.2+1+29) = 0.868$. Then

$$
\begin{aligned}
V_{29}(0.834) &= \min\{0.834 \times 5, 1 + 0.834 \times 4.83, 0.001 + 0.834 \times 5\} \\
&= \min\{4.170, 5.028, 4.171\} \\
&= 4.170 \\
V_{29}(0.868) &= \min\{0.868 \times 5, 1 + 0.868 \times 4.83, 0.001 + 0.868 \times 5\} \\
&= \min\{4.340, 5.192, 4.341\} \\
&= 4.340
\end{aligned}
$$

This means that if the posterior probability of hurricane strike estimated at stage 29 is 0.834 or 0.868, the optimal choice at this stage is "Ignore." This result is possible because the percentage of loss that can be saved by evacuation is very little compared to the cost of evacuation.

At stage 28, $V_{28}(p_{28})$ is calculated as $\min\{p_{28}L_{30}, C_{28} + p_{28} \cdot L_{28}, \gamma + \overline{V}_{29}(p_{28})\}$.

$$
\begin{aligned}
V_{28}(0.863) &= \min\{0.863 \times 5, 1 + 0.863 \times 4.83, 0.001 + \overline{V}_{29}(0.863)\} \\
&= \min\{4.315, 5.030, 0.001 + \overline{V}_{29}(0.863)\} \\
&= \min\{4.315, 5.030, 0.001{+}0.137{\times}\overline{V}_{29}(0.834){+}0.863{\times}\overline{V}_{29}(0.868)\} \\
&= \min\{4.315, 5.030, 0.001 + 0.137 \times 4.170 + 0.863 \times 4.340\} \\
&= 4.315
\end{aligned}
$$

Similarly, we can calculate all the values of $V_j(p_j)$, and finally we get $V_0(p_0) = V_0(0.167) = 0.485$.

Figure 2 shows the ranges of p_j with which the optimal decision is "Act," "Ignore," or "Wait." At each stage, the optimal decision can differ according to the value of p_j. The upper threshold $\overline{p}_j$ and the lower threshold $\underline{p}_j$ define the boundaries between which "Wait" is optimal choice. The thresholds are defined as follows:

$$\overline{p}_j = \min\{p_j : V_j(p_j) = C_j + p_j L_j\} \tag{4.2}$$

$$\underline{p}_j = \min\{p_j : V_j(p_j) = p_j L_N\} \tag{4.3}$$

The thresholds imply that the optimal decision is "Act" if the value of p_j is greater than or equal to $\overline{p}_j$, "Ignore" if the value of p_j is less than or equal to $\underline{p}_j$, and "Wait" if the value of p_j is between $\overline{p}_j$ and $\underline{p}_j$. As the cumulative information increases, the uncertainty about whether the hurricane will hit the area decreases and gathering more information becomes less beneficial. Therefore, the thresholds get closer and meet at the point where the DM stops collecting additional information and makes a decision of "Act" or "Ignore."

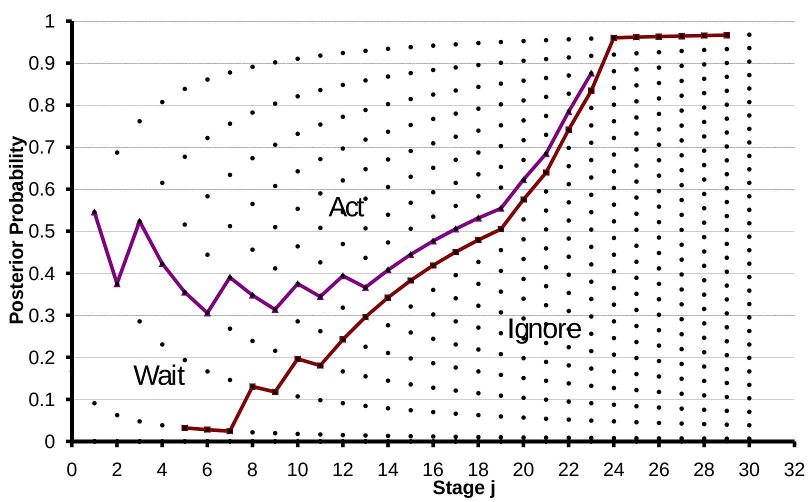

FIGURE 2. Policy region for linear loss profile

Figure 2 shows all possible posterior probabilities of hurricane strike at each stage. Since this information structure is discrete and the number of information signals is limited at each stage, the number of possible posterior probabilities is also limited. For stage j, there are $j+1$ possible posterior probabilities. For this diagram, α is 0.2, β is 1, and γ is 0.001. Therefore, the prior probability of hurricane strike is $\alpha/(\alpha+\beta)$=0.167.

In Equation (3.1), if the value of γ is increased, "Wait" becomes less attractive. If the value of γ is decreased, "Wait" becomes more attractive at the expense of "Ignore." If the value of γ is 0, "Wait" and "Ignore" further diverge. In this case, "Ignore" cannot be an optimal choice in early stages but can become optimal when the final stage N is imminent but hurricane strike is unlikely.

Since the expected expense of evacuation is $C_j + p_j L_j$ and the expected expense of ignoring the hurricane is $p_j L_j$, define $p' = C_j/(L_N - L_j)$ to be the break-even point: $C_j + p' L_j = p' L_N$. Because the loss from the hurricane changes at every stage, so does the break-even point. Since $L_N - L_j$ can be interpreted as the protectable portion of the loss, the optimal decision is based on the ratio of action cost to the protectable portion of the loss if the DM ceases information gathering. Therefore, even if the protectable portion of loss is constant while the evacuation cost increases, the break-even point increases and the optimal choice could change from "Act" to "Ignore." At stage 1, the break-even point is 1/(5-5/30) = 30/145 = 0.207. At stage 23, the break-even point is 1/(5-523/30) = 30/35 = 0.857. As the protectable portion of loss decreases over time, upper and lower thresholds converge to the moving break-even point. From stages 23 to 29, however, there is no break-even point and "Ignore" is the optimal decision, as shown in Figure 2.

At stage 0, the prior probability of hurricane strike is 0.167 and the optimal choice is "Wait." Depending on the information, the posterior probability of hurricane strike can be greater or less than 0.167 at stage 1. If the DM moves on to stage 1 with a positive signal, the posterior probability will increase to 0.55 and the optimal choice changes to "Act" because the DM is sure enough about the risk to justify action. If the DM is at an early stage such as stage 5, the optimal decision depends on the value of p_j. After stage 12, "Wait" can no longer be the optimal decision, that is, additional information no longer has any effect.

Illustration: Exponential loss

To understand the effect of increasing evacuation speed, we consider exponential loss as shown in Equation (4.4).

$$L_j = L_N - \frac{e^{\mu N} - e^{\mu j}}{e^{\mu N} - 1} L_N \qquad for\ j \le N \tag{4.4}$$

where μ is the exponential growth rate.

The policy region in this exponential loss structure is shown in Figure 3. In this case, $V_0(p_0) = V_0(0.167) = 0.444$, which is lower than that of the linear loss structure. Exponential loss implies shorter evacuation speeds. Linear is a special case of exponential where $\mu \to 0$, because

$$\lim_{\mu \to 0} \frac{e^{\mu N} - e^{\mu j}}{e^{\mu N} - 1} = \frac{0}{0} \tag{4.5}$$

By LH́opitalś rule,

$$\lim_{\mu \to 0} \frac{e^{\mu N} - e^{\mu j}}{e^{\mu N} - 1} = \lim_{\mu \to 0} \frac{N e^{\mu N} - j e^{\mu j}}{N e^{\mu N} - 1} = \frac{N - j}{N} \tag{4.6}$$

In other words, linear loss is the special case of exponential loss where the exponential growth rate is at the lowest level. Higher growth rate implies faster evacuation, and $V_0(p_0)$ values of linear and exponential loss show that faster evacuation is more valuable.

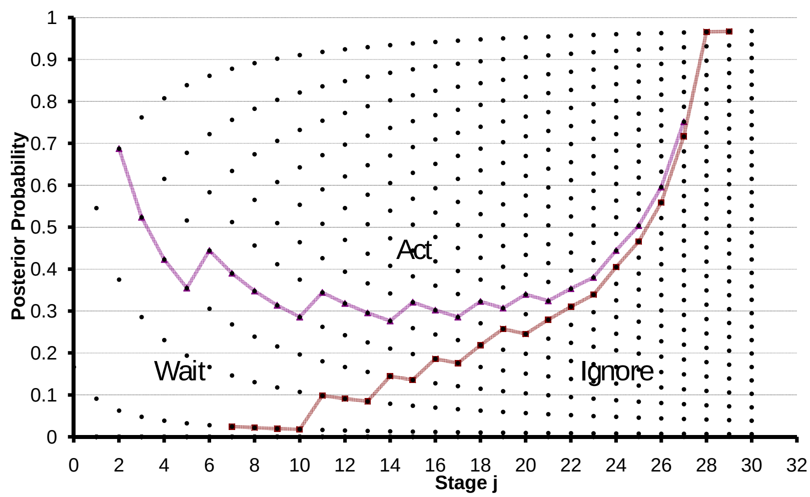

FIGURE 3. Policy region for exponential loss profile

Figure 4 superimposes the policy regions of the two loss structures. It shows that exponential loss structure, with its faster evacuation, allows more time to collect information before making a decision.

4.2 Effect of evacuation speed

As discussed above, evacuation speed or efficiency has an important effect on the optimal policy and the optimal value of the dynamic program. Evacuation speed can be represented as loss saving rate or loss increment rate, and it is realized as the slope of loss structure. Since the change in evacuation speed can be understood as the change in loss change rate, doubling of slope of the loss curve implies doubling of evacuation speed.

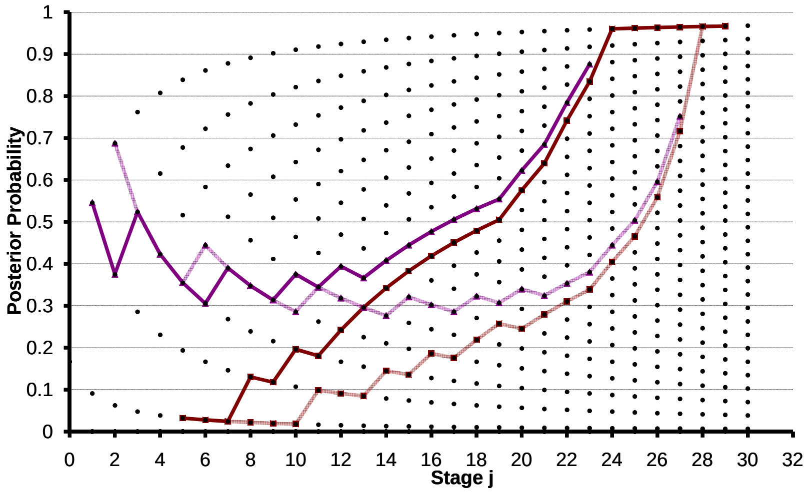

FIGURE 4. Policy region for linear (solid) and exponential (faint) loss profiles

In the exponential loss structure, evacuation speed increases over time until the terminal stage. Change in evacuation speed does not change the maximum loss, but it changes the slope of loss structure and the critical point of loss. Slope changes as the evacuation speed changes, but loss at the final stage is always L_N .

In Equation (4.4), the loss structure is rescaled so that the range of L_j is from 0 to L_N , irrespective of the value of μ . Therefore, doubling of μ does not imply precise doubling of evacuation speed. Since we need to control the evacuation speed without rescaling, we introduce the parameter, evacuation speed change ratio. In the exponential loss structure de-fined in Equation (4.4), the slope at stage j is $\frac{L_N}{e^{\mu N}-1}\mu e^{\mu j}$. The slope at stage j in the loss structure with changed evacuation speed is $r_S\frac{L_N}{e^{\mu N}-1}\mu e^{\mu j}$, where r_S is the evacuation speed change ratio. Doubling of r_S implies doubling of evacuation speed. Even with the change of r_S , terminal value of L_j does not change. Instead, its value for earlier stages changes. Since the value of L_j cannot be below 0, the exponential loss function with the evacuation speed change ratio r_S can be defined as follows:

$$L_j = \max\left\{0, L_N - r_S\frac{e^{\mu N}-e^{\mu j}}{e^{\mu N}-1}L_N\right\} \tag{4.7}$$

In the changed exponential loss function, the critical point gets closer to the final stage with higher evacuation speed and the new critical point is $\frac{1}{\mu}\ln\left(\frac{(r_S-1)e^{\mu N}+1}{r_S}\right)$. From stage 0 to the critical point, the loss is 0. After passing the critical point, loss begins to in-crease. With different evacuation speed change ratios, the loss structure has different slopes and critical points.

In this changed loss structure, the policy region changes as shown in Figure 5.

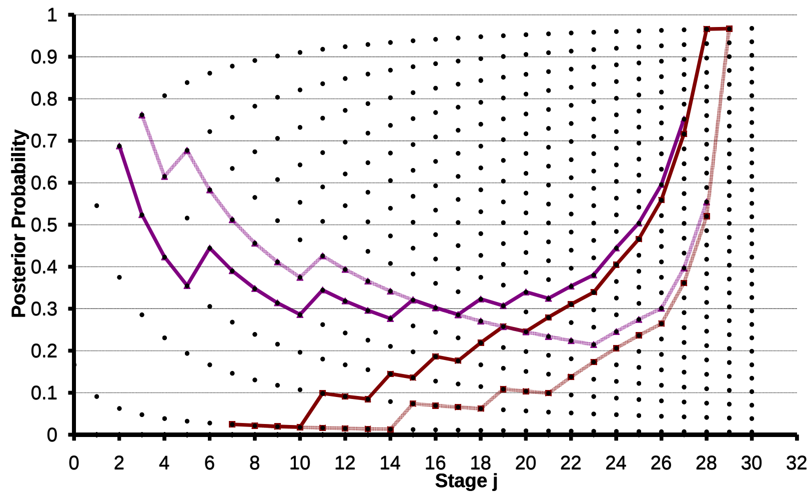

FIGURE 5. Policy region with normal (solid) and double (faint) evacuation speeds

With normal evacuation speed, the DM can wait up to stage 18. With doubled evacuation speed, the DM can wait up to stage 22.

Figure 6 shows the values of $V_0(p_0)$, the value of optimal decision at the initial stage, for different evacuation speeds. Increasing evacuation speed is shown to be valuable be-cause it decreases $V_0(p_0)$.

Figure 6 shows that small increases in evacuation speed have a large effect on the value of the optimal policy, but the benefit from further improvement is limited. The latter is mainly due to the shifted critical point. In this example, the critical points for evacuation speeds x1.0, x1.2, x1.4, x1.6, x1.8, and x2.0 are 0.0, 14.3, 18.6, 21.0, 22.5, and 23.6, respectively. As the evacuation becomes faster, the new critical point moves closer to the final stage. Then the value of $V_0(p_0)$ becomes less sensitive to change in loss structure be-cause the loss is constant at 0 until the critical point and it changes only after the critical point.

5 Conclusion and Future Research

We developed a framework to assess the value of improved evacuation speed in a dynamic multistage decision setting. Using this framework, we can com-

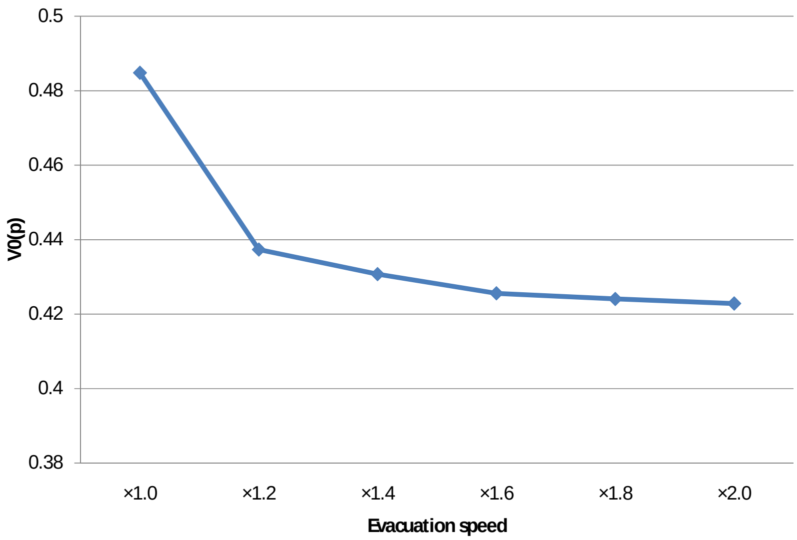

FIGURE 6. Values of optimal decision under different evacuation speeds

pare the value of investment in improved evacuation to other investments. Examining various loss profiles shows that speeding evacuation moves the critical point toward the moment of hurricane strike. In other words, faster evacuation allows more time to wait without increasing the risk of loss from the hurricane. This shows an interesting parallel between the value of evacuation speed and the value of information. An improvement on evacuation speed is equivalent to some level of improvement on information quality. For example, the value of instantaneous evacuation is equal to the value of perfect information on the storm.

Future research will focus on forecast accuracy in order to compare the value of in-vestment in evacuation efficiency and in forecast improvement. We will also consider variable evacuation cost and different loss profiles based on the decision timing. By doing so, we will formulate a more powerful tool to determine which investment is more valuable: roads or radar.

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