Assessing and Managing Hurricane Risk in a Changing Climate

Ning Lin
Department of Civil and Environmental Engineering, Princeton University

Hurricanes, through their strong winds, heavy rainfall, and storm surges, cause much damage and loss of life worldwide. Recent disasters, including Hurricanes Katrina in 2005 and Sandy in 2012, Cyclone Nargis in 2008, and Typhoon Haiyan in 2013, underscore the significant vulnerability of the U.S. and the world to landfalling hurricanes. The impacts of these storms may worsen in the coming decades because of rapid coastal development coupled with sea level rise and possibly increasing hurricane activity due to climate change. Thus, major advances in hurricane risk management are urgently needed. Given the inherent uncertainties in hurricane activity, hurricane risk management should be strongly informed by probabilistic risk assessment. Furthermore, hurricane risk assessment cannot rely solely on the historical records: to account for the future changes, the risk assessment should integrate physical knowledge/models with observational data.

A physically-based probabilistic hurricane risk assessment framework should integrate the analysis of storm activity, hazards, and risk. Due to the limitation of historical records and the complexity of the problem, Monte Carlo (MC) methods, based on numerous synthetic simulations, are often applied. In a MC approach, large numbers of synthetic but physically possible storms, characterized by their various track, intensity, and size, are simulated (with their frequencies/probabilities estimated), under observed or climate-model projected future climate conditions. Hazard models are then used to estimate the wind, surge, and rainfall flooding associated with the simulated storms, with the probabilistic description of the hazards (e.g., return periods) obtained. Given the estimated hazards and coastal exposure, vulnerability models can be applied to estimate the storm-induced consequences (e.g., damage and/or economic losses) and thus the risk. The risk assessment can inform risk management from various perspectives to achieve coastal resiliency. In the following sections, we discuss about the main components of such a risk assessment framework and its application to evaluating risk mitigation strategies.

Hurricane activity

Various MC methods have been developed to simulate synthetic storms to depict hurricane activity and climatology. Most of these methods (e.g., Vickery et al. 2000, Toro et al. 2010, Hall and Sobel 2013) simulate synthetic storms based on the statistics of the historical storm records. We apply the statistical-deterministic model developed by Emanuel et al. (2006 and 2008), which simulates storm environments statistically but generates synthetic storms in the simulated environments deterministically (with physical models). This model does not rely on the historical storm data but generates large samples of synthetic storms that are in statistical agreement with the (albeit limited) observations. Moreover, as the synthetic hurricane environments can be generated for any given climate state, this model can simulate synthetic storms not only in the current and past climates but also in projected future climates. This model has been used to simulate storms in various ocean basins under projected climates over the 21st century to investigate how the storm intensity and frequency may change with the changing climate (Emanuel 2013). It has also been used to simulate storms at city scales for, e.g., New York City (NYC; Lin et al. 2010a and 2012), Miami (Klima et al. 2011), Apalachee Bay (Lin et al. 2014), and Tampa (Lin et al. 2015) in Florida, Galveston in TX (Lickley et al. 2014), Cairns in Australia (Lin et al. 2015), and Dubai in the

Persian Gulf (Lin et al. 2015). These city-scale simulations can be used to analyze local hazards and risk. Fig. 1 shows an example of 5000 storms we simulated for NYC (under the observed climate of 1981-2000 and with an estimated annual frequency of 0.34).

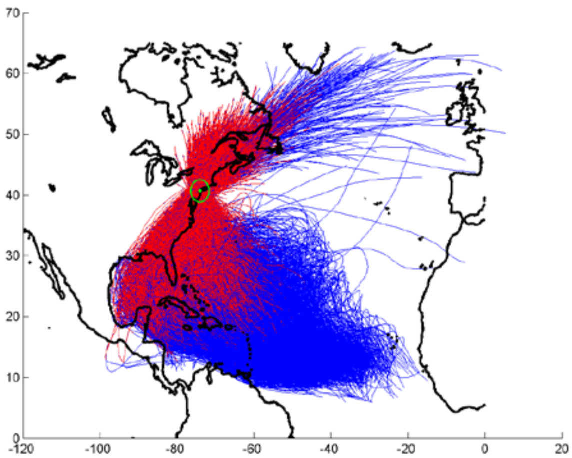


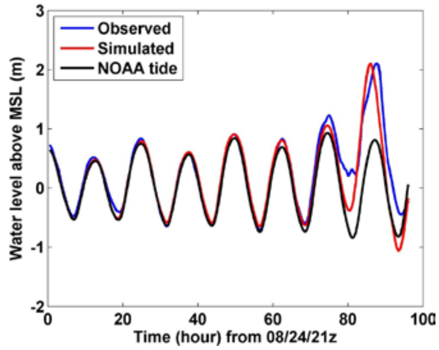
Fig. 1. 5000 synthetic storms simulated, using the Emanuel et al. (2006) model, that pass within 200 km of Battery, NYC with a maximum wind speed greater than 21 m/s. The green circle shows the 200-km-radiu area around the Battery. The red potion of each track shows the 100-hour period before and during landfall (the main time period considered for hazard modeling).

Hurricane hazards

Given the storm characteristics, hazard models can be applied to estimate the wind, surge, and rainfall flooding induced by the storm during its landfall. As large numbers of simulations are required for the MC-based risk analysis, the hazard models should be (computationally) "simple": often there is a balance between accuracy and efficiency.

Various simple parametric methods have been developed to model the wind fields. Specially, one can estimate the storm wind field using a parametric wind profile (e.g., Holland 1980; Jelesnianski et al., 1992) and add an estimated background wind (Lin and Chavas 2012) to obtain the total wind field. We have recently developed a new complete wind profile (Chavas et al. 2015), motivated by the fact that although the canonical wind fields of mature hurricanes are approximately circularly symmetric, a single mechanism cannot describe a hurricane's entire structure. Emanuel (2004) developed a physical model of the outer non-convecting region of the storm. Emanuel and Rotunno (2011) established an analytical profile that is physically valid only for the inner convecting region. The complete wind profile is constructed by mathematically merging these two theoretical solutions to cover the entire domain of the storm. This new physical model, evaluated and calibrated with various observational datasets, will have broad applications in hurricane hazard analyses.

The storm surge is driven mainly by the storm surface wind and pressure, and it is particularly sensitive to the wind as well as coastal bathymetry and topography. Various hydrodynamic surge models, basically solving coastal shallow water equations, have been developed, including the Sea, Lake, and Overland Surges from Hurricanes (SLOSH; Jelesnianski et al., 1992) model used by the National Hurricane Center for real time forecasting and the Advanced Circulation (ADCIRC) model (Westerink et al. 2008). While the SLOSH model is computationally more efficient, the ADCIRC model can better resolve the physical processes and produce results with much higher resolutions. Fig. 2 shows that, as an example, the ADCIRC-model simulated storm surges from Hurricanes Irene (2011) and Sandy for the NYC area compare very well with the tidal gauge data. In these stimulations, we applied high-resolution bathymetry and topography data, observed storm characteristics, as well as the parametric wind model and a similarly simple parametric pressure model (Holland 1980).



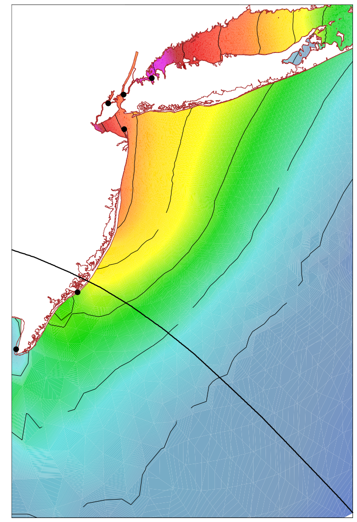


Fig. 2 Storm surge estimation for NYC for Irene (left; time series of water level at the Battery) and Sandy (right; spatial distribution of the simulated peak surge; the estimated peak surge at the Battery, about 2.9 m, is close to the observed value of about 2.8 m above high tide; black curve shows the observed track).

Hurricane rainfall is relatively difficult to model due to its large spatial and temporal variation, compared to the wind and surge. Thus, most hurricane rainfall modeling applies full numerical weather prediction models (e.g., Tuleya et al. 2007, Lin et al. 2010b). However, this approach is not directly applicable to risk analysis, due to the required large input data and high computational cost. Recently, simpler parametric models have been developed based on historical rainfall statistics (e.g., Tuleya et al. 2007; Lonfat et al. 2007) and physical principles (e.g., Langousis et al. 2009). The basic physics of hurricane rainfall is that it is determined mainly by the environmental moisture and the speed of the storm updraft, which depends on low-level convergence due to surface friction, interaction with topography, and interaction with the background baroclinic state. A model that describes these processes has been shown to generate rainfall statistics comparable to the observations (Zhu et al. 2013). Research is ongoing to evaluate and further develop this physical rainfall model, which can then be coupled with a hydrologic model (e.g., Cunha et al. 2012) to simulate inland flooding.

Hurricane risk

The hazard models can be applied to the simulated synthetic storms to generate large samples of hazards, based on which the probabilities of the hazards can be estimated. For example, ASCE building code has applied such an approach to establish the design wind map (showing wind speeds for various return periods) for the entire U.S. coast. The FEMA flood map, depicting the 100- and 500-year floodplains to provide a basis for the federal flood insurance policy, is also developed with such an approach, although different storm and hazard models have been used in these different applications. If the hurricane model used to generate the synthetic storms can be driven by climate-model projected climate environments (Emanuel et al. 2008), the probabilistic hazards under future climate can be estimated. Fig. 3 shows, as an illustration of such an analysis we performed, the estimated storm surge level as a function of return period for NYC, under the observed and climate-model-estimated current climates as well as the climate-model-projected future climates.

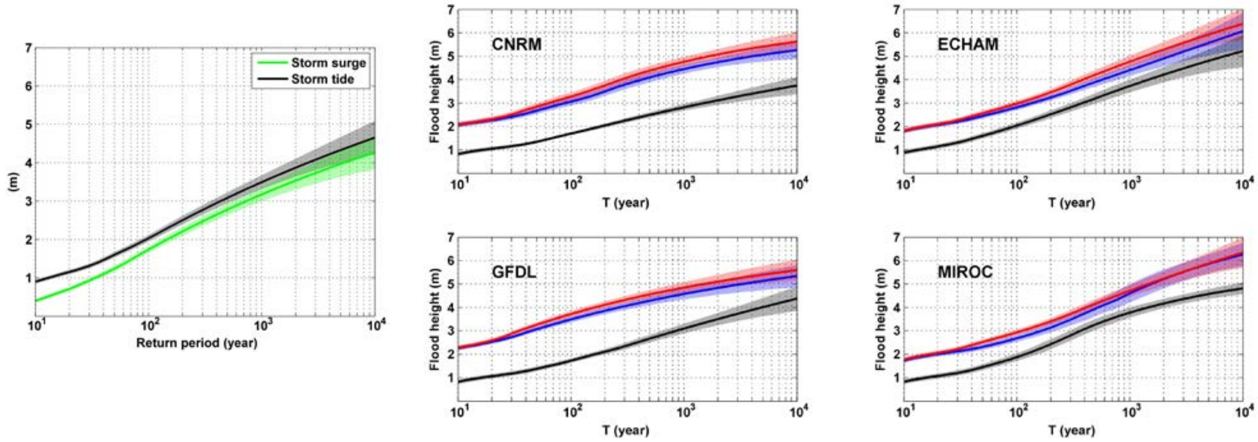


Fig. 3. Estimated storm surge return level curves for NYC, under (left) observed climate of 1980-2000 and (four panels on the right) four climate-model-projected climates of 1980-2000 (black) and of 2080-2100 (blue and, when accounting also for potential changes in storm size, red; with projected 1-m SLR accounted for). Each curve is based on 5000 synthetic storms; e.g., the curves on the left panel is based on the 5000 storms shown in Fig. 1. (from Lin et al. 2012)

The hazard probabilities can also be combined with the estimated consequences of the hazards to quantify the risk. (The damage/losses can be estimated with vulnerability models such as the HAZUS model developed by FEMA.) The risk is often expressed by the expectation (mean) of the damage/loss in a year (annual expected damage, e.g., Aerts et al. 2013). However, the full probabilistic distribution of the loss, if available, is more informative. In the context of climate change and coastal development, this risk is non-stationary and likely increasing. To obtain a temporally integrated measure, the losses are also typically quantified by their present value (PV), the sum of all discounted losses occurring over a given time horizon (e.g., next 100 years). Then the risk can be considered as the mean or, better, the probability distribution of the PV of the potential losses.

Moreover, the PV provides a convenient metric for comparing the benefit and cost of risk mitigation strategies. Specifically, the benefit can be considered as the PV of the avoided losses due to the mitigation, and the cost is the PV of the total cost of the mitigation (including construction and maintenance). While the cost is largely deterministic, the benefit is random. Most previous studies have focused on comparing the cost and the mean of the benefit (e.g., Aerts et al. 2014). Here we show a more informative way of comparing the cost and the probability distribution of the benefit, for three coastal flood mitigation strategies proposed for NYC. As shown in Fig. 4., for each strategy, we estimate the full distribution of the PV of the benefit and plot its exceedence probability to compare with the cost. The crossing of the probability curve of the benefit and the line of the cost gives the probability that the benefit is greater than the cost. The probabilities of getting any higher or lower benefits can also be easily read from the curve. Thus, the full probabilistic benefit-cost analysis provides the full information for making decisions for any specific risk tolerance (decisions made based on the mean assumes “risk neutral”). Moreover, these analyses have accounted for the projected coastal development and changes in the storm activity and the sea level over the 21^{st} century. Such probabilistic risk management analyses rely on the physically-based risk assessment discussed above.

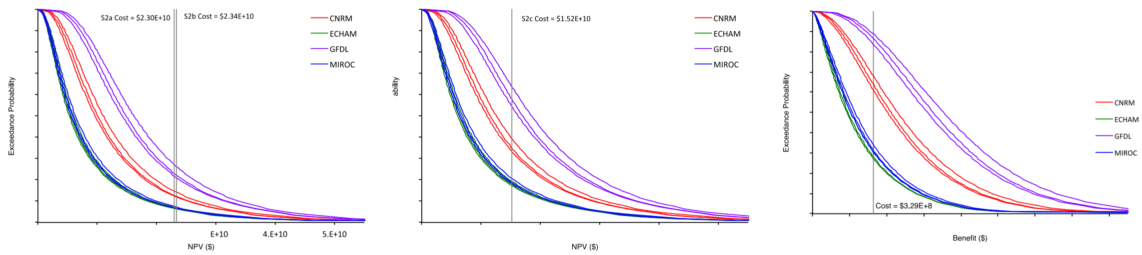


Fig. 4. Estimated exceedance probability of PV of the benefit (curve) compared to the cost (vertical line), for strategies S2a and S2b (left), strategy S2c (middle), and strategy of elevating new houses on the floodplain by 6 feet (right), for NYC. S2a consists of three barriers to close off parts of NYC and NJ that preserve wetland dynamics of Jamaica Bay. S2b expands on S2a by adding a fourth barrier that closes off Jamaica Bay. S2c replaces three barriers from S2b with one large barrier in the outer harbor to protect a larger area. The details of these mitigation stratigies are discussed in Aerts. et al. (2014). The analyses acount for the projected coastal development and changes in storm activity and the sea level over the 21^{st} century. Current and future building stock data is obtained from the New York City Office of Emergency Management. The sythetic storm surge events were generated by Lin et al. (2012) for the four climate models, as shown by the return level curves in Fig. 3. The probabilistic SLR projection is obtained from Kopp et al. (2014); the three curves of the same color shows results with SLR projected for the three representative concentration pathways (RCPs): RCP 2.6, RCP 4.5, and RCP 8.5, respectively.

Future research

It is still quite uncertain how hurricanes, especially their frequency and size, will vary with the climate. As scientific investigation continues, more physically-based methods for simulating synthetic storms should be developed for risk analysis. Hurricane rainfall models, especially those based on physics, are needed to estimate inland flooding risk. Hurricane hazards are correlated (e.g., hurricane wind affects both storm surge and rainfall; coastal and inland flooding may interact); multi-hazards approaches may be applied to estimate how the hazards will jointly evolve in the future and how the joint risk should be dealt with. In addition to engineering measures, urban planning and federal and private insurance play important roles in coastal risk mitigation; the physically-based probabilistic risk assessment should be applied to inform broader and more integrated risk management strategies.

References

Aerts, J. C. J. H., Lin, N., Botzen, W., Emanuel, K. & de Moel, H. (2013). Low-Probability Flood Risk Modeling for New York City. *Risk Analysis* **33,** 772–788.

Aerts, J. C. J. H., Botzen, W. W., Emanuel, K., Lin, N., de Moel, H., & Michel-Kerjan, E. O. (2014). Evaluating flood resilience strategies for coastal megacities. *Science*, *344*(6183), 473-475.

Chavas, D. R., Lin, N., & Emanuel, K. (2015). A model for the complete radial structure of the tropical cyclone wind field. Part I: Comparison with observed structure. *Journal of the Atmospheric Sciences*.

Cunha, L. K. da, P. V. Mandapaka, W. F. Krajewski, R. Mantilla, and A. Bradley (2012). Impact of radar-rainfall error structure on estimated flood magnitude across scales: An investigation based on a parsimonious distributed hydrological model, *Water Resour. Res.*, doi:10.1029/2012WR012138.

Emanuel, K. (2004), Tropical cyclone energetics and structure, in *Atmospheric Turbulence and Mesoscale Meteorology*, edited by E. Fedorovich, R. Rotunno, and B. Stevens, pp. 165–192, Cambridge Univ. Press, Cambridge, U. K., doi:10.1017/CBO9780511735035.010.

Emanuel, K., Ravela, S., Vivant, E. & Risi, C. (2006). A Statistical deterministic approach to hurricane risk assessment. *Bull. Amer. Meteor. Soc.*, 87, 299-314.

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

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

Emanuel, K. A. (2013). Downscaling CMIP5 climate models shows increased tropical cyclone activity over the 21st century, *Proc. Natl. Acad. Sci*., 110(30), 12,219–12,224.

Hall, T. M., & Sobel, A. H. (2013). On the impact angle of Hurricane Sandy's New Jersey landfall. *Geophysical Research Letters*, 40(10), 2312-2315.

Holland, G. J. (1980). An analytic model of the wind and pressure profiles in hurricanes. *Monthly weather review*, *108*(8), 1212-1218.

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.

Klima, K., Lin, N., Emanuel, K., Morgan, M. G. & Grossmann, I. (2012) Hurricane Modification and Adaptation in Miami-Dade County, Florida. *Environ. Sci. Technol.* **46,** 636–642.

Lickley, M. J., Lin, N. & Jacoby, H. D. (2014). Analysis of coastal protection under rising flood risk. *Climate Risk Management* **6,** 18–26.

Lin, N., Emanuel, K. A., Smith, J. A. & Vanmarcke, E. (2010a). Risk assessment of hurricane storm surge for New York City. *J. Geophys. Res.* **115,** D18121.

Lin, N., Smith, J. A., Villarini, G., Marchok, T. P. & Baeck, M. L. (2010b). Modeling Extreme Rainfall, Winds, and Surge from Hurricane Isabel (2003). *Wea. Forecasting* **25,** 1342–1361.

Lin, N. & Chavas, D. (2012). On hurricane parametric wind and applications in storm surge modeling. *J. Geophys. Res.* **117,** D09120.

Lin, N., Emanuel, K., Oppenheimer, M. & Vanmarcke, E. (2012). Physically based assessment of hurricane surge threat under climate change. *Nature Climate Change* **2,** 1–6.

Lin, N., Lane, P., Emanuel, K. A., Sullivan, R. M. & Donnelly, J. P. (2014). Heightened hurricane surge risk in northwest Florida revealed from climatological-hydrodynamic modeling and paleorecord reconstruction. *J. Geophys. Res. Atmos.* 119.

Lin, N. and Emanuel, K. (2015). Grey swan tropical cyclones. *Nature Climate Change*.

Lonfat, M., Rogers, R., Marchok, T. & Marks, F. D., Jr. (2007). A Parametric Model for Predicting Hurricane Rainfall. *Mon. Wea. Rev*. 135, 3086–3097.

Toro, G. R., D. T. Resio, D. Divoky, A. W. Niedoroda, and C. Reed (2010). Efficient joint-probability methods for hurricane surge frequency analysis, *Ocean Eng*., 37(1), 125–134.

Tuleya, R. E. & DeMaria, M. (2007). Evaluation of GFDL and simple statistical model rainfall forecasts for US landfalling tropical storms. *Weather and Forecasting*. doi:10.1175/WAF972.1

Vickery, P., P. Skerlj, and L. Twisdale. (2010). Simulation of hurricane risk in the U.S using empirical track model, *J. Struct. Eng*., 126(10), 1222–1237.

Westerink, J. J., J. C. Feyen, J. H. Atkinson, H. J. Roberts, E. J. Kubatko, R. A. Luettich, C. Dawson, M. D. Powell, J. P. Dunion, and H. Pourtuheri (2008), A basin- to channel-scale unstructured grid hurricane storm surge model applied to southern Louisiana, *Mon. Weather Rev.*, 136, 833–864, doi:10.1175/2007MWR1946.1.