APPLICATION OF SPATIAL VISUALIZATION FOR PROBABILISTIC HURRICANES RISK ASSESSMENT TO BUILD ENVIRONMENT

Yue Li

Dept. of Civil and Environmental Engineering Michigan Technological University Houghton, MI, 49931 USA Tyler A. Erickson

Michigan Tech Research Institute Michigan Technological University Ann Arbor, Michigan 48105 USA

ABSTRACT

Hurricanes have caused extensive economic losses and social disruption in the past two decades in the United States. A key component for improving building and infrastructure practices and public planning to reduce the economic losses due to hurricanes and their social impact is the ability to predict the expected damage that such events cause in buildings and other structures as well as the uncertainties in such predictions. Federal, state and county emergency management officers need an effective realtime tool to facilitate the decision regarding when evacuate should begin and who should evacuate before a hurricane, as long as how to timely conduct post-disaster relief. Modern internet-based geospatial tools can be effectively used to provide decision makers with real-time data, model results, and geospatial reference datasets. Probabilistic risk assessment model combined with spatial distributed visualization is proposed in this paper for more efficient hurricane hazard mitigation through risk informed communication.

1 INTRODUCTION

The United States currently sustains an average of \$5 billion annually in economic damages due to hurricanes. In recent decades, rapid development and population growth in coastal areas in the Southeast and along the Gulf has greatly increased the overall vulnerability of built environment to damages and losses from hurricanes. Combined with the apparent increase in frequency and intensity of hurricanes in recent years, this situation has led to increasing and substantial economic losses to buildings and other structures. For example, Hurricane Andrew (1992) alone caused \$20 billion in insured losses; insured losses due to Hurricane Hugo (1989), Iniki (1992) and Opal (1995) totaled approximately \$10 billion. The more recent Hurricanes Isabel (2003), and Charley, Frances, Ivan and Jeanne (2004) are further reminders of the devastation and disruption caused by such events. The four major hurricanes in 2004 reportedly have caused more than \$30 billion losses. In 2005, Hurricanes Katrina and Rita caused damages estimated to be approximately \$120 billion; Hurricane Katrina was the most costly natural catastrophe in United States history. The significant impact of hurricanes on individuals, communities and the insurance industry demonstrates the need for a better understanding of the performance of buildings and lifelines under severe wind effects.

The aftermath of recent natural disasters and the potential for higher losses in the future have led to intense professional and public scrutiny on how hurricane risk can be communicated more efficiently in a timely manner. This scrutiny has pointed to the need for an improved method for risk assessment, prediction of potential vulnerability to future hazards, or communication of impending risk. Such improvements in hazard mitigation require tools for evaluating vulnerability of new, existing, and retrofitted building products and infrastructure, for modeling the uncertainties that are inherent to the prediction of the performance, and communicated the risk through assistance of visualization tool, and managing the risk that is consequent to these uncertainties economically. Such advances require an integration of analytical models of structural behavior and methods of structural reliability assessment for treating the large uncertainties that are inherent to natural hazard mitigation, along with advancement in visualization simulation techniques.

2 HURRICANE WIND FIELD MODEL

The hurricane hazard is expressed by a wind speed distribution function for a standard averaging time (3 sec), open terrain (Exposure C), and elevation 33 ft (10m). Because of a lack of statistics of occurrence of hurricanes at specific mileposts along the coast and the need for estimate wind speeds at long return periods for design and risk analysis purposes, hurricanes are simulated probabilistically from

fundamental climatological modeling principles and data (described in more detail below), and the resulting wind speeds at specific mileposts are derived from wind field models. These wind speed are post-processed statistically and are used to develop design wind speed maps for ASCE Standard 7 (2005) and for other purposes.

Several hurricane wind prediction models have been developed (Batts et al. 1980; Georgiou et al. 1983; Georgiou, 1985; Vickery and Twisdale, 1995 a, b; Vickery et al. 2000). The general approach used in these models is similar (Vickery et al. 2000). Statistical models of key sitespecific parameters, including hurricane central pressure, radius, heading, and crossing point along the coast, are collected. Then Monte Carlo simulation is used to sample the parameters, and the wind speed is recorded when a mathematical representation of the hurricane passes the site. The physical models of the hurricane, such as filling rate and wind field, and the area over which the local climatology is assumed to be uniform, which is used to derive the statistical characterization of the hurricane, differ from model to model. In addition, some hurricane prediction models use a coast segment crossing approach, while others use a circular sub-region approach. These differences in wind field modeling affect the wind speed prediction.

Although the wind field models are different, the Weibull distribution appears to be a suitable model for hurricane wind speeds determined from all models (Peterka and Shahid, 1998; Batts et al. 1980; Vickery et al. 2000). The two-parameter Weibull distribution CDF is given by

$$F_V(v) = P(V < v) = 1 - \exp[-(v/u)^{\alpha}]$$
 (1)

The scale and dispersion parameters, u and α , are sitespecific. The Weibull distribution parameters for the three hurricane wind speed models in south Florida are summarized in Table 1. The estimated wind speeds with return period of 50, 100 and 1000 years for the three wind field models are listed in the table. The parameters can be determined from the published wind speed maps from the above hurricane studies that define the relationship between wind speed, V_T, and return period, T:

$$v_{T} = u * [-ln(1/T)]^{1/\alpha}$$
 (2)

Table 1: Weibull Distribution Parameters for Different Hurricane Wind Speed Models in South Florida (1 mph = 0.447 m/s)

Hurricane Wind Speed Model		Batts et al.	Vickery et al.	Georgiou
Wind Speed (mph)	50 year	120	132	150
	100 year	130	150	162
	1000 year	155	182	208
Weibull Distribution Parameters	u	64.86	61.07	68.33
	α	2.218	1.769	1.738

3 PROBABILISTIC HURRICANE RISK ASSESSMENT

A key aspect of improving building practices to reduce the economic losses and the social impact from hurricanes is the ability to predict expected damage to buildings, other structures and to assess uncertainties in damage. The hurricane risk assessment is affected by the probabilistic nature of wind loads and structural capacities that govern the structural performance. Hurricane risk assessment is affected by the uncertain nature of wind loads and structural capacities that directly impact structural performance. There are two types of uncertainty that affect the reliability analysis of a structural system exposed to a hurricane. One type (aleatoric) is associated with factors that are inherently random in nature. For example, wind loads on buildings depend on a number of uncertain variables: wind speed, gustiness, building exposure, external and internal pressure coefficients, directionality effects and local topography, as shown in Equation (3) to (5) in ASCE-Standard 7-05 (2005).

$$W = q_h[GC_p - GC_{pi}]$$
(3)

$$q_{\rm h} = 0.00256 \, \rm K_h \, K_{zt} \, \rm K_d \, V^2 \, (lb/ft^2) \tag{4}$$

$$q_{\rm h} = 0.613 \ {\rm K}_{\rm h} \ {\rm K}_{\rm zt} \ {\rm K}_{\rm d} \ {\rm V}^2 \ ({\rm N/m}^2) \tag{5}$$

Such uncertainties are essentially irreducible at the current state of the art.

A second type (epistemic) is associated with lack of knowledge - modeling assumptions and simplifications, and incomplete databases – that are required to support probabilistic descriptions of resistance and loading needed

for reliability and risk assessment. In contrast to aleatory uncertainties, the epistemic uncertainty generally can be reduced by using more comprehensive (and costly) models and analyses. Inherent randomness in strength and loading and epistemic uncertainties in the hurricane models are considered in the prediction of various levels of damage to built facilities. Effect of epistemic uncertainty associated with hurricane path on risk assessment will be reflected on the visualization simulation model discussed herein. Identification of the relative contributions of each uncertain variable to the overall risk assessment can provide insights on areas where it is worthwhile to invest in further modeling and data collection for the improvement in the prediction of hurricane impacts.

Limit states, or conditions in which the structural system ceases to perform its intended functions in some way, is a response quantity that can be checked using principles of structural analysis and mechanics. Such a mapping invariably requires that the behavior of the structural system be considered as a whole. The performance objective can be related to damage state, such as the "light", "moderate", and "severe" damage.

The probability of any damage limit state related to exceedance of limit state (LS) of a structure subjected to hurricane hazards can be defined as (Li and Ellingwood, 2006)

$$P(D) = \sum P(D \mid V = v) P(V = v)$$
(6)

where P(V = v) is the probability that the demand (wind intensity v) equals a specific level, and P(D | V = v) is the conditional probability conditional probability of a damage state (e.g., minor, moderate, severe). The summation emphasizes the role of the theorem of total probability in risk assessment. The conditional probability of failure of the system for a given loading condition is defined as the system *fragility*. Equation (6) shows that the fragility P(D | V = v) is a key ingredient for determining the damage limit state probability of a structural system.

Figure 1 illustrates the fragility curves (Li and Ellingwood, 2007) for the three hurricane damage states (minor, moderate and severe) for a residence constructed to a minimum level of protection (dashed lines) or enhanced level of protection (solid lines) for hurricane wind resistance, as an example of probabilistic risk assessment for built environment. The damage probabilities at all damage levels for the residence built to enhanced practice are reduced from levels for the similar building built to the minimum practice, with the reductions at the severe damage level being substantial. At v = 140 mph (63 m/s), the probability of severe damage decreases from 25% to less than 1%. The assessment helps to evaluate the vulnerability due to hurricanes for different levels of wind resistance.



Figure 1: Probability of Hurricane Damage (Minimum and Enhanced Construction Practices)

The fragility curves for different building and infrastructure construction and characteristics in an area must be aggregated to evaluate damage levels in groups of construction in the build environment for regional loss estimation. That presents a challenge due to the complex nature of the hurricane hazard, the mix of construction types in the area affected by the hurricane, and the lack of statistics suitable for modeling all structural systems. In a specific area under study, there would be a wide variety of construction configurations with various plan sizes and shapes, structural systems, ages, governing building codes (if any) and design practices.

4 SPATIAL VISUALIZATION FOR HURRICANES RISK ASSESSMENT

In 2004, the prediction of loss due to Hurricane Charley demonstrated the uncertainty in loss estimation due to shifting of the hurricane track and change of wind intensity. On August 12, the real time estimation for predicted damage was between \$2-3 billion. However, the prediction jumped to \$50 billion for a short period time when the hurricane appeared heading to Tampa Bay (Iman et al. 2005).

To enable interactive visualization of hurricane risk data by multiple users for multiple hurricane track scenarios, a web-based geospatial information system can be used. The geospatial information system illustrated in Figure 2 is composed of three tiers of software applications: (1) a Data Storage tier which contains the spatial and attribute data related to storm observations, spatial fields of predicted wind speeds, and the location and characteristics of infrastructure assets; (2) a Content Server tier which contains applications that implement the risk assessment models, estimate wind fields from storm observations, and format model results in standard geospatial data formats used by visualization clients; and (3) a Client Application tier of visualization applications that allow users to interact with the underlying data and models.



Figure 2: Overview of a 3-tier geospatial information system designed to communicate hurricane risk assessment information to a visualization client

Figure 3 shows an example screenshot of a Google Earth visualization client displaying tropical storm observations and storm tracks for Hurricane Katrina. Google Earth is a visualization application that allows users to navigate in



Figure 3: Example of using a virtual globe application to display storm track and observation information. The maximum wind speed for each observation is indicated by the color of the observation.

three spatial dimensions as well as time to interact with datasets that are referenced to a virtual globe.

By applying a model for model of the wind field distribution, such as Boose et al. (1994) or Ramsey et al. (2001), wind speeds can be estimated for ZIP Codes (or other geographic areas) along the storm path. These estimated wind speeds can be used in Equation (5).

Loss estimation for hurricane risk assessment can adopt the following framework:

$$P[Loss] = \sum_{v} \sum_{d} P[Loss|D=d)P(D|V=v) P(V=v)$$
(7)

where "Loss" is an appropriate loss metric: deaths or injuries, direct economic losses from building or infrastructure damage, indirect losses due to interruption of function or loss of business opportunity etc. P(D|V = v) and P(V = v)are defined in Equation (6) as conditional probability of a damage and probability of wind intensity v. Figure 4 demonstrates the uses of a visualization client to display the results of risk assessment model (estimated storm damage by ZIP Code for Hurricane Hugo).



Figure 4: Example of visualizing estimated storm 'Loss' by ZIP Code with a virtual globe client. (Note: the storm damage dataset is used for demonstration purposes and is not reflective of the actual damages)

In the framework shown in Figure 5, P[V=v] is the predicted hurricane wind speed, which can be extracted from the hurricane track and wind speed model discussed earlier. For regional risk assessment, this wind speed can be characterized by ZIP Code to facilitate the analysis. The geospatial information system described can augment to provide advanced decision support capabilities to users by using client applications that allow users to interactively set parameters used in the underlying models. For example, a user may specify an arbitrary boundary for which the risk assessment model will aggregate estimated damages. Uncertainty in wind speed and damage prediction can be propagated through the models to estimate the total loss.



Figure 5: Regional hurricane loss estimation framework using fragility and virtual globe application to display storm track and observation information.

Other than using the above framework to estimate loss resulted from a specific hurricane, the framework can be used to relate annual probability of exceedance of performance limit states due to hurricane to expected annual loss. The probability of loss under a spectrum of possible hurricane winds is determined by convolving the structural fragility curve and hurricane hazard:

$$P(\text{Loss}) = \int F_{R}(v) * f_{v}(v) dv \qquad (8)$$

where $F_R(v)$ is the hurricane fragility defined in Equation (6) and fv(v) is the probability density function for hurricane wind speed that can be derived from Equation (1). The wind speed, v, can be expressed with reference to an annual extreme wind speed, a 50-year extreme wind speed, or extreme for another reference period, depending on the purpose of the risk analysis.

5 CONCLUSION

The integrated spatial visualization with probabilistic risk assessment system can be useful for engineering decisionmaking in evaluating the potential impact of a natural hazard in public planning, and mitigating the consequent economic losses and social disruption. It also provides a basis for loss estimation and appropriate underwriting by the insurance industry to project losses for specific constructed facility for insurance purposes. The system is crucial for emergency managers to make decision on evacuation in real time before hurricanes and timely allocate postdisaster relief.

ACKNOWLEDGEMENTS

This work was partially supported by the Department of Defense University Research Instrumentation Program (DURIP) (FA-9550-07-1-0500). The views expressed herein are those of the authors and may not reflect the views of the sponsor.

REFERENCES

- ASCE (2005). Minimum Design Loads for Buildings and Other Structures (ASCE Standard 7-05), Am. Soc. of Civil. Engineers, Reston, VA.
- Batts, M. E., Cordes, M. R., Russell, L. R., Shaver, J. R., and Simiu, E. 1980. *Hurricane Wind Speeds in the United States. Rep. No. BSS-124*, National Bureau of Standards, U.S. Department of Commerce, Washington, D.C.
- Boose, E. R., Foster, D. R., and Fluet, M. 1994 *Hurricane Impacts to Tropical and Temporate Forest Landscapes. Ecological Monographs*, 64(4)369-400.
- Georgiou, P. N. 1985. Design Wind Speeds in Tropical Cyclone-Prone Regions. *PhD Thesis, Fac. of Engineering Sci.*, University of Western Ontario, London, Ont., Canada.
- Georgiou, P. N., Davenport, A. G., and Vickery, B. J. 1983. Design Wind Speeds in Regions Dominated By Tropical Cyclones. *Journal of Wind Engineering and Industrial Aerodynamics*, Amsterdam, the Netherlands, 13(1), 139–152.
- Iman, R. L., Johnson, M. E., and Watson, C. C. 2005. Uncertainty Analysis for Computer Model Projections of Hurricane Losses, *Risk Analysis*, Vol. 25, No. 5.
- Li, Y. and Ellingwood, B.R. 2006 Hurricane Damage to Residential Construction in the US; Importance of Uncertainty Modeling in Risk Assessment, *Engineering Structures*, 28(7), 1009-1018.
- Li, Y. and Ellingwood, B.R. 2007. Risk-based Decision Making for Multi-hazard Mitigation for Wood-frame Residential Construction, *The Third International Forum on Engineering Decision Making Decision Making (IFED)*, Port Stephens, Australia, December, 2007.
- Peterka J.A. and Shahid, S. 1998. Design Gust Wind Speed in the United States, *Journal of Structural Engineering*, ASCE, 124(2): 207-214.
- Ramsey, E. W., Hodgson, M. E., Sapkota, S. K., Nelson, G. A. 2001. Forest Impact Estimated with NOAA AVHRR and Landsat TM Data Related to an Empirical Hurricane Wind-Field Distribution. *Remote Sensing of Environment* 77, 279-292.
- Vickery, P. J., Skerlj, P. F., Steckley, A. C., and Twisdale, L. A. (2000). Simulation of Hurricane Risk in the United States Using Empirical Track Modeling Technique. *Journal of Structural Engineering, ASCE*, 126(10), 1222–1237.

- Vickery, P. J., and Twisdale, L. A. (1995a). Prediction of Hurricane Wind Speeds in the United States. *Journal* of Structural Engineering, ASCE, 121(11), 1691– 1699.
- Vickery, P. J., and Twisdale, L. A. (1995b). Wind-Field and Filling Models for Hurricane Wind-Speed Predictions. *Journal of Structural Engineering, ASCE*, 121(11), 1700–1709.

AUTHOR BIOGRAPHIES

YUE LI is the Donald and Rose Ann Tomasini Assistant Professor in the Department of Civil and Environmental Engineering at Michigan Technological University (MTU). He joined MTU after receiving his Ph.D. degree in Civil Engineering from Georgia Institute of Technology in August 2005. His research interests include risk assessment, natural and man-made hazard mitigation, and infrastructure modeling. His teaching interests include basic structural engineering, probability, statistical and engineering decision analysis, structural reliability and performance-based structural design. His is a member of American Society of Civil Engineers (ASCE), American Association for Wind Engineering (AAWE) and Civil Engineering Risk and Reliability Analysis Association (CERRA). His email address is <yueli@mtu.edu>.

TYLER A. ERICKSON is a research scientist at the Michigan Tech Research Institute (MTRI). He received his BS in Civil Engineering from Colorado State University, his MS in Civil Engineering from the California Institute of Technology, his Engineer degree in Civil & Environmental Engineering in Stanford, and his PhD in Geography from the University of Colorado. His research interests are in the areas of developing geostatistical methods for merging spatial datasets with differing spatial characteristics, and in building web-accessible geospatial decision support systems from both proprietary and opensource software components. He is the lead of the MichiganView consortium and a member of the American Society of Photogrammetry and Remote Sensing and the American Geophysical Union. His email address is <taericks@mtu.edu>