The Decision to Evacuate Facing Uncertain Hurricane Landfall Track, Intensity, and Lead Time

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ABSTRACT

The failure to evacuate on time (i.e., evacuation under-response) can tragically increase the cost of a hurricane; unnecessary or premature evacuation (i.e., shadow evacuation) can also make a hurricane more costly than might otherwise be necessary. Due to the constantly evolving storm characteristics over the days prior to landfall, the decision of whether and when to evacuate from an impending hurricane is a complex dynamic decision under uncertainty. Consequently, an understanding of the evolving probabilistic risk of the storm in terms of its track, intensity, and lead time is a critical aspect of the evacuation decision. This paper models these various aspects of a hurricane's risk within a dynamic model of a household's hurricane evacuation decision in order to ultimately better understand the decision to evacuate. The optimal behavior is solved using a dynamic optimization problem in which the value function is approximated as a discrete function of the state variables that convey the relevant track, intensity, and lead time risk information. Our baseline results indicate that from an economic perspective what may be deemed evacuation under-response and shadow evacuation are actually rational outcomes of the dynamic framework. These patterns are robust when sensitivity analysis of our cost of evacuation function is carried out, suggesting that the problems of evacuation under-response and shadow evacuation stem from the dynamic uncertainty that decision makers face when considering an approaching hurricane.

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I. INTRODUCTION

Hurricanes are one of the most destructive and costly natural phenomena, unleashing severe levels of destruction to extensive areas that have the misfortune to lie in their path. However, the social costs of hurricanes are heavily influenced not only by their magnitude, but also by the behavior of the public that will be in their path. The failure to evacuate on time can tragically increase the cost of the hurricane; unnecessary or premature evacuation can also make a hurricane more costly than might otherwise be necessary. Alas, due to the constantly evolving storm characteristics over the days prior to landfall coupled with household constraints, evacuating in a timely fashion is not a simple task. Rather, the decision of whether and when to evacuate from an impending hurricane is a complex dynamic decision made under uncertainty (Regnier and Harr, 2006; Czajkowski, 2007; 2010).

For example, the average Atlantic hurricane track (intensity) forecast error over 2005 – 2009 for an issued 12 hour forecast is approximately 37 miles (8 mph), increasing by nearly 683% (180%) to 290 miles (23 mph) for an issued 120 hour forecast (NHC Forecast Accuracy, 2010). Assuming that at landfall the expected costs of not evacuating from a hurricane are most notably a function of how intense the storm is at landfall in conjunction with how close it tracks to one's location, households undoubtedly face a great deal of forecast uncertainty over time in regard to the ultimate outcome of their evacuation decision as a hurricane approaches landfall. Further, the decision to evacuate is not a costless one, even under conditions of forecast certainty. A household must also factor in the costs of evacuation into their evacuation decision which are often variable over time due to the uncertain forecast track, intensity, and lead time information which has a corresponding effect on other household evacuation decision making. Not surprisingly, the empirical evidence reflects heterogeneous evacuation behaviors among households where some evacuate while others wait; with common hurricane evacuation issues being some households evacuating unnecessarily (a problem called *shadow evacuation*) and others facing a high probability of damages waiting too long (*evacuation under-response*) (Mitchell et al., 2007; USACE Post-Storm Assessments, 2010).

Despite a timely evacuation's critical role, an understanding of household evacuation incorporating the temporal aspects of the evacuation decision making process is deemed to be especially inadequate (Dash and Gladwin, 2007; Gladwin et al., 2007). In their overview of social science research needs related to hurricane forecasts and warnings, Gladwin et al. (2007) highlight the need for research that dynamically models evacuation behavioral response in more precise and comprehensive ways to allow for a better understanding of household evacuation. Given that an understanding of the evolving probabilistic risk of the storm in terms of its uncertain landfall track, intensity, size, and lead time is a critical aspect of the evacuation decision (Regnier & Harr, 2006; Czajkowski, 2007; 2010), it is essential to incorporate these risk components into a dynamic evacuation decision model. The purpose of this paper is to therefore model the track, intensity, and lead time aspects of a hurricane's risk within a dynamic model of a household's hurricane evacuation decision in order to construct a more precise and comprehensive evacuation decision model to ultimately better understand the decision to evacuate.[1]

Specifically, a household's evacuation decision is framed as an optimal stopping problem in which in each time period prior to the actual hurricane landfall, the household's choice is to either evacuate or to wait one more time period for a revised hurricane forecast. This optimal choice is predicated upon households selecting the minimum value of the known costs of evacuating in the current period vs. the expected costs ensuing in the following period (either from evacuation or waiting), both of which are a function of the forecasted lead time, intensity,

[1] We abstract away from the uncertainty in the size of the storm at this time.

and track of the storm. The optimal behavior is solved using a dynamic optimization problem in which the value function is approximated as a discrete function of the state variables with the computational methods employed allowing for tractability in the model. Using the National Hurricane Center (NHC) issued forecast advisories, a vector of state variables and their associated probability distributions that convey the relevant track, intensity, and lead time risk information are constructed and utilized as a critical component of the dynamic programming model. The model is calibrated using actual hurricane forecast data from a number of storms as well as actual evacuation cost data.

Whereas previous research has modeled a household's hurricane evacuation decision from a dynamic perspective (Czajkowski, 2007; 2010), the uncertain intensity and track risk information was combined into a single hurricane risk index state variable. Regnier and Harr's (2006) dynamic modeling of the hurricane evacuation decision from a public official's perspective likewise only modeled a single value of risk via a location state variable accounting for track and direction uncertainty. Kim and Bickel (2010) expand the dynamic modeling state space by incorporating separate state variables for both track and intensity in their local emergency manager dynamic decision making model. All three of these studies assume a known landfall timing. Thus, this research improves upon both the existing household and emergency manager dynamic evacuation modeling by expanding the modeling framework to account for the uncertain landfall timing of the storm which we accomplish through a forecast lead time state variable.[2] Regnier (2006) found that landfall timing is indeed uncertain with the mean absolute error from 1976-2000 ranging from 8.8 to 11.5 hours at lead times between 31 and 54 hours, which would represent the issuance of two more NHC hurricane forecast advisories containing important storm forecast information households could use in their evacuation decision. More

[2] Aforementioned constructed risk indices also potentially introduce a loss of information by reducing a multidimensional problem to a single value of risk. However, we do not focus further on this potential issue here.

recently, Petrolia and Bhattacharjee (2010) found that landfall timing is a significant storm forecast attribute used in evacuation decisions, providing further impetus for including a separate state variable for landfall timing in the dynamic modeling framework.

Furthermore, while previous research has utilized storm data in constructing their probability transition matrices (Regnier and Harr, 2006; Kim and Bickel, 2010), the state variable probability transition matrices constructed in this study use previous storm forecast data, or the data that households would see during their evacuation decision. Calibrating our model with actual forecast data accounting for the three significant risks of track, intensity, and lead time embedded in the hurricane evacuation decision makes for a more realistic modeling framework. Additionally, we use the evacuation costs and timing data produced by Whitehead (2003) to derive a household's evacuation costs as a function of the forecasted distance from the storm 24, 48, and 72 hours from the storm's landfall. This is the first estimation of evacuation costs accounting for the forecasted distance from the storm one to three days out from landfall the authors are aware of, which further reinforces the more realistic modeling framework.

Our baseline results highlight three main findings: 1) optimal evacuation choices (i.e., our "evacuation region") do not always disappear as distance from the forecasted landfall location increases; 2) evacuation regions are not always greater as the lead time falls, especially for shorter distances from the forecasted landfall location; and 3) while evacuation regions tend to expand as the forecasted storm intensity increases, they sometimes do so in perverse ways. Consequently, from an economic perspective, what may be deemed evacuation under-response and shadow evacuation can actually be explained as rational outcomes of our dynamic framework.. Moreover, our results accounting for the uncertain lead time are in-line with previous dynamic models that do not account for this uncertainty, indicating evacuation regions primarily within only 24 hours of forecasted landfall (Czajkowski, 2007; 2010; Kim and Bickel, 2010). Given that recommended safe evacuation times for major coastal communities are at least 30 hours in advance of a hurricane's expected landfall (Lindell et al., 2007), the optimal evacuation response of private households do not coincide well with the desired socially optimal evacuation timing outcome. Finally, we perform sensitivity analysis on our cost of evacuation and this confirms these baseline findings. These results suggest that less than desirable evacuation patterns most likely stem from the dynamic uncertainty that decision makers face when considering an approaching hurricane.

The remainder of this paper is organized as follows: Section II provides the dynamic programming model; Section III details the calibration of the model's inputs and parameters; Section IV presents and discusses the expected, baseline, and sensitivity analysis results; and Section V gives the concluding comments.

II. OPTIMAL TIMING OF HOUSEHOLD HURRICANE EVACUATION: THE DYNAMIC PROGRAMMING MODEL

Once a tropical depression, tropical storm, or hurricane has developed, the NHC issues an official forecast advisory every six hours such as shown in Figure 1. We focus on three critical aspects of information contained in each NHC forecast advisory. First is the forecast of the lead time, L, which is an estimate of how long it will be until landfall and takes on the discrete values 12, 24, 36, 48, 72, 96, or 120. Second is a forecast of the approaching hurricane's center position that indicates the distance from a given household's location, D. Finally, the forecast predicts the maximum one-minute sustained wind speeds at landfall, I, i.e., intensity forecast. Consequently, we can think of households potentially affected by the storm as being placed into a discrete-time multi-period evacuation decision situation, where each report represents a discrete evacuation decision time period, t. Decisions are made based on state vector, which consists of the forecasted lead time, L_t, predicted distance at landfall from the household, D_t, and the predicted intensity of the center of the storm, I_t.

Since forecast advisories are issued every six hours and hurricanes do not move at a constant forward speed and/or direction, potentially affected households will most likely face more than one forecasted lead time of any 12 to 120 hour lead time increment. That is, there are not seven discrete evacuation decision time periods associated with a single 12, 24, 36, 48, 72, 96, and 120 hour lead time, but rather an uncertain number of forecasted lead times. For example, on average there should be two 24-hour forecasts, followed by a 12-hour forecast. However, in Hurricane Erin there were seven 24-hour forecasts while in Hurricane Claudette there was a single 24-hour forecast, followed six hours later by a 12-hour forecast. Hence, a given lead time forecast is comprised of two elements, the announced lead time, and the number of times this has been written. We denote L_t=36.01 to be the first announcement of a lead time of 36 hours. This could be followed by L_{t+1}=36.02 or L_{t+1}=24.01. The probability that a given lead time increment advances (e.g. from 36 to 24) rises with the number of repetitions of the same lead time. This stochastic process can be represented using a discrete-time Markov transition matrix with an absorbing state when L_t=0, i.e. landfall occurs.

The other two elements of the state vector are also stochastic. After a report, t, the values of D_t and I_t are known, but these forecasts are likely to change by the next report t+1 (NHC Forecast Accuracy, 2010). We assume that D and I follow independent Markov processes such that the probability of a particular realization of any D and I in t+1, depends only on their current values, D_t and I_t. If $P(D_{t+1}^k|D_t)$ is the probability that D takes on the k^{th} value in t+1, then for any D_t $\sum_k P\left(D_{t+1}^k \mid D_t\right)=1$ and likewise for I.

In each evacuation decision time period, households face a binary choice of either waiting another period for a revised hurricane forecast, or evacuating immediately. If a household evacuates it faces a known cost denoted $c_E\left(L_t, D_t, I_t\right)$, that is a function of the forecasted lead time, intensity, and track of the storm. We assume that the decision to evacuate is not reversible as evacuation is assumed to be immediate and evacuation costs are sunk.[3] The final opportunity to evacuate occurs when L_t=12 at which time the option is to evacuate immediately or simply ride out the storm at landfall, incurring the costs of staying, $c_S\left(D,I\right)$, which is a function of D and I.

We assume that the objective of the decision maker is to minimize the expected costs of the hurricane. In solving this problem, however, the decision maker takes into account that information will change over time and, based on the updated information, can make decisions in the future. The expected cost minimization problem is solved by backward induction as follows. Suppose a decision maker has reached the fourth 12 hour warning, L_t=12.04, and has still not evacuated. At that point based on historical data, there will be no more 12 hour warning, she must evacuate now or ride out the storm. At this point, therefore, the optimal choice is found by solving

$$V\left(L_t,D_t,I_t\right)=\min\begin{cases}c_E\left(L_t,D_t,I_t\right) & \text{if Evacuate}\\ E_t c_S\left(D_0,I_0\right) & \text{if Stay.}\end{cases}$$

where D_0 and I_0 represent the actual distance from the household's home and the actual intensity at landfall. $V\left(L_t,D_t,I_t\right)$, therefore, represents the expected cost of a household that had not evacuated at L_t=12.04.

For forecasts prior to L_t=12.04, a household does not know with certainty if the current period is her last opportunity to evacuate. Hence in general the decision maker solves the problem

[3] While this assumption does not hold in every case, e.g., severe highway congestion causing some evacuees to return, we feel it is a reasonable assumption for most evacuation situations. For example, mean evacuation distance traveled for Hurricane Ivan was 182 miles (Morrow and Gladwin, 2005) – clearly not an easily reversible distance to cover.

$$V\left(L_t, D_t, I_t\right) = \min \begin{cases} c_E\left(L_t, D_t, I_t\right) & \text{if Evacuate} \\ E_t V\left(L_{t+1}, D_{t+1}, I_{t+1}\right) & \text{if Stay.} \end{cases} \qquad (1)^4$$

Where $V\left(L_t, D_t, I_t\right) = c_S\left(D_0, I_0\right)$ at L_t=0. The intuition behind the solution to is that for certain forms of c_E and c_S, a unique cutoff for households exists where waiting is optimal on one side of the forecast, and evacuating on the other. This critical point changes for different value of L_t.

III. MODEL DATA INPUTS

In order to solve our multi-period dynamic model of evacuation decision making, four main data inputs are needed: 1) the transition probabilities for the lead time state variable, $p\left(L_{t+1} \middle| L_t\right)$; 2) the vector of possible forecast states, D_t and I_t, and their associated transition probabilities, $p\left(D_{t+1}, I_{t+1} \mid D_t, I_t\right)$; 3) the costs of evacuation, $c_E\left(L_t, D_t, I_t\right)$, as a function of the forecasted lead time, intensity, and track of the storm; and 4) the expected costs of not evacuating, $c_S\left(D_0, I_0\right)$. The construction of these inputs is detailed below.

Evacuation Time Period State Space

We construct our multi-period model evacuation time periods and associated state space (state variables and associated probability distributions) from actual historical storm forecast advisory and realized landfall data stemming from 19 storms affecting 15 coastal locations in the Gulf of Mexico during 1992-2005. Specifically, we use the storm tracking and decision assistance software program HURREVAC to stipulate a 900 nautical mile (NM) by 180 NM Gulf of Mexico region that includes the 15 coastal locations listed in Table 1. We select the 19 historical storm tracks from 1992-2005 passing through this region listed in Table 2. For the years 2004 and 2005 historical storm tracks for storms achieving either tropical storm or hurricane strength are utilized, while for 1992-2003 only those storms making landfall as a

4 Due to the finite and short time horizon nature of the problem, we ignore discounting.

hurricane are utilized. Although we are only utilizing data from 19 storms, a healthy mixture of storm intensity levels and storm tracks are included.

For each of our 19 storms we use the NHC Hurricane Season Tropical Cyclone Advisory Archive (NHC Advisory Archive, 2009) text in conjunction with the HURREVAC graphical forecast tracks in order to identify the specific forecasted lead time within each issued forecast advisory[5] where the storm was forecasted to have moved "inland" within our stipulated Gulf of Mexico region, and consequently hurricane evacuation would be too late. Accordingly, the forecasted lead time prior to the inland forecast is the designated evacuation lead time for a particular advisory. Figures 1 and 2 illustrate this process for the 2005 Hurricane Dennis forecast advisory #19. From Figure 1 we see that the first inland forecast in advisory #19 is associated with the 48 hour forecast advisory lead time, and from Figure 2, we see that this inland forecast is located well-within the state of Mississippi. Similarly, from Figure 1 the forecasted lead time prior to the inland forecast is 36 hours, and from Figure 2, we see that this 36 hour forecast is roughly 40 to 50 miles off the coast of Florida. Thus, somewhere between 36 and 48 hours the storm is forecasted to make landfall and we therefore designate 36 hours as the amount of lead time households have to make their evacuation decision according to the information provided to them within this forecast advisory.

These forecast lead times are collected for each storm over all advisories where an inland forecast has been issued. The collected lead times are of varying time lengths ranging from 26 advisories starting with a 96 hour lead time for Hurricane Ivan, to only 6 advisories starting with a 48 hour lead time for Tropical Storm Matthew. We construct our lead time Markov transition probability matrix by combining this information across all storms. A partial example of this entire matrix is shown in Figure 3. From Figure 3 we see that there are a maximum of six 96

[5] For purposes of this exercise any intermediate advisories issued were ignored.

hour and twelve 72 hour lead times for any particular storm forecast. If, for example, a household has received its first 96 hour forecast (96.01) there is an 83% chance it will receive a second 96 hour forecast (96.02), and a 17% chance that the next forecast lead time it receives will be 72 hours (72.01). By the sixth 96 hour forecast lead time (96.06) a household receives, based on the historical data there is a 100% chance that the next forecast lead time will be 72 hours (72.01).

Distance and Intensity State Variables

The remaining state variables, *D* and *I*, are also constructed using the forecast advisories. As shown in Figure 1, for each forecast lead time the intensity forecast is given in knots rounded to the nearest 5 knot amount, and the track forecast is given in specific degrees of latitude and longitude. We discretize I_t using the Saffir-Simpson Hurricane Scale (SSHS) since it naturally lends itself to this discretization it is reasonable to assume that households focus on the forecasted SSHS category level of the hurricane as opposed to the storm's specific wind speed when thinking about the hurricane's intensity. We add one additional wind speed category, CAT 0, to account for winds falling to tropical storm strength. The intensity forecasts are collected for each storm over all advisories, and we construct our discretized intensity forecast transition probability matrix by combining this information across all storms. Figure 4 provides the final intensity forecast Markov probability transition matrix. From Figure 4 we see that if at any I_t= CAT 2, there is 15% chance that the next period's forecast will be for a CAT 1, a 60% chance that it will forecast a CAT 2, and 25% chance of a CAT 3 intensity forecast in the next period.[6] Similar to Kim and Bickel (2010) as an exceptional case to our wind transition matrix, if the

[6] There was insufficient data to vary these transition values by forecast lead time.

wind speed falls to the tropical storm level, CAT 0, then it will remain at that level in all subsequent periods.[7]

We model the distance from a given point D_t state variable as the great circle distance from the previous designated evacuation lead time track coordinates. Again, from Figure 1 the 36 hour forecast track coordinates are 29.8N, 87.1W for Hurricane Dennis advisory #19. The previous advisory also had a designated 36 hour lead time but with track coordinates of 28.5N, 86.2W, or a great circle distance of 105.1 miles.[8] The track forecasts are collected for each storm over all advisories, great circle distances are calculated, and we construct our track forecast/great circle distance transition probability matrix by combining this information across all storms. Figure 5 provides the final track forecast/great circle distance Markov probability transition matrix. From Figure 5 we see that hurricanes have a tendency to wander. For example, if in one report the hurricane is predicted to hit at exactly that point, D_t=0, by the next report, six hours later, there is a 70% chance that the forecasted distance will be 75 miles away or more.

Cost of Evacuation

We use the evacuation costs and timing data produced by Whitehead (2003) to estimate a household's evacuation costs as a function of the forecasted distance from the storm 24, 48, and 72 hours from the storm's landfall. As Whitehead's data is for Hurricane Bonnie, a forecasted CAT 3 hurricane, we derive the initial cost function for a CAT 3 hurricane solely.[9]

[7] We did not also use an exceptional case for a CAT 5 as Kim and Bickel (2010) did in their paper.
[8] Some of this distance is simply due to the 36 hour lead time forecast for advisory #19 being closer to the mainland then the 36 hour lead time forecast for advisory #18 caused by the forward movement of the storm. Nonetheless, both 48 hour forecasts for these advisories had the storm already moving inland and hence evacuation too late.
[9] Hurricane Bonnie made landfall in North Carolina, clearly outside of our Gulf of Mexico region for which our state space data were collected. This data is used for two reasons 1) it is the only evacuation cost data we have that also has evacuation timing data associated with it; and 2) the actual cost numbers collected by Whitehead reflect well other evacuation cost data collected for other storms, some of which occurring in the Gulf of Mexico region.

Whitehead's original study collected evacuation cost and timing data from 277 people that stated they evacuated for Hurricane Bonnie. Cost data included monetary information on lodging costs, travel time costs, travel cost, direct costs, and lost income. Evacuation timing data included what day the evacuee left, which we translated into 72, 48, and 24 hours prior to landfall. For example, if a household indicated they left on Monday the 24th of August 1998, given landfall at 10:00 p.m. on Wednesday the 27th of August, we translated this to evacuation between 48 and 72 hours prior to landfall and designate it as 72 hour evacuation timing. A final critical piece of information collected from the Whitehead survey data was the zip code of the respondent. We used the zip code of each respondent, the timing of their evacuation, and the actual forecast information from Bonnie to determine the point-to-point distance from the forecasted landfall during the 72, 48, or 24 hour timeframe the respondent evacuated. For example, 48 hours from landfall the forecast called for Hurricane Bonnie to make landfall within Carteret County. Using this information, any respondent that evacuated 48 hours out from landfall we calculated the point-to-point distance from their zip code location to Carteret County. After deleting respondents that stated they evacuated but for which no relevant evacuation cost, timing, or zip code data were available, we were left with a dataset of 187 respondents from the original 277.

We empirically estimate inflation adjusted evacuation cost data as a function of the 24 hour distance from landfall, the 48 hour distance from landfall, and the 72 hour distance from landfall across all 187 respondents. Results of the estimation are presented in Table 3. While our constant is the only coefficient significant at the 10% level or less, the signs on our explanatory variables reflect evacuation costs declining in distance from the forecasted landfall as would be expected. Also, the magnitude of the decline in distance is most significant 24 hours from landfall when there is the highest confidence in the forecast track. It is also interesting to note that the magnitude of costs declining in distance 72 hours from landfall is roughly three times as great as the declining distance 48 hours from landfall. This also makes intuitive sense as the uncertainly in the 72 hour forecast is much greater than the 48 hours where the storm is becoming closer but still not relatively definite as to where it will go. Overall then, evacuation costs decline in distance at the greatest rate 24 hours prior to landfall where track forecast uncertainty is the least, followed by 72 hours out from landfall where uncertainty is the greatest and fewer people should be evacuating outside of the predicted landfall location, and finally the slowest rate 48 hours from landfall due to the relative uncertainly of where the storm is headed.

Using the coefficient values from our regression results, Figure 6 illustrates these declining evacuation costs as a function of the 24, 48, and 72 hour forecasted distance from landfall. As seen in Figure 6, applying the estimated coefficients directly leads to negative evacuation costs as distance from forecasted landfall becomes very large; clearly this is not feasible. Therefore, in our model estimation we specify a minimum level of evacuation costs ranging from \$25 - \$300 depending on the timing of evacuation and the CAT level.[10] Finally, two other major modifications were made to the cost of evacuation data. One, these evacuation costs were only empirically estimated for a CAT 3 hurricane. We use data from Lindell et al. (2002) on the predicted increases in the number of cars and associated number of hours to evacuate along the Texas Gulf Coast for CAT 1 to CAT 5 hurricanes to estimate the varying levels of average CAT 1 to CAT 5 evacuation costs from our derived average CAT 3 evacuation cost base. Intercept and coefficient values were both adjusted accordingly in this exercise. Two, while not able to be estimated from the Whitehead dataset, 12 hour coefficient values and minimum values were added to account for the assumption of increased evacuation costs as landfall draws near. These are also illustrated in Figure 6.

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[10] The full set of values, all data and the program used to solve the problem will be made available to the reader via the Internet.

Cost of Not Evacuating

If a household chooses not to evacuate and the hurricane ultimately makes landfall at their location, they will be forced to ride out the storm which has an associated probability of being injured, or even killed. We follow Czajkowski (2007; 2010) to obtain expected costs of not evacuating of $1,694, $6,775, $15,244, $28,795, and $32,182 for a CAT 1, CAT 2, CAT 3, CAT 4, and CAT 5 hurricane respectively. Similar to Czajkowski, we have assumed that the probability of injury/death from a tropical storm is 0.0% and therefore expected cost $0 despite the fact that tropical storms have produced injuries and deaths. However, we also have these costs of not evacuating decaying in distance to reflect the decaying distance of wind speeds (Nordhaus, 2006). We initially assume that 0-100 miles out from the center of the storm the expected costs of not evacuating are at 100%, 101-150 miles out they are at 67%, 150-200 miles they are at 33%, and greater than 200 miles away from the center of the storm the expected costs of not evacuating are at 0%. Given that hurricanes are typically thought of affecting about 150 miles of coastline per landfall (Regnier and Harr, 2006), we feel these initial decay functions are relatively conservative.

IV. SOLUTION AND RESULTS

Using the aforementioned baseline model, the multi-period dynamic model of evacuation is solved through backward recursion from the last safe possible time to evacuate, when L_t=12.04, for a general household in the Gulf of Mexico region. The solution of the model yields an optimal evacuation region surface, which tells us whether a decision maker should evacuate after receiving an advisory with a prediction of windspeed, time to landfall, and distance of the point of landfall from the decision maker. Again, the intuition behind the solution to is that for certain forms of c_E and c_S, the evacuation surface will indicate a unique cutoff for households where waiting is optimal on one side of the forecast, (i.e. weaker storms, longer time predictions, or greater distances) and evacuating is optimal on the other side.

Expected and Baseline Solution

It is plausible to expect that cost-minimizing households forecasted to be far from the storm, and/or to have long lead times, would not optimally choose to evacuate. Thus, as depicted in Figure 7, we expect that for a given storm intensity as the forecasted distance from landfall and/or lead time increase (moving from bottom to top on the y-axis and left to right on the x-axis respectively), the evacuation region (shaded) should generally shrink. As the predicted storm intensity increases so that, everything else being equal, the expected costs of not evacuating increase, we hypothesize that cost-minimizing households will be more likely to evacuate. Thus as also depicted in Figure 7 moving, for example, from a CAT 3 to a CAT 4 hurricane, we expect that the evacuation region would generally increase in lead time and distance as the storm intensity increases.

As elaborated above, our baseline multi-period model was developed with an underlying empirical foundation for each piece of the optimal evacuation decision model, and each of the pieces seems economically sensible. As such, we expected that the model would yield results that are largely consistent with the hypothesized pattern of Figure 7. In fact, however, as we discuss below and is exhibited in Figure 8, our baseline model ends up finding optimal behavior that is inconsistent with our expectations in a number of ways. Specifically: 1) evacuation regions do not always disappear as distance increases; 2) evacuation regions are not always greater as the lead time falls, especially for shorter distances; and 3) while evacuation regions tend to expand as the forecasted storm intensity increases, they sometimes do so in perverse ways with evacuation being optimal at large distances and large lead times while the evacuation region actually shrinks at shorter distances and lead times.

To illustrate these three main findings from our baseline model results, consider the evacuation regions for a CAT 2 and CAT 4 hurricane as illustrated in Figure 8. Firstly, we see that during any of the four possible 12 hour forecasted lead times at all forecasted distances from 0 to 275 miles, it is optimal to evacuate for any forecasted hurricane, even distances where the expected damages at landfall are quite small. In terms of evacuation regions not always being greater as the lead time falls, we see that when receiving any of the seven possible 24 hour forecasted lead times, it is optimal to wait if the forecasted distance is close (generally < 75 miles), while evacuation is optimal at greater distances (generally > 75). Finally, we note two significant differences between the CAT 2 and CAT 4 cases which highlight the expansion of the evacuation region in perverse ways as storm intensity increases. First, while evacuation is optimal given a 24 hour lead time forecast for a forecasted CAT 2 hurricane to hit 75 miles from a decision maker, if the same lead time and distance is forecasted for a CAT 4 hurricane, the optimal thing to do is to wait. Second, for CAT 4 hurricanes, during the 72 and 96 hour forecasted lead times, evacuation is optimal at large forecasted distances of 225 and 275 miles.

While counterintuitive, our baseline results are evacuation patterns that are observed in actual hurricanes. For instance, the optimal evacuation at large distances is analogous to the phenomenon of shadow evacuation where those not directly at risk will try to move out of harm's way under an impending threat such as a hurricane (Tierney et al., 2006), essentially evacuating unnecessarily (Dash and Morrow, 2001). Existing empirical estimates of shadow evacuation range from 20-50% of residents in low risk areas (Lindell and Prater, 2007), with Hurricane Andrew in 1992, Hurricane Floyd in 1999 (35% of the 2 million evacuees from Florida, [Wolshon, 2008]), and Hurricane Rita in 2005 (Mitchell, et al., 2007) being some of the most notable recent shadow evacuation events. In fact, Dash and Gladwin (2007) highlight shadow evacuation as a serious concern that is currently not well-studied, identifying it as a hurricane evacuation research priority moving forward. On the opposite side of the spectrum is the common problem of evacuation under-response where residents remain in harm's way instead of heeding warnings to evacuate (Mitchell et al., 2007; USACE Post-Storm Assessment, 2010). Our results where evacuation regions are not always greater as the lead time falls, especially for shorter distances, correspond well to the under-response issue. Evacuation under-response is most often cited to be an outcome of miscommunication, mistrust, misperception of risk, or having had previous hurricane experience (Mitchell et al., 2007). Our model suggests an alternative explanation – it could be cost minimizing behavior.

The economic reasons behind the results from our baseline model and the similar patterns in the "real world" can be clarified by expounding upon the model's recursive solution given the baseline cost of evacuation and not evacuating inputs. Focusing on the outcomes from our 12 hour lead time periods can help to clarify the result of evacuation regions not always disappearing as distance increases, i.e., shadow evacuation. To begin with, at any of the 12 hour lead times for any given CAT level and at all distances, the baseline costs of evacuation never rise above \$600 with a median value of \$252. Due to the decaying evacuation cost structure in distance shown in Figure 6, at great distances this median cost of evacuation value is even lower. On the other hand, the expected costs of not evacuating at any of the 12 hour lead times for any given CAT level and at all distances are as high as \$25,861 with a median value \$3,335.[11] Even for distances forecasted to be 275 miles from the center of the storm which have corresponding landfall terminal values of \$0 at that distance, because hurricanes can drift widely as they approach landfall, the median value of the expected costs of not evacuating at any of the 12 hour lead times across all CAT levels is \$1,292. Cost-minimizing households choose the lower of these two amounts; hence the decision to evacuate is optimal during half-day lead times.

[11] Expected costs of not evacuating are a probabilistic mixture of the terminal values and the costs of evacuation multiplied by our wind speed and distance Markov transition matrices.

Accordingly, shadow evacuation at large distances during 12 hour lead times is actually rational behavior on the part of households from an economic perspective given the disparity between the costs of evacuation and the expected costs of not evacuating ensuing from the storm forecast uncertainty. Although not expounded upon here, similar economic reasoning applies for other evacuation at large distances and non-12 hour lead times.

As seen in Figure 8, at 24 hours, evacuation is never optimal if the predicted landfall point is 25 miles or less from an individual, while at greater distances for all hurricane levels some evacuation is preferred. Focusing on the 24 hour lead time outcomes can help to clarify why this occurs. Figure 9 illustrates the daily evacuation costs for a forecasted CAT 4 hurricane at forecasted distances of 20, 80, 150, and 200 miles where we see that the 24 hour evacuation costs (one day) are lower than the 12 hour evacuation costs (half day) for all distances. However, as the evacuation costs decay in forecasted distance, the difference between 12 and 24 hour evacuation costs varies significantly by distance. The 24 hour evacuation costs are significantly lower than 12 hour evacuation costs for large distances, but not for short distances. For example, at a distance of 200 miles 24 hour evacuation costs are lower than 12 hour evacuation costs by $188, while at a distance of 20 miles this difference is only $19. Hence, while cost-minimizing households at a long distances from the predicted landfall point evacuate when receiving a 24 hour warning, it ends up being optimal for those who receive a 24 hour warning for a hurricane predicted to land near them choose to wait until the 24 hour warning and evacuate then. For example, median costs of evacuation across all CAT levels for a location forecasted to be 25 miles from the center of the storm are $385 vs. the analogous median value of the expected costs of not evacuating of $329. In contrast, median values for a location forecasted to be 175 miles from the center of the storm are $100 and $231 respectively. Consequently, we can think of evacuation under-response for locations forecasted to be close to the center of the storm as being an economic outcome stemming from the expensiveness of evacuating now vs. the lower expected value of waiting.

Lastly, we can use our two day evacuation costs to understand the shadow evacuation problem in which evacuation regions tend to expand in perverse ways at large distances while also understanding the non-existent evacuation regions at all distance and CAT levels within any two-day (48 hour) lead time period. To find the cost-minimizing choice, the 48 hour costs of evacuation are compared to the expected value of the 24 and 36 hour value function results, and the minimum value of these two dictates the choice of evacuating or waiting during 36 and 48 hour lead times respectively. Clearly from Figure 9, in the baseline model the 48 hour costs of evacuation are higher than those in the 24 hour period, again varying by distance. Because the decision maker takes into account that he or she can make decisions in the future, at 48 hours these high two-day evacuation costs are compared with the either lower one-day evacuation costs or a 24 hour expected value lower associated with not evacuating. As a result, it is always cheaper to wait during the two-day lead time periods. Notably, given that recommended safe evacuation times for major coastal communities are at least 30 hours in advance of a hurricane's expected landfall (Lindell et al., 2007); these optimizing private household evacuation results do not coincide well with the desired socially optimal evacuation timing outcome. In contrast, the 72 hour costs of evacuation are compared with the value function reflecting the expected cost of not evacuating. Hence, for certain lead times and distances for CAT 3 and CAT 4 forecasts evacuation is optimal during the three day lead times at long distances due to the relatively high decay of the evacuation costs during this timeframe.

While not meeting our expectations, the baseline results provide a economic insights into the reasons behind frequent occurrence of shadow evacuation and under-response scenarios. These phenomena can be explained as a result of the relative cost of evacuating at a particular point in time coupled with the ability to wait for more information given the uncertainty in the distance, lead time, and intensity forecasts. Plainly though, our baseline results are dependent upon the inputs used in the model, especially how the costs of evacuation vary over lead time and distance. Consequently, we analyze our evacuation region results using different cost of evacuation forms.

Cost of Evacuation Sensitivity Analysis

We investigate how our baseline evacuation region results change by modifying our costs of evacuation in the following ways: 1) evacuation costs with less decay in distance and time (monotonically increasing); 2) evacuation costs with more decay in distance and time (monotonically decreasing); 3) evacuation costs highest three days out from landfall but decaying prior to this (following Czajkowski, 2010); 4) constant cost of evacuation over time but decaying in distance; and 5) higher overall baseline values stemming from changing the constant coefficient values to range from \$1,000 (tropical storm) to \$3,000 (CAT 5). Figure 10 presents the various shapes of our modified evacuation costs, while Table 4 summarizes the results in comparison to the baseline cost of evacuation region.

For all of these cost function scenarios, we still observe shadow evacuation, under-response, and perverse results. For example, while evacuation costs with less decay over distance and time (scenario 1) choke off perverse evacuation at large distances in the 72 and 96 hour lead times in comparison to the baseline results, other perverse large distance evacuation occurs for CAT 1 and 2 storm in the 36 and 48 hour lead time periods. Or while the 3rd day highest values (scenario 3) seemingly expand the evacuation region at close forecasted distances in the 24, 36, and 48 hour lead time periods, they do not accomplish this in a monotonic fashion with the CAT 2 evacuation region larger than the CATs 3-5 at a forecasted distance of 25 miles vs. 75 in the 24 lead time periods. Furthermore, perverse CAT 1 results at large distances occur for these values in the 72 hour lead time. Numerous other similar examples are shown throughout the table. Finally, as empirical estimates of the costs of evacuation are often collected from those that actually evacuated, there is reason to suspect these estimates may be biased downward. Therefore, it is interesting to note the parallel results from the higher overall baseline values (scenario 5).

Although our baseline cost of evacuation estimates were generated from actual survey data, the possibility exists that the resulting decaying evacuation cost structure could be specific to that event and consequently not applicable in other evacuation scenarios. The sensitivity analysis suggests, however, that seemingly rational shadow evacuation, under-response, and perverse results are typical outcomes of the evacuation decision making process, not dependent on specific cost of evacuation functional forms. More than anything else, these patterns seem to stem from the dynamic uncertainty that decision makers face when considering an approaching storm.

V. CONCLUSION

The failure to evacuate on time can tragically increase the cost of the hurricane; unnecessary or premature evacuation can also make a hurricane more costly than might otherwise be necessary. Alas, due to the constantly evolving storm characteristics over the days prior to landfall coupled with household constraints, evacuating in a timely fashion is not a simple task. Rather, the decision of whether and when to evacuate from an impending hurricane is a complex dynamic decision made under uncertainty. Given that an understanding of the evolving probabilistic risk of the storm in terms of its uncertain landfall track, intensity, size, and lead time is a critical aspect of the evacuation decision it is essential to incorporate these risk components into a dynamic evacuation decision model used to better understand a household's decision to evacuate.

Consequently we model the track, intensity, and lead time aspects of a hurricane's risk within a dynamic model of a household's hurricane evacuation decision in order to construct a more precise and comprehensive evacuation decision model to ultimately better understand the decision to evacuate. Specifically, a household's evacuation decision is framed as an optimal stopping problem in which in each time period prior to the actual hurricane landfall, the household's choice is to either evacuate or to wait one more time period for a revised hurricane forecast. The optimal behavior is solved using a dynamic optimization problem in which the value function is approximated as a discrete function of the state variables with the computational methods employed allowing for tractability in the model. Using the National NHC issued forecast advisories, a vector of state variables and their associated probability distributions that convey all of the relevant track, intensity, and lead time risk information are constructed and utilized as a critical component of the dynamic programming model. The model is calibrated using actual hurricane forecast data from a number of storms as well as actual evacuation cost data.

Shadow evacuations and evacuation under-response are real problems for planners trying to develop a strategy to address an impending hurricane. Understanding the reasons for these problems is an important first step toward finding a solution to these problems. Our results suggest a surprising possible reason – because it is economically rational. The results presented here, which account for the uncertain lead time, are in-line with previous dynamic models that do not account for this uncertainty (Czajkowski, 2007; 2010; Kim and Bickel, 2010). Moreover, after conducting sensitivity analysis on the cost of evacuation, the patterns observed in our baseline findings remain. This suggests that the undesirable evacuation patterns appear to stem from the dynamic uncertainty that decision makers face when considering an approaching hurricane. An important area for future research then is to determine how policies might be developed to alter the individual decision problem so that private behavior coincides with the evacuation patterns that are socially desirable.

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TABLES

Table 1. 15 Coastal Gulf of Mexico Locations – County/Parish (Nearest Major City)

#	State	Locations
1	TX	Calhoun County (Port Lavaca / Port O Connor)
2		Brazoria County (Freeport)
3		Galveston County (Galveston)
4		Jefferson County (Port Arthur)
5	LA	Iberia Parish (New Iberia)
6		St. Charles Parish (New Orleans)
7		Plaquemines Parish (Buras)
8	MS	Harrison County (Gulfport)
9	AL	Mobile County (Mobile)
10	FL	Escambia County (Pensacola)
11		Bay County (Panama City)
12		Franklin County (Apalachicola)
13		Wakulla County (St. Marks)
14		Levy County (Cedar Key)
15		Hillsborough County (Tampa)

Table 2. 19 Identified Gulf of Mexico Storms

#	Year	Storm	Landfall CAT	Max CAT
1	2005	Arlene	0	0
2		Cindy	0	0
3		Dennis	3	4
4		Katrina	4	5
5		Rita	3	5
6	2004	Bonnie	0	0
7		Charley	4	4
8		Frances	0	4
9		Ivan	3	5
10		Matthew	0	0
11	2003	Claudette	1	1
12	2002	Lili	1	4
13	1998	Earl	1	2
14		Georges	2	4
15	1997	Danny	1	1
16	1995	Allison	1	1
17		Erin	1	1
18		Opal	3	4
19	1992	Andrew	3	5

Table 3: Evacuation Cost Regression Results

Variable	Coefficient Value	Robust Std. Err.	t value
24 hour distance	-2.44	1.83	-1.34
48 hour distance	-0.54	1.41	-0.38
72 hour distance	-1.82	1.23	-1.48
Contant	516.05	151.60	3.40

R^2= .01 *n*= 187

Table 4: Cost of Evacuation Sensitivity Analysis Evacuation Region Summary

	Lead Times					
Evacuation Cost	**12**	**24**	**36**	**48**	**72**	**96**
Baseline	CATs 1-5 all distances	▪ CAT 1: 75 -225 miles ▪ CAT 2: 75 – 275 miles ▪ CAT 3-5: 125 – 275 miles	N/A	N/A	▪ CAT 3:175 miles ▪ CAT 4: 225 – 275 miles	▪ CAT 4: 275 miles
Scenario 1 Less Decay	CATs 1-5 all distances	▪ CAT 2: 125 & 175 miles	▪ CAT 1 & 2: 225 & 275 miles	▪ CAT 1: 275 miles ▪ CAT 2: 225 & 275 miles	N/A	N/A
Scenario 2 More Decay	CATs 1-5 all distances	▪ CAT 2 & 3: 75 – 275 miles ▪ CAT 4 & 5: 125 – 275 miles	CATs 1-5: 75 – 275 miles	▪ CAT 1 & 2: 75 – 275 miles ▪ CAT 3: 125 – 275 miles ▪ CAT 4 & 5: 175 – 275 miles	N/A	N/A
Scenario 3 3rd Day Highest	CATs 1-5 all distances	▪ CAT 2: 25 -275 miles ▪ CAT 3-5: 75 -275 miles	▪ CAT 2: 25 -175 miles ▪ CAT 3: 75 -275 miles ▪ CAT 4&5: 125 – 275 miles	▪ CAT 2: 75 miles ▪ CAT 3: 75 -275 miles ▪ CAT 4: 125 – 175 miles ▪ CAT 5: 125-275 miles	▪ CAT 1: 225-275 miles	N/A
Scenario 4 Constant	CATs 1-5 all distances	CATs 1-5: 225-275 miles	CATs 2-5: 225-275 miles	CATs 2-5: 225-275 miles	N/A	N/A
Scenario 5 Higher Overall Baseline	▪ CAT 1: 0-125 miles ▪ CAT 2-5: all distances	▪ CAT 1: 175-275 miles ▪ CAT 2: 75-275 miles ▪ CAT 3: 25-275 miles ▪ CAT 4: 125-275 miles	N/A	N/A	▪ CAT 2 &3: 125 -275 miles	▪ CAT 2 &3: 175 - 275 miles

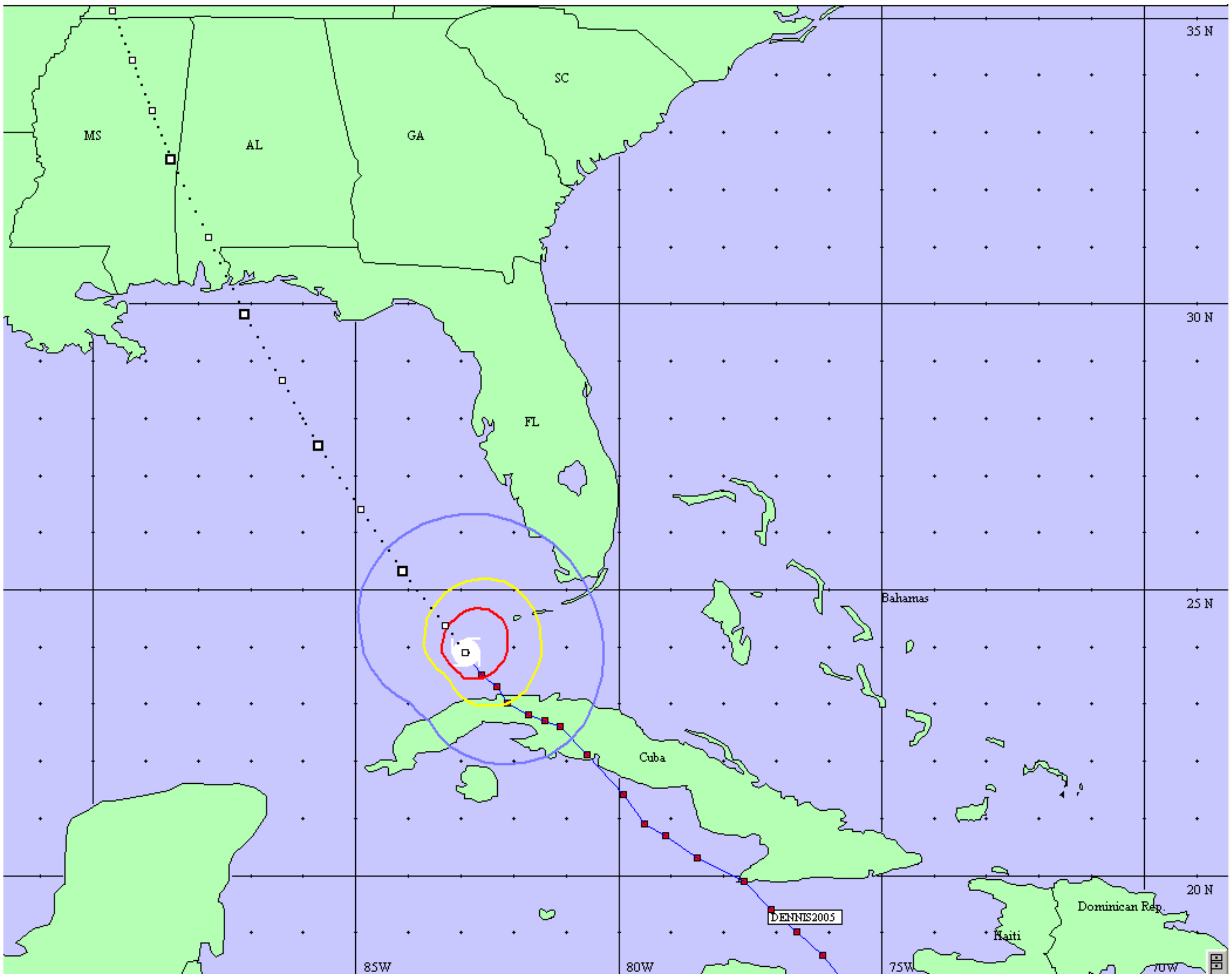
FIGURES

Figure 1: Hurricane Dennis Forecast Advisory #19 Text

```
                REPEAT...CENTER LOCATED NEAR 23.9N  82.9W AT 09/0900Z
                AT 09/0600Z CENTER WAS LOCATED NEAR 23.4N  82.5W

(12 hr)         FORECAST VALID 09/1800Z 25.3N  84.1W
                MAX WIND  90 KT...GUSTS 110 KT.
                64 KT... 55NE  35SE  20SW  30NW.
                50 KT... 90NE  75SE  30SW  55NW.
                34 KT...150NE 150SE  75SW 140NW.

(24 hr)         FORECAST VALID 10/0600Z 27.5N  85.7W
                MAX WIND 100 KT...GUSTS 120 KT.
                64 KT... 55NE  45SE  25SW  35NW.
                50 KT... 90NE  80SE  40SW  60NW.
                34 KT...150NE 150SE  80SW 150NW.

(36 hr)         FORECAST VALID 10/1800Z 29.8N  87.1W
                MAX WIND 110 KT...GUSTS 135 KT.
                64 KT... 55NE  45SE  25SW  35NW.
                50 KT... 90NE  80SE  40SW  60NW.
                34 KT...150NE 150SE  80SW 150NW.

(48 hr)         FORECAST VALID 11/0600Z 32.5N  88.5W...INLAND
                MAX WIND  45 KT...GUSTS  55 KT.
                34 KT... 75NE  75SE  50SW  50NW.

(72 hr)         FORECAST VALID 12/0600Z 36.0N  90.0W...INLAND
                MAX WIND  30 KT...GUSTS  40 KT.
```

(Source: Modified from NHC Advisory Archive)
KT = knots

Figure 2: Hurricane Dennis Forecast Advisory #19 Graphical Forecast



Note: the center of the storm is designated by the hurricane symbol approximately 70 miles north from the northern coast of Cuba. Each large white square represents the 12, 24, 36, and 48 forecast for this particular advisory.

(Source: HURREVAC)

Figure 3. Lead Time Forecast Markov Probability Transition Matrix

	96.01	96.02	96.03	96.04	96.05	96.06	72.01	72.02	72.03	72.04	72.05	72.06	72.07	72.08	72.09	72.1	72.11	72.12	48.01
96.01		83%					17%												
96.02			67%				34%												
96.03				50%			50%												
96.04					40%		60%												
96.05						30%	70%												
96.06							100%												
72.01								81%											19%
72.02									72%										19%
72.03										81%									19%
72.04											78%								22%
72.05												75%							25%
72.06													71%						29%
72.07														67%					33%
72.08															61%				39%
72.09																56%			44%
72.1																	50%		50%
72.11																		25%	75%
72.12																			100%
48.01																			

Figure 4: Intensity Forecast Markov Probability Transition Matrix

Cat Level

I_t \ I_{t+1}	**0**	**1**	**2**	**3**	**4**	**5**
0	100%	0%	0%	0%	0%	0%
1	11%	83%	6%	0%	0%	0%
2	0%	15%	60%	25%	0%	0%
3	0%	0%	4%	68%	28%	0%
4	0%	0%	0%	18%	79%	4%
5	0%	0%	0%	0%	50%	50%

Figure 5: Track/Distance Forecast Markov Probability Transition Matrix

Distance from a given point

D_t \ D_{t+1}	0	25	75	125	175	225	275
0	0.4%	30.0%	39.5%	19.8%	4.9%	3.7%	1.6%
25	15.0%	20.2%	24.9%	22.2%	11.7%	3.3%	2.7%
75	19.8%	24.9%	2.9%	16.9%	20.6%	9.9%	5.1%
125	9.9%	22.2%	16.9%	1.2%	15.0%	19.8%	15.0%
175	2.5%	11.7%	20.6%	15.0%	0.4%	15.0%	34.8%
225	1.9%	3.3%	9.9%	19.8%	15.0%	0.4%	49.8%
275	0.8%	1.9%	2.5%	9.9%	19.8%	15.0%	50.2%

Figure 6: Evacuation Costs for a CAT 3 Hurricane Varying by Distance and Lead Time

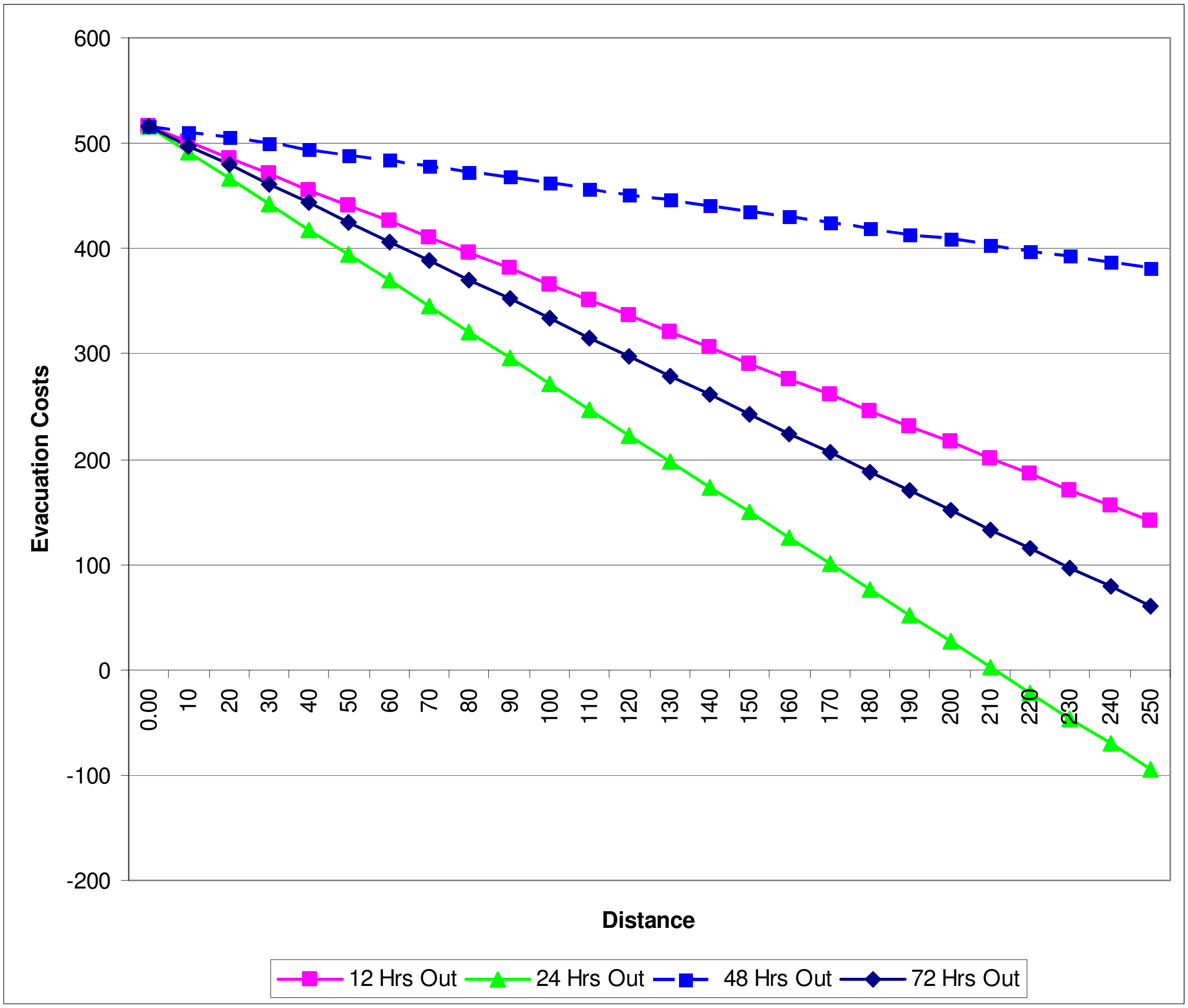


Figure 7: Expected Evacuation Region

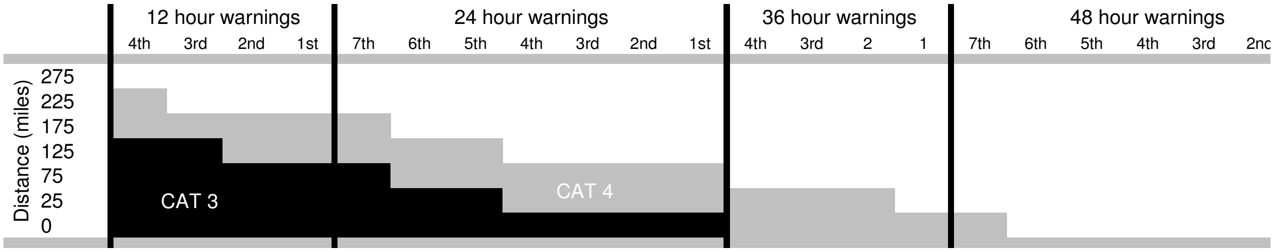


Figure 8: Baseline Evacuation Regions for All CAT levels

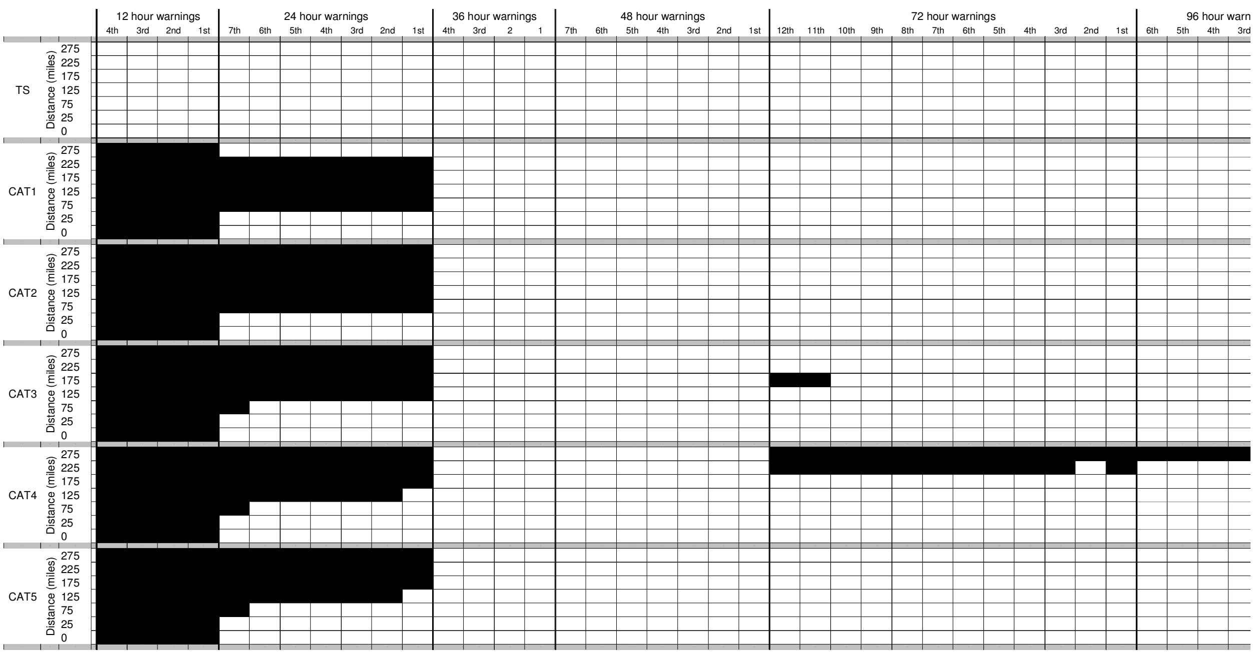


Figure 9: CAT 4 Evacuation Costs at Varying Distances and Days out from Landfall

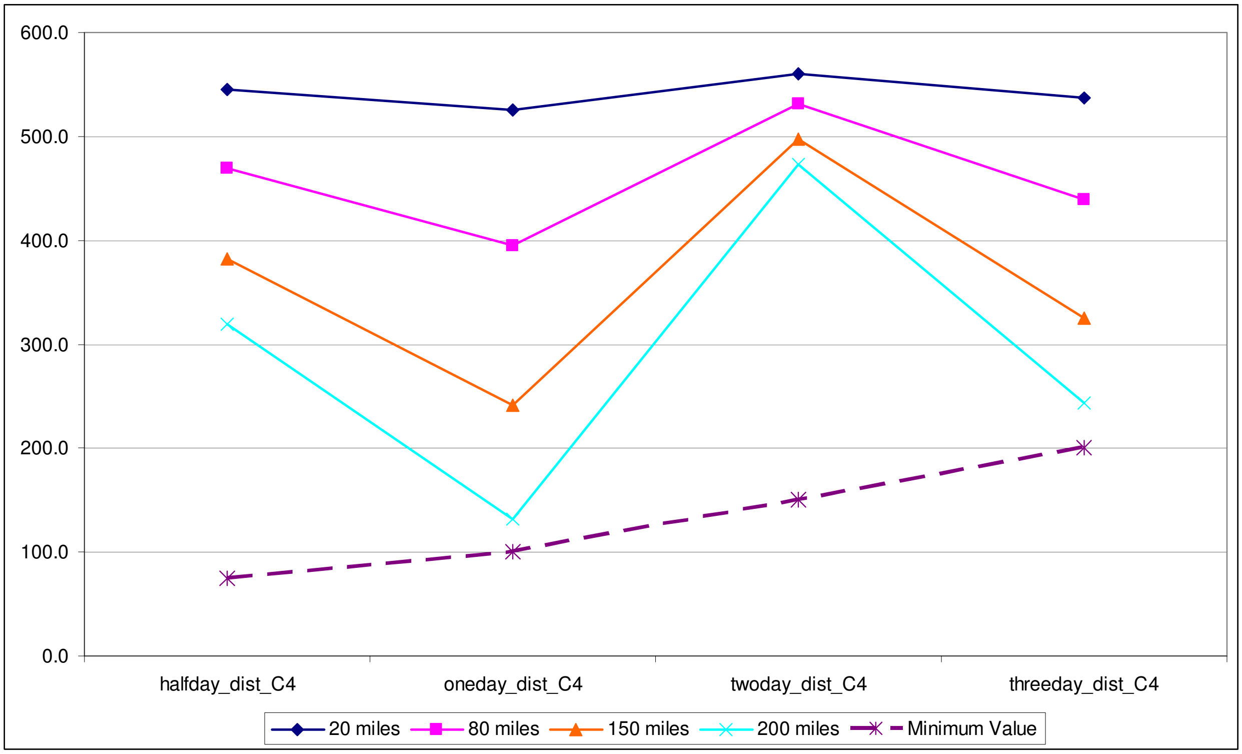


Figure 10: Varying CAT 4 Evacuation Cost Forms by Day at a location forecasted to be 80 miles from Landfall