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ABSTRACT: This paper reviews recent studies that take a physically-based approach to better assess and manage hurricane risk. Such a methodology includes three components: modeling the storm climatology (which defines TC risk in terms of the upper tail of the storm statistics); modeling landfalling hazards; and characterizing damage and losses.

1 INTRODUCTION

Tropical cyclones (TCs) cause tremendous damage worldwide due to the associated strong winds, heavy rainfall, and storm surge. As the climate warms, these TC hazards may intensify (e.g., Emanuel et al. 2008; Knutson et al. 2010; Lin et al. 2012), making their societal impacts an increasing concern (Mendelsohn et al. 2012). Recent events have revealed the vulnerability of the US to severe TCs. In 2011, Hurricane Irene produced more than $10 billion in damage in the Northeastern US. In 2012, Hurricane Sandy struck the Northeastern Seaboard, again, causing more than $65 billion in damage, killing over two hundred people, and leaving millions without electric service. Hurricane Katrina of 2005, the costliest natural disaster in US history, caused more than $80 billion in losses and resulted in more than 1800 fatalities. To prevent such TC disasters in the future, major advances in TC risk management are urgently needed.

Due to uncertainties in future climate and demographic conditions, including TC activity, sea level rise (SLR), and exposure and vulnerability, effective TC risk management should be based on probabilistic risk assessment. Currently, increases in exposure appear to dominate over the effects of anthropogenic climate change as the leading cause of change in TC damage (Handmer et al. 2012, Pielke 2007). However, potential changes in storm characteristics and hazards due to climate forcing and related SLR also affect risk (Mendelsohn et al. 2012). Accordingly, changes in the physical state of the atmosphere and ocean also must be accounted for. Thus reliable TC risk assessment, unlike traditional assessments, cannot rely solely on direct statistical analyses of the (quite limited) historical TC records and damage data. Rather, it requires a new physically-based approach that incorporates information on current and projected future climates as well as exposure and vulnerability.

2 TC RISK ASSESSMENT

A challenge in TC risk assessment is that historical records of TCs, especially those making landfall in a local area, are very limited. Statistical methods based solely on local TC landfall history are unreliable because the estimated frequency of high-intensity events is highly sensitive to exactly how the tail of the probability distribution is modeled. Hurricane return levels may be estimated from geological information and/or the historical data about hurricanes landfalling in neighboring regions (Elsner et al., 2008). More often, TC risk assessment makes use of Monte Carlo simulation to generate synthetic basin-wide storms to obtain landfall statistics; two principal approaches have been developed. One approach, pioneered by Vickery et al. (2000) (e.g., Powell et al. 2005; Rumpf et al. 2007; Hall and Jewson, 2007), uses the statistics of the storm parameters (i.e., track, intensity, and size) to construct synthetic storm sets. A drawback of this method is that it relies entirely on historical TC data and cannot readily incorporate or predict future changes. An extension of this method is to develop statistical relationships between the storm parameters and environmental parameters (e.g., Yonekura and Hall 2011) so that future storms maybe simulated using projected future environments, assuming that the statistical relationships remain the same under different climate conditions. The other approach, developed by Emanuel et al. (2006 and 2008), applies a deterministic, coupled ocean-atmosphere TC model to simulate storm development driven by large-scale environmental conditions whose statistics are derived from reanalysis or global climate model data. This statistical/deterministic TC risk model does

not rely on the limited historical TC data but generates large samples of synthetic storms that are in statistical agreement with observations (Emanuel et al. 2006), and compares well with other methods used to study the effects of climate change on TCs (Emanuel et al. 2008 and 2010; Bender et al. 2010; Knutson et al. 2010). This approach has been used to investigate TC wind and surge risk (e.g. Lin et al. 2010 and 2012; Klima et al. 2011; Mendelsohn et al. 2012).

Here we briefly summarize the Emanuel et al. method for generating synthetic storms. Storm genesis points are randomly selected from a distribution constructed from the Best-Track historical dataset or generated by a random seeding technique. Once initiated, storm displacements are calculated using the 'beta and advection model' in which 850 and 250 mb environmental steering flows vary randomly but in accordance with the monthly mean, variance and covariances of the reanalysis data or the climate model prediction. Along each simulated track, the Coupled Hurricane Intensity Prediction System (CHIPS), a deterministic ocean-atmospheric coupled model, is used to simulate the intensity evolution of the storm (Emanuel et al. 2004). TC risk for a certain area is estimated by examining the frequency and characteristics of storms passing by the area (e.g., crossing a boundary of the area or passing within a certain radius of the center of the area). The CHIPS model also estimates the storm radius of maximum wind, conditional on the storm outer radius (where the storm wind vanishes). The storm outer radius was found to obey a lognormal distribution (Chavas and Emanuel 2010). Theoretically, the storm outer radius scales with the storm potential intensity (Emanuel 1986); however, the scaling relationship remains to be evaluated against observations; at the same time, further investigation is needed to determine how storm outer radii will change with climate. Storm size (as described by the storm radius of maximum wind, the outer radius, and other related parameters) is an important factor, in addition to storm intensity and track, in determining TC hazards, as amply demonstrated by Hurricanes Katrina, Irene, and Sandy.

3   TC HAZARD MODELING
TCs induce multiple hazards during and after landfall, including strong winds, heavy rainfall, and storm surge. TC wind and rainfall may be simulated using high-resolution dynamic models, such as the Weather Research and Forecasting (WRF; Skamarock et al. 2005) model. For example, Lin et al.

(2010b) carried out a case study for Hurricane Isabel (2003), applying the WRF model to examine storm properties and wind and rainfall hazards down to 1-km resolution at landfall. They further coupled the WRF model with a hydrodynamic model to simulate the storm surge in Chesapeake Bay. This approach may be applied to studying the impact of climate change on TC hazards; in particular, high-resolution dynamic models can be used to downscale relatively lower-resolution TC simulations, such as Knutson et al.'s (2012 and 2013) projection of storms in different climates, to local scales. However, this approach is, at present, computationally too expensive to be applied directly to risk assessment, which should involve very large numbers ($\sim 10^4$) of simulations to cover many possible scenarios. Consequently, computationally much more efficient parametric models are often used in risk analysis. Parametric wind and pressure models can also be applied to storm surge analysis. Such parametric modeling and analysis can be readily coupled with TC risk models (see above) to estimate TC hazard risk. In this section, we review parametric wind modeling and storm surge modeling as well as statistical methods to estimate TC hazard risk from physical model results. A physically-based parametric rainfall model, which depends on the wind model, is currently under development by Emanuel.

Wind modeling
In the parametric approach, the TC surface wind field may be estimated as the sum of an axisymmetric wind field associated with the storm itself and a background wind field representing the local environment. The surface background wind is often related to the storm's translation velocity, based on two assumptions: the storm's movement is mainly due to advection by (some vertically integrated measure of) the background wind in the free troposphere near the storm, and surface friction causes the surface background wind to deviate from the free tropospheric wind in magnitude and direction. However, previous applications disagreed on the nature of this deviation. Some assumed that the surface background wind is approximately equal in direction to the storm translation velocity and reduced in magnitude by a variously-valued factor (e.g., 0–0.5 used by Jelesnianski et al. 1992 and Phadke et al. 2003, 0.6 by Emanuel et al. 2006, and 0.5 by Lin et al. 2012). In many other applications, the full velocity of the storm's translation is added to the storm's wind field (e.g., Powell et al., 2005; Mattocks and Forbes, 2008; Vickery et al., 2009b), neglecting the velocity difference between the free tropospheric wind and surface background wind. Lin and Chavas

(2012) performed an observational analysis to estimate the magnitude and orientation of the surface background wind relative to the storm translation velocity and found that with relatively small spatial variations, the surface background wind on average was reduced in magnitude from the storm translation velocity by a factor of about 0.55 and was rotated in the counter-clockwise direction by about 20 degrees. They also showed that the wind fields are very sensitive to the representation of the surface background wind, so that previous methods may have significantly under- or over-estimated wind speeds.

Given storm characteristics (i.e., track, intensity, and size), the axisymmetric component of the surface wind may be estimated by calculating the wind velocity at gradient level with a TC gradient wind profile and translating the gradient wind to the surface level with an empirical surface wind reduction factor (SWRF) (e.g., Powell et al., 2003) and inflow angle (e.g., Bretschneider, 1972) to account for the effect of surface friction on the storm. A boundary layer model (e.g., Thompson and Cardone, 1996; Vickery et al., 2009; Kepert, 2010) may be applied to more accurately calculate the surface wind from the gradient condition, but it is nonparametric and more computationally demanding. A number of gradient wind profiles (e.g., Holland, 1980; Jelesnianski et al., 1992; Emanuel, 2004; Emanuel and Rotunno, 2011) have been used in wind and surge analysis; it may be difficult at this point to identify the "best" wind profile, as each profile has its own strengths and limitations. Lin and Chavas (2012) investigated the sensitivities of simulated wind and associated surge fields to these gradient wind profiles and the other above-mentioned factors, which may then also be used to quantify the uncertainties in parametric wind modeling.

It is noted that Lin and Chavas's (2012) parametric representation of the surface background wind assumed a uniform surface background wind to be added to the symmetric storm wind, which may only be valid for storms developing in a relatively uniform wind environment. TCs moving to higher latitudes may undergo extratropical transition and become "hybrid" storms (Hart and Evans 2001) – a critical aspect responsible for much of Hurricane Sandy's devastating impact – about which our current knowledge is limited (Emanuel 2005). These hybrid events, having a partially baroclinic structure, are often highly asymmetric. To account for this baroclinic effect, new methods need to be developed to improve the surface background wind estimation by developing a representation of the interaction between the highly localized potential vorticity anomaly of the TC and its environmental baroclinic fields. In particular, Hart's (2003) TC phase space technique may be applied to study the characteristics of hybrid storms and facilitate these developments.

Surge Modeling

The storm surge is a rise of coastal shallow water driven by a storm's surface wind and pressure gradient forces; its magnitude is determined, in a complex way, by the characteristics of the storm plus the geometry and bathymetry of the coast. When observed wind and pressure fields are used, state-of-the-art storm surge models can often produce successful hindcasts of surges (e.g., Houston et al., 1999, Westerink et al., 2008; Bunya et al., 2010). In real-time forecasting, predictions of winds, and thus surges, can be performed using advanced numerical weather forecasting models (e.g., Colle et al., 2008; Lin et al., 2010b). In risk analysis, parametric wind and pressure field models may be used to drive the storm surge simulations. Although high-resolution numerical grids can better capture the spatial variation of the storm characteristics and coastal features, in order to conduct surge estimates for large numbers of storm scenarios in risk analysis, a trade-off between efficiency and accuracy is often required.

Here we introduce two widely used storm surge models, representing the hydrodynamics of the storm surge by means of shallow water equations. One is the Sea, Lake, and Overland Surges from Hurricanes (SLOSH; Jelesnianski et al. 1992) model, used by the Natural Hurricane Center for real-time forecasting of hurricane storm surge. The performance of the SLOSH model has been evaluated using observations of storm surge heights from past hurricanes (Jarvinen and Lawrence, 1985; Jarvinen and Gebert, 1986); the accuracy of surge heights predicted by the model is ±20% when the hurricane is adequately described (Jelesnianski et al., 1992). The SLOSH model applies finite difference methods to solve the equations and uses a polar grid, which allows for a fine mesh in primary coastal regions of interest and a coarse mesh in the open ocean. For example, the New York basin grid is a polar coordinate system with 75 arcs and 82 radials, with resolution of about 1 km near New York City (NYC). With some simplification in the physics represented (Jelesnianski et al. 1992) and with relatively coarse grids, the SLOSH simulation runs relatively fast. Another storm surge model is the Advanced Circulation model (ADCIRC; Luettich et al. 1992, Westerink et al. 1992). It has been evaluated and applied to simulate storm surges and make forecasts for vari-

ous coastal regions (e.g., Westerink et al. 2008; Colle et al. 2008; Dietrich et al. 2011; Lin et al. 2010b; Lin et al. 2012). The ADCIRC model fully describes the complex physical process associated with storm surge and can also simulate astronomical tides and wind waves during the surge event (Dietrich et al. 2011). It allows the use of an unstructured grid over a relatively large domain, with very fine resolution near the coast and much coarser resolution in the deep ocean. The high-resolution ADCIRC model is computationally expensive, compared to the SLOSH model, and thus is not feasible for very large numbers of simulations.

Lin et al. (2010a) compared 9 storm surge estimates for NYC using the SLOSH model (with resolution of ~1 km around NYC) and the ADCIRC model (with resolution as high as 10 m around NYC). When driven by the same wind fields, the SLOSH model performed well, (judging by the ADCIRC model) in simulating the maximum storm surge at a location with relatively simple coastal features, although sub-grid scale variations in the local surge were averaged out. Lin et al. (2012) further carried out comparisons of over 1000 storm surge estimates from the SLOSH (with a resolution of ~ 1 km) and ADCIRC (with a resolution of ~ 100 m) simulations for NYC. They also found that the results from SLOSH simulations were not biased relative to those of the ADCIRC simulations when the same wind fields were applied, although the SLOSH simulations were less sensitive to storm characteristics and often predicted similar surges for a range of different storms, compared to the ADCIRC simulations. However, it should be noted that the SLOSH model has an internal parametric wind model, which may underestimate the surface background wind and thus underestimate wind-field intensity. Thus, when the SLOSH wind fields are used, the storm surge may be underestimated; nevertheless, the estimated surges from the two model simulations are highly correlated (see Lin et al. 2012 supplementary material).

The SLOSH and ADCIRC models may be applied together in surge risk analysis. To make it possible to simulate surges with reasonable accuracy for the large synthetic storm sets for a risk assessment for NYC, Lin et al. (2012) applied the two hydrodynamic models with numerical grids of various resolutions in such a way that the main computational effort is concentrated on the storms that determine the risk of concern. First, the SLOSH model with resolution of ~1 km around NYC is applied as a filter to select the storms that have return periods, in

terms of the surge height at the Battery, greater than 10 yr. Second, the ADCIRC model with a resolution of ~100 m around NYC is applied to each of the selected storms. To determine whether the resolution of the ADCIRC simulation is sufficient, another ADCIRC mesh with resolution as high as ~10 m around NYC is used to simulate over 200 most-extreme events under present climate conditions. The differences between the results from the two grids are very small. Thus, the ~100-m ADCIRC simulations were used, with a 2.5% reduction of the surge magnitude motivated by the ~10-m simulations, to estimate the surge levels at the Battery for return periods of 10 yr and longer. Applying the two storm surge models in this way, large numbers of surge events can be efficiently simulated to estimate the risk. In addition to the analysis for the current climate, Lin et al. (2012) applied this approach, together with the Emanuel et al.'s (2008) TC risk model, to study the impact of climate change on surge risk through simulating 40,000 synthetic storm surge events under current and future climate conditions projected by four climate models. Their results, indicate a greatly increased storm surge threat in a future climate, due to the change in storm climatology. The combination of the change of storm climatology and projected sea level rise indicates greatly reduced coastal-flood return periods for New York City.

TC hazard risk assessment

The risk of TC hazards, such as wind speed and surge height, may be estimated from physically simulated database of the hazards. One may assume the annual storm counts for a region to be Poisson-distributed (Elsner and Bossak 2001; Lin et al. 2012), with the mean estimated by the TC risk model. The probability density function (PDF) of TC hazards appears to be characterized by a fat upper tail, which tends to control the risk (Lin et al. 2012). For the (marginal) PDFs of wind speed and surge height, one may apply a Peaks-Over-Threshold (POT) method to model the upper tail with a Generalized Pareto Distribution (GPD) and the rest of the distribution through non-parametric density estimation. The PDF of coastal-flood levels will be a convolution of the PDFs of surge, astronomical tide, wave setup, and sea level rise, with their nonlinear interactions empirically accounted for (see Lin et al. 2012). These PDFs and the storm frequency model can then be combined to estimate hazard-specific return-period curves and associated statistical confidence intervals. Return-period maps can also be generated, and one can proceed to estimate joint dis-

tributions for wind and coastal flooding and for wind and inland flooding.

4 TC DAMAGE MODELING

TCs cause damage to the natural and built environment, via a multiplicity of hazards. Residential buildings, in particular, are often heavily damaged by TC winds, surge/wave, and flooding caused by severe rainfall, as seen in recent storms such as Hurricane Sandy. Hurricane wind damage to residential buildings is mainly due to direct wind pressure effect, windborne debris impact, and their interaction over time. The typical debris sources are roof materials, such as roof covers, sheathings, and timbers. These roof materials may become windborne, due to high wind pressure on the roof, and fly at high speeds so as to damage surfaces of neighboring buildings. When the building envelopes are penetrated, in addition to causing wind and rain damage to building contents, internal pressurization increases the net loading in suction zones, possibly leading to failure of roofing and wall cladding, generating new debris and thus starting a chain reaction in the whole residential area. Lin and Vanmarcke (2010) developed a debris risk model, based on the Poisson theory, large numbers of wind-tunnel experiments (Lin et al. 2006 and 2007), and available post-damage survey data (Twisdale et al. 1996). Lin et al. (2012) further integrated this debris model with a component-based pressure damage model to estimate the wind damage to a residential area during the passage of a storm. This wind damage model is an improvement over other methods, such as the FEMA HAZUS-MH Hurricane Model (Vickery et al. 2006) and the Florida Public Hurricane Loss Projection model (Gurley et al. 2005), in that it explicitly models, for the first time, the (two-way) interaction between pressure damage and debris damage over time. Results from a case study involving a residential area in Florida were shown, which indicate that wind damage to residential areas may be greatly underestimated if the effects of windborne debris are not accounted for. Yau et al. (2011) made use of this wind damage model to estimate economic losses from TCs.

This wind damage model can be extended to account for the effects of the surge/wave and rainfall. Damage due to rainfall may be modeled by converting amounts of water penetrated (through openings created by pressure and debris) into an interior damage ratio (Pita et al. 2012). The surge/wave damage component can be developed using damage survey data. Based on data from Hurricane Ike (2008),

Kennedy et al. (2011) developed empirical relationships between surge/wave damage and the freeboard height and significant wave height. Such empirical damage functions can be tested and further improved using recent damage data, for example, from Hurricane Sandy.

TC vulnerability models can be combined with the TC risk assessment and hazard modeling (see above) to predict the aggregate impact of TCs in coastal regions. Aerts et al. (2013) predicted the storm surge damage risk, in terms of expected annual losses, for NYC. Klima et al. (2011) estimated and compared expected damage/losses with the costs of alternative mitigation measures (and their combinations) for Miami-Dade County, Florida. Further improvements may include accounting for the correlation of the TC hazards to develop joint (or multiply effective) mitigation strategies. Also, dynamic economic models may be applied to derive near-optimal mitigation strategies and implementation time paths.

5 CONCLUDING REMARKS

We sought to assess the status of quantifying risks associated with hurricanes, including the effect on TC risk of various climate-change scenarios. The principal hazards, entailing various combinations of catastrophic loss potential, are storm surge, strong wind pressures, high-impact debris, and heavy rainfall and flooding. Recent approaches to modeling in each of these areas are reviewed and illustrated with (references to and summaries of) case studies. The challenge remains to tackle the multiplicity of hazards in an integrated way, aiming at improved risk estimation and quantification of uncertainties across a range of spatial scales. The results are of considerable interest to those seeking to quantify the effectiveness of risk mitigation measures and perform risk-based scientific and policy analysis pertaining to the resilience of the natural and built environments.

6 REFERENCES

Aerts, J., N. Lin, H. Moel, K. Emanuel and W. Botzen, 2013: Low probability flood-risk modeling for New York City. *Risk Analysis*, in press.

Bender, M. A., T. R. Knutson, R. E. Tuleya, J. J. Sirutis, G. A. Vecchi, S. T. Garner, and I. M. Held, 2010: Modeled impact of anthropogenic warming on the frequency of intense Atlantic

hurricanes. *Science*, 327(5964), doi:10.1126/science.1180568.

Bretschneider, C.L (1972), A non-dimensional stationary hurricane wave model, paper presented at the Offshore Technology Conference, Houston, Texas.

Bunya, S., et al. (2010), A High-Resolution Coupled Riverine Flow, Tide, Wind, Wind Wave, and Storm Surge Model for Southern Louisiana and Mississippi. Part I: Model Development and Validation, *Mon. Wea. Rev.*, *138*, 345-377, doi: 10.1175/2009MWR2906.1.

Chavas, D. R. and K. A. Emanuel, 2010: A QuikSCAT climatology of tropical cyclone size, *Geophys. Res. Lett.*, *37*, L18816, doi:10.1029/2010GL044558.

Colle, B. A., F. Buonaiuto, M. J. Bowman, R. E. Wilson, R. Flood, R. Hunter, A. Mintz, and D. Hill, 2008: New York City's vulnerability to coastal flooding, *Bull. Am. Meteorol. Soc.*, *89*, 829-841, doi:10.1175/2007BAMS2401.1.

Dietrich J.C. et al. Modeling hurricane waves and storm surge using integrally-coupled, scalable computations. *Coast. Eng.*, 58, 1, 45-65 (2011).

Elsner, J. B. and B. H. Bossak, 2001: Bayesian analysis of U.S. hurricane climate. *J. Climate*, 14, 4341-4350 (2001).

Elsner, J. B., T. H. Jagger, and K.B. Liu (2008), Comparison of hurricane return levels using historical and geological records, *J. Appl. Meteorol.*, 47, 368–374, doi:10.1175/2007JAMC1692.1.

Emanuel, K. A. An air-sea interaction theory for tropical cyclones, 1986: Part I: Stady-state maintenance. *J. Atmos. Sci.*, 43, 585-605.

Emanuel, K., 2004: Tropical Cyclone Energetics and Structure, in *Atmospheric Turbulence and Mesoscale Meteorology*, edited by E. Fedorovich, R. Rotunno and B. Stevens, Cambridge University Press, 280 pp.

Emanuel, K.A., 2005: *Divine Wind: The History And Science Of Hurricanes,* ISBN 0-19-514941-6.

Emanuel, K., S. Ravela, E. Vivant, and C. Risi, 2006: A statistical deterministic approach to hurricane risk assessment, *Bull. Am. Meteorol. Soc.*, *87*, 299-314, doi:10.1175/BAMS-87-3-299.

Emanuel, K., R. Sundararajan and R. Williams, 2008: Hurricanes and global warming: results from downscaling IPCC AR4 simulations. *Bull. Am. Meteor. Soc.,* 89, 347–367.

Emanuel, K., K. Oouchi, M. Satoh, T. Hirofumi and Y. Yamada, 2010: Comparison of explicitly simulated and downscaled tropical cyclone activity in a high-resolution global climate model. *J. Adv. Model. Earth Sys.,* 2, 9. doi:10.3894/JAMES.2010.2.9.

Emanuel, K. and R. Rotunno, 2011: Self-Stratification of tropical cyclone outflow. Part I: Implications for storm structure, *J. Atmos. Sci.,* 68, 2236–2249. doi: http://dx.doi.org/10.1175/JAS-D-10-05024.1

Gurley, K., J. P. Pinelli, C. Subramanian, A. Cope, L. Zhang, J. Murphree, A. Artiles, P. Misra, S. Culati, and E. Simiu, 2005: Florida Public Hurricane Loss Projection Model engineering team final report, Technical report, International hurricane Research Center, Florida International University.

Hall, T. and S. Jewson, 2007: Statistical modelling of North Atlantic tropical cyclone tracks. *Tellus A*, 59(4), 1600-0870.

Handmer, J., Y. Honda, Z.W. Kundzewicz, N. Arnell, G. Benito, J. Hatfield, I.F. Mohamed, P. Peduzzi, S. Wu, B. Sherstyukov, K. Takahashi, and Z. Yan, 2012: Changes in impacts of climate extremes: human systems and ecosystems. In: Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation [Field, C.B., V. Barros, T.F. Stocker, D. Qin, D.J. Dokken, K.L. Ebi, M.D. Mastrandrea, K.J. Mach, G.-K. Plattner, S.K. Allen, M. Tignor, and P.M. Midgley (eds.)]. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change (IPCC). Cambridge University Press, Cambridge, UK, and New York, NY, USA, pp. 231-290.

Hart, R.E. and J. L. Evans, 2001: A Climatology of the Extratropical Transition of Atlantic Tropical Cyclones. *J. Climate*, 14, 546–564. doi: http://dx.doi.org/10.1175/1520-0442(2001)014<0546:ACOTET>2.0.CO;2

Hart, Robert E., 2003: A Cyclone Phase Space Derived from Thermal Wind and Thermal Asymmetry. *Mon. Wea. Rev.*, 131, 585–616. doi: http://dx.doi.org/10.1175/1520-0493(2003)131<0585:ACPSDF>2.0.CO;2

Holland, G.J., J.I. Belanger and A. Fritz, 2010: A revised model for radial profiles of hurricane winds, *Mon. Wea. Rev.*, 138, 4393–4401, doi: 10.1175/2010MWR3317.1.

Houston, S. H., W. A. Shaffer, M. D. Powell, and J. Chen (1999), Comparisons of HRD and SLOSH surface wind fields in hurricanes: Implications

for storm surge modeling, *Weather Forecast.*, *14*, 671–686, doi:10.1175/1520-0434(1999)014<0671:COHASS>2.0.CO;2.

Jarvinen, B. R., and M. B. Lawrence (1985), An evaluation of the SLOSH storm surge model, Bull. Am. Meteorol. Soc., 66, 1408–1411.

Jarvinen, B., and J. Gebert (1986), Comparison of observed versus SLOSH model computed storm surge hydrographs along the Delaware and New Jersey shorelines for Hurricane Gloria, September 1985, NOAA Tech. Memo NWS NHC 32.

Jelesnianski, C. P., J. Chen, and W. A. Shaffer, 1992: *SLOSH: Sea, lake, and overland surges from hurricanes*, *NOAA Tech. Rep. NWS 48*, NOAA/AOML Library, Miami, Fla.

Kennedy, A., S., Rogers, A., Sallenger, U. Gravois, B. Zachry, M. Dosa, and F. Zarama, 2011: Building destruction from waves and surge on the Bolivar Peninsula during Hurricane Ike. *J. Watersay, Port, Coastal, Ocean Eng.*, 137(3), 132-141.

Kepert, J.D., 2010: Slab- and height-resolving models of the tropical cyclone boundary layer. Part I: Comparing the simulations, *Q. J. R. Meteorol. Soc. 136*, 1686–1699, doi: 10.1002/qj.667.

Klima, K., N. Lin, K.A. Emanuel, M.G. Morgan and I. Grossmann, 2011: Hurricane modification and adaptation in Miami-Dade County, Florida. *Environmental Science and Technology*, 45, 636-642, doi: 10.1021/es202640p.

Knutson, T. R., J. J. Sirutis, S. T. Garner, I. M. Held and R. E. Tuleya, 2007: Simulation of the recent multi-decadal increase of Atlantic hurricane activity using an 18-km-grid regional model. *Bull. Amer. Meteor. Soc.,* 88, 1549–1565.

Knutson, T. R., J. McBride, J. Chan, K. A. Emanuel, G. Holland, C. Landsea, I. M. Held, J. Kossin, A. K. Srivastava, and M. Sugi, 2010: Tropical cyclones and climate change. *Nature Geoscience*, 3, doi:doi:10.1038/ngeo779.

Knutson, T.R., J. J. Sirutis, G. A. Vecchi, S. Garner, M. Zhao, H. Kim, M. Bender, R. E. Tuleya, I. M. Held, and G. Villarini, 2013: Dynamical Downscaling Projections of 21st Century Atlantic Hurricane Activity: CMIP3 and CMIP5 Model-based Scenario. *J. Climate*, submitted for publication.

Lin, N., C.W. Letchford and J.D. Holmes, 2006: Investigations of plate-type windborne debris, I. Experiments in wind tunnel and full-scale. *Journal of Wind Engineering and Industrial Aerodynamics*, 94, 51-76.

Lin, N., J.D. Holmes and C.W. Letchford, 2007: Trajectories of windborne debris and applications to impact testing. *ASCE Journal of Structural Engineering*, 133(2), 2, 274-282.

Lin, N. and E. Vanmarcke, 2008: Windborne debris risk assessment. *Probabilistic Engineering Mechanics*, 23(4) (Special Issue dedicated to Ove Ditlevsen), 523-530.

Lin, N., K.A. Emanuel, J.A. Smith and E. Vanmarcke, 2010a: Risk assessment of hurricane storm surge for New York City. *Journal of Geophysical Research-Atmospheres*, 115, D18121, doi:10.1029/2009JD013630.

Lin, N., J.A. Smith, G. Villarini, T. Marchok and M.L. Baeck, 2010b: Modeling extreme rainfall, winds, and surge from Hurricane Isabel (2003). *Weather and Forecasting*, 25, 1342–1361, doi: 10.1175/2010WAF2222349.1.

Lin, N. and E. Vanmarcke 2010: Windborne debris risk analysis: Part I. Introduction and methodology. *Wind and Structures*, 13(2) (Special Issue on Windborne Debris), 191-206.

Lin, N., E. Vanmarcke and S.C. Yau, 2010c: Windborne debris risk analysis: Part II. Application in structural vulnerability modeling. *Wind and Structures*, 13(2) (Special Issue on Windborne Debris), 207-220.

Lin, N., K.A. Emanuel, M. Oppenheimer and E. Vanmarcke, 2012: Physically based assessment of hurricane surge threat under climate change. *Nature Climate Change*, doi: 10.1038/NCLIMATE1389.

Lin, N. and D. Chavas, 2012: On hurricane parametric wind and applications in storm surge modeling. *Journal of Geophysical Research-Atmospheres*, 117, D09120, doi:10.1029/2011JD017126.

Luettich R.A., J. J. Westerink, and N. W. Scheffner, 1992: ADCIRC: An Advanced Three-dimensional Circulation Model for Shelves, Coasts and Estuaries, Report 1: Theory and Methodology of ADCIRC-2DDI and ADCIRC-3DL. DRP Technical Report DRP-92-6. (Department of the Army, US Army Corps of Engineers, Waterways Experiment Station, Vicksburg, MS, 1992).

Mattocks, C. and C. Forbes (2008), A real-time, event-triggered storm surge forecasting system for the state of North Carolina, *Ocean Model.*, *25*, 95-119.

Mendelsohn, R., K. Emanuel, S. Chonabayashi, and L. Bakkensen, 2012: The impact of climate change on global tropical cyclone damage. *Nature Clim. Change*, 10.1038/nclimate1357.

Phadke, A.C., C.D. Martino, K.F. Cheung and S.H. Houston (2003), Modeling of tropical cyclone winds and waves for emergency management, *Ocean Eng.*, *30*, 553-578.

Pielke, Jr., R.A., 2007: Future economic damage from tropical cyclones: sensitivities to societal and climate changes. *Philosophical Transactions of the Royal Society A*, 365(1860), 2717-2729.

Pita, G., J.-P. Pinelli, S. Cocke, K. Gurley, J. Mitrani-Reiser, J. Weekes, S. Hamid, 2012, Assessment of hurricane-induced internal damage to low-rise buildings in the Florida Public Hurricane Loss Model, *Journal of Wind Engineering and Industrial Aerodynamics*, Volumes 104–106, May–July 2012, Pages 76-87, ISSN 0167-6105, 10.1016/j.jweia.2012.03.023.

Powell, M. D., S. H. Houston, L. R. Amat, and N. Morisseau-Leroy, 1998: The HRD real-time hurricane wind analysis system, *J. Wind Eng. Indust. Aerodyn.*, *77&78*, 53-64.

Powell, M. D., P. J. Vickery, and T. A. Reinhold (2003), Reduced drag coefficient for high wind speeds in tropical cyclones, *Nature*, *422*(6929), doi:10.1038/nature01481.

Powell, M., G. Soukup, S. Cocke, S. Gulati, N. Morisseau-Leroy, S. Hamid, N. Dorst, L. Axe, 2005: State of Florida hurricane loss projection model: Atmospheric science component, *Journal of Wind Engineering and Industrial Aerodynamics*, Volume 93, Issue 8, August 2005, Pages 651-674, ISSN 0167-6105, 10.1016/j.jweia.2005.05.008.

Resio D.T. and J. J. Westerink, 2008: Modeling the Physics of Storm Surges, *Physics Today,* 33-38, September 2008.

Rumpf, J., H., Weindl, P., Höppe, E. Rauch and V. Schmidt, 2007: Stochastic modeling of tropical cyclone tracks. *Math Meth Oper Res*, 66, 3, 475–490.

Skamarock, W. C., J. B. Klemp, J. Dudhia, D. O. Gill, D. M. Barker, W. Wang, and J. G. Powers, 2005: A description of the Advanced Research WRF version 2. NCAR Tech. Note NCAR/ TN-4681STR, 88 pp.

Thompson, E. F., and V. J. Cardone, (1996), Practical modeling of hurricane surface wind fields, *J. Waterw. Port Coast. Ocean Eng.*, *122*, 195-205.

Twisdale, L.A., P. J. Vickery, and A. C. Steckley, 1996: Analysis of hurricane windborne debris risk for residential structures, Technical report, Raleigh (NC): Applied Research Associates, Inc.

Vickery, P. J., P. F. Skerjl, and L. A. Twisdale, 2000: Simulation of hurricane risk in the U.S. using empirical track model, *J. Struct. Eng.*, *126*, 1222-1237.

Vickery, P.J., P. F. Skerlj, J. Lin, L. A., Twisdale, M.A. Young, and F. M. Lavelle, 2006: HAZUS-MH Hurricane Model methodology. II: Damage and loss estimation, *Nat. Hazards Rev.*, 7(2), 94-103.

Vickery, P.J., D. Wadhera, M.D. Powell and Y. Chen, 2009: A hurricane boundary layer and wind field model for use in engineering applications, *J. Appl. Meteorol. Climatol.*, *48*, 381-405, doi: 10.1175/2008JAMC1841.1.

Westerink, J.J., R.A. Luettich , J.C. Feyen, J.H. Atkinson, , C. Dawson, H.J. Roberts, M.D. Powell, J.P. Dunion, E.J. Kubatko, H. Pourtaheri, 2008: A Basin to Channel Scale Unstructured Grid Hurricane Storm Surge Model Applied to Southern Louisiana, *Mon. Wea. Rev*, 136, 3, 833-864.

Yau, S.C., N. Lin and E. Vanmarcke, 2011: Hurricane damage and loss estimation using an integrated vulnerability model. *Natural Hazards Review*, doi:10.1061/(ASCE)NH.1527-6996.0000035.

Yonekura, E., and T. M. Hall, 2011: A statistical model of tropi- cal cyclone tracks in the Western North Pacific with ENSO- dependent cyclogenesis. J. Appl. Meteor. Climatol., 50, 1725- 1739, doi:10.1175/2011JAMC2617.1.