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ORIGINAL PAPER

Strike probability judgments and protective action recommendations in a dynamic hurricane tracking task

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Abstract This experiment assessed the strike probability (p_s) judgments and protective action recommendations (PARs) of students playing the roles of county emergency managers during four different hurricane scenarios. The results show that participants' p_s judgments (1) increased for target cities (projected landfall locations) and generally decreased for adjacent cities and remote cities as hurricanes approached landfall, and (2) were significantly correlated with PARs, but (3) were not consistent with the requirement that $\Sigma p_s < 1.0$ for a set of non-exhaustive events. Participants also (4) chose more PARs as hurricanes approached landfall, especially for the counties to which they participants were assigned, but (5) failed to choose as many PARS as appropriate, especially evacuating areas at risk of hurricane impacts. Overall, the results suggest that participants were able to utilize the available hurricane information to make reasonable p_s judgments, but failed to make the appropriate inferences about the significance of those p_s judgments. This suggests a need for further research on people's interpretation of threat information, development of better training manuals on hurricane evacuation decision making, and better hurricane information displays to guide people's responses to hurricane threats.

Keywords Hurricane tracking · Hurricane strike probability · Protective action recommendations · Hurricane evacuation

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1 Introduction

Effective hurricane evacuations are important because thousands of lives are at risk in major urban areas. There has been a substantial amount of social science research on hurricane evacuation behavior, but most studies have been post-storm surveys of people's risk perceptions and evacuation decisions (Baker 1991; Huang et al. 2015). This research has identified many valuable principles that can be used to design evacuation warnings, but these studies necessarily rely on people's *retrospective* reports of the extent to which they relied on different types of information in making their evacuation decisions. By contrast, experiments can capture *concurrent* measurements of people's information processing. Moreover, post-storm surveys are necessarily limited to conditions that did occur, whereas experiments can examine conditions that have not yet occurred but might occur in the future. Finally, past hurricane evacuation studies have focused on the decision processes of risk area residents but overlooked those of local officials. This is an important oversight because risk area residents tend to rely substantially on local officials' protective action recommendations—PARs (Baker 1991, 1995; Huang et al. 2015; Lin et al. 2014). The types of information available to local officials are well understood; the National Hurricane Center (NHC) and regional Weather Forecast Offices (WFOs) provide information about a hurricane's current status—including location, intensity (Saffir–Simpson category), and size (radius of tropical storm wind)—and likely future behavior (e.g., forecast track, uncertainty cone, storm surge, and rainfall). Unfortunately, it is unclear how local officials integrate this information about storm behavior with their counties' evacuation time estimates (ETEs) in order to decide whether and when to issue evacuation orders (Baker 2000; Lindell 2008, 2013; Murray-Tuite and Wolshon 2013)—a process that can be modeled as a dynamic decision in which the long periods of forewarning for most hurricanes allow decision makers to periodically update their threat perceptions and their PARs (Czajkowski 2011). Specifically, local officials should initiate evacuations everyplace that is likely to be affected by wind, storm surge, and inland flooding of that storm's intensity (i.e., the hurricane risk area). Moreover, these evacuations should be initiated soon enough to clear the risk area before arrival of these storm conditions (the evacuation deadline). For example, the evacuation deadlines presented in hurricane ETE tables for some Texas counties range from 15 h for a Category 1 hurricane to 33 h for a Category 5 hurricane (Lindell et al. 2002).

This article begins by introducing the protective action decision model (PADM—Lindell and Perry 2004, 2012) as a theoretical framework for addressing hurricane threat perceptions and protective actions and continues with a review of previous experiments on hurricane evacuation decision making that leads to five research hypotheses and five research questions. The following section explains the methods by which experiment participants were provided with numeric (storm parameters), graphic (tracking maps), and verbal (NHC/WFO watch and warning) information and asked to report strike probability (p_s) judgments and PARs after each of six forecast advisories in a series of four different hurricane scenarios. The presentation of results is followed by a discussion of their significance and an examination of study limitations.

2 Literature review

Lindell and Perry (2012) proposed a revised version of the PADM that explains how people decide how to respond in an emergency. The information flow in this model starts with observations of environmental/social cues and receipt of information from social sources such as authorities, news media, and peers (Arlikatti et al. 2007; Lin et al. 2014). The PADM also proposes that—after being received, heeded, and comprehended—this information produces perceptions of the stakeholders, threats, and protective actions. In turn, these perceptions produce protective action decisions that, depending upon the effects of facilitating and inhibiting conditions, result in behaviors such as information seeking, protective action, or emotion-focused coping. The role of information seeking is particularly important when a threat is believed to be imminent but not immediate and potentially severe but uncertain with respect to the location, severity, and timing of impact. Thus, decision makers seek updated information and might engage in an increasing number of preparedness activities as a storm approaches. Of particular interest for this study is an examination of the effects of hurricane information on participants' p_s judgments and PARs.

To date, few experiments have examined hurricane threat perceptions or protective action decisions. Christensen and Ruch (1980) studied 24 Galveston Island residents by providing a series of forecast advisories that described the hurricane's behavior at 6-h intervals. Similar to NHC forecast advisories (see www.nhc.noaa.gov), each forecast advisory provided information about the hurricane's current location, track, forward movement speed, and maximum wind speed. In response to each forecast advisory, participants decided which protective action to take—ranging from wait for further information (=1) to evacuate immediately (=10). The researchers found that participants' protective actions escalated as the storm approached landfall.

Baker (1995) conducted a study of hurricane protective action decisions with 400 Pinellas County, FL residents. He provided four threat cues (storm location, wind speed, hurricane watch/warning, and local officials' evacuation action) and hurricane strike probabilities ($p_s = 50$, 30, 10 %, or none). Consistent with survey study findings, he concluded that participants' evacuation expectations were strongly affected by local officials' PARs.

Wu et al. (2014) conducted a study of p_s judgments in which participants viewed eight hurricane tracking maps (4 hurricane directions $\times$ 2 intensities) plus one hurricane map showing hurricane location only. As a between-subject manipulation, each group received a different type of information display—forecast track only, uncertainty cone only, and forecast track and uncertainty cone. Participants were asked to make p_s judgments for the eight cardinal and ordinal directions (north, northwest, …, northeast) from the center of each hurricane, which resulted in p_s distributions that were unimodal and centered on the direction that the hurricane forecast track/uncertainty cone was pointed. Moreover, participants' p_s judgments steadily decreased as the angle from the hurricane direction increased, and they assigned nonzero p_s values to the direction that was exactly opposite to forecast track/uncertainty cone. Although the participants provided qualitatively appropriate p_s distributions, the values of Σp_s over the eight sectors were consistently greater than 1.0—the normatively appropriate value for a set of mutually exclusive and exhaustive categories.

Meyer et al. (2013) examined information search processes with their *Stormview* laboratory that allows experiment participants to use a "virtual living room" to search for information from simulated television, radio, newspaper, Internet, and peer channels as a hurricane approaches. Consistent with Christensen and Ruch's (1980) findings, Meyer and his colleagues found that *Stormview* participants' expectations of being struck by the hurricane, levels of worry, and number of protective actions increased over time. However, those who viewed uncertainty cones with track forecasts expected to take more protective actions than those who saw only uncertainty cones, no matter how close they were to the forecast point of landfall.

Finally, Wu et al. (2015) examined the information search patterns of university students taking the roles of emergency managers determining which PARs to implement in coastal counties. After reading the *Local Official's Guide to Making Hurricane Evacuation Decisions*[1] (Lindell et al. 2008) to provide them with basic knowledge about hurricanes and appropriate protective actions, participants were assigned to two different coastal counties and participated in a process tracing study in which they could select which numeric (hurricane parameter table), graphic (hurricane tracking map), and verbal (NHC watches and warnings) display elements to view in each of six different forecast advisories about four different hurricane scenarios. The study found that participants (1) had higher click counts and click durations on the (verbal) NHC watch/warning message box than on the numeric hurricane parameter table or the graphic hurricane tracking map. Within the numeric hurricane parameter table, there were higher click counts and click durations on hurricane intensity than on the other hurricane parameters as well as higher click counts and click durations on the current day's value and the 5-day forecast than on the other forecast horizons. Moreover, within the graphic hurricane tracking map, they had higher click counts for the forecast track than for the uncertainty cone but had higher click durations for the uncertainty cone than for the forecast track and also had higher click counts and click durations for the 5-day forecast than for the other forecast horizons.

In summary, previous experiments have shown that people are capable of using different types of information to make p_s judgments in static decision tasks (Baker 1995; Wu et al. 2012). In addition, people increase their protective actions as a hurricane approaches (Christensen and Ruch 1980; Meyer et al. 2013). However, most of the experiments collecting p_s judgments have ignored PARs and vice versa. Moreover, most of these studies have only examined the effects of a limited amount of hurricane information on responses at a single coastal location.

The limitations of previous hurricane experiments can be addressed by a dynamic hurricane tracking task—the procedure used by Wu et al. (2015) in which participants were seated at workstations where they were provided with the basic information an emergency manager would need to track an approaching hurricane and issue PARs. They began by reading the *Official's Guide* to ensure they had basic knowledge about hurricane evacuation decisions and were provided with a risk area map that identified which portions of their county were exposed to hurricane wind, storm surge, and inland flooding. At the time the study was conducted, the state of Texas divided most coastal counties into five risk areas, with Risk Area 1 being the area exposed to any hurricane that was Category 1 or greater and Risk Area 5 being the area exposed only to a Category 5 hurricane. The workstation also included an ETE table that displayed the time required to evacuate each of the county's risk areas. Participants were assigned to EOCs in two different counties to ensure that their reactions to the hurricane scenarios were not determined by the unique characteristics of a specific coastal location. Each participant viewed four hurricane scenarios, each of which was defined by six forecast advisories. At each forecast advisory, participants could search tables of numerical hurricane parameters such as the storm's distance from possible points of landfall, its intensity, and its forward movement speed. The parameter table provided information about the storm's current status as well as at forecast horizons ranging 1–5 days. Each forecast advisory also included a tracking map that presented the storm's current location, as well as its past track, forecast track, and uncertainty cone over forecast horizons ranging 1–5 days. Finally, each forecast advisory included a text box containing any NHC/WFO watches and warnings. Wu et al. (2015) analyzed participants' information search processes, but did not examine how participants integrated the information they obtained into p_s judgments for different cities around the

[1] A copy of the *Local Official's Guide* is available from the first author.

Gulf of Mexico or the PARs they would choose for their own county. These latter data are addressed here.

3 Research hypotheses and research questions

This experiment employs two within-subject manipulations (multiple forecast advisories and multiple hurricane scenarios) and two between-subject manipulations (multiple hurricane sequences and different decision-maker locations). Multiple forecast advisories are needed because hurricanes change characteristics such as their intensity over time. Consequently, researchers need to understand how threat perceptions and PARs change as hurricanes approach landfall. In addition, it is important to assess how threat perceptions and PARs differ for a *target city* (the city toward which the storm is traveling), an *adjacent city* (one of the two reference cities on either side of the target city—a "near miss"), or a *remote city* (any of the reference cities farther away than the adjacent cities—a "far miss").

Multiple hurricane scenarios are needed to verify that results are not limited to a single set of storm conditions, a limitation of Christensen and Ruch (1980). Moreover, multiple hurricane sequences are needed to detect order effects because research suggests that anchoring and adjustment could cause participants' responses to a near miss that was preceded by a hit to differ from their responses to a near miss preceded by a "far miss" (Kahneman and Tversky 1979) and to avoid confounding the characteristics of individual hurricanes with participants' learning from their experience in successive hurricane scenarios. Participants need to be assigned to multiple target counties to preclude the possibility that p_s judgments and PARs are influenced by the specific characteristics of a given coastal location. These experiment design features, together with the findings and limitations of previous research, lead to five research hypotheses (RHs) and five research questions (RQs).

- RH1 Participants' p_s judgments for target cities will start at a moderately high level and increase over forecast advisories as each hurricane approaches landfall
- RH2 Participants' p_s judgments for adjacent cities will start at a moderately high level and decrease over forecast advisories as each hurricane approaches landfall
- RH3 Participants' p_s judgments for remote cities will start at a low but nonzero level and remain low over forecast advisories as each hurricane approaches landfall

The first three RHs test the generalizability of the findings from Wu et al. (2014), which assessed p_s values for different sectors around the Gulf of Mexico, but only at a single point in time for hurricanes that were approximately 600 miles from landfall. Support for RH 1–3 will indicate that participants' risk perceptions change as a result of the information they obtained in the information search phase of the experiment.

- RH4 PARs will increase over forecast advisories as each hurricane approaches landfall, but participants will implement more PARs when the projected landfall location is their own county than when the projected landfall location is farther away

The first part of the RH4 tests the replicability of Christensen and Ruch's (1980) research findings, which only examined reactions to a single hurricane that was approaching the participant's location. The second part of RH4 tests whether participants assign PARs in a different way when a hurricane is tracking elsewhere.

- RH5 The number of PARs will be positively correlated with respondents' p_s judgments for their counties

As noted earlier, previous hurricane experiments have assessed participants' p_s judgments or their protective actions but not both. RH5 is a basic proposition of the PADM, which hypothesizes that people's protective action decisions are determined by their perceived risk, has not previously been tested in any of the hurricane experiments conducted to date.

RQ1 Will $\Sigma p_s \leq 1$, since the six reference cities are not an exhaustive list of all possible points of landfall even though they are mutually exclusive?

RQ1 tests the replicability of results from Wu et al. (2014), which found that—contrary to the tenets of probability theory—$\Sigma p_s > 1$ for a set of mutually exclusive and exhaustive sectors around the Gulf of Mexico.

RQ2 Will participants activate the local Emergency Operations Center (EOC) after the first forecast advisory in each hurricane scenario?

RQ3 What percentage of participants will follow the instructions in the *Official's Guide* by evacuating the appropriate number of risk areas before the ETE deadline?

RQ2 and RQ3 examine whether participants follow two essential PAR principles listed in the *Official's Guide*. Activation of the EOC is important because it is the location from which local officials monitor hurricanes and issue PARs. Evacuating the appropriate number of risk areas before the ETE deadline provides reasonable assurance that local residents will be protected from hurricane wind and storm surge.

RQ4 Will participants issue a different number of PARs after their last hurricane scenario than after their first hurricane scenario?

RQ4 examines whether participants change their PAR judgment strategies over a series of hurricane scenarios, just as Wu et al. (2015) found they changed their information search strategies. It is unclear whether this will happen because they did not receive feedback about whether they have made a decision error (e.g., failed to recommend an evacuation as soon as they should or as extensively as they should).

RQ5 Will participants' demographic characteristics—age, gender, permanent residence, hurricane experience, or evacuation experience—account for differences in their judgments of p_s and PARs?

This RQ will examine whether demographic characteristics that have been found in some previous studies to be correlated with risk perceptions or evacuation decisions in actual evacuations influence in risk perceptions and protective action decisions in an experiment.

4 Method

4.1 Experimental design

This experiment is a four-factor mixed design. Hurricane scenario has four levels, forecast advisory has six levels, scenario sequence has four levels, and EOC location has two levels. For the within-subject design, there were four different hurricane scenarios that varied in their target (projected landfall location). The target for Hurricane A was Brownsville; the target for Hurricane B was Port Arthur; the target for Hurricane C was a point just north of

Corpus Christi, which is roughly 300 mi. (500 km) southwest of Port Arthur; and the target for Hurricane D was New Orleans, which is just over 250 mi (400 km) east of Port Arthur. Each of the four hurricanes had six different forecast advisories that described the hurricane traveling in a straight line progressively closer to the coast.

For the between-subject design, there were four different sequences in which the hurricane scenarios were presented so as to control order effects (Sequence 1 = CADB; Sequence 2 = ABCD; Sequence 3 = DCBA; and Sequence 4 = DBAC). In addition, participants were randomly assigned to play the role of an Emergency Management Coordinator in the EOC for either the Cameron County TX (Brownsville, the landfall for Hurricane A) or Jefferson County TX (Port Arthur, the landfall for Hurricane B). All hurricanes originated at points approximately 750 mi. (1200 km), which was 144 h. of travel time from the US Gulf coast, and had approximately the same average forward movement speed, radius of hurricane wind, and radius of tropical storm wind.

There were two sets of dependent variables (DVs) for this study. The first set of DVs comprised the p_s judgments for six reference cities located at roughly equal distances (approximately 200–300 miles) around the Gulf of Mexico—Tampa, Apalachicola, New Orleans, Beaumont/Port Arthur, Brownsville, and Tampico. Brownsville is the location of the Cameron County EOC (to which one half of the participants were assigned), and Beaumont/Port Arthur is the location of the Jefferson County EOC (to which the other half of the participants were assigned). Participants were asked to provide p_s judgments on a scale of 0–100 % for each of the six reference cities.

The second set of the DVs consisted of 11 PARs that emergency managers commonly issue in response to approaching hurricanes (see Lindell 2013). These PARs, which were generally described in the *Official's Guide*, are (1) activate the EOC, (2) activate the emergency alert system (see http://en.wikipedia.org/wiki/Emergency_Alert_System), (3) advise beach motel/hotel businesses of the potential storm, emergency evacuation may be required, (4) recommend schools to close tomorrow, (5) recommend immediate activation of public shelter (where people can stay while evacuating), (6) recommend immediate evacuation of the following residents: people with special needs, people without transportation, tourists, mobile homes, and recreational vehicles, (7) recommend immediate evacuation Risk Area 1—the area at risk from a Category 1 hurricane, (8) recommend immediate evacuation of Risk Area 2, (9) recommend immediate evacuation of Risk Area 3, (10) recommend immediate evacuation of Risk Area 4, and (11) recommend immediate evacuation of Risk Area 5—the area at risk from a Category 5 hurricane. After each forecast advisory, participants clicked a radio button indicating whether they would (=1) or would not (=0) issue each of these PARs.

4.2 Procedure

This research was performed in a laboratory setting using 80 volunteers recruited from Texas A&M University, each of whom was paid $20 for participating in the experiment. In accordance with an approved IRB protocol, the experimenter posted recruiting flyers on bulletin boards and personally distributed them on campus. The recruiting process continued until 80 participants successfully completed the experiment.[2]

[2] After each participant finished the experiment, the experimenter checked to see whether she had finished all the tasks properly. If not, the data were deleted and the same experimental condition was assigned to the next available participant. In total, 98 participants took part in the experiment; 80 of them completed it successfully.

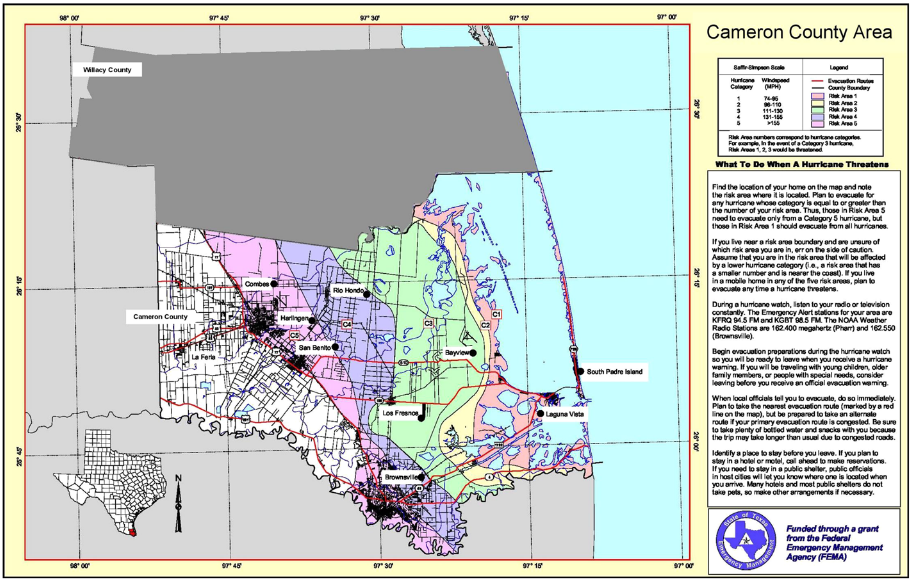

Fig. 1 Cameron County risk area map

Each participant was assigned to one of the eight (4 hurricane sequences × 2 EOC locations) between-subject conditions using a systematic random assignment method that increased the probability of assignment to each condition in proportion to the number of remaining slots in that condition. Before the participants began, the experimenter displayed four documents in each participant's workstation. These were (1) a sign identifying which county EOC the participant represented; (2) a hurricane ETE table for that county from Lindell et al. (2002), (3) a hurricane risk area map for that county (see Fig. 1 for the Cameron County map), and (4) a map showing all US counties bordering the Gulf of Mexico. Half of the participants saw the display documents for the Cameron County EOC; the other half of the participants saw the display documents for the Jefferson County EOC. All participants saw the same Gulf of Mexico counties map. These documents were posted on the walls of each workstation throughout the experiment. Once the participants were seated, they were asked to read the 12 page *Local Official's Guide to Making Hurricane Evacuation Decisions* (*Official's Guide*) and took the 43 item *Hurricane Knowledge Test* (*HKT*) before the experiment (Lindell et al. 2008). Reading the *Official's Guide* allowed participants to acquire basic knowledge about hurricanes and appropriate PARs for coastal counties; taking the *HKT* assessed their knowledge of the material in the *Official's Guide*. In particular, the *Official's Guide* indicated that participants should "take a number of actions such as activating the community Emergency Operations Center as soon as a hurricane forms in the Gulf of Mexico or moves into it from the Atlantic Ocean or Caribbean Sea." In addition, they should recommend evacuation of the same number of risk areas as a hurricane's forecast intensity at landfall. That is, Risk Areas 1–4 should be evacuated for a Category 4 hurricane.

After participants read the *Official's Guide* and took the *HKT*, the experimenter gave them a city classification sheet, which was used along with the hurricane risk area map in Fig. 1 to identify the cities within their assigned counties. This task was intended to ensure that each participant was able to recognize their assigned county's locations on the *DynaSearch* hurricane tracking maps and to pay attention to the differences among their county's risk areas. After completing these preliminary tasks (*Official's Guide*, *HKT*, and city identification), participants began the hurricane tracking experiment using *DynaSearch*, a program developed by the Texas A&M University Hazard Reduction and Recovery Center in conjunction with Clemson University Savage Visualization Laboratory (Lindell et al. in preparation).

When the participants first logged into the *DynaSearch* Program, they viewed a video clip explaining how to operate the system. Next, *DynaSearch* presented the participants with four different hurricanes scenarios, each of which had six forecast advisories. There were slight variations from one forecast advisory to the next in order to simulate the changing behavior of actual hurricanes. However, all four hurricane scenarios had the same pattern of change in hurricane intensity over forecast advisories. Each forecast advisory in this experiment represented a single day rather than the 6-h period that the NHC forecast advisories represent. This 1-day time interval was used in order to move the hurricane scenarios at a pace that seemed likely to maintain participants' interest. The first forecast advisory was 7 days before hurricane landfall, and the sixth forecast advisory was 1 day before hurricane landfall. Each hurricane forecast advisory provided the hurricane's current information as well as the forecast information for the following 5 days. *DynaSearch* displayed a hurricane parameter table, a hurricane tracking map, and an NHC watch/warning message box on a single forecast advisory screen (Fig. 2). The parameter table provided information about hurricane distance to Port Isabel (the nearest point on the coast to the Cameron County EOC), hurricane distance to Sabine Pass (the nearest point on the coast to the Jefferson County EOC), hurricane forward movement speed (changes ranged from 1.24 to 8.33 mph), hurricane intensity (intensities were tropical storm, Category 2 hurricane, Category 5 hurricane, Category 4 hurricane, Category 3 hurricane, and finally tropical depression), and hurricane wind size (changes ranged 0–180 mile radius). The changes in hurricane parameters other than center location were adapted from Hurricane Katrina (see www.nhc.noaa.gov/archive/2005/KATRINA.shtml?). The hurricane tracking map showed a hurricanes' current location, past track, forecast track, and uncertainty cone. Finally, the text message box showed hurricane watch/warning messages for counties.[3] This interactive hurricane forecast advisory screen was adapted from the typical text and graphic hurricane information typically provided by the NHC (2014). Unlike NHC forecast advisories, the *DynaSearch* forecast advisories provided a limited amount of information in a single screen. Participants clicked on a blank cell in the table or on the text messages box to reveal the hidden information. Similarly, they click on the map legend elements to see the map features. Participants had as long as 5 min to view the information on each forecast advisory screen, although they could proceed to the next screen when they were finished with their information search. Next, *DynaSearch* elicited participants' p_s judgments for six locations around the Gulf of Mexico and their choices of as many as 11 PARs for the county to which they were assigned. The participants used the keyboard to type in p_s judgment for each city, scrolled down the screen to click on their PAR choices, and

[3] The following is an example of warning/watch warning messages provided to experiment participants. This is modified from NHC's official hurricane warning/watch messages—"*A HURRICANE WATCH IS IN EFFECT FROM CAMERON COUNTY, TX TO OKALOOSA COUNTY, AL. A HURRICANE WATCH MEANS THAT HURRICANE CONDITIONS ARE POSSIBLE WITHIN THE WATCH AREA GENERALLY WITHIN 36 HOURS.*"

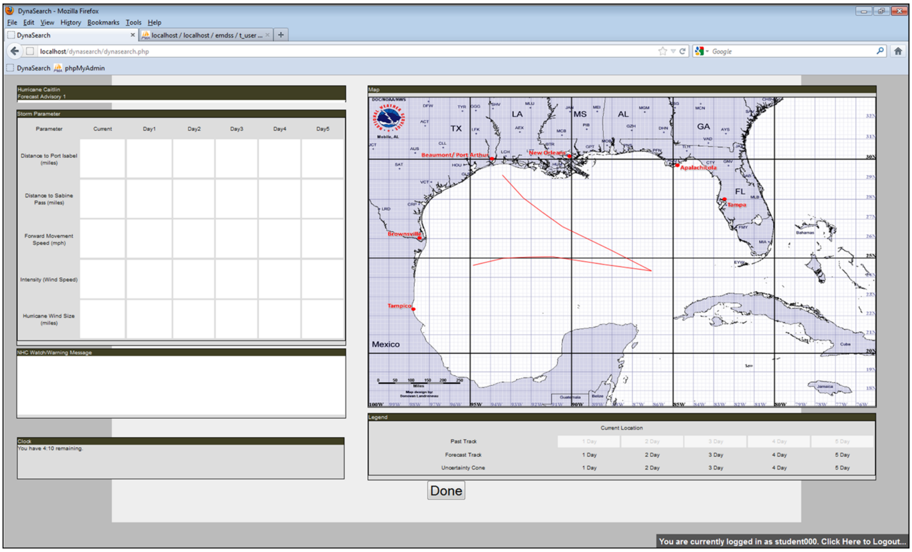

Fig. 2 *DynaSearch* display—Hurricane Forecast Advisory Screen. This forecast advisory screen shows the result of a participant clicking on the map legend element for the “5-day uncertainty cone” (see the two diverging *red lines* in the middle of the Gulf of Mexico). A PowerPoint presentation of this hurricane forecast advisory screen is available at https://www.researchgate.net/publication/268091187_Perceptions_on_Hurricane_Information_and_Protective_Action_Decisions

clicked a “Submit” button to go to the next forecast advisory. Unlike the forecast advisory screen, participants had unlimited time to assign p_s and PARs; however, they were prevented from returning to any previous screen. The experiment concluded with collection of data on four demographic variables—years of education, gender, hometown (high school location), and citizenship—and three questions about hurricane experience—personal loss, property loss, and evacuation.

4.3 Analytic method and sample size

Multivariate analysis of variance (MANOVA) was used as a preliminary test of the differences among conditions. This was followed by analysis of variance (ANOVA) for RH1–RH4; Pearson’s correlation was used for RH5; Student’s t test was used for RQ1, EQ3, and RQ5; χ^2 tests were used for RQ2 and RQ4. To determine sample size, $\alpha = .05$, $\beta = .20$, and the Hair et al. (2009) sample size range tables indicated $14 \le N \le 23$ would be appropriate. The 24 repeated measures (4 hurricane scenarios × 6 forecast advisories) provided increased power to detect even a moderate effect size (Cohen 1992).

5 Results

5.1 Participants

The participants had an average age of 24.9 years, with 3.8 % being younger than 20 years old, 85.0 % in their 20s, 7.5 % in their 30s, and 3.8 % over 39. With respect to gender, 48.8 % were male and 51.3 % were female. They were highly educated—2.5 % freshmen, 5.0 % sophomores, 8.8 % juniors, 22.5 % seniors, and 56.3 % graduate students (5.0 % did not respond to this item). With respect to citizenship, 45.0 % were international students and 55.0 % were US citizens (none of them from Cameron County or Jefferson County). Only 25.0 % had hurricane evacuation experience, 10.0 % reported personal injury, and 23.8 % reported property damage.

5.2 Research hypotheses

Consistent with RH1 (strike probability judgments for target cities will increase over forecast advisories as each hurricane approaches landfall), the p_s judgments for each target city (the ones at which the hurricanes made landfall) increased significantly over forecast advisories for Hurricanes A (Brownsville, Fig. 3, $F_{5,\ 395} = 26.95$, $p < .01$), B (Port Arthur, Fig. 4, $F_{5,\ 395} = 14.69$, $p < .01$), and D (New Orleans, Fig. 5, $F_{5,\ 395} = 47.15$, $p < .01$).

Consistent with RH2 (strike probability judgments for adjacent cities will decrease over forecast advisories as each hurricane approaches landfall), the p_s for the adjacent cities (those on either side of the target city) generally decreased over time, especially for Hurricane A/Brownsville. In Fig. 4 (Hurricane B/Port Arthur), the mean p_s for New Orleans did not decline until FA6. Conversely, Fig. 5 (Hurricane D/New Orleans) shows that the mean p_s for Port Arthur did not decline at all. The target city for Hurricane C was Corpus Christi (Fig. 6), which was not a city to which the participants could assign strike probabilities, but the p_s for the adjacent cities (Brownsville and Port Arthur) both declined over the six forecast advisories—although the participants did provide significantly ($F_{1,\ 79} = 78.56$, $p < .05$) higher p_s for Brownsville than Port Arthur during FA2–FA6.

Consistent with RH3 (strike probability judgments for remote cities will be small but nonzero and remain low over forecast advisories as each hurricane approaches landfall), participants assigned small but nonzero strike probabilities to remote cities (cities farther away from the target city than the adjacent cities). For example, in Hurricane A/Brownsville (Fig. 3), the mean p_s for Tampa, Apalachicola, and New Orleans (the remote cities for this hurricane scenario) was lower than the mean p_s for Port Arthur and

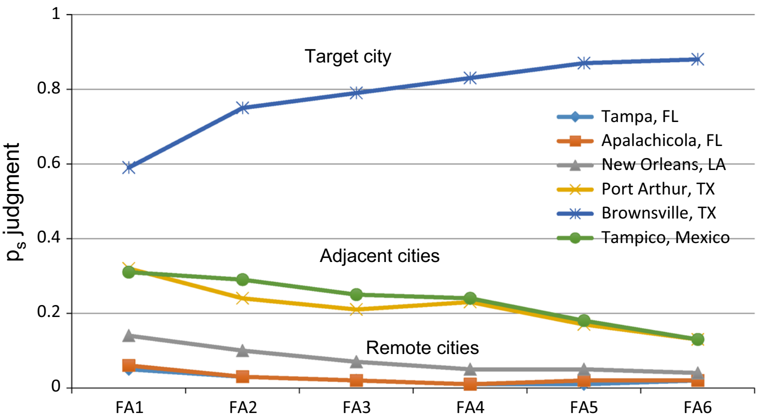

Fig. 3 Mean p_s for hurricane A (Brownsville)

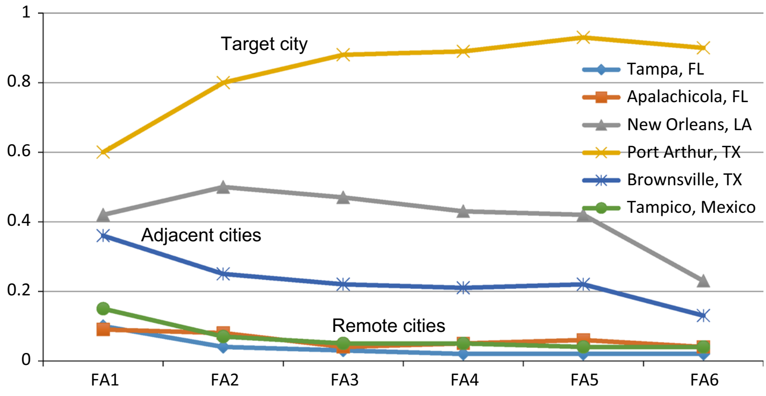

Fig. 4 Mean p_s for hurricane B (Port Arthur)

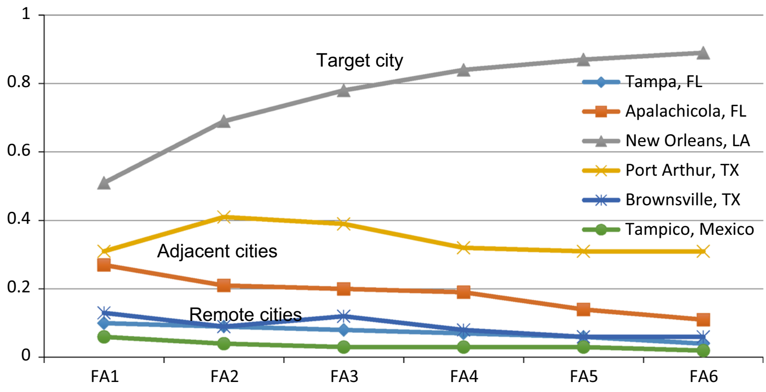

Fig. 5 Mean p_s for hurricane D (New Orleans)

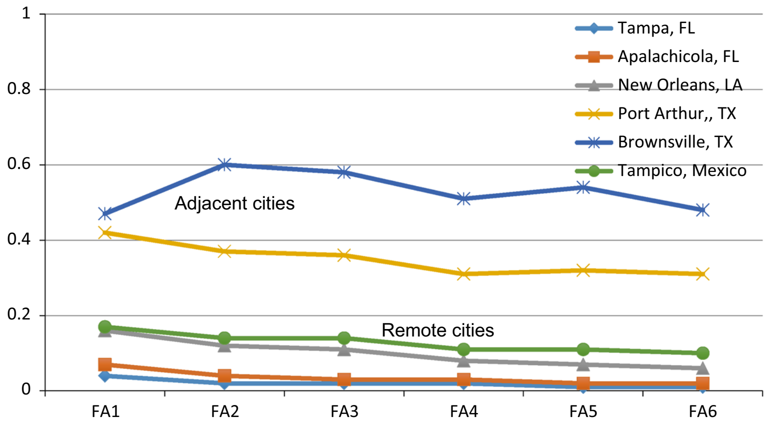

Fig. 6 Mean p_s for hurricane C (Corpus Christi)

Tampico (the adjacent cities for this hurricane scenario) in all six of the forecast advisories ($F_{4,\ 316} = 86.32$, $p < .01$).

Consistent with RH4 (PARs will increase over forecast advisories as each hurricane approaches landfall, but participants will implement more PARs when the projected landfall location is their own county than when the projected landfall location is farther away), Table 1 shows that the relationship between hurricane scenarios and forecast advisories was significantly different between the participants assigned to the Cameron County EOC and those assigned to the Jefferson County EOC ($F_{15,1170} = 6.31$, $p < .01$). Participants assigned to both counties significantly increased their PARs over the six forecast advisories for all four hurricane scenarios ($F_{15,1170} = 2.41$, $p < .01$). However, analysis of Hurricanes A and B revealed a significant forecast by county interaction in which the increase in PARs for Hurricane A (Brownsville landfall) was greater for those assigned to the Cameron County EOC—from 2.75 to 8.25—than for those assigned to the Jefferson County EOC—from 1.76 to 4.29 ($F_{1,78} = 7.17$, $p < .01$). This pattern was reversed in Hurricane B (Port Arthur landfall), where the increase was greater for those assigned to the Jefferson County EOC—from 2.53 to 8.36— than for those assigned to the Cameron County EOC—from 1.76 to 3.30($F_{1,78} = 19.14$, $p < .01$). For Hurricane C (Corpus Christi landfall), there was a significant effect for forecast advisory but not county or forecast advisory by county because PARs increased by roughly the same amount in both counties—from 1.65 to 4.40 for those assigned to the Jefferson County EOC and from 2.53 to 6.16 for those assigned to the Cameron County EOC ($F_{1,78} = .81$, *ns*). For Hurricane D (New Orleans landfall), there were nonsignificant effects for forecast advisory and county ($F_{1,78} = 6.53$, *ns*) but not forecast advisory by county because PARs increased more for those assigned to the Jefferson County EOC (from 1.43 to 4.62) than for those assigned to the Cameron County EOC (from 1.10 to 1.87).

RH5 (the number of PARs will be positively correlated with respondents' p_s judgments for their counties) was supported by data, showing that p_s judgments were positively correlated with mean PARs (average $r = .40$ for those assigned to the Cameron County EOC and .53 for those assigned to the Jefferson County EOC). All six correlations were significant for those assigned to the Jefferson County EOC, but only four of them were significant for those assigned to the Cameron County EOC. The two nonsignificant correlations were for Forecast Advisories 4 ($r = .29$) and 5 ($r = .25$) for those assigned to the Cameron County EOC.

5.3 Research questions

The *t*-test results for RQ1 (Will $\Sigma p_s \leq 1$, since the six reference cities are not an exhaustive list of all possible points of landfall even though they are mutually exclusive?) indicate that, among the 24 advisories (4 hurricane scenarios x 6 forecast advisories per hurricane scenario), 21 of them produced Σp_s that significantly ($p < .05$) exceeded 1.0. Interestingly, $\sum p_s$ decreased from Forecast Advisory 1 to Forecast Advisory 6 for Hurricanes A ($M = 1.48$ vs. 1.21, Cohen's $d = .79$, $t = 3.02$, $p < .01$), and C ($M = 1.32$ vs. .98, $d = .99$, $t = 3.07$, $p < .01$), but not for Hurricane B ($M = 1.72$ vs. 1.35, $d = 2.56$, $t = 1.27$, *ns*) or Hurricane D ($M = 1.38$ vs. 1.42, $d = .83$, $t = -.43$, *ns*).

Regarding RQ2 (Will participants activate the EOC on the first forecast advisory in each hurricane scenario?), the results indicate that not all participants did so. However, the percentage of the participants who activated the EOC after the first forecast advisory increased from the first to the fourth hurricane scenario—52 % during first hurricane

Table 1 Mean PARs by Forecast Advisory, hurricane, and EOC location

Forecast advisory	Hurricane A (Brownsville)		Hurricane B (Port Arthur)		Hurricane C (Corpus Christi)		Hurricane D (New Orleans)	
	Cameron EOC	Jefferson EOC	Cameron EOC	Jefferson EOC	Cameron EOC	Jefferson EOC	Cameron EOC	Jefferson EOC
FA 1	2.75	1.76	1.76	2.53	2.53	1.65	1.10	1.43
FA 2	4.40	1.32	1.32	4.07	3.19	2.20	1.10	1.98
FA 3	5.72	2.09	2.86	4.62	4.29	2.75	1.65	3.19
FA 4	6.82	2.64	3.30	5.61	5.06	3.08	1.76	3.63
FA 5	7.70	4.07	3.30	8.03	6.05	4.62	1.87	4.40
FA 6	8.25	4.29	3.30	8.36	6.16	4.40	1.87	4.62

Cameron County is the landfall for Hurricane A (Brownsville); Jefferson County is the landfall for Hurricane B (Port Arthur)

Table 2 Percentage of participants who recommend evacuation for each risk area after viewing Forecast Advisory 5

	Hurricane A Brownsville, (Cameron County) landfall (%)	Hurricane B Port Arthur, (Jefferson County) landfall (%)
Risk area		
RA1	77.5	65.0
RA2	70.0	65.0
RA3	55.0	60.0
RA4	32.5	50.0
RA5	27.5	47.5

scenario; 65 % in the second hurricane scenario; 72 % in third hurricane scenario; and 76 % in the fourth hurricane scenario. These differences are statistically significant (χ^2 (3) = 11.84, $p < .01$).

In addressing RQ3 (What percentage of participants will evacuate the appropriate number of risk areas—e.g., Risk Areas 1–4 for a CAT 4 hurricane—before the evacuation time estimate deadline—i.e., at least 32 h before storm arrival for both counties?), Table 2 indicates participants' evacuation recommendations were far below the standard described in the *Official's Guide*. Specifically, only 50 % of participants assigned to the Jefferson County EOC recommended evacuation of Risk Areas 1–4 in Hurricane B (Port Arthur landfall) and only 33 % of participants assigned to the Cameron County EOC did so for Hurricane A (Brownsville landfall) even though both were Category 4 hurricanes so the percentages should have been 100 %. For those assigned to the Cameron County EOC in Hurricane A, the percentages of participants who recommend evacuation are significantly higher in Risk Areas 1, 2, and 3 than in Risk Area 4—$\chi^2(4) = 31.48$, $p < .01$. However, there were no significant differences in the corresponding test for those assigned to the Jefferson County EOC in Hurricane B—$\chi^2(4) = 4.50$, *ns*.

Regarding RQ4 (Will participants issue a different number of PARs after their fourth hurricane scenario than after their first hurricane scenario?), there were no significant differences. Participants chose 5.34 PARs after the first hurricane scenario and 4.69 after the fourth hurricane scenario ($t_{79} = .97$, *ns*).

In regard to RQ5 (Will participants' demographic characteristics—age, gender, permanent residence, hurricane experience, or evacuation experience—account for differences in their judgments of p_s and PARs?), international students tended to assign higher p_s to Port Arthur ($M = .47$ vs. .39, $d = .42$, $t = 1.99$, $p < .05$) and Brownsville ($M = .44$ vs. .37, $d = .44$, $t = 2.07$, $p < .05$) and also recommended more PARs ($M = 4.17$ vs. 3.06, $d = .44$, $t = 2.90$, $p < .01$). Participants who had hurricane evacuation experience tended to assign higher p_s to all six cities, four of them significantly so—Apalachicola ($M = .12$ vs. .06, $d = .75$, $t = 2.84$, $p < .01$), Port Arthur ($M = .51$ vs. .41, $d = .53$, $t = 2.07$, $p < .05$), Brownsville ($M = .48$ vs. .39, $d = .56$, $t = 2.42$, $p < .05$), and Tampico ($M = .18$ vs. .09, $d = .75$, $t = 2.33$, $p < .05$), but had no significant differences in the number of PARs.

6 Discussion

This study shows that participants had reasonably adequate but not highly proficient mental models (Wood et al. 2012) of the hurricane evacuation decision task. These mental models promoted qualitatively, but not necessarily quantitatively, appropriate p_s judgments. Specifically, all four hurricanes revealed a forecast advisory by city interaction in which p_s judgments started moderately high and increased over forecast advisory for target cities. In addition, p_s judgments started moderately high and then decreased for adjacent cities in Hurricane A, but not B, C, and D. The p_s judgments began low and remained low for remote cities in all hurricanes. These results are consistent with those of Wu et al. (2014) in showing that, at each forecast advisory, p_s judgments declined with increasing distance from the projected point of landfall. These results also are consistent with those of Meyer et al. (2013) in revealing that p_s judgments increased as each hurricane approached its target city. These results extend those of previous studies because, unlike the Meyer et al. (2013) and Wu et al. (2014) studies, the participants in the present study could choose whether to view the forecast track or the uncertainty cone (or both) as an indicator of each hurricane's direction.

Overall, the present study is consistent with others' (Meyer et al. 2013; Wu et al. 2014) in suggesting that participants might be extracting little information from the uncertainty cone other than its direction (i.e., the same information as provided by the forecast track) because the *Official's Guide* explained that there was uncertainty in track forecasts (if they did not already know this). Consequently, it is possible that participants used a *distance-decay heuristic* that generates a perceived risk gradient (Lindell and Earle 1983) in which p_s judgments decrease with distance from the expected landfall location—but do not reach zero. Although a distance-decay heuristic would cause the p_s distributions to have appropriate shapes, it would not necessarily cause participants' p_s judgments to be adequately calibrated—that is, to correspond exactly to the p_s distributions that the National Hurricane Center would post in forecast advisories based upon its meteorological models. Thus, people who observe forecast tracks or uncertainty cones on TV might still underestimate their probability of being struck even though they recognize that they might be struck.

Interestingly, the present study provided mixed support for *border bias*—distortions in probabilities due to people considering "locations within a state to be part of the same superordinate category, but … locations in two different states to be parts of different superordinate categories" (Mishra and Mishra 2010, p. 1582). For example, Fig. 3 shows that Tampico and Port Arthur had almost identical p_s plots—suggesting that Port Arthur's location in the same state offset its significantly greater distance (351 mi/565 km) from Brownsville than Tampico's (255 mi/410 km). However, Fig. 4 shows that New Orleans' location in a different state than Port Arthur failed to offset its much closer proximity (231 mi/372 km) to Port Arthur than Brownsville's (351 mi/565 km).

In addition, the results confirmed that people have difficulty producing responses consistent with one of the basic principles of probability theory because $\Sigma p_s > 1.0$ for the six coastal cities (a mutually exclusive but non-exhaustive set). This is consistent with previous findings by Wu et al. (2014), as well as by Wright and Whalley (1983), Fox and Tversky (1998), and Tversky and Koehler (1994). As Wu and his colleagues noted, the simplest explanation for $\Sigma p_s > 1.0$ is that participants had a basic understanding of probabilities—all $.0 \le p_s \le 1.0$—but working memory limitations prevented them from adjusting the numbers for the six reference cities to be consistent with the summation property of probabilities. Since the participants treated p_s judgments like a set of six rating scales, which do not have a summation property, it is important to continue to examine the ways in which people interpret probabilities that others communicate to them as well as the ways in which they use probabilities to express their uncertainty about different possible events.

Participants' p_s judgments evidently had an effect on their PARs because the two types of variables were significantly, and moderately highly, correlated with each other. This result is consistent with the results of Meyer et al. (2013), who reported $r = .64$ between p_s judgments and the number of household evacuation preparation actions before hurricane landfall. Accordingly, PARs in the present study increased over forecast advisories—just as in Christensen and Ruch (1980). Moreover, participants issued more PARs when their county contained the target city than when it did not. In broad terms, these results indicate that participants issued appropriate PARs, but there were some notable deficiencies because they failed to order suitably extensive evacuations. Specifically, the *Official's Guide* (Lindell et al. 2008, p. 4) stated

> each Risk Area comprises the portion of a county that is expected to be affected by the corresponding hurricane category (see Fig. 2). That is, Risk Area 1 is the area expected to be affected by hurricane Category 1 (74–95 miles per hour winds), Risk Area 2 is the area expected to be affected by hurricane Category 2 (96–110 miles per hour winds), and so on.

Consequently, because all scenarios indicated that the storm was a Category 4 hurricane, participants should have recommended evacuation of Risk Areas 1–4. However, as indicated in Table 2, only 33 % of the participants assigned to the Cameron County EOC and 50 % of those assigned to the Jefferson County EOC recommended evacuation for Risk Area 4 at least 36 h before the arrival of Tropical Storm force wind. This is somewhat surprising because the *Official's Guide* explained the concept of ETEs and each county's ETE table was posted on the wall of the participant's workstation. Even more troubling is the fact that 22 % (of those assigned to the Cameron County EOC) to 35 % (of those assigned to the Jefferson County EOC) of the participants failed to even issue an evacuation recommendation for Risk Area 1 at this time—even though the *Official's Guide* was available to the participants throughout the entire experiment. This result, together with the tardy activation of the EOC (only 76 % activated this facility on the first forecast advisory of the fourth hurricane scenario), indicates that—although participants drew reasonable inferences about p_s—neither their preexisting mental models nor the information they gleaned from the *Official's Guide* led them to draw all of the appropriate implications for responding to the hurricane threat. This finding does not appear to be an artifact of the laboratory setting because some local officials failed to issue timely evacuation orders in Hurricanes Katrina (Knabb et al. 2005) and Ike (Berg 2009).

The difference between the results for the p_s judgments, which suggested that participants understood the risk to their counties, and the results for PARs, which failed to initiate actions that were sufficiently timely and extensive, is a very important finding that is consistent with the PADM's emphasis on the distinction between these two concepts (Lindell and Perry 2004, 2012). In turn, this finding suggests that one of a number of corrective actions might be necessary. The fact that many participants failed to activate the EOC as soon as they received the first forecast advisory, despite the fact that an EOC is the essential local facility supporting response to tropical cyclones, suggests that the *Official's Guide* should be revised to better explain the importance of each PAR and, especially, its appropriate timing.

An even more important problem is the inadequate level of evacuation recommendations. If this occurred because participants had an inadequate understanding of the relationship between storm intensity and the determination of the relevant risk areas to be evacuated, the *Official's Guide* should devote more space to a discussion of the importance of this relationship. Alternatively, if the problem was one of participants' inadequate attention to storm intensity on the display screens, graphical displays could be added to draw participants' attention to this variable (it was displayed numerically in the hurricane parameter table, but not graphically on the tracking map). Moreover, participants could be shown graphical displays of the potential impact area associated with the hurricane's current storm intensity to make this consequence more salient. Finally, the urgency of implementing different PARs, especially evacuation, could be enhanced by modifying the information displays to provide data on the percentage of risk area residents that would be inundated if an evacuation order was delayed until later forecast advisories.

One plausible explanation for participants' inability to properly apply the PAR guidance in the *Official's Guide* is that the amount of new information in that document was so substantial that inexperienced evacuation decision makers could not apply it effectively unless they were given opportunities to practice what they had learned. A logical implication of this explanation is that coastal states provide local officials with a copy of the *Official's Guide* and allow them to practice on a hurricane tracking such as HURREVAC (http://www.seaislandsoftware.biz/) with critiques provided by experienced emergency managers who are aware of the potential consequences of failing to issues PARs that are sufficiently timely or extensive.

One common concern about laboratory experiments such as this one is the use of student samples, which raises the question of whether the participants are "reasonably representative"—that is, whether the results will generalize to other population segments. In order to assess sample representativeness, one must consider what is the population to which any findings are to be generalized and whether there are any critical characteristics on which the sample and population might differ. The major difference between student and non-student samples that affect generalizability is task familiarity (Gordon et al. 1986). Although the students in this experiment were clearly unfamiliar with hurricane evacuation decision making prior to beginning the experiment, the same is true for most local elected officials—even in coastal counties. Indeed, the rarity of hurricane strikes is why the State of Texas originally prepared the *Official's Guide*. The participants in this experiment were required to read the *Official's Guide* before beginning the hurricane tracking experiment, but it is unknown if *any* local elected officials have ever read it before hurricanes approached their counties. Thus, it is likely that the experiment participants are reasonably representative of these local elected officials with respect to task familiarity because neither had any significant degree of prior experience in hurricane evacuation decision making.

In addition to their similarity to the target population with respect to task familiarity, the experiment participants are likely to have been representative of local elected officials in terms of their verbal, quantitative, and spatial abilities because the university from which they were recruited admits undergraduate students in the top 10 % of their high school classes and the graduate students have even higher levels of cognitive ability. Although there is no reason to believe that local elected officials in Texas are substantially above this level of intellectual ability, it is also unlikely that they are significantly below it either. Even if there were differences in intellectual ability, there appears to be no evidence that this would make a difference in the processing of the probability information that is a central part of this experiment. Specifically, the Visschers et al.'s (2009) review of probability information in risk communication examined studies based upon a variety of different types of samples and observed only that students "*may* have higher numeracy skills than the general public" (pp. 283–284, our emphasis). Moreover, a wide range of research suggests that findings from laboratory experiments on judgment and decision making generalize over a wide range of samples (see Baron 2008; Kunreuther et al. 2013; Lindell 2014; Yates 1990). In summary, the available evidence indicates that it is reasonable to generalize from this student sample to other population groups that have similar levels of task familiarity and intellectual ability.

The generalizability of results from student sample to other population segments is further strengthened by the fact that, even though Dash and Gladwin (2007) suggested that a variety of demographic characteristics (e.g., age, gender, education) might have an effect on household evacuation decision making, the more recent Huang et al. (2015) statistical meta-analysis found that few demographic characteristics had reliable effects across studies. That conclusion is consistent with the findings of Meyer et al. (2013), who reported that demographic characteristics had only an average $r = .02$ with p_s judgments and an average $r = .01$ with the number of evacuation preparation actions. In the present study, only evacuation experience and citizenship were related to p_s and PAR judgments and even those variables had small correlations. Thus, the available evidence suggests that this study sample's differences in demographic characteristics from the ultimate target populations (coastal elected officials) are unlikely to impair the generalizability of the findings.

Nonetheless, future researchers will be able to obtain data on hurricane information search, threat perception, and protective action from more diverse samples by using a new version of *DynaSearch* that can collect experiment data over the Internet. This new version of *DynaSearch* will also allow researchers to use more complex hurricane scenarios. Specifically, the present study only presented hurricanes having straight-line tracks and relatively constant intensity, size, and forward movement speed. Future studies should examine the effects of recurved and stalled tracks, as well as substantial changes in other hurricane parameters. Ultimately, a systematic program of research on hurricane tracking and protective action decision making could lead to the development of better training materials and improved tracking displays that will allow emergency managers, local elected officials, and coastal residents to make more informed decisions about whether and when to evacuate from approaching hurricanes.

Appendix

See Figs. 7, 8, 9, 10, 11, 12, and 13, and Tables 3 and 4.

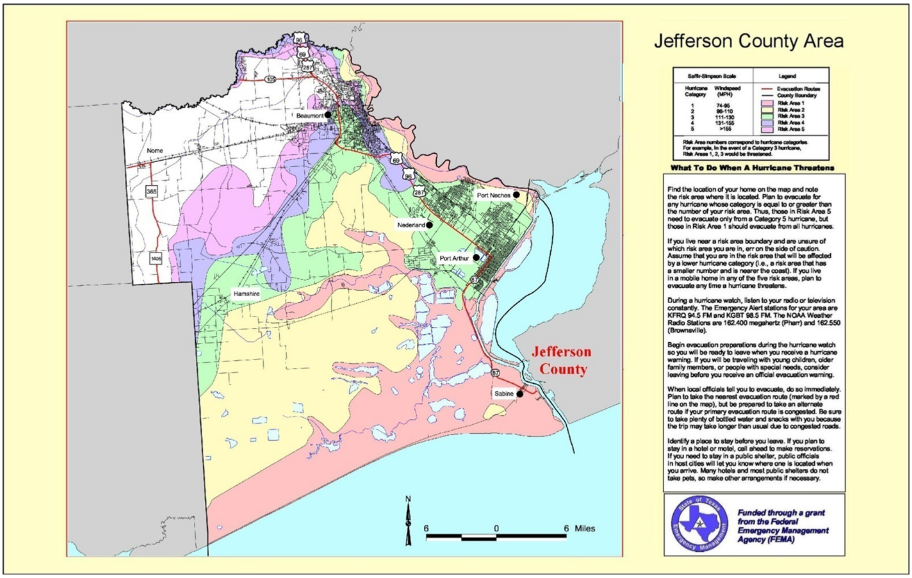

Fig. 7 Jefferson County risk area map

Fig. 8 Gulf of Mexico coastal counties

____
Identification Number

City Classification Sheet

Please mark the cities that are located in the Cameron County. For those cities that are in the Cameron County, indicate which Risk Area the city is in. A Cameron County hurricane risk area map is available for you on the white board. There are five risk areas identified in the map.

City	City Location	Risk Area
Beaumont	◯ in Cameron County ◯ not in Cameron County	Risk Area ____
Rio Hondo	◯ in Cameron County ◯ not in Cameron County	Risk Area ____
Bayview	◯ in Cameron County ◯ not in Cameron County	Risk Area ____
Hamshire	◯ in Cameron County ◯ not in Cameron County	Risk Area ____
Sabine	◯ in Cameron County ◯ not in Cameron County	Risk Area ____
Los Fresnos	◯ in Cameron County ◯ not in Cameron County	Risk Area ____
Port Arthur	◯ in Cameron County ◯ not in Cameron County	Risk Area ____
Combes	◯ in Cameron County ◯ not in Cameron County	Risk Area ____
San Perlita	◯ in Cameron County ◯ not in Cameron County	Risk Area ____
Nederland	◯ in Cameron County ◯ not in Cameron County	Risk Area ____
Port Neches	◯ in Cameron County ◯ not in Cameron County	Risk Area ____
Brownsville	◯ in Cameron County ◯ not in Cameron County	Risk Area ____
Laguna Vista	◯ in Cameron County ◯ not in Cameron County	Risk Area ____

Fig. 9 Cameron County city classification sheet

Identification Number

City Classification Sheet

Please mark the cities that are located in the Jefferson County. For those cities that are in the Jefferson County, indicate which Risk Area the city is in. A Jefferson County hurricane risk area map is available for you on the white board. There are five risk areas identified in the map.

City	City Location	Risk Area
Beaumont	◯ in Jefferson County ◯ not in Jefferson County	Risk Area ____
Rio Hondo	◯ in Jefferson County ◯ not in Jefferson County	Risk Area ____
Bayview	◯ in Jefferson County ◯ not in Jefferson County	Risk Area ____
Hamshire	◯ in Jefferson County ◯ not in Jefferson County	Risk Area ____
Sabine	◯ in Jefferson County ◯ not in Jefferson County	Risk Area ____
Los Fresnos	◯ in Jefferson County ◯ not in Jefferson County	Risk Area ____
Port Arthur	◯ in Jefferson County ◯ not in Jefferson County	Risk Area ____
Combes	◯ in Jefferson County ◯ not in Jefferson County	Risk Area ____
San Perlita	◯ in Jefferson County ◯ not in Jefferson County	Risk Area ____
Nederland	◯ in Jefferson County ◯ not in Jefferson County	Risk Area ____
Port Neches	◯ in Jefferson County ◯ not in Jefferson County	Risk Area ____
Brownsville	◯ in Jefferson County ◯ not in Jefferson County	Risk Area ____
Laguna Vista	◯ in Jefferson County ◯ not in Jefferson County	Risk Area ____

Fig. 10 Jefferson County city classification sheet

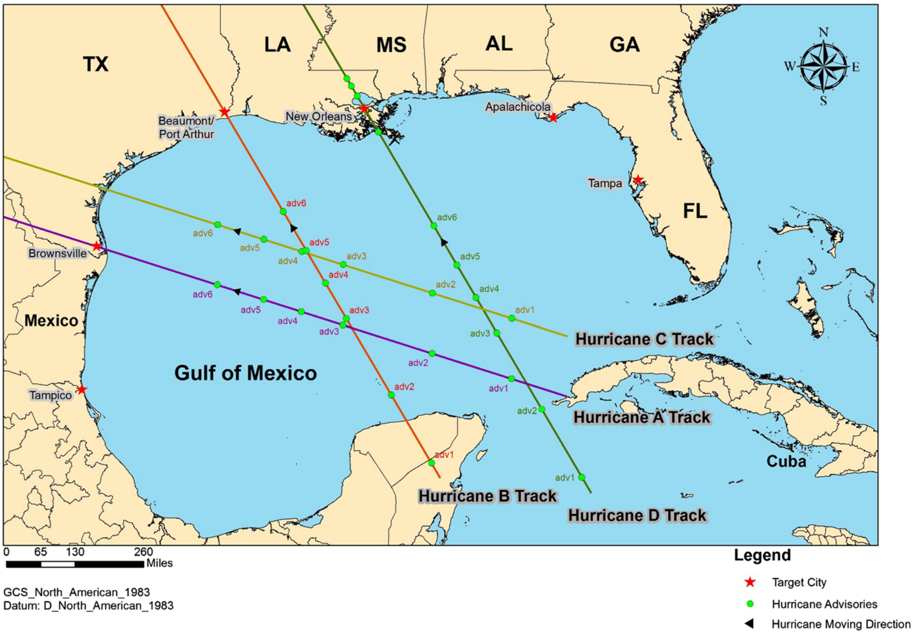

Fig. 11 Hurricane scenario tracks

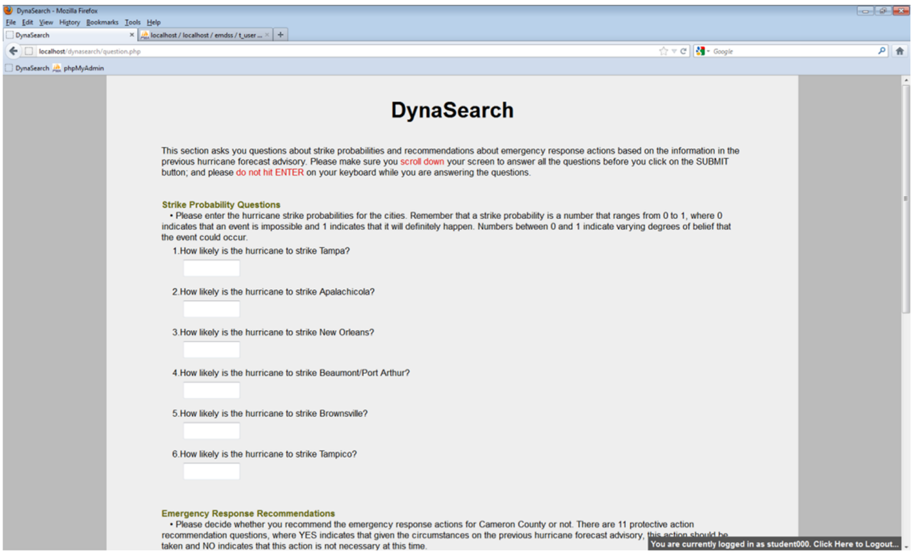

Fig. 12 p_s Judgments

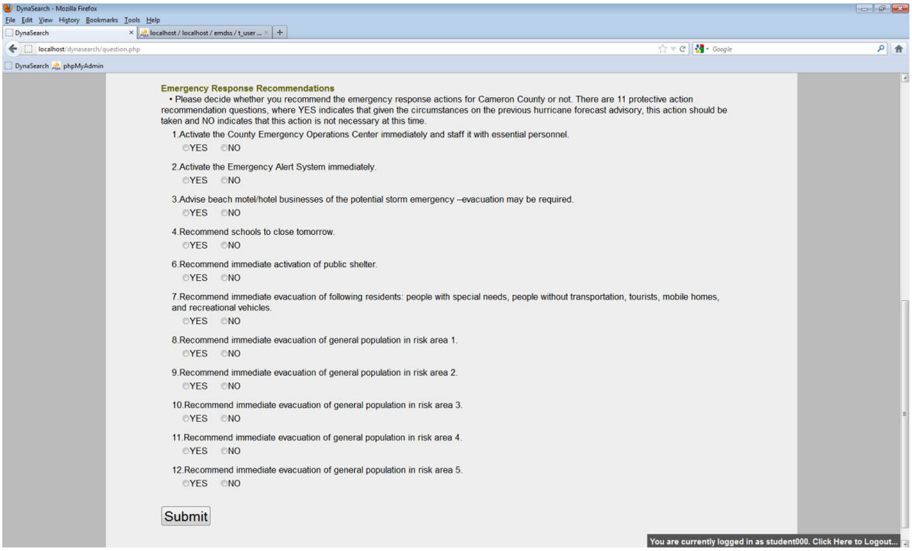

Fig. 13 PAR selection screen

Table 3 Cameron County evacuation time estimates

Saffir–Simpson category	Category 1	Category 2	Category 3	Category 4	Category 5
Risk area	1	2	3	4	5
ETE (h)	15	21	28	32	33

Table 4 Jefferson County evacuation time estimates

Saffir–Simpson category	Category 1	Category 2	Category 3	Category 4	Category 5
Risk area	1	2	3	4	5
ETE (h)	15	21	28	32	33

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