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Stochastic Simulation of Hurricane Wind and Rain Hazards

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STOCHASTIC SIMULATION OF HURRICANE WIND AND RAIN HAZARDS

A Dissertation
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy
Civil Engineering

by
Prashant Rawal
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Accepted by:
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ABSTRACT

Quantification of hurricane hazard, which includes wind, rainfall and storm surge, is essential for engineering design as well as financial loss assessment. The objective of this study is to develop a stochastic simulation framework which integrates the simulation process of hurricane rainfall and wind hazard. This study is divided into two parts. The main objective of the first part is to develop a method for the estimation of the hurricane wind field parameters radius to maximum wind speeds ($R_{max}$) and Holland $B$ parameter ($B$). The second part develops a stochastic model to simulate hurricane rainfall, which is named the ‘NormRain’ model.

The first part develops a hurricane wind speed computation method, which is validated by comparing with wind speed observations from meteorological stations. Then, a method to estimate $R_{max}$ and $B$ for historical storms is developed using this wind speed computation algorithm. Finally, based on the analysis of historical storms using the $R_{max}$ and $B$ estimation method, equations for stochastic simulation of $R_{max}$ and $B$ time history are developed. These equations can simulate the temporal correlation (i.e. correlation of the simulated value in current time-step with the previous timesteps) of $R_{max}$ and $B$, which is an improvement over other commonly used method.

Besides $R_{max}$ and $B$ estimation, another important application of the wind speed computation framework is to develop a database of hurricane wind speed hazard curves for
the 30 Eastern US states, which is expected to aid the research of performance-based wind engineering.

The hurricane rainfall distribution about the storm center can be very asymmetric and irregular, with high rainfall rates far from storm center. The existing statistical models for hurricane rainfall usually estimate the mean rainfall rate profile, and do not explicitly consider the total rainfall volume. However, the mean rainfall rate profiles cannot account for high localized rainfall rates which can be much larger than the mean value and can contribute a significant portion of the total rainfall volume. To overcome this limitation, this study develops a rainfall simulation model which explicitly simulates total rainfall volume using central pressure, relative vorticity and total precipitable water. Since the irregular shape of hurricane rain field is difficult to describe using equations, this study simulates the hurricane rain field using the concept of normalized rain field shape from historical storms. The hurricane simulation model can thus simulate realistic hurricane rain fields.

The hurricane rain simulation model ‘NormRain’ developed in the second part of this study consists of two parts. The first part estimates the total rainfall volume and extent of hurricane rain field at any time-step, and the second part determines how the rainfall rates associated with this rainfall volume are distributed within the rain field extent.
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CHAPTER 1. INTRODUCTION

1.1. Motivation

In the North Atlantic basin, on an average, 12±4.5 named tropical storms occur annually (1968-2018 data). Of these, 6.3±2.9 are hurricanes (Landsea 2018). Moreover, between 1851-2018, a total of 294 tropical cyclones have impacted the continental USA (NOAA HRD 2019). With the advent of advanced weather forecasting methods, it has become possible to forecast the storm track with greater accuracy several days in advance. This has enabled the timely evacuation of the population in hurricane-threatened regions possible, resulting in a drastic reduction in human casualties. However, the likelihood of damage to properties due to hurricane hazard in the form of wind, surge and flooding remains an ever-present threat. To perform safe and economic engineering design as well as to estimate financial loss, it is necessary to quantify all three types of hazards. Since these three occur together, their interaction can further amplify the overall hurricane hazard and financial loss. Therefore, it is necessary to have a model that can consider the interaction of all three types of hazards. This study aims to meet this need by integrating two of the main hurricane hazards, namely, wind and rain hazards.

1.2. Objectives and dissertation organization

The main objective of this study is to integrate the process of hurricane wind and rain hazard assessment. This involves integrating the following 3 components:
i. Stochastic simulation method of hurricane track and intensity

ii. Hurricane wind speed computation method

iii. Hurricane rain simulation model

Therefore, this study is divided into following objectives and sub-objectives.

**Objective 1:** To identify a pre-existing simulation framework for hurricane track and intensity model which is suitable for integration with wind and rain simulation, and improve upon its limitations. Following are the sub-objectives of this objective:

i. Find a method to constrain the upper and lower limits of simulation parameters so that unrealistic value is not generated during simulation. (CHAPTER 2)

ii. To ensure that the probability distribution of simulated hurricane parameters is similar to the parameters in actual hurricanes. (CHAPTER 2)

**Objective 2:** To develop a wind speed computation method. This objective also achieves the following sub-objectives:

i. Develop a method to estimate radius to maximum winds ($R_{max}$) and Holland $B$ parameter for historical storms. (CHAPTER 3)

ii. Develop a method for stochastic simulation of $R_{max}$ and $B$ which ensures correlation between consecutive time-steps. (CHAPTER 3)
iii. Generate a database of hurricane wind hazard curves for the 30 Eastern US states. (CHAPTER 4)

**Objective 3:** To develop a model for stochastic simulation of hurricane rainfall which involves the following tasks:

i. Develop a method to simulate hurricane rainfall volume and rain field extent. (CHAPTER 5)

ii. Develop a method to spatially distribute the rainfall volume within the rain field extent such that the location of various rainfall rates is similar to that of actual tropical cyclones. (CHAPTER 6)

A detailed literature review related to the research objectives is presented in the rest of this chapter. The dissertation concludes by suggesting some areas of research relevant to the current field of study (CHAPTER 7).

1.3. **Literature Review**

1.3.1. Hurricane wind hazard analysis

To achieve a safe and economic design, engineering applications require wind speed estimates at several return periods. Moreover, allocating financial resources to deal with hurricane damage, as in the case of insurance loss estimating, also requires considering several hurricane scenarios of varying degrees of severity. This again requires estimating wind speed at multiple return periods. However, the historical hurricane
database is insufficient to yield such estimates. For instance, National Hurricane Centre HURDAT (Landsea et al. 2013), which is the most comprehensive historical hurricane track database for the North Atlantic, has data from the year 1851; with only about 168 years of historical data, it is difficult to estimate wind speed with larger return periods, such as 1700 years frequently used in engineering design. To overcome this limitation, several researchers have proposed techniques such as simulation of hurricane tracks, using which, we can create a synthetic track database covering thousands of years.

1.3.1.1. Overview of wind hazard analysis methods

Vickery et al. (2009a) presents a thorough discussion on the various approaches used to model hurricane risk. Since the method of hurricane wind hazard analysis through stochastic simulation of storm tracks was first proposed by Russell (1971), several researchers have improved upon this method or developed a similar approach (Tryggvason et al. 1976; Batts et al. 1980; Twisdale et al. 1983; Georgiou 1986; Neumann 1987; Vickery et al. 1995, 2000b, 2009b; Casson et al. 2000; Emanuel et al. 2006; Nakajo et al. 2014; Nakamura et al. 2015). Simulation of hurricane tracks, however, is not the only approach to perform hurricane hazard analysis, and methods which do not require simulated tracks have also been proposed (Darling 1991; Rupp et al. 1996; Chu et al. 1998; Murnane et al. 2000; Emanuel et al. 2010).

Hall et al. (2008) classify the tropical cyclone landfall models into two types – the local model (models developed exclusively from landfalling historical events) and the track model (models which utilize simulated tracks) and conclude that track models can
represent the storm landfall rates close to the observed rates and are therefore appropriate for landfall risk assessment.

1.3.1.2. Early development of stochastic simulation-based hazard analysis methods

The methods based on stochastic simulation, in general, start by representing the statistics for hurricane parameters (such as central pressure, radius to maximum winds, translational speed, heading angle) by suitable probability distributions, and then perform the simulation by sampling from these distributions through Monte Carlo simulation (Vickery et al. 2009a). Once the storm makes landfall, its intensity is reduced through appropriate decay model.

Along with description of the first stochastic hurricane simulation framework, Russell (1971) also demonstrated that if the occurrence of hurricane can be modelled using Poisson distribution, then the exceedances of effects of hurricane (such as wind) can also be represented using the same distribution. This approach is widely accepted, and most studies use Poisson distribution to model the hurricane hazard (i.e. the probability that a particular magnitude of wind speed is exceeded at least once within a specified period). A slightly different approach was taken by Murnane et al. (2009), who used binomial distribution for this purpose.

Tryggvason et al. (1976) generated a time history of wind speed and direction using Monte Carlo simulation based synthetic hurricane tracks for a site in New Orleans. The design wind loads for a building planned at that site were then derived by converting these
wind speeds to wind pressures using wind tunnel data. Similarly, Twisdale et al. (1983) performed wind risk analysis for Indian Point Nuclear Generation Station. Batts et al. (1980), however, became the first study to perform wind hazard analysis for the entire US coastline in contrast to the previous studies which were limited to only a few sites (Vickery et al. 1995). The simulation process was refined further by Georgiou (1986), who developed a wind field model capable of considering the variation in wind speed and direction in the atmospheric boundary layer, and also attempted to validate this model by comparing its predictions with wind speed data recorded during recent cyclones. A program named HURISK was developed by Neumann (1987), which performed Monte Carlo simulation to generate 10,000 storms within 150 n.m. from a user specified site. Neumann also pointed out the unfeasibility of quantifying uncertainty (i.e. establishing confidence intervals) in the wind speeds thus estimated owing to the limited computational power available at that time. However, Vickery et al. (2009c) estimated the wind speed uncertainty by repeating 100,000 years of simulation 5000 times and found that the main sources of wind speed uncertainty were the central pressure and the Holland $B$ parameter.

1.3.1.3. Development of stochastic track simulation methods

A major contribution to the modelling of hurricane tracks was made by Vickery et al. (2000b), which became the first study to stochastically simulate storm tracks completely from genesis to dissipation. This method used the storm spawn locations from HURDAT to initiate track simulation and utilized the concept of relative intensity as described by Darling (1991) to simulate the central pressure. The models proposed until that point did
not simulate tracks completely. For instance, Casson et al. (2000) simulated tracks by introducing random perturbation to historical tracks in HURDAT database. Vickery’s track modelling approach considered only the storm heading angle, translational speed and intensity. So, to better account for the environmental physics (i.e. influence of factors such as potential intensity, ocean coupling, vertical wind shear and landfall effects) Emanuel (2006) proposed two methods of track modelling. The first method constructs the track using Markov chain approach and can represent the interaction between tropical and extratropical systems. The second method develops the track using weighted average of upper (250hPa) and lower(850hPa) tropospheric flow vectors coupled with a beta-drift correction (Holland 1983) and is better suited to incorporate the effect of atmospheric oscillations (such as El Nino, Atlantic Meridional Oscillation, North Atlantic Oscillation) or climate change.

1.3.1.4. Later developments in simulation methods

In recent years, researchers have continued to expand the array of simulation techniques by incorporating various mathematical techniques. In the aforementioned track models, the spawn location of a storm is randomly sampled from historical data. An alternative approach is the use of kernel density estimation, as exemplified by Haikun et al. (2009) and Rumpf et al. (2009), which allows the selection of points in the vicinity of historical spawn locations as simulation genesis points. Furthermore, since simulation requires the tropical cyclone parameters to be represented by appropriate probability distributions, use of more accurate methods such as principal component analysis (Nakajo
et al. 2014) in approximating the probability density functions has the potential to further improve simulations.

Since hurricanes are driven by the atmospheric and oceanic processes which do not change abruptly, any change in the behavior of a hurricane between subsequent time-steps is likely to be gradual. This similarity in hurricane parameters between closer time-steps is referred to as ‘memory effect’ in the context of simulated tracks. So, yet another way to improve the simulated tracks is to use methods which represent the memory effect better. Nakamura et al. (2015) state that the Markovian simulation methods (such as Emanuel et al. 2006) tend to lose the memory quicker than what is observed naturally and propose a simulation technique which randomly samples segments of varying lengths from historical tracks, instead of only a single point.

Apart from improving tracks, wind field models can also be modified to better account for the modification a hurricane wind field undergoes as it moves to higher latitudes. Loridan et al. (2015) point out that the assumption of right quadrant of a storm (relative to its direction of motion) being more damaging is not valid in case of storms undergoing extratropical transition. They propose a parametric wind field model to represent such cases for risk assessment applications.

1.3.1.5. Non-simulation methods of hurricane hazard analysis

In this context, ‘non-simulation method’ refers to any method that does not generate a database of synthetic storm tracks. Even though stochastic simulation of tracks remains
the most widely adopted method of quantifying hurricane hazards at present, in the past less powerful computers greatly limited the ability to perform simulations, which encouraged several researchers to seek alternate methods. Simulation based models widely use extreme value distributions (EVD) to fit central pressures or wind speeds; however, Darling (1991) presented several arguments against such use. The major argument was that since there is less observed data for rare events, we do not have enough information to accurately determine the shape of the tail of the EVD, and therefore any predictions made using the tail derived from inadequate data is bound to be inaccurate. Therefore, Darling developed an approach completely independent of EVD and instead based on the use of empirical distribution of relative intensity (which is the ratio of the actual central pressure drop in the eye of the storm to the maximum possible central pressure drop allowed by mean seasonal condition). Chu and Wang (1998) performed wind hazard analysis for Hawaii using relative intensity (which was generated via Monte Carlo simulation based on EVD) as described by Darling.

Other non-simulation methods, however, still rely on EVD in some way. Rupp et al. (1996) applied wind field models to historical tracks and using these tracks generated a time series of highest annual wind. Fitting this series to Gumbel distribution, wind speeds for several recurrence intervals were derived. Jagger et al. (2001) used maximum likelihood estimation to determine the parameters of Weibull distribution, which was used to model the maximum wind speed distribution. In a later study, Jagger et al. (2006) applied extreme value theory upon HURDAT reanalysis data to obtain wind speeds for various
return periods and recognizing that HURDAT data from early twentieth century could be biased, used Bayesian approach to address this limitation.

Murnane et al. (2000) present an algorithm to determine wind speed exceedance probabilities based on equations derived using a least square fit of exponential or power law which relate the cumulative frequency of wind speeds CF(s) to wind speed from historical data (HURDAT). Once the cumulative frequency for a wind speed is calculated, the probability that this wind speed is experienced within a particular time interval is obtained using binomial distribution (the binomial distribution accepts the CF(s) as a parameter). This method also validates some results using geological records (i.e. wind speed estimates based on palotempestology).

An approach quite different from the others was presented by Emanuel et al. (2010), in which open-ocean hurricanes are also used to estimate the probability of occurrence of a certain wind speed. The key assumption behind this approach is that hurricanes make landfall at random stage of their lifetime and so, if the probability of wind speeds over oceans are quantified, a probability that these wind speeds make landfall can also be quantified.

1.3.1.6. Some applications of simulated storms

Some examples of application of stochastic hurricane simulation are briefly presented in this section. Combining the simulation frameworks developed by Vickery et al. (2000a, 2000b, 2005, 2009b, 2009c) with the ESDU methodology (ESDU 1982, 1983)
to determine wind speeds at transition regions (regions close to coastline), ASCE 7-10 design wind maps (ASCE 2010) were developed. A study by Li et al. (2014) concluded that the method developed by Vickery is robust, based on comparison with results obtained through different methods. The ASCE 7-10 wind maps, which are currently used as a source of structural design data, also combine the non-hurricane based on Peterka et al. (1998).

Besides ASCE 7-10, other researchers (James et al. 2005; Lee et al. 2007; Rumpf et al. 2009) have also generated wind speed databases for US and other countries using simulation methods similar to those discussed in the previous section.

Pei et al. (2014) developed a methodology to integrate the hurricane wind hazard with storm surge to generate a joint wind-surge hazard map for Charleston (South Carolina) region. Based on similar methodology, the wind speed database generated by this study can be integrated with a storm surge database to generate joint wind-surge hazard map for the entire US East coast.

Another category of application involves performing simulations considering future climate change scenario. Hallegatte (2007), using Emanuel et al. (2006) simulation framework, performed economic loss estimate based on the simulation of various climate change scenarios.

Based on the simulation methodology developed by Vickery, Liu (2014), developed a hurricane simulation framework capable of considering various climate
change scenarios (as proposed by Intergovernmental Panel on Climate Change), and used it to study the impact upon civil engineering design wind speeds. This study improves upon and utilizes the framework developed by Liu (2014), excluding the climate change scenario.

1.3.1.7. Application of simulated wind database for the design of offshore structures

The hurricane wind hazard analysis methodologies described in previous sections are concerned about the effects of hurricane on land. However, these methods are equally useful for the design and hurricane risk assessment of offshore structures. This study, therefore, develops a wind database with hazard curves directly over the ocean (i.e. the US Maritime Exclusive Economic Zone (EEZ)). Recent studies (Carta et al. 2009; Musial et al. 2010; Morgan et al. 2011; Rose et al. 2013; Valamanesh et al. 2016; Hallowell et al. 2018) have focused on various aspects of offshore structure design, such as probability distributions relevant in offshore structure engineering as well as hurricane risk to offshore structures. By developing a wind speed database directly over the EEZ, this study expects to aid research of such nature as well as provide data for the design and risk assessment of offshore structures.

1.3.2. Performance Based Wind Engineering (PBWE)

When designing structures to resist wind or earthquake loads, the conventional approach is to design a structure for a load level as prescribed by design codes. The codes accept a certain risk of collapse of the structure if designed according to the loads thus
prescribed. The intention behind this approach is to ensure structural safety while achieving economic design. However, the performance needs of the building may not be satisfied by this approach. Practically, the level of collapse risk acceptable in case of a residential building cannot be the same as that in case of a nuclear reactor or a hospital building. Or, a business owner might prioritize collapse prevention of office building in event of natural disaster over economy during the phases of design and construction. The branch of engineering design that addresses the need for specialized design to meet a specified structural performance is known as performance-based engineering. Methodologies for performance-based earthquake engineering (PBEE) have already been well developed and adopted by engineering community. However, to date, no such widely accepted framework exists for PBWE.

In recent times, various studies (van de Lindt et al. 2009; Wang 2010; Ciampoli et al. 2011; Griffis et al. 2012; Barbato et al. 2013; Unnikrishnan et al. 2015; Spence et al. 2015; Spence et al. 2016) have proposed frameworks for PBWE. A key component in most of these frameworks is wind hazard curve, which gives the probability that a certain value of wind speed is exceeded at least once in a specified return period. This study does not develop a PBWE framework. It, however, develops a database of wind hazard curves for the entire US East coast to aid further research and implementation of PBWE.

1.3.3. Hurricane Rain Model Development

Although in recent years timely tropical storm warnings due to improved forecasting has caused significant reduction in loss of lives, the potentiality for property
damage remains high. According to a study by Rappaport (2014), hurricane fatality statistics (1963-2012) show that storm surge is the leading cause of deaths (49% of all fatalities), whereas rain is the second most frequent cause of death (27% of all fatalities). Between 1970 and 1999 (during this period rain was the main cause of deaths), deaths due to storm surge were almost absent, but in 2005 Hurricane Katrina alone caused at least 1200 deaths. However, rain induced flooding remains the most common hurricane hazard. Storm surge causes death in only 1 in 10 storms. Moreover, hurricane rain can cause severe financial losses. Tropical storm Allison (2001) resulted in about $8.5 billion losses, whereas Hurricane Harvey (2017) caused a loss of at least $125 billion, making it the costliest US hurricane. Both events caused such heavy losses due to severe flooding induced by heavy rainfall.

Modelling hurricane rainfall is challenging because rain damage is not necessarily caused only by major hurricanes (only 3 of the top 10 deadliest storms in the US were category 3 or higher), and also, the damage can occur far from the storm center, even after the main storm has already begun to dissipate (Rappaport 2014). So far, much effort has been devoted to the improvement of hurricane track and intensity modelling, but hurricane rain model has received relatively less attention.

An overview of the research field of hurricane rain modelling as provided by Rogers et al. (2009) shows that this is a relatively new field. Several researchers (Rutledge et al. 1984; Cerveny et al. 2000; Galarneau et al. 2010; Houze 2010; Matyas 2007; 2010,2013) have studied the physical processes behind the hurricane rainfall phenomenon
which are significant to the development of hurricane model. Zhu et al. (2013) represents an example of hurricane rainfall risk assessment using simulated tracks. A brief discussion of various rain models is presented in the following sections.

1.3.3.1. Early approach to hurricane rainfall modelling

Kraft’s rule proposed in the 1960s, is one of the most well-known empirical rule for estimating the amount of rainfall. According to this rule (Pfost 2000), maximum rainfall from a landfalling tropical cyclone ($RF_{max}$) in inches is 100 divided by the storm translational speed ($V_t$) in knots i.e., $RF_{max} = \frac{100}{V_t}$.

This rule is based on the observation that slow-moving storms tend to cause more rainfall, but storm translational speed is not the only factor affecting the rainfall. Other methods of rainfall estimation have been proposed, which attempt to account for several other factors affecting the tropical cyclone rainfall. The earliest rainfall models described the rainfall distribution as logarithmically decreasing away from the storm center (Simpson et al. 1981; Riehl et al. 1961), whereas some other early studies proposed statistical models derived from regression analysis of observed rainfall data (Pfost 2000; Dutcher 1993; Enman 1993). Ever since its launch in 1997, the Tropical Rainfall Measuring Mission (TRMM) satellite has been providing high quality rainfall data which has provided great impetus to proper understanding of the physical processes involved in hurricane rainfall as well as made the detailed study of hurricane possible (Lonfat 2004; Lonfat et al. 2004).
has aided the further development of other rain models, which are briefly described in the following sections.

1.3.3.2. R-CLIPER (Rainfall – CLImatology and PERsistence)

R-CLIPER is one of the simplest rain models, which considers storm intensity, size and mean radial distribution of rainfall. This model was first proposed by DeMaria and Tuleya in 2001 and was further updated by Tuleya et al. (2007). The original purpose of R-CLIPER was to serve as a baseline model for Geophysical Fluid Dynamics laboratory (GFDL) hurricane model, but it can also be used as a baseline model to evaluate the prediction skill of any other models.

R-CLIPER was developed using the hourly rain gauge data from the primary and secondary stations in the United States as provided by the National Climatic Data Center (NCDC) archives. The model thus developed is known as ‘Gauge R-CLIPER’. However, rain gauge data does not properly represent the rain rates for category 3-5 hurricanes. Past studies have also indicated that at wind speeds above ~60mph (50knots), typical rain gauges fail to catch more than half of the actual rainfall (Simpson et al. 1981). Therefore, to overcome such limitations posed by rain gauge data, TRMM data was used instead. The use of TRMM data instead of rain gauge data was justified because the radial rainfall rate profiles for both these data sources matched closely. The version of R-CLIPER using the TRMM data is known as the TRMM R-CLIPER, or simply R-CLIPER.
The rain rate (denoted by $T_{RR}$), is modelled as a function of distance from the center of the storm ($r$) and the maximum wind ($V$), as shown by Equations 1.1 and 1.2.

$$T_{RR}(r, V) = T_0 + (T_m - T_0) \left( \frac{r}{r_m} \right) \quad \text{(for } r < r_m) \quad (1.1)$$

And,

$$T_{RR}(r, V) = T_m \exp \left[ -\frac{(r-r_m)}{r_e} \right] \quad \text{(for } r \geq r_m) \quad (1.2)$$

Where,

$r_m$ = the radial extent of the inner core rain rate

$r_e$ = the radial extent of the tropical system rainfall

$r$ = radial distance from the center of the storm

$T_0$ and $T_m$ are the rain rates at $r_0$ and $r_m$ respectively. The quantities $T_0, T_m, r_0$ and $r_m$ are calculated using Equation 1.3.

$$T_{0 \ or \ m}(r_0 \ or \ r_m) = a_i + b_i \ U \quad (1.3)$$

Where, $a_i$ and $b_i$ are constants, and, $U$ is the normalized maximum wind given by Equation 1.4.

$$U = 1 + \frac{V_m - 35}{33} \quad (1.4)$$

Where, $V_m$ = the maximum wind speed in knots
By thus relating rainfall rate to wind speed (because wind speeds are correlated to rainfall rates), the model assumes that the main factor causing a decrease in the average rainfall rate after landfall is the decay of storm intensity. This model does not consider other factors affecting the rainfall and yields a symmetric rainfall pattern even though hurricane rainfall patterns tend to be asymmetric. When combined with a track, the model can produce a continuous swath of rainfall. This model can be used over land as well as water, as it does not account for the presence of landmass.

1.3.3.3. Parametric Hurricane Rainfall Model (PHRaM)

Parametric Hurricane Rainfall Model (PHRaM), proposed by Lonfat et al. (2007), is built upon R-CLIPER, and improves it further by modelling the asymmetry in the rain field. It does so by separately modelling the rain fields due to vertical shear \( R_{\text{shear}} \) and topography \( R_{\text{topography}} \), and adding them to the R-CLIPER rain field \( R_{\text{R-CLIPER}} \). The main equation used by PHRaM is as follows,

\[
R_{\text{PHRaM}} = R_{\text{R-CLIPER}} + R_{\text{shear}} + R_{\text{topography}} \quad (1.5)
\]

The vertical shear rain field is modelled as follows:

\[
R_{\text{shear}}(r, \theta) = \sum a_i(r) \cos(i\theta) + \sum b_i(r) \sin(i\theta) \quad (1.6)
\]

Where,

\[ r = \text{radial distance from the center of the storm} \]
\[ \theta = \text{azimuthal angle} \]

\[ a_i, b_i = \text{Fourier coefficients describing the azimuthal variation of wavenumber-i fields; } i = 1,2 \]

The topography is considered by introducing perturbation to the instantaneous rainfall footprint. It is described by the following equation,

\[ R_{\text{topography}} = c \mathbf{V}_s \cdot \nabla h_s \quad (1.7) \]

Where,

\[ c = \text{a proportionality constant} \]

\[ \mathbf{V}_s = \text{surface wind field at } 10\text{m elevation} \]

\[ h_s = \text{ground elevation} \]

The wind field above the boundary layer is computed using simplified Willoughby radial profile (Willoughby et al. 2006), shown by Equations 1.8 and 1.9.

\[ V(r) = V_{\text{max}} \left( \frac{r}{R_{\text{max}}} \right)^n, (0 \leq r \leq R_{\text{max}}) \quad (1.8) \]

\[ V(r) = V_{\text{max}} \exp \left[ -\frac{r - R_{\text{max}}}{x_1} \right], (R_{\text{max}} \leq r) \quad (1.9) \]

Where,
\( V_{max} \) = maximum wind speed

\( R_{max} \) = radius to the maximum winds

\( n \) = exponent for power law inside the eye, assumed equal to 1

\( X_1 \) = exponential decay length in the outer vortex, assumed to be 250 km

The wind field thus defined is then reduced to 10m elevation by simply multiplying \( V(r) \) by 85%.

The main limitation of this model is that it is unable to model the extreme asymmetries seen in certain storms.

1.3.3.4. HAZUS Hurricane Rainfall Rate and Distribution Estimator (HuRRDE)

HAZUS program contains a rain model known as Hurricane Rainfall Rate and Distribution Estimator (HuRRDE) (FEMA 2012). The model was developed by Sethu Raman of North Carolina State University and is used to estimate rainfall rates for use in modelling rain water intrusion through damaged shutters, but not rainfall induced inland flooding (Vickery et al. 2006). Since the primary purpose of HuRRDE model is to perform risk assessment, it is also used to generate the total rainfall at a location due to a storm event.

This model is also a statistical model based on the rainfall rate data compiled from several studies, the main source of data being Rodgers et al. (1994). The selected studies
all focus on the analysis of Special Sensor Microwave/Imagery (SSM/I) data. The HuRRDE modelling approach is based on deriving an empirical equation for baseline rainfall rate and then modifying its results with appropriate correction factors.

The baseline rainfall rate ($RR$) is a function of radial distance from the storm center, as expressed by the following polynomial equation (rather than an exponential equation, as suggested by previous studies),

$$RR_{base} = -5.5 + 110 \left( \frac{R_{max}}{R} \right) - 390 \left( \frac{R_{max}}{R} \right)^2 + 550 \left( \frac{R_{max}}{R} \right)^3$$

$$- 250 \left( \frac{R_{max}}{R} \right)^4 \quad \text{(For } \frac{R}{R_{max}} \geq 1)$$

$$RR_{base01} = \left( \frac{R}{R_{max}} \right) RR_{base} \quad \text{(For } 0 \leq \frac{R}{R_{max}} \leq 1) \quad (1.10)$$

$R_{max}$, which is the distance to the edge of the inner core from the eye, is assumed to be of a constant value of 30 km. This assumption is based on the argument that the results may not be impacted significantly considering the overall uncertainty associated with the model. At the center of the storm (i.e. at $R = 0$), it is assumed that no rainfall occurs.

The baseline rainfall rate from Equation 1.10 is applicable only to hurricane category 1. So, to convert its results to the appropriate storm category, it is multiplied by a category correction factor (or storm intensity factor) ($k_{cat}$) to obtain the rainfall rate corrected for category ($RR_e$) as shown by Equation 1.11.

$$RR_e = k \ (RR_{base}), \ k_{cat} = 0.0319\Delta p - 0.0395 \quad \text{(for } k \geq 1k) \quad (1.11)$$
Where, \( \Delta p \) is the central pressure deficit in mbar.

To account for the fact that storm intensity changes within any category, \( RR_e \) is further multiplied by a factor \( k_{cp} = [1 - (dP/dt)/100] \) to obtain \( RR_p \), the rainfall rate corrected for rate of change of central pressure. \( dP/dt \) is measured in mbar/hr. The asymmetry inducing effect of storm motion on the rainfall rate is considered by multiplying \( RR_p \) by sectorial storm motion correction factor \( (s) \) (Table 1), to obtain \( RR_{sp} \).

Table 1.1: Values of sectorial storm motion correction factor \( (s) \)

<table>
<thead>
<tr>
<th>Sector (degrees)</th>
<th>s for slow storms (&lt;8 knots)</th>
<th>s for fast storms (&gt;15 knots)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-45</td>
<td>1.45</td>
<td>1.15</td>
</tr>
<tr>
<td>46-90</td>
<td>1.05</td>
<td>1.15</td>
</tr>
<tr>
<td>91-135</td>
<td>0.55</td>
<td>1.35</td>
</tr>
<tr>
<td>136-180</td>
<td>0.65</td>
<td>1.15</td>
</tr>
<tr>
<td>181-225</td>
<td>0.85</td>
<td>0.85</td>
</tr>
<tr>
<td>226-270</td>
<td>0.95</td>
<td>0.65</td>
</tr>
<tr>
<td>271-335</td>
<td>1.15</td>
<td>0.80</td>
</tr>
<tr>
<td>336-359</td>
<td>1.35</td>
<td>0.95</td>
</tr>
</tbody>
</table>
After calibrating the rainfall model using rainfall data for several hurricanes as measured by a wide array of meteorological stations, it was found that the off-peak rainfall rates were significantly over-estimated. To correct this, \( RR_{sp} \) was multiplied by a modification factor \((MF)\),

\[
MF = -0.7 \ln \left( \frac{R}{R_{max}} \right) + 1.0 \quad (0.2 \leq MF \leq 3.0) \quad (1.12)
\]

This gives the final rainfall rate \((RR_{Final})\) in mm/hr. The above steps can be summarized by Equation 1.13.

\[
RR_{Final} = (RR_{base}) (k_{cat}) (k_{cp}) (s) (MF) \quad (1.13)
\]

Could calibrating with rainfall data from meteorological stations have reduced the model’s skills, considering the observation that rain gauges tend not to represent the rainfall at higher speeds well (Simpson et al. 1981)? A comparison with models based upon satellite data could offer a proper answer to this question.

1.3.3.5. Tropical Rainfall Potential (TRaP models)

TRaP refers to a family of several models. Spayd et al. (1984) proposed a technique referred to as “The Tropical Cyclone Precipitation Estimation Technique” to estimate the hourly precipitation amount using infrared and visible data provided by geostationary satellites. Kidder et al. (2005) considers this the earliest version of TRaP model. The
starting point of this method is to identify a tropical cyclone and locate its cloud features using satellite image. The cloud features of interest are the eye (or the cloud system center), wall clouds (20 n.m. on either side of the eye), central dense overcast (CDO) area, outer banding area (OBA) and the area of embedded cold convective cloud tops (ECT) in the OBA area. After drawing isolines around these features, empirical rainfall estimates are made for these isolines based on how these features change in consecutive photographs. Finally, the rainfall is estimated using the following relation,

$$ RF = \frac{(R_{CDO}D_{CDO} + R_{WC}D_{WC} + R_{OBA}D_{OBA} + R_{ECT}D_{ECT})}{V} $$  

(1.14)

Where,

$$ RF = \text{Rainfall depth} $$

$$ D \text{ and } R = \text{Diameter of rainfall rates in the direction of motion and rainfall estimates for the regions CDO, OBA, WC and ECT} $$

$$ V = \text{Speed of the tropical cyclone} $$

This original approach was significantly modified by later researchers leading to the development of a models such as NESDIS TraP (Kidder et al. 2000), Areal TRaP (Kidder et al. 2005) and ensemble TRaP (eTRaP) (Ebert et al. 2011).
1.3.3.6. Langousis and Veneziano’s model

The methods discussed above (other than HAZUS HuRRDE) primarily aim to model rainfall in order to produce real-time weather forecasts. Langousis et al. (2009a) proposed a tropical cyclone rainfall model, with the primary aim of carrying out risk assessment. In another paper, Langousis et al. (2009b) also propose a methodology for the frequency estimation of extreme rainfall intensities due to tropical cyclones. Langousis et al. rule out the suitability of purely physics-based complex models for risk assessment on the grounds that their computational time does not allow one to run the model several thousands of times as might be necessary, and instead suggest a combination of simple physics based approach with statistical approach. The main assumption of this model is “upward water vapor flux from the TC boundary layer equals the downward flux of rainwater.” The model is based on the gradient wind profile proposed by Holland (1980), and Smith (1968) boundary layer profile, as modified by Langousis et al (2008). The major limitation of this methodology is that, it is applicable only over sea and sites close to coastline, because it does not consider the condition after landfall.

1.3.3.7. Numerical models

Besides the models described in the previous sections, several numerical models exist which are in use by researchers and weather agencies worldwide. Some examples are Global Forecast System (GFS) model, European Center for Medium range Weather Forecasting (ECMWF) model, MM5 (Warner et al. 1978, Grell et al. 1994), and Weather Research and Forecasting (WRF) (Skamarock et al. 2008). These models utilize the three-
dimensional equations pertaining to atmospheric and oceanic circulations, and currently represent the most advanced weather modelling techniques.

Hurricane risk assessment requires the simulation of a large number (of the order of several hundred thousand) of scenarios. But doing so using numerical models is not feasible since they are computationally expensive. Nonetheless, the results from these models can serve as a benchmark for testing and developing more simplistic models.

1.4. References

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CHAPTER 2. STOCHASTIC SIMULATION FRAMEWORK FOR HURRICANE TRACK AND INTENSITY

2.1. Introduction

Stochastic simulation of a tropical cyclone (hurricane) track and intensity involves simulating various parameters such as translation speed, heading angle, central pressure, Holland $B$ parameter and radius to maximum winds ($R_{\text{max}}$). Knowing these parameters, the wind speed of a hurricane can be calculated, as described in Chapter 2. In addition to these parameters, this study also presents a method to simulate hurricane rain field, which is described in Chapters 5 and 6.

Researchers have developed various equations to simulate the track and intensity parameters. Correctly implementing these equations require constraining the values of the parameters within physically possible limits, otherwise, the simulation can result in unrealistic values. This chapter discusses the implications of not constraining the simulation parameters and presents methods to constrain them to obtain realistic values.

This study applies the concept of parameter constraint upon the stochastic simulation framework developed by Liu (2014). This chapter first describes the simulation method for hurricane genesis, track (i.e. heading direction and translation speed), relative intensity and central pressure decay. Then, the application of parameter constraints for central pressure and translation speed is described.

The simulation of $R_{\text{max}}$ and Holland $B$ parameters is described in Chapter 3.
2.2. Genesis model

2.2.1. Genesis model description

The genesis model determines the total number of storms in any simulated year and selects the initial values for the various storm parameters, namely, date and time, storm location (latitude and longitude), translational speed, heading direction and central pressure. The number of storms in each year in HURDAT is first fitted to a negative binomial distribution with parameters $R$ and $P$, which are determined using maximum likelihood estimation. Equation 2.1 shows the probability mass function of this distribution, where, the random variable $N$ indicates the number of storms. As shown by the comparison between the cumulative distribution function (CDF) of historical and simulated number of events in Figure 2.2, the historical annual storm frequency data can be closely represented by negative binomial distribution. Then, the number of storms in each year is randomly selected from a negative binomial distribution with parameters $R$ and $P$.

$$P(N = n|R, P) = \binom{n - 1}{R - 1} R^R (1 - P)^n - R \quad (2.1)$$

According to HURDAT2 2015, the mean and standard deviation of the historical annual storms are equal to 10.99 storms/year and 5.59 storms/year. To select the initial hurricane parameters (i.e. latitude, longitude, translational speed, central pressure, Cell ID, as described in Liu 2014), these parameters for all the storms in HURDAT are tabulated, and then for the first timestep of the simulation, the parameters are selected randomly. The
initial values can either be spatially discrete (as shown in Figure 2.1) or could be made continuous using methods such as Kernel Density Estimation (KDE).

It has been observed that the genesis location varies seasonally. This study, however, does not consider this effect, which is a subject for future study.

Figure 2.1: Historical genesis points (1851-2015)
2.2.2. Impact of data duration

The development of the stochastic hurricane simulation framework described in this document uses historical data from 1851 onwards. It should be noted that the appropriate historical data range for the development of genesis and tracking models has been a contentious issue. The aircraft reconnaissance of hurricanes began in the 1940s, and the weather satellites began regular operations since the 1970s. So, one may argue that it is appropriate to consider only the data from 1940s or 1970s onwards instead of the data from 1850s onwards. However, this raises the following concerns:

Will there be sufficient data to build a statistical model if shorter time frame is considered? There will be certain regions where there may be little to no data. To simulate hurricane parameters in such regions, one will need to make some assumptions. Our view
is that if older data provides some guidance in those regions, it is still better than making assumptions.

Is the increase in average annual hurricanes past 1970s solely due to better observations via satellites, or is it a result of climatic cycles (such as Atlantic Multidecadal Oscillation) or even climate change? If climatic cycles on decadal timescales are responsible for these effects, there could be less active hurricane seasons in the coming years or decades. In this scenario, if we were to use only the recent data, we might bias the model towards periods of greater hurricane activity. On the other hand, if climate change is responsible for increasing hurricane activity, considering various climate change scenarios explicitly could provide more useful information than simply using more recent historical data for model development.

Since these issues are still a matter of scientific research and debate, more investigations are needed. For our current purpose, however, we have decided to use historical data from 1850s onwards for the reasons discussed above.

Moreover, if the mean and standard deviation of annual rate of occurrence of named storms, hurricanes and major hurricanes are compared (Table 2.1) for the years 1968-2018, 1944-2018 and 1851-2018, it is found that the values are relatively close. So, it is assumed that the choice of data period is not critical to the simulation process.
Table 2.1: Average annual occurrence rate of hurricanes for different time periods (Landsea 2018)

<table>
<thead>
<tr>
<th>Year</th>
<th>1968-2018</th>
<th>1944-2018</th>
<th>1851-2018</th>
</tr>
</thead>
<tbody>
<tr>
<td>Storms/year</td>
<td>Average</td>
<td>Standard</td>
<td>Average</td>
</tr>
<tr>
<td></td>
<td>Deviation</td>
<td>Deviation</td>
<td>Deviation</td>
</tr>
<tr>
<td>Named Storms</td>
<td>12.0</td>
<td>4.5</td>
<td>11.2</td>
</tr>
<tr>
<td>Hurricanes</td>
<td>6.3</td>
<td>2.8</td>
<td>6.2</td>
</tr>
<tr>
<td>Major Hurricanes</td>
<td>2.5</td>
<td>1.8</td>
<td>2.7</td>
</tr>
</tbody>
</table>

2.3. Tracking model

The path of the storm is defined by the translational speed ($V_t$) and the heading direction ($\theta$). The tracking model, based on the following equations from Vickery et al. (2000), is used to simulate the path of the storm.

\[
\Delta \ln V_t = \ln V_{t(i+1)} - \ln V_{t(i)} = a_1 + a_2 \psi + a_3 \lambda + a_4 \ln V_{t(i)} + a_5 \theta_i + \epsilon_{V_t} \tag{2.2}
\]

\[
\Delta \theta = \theta_{i+1} - \theta_i = b_1 + b_2 \psi + b_3 \lambda + b_4 V_{t(i)} + b_5 \theta_i + b_6 \theta_{i-1} + \epsilon_{\theta} \tag{2.3}
\]
The Equations 2.2 and 2.3 give the difference between the logarithm of translational speed $\Delta \ln V_t$ and the difference between heading angles $\Delta \theta$ between two subsequent time-steps. The current time-step is represented by the index $i$ whereas the previous and the next time-steps are denoted by $i - 1$ and $i + 1$ respectively. The terms $\psi$ and $\lambda$ denote the latitude and the longitude of the storm center at the current time-step $i$. The difference in the values of $\Delta \ln V_t$ and $\Delta \theta$ between those obtained using historical data and the model (i.e. Equations 2.2 and 2.3) is represented by the normally distributed error terms $\epsilon_{V_t}$ and $\epsilon_{\theta}$ respectively.

The coefficients $a_i$ ($i = 1 \ldots 5$) and $b_j$ ($j = 1 \ldots 6$) are specific to the cells of the grid covering the simulation domain and are determined by least squares regression performed using historical data available at the cells, as described by Liu (2014). That is, each of the cells will have a certain set of coefficients $a_i$ and $b_j$. These coefficients are also dependent on the direction of storm. So, for each cell, two sets of coefficients $a_i$ and $b_j$ exist: first set for storms travelling Westwards, and the second set for storms travelling Eastwards. Based on the values of $V_t$ and $\theta$, the coordinates of the new position of the storm is calculated. If the newly calculated coordinates are no longer within the simulation domain, the simulation is terminated.

After the simulation is complete, it is necessary to check if the simulated value is realistic by comparing with historically observed values. Unrealistic simulated values are replaced by resimulated values based on the simulation constraints. A method to constrain the simulated value of $V_t$ is described next. Since the heading angle is always between $0^\circ$
and 360°, it is not necessary to constrain \( \theta \). Moreover, not constraining \( \theta \) also allows the simulated storm track to occasionally form a looping shape, as observed in some historical events.

According to HURDAT2 (2015), the maximum value of \( V_t \) is 115 mph. It is assumed that the maximum value of simulated \( V_t \) should also be close to this historically observed maximum value. According to the cumulative distribution function (CDF) curve of all \( V_t \) values in HURDAT2 as shown in Figure 2.5, the 99.99th percentile value of \( V_t \) is 78.2 mph, and the 100th percentile value is 115 mph, i.e. the maximum observed value.

Considering the upper limit of \( V_t \) to be 115mph, if simulated \( V_t \) exceeds 115mph, a resimulated value in the highest 0.01 percentile (i.e. a value between 78.2mph and 115 mph) is randomly selected. That is,

\[
\text{Resimulated } V_t = V_t \text{ corresponding to probability } [99.99\% + (0\sim1) 0.01\%]
\]

Where, \((0\sim1)\) represents a random uniform probability between 0 and 1.

As demonstrated by Figure 2.3 and Figure 2.4, the simulated and historical probability density functions are similar, which shows that the simulated values for heading direction and translational speed are realistic. In these figures, the simulated curve represents 100,000 years of simulated data.
Figure 2.3: Probability density function comparison between historical and simulated heading direction

Figure 2.4: Probability density function comparison between historical and simulated translation speed
Once the path of the storm is modelled, it is necessary to model the intensity of the storm, which is represented by the central pressure of the storm. However, the central pressure is not modelled directly. Instead, it is represented by relative intensity as described by Darling (1991). The relative intensity is defined as the ratio of actual central pressure drop to the maximum permissible central pressure drop for a certain climatic condition. If the storm is on ocean, the relative intensity is simulated by the following equation proposed by Vickery et al. (2000),

\[
\ln I_{i+1} = c_1 + c_2 \ln I_i + c_3 \ln I_{i-1} + c_4 \ln I_{i-2} + c_5 T_{s(i+1)} \\
+ c_6 [T_{s(i+1)} - T_{s(i)}] + \epsilon_i
\]  

(2.4)
The coefficients $c_i$ ($i = 1 \ldots 6$) are derived in a manner similar to the derivation of the coefficients for the tracking model as described by Liu (2014). However, $c_i$ is not derived separately for Easterly and Westerly storms. If the storm is on land, the intensity is reduced using the decay model described in Section 2.5.

The terms $I, T_s$ and $\epsilon_i$ represent the relative intensity, sea surface temperature and normally distributed random error term respectively. The subscript $i$ denotes the current timestep whereas $i - 1$ and $i - 2$ denote the previous two timesteps. The next timestep to be calculated has the subscript $i + 1$.

After the relative intensity is calculated, it is converted to central pressure using the following relation proposed by Darling (1991),

$$I = \frac{1013 - P_c + (1 - RH)e_s}{(1 - x)[1013 - (RH \times e_s)]}$$ \hspace{1cm} (2.5)

$P_c$ is the value of central pressure corresponding to relative intensity value of $I$ whereas $RH$ denotes the relative humidity of ambient air, taken as 0.75 (for better accuracy, the relative humidity must be sampled from historical data during the simulation) and $e_s$ is the saturation vapor pressure, given by,

$$e_s = 6.112 \exp \left[\frac{17.67 (T_s - 273)}{T_s - 29.5}\right]$$ \hspace{1cm} (2.6)

Where, $T_s =$ sea surface temperature in Kelvin, based on HadISST database

The various terms used in the calculation of the term $x$ are defined as follows.
\[ x = \exp \left[ -A \left( \frac{1}{x} - B \right) \right], \quad A = \frac{\epsilon L_v e_s}{(1-\epsilon)R_v T_s P_{da}}, \]

\[ B = RH \left[ 1 + \frac{\epsilon s \ln(RH)}{P_{da} A} \right] \]  

Where,

\[ \epsilon = \text{efficiency of the cyclone as a heat engine, given by } \epsilon = \frac{T_s - T_0}{T_s} \]

\[ T_0 = \text{temperature at the top of the troposphere (assumed to be at 100 mbar pressure) in Kelvin, assumed to be } 203 \text{ K} \]

\[ L_v = \text{the latent heat of vaporization in J/kg, given by, } L_v = 2.5 \times 10^6 - 2320(T_s - 273) \]

\[ R_v = \text{specific gas constant of water vapor, taken to be } 461 \text{ J/(kg K)} \]

\[ P_{da} = \text{surface value of the partial pressure of ambient dry air (in mbar), given by, } P_{da} = 1013 - RH \times e_s \]

During the simulation it is necessary to impose a lower limit to the value of central pressure \( P_c \), so that the program does not yield unrealistically low central pressure values, as shown in Figure 2.6 and Figure 2.7. This is done by calculating the minimum sustainable pressure \( P_{c-min} \) at the particular sea surface temperature and if the program yields a value lower than \( P_{c-min} \) at any time-step, the program considers \( P_{c-min} \) to be the value of central pressure at that time-step, which is calculated as,
\[ P_{c-min} = P_{dc} + e_s, \ P_{dc} = x P_{da} \] (2.8)

Where, \( P_{dc} \) = minimum sustainable surface value of central pressure of dry air for a hurricane.

Figure 2.6: An example of central pressure \( (P_c) \) simulation with and without physical lower bounds. The curve without the physical minimum \( P_c \) limit uses 860 mbar as the lower limit during simulation. In absence of physical lower bound, the simulation can sustain the lowest \( P_c \) value for unrealistically long period.

This method of constraining the lower limit of central pressure is simplistic, yet easy to successfully implement in a stochastic simulation framework and gives similar results as compared to historical events (Figure 2.9). It should be noted that more advanced methods have been developed by other researchers (Holland 1997; Emanuel 1988) to
estimate the theoretical lower limit of the central pressure, or the maximum potential intensity (MPI) of a hurricane.

Figure 2.7: Values of simulated $P_c$ below 900 mbar for 168 years with (right) and without (left) physical lower limits. Without physical lower limits, the simulation can yield low $P_c$ values at higher latitudes which may not be physically possible due to low sea surface temperatures. With physical limits, $P_c$ less than 900 mbar is confined to latitudes below 30°, which is similar to historically observed behavior shown in Figure 2.8.

Figure 2.8: Values of $P_c$ below 900 mbar in HURDAT2 (2015). Since HURDAT2 contains detailed $P_c$ data only for about last 40 years, the data looks sparse in comparison to Figure 2.7.
2.5 Decay model

At every time-step, the simulation program checks if the storm has already made landfall or is still on the ocean. If the storm is still on the ocean, the central pressure is calculated using the relative intensity model as described in the previous section. However, if the storm has already made landfall, the central pressure is determined using the decay model proposed by Vickery (2005).

This model quantifies the decay of a storm in terms of central pressure deficit ($\Delta P_c$), which increases exponentially as a function of landfall location and time ($t$) after landfall, as shown by Equation 2.9.
\[
\Delta P_c(t) = P_c(t) - P_{co} = (P_a - P_{co})e^{at}
\]  

(2.9)

In this equation, the terms \(P_c(t), P_{co}, P_a\) and \(a\) denote the post-landfall central pressure after time \((t)\), the central pressure at landfall, the ambient atmospheric pressure (considered to be 1013 mbar), and the geographic region dependent decay constant respectively. The decay constant has been derived separately for five regions along the US Atlantic coast and is calculated using Equation 2.10, where, \(a_o\) and \(a_1\) are region specific constants as stated in Table 2.2. In this equation, \(\epsilon_a\) is a normally distributed error term with mean of 0 and standard deviation \(\sigma_\epsilon\), which is also region dependent as specified in Table 2.2.

\[
a = a_o + a_1(P_a - P_{co}) + \epsilon_a
\]  

(2.10)

Table 2.2: Constants and error term standard deviation for decay constant (Vickery 2005).

<table>
<thead>
<tr>
<th>Location</th>
<th>Extents</th>
<th>(a_1)</th>
<th>(a_0)</th>
<th>(r^2)</th>
<th>(\sigma_\epsilon)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gulf Coast</td>
<td>(\psi &lt; 31.5^\circ, \lambda &lt; -82^\circ)</td>
<td>0.00068</td>
<td>0.0244</td>
<td>0.2683</td>
<td>0.0225</td>
</tr>
<tr>
<td>Florida Peninsula</td>
<td>(25^\circ &lt; \psi \leq 31.5^\circ, \lambda \geq -82^\circ)</td>
<td>0.00116</td>
<td>-0.0213</td>
<td>0.3149</td>
<td>0.0325</td>
</tr>
<tr>
<td>Atlantic Coast</td>
<td>(31.5^\circ &lt; \psi \leq 34.0^\circ)</td>
<td>0.0008</td>
<td>0.011</td>
<td>0.366</td>
<td>0.0156</td>
</tr>
<tr>
<td>Mid-Atlantic Coast</td>
<td>(34.0^\circ &lt; \psi \leq 38.0^\circ)</td>
<td>0.00074</td>
<td>0.0128</td>
<td>0.3212</td>
<td>0.0174</td>
</tr>
</tbody>
</table>
The Equations 2.9 and 2.10 are used to gradually increase the central pressure until its value rises to 1013 mbar. At this point, the storm is considered to have dissipated and the simulation is terminated.

2.6 Discussion

This chapter described a method to simulate hurricane track (translational speed and heading direction), intensity (central pressure) and the exponential decay of central pressure after landfall. These methods were developed by past researchers. To these methods, this study adds the concept of constraining the parameters during simulation such that the simulated result is physically possible, as supported by historical records. For instance, in the North Atlantic basin central pressures below 900 mbar tend to occur at latitudes below 30°. At higher latitudes, such low values of central pressure cannot occur due to lower sea surface temperatures (SST). That is, there is a value of minimum sustainable central pressure corresponding to environmental conditions such as sea surface temperature, below which, the central pressure must not be allowed to drop during simulation. If the central pressure dropped too low, that would result in unrealistic over-estimation of wind hazards. Therefore, this study suggests methods to constrain the hurricane parameters during simulation. Appendix A presents a detailed validation of the simulation methods discussed in this chapter.
The wind speed computation method, radius to maximum wind speed ($R_{\text{max}}$) and Holland $B$ parameter simulation method described in Chapter 3 and the rain field simulation method described in Chapters 5 and 6 is combined with the track and intensity simulation framework described in this chapter to result in an integrated hurricane wind and rain simulation method.

2.7. References


CHAPTER 3. WIND SPEED COMPUTATION METHOD AND SIMULATION OF RADIUS TO MAXIMUM WINDS AND HOLLAND B PARAMETER

3.1. Introduction

The radius to maximum winds ($R_{max}$) and Holland $B$ are commonly used parameters used to describe the shape of tropical cyclone (hurricane) wind field. The estimate of hurricane wind speed footprint is very sensitive to these parameters. Holland $B$ parameter defines the shape of a hurricane wind field (Holland 1980). Other approaches to describe the wind field shape, such as Willoughby’s model (Willoughby et al. 2006), have also been proposed. Willoughby’s model defines the wind field using a set of piecewise continuous functions, whereas Holland $B$ model requires only a single parameter. Due to the simplicity of the Holland $B$ model, it is preferred in various applications, such as estimation of historical wind footprints and stochastic simulation of hurricane wind field.

This study presents a method to estimate the $R_{max}$ and $B$ parameters using historical data, as well as equations for stochastic simulation of both parameters. The characteristics of $R_{max}$ and $B$ parameters generated by stochastic simulation, should be similar to that of historical values. The equations presented herein can better maintain the temporal correlation (i.e. the correlation between current and previous two time-steps) of simulated $R_{max}$ and $B$.

The first requirement for studying $R_{max}$ and $B$ is a wind field model. So, this section begins by providing detailed description of a simplified method to estimate the
magnitude of tropical cyclone wind speeds. This wind speed computation method is validated by comparing to observed wind speeds. This wind speed computation method, as well as the equations for stochastic simulation of $R_{\text{max}}$ and $B$ can be readily integrated with the stochastic simulation framework described in Chapter 2.

3.2. Wind speed computation method

The first requirement for studying the $R_{\text{max}}$ and $B$ is a wind field model. This section describes a general method used to estimate the magnitude of a tropical cyclone wind speed at a location using one or more tracks.

To calculate wind speeds at any site, the events in the simulated catalog that pass within a user-defined preselection distance are selected one by one. Since the $R_{\text{max}}$ is less than 250 km in about 95% of historical hurricane time-steps (as estimated using HURDAT2 data), a preselection distance of 250 km is considered appropriate to capture the maximum winds due to any event. Preselecting events in this manner also helps to expedite the calculations. For each event, hurricane parameters can be interpolated between any successive time-steps to increase the temporal resolution of the track data. For instance, if time-steps in track data are at 6-hour intervals, they can be interpolated to 15-minute intervals. It should be noted that translation speed and heading direction should be held constant between two successive time-steps and cannot be interpolated linearly as other parameters such as $R_{\text{max}}, B$, central pressure and the site coordinates. Figure 3.1 illustrates this process. After events are thus selected the following five steps are followed to calculate the wind speed at the site due to each time-step.
Figure 3.1: Selection of maximum wind speeds at a site from a hurricane track. Interpolation can be done between time-steps $t_i$ and $t_{i+1}$. (Background image credit: CIMSS Tropical Cyclones Archives)

The first step in calculating wind speeds is the calculation of gradient level wind speed ($V_g$) using Georgiou’s gradient wind field equation (Georgiou 1986), which represents the wind at an elevation of 3000 m above the earth’s surface. However, for the present purpose wind speeds at 10 m elevation ($U_{10}$) is desired. This conversion of $V_g$ to $U_{10}$ is accomplished using empirical equation representing boundary layer wind profile, which accounts for the fact that the wind speed diminishes closer to the earth surface.

But since this equation is only valid up to an elevation of 1000 m, the second step involves converting $V_g$ to wind speed at 1000 m (i.e. $V_{1000}$) using the mean wind profile derived from dropsonde data as presented by Vickery et al. (2009).

The wind speed at 10 m elevation ($U_{10}$) is calculated in the third step using the logarithmic boundary layer equation. Since $V_g$ represents 10-minute sustained wind, after
it is converted to $U_{10}$, it is converted to the desired time averaged value such as 3-second gust in the fourth step.

The wind speed is significantly higher over the ocean than on land. This means that the roughness lengths for sites on land and ocean must differ. However, at points on land close to the coast, the wind speed is lesser than that over the ocean, but still higher than the wind values far inland. Thus, there is a gradual reduction in wind speed as it moves from sea to land. Similar effect is seen whenever wind travels across any surfaces with differing roughness. This phenomenon is considered using the fetch factor. The final wind speed is obtained by multiplying $U_{10}$ (already adjusted to 10m-3s gust in previous steps) by the fetch factor in the fifth step.

The above steps are illustrated in Figure 3.2 and are described in detail in the following sections.
Figure 3.2: Flowchart to illustrate wind speed computation procedure
3.2.1. Step 1: Gradient wind speed calculation

\[ V_g = \frac{1}{2} A_f + \frac{B}{\rho} (P_a - P_e) R_r e^{-R_r} + \frac{1}{4} A_f^2 , R_r = \left( \frac{R_{max}}{r} \right)^B A_f \]

\[ = V_t \sin \alpha - f r \]  

Where,

\( V_g \) = Gradient wind speed (m/s)

\( V_t \) = Translational speed of storm (m/s)

\( P_e \) = Central pressure of the storm (Pascal)

\( B \) = Holland B parameter (dimensionless), which describes the shape of storm wind field

\( R_{max} \) = Radius to maximum winds of the storm (m)

\( r \) = Distance between the center (eye) of the storm, and the site where the wind speed is to be calculated

\( f = 2\Omega \sin \phi \), is the Coriolis parameter, \( \Omega = 7.272(10^{-5}) \text{ rad/s} \) is the angular rate of rotation of the Earth and \( \phi \) is the latitude of the site.

\( \alpha = A_z - \theta \), \( A_z \) is the azimuth to the site represented by angle in degrees, measured clockwise from the true North.
\[ \theta = \text{Heading direction of the storm} \]

\[ P_a = \text{Standard atmospheric pressure} = 101325 \text{ Pa} \]

\[ \rho = \text{Density of air} = 1.204 \text{ kg/m}^3 \text{ (at } 20^\circ \text{C)} \]

The terms \( P_e, V_t, \theta, R_{max}, B \) and \( \phi \) are obtained from either simulated or historical tracks.

Figure 3.3: Sketch illustrating the fact that when wind blows from one surface to another (single step transition), a transition zone is created before equilibrium profile develops over the new surface.

3.2.2. Step 2: Gradient wind speed conversion

In the second step of wind speed calculation, the gradient wind speed \( (V_g) \) is converted to wind speed at 1000 m \( (V_{1000}) \). Figure 3.3 illustrates some of the important variables used during wind speed computation. The conversion of \( V_g \) to \( V_{1000} \) is based on the mean wind profiles from Vickery et al. (2009), which was developed by analyzing
reconnaissance aircraft dropsonde data provided by the Atlantic Oceanographic and Meteorological Laboratories Hurricane Research Division (AOML HRD).

The conversion from 3000 m to 1000 m is necessary because the boundary layer equation is valid only up to an elevation of 1000 m. The approximate values of wind speeds at these elevations (based on Vickery et al. 2009) are given in Table 3.1. Depending upon which wind speed group the calculated $V_g$ belongs to, $V_{1000}$ can be obtained by interpolation from Table 3.1.

Table 3.1: Approximate values of wind speeds at 3000m and 1000m elevation for various wind speed groups from Vickery et al. (2009)

<table>
<thead>
<tr>
<th>Wind speed group (m/s)</th>
<th>Wind at 3000m (m/s)</th>
<th>Wind at 1000m (m/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>25</td>
<td>22.4</td>
<td>26.4</td>
</tr>
<tr>
<td>35</td>
<td>33.5</td>
<td>35.8</td>
</tr>
<tr>
<td>45</td>
<td>41.5</td>
<td>45.8</td>
</tr>
<tr>
<td>55</td>
<td>46.2</td>
<td>53.8</td>
</tr>
<tr>
<td>65</td>
<td>54.2</td>
<td>63.6</td>
</tr>
<tr>
<td>77.5</td>
<td>60.5</td>
<td>74.1</td>
</tr>
</tbody>
</table>
3.2.3. Step 3: Surface wind speed calculation

The third step (based on Vickery et al. 2008, 2009) involves calculating the wind speed at surface, i.e. 10 m elevation. The empirical hurricane boundary layer equation models the shape of hurricane wind profile from the ground to an elevation of 1000 m and is represented by Equation 3.2 (Vickery et al. 2009). In this equation, the constant parameters are, von Karman constant $k = 0.4$, $a = 0.4$ and $n = 2$. The variable $z$ represents the elevation above the ground where the wind speed is to be calculated and $z_0$ denotes the surface roughness parameter, which is a constant value of 0.03 m for open terrain but is defined by Equation 3.8 for ocean. The value of $z_0$ can also be obtained from actual land use data (Appendix B). In Equation 3.2, $u(z)$ is equal to $V_{1000}$ i.e., $z = 1000$ m. The only unknown in this equation is the wind speed at 10 m elevation $U_{10}$ contained within the term $u_\ast$. After substituting all the known parameters into Equation 3.2, a non-linear equation is obtained with $U_{10}$ as the only unknown, which can be solved by any numerical method. Here, regula falsi method has been used to solve this non-linear equation.

$$u(z) = \frac{u_\ast}{k} \left[ \ln \left( \frac{Z}{z_0} \right) - a \left( \frac{Z}{H^*} \right)^n \right]$$  \hspace{1cm} (3.2)

If the point (i.e. the site at which wind speed is to be calculated) is over ocean, the boundary layer height parameter ($H^*$) and inertial stability parameter ($I_s$) are calculated as follows (Vickery et al. 2009; Kepert 2001),
\[
H^* = 343.7 + \frac{0.260}{I_s}, I_s = \sqrt{f + \frac{2V_g}{r} \left( f + \frac{V_g}{r} + \frac{\partial V_g}{\partial r} \right)},
\]
\[300 \leq H^* \leq 1200\] (3.3)

If the point is on land, \(H^*\) is calculated by the following equation (Kepert 2001),

\[
H^* = \sqrt{\frac{2K}{I_s} \tan^{-1} \left[ -1 - \frac{2}{\chi} \right]}, K = k u_* \chi = C_{do} V_g \sqrt{\frac{2}{KI_s}}
\] (3.4)

The term \(u_*\) represents the shear friction velocity and is defined by Equation 3.5. \(U_{10}\) represents the wind speed at an elevation of 10m, and \(C_d\) is the surface drag coefficient which is equal to \(C_{do}\) if the point is on ocean, or \(C_{dl}\) if the point is on land.

\[u_* = U_{10} \sqrt{C_d}\] (3.5)

The sea surface drag coefficient \(C_{do}\) is defined by Equation 3.6 whereas the land surface drag coefficient is defined by Equation 3.7. The term \(C_{do}\) cannot exceed the limits defined by \(C_{do, max}\).

\[C_{do} = (0.49 + 0.065U_{10})(10^{-3}),\]

\[C_{do, max} = (0.0881r + 17.66)(10^{-4}),\] (3.6)

\[0.0019 \leq C_{do, max} \leq 0.0025\]
\[ C_{dL} = \left[ \frac{0.4}{\ln \left( \frac{z}{z_{0L}} \right)} \right]^2 \]  \hspace{1cm} (3.7)

The terms \( z_{0L} = 0.03 \text{ m} \) (or other value based on land use data) and \( z = 10 \text{ m} \) if the wind speed is being calculated at 10 m elevation in open terrain.

The roughness parameter over ocean is defined by,

\[
Z_{\text{oo}} = \frac{z_{Cdo}}{\exp \left[ k \frac{z_{Cdo}}{H^*} + a \left( \frac{z_{Cdo}}{H^*} \right)^n \right]}, \quad z_{Cdo} = 10 \text{ m} \]  \hspace{1cm} (3.8)

3.2.4. Step 4: Wind speed duration conversion

The preceding steps calculate the wind speed averaged to a duration of 10 minutes. At the fourth step, the wind speed should be converted to the desired averaging duration, such as 3 seconds. A simpler conversion method using gust factors (Appendix C) can be found in Harper et al. (2010). The conversion process described in the following steps is based on Vickery et al. (2005) and ESDU (1983).

1. Compute the integral scale time parameter \( T_u \).

\[
T_u = 3.13 \, z^{0.2} \]  \hspace{1cm} (3.9)

2. Compute the cycling rate \( \nu \).
\[ \nu = \frac{0.007 + 0.213(T_u/\tau)^{0.654}}{T_u} \]  

(3.10)

Where, \( \tau = \) Wind speed duration after conversion (such as 3 s)

3. Compute the standard deviation of the wind speed having been passed through a low pass filter with a cutoff frequency of \( 1/\tau \) Hz, as a function of \( u_* \).

\[ \sigma_u(z, \tau) = \sigma_u(z) \left[ 1 - 0.193 \left( \frac{T_u}{\tau} + 0.1 \right)^{-0.68} \right] \]  

(3.11)

Where, the theoretical value of standard deviation of wind speed is given by,

\[ \sigma_u(z) = \frac{7.5 \eta u_*[0.538 + 0.09 \ln(z/z_0)^{\eta 16}]}{1 + 0.156 \ln[u_*/(f z_0)]} \]  

(3.12)

Here, \( z \) is the height of wind speed, \( z_0 \) is the surface roughness length at the location where wind speed is being calculated, \( f \) is the Coriolis parameter and \( \eta \) is the height scaling parameter defined as,

\[ \eta = 1 - \frac{6f z}{u_*} \]  

(3.13)

4. The peak factor is then computed using,

\[ g(\nu, \tau, z) = \left[ \sqrt{2 \ln(T_0 \nu)} + \frac{0.557}{\sqrt{2 \ln(T_0 \nu)}} \right] \frac{\sigma_u(z, \tau)}{\sigma_u(z)} \]  

(3.14)

where, \( T_0 \) is observation period which is set equal to 3600 s.
5. The peak wind speed at height $z$ averaged over time period $\tau$ occurring over an observation time of 3600 s (1 hr) is determined by the following equation,

$$U_0 = U(3600, z) \left[ 1 + \frac{g(v, \tau, z) \sigma_u(z)}{U_{1hr}} \right]$$  \hspace{1cm} (3.15)

Where, $U_0$ is the windspeed before conversion and, the mean velocity profile $U_{1hr}$ is given by,

$$U_{1hr} = 2.5u_* \ln(z/z_o)$$  \hspace{1cm} (3.16)

6. Up to this point $u_*$ is an unknown quantity. Solving the Equation 3.15 gives us $u_*$. Now, we can back substitute the value of $u_*$ in the preceding steps and determine the values of $\sigma_u(z, \tau)$ and $U_{1hr}$. We can also recalculate the peak factor for $\tau$ equal to the desired windspeed after conversion. Then, the final wind speed after duration conversion is given by,

$$U = U(3600, z) \left[ 1 + \frac{g(v, \tau, z)\sigma_u(z)}{U_{1hr}} \right]$$  \hspace{1cm} (3.17)

3.2.5. Step 5: Adjust for fetch

When wind blows across surfaces of different roughness lengths, the wind speed values undergo a gradual transition from one surface to the next. This effect is accounted for in the fifth step, where, $U_{10}$ is modified using a fetch factor as described in the following steps.
With reference to Figure 3.3, \( U_{102} \) is the fully transitioned wind speed with surface roughness \( z_{02} \), and is located on the downwind side. Similarly, \( U_{101} \) is the fully transitioned wind speed with surface roughness \( z_{01} \), and is located on the upwind side. Using the procedure described in Section 3.2.3, \( U_{102} \) and \( U_{101} \) are calculated. The final windspeed \( U_{10} \) at site is obtained by multiplying \( U_{102} \) by fetch factor \( K_x \), which itself is a function of \( U_{101} \) and \( U_{102} \).

\[
U_{10} = K_x(U_{101}, U_{102}) \times U_{102}
\]  

(3.18)

The fetch factor can be computed using the following steps.

1. The inputs required for the computation of fetch factor are \( U_{101}, U_{102}, z_{01}, z_{02} \), latitude of site, wind speed duration and fetch distance \( (x) \).

2. If \( z_{01} = z_{02} \), then, no transition has occurred; i.e. fetch factor calculation is not needed. So, \( U_{10} = U_{101} \), and the calculation ends in this step. Otherwise, proceed to the next step.

3. Calculate land drag coefficient \( C_{dL} \) using Equation 3.7, where \( z_0 = z_{02} \).

4. Calculate friction velocity using \( u_* = U_{102} \sqrt{C_{dL}} \).

5. Calculate Coriolis parameter as described under Equation 3.1.
6. The condition $z_{01} < z_{02}$ (denoted by 'S to R') implies that wind is moving from smooth to rough surface, whereas, the condition $z_{01} > z_{02}$ (denoted by R to S) means the wind is blowing from rough to smooth surface, such as from land to sea.

7. Determine the constant $n$. For S to R, $n_{SR} = 0.23$, whereas for R to S, $n_{RS} = 0.14$ (ESDU 1982).

8. Define various parameters to be used in subsequent steps.

Calculate the roughness change parameter R (ESDU 1982).

$$R = \frac{|\ln(z_{02}/z_{01})|}{[u_*/(fz_{02})]^n}$$ \hspace{1cm} (3.19)

Substituting $n = n_{SR}$ gives $R_{SR}$ and using $n = n_{RS}$ gives $R_{RS}$.

Compute the logarithm of fetch distance ($x$).

$$X = \log_{10} x$$ \hspace{1cm} (3.20)

Determination of the parameter $f_p$:

For S to R: \hspace{0.5cm} $f_{PSR} = 0.1869X^2 - 1.754X + 4.087, i.f \ X \leq 4.301$

For R to S: \hspace{0.5cm} $f_{PRS} = 0.0325X^2 - 0.716X + 2.477, i.f \ X \leq 4.301$ \hspace{1cm} (3.21)

$$f_p = 0, i.f \ X > 4.301$$
Where, \(4.301 = \log_{10} 20000\) because the effect of fetch is considered only if the transition distance is less than \(20km\). Equation 3.21 has been obtained by modifying ESDU equations (ESDU 1982).

9. Compute the fetch factor for hourly mean wind speed \(K_{x,h}\) based on (ESDU 1982).

\[
\text{For } S \text{ to } R: \quad K_{xSR,h} = 1 + f_{pSR} 0.67 (R_{SR})^{0.85}
\]

\[
\text{For } R \text{ to } S: \quad K_{xRS,h} = 1 - f_{pRS} (0.41 R_{RS})
\]

10. Convert \(K_{x,h}\) to the desired duration \((T)\), to obtain the duration-adjusted fetch factor \(K_x\). (ESDU 1983)

\[
\text{For } S \text{ to } R:\quad K_{xSR} = (1 - 0.595 e^{-0.05T^{0.65}})(K_{xSR,h} - 1) + 1
\]

\[
\text{For } R \text{ to } S:\quad K_{xRS} = (1 - 0.502 e^{-0.05T^{0.65}})(K_{xRS,h} - 1) + 1
\]

11. We assume that for distance less than 16 m, no transition occurs. i.e., for \(x \leq 16\) m, \(K_x = 1\). First, we determine a conversion factor \(f_c\), which shall then be used to convert the ESDU fetch factor \(K_x\) to obtain the adjusted fetch factor \(K_x'\).

\[
\text{For } S \text{ to } R: \quad f_{CSR} = 1.505 R_{SR}^{0.85} (1 - 0.595 e^{-0.05T^{0.65}}) + 1
\]
For $R$ to $S$: 
\[ f_{CRS} = -0.6814R_{RS}(1 - 0.502e^{-0.057T_{0.65}}) + 1 \]

Then, the adjusted fetch factor can be determined using the following equations.

For $S$ to $R$: 
\[ K'_{xSR} = K_{xSR} \left( (1 - \frac{U_{1SR}}{U_{2SR}f_{cSR}}) \frac{\ln(x_{SR} - 16)}{\ln(20000 - 16)} + \frac{U_{1SR}}{U_{2SR}f_{cSR}} \right) \]

For $R$ to $S$: 
\[ K'_{xRS} = K_{xRS} \left( (1 - \frac{U_{1RS}}{U_{2RS}f_{cRS}}) \frac{\ln(x_{RS} - 16)}{\ln(20000 - 16)} + \frac{U_{1RS}}{U_{2RS}f_{cRS}} \right) \]

(3.25)

If $x \leq 16$ m: 
\[ K_{x16} = \frac{U_1}{U_2} \]

For brevity, $U_{101}$ and $U_{102}$ have been represented by $U_1$ and $U_2$ respectively in the preceding expression.

Finally, the desired wind speed at the point of interest is obtained using the following relations.

For $S$ to $R$: 
\[ U = K'_{xSR}U_2 \]

For $R$ to $S$: 
\[ U = K'_{xRS}U_2 \]

(3.26)

If $x \leq 16$ m: 
\[ U = K_{x16}U_2 \]
The parameters $f_p$, $f_c$ and Equation 3.25 ensure that the transition begins at upwind equilibrium wind speed $U_{101}$ and 100% of the transition is completed at downwind equilibrium wind speed $U_{102}$. The original ESDU method assumes the fetch distance to be about 100 km and the boundary layer height to be about 3000 m. But according to Vickery et al. (2009), in case of hurricanes, the boundary layer height is usually around 600 m and therefore, the ESDU fetch distance was reduced to 20 km to reflect this fact.

3.2.6. Accounting for actual land use

The wind speed computation method described in preceding sections can also be used to calculate wind speeds by considering the actual land use, but this requires some simplifying assumptions. The above methodology only considers a single step transition in wind speed, i.e., it is valid if wind blows across two surfaces. It does not consider multiple transition, i.e. wind blowing over several surfaces with different roughness lengths. If there are several roughness lengths along the upwind fetch, this methodology requires representing all these roughness lengths by a single value. After such representation, this method assumes that the equilibrium profile corresponding to this single roughness already exists on the upwind direction.

In general, higher the elevation where the wind speed is desired, greater the impact of roughness along the distant fetch. As Figure 3.4 illustrates, for the short structure with height $h_1$, considering single step transition is sufficient since the wind profile between portion GA is created by transition from roughness $z_{02}$ to $z_{03}$. However, for the taller
structures with heights $h_2$ and $h_3$, the impact of profiles 2 and 1 respectively are felt. That is, if the wind speed at $h_3$ is required, we should also consider the impact of $z_{01}$.

Since for our present purpose, we require only the wind speeds at 10 m from the ground, the situation is similar to the structure $h_1$, i.e. considering single step transition is sufficient. But even then, if wind speeds are needed at point G, a method to approximately represent the upwind roughness lengths $z_{02}, z_{01}$ etc. by a single roughness length is needed. ESDU (1983) provides some guidelines for this purpose. It states that unless the consecutive roughness lengths vary by more than a factor of 3, they may be averaged. Also, if the upwind surface length is short, it may be neglected; for example, if wind speed is to be calculated at point G, the presence of surface $z_{02}$ may be neglected if its total length is less than the distance from point G to the surface $z_0$. This allows us to ignore the presence of tiny patches of variation in surface roughness across a wider area.
Figure 3.4: Impact of multiple step transition on wind profile; $d_0 = \text{zero-plane displacement, } h_1, h_2, h_3 = \text{structure heights}$

In cases where the consecutive roughness lengths vary by more than a factor of 3, the upwind roughness is selected as follows:

- If water body persists for more than 1 km in the immediate vicinity of the site, the upwind roughness is considered to be that of the water body. This is because based on the assumption that complete transition occurs within a distance of 20 km, at a distance of 1 km, about 70% of transition can occur. Thus, conservative estimates of wind speeds can be obtained.

- If the roughness lengths up to 20 km upwind from the site contain wide variation and cannot be averaged, the roughness lengths 10 km upwind are averaged. If this is also not possible, roughness lengths up to 5 km upwind are averaged. This is because at distance between 5 to 10 km, approximately 80 to 90% can occur. Also, since we need wind speeds at 10 m, it is appropriate to consider shorter upwind fetches.
The land cover data has been obtained from the 500 m resolution MODIS-based global land cover climatology (Broxton et al. 2014).

Figure 3.5: Roughness length selection for a site located in Florida and land cover data for Florida. The red dots indicate the land cover data and the blue dots indicate a direction upwind to the site, which is located at the center of the circle.

To select the upwind roughness length for a site, a circle of 20 km radius is drawn around the site and the land cover data included in this circle are extracted, as shown in Figure 3.5. Then, as described in Appendix B, roughness lengths corresponding to the land use types are determined. Next, the roughness lengths along 16 directions for a distance of 20 km are selected at 500 m intervals. Finally, along each of these 16 directions, a single value of roughness is determined according to the process described in the preceding section.

Some limitations of the current model are:
1. The current database does not include the reduction of wind speed due to drop in air density caused by increase in elevation. This, however does not introduce significant error because the terrain elevation along the US Atlantic coastline is mostly plain. This approach is also consistent with ASCE 7-16 (ASCE 2017).

2. In dense urban centers, especially where high-rise buildings are present, various local effects occur which can reduce or increase the wind intensity. The current model does not take this into account.

3. The calculation neglects the effect of zero plane displacement ($d_0$) (Figure 3.4). Below the zero-plane displacement height, wind speed cannot be calculated with certainty, but neglecting $d_0$ usually gives conservative results. However, this may not be true if high rise buildings are present.

4. For tall or slender structures, 3 s gust factor is not suitable; 10 min or longer averaged wind speeds are more suitable.

5. This model cannot account for small scale convective gusts.

3.3 Validation of wind speed computation method

A detailed comparison between the hurricane wind speed observations from meteorological stations and the wind speeds calculated using the method described in the preceding section is presented in Appendix D (time history comparison) and Appendix E
(foot print comparison via scatter plots). The comparison between calculated wind footprint and H*Wind footprint is presented in Appendix F.

The validation of the wind speed model involves comparing model output with wind speed observations from meteorological stations located at different regions (coastal as well as inland). The observation data has been obtained from Automated Surface Observing System (ASOS) network, downloaded from Iowa Environmental Mesonet of Iowa State University. The following section discusses the limitations involved in comparing the computed wind speeds with observed wind speeds.

It should be noted that the quality of calculated wind time history depends significantly on the value of $R_{max}$ and $B$ estimated using the wind field data from HURDAT2. Therefore, any deviation of the calculated windspeeds from observations may not necessarily be due to limitations in the wind speed calculation methodology; it may be due to improper estimate of $R_{max}$ and $B$. The difficulty in estimating these quantities can be caused by insufficient wind field data in HURDAT2, which provides a single set of distances to maximum winds ($V_{max}$) and 34 kt, 50 kt, 64 kt winds for each of the four quadrants, if available. However, in reality, these distances can vary within a single quadrant, but the spatial resolution of HURDAT2 wind field data is not fine enough to reflect this fact.

The ASOS wind speed data is provided at 1 hour intervals while HURDAT2 data is provided at 6 hour intervals at landfall locations. This means $R_{max}$ and $B$ can only be estimated at the 6 hourly and landfall data points. However, to calculate the wind time
history, it is necessary to interpolate hurricane parameters between these time-steps. The $R_{\text{max}}$ and $B$ obtained by linear interpolation may underestimate the results close to storm center at sites near coastline. This is because storm intensity tends to decay exponentially after landfall, which means that for a short distance inland immediately after landfall the intensity might remain higher than that estimated by linear interpolation. Nonetheless, interpolated $R_{\text{max}}$ and $B$ still provide a rational basis for estimating wind speeds between the 6 hourly observation time-steps.

An estimate of $R_{\text{max}}$ at any time-step can be considered reasonable if it is slightly greater than eye diameter but less than the distance to next largest wind speed ($34 \text{ kt}$, $50 \text{ kt}$ or $64 \text{ kt}$) available at that time-step. Likewise, the estimated value of $B$ can be considered reasonable if the modelled peak wind speed does not exceed the observed peak wind speed.

Even if $R_{\text{max}}$ and $B$ are estimated quite well, there will still be a few cases where the model can fail to capture the peak wind speeds. This is because the model cannot account for multiple eye walls and local convective gusts. Moreover, at lower wind speeds ($< 20 \text{ mph}$), the observations appear more scattered from the computed data. This is because lower wind speeds can be caused by any other atmospheric disturbances, which the hurricane wind field does not capture. Yet another reason why the model may fail to capture the wind speeds is due to the use of mean peak gust factors. The actual gust factors may be higher or lower than the mean peak gust factors.
3.4. Method to estimate $R_{\text{max}}$ and $B$ from historical data

The HURDAT2 historical data from 2004 onwards describes the shape of hurricane wind field at each time-step by giving the maximum wind speed ($V_{\text{max}}$) and the distances (denoted by $R_{34}, R_{50}$ and $R_{64}$) to 34 kt, 50 kt and 64 kt winds (represented by $V_{34}, V_{50}$ and $V_{64}$ respectively), in the four quadrants of the storm. The ‘Extended Best Track’ or Ebtrack database (Demuth et al. 2006) from Regional and Mesoscale Meteorology Branch (RAMMB) provides this data for storms from year 1988 onwards. This information, together with the surface wind field model (Section 3.2), can be used to estimate the radius to maximum winds ($R_{\text{max}}$) and Holland $B$ parameter.

The computation of surface wind speed ($U_{10}$) requires the gradient wind speed ($V_g$), elevation conversion factor, gust factor and surface roughness. As Equation 3.1 shows, $V_g$ at any location is a function of the translational speed, central pressure, far field atmospheric pressure, air density, Coriolis force, distance and azimuth from storm center to the location, as well as $R_{\text{max}}$ and $B$. If historical data is available, in this equation, there remain only two unknowns, i.e., $R_{\text{max}}$ and $B$. Also, if wind field data is available at any timestep, there are at least two points: ($V_{\text{max}}, R_{\text{max}}$) and ($V_{34}, R_{34}$), which yield two equations to solve for the two unknowns. The $R_{\text{max}}$ is assumed to occur wherever $V_{\text{max}}$ occurs. For more intense time-steps of the storm, there are more points: ($V_{\text{max}}, R_{\text{max}}$), ($V_{34}, R_{34}$), ($V_{50}, R_{50}$), and/or ($V_{64}, R_{64}$). Figure 3.6 presents an example of horizontal wind speed profiles showing the availability of various number of such points. Thus, two, three or four equations are available to solve for the two unknowns. Even though only two
equations are needed to solve for the two unknowns, using more equations improves the quality of estimated results. The equations are then solved, which yields the values of $R_{max}$ and $B$, by finding the minimum error for the following expression:

$$\min\{w_{max}\{-V_{max} + U_{10}(R_{max}, R_{max}, B)\}^2$$

$$+ w_{34}\{-V_{34} + U_{10}(R_{34}, R_{max}, B)\}^2 + w_{50}\{-V_{50} + U_{10}(R_{50}, R_{max}, B)\}^2 + U_{10}(R_{64}, R_{max}, B)\}^2 + w_{64}\{-V_{64} + U_{10}(R_{64}, R_{max}, B)\}^2\}$$

(3.27)

In this expression, $U_{10}(R_i, R_{max}, B)$ ($i = max, 34, 50 or 64$) denotes the surface wind field model obtained after substituting all the known parameters with only the $R_{max}$ and $B$ as the unknowns, and $w_i$ is the weightage assigned to each equation, as specified in Table 3.2. The surface wind field model should use the surface roughness corresponding to open terrain ($0.03 \, m$) over land, and the ocean roughness over points on ocean as described in Section 3.2.3.

Table 3.2: Weightage factors to be used for different amount of data available

<table>
<thead>
<tr>
<th>Wind speed points available</th>
<th>Weightage value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$V_{max}, V_{34}$</td>
<td>$w_{max} = 1, w_{34} = 1$</td>
</tr>
<tr>
<td>$V_{max}, V_{50}, V_{34}$</td>
<td>$w_{max} = 0.8, w_{50} = 0.1, w_{34} = 0.1$</td>
</tr>
<tr>
<td>$V_{max}, V_{64}, V_{50}, V_{34}$</td>
<td>$w_{max} = 0.8, w_{64} = 0.05, w_{50} = 0.05, w_{34} = 0.1$</td>
</tr>
</tbody>
</table>
Estimated $R_{max} = 90.06 \text{ km}, B = 1.11, \text{ SRSSE} = 0.000009$

Estimated $R_{max} = 57.13 \text{ km}, B = 2.11, \text{ SRSSE} = 5.989019$
3.5. Analysis of $R_{max}$ and $B$ from historical data and quality control

Using the method described in Section 3.4, $R_{max}$ and $B$ parameters were estimated for events in the Ebtracks dataset from 1988 to 2017, which includes 261 events ranging from tropical storm to category 5 strength. These events contain 5285 time-steps in total prior to the application of quality control. The histogram and the cumulative distribution function (CDF) for $R_{max}$ and $B$ based on the estimates are presented in Figure 3.7 and Figure 3.8.

Since the most intense winds of a hurricane are located towards its Northeastern quadrant, the wind field parameters for this quadrant were used for $R_{max}$ and $B$ estimation. After the estimation, it is necessary to filter the results based on the quality control criteria.
as described in this section. These criteria ensure that only the cases where the minimization algorithm (Equation 3.27) converge to obtain a valid result are accepted.

Figure 3.7: Histogram and CDF of $R_{\text{max}}$ estimated using Ebtracks data (1988-2017)

After estimating $R_{\text{max}}$ and $B$ the square root of sum of squared errors (SRSSE) is calculated for wind speeds, as described by the following equation.
\[ SRSSE = \sqrt{\sum_{i}^{34,50,64kt} (V_{i,observed} - V_{i,calculated})^2} \] (3.28)

In this equation, \( V_{i,observed} \) represents the wind speeds 34 \( kt \), 50 \( kt \) or 64 \( kt \), which are represented as \( V_{34} \), \( V_{50} \) and \( V_{64} \) respectively. The term \( V_{i,calculated} \) represents the surface wind speeds (1 \( min \) gust at 10 \( m \)) at \( R_{34} \), \( R_{50} \) and \( R_{64} \) calculated using the method described in Section 3.2, with the estimated \( R_{max} \) and \( B \) as input.

![Histogram and CDF of Holland B parameter estimated using Ebtracks data (1988-2017)](image)

Figure 3.8: Histogram and CDF of Holland B parameter estimated using Ebtracks data (1988-2017)

By definition, the wind speed at, for instance, \( R_{34} \) should be 34 \( kt \). However, the calculated wind speed will not be exactly 34 \( kt \), but quite close to it if the \( R_{max} \) and \( B \)
estimates are good. This difference between the observed and calculated wind speeds is the error, which is represented by SRSSE. The acceptable range of SRSSE for different scenarios is given in Table 3.3. This range is derived based on the observation of the 5285 horizontal wind speed profiles generated using the estimated $R_{\text{max}}$ and $B$. An example of comparison between calculated and observed horizontal wind speed profiles along with SRSSE values is presented in Figure 3.6 above.

Table 3.3: SRSSE limits for quality control of estimated horizontal wind speed profiles

<table>
<thead>
<tr>
<th>Available points in addition to $(V_{\text{max}}, R_{\text{max}})$</th>
<th>Acceptable SRSSE values</th>
</tr>
</thead>
<tbody>
<tr>
<td>$(V_{34}, R_{34})$</td>
<td>$\leq 1$</td>
</tr>
<tr>
<td>$(V_{34}, R_{34}), (V_{50}, R_{50})$</td>
<td>$\leq 20$</td>
</tr>
<tr>
<td>$(V_{34}, R_{34}), (V_{50}, R_{50}), (V_{64}, R_{64})$</td>
<td>$\leq 30$</td>
</tr>
</tbody>
</table>

The quality control criteria to determine acceptable horizontal wind speed profile includes primary and secondary criteria, which are described as follows:

1) Primary criteria: The profile should be within the SRSS limits specified in Table 3.3, and the Holland $B$ parameter should be less than or equal to 3.5. Profiles satisfying the primary criteria can be used for any purpose that does not require the correlation between current and previous time-steps.
2) Secondary criteria: The profile at the current time-step $i$ should first satisfy the primary criteria. The time-step $i$ profile is considered to satisfy the secondary criteria if the previous timesteps $i-1$ and/or $i-2$ also satisfy the primary criteria. The secondary criteria must be satisfied if we need to study the correlation between the $R_{max}$ and $B$ values at current and previous timesteps, as described in Sections 3.6 and 3.7.

The total number of data points (i.e. time-steps where horizontal wind speed profile, $R_{max}$ and $B$ values have been estimated) before and after the application of primary and secondary quality control criteria are listed in Table 3.4 and Table 3.5 respectively.

Table 3.4: Total number of horizontal wind speed profile time-steps available before and after applying primary quality control criteria

<table>
<thead>
<tr>
<th>Available points in addition to $(V_{max}, R_{max})$</th>
<th>Before quality control</th>
<th>After primary quality control</th>
</tr>
</thead>
<tbody>
<tr>
<td>$(V_{34}, R_{34})$</td>
<td>2117</td>
<td>1280</td>
</tr>
<tr>
<td>$(V_{34}, R_{34}), (V_{50}, R_{50})$</td>
<td>1288</td>
<td>937</td>
</tr>
<tr>
<td>$(V_{34}, R_{34}), (V_{50}, R_{50}), (V_{64}, R_{64})$</td>
<td>1880</td>
<td>1611</td>
</tr>
<tr>
<td>Total points</td>
<td>5285</td>
<td>3892</td>
</tr>
</tbody>
</table>
Table 3.5: Total number of horizontal wind profile time-steps available after applying secondary quality control criteria

<table>
<thead>
<tr>
<th>Timesteps available (i is the current timestep)</th>
<th>Time-steps available after secondary quality control</th>
</tr>
</thead>
<tbody>
<tr>
<td>$i, i - 1$</td>
<td>3338</td>
</tr>
<tr>
<td>$i, i - 1, i - 2$</td>
<td>2937</td>
</tr>
</tbody>
</table>

3.6. Stochastic simulation model for $R_{max}$

Based on the $R_{max}$ values estimated as described in preceding sections, this section describes a method for stochastic simulation of $R_{max}$ of simulated storms.

Upon the examination of correlation between $R_{max}$ and various hurricane parameters, it is found that the correlation coefficient with latitude, central pressure deficit and Holland $B$ parameters are 0.27, -0.25 and 0.33 respectively, as shown in Figure 3.9. However, there is a strong correlation between $R_{max}$ at current time-step $i$ and the previous time-steps $i - 1$ and $i - 2$, with the correlation coefficients being 0.91 and 0.80 respectively.
Based on this information, it is possible to generate equations for stochastic simulation of $R_{\text{max}}$ in synthetic tropical cyclone tracks. A set of possible equations for simulated $R_{\text{max}}$ is listed as follows.

$$R_{\text{max},i} = a_0 + a_1 P_c + a_2 R_{\text{max},(i-1)} + \epsilon$$ (3.29a)

$$R_{\text{max},i} = a_0 + a_1 \Delta P_c + a_2 R_{\text{max},(i-1)} + \epsilon$$ (3.29b)

$$R_{\text{max},i} = a_0 + a_1 P_c + a_2 R_{\text{max},(i-1)} + a_3 \psi + \epsilon$$ (3.29c)

$$R_{\text{max},i} = a_0 + a_1 P_c + a_2 R_{\text{max},(i-1)} + a_3 R_{\text{max},(i-2)} + \epsilon$$ (3.29d)
\[ R_{\text{max},i} = a_0 + a_1 P_c + a_2 R_{\text{max},(i-1)} + a_3 R_{\text{max},(i-2)} + a_4 \psi + \epsilon \]  
\[ (3.29e) \]

\[ R_{\text{max},i} = a_0 + a_1 P_c + a_2 R_{\text{max},(i-1)} + a_3 R_{\text{max},(i-2)} + a_4 \psi + a_5 B_i + \epsilon \]  
\[ (3.29f) \]

In the above equations, \( i \) represents the current time-step, whereas \( i - 1 \) and \( i - 2 \) represent the preceding time-steps. The terms \( R_{\text{max}}, P_c, \Delta P_c, \) and \( \psi \) denote the radius to maximum wind speed (km), central pressure (mbar), central pressure deficit (i.e. standard atmospheric pressure minus the \( P_c \) at time-step \( i \) in mbar) and latitude (degree) of the storm center at time-step \( i \). The regression coefficients and the error term are represented by \( a_k \) (\( k = 0 \ldots 5 \)) and \( \epsilon \) (km) respectively.

In Equations 3.29a to 3.29f, the \( R_{\text{max}} \) term could have been represented by \( \log R_{\text{max}} \) as well. If the \( R_{\text{max}} \) terms without the logarithm are used, \( R_{\text{max},i} \) can sometimes be negative after the applying error term \( \epsilon \). In such case, error term must be resampled until an acceptable \( R_{\text{max},i} \) value is obtained. Using the terms with logarithm prevents \( R_{\text{max},i} \) from being negative, but \( R_{\text{max},i} \) values can sometimes be close to 0 and 1 km. This must also be adjusted. Since in both cases adjustments are necessary, in this study, the \( R_{\text{max},i} \) equation without logarithm is selected for simplicity.

The results of regression for Equations 3.29 are shown in Table 3.6. Since the Equation 3.29e is found to be the least biased, it is recommended for simulating \( R_{\text{max}} \). The scatter plot of residual and the error term of Equation 3.29e is shown in Figure 3.10 and Figure 3.11 respectively.
Table 3.6: Regression coefficient and error for $R_{\text{max}}$ simulation equations

<table>
<thead>
<tr>
<th>Equation</th>
<th>$R^2$ %</th>
<th>Standard deviation of error $\epsilon$ (km)</th>
<th>$a_0$</th>
<th>$a_1$</th>
<th>$a_2$</th>
<th>$a_3$</th>
<th>$a_4$</th>
<th>$a_5$</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.29a</td>
<td>82</td>
<td>21.85</td>
<td>-25.147</td>
<td>0.0307</td>
<td>0.941</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>3.29b</td>
<td>82</td>
<td>21.85</td>
<td>-25.147</td>
<td>0.0307</td>
<td>0.941</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>3.29c</td>
<td>82.3</td>
<td>21.72</td>
<td>-36.923</td>
<td>0.0369</td>
<td>0.927</td>
<td>0.256</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>3.29d</td>
<td>82.4</td>
<td>20.92</td>
<td>-41.414</td>
<td>0.0480</td>
<td>1.047</td>
<td>-0.111</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>3.29e</td>
<td>82.7</td>
<td>20.78</td>
<td>-49.482</td>
<td>0.0503</td>
<td>1.034</td>
<td>-0.113</td>
<td>0.260</td>
<td>-</td>
</tr>
<tr>
<td>3.29f</td>
<td>83.4</td>
<td>20.32</td>
<td>-53.653</td>
<td>0.0336</td>
<td>0.983</td>
<td>-0.097</td>
<td>0.428</td>
<td>11.299</td>
</tr>
</tbody>
</table>

Figure 3.10: Scatter plot of error for the $R_{\text{max}}$ simulation Equation 3.29e
Figure 3.11: Error term for $R_{\text{max}}$ simulation Equation 3.29e is selected based on the various bins of $P_c$, since the standard deviation (sd) of error term is found to differ for various $P_c$. The mean of error term in all the five cases is 0.

3.7 Stochastic simulation of Holland $B$ model

Equation for the stochastic simulation of the $B$ parameter is selected in a manner similar to that for the $R_{\text{max}}$, based on the correlation of $B$ with other parameters as shown in Figure 3.12 and Figure 3.13. The parameters considered as possible predictors for $B$ parameter in the current time-step $i$ (denoted as $B_i$) are, central pressure deficit ($\Delta P_c$ in mbar), latitude ($\psi$ in degrees), radius to maximum wind speed in the current and previous time-steps ($R_{\text{max},i}$ and $R_{\text{max},i-1}$ in km), $B$ parameter in previous two time-steps ($B_{i-1}$ and $B_{i-2}$) and sea surface temperature (SST in Kelvin). Based on these parameters, the following set of candidate equations were selected for the simulation of $B$ parameter:
\[ B_i = b_0 + b_1 \Delta P_c + b_2 \psi + b_3 R_{max,i} + \epsilon \]  

(3.30a)

\[ B_i = b_0 + b_1 \Delta P_c + b_2 \psi + b_3 R_{max,i} + b_4 \text{SST} + \epsilon \]  

(3.30b)

\[ B_i = b_0 + b_1 \Delta P_c + b_2 \psi + b_3 R_{max,i} + b_4 B_{i-1} + \epsilon \]  

(3.30c)

\[ B_i = b_0 + b_1 \Delta P_c + b_2 \psi + b_3 R_{max,i} + b_4 B_{i-1} + b_5 B_{i-2} + \epsilon \]  

(3.30d)

\[ B_i = b_0 + b_1 \Delta P_c + b_2 \psi + b_3 R_{max,i} + b_4 R_{max,i-1} + b_5 B_{i-1} + b_6 B_{i-2} + \epsilon \]  

(3.30e)

Equation 3.30e has the lowest bias as revealed by the residual scatter plot (Figure 3.14), and is selected as the simulation equation for the \( B \) parameter. Inclusion of SST in Equation 3.30e did not significantly improve the value of \( R^2 \) or the residual scatter plot. Therefore, SST was omitted for simplicity, and also to enable the use of the same equation on land and ocean.

The values of the coefficients in Equation 3.30e are as follows:

\[ b_0 = 0.3743, \ b_1 = -4.1856 \times 10^{-4}, \ b_2 = -0.0052, \ b_3 = 0.0054, \ b_4 = -0.0049, \ b_5 = 0.0025 \text{ and } b_6 = 0.0117, \]  

where, \( R^2 = 0.7401 \), standard deviation of error = 0.2194 and mean of error = 0.

The scatter plot (Figure 3.14), histogram and the CDF (Figure 3.15) for the residuals of Equation 3.30e show that the equation is unbiased, and suitable for simulation of \( B \) parameter over ocean as well as land. A separate equation to simulate the \( B \) parameter is found to be unnecessary for reasons discussed in Section 3.8.
Figure 3.12: Scatter plot between Holland $B$ parameter and latitude, radius to maximum winds, central pressure deficit and mean sea surface temperature within 25-percentile rainfall extent with correlation coefficients.

Figure 3.13: Relationship between Holland $B$ parameter at current time-step with $R_{\text{max}}$ and $B$ at various time-steps with correlation coefficients.
Figure 3.14: Error vs estimated value (mean model) plot for Equation 3.30e for Holland $B$ parameter

Figure 3.15: Error histogram and CDF for the Holland $B$ simulation Equation 3.30e with mean = 0 and standard deviation = 0.2194
3.8. Evolution of $R_{max}$ and $B$ after landfall

To determine if it is necessary to use separate equations to simulate $R_{max}$ and $B$ on land and ocean, the change in the values of these parameters relative to their values immediately before landfall needs to be examined. This is done by studying the normalized values of $B$ or $R_{max}$ parameters as shown in Figure 3.16 and Figure 3.17 respectively. The lines in these figures appear discontinuous because only the landfalling points satisfying the quality control criteria are shown. To calculate the normalized values, the value on land for any storm segment is divided by the value just prior to landfall in that segment.

Since a normalized value of 1 represents the value just prior to landfall, values less than 1 indicate that the parameter reduces in magnitude after landfall, while a value greater than 1 indicates otherwise. In case of the $B$ parameter, the values in Figure 3.16 appear evenly distributed above and below 1. Quantitatively speaking, out of 177 landfalling time-steps in total, 78 time-steps (44% of total) are below 1 and 99 (56% of total) are greater than 1. This indicates that Holland $B$ parameter does not consistently increase or decrease after landfall. For this reason, the simulation equation presented in Section 3.7 does not include a decay equation and allows for either increase or decrease in the value of $B$ parameter after landfall.

Similarly, in case of $R_{max}$, out of 174 landfalling time-steps in total, 57 time-steps (33% of total) are below 1 and 117 (67% of total) are greater than 1. This indicates that most of the time, the wind field increases in size after the storms makes landfall, even as the intensity of the storms reduces.
Figure 3.16: Normalized Holland B parameter for time-steps after landfall

Figure 3.17: Normalized radius to maximum winds for time-steps after landfall
The equation to simulate $R_{\text{max}}$ described in Section 3.6 does not explicitly consider the increase in $R_{\text{max}}$ after landfall, but instead considers it indirectly by using central pressure as a predictor in the $R_{\text{max}}$ simulation equation. Whether a separate equation is necessary to simulate $R_{\text{max}}$ after landfall can be a subject for future investigation.

3.9 Discussion

This chapter presented a method to estimate hurricane wind speed and validated it using data from historical storms as recorded by ASOS network meteorological stations. The validation plots reveal that the model can replicate the historical wind footprint as well as storm time history reasonably well. This indicates that the wind speed computation framework is suitable for calculating wind speeds for simulated storms or any other application.

After successful validation, the wind speed computation method is used to develop an algorithm to estimate the wind field shape parameters $R_{\text{max}}$ and $B$ at the surface (i.e. 10 m elevation) for historical storms. The $R_{\text{max}}$ and $B$ are then estimated at all the time-steps in historical storms from 1988 to 2017 with sufficient data. Using the $R_{\text{max}}$ and $B$ values thus estimated, equations to simulate the time-history of $R_{\text{max}}$ and $B$ are developed, which can better represent the temporal correlation (i.e. the correlation between the value of a parameter at current time-step to the values in previous two time-steps) of these parameters compared to other commonly used methods. Since the wind speed estimate at any location is quite sensitive to the values of $R_{\text{max}}$ and $B$, a more realistic estimate of these parameters will improve the quality of wind speed estimates.
Another application of the wind speed computation framework is to generate a database of hurricane wind hazard curves for the Eastern US, which will be discussed in the Chapter 4.

3.10. References


CHAPTER 4. US HURRICANE WIND SPEED DATABASE

4.1 Introduction

Simulation of hurricanes is a widely accepted method of studying hurricane wind hazards. By using a catalogue of simulated hurricanes, for any site of interest, we can obtain a wind speed vector corresponding to hurricane events from several thousands of years. The next step in hazard analysis is to represent this wind speed vector using a suitable continuous probability distribution. This chapter checks the suitability of 11 types of distributions for this purpose and presents some applications of the wind speed data represented by the distributions thus selected.

For the purposes of wind-resistant engineering design as well as hurricane risk assessment at any location, it is necessary to know the values of wind speeds corresponding to large return periods, such as several hundreds or thousands of years. However, historical hurricane databases such as HURDAT contain records of less than 200 years of hurricane activity, using which it not possible to estimate the wind speeds for larger return periods directly. A widely accepted method of overcoming this limitation is to generate a synthetic hurricane wind database by simulating hurricanes occurring over a period of thousands of years (Emanuel et al. 2006; Georgiou 1986; Hallegatte 2007; James et al. 2005; Lee et al. 2007). Once the process of wind speed calculation at a location is complete, it is convenient to represent the results obtained using a continuous probability distribution.

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1 A version similar to this chapter was presented in the ICOSSAR 2017 - 12th International Conference on Structural Safety & Reliability
A wind speed database covering the 30 Eastern US states as well as the exclusive economic zone along the Gulf and the Atlantic coast was developed based on the simulated hurricane catalogue developed by Liu (2014), and methodologies established by Vickery et al. (2009a, 2009b), as described in previous chapters. This paper examines the suitability of 11 probability distributions (as enlisted in Table 4.1) to model the wind speeds in this database. The distributions selected here include some distributions that are not commonly used for modelling wind speeds. Since wind speed data cannot have negative values, distributions supporting only positive values have been selected, with the exception of Gumbel Largest distribution, which has been chosen due to its widespread use in representing wind speed data. Besides the distributions enlisted here, other distributions of varying levels of complexity have been described in other studies (Carta et al. 2009; Morgan et al. 2011).

The first part of this study provides a brief description of the simulation of hurricane catalogue and calculation of wind speed in the 30 Eastern US states. The second part deals with the selection of appropriate continuous probability distribution to represent the wind speed database generated in the first part and is the main subject of this study.

4.2 Generation of wind speed database

In order to generate the wind speed database, a variable resolution grid as shown in Figure 1 is used. There are a total of 246,798 points in the grid portion on land and 59,344 points in the maritime exclusive economic zone (EEZ). The resolution of the grid is 0.01°
(~1.1km) for a distance of about 20 miles inland from the coastline, 0.05° (~5.6km) for up to 300 miles inland, 0.10° (~11.1km) for beyond 300 miles inland and 0.05° (~5.6km) for the EEZ. Such a choice was made in order to reduce the computation time as well as the database size, while giving due importance to the sites near the coastline. Since this study primarily aims to discuss the method of distribution selection, only the results on land are discussed for illustrative purpose; similar method can be applied to results on ocean.

Figure 4.1: Domain of wind speed database

The hurricane catalogue used to calculate wind speeds at each point in the grid contains about 900,000 events, corresponding to 100,000 years of simulated storms. During the wind speed calculation, storms located within a 250 km radius of the point of interest are selected, and only the maximum wind speed due to each storm is saved as described in Section 3.2.
4.3 Selection of probability distribution

4.3.1. Extraction of subset-vector of wind speed

The output of the wind speed calculation contains a vector of wind speeds corresponding to the events affecting the point of interest. In order to determine the probability distribution to represent the wind speed at various return periods, the first step is to divide the output vector into several bins equal to the desired return period, and then extract the maximum wind speed in each bins to obtain a subset-vector.

For example, let us consider a site in Charleston, SC at latitude 32.72° and longitude -79.89. This site is affected by 123,720 events when subjected to a 100,000-year catalogue, and so, the wind speed vector also contains the same number of data points. If we need to derive a distribution for a return period of 1000 years, we should divide it into 100,000/1000 = 100 bins.

That is, the bins are as follows: bin 1 = wind speeds corresponding to events within year 1 to 1000, bin 2 = year 1001 to 2000,…, bin 100 = year 99,901 to 100,000. The subset-vector, which will contain 100 values, is obtained by choosing the maximum values in each bin, i.e.,

\[
\text{Subset-vector for 1000 year return period} = [\max(\text{bin } 1), \max(\text{bin } 2), \ldots, \max(\text{bin } 100)]
\]

4.3.2. Fitting the subset-vector to probability distributions

The subset-vectors for selected return periods (10, 25, 50, 100, 300, 500, 700, 1000, 1700 years, which include ASCE 7 (ASCE 2010) wind speeds) are then fitted to the
Probability distributions as tabulated in Table 4.1 using the maximum likelihood estimation (MLE) method. A limitation of MLE method is that it requires an initial guess for the values of the distribution parameters to be determined, which may need to be reasonably close to the actual values. So, to determine the initial guess, any methods such as method of moments, probability paper method or least squares method can be used. The ease of application of these three methods can differ for various distributions. Method of moments can be useful if it yields closed form solutions, but in cases where it requires the simultaneous solution of nonlinear equations, convergence issues might appear. Similarly, least squares method, although much easier to compute than MLE method, also requires an initial guess, and may occasionally fail to converge. On the other hand, probability paper method does not require any initial guesses and thus avoids convergence issues, but instead it requires linearizing the nonlinear cumulative distribution function, which may not be feasible in all cases. Therefore, to calculate an initial guess for any distribution, we can select the easier of these methods for that particular distribution.

Table 4.1: Continuous probability distributions considered for modelling simulated hurricane wind speed data

<table>
<thead>
<tr>
<th>Distribution</th>
<th>PDF</th>
<th>CDF</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lognormal</td>
<td>( \frac{1}{x \sigma \sqrt{2\pi}} \exp \left[ -\frac{(\ln(x) - \mu)^2}{2\sigma^2} \right] )</td>
<td>( \frac{1}{2} + \frac{1}{2} \text{erf} \left[ \frac{\ln(x) - \mu}{\sigma \sqrt{2}} \right] )</td>
<td>( \sigma &gt; 0, x &gt; 0 )</td>
</tr>
<tr>
<td>Gumbel Largest</td>
<td>( \frac{1}{\beta} e^z e^{-e^z} )</td>
<td>( e^{-e^z}, z = \frac{x - \mu}{\beta} )</td>
<td>( \beta &gt; 0, -\infty \leq x \leq \infty )</td>
</tr>
<tr>
<td>Frechet Largest</td>
<td>( \frac{k}{v} z^{k+1} e^{-z^k} )</td>
<td>( e^{-z^k}, z = \frac{v}{x} )</td>
<td>( k &gt; 0, x &gt; 0 )</td>
</tr>
<tr>
<td>Weibull Smallest</td>
<td>( \frac{k}{u} z^{k+1} e^{-z^k} )</td>
<td>( 1 - e^{-z^k}, z = \frac{u}{x} )</td>
<td>( k &gt; 0, x &gt; 0 )</td>
</tr>
</tbody>
</table>

\( \mu: \text{location} \)

\( \sigma: \text{scale} \)

\( v: \text{location} \)

\( k: \text{shape} \)

\( u: \text{scale} \)
<table>
<thead>
<tr>
<th>Distribution</th>
<th>Density Function</th>
<th>Parameters</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generalized Extreme Value</td>
<td>( \frac{1}{\sigma} e^{-t(x)} t(x)^{k+1} )</td>
<td>( k &gt; 0, u &gt; 0, x \geq 0 )</td>
<td></td>
</tr>
<tr>
<td></td>
<td>( e^{-t(x)} )</td>
<td>( t(x) = \left[ 1 + k \left( \frac{x - \mu}{\sigma} \right) \right]^{-\frac{1}{k}} )</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>( k \neq 0, t(x) &gt; 0 )</td>
<td></td>
</tr>
<tr>
<td>Loglogistic</td>
<td>( \frac{1}{\mu} \left( \frac{x}{\mu} \right)^{\beta - 1} \left( 1 + \left( \frac{x}{\mu} \right)^{\beta} \right)^{-\frac{1}{\beta}} )</td>
<td>( \beta &gt; 0, \mu &gt; 0 ) ( x \geq 0 )</td>
<td></td>
</tr>
<tr>
<td>Burr (Type XII)</td>
<td>( \frac{k \alpha}{\beta} z^{-c} )</td>
<td>( c &gt; 0, k &gt; 0, \alpha &gt; 0 ) ( x \geq 0 )</td>
<td></td>
</tr>
<tr>
<td>Nakagami</td>
<td>( \frac{2 \mu^3}{\Gamma(\mu)} e^{-\mu x^2} )</td>
<td>( \mu \geq 0.5, \omega &gt; 0 ) ( x &gt; 0 )</td>
<td></td>
</tr>
<tr>
<td>Rician</td>
<td>( \frac{x}{\sigma^2} \exp \left[ -\frac{x^2 + s^2}{2 \sigma^2} \right] ) ( \frac{1}{\sigma^2} I_0 )</td>
<td>( s \geq 0, \sigma &gt; 0 ) ( x &gt; 0 )</td>
<td></td>
</tr>
<tr>
<td>Gamma</td>
<td>( \frac{1}{b^a \Gamma(a)} x^{a-1} e^{-\frac{x}{b}} )</td>
<td>( a &gt; 0, b &gt; 0 ) ( x &gt; 0 )</td>
<td></td>
</tr>
<tr>
<td>Dagum</td>
<td>( \frac{a p}{z} \left( \frac{z^{ap}}{(z^a + 1)^{p+1}} \right) )</td>
<td>( p &gt; 0, a &gt; 0, b &gt; 0 ) ( x &gt; 0 )</td>
<td></td>
</tr>
</tbody>
</table>
4.3.3. Goodness of fit test to select the appropriate distribution

After the continuous probability distribution parameters have been determined for the selected return periods, Kolmogorov-Smirnov (KS) goodness of fit test is done to select the best fitting distribution for that return period. Even though there are other goodness of fit tests such as the Anderson-Darling (AD) test, an observation of large number of test results shows that KS test is more difficult to satisfy, and if KS test is satisfied, AD test is usually satisfied. Therefore, performing only the KS test is deemed sufficient.

KS test requires calculating the p-value, which indicates the probability that the data being tested belongs to the distribution under consideration. That is, lower p-value implies lesser likelihood of the data belonging to the distribution. However, if the p-values are greater than the level of significance, which is usually considered as 0.05, the KS test is considered to be satisfied. Thus, the p-values are used to determine whether each of the 11 distributions pass the KS test in the selected return periods. Additionally, in case several distributions satisfy the KS-test, p-values can be used to compare these distributions with each other, the one with the higher p-value being considered a better fit.

4.3.4. Results

Table 4.2 presents the percentage of sites where the MLE method converged to a solution, and Table 4.3 presents the results of the KS test as total sites that satisfy the KS-test as a percentage of the entire points in the grid.

The MLE method shows a 100% or close to 100% convergence in most of the cases except for higher return periods in Dagum distribution. Due to such a high convergence
rate, the results provide sufficient basis to decide the suitability of various distributions.

Table 3 shows that for return periods of 10 and 25 years, very few points pass the KS-test, whereas, for higher return periods, more distributions tend to satisfy the test. With reference to Section 4.3.1., this is due to large number of data at lower return periods, and less data at higher return periods. However, as shown in Figure 4.4, even though KS-test is not satisfied, it is possible that the fitted distribution approximates the data closely enough to be acceptable for practical purposes.

Table 4.2: Percentage of the total number of sites where MLE method successfully converges

<table>
<thead>
<tr>
<th>Distributions</th>
<th>Return Periods (Years)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>10</td>
</tr>
<tr>
<td>Lognormal</td>
<td>100</td>
</tr>
<tr>
<td>Gumbel Largest</td>
<td>100</td>
</tr>
<tr>
<td>Frechet Largest</td>
<td>14.4</td>
</tr>
<tr>
<td>Weibull Smallest</td>
<td>100</td>
</tr>
<tr>
<td>GEV</td>
<td>100</td>
</tr>
<tr>
<td>Loglogistic</td>
<td>100</td>
</tr>
<tr>
<td>Burr (Type XII)</td>
<td>86.1</td>
</tr>
<tr>
<td>Nakagami</td>
<td>100</td>
</tr>
<tr>
<td>Rician</td>
<td>100</td>
</tr>
<tr>
<td>Gamma</td>
<td>100</td>
</tr>
<tr>
<td>Dagum</td>
<td>99.8</td>
</tr>
</tbody>
</table>
Table 4.3: Percentage of the total number of sites that satisfy the KS-test in different return periods

<table>
<thead>
<tr>
<th>Distributions</th>
<th>Return Periods (Years)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>10</td>
</tr>
<tr>
<td>Lognormal</td>
<td>0.22</td>
</tr>
<tr>
<td>Gumbel Largest</td>
<td>0.44</td>
</tr>
<tr>
<td>Frechet Largest</td>
<td>0.05</td>
</tr>
<tr>
<td>Weibull Smallest</td>
<td>2.51</td>
</tr>
<tr>
<td>GEV</td>
<td>2.32</td>
</tr>
<tr>
<td>Loglogistic</td>
<td>0.39</td>
</tr>
<tr>
<td>Burr (Type XII)</td>
<td>1.32</td>
</tr>
<tr>
<td>Nakagami</td>
<td>1.22</td>
</tr>
<tr>
<td>Rician</td>
<td>1.76</td>
</tr>
<tr>
<td>Gamma</td>
<td>0.69</td>
</tr>
<tr>
<td>Dagum</td>
<td>1.27</td>
</tr>
</tbody>
</table>

But for return periods of 50 years and above, sufficiently large number of points satisfy the KS-test. Of all the 11 distributions, the GEV distribution consistently shows a good fit in all the return periods above 50, closely followed by Loglogistic and Burr distributions. For return periods of 50 to 300, Dagum distribution also shows a good fit. If the MLE convergence rate of Dagum distribution is improved, it could display a good fit at higher return periods as well.

It should be noted that, among the distributions that pass the KS-test, different distributions show better fit (i.e. greater p-value) at different locations. But from a practical standpoint, it is more convenient to use as less types of distributions as possible to represent the entire data. For instance, at a location even if the p-value of lognormal or GEV distribution is greater than that of Dagum distribution, we can still use Dagum distribution to represent the data if it passes the KS-test.
Figure 4.2: For a return period of 50 years, Dagum distribution satisfies the KS test at 69% of the sites as indicated by the coloured region. For higher return periods, several distributions cover almost the entire domain.

Figure 4.3: An example of selected distributions fitted to a sample data at (26.25°,-97.4°) for a return period of 100 years.
Figure 4.4: Simulated CDF plotted with Burr (TypeXII) CDF at (32.28°, -80.66°) for a return period of 10 years. Even though Burr distribution does not pass the KS-test in this case, Burr CDF is quite close to the empirical CDF.

4.4. Applications

4.4.1. Representation of the distribution parameters as a function of return period

An immediate advantage of representing a wind speed database with a distribution is that a reduction in the size of database is achieved, which can also help to expedite computations. That is, instead of using the original wind speed vector, it is sufficient to store only the probability distribution parameters. However, this still necessitates storing the values of the parameters for several return periods. This limitation can be overcome by fitting these parameters to equations which represent them as a function of return period. It will then be necessary to store only the values of the coefficients of these equations. For example, for a site located at latitude $25.9^\circ$ and longitude $-80.24^\circ$ it is determined that
loglogistic distribution best describes the simulated wind speed data. Then, as shown by Figure 4.5, the scale ($\alpha$) and shape ($\beta$) parameters can be represented by equations of type 4.1 and 4.2 respectively.

$$\alpha(r) = l \, r^m + n$$  \hspace{1cm} (4.1)

$$\beta(r) = a \, e^{br} + c \, e^{dr}$$  \hspace{1cm} (4.2)

Where, $r$ is the return period and $l$, $m$, $n$, $a$, $b$, $c$ and $d$ are the coefficients to be determined by curve fitting. The values of these coefficients will vary from site to site. An obvious advantage of representing the parameters in this manner is that the parameters, and consequently the wind speed, can be determined for any desired return period.
Figure 4.5: Loglogistic distribution parameters represented by Equations 4.1 and 4.2 at (25.9°, -80.24°), with coefficients \( l = -65.64, m = -0.175, n = 81.37, a = 21.19, b = 7.24 \times 10^{-6}, c = -15.06, \) and \( d = -0.0127. \) The \( R^2 \) value is about 99% for both of the fitted curves.

4.4.2. Determination of wind hazard

Wind hazard represents the likelihood of occurrence of different values of wind speeds within a certain time interval. Assuming that the temporal occurrence of hurricane events can be considered a Poisson process, the wind hazard curve can be represented by Equation 4.3.

\[
P[N \geq 1] = 1 - e^{-\Lambda T}
\]  

(4.3)

Where, \( P[N \geq 1] \) represents the probability that the wind speed \( W \) of a particular magnitude will be exceeded at least once in an interval of \( T \) years (or the return period).
The $\lambda$ is the mean annual rate of occurrence of $W$ given by the relation $\lambda = n/Y$, where, $n$ is the total number of times $W$ occurs in $Y$ years. If the simulated wind speed data at a return period $T$ is represented using a continuous probability distribution function with a cumulative distribution function $F_T$, then the hazard curve can be represented by Equation 4.4. Figure 5 shows an example of the wind hazard curves plotted using Equations 4.3 and 4.4.

$$P[N \geq 1] = 1 - F_T$$  \hspace{1cm} (4.4)

Figure 4.6: Wind hazard curves for a site located at (32.72°, -79.89°) obtained using simulated data (Equation 4.3) overlain with the curves obtained using the data fitted to Gumbel Largest distribution (Equation 4.4). The thicker lines and the dotted lines represent the simulated data.

In recent years, various frameworks for performance-based wind engineering (PBWE) have been proposed (Ciampoli et al. 2011; Spence et al. 2016; Unnikrishnan et al. 2018).
2015), which require site specific wind hazard information as an input. A wind hazard curve database, therefore, is needed to aid further research and implementation of PBWE methods. The hazard curves provided by the database discussed in this study can address this need.

4.4.3. Calculation of failure probabilities

For assessing the risk of failure of a structure, it is necessary to calculate the probability of failure (\( P_f \)) of a structural component, as given by Equation 4.5. The results thus obtained can be used for tasks such as calibration of factors of safety used in design codes or estimating financial losses due to hurricanes.

\[
P_f = \int_0^\infty [1 - F_D(r)] \ f_r \ dr
\]

(4.5)

Where, \( F_D(r) \) represents the cumulative distribution function (CDF) of the demand, and \( f_r \) represents the probability distribution function (PDF) of the resistance. For example, the CDF of wind speed can be converted into a CDF of uplift pressure on the roof of a building (i.e. the demand) using equations commonly used in design codes such as ASCE 7. The PDF of the roof panel uplift resistance of the structural component can be selected from the relevant research literature. Thus, knowing \( F_D(r) \) and \( f_r \), the failure probability can be computed using Equation 4.5.
4.5 Discussion

This chapter discussed the suitability of 11 probability distributions in modelling the simulated hurricane wind speed data for the Eastern United States. Distributions such as Gumbel and Weibull have been used quite widely to model wind speed data, but this study shows that other distributions such as Generalized Extreme Value, Loglogistic, Burr (Type XII) and Dagum distributions are quite capable of modelling the data closely, as evidenced by KS-test results. For lower return periods (i.e. below 50 years) where very few cases satisfy the KS-test, the agreement between the actual and fitted data can still be close enough to be sufficient for practical purposes. The wind speed database can therefore be represented by suitable probability distributions, which greatly reduces the size of the database, and can also help to expedite the computations. The parameters of the distributions can also be represented by equations which are functions of return period, using which, wind speeds for any desirable return period can easily be obtained. These results can be used for determining the wind hazard at a particular location, as well as the failure probability of a structural component, making it useful for applications such as performance-based wind engineering and risk assessment.
4.6 References

American Society of Civil Engineers (ASCE) (2010). *Minimum design loads for buildings and other structures (ASCE/SEI 7-10).* ASCE, Reston.


CHAPTER 5. SIMULATION OF HURRICANE RAINFALL VOLUME AND EXTENT

5.1. Introduction

In a tropical cyclone, the wind speed is maximum at the eye wall, and its value drops farther from the eyewall gradually (in case of less intense storms) or sharply (in case of more intense storms). In general, most intense rainfall also occurs near the eyewall, but it can also occur far from storm center. Unlike wind, which occurs continuously throughout the region occupied by the storm, rainfall only occurs in regions where rain clouds or rain bands are concentrated. The distribution of rain clouds or bands can be very irregular and asymmetric, and usually in every rain field, there are areas completely devoid of rainfall. Determining the precise location of rain cloud and the rainfall rate associated with it is very challenging even for a complex physical model. On the other hand, existing statistical models can only represent a generalized behavior of rainfall rate and distribution, and they cannot replicate the irregular and scattered shape of the rain field in two-dimensions. This study has been undertaken to overcome this limitation in statistical models.

Hurricane rainfall models may be concerned with weather forecasting in real time, or with the assessment of rainfall hazard at any location, as described in detail in Section 1.3.3. The objective of this study is to create a stochastic simulation model to perform long-term hurricane rainfall hazard assessment. The simulation model developed in this study consists of two parts. The first part, described in this chapter, quantitatively answers the question – what is the total rainfall volume at any time-step of a storm and how much area does it occupy, if the storm intensity and environmental parameters are known? The second
part deals with how this rainfall volume is distributed within the rain field extents and is described in the following chapter. In this chapter and the next, the term ‘rain’ refers exclusively to hurricane rainfall. Any rainfall phenomenon not related to hurricane is beyond the scope of this study.

5.2. Dataset and quality control

This study uses the TRMM 3B42 rainfall data from the Tropical Rainfall Measuring Mission (TRMM) satellite (TRMM 2011), which provides a global coverage of rainfall data from 1998 onwards, the year of the TRMM satellite launch. The spatial range of the TRMM 3B42 data used in this study is -120° West to 5° East longitude and -5° South to 50° North latitude, which completely encloses the region of hurricane activity in the North Atlantic basin. The rainfall data in this database is available at a spatial resolution of 0.25° × 0.25°, and at a temporal resolution of 3 hours. The dataset is available for all tropical storms between the year 1998 to 2017.

Since a radius of 700 km from the storm center is used to determine the rain field extent (as described in Section 5.3), only the points where the storm center latitude is less than or equal to 45° North are selected from the TRMM dataset.

The environmental parameters such as vorticity, total precipitable water, relative humidity, sea surface temperature and wind shear are obtained from Statistical Hurricane Intensity Prediction Scheme (SHIPS) dataset. The SHIPS model (DeMaria et al. 2005; Jones et al. 2006; Kaplan et al. 2015) is a statistical-dynamical model based on standard multiple regression technique and is one of the several models used by the National
Hurricane Center to make operational forecast for hurricane intensity. SHIPS data has been used to study hurricane rainfall by previous studies such as Zhou et al. (2018).

5.3. Instantaneous rainfall volume definition

Instantaneous rainfall volume \( R_{vl} \) is defined as the product of the rainfall rate \( R_R \) and the total area influenced by that rate. Since the \( R_R \) is commonly measured in \( mm/hr \) and the area is in \( km^2 \), it is convenient to represent the unit of \( R_{vl} \) in \( km^3/hr \).

\[
R_{vl}, g = R_{R,g} \times A_g \tag{5.1a}
\]
\[
R_{vl} = \sum_{g=1}^{N} R_{vl,g} \tag{5.1b}
\]

In the above equation, the subscript ‘\( g \)’ refers to a grid point, and \( N \) refers to the total number of grid points in the hurricane rain field. The term \( A_g \) denotes the area covered by one grid point.

The \( R_{vl} \) is calculated using a radius of 700 km around the storm center.

5.4. Rain field extent definition

In a tropical cyclone, the wind speed has maximum value at the eyewall (i.e. around the storm center), and it gradually drops at regions farther from the storm center. But this is not always true in case of rain field. There can be high rainfall rates far from storm center due to outer rain bands (Figure 5.1). In some cases, the cyclone rain field merges with the surrounding rain field (Figure 5.2), which makes it difficult to determine where the cyclone rain field terminates. Moreover, rain fields tend to be larger than wind fields. For these reasons, a quantitative definition of tropical cyclone rain field extent is necessary.
Some studies have used a specific radius (usually 500 km) to define the rain field. This approach assumes that the rain field is completely enclosed within the specific radius. The main limitation of this approach is that it does not define the actual rain field extent, even though it can enclose the storm’s total rainfall volume in most cases. Additionally, observation of the TRMM rain field data shows that larger storms can have rain fields between 700km (Figure 5.1) to 900km, although the rain field of most storms is less than 700 km. Figure 5.3 presents an example of how the choice of 500 km, 600 km and 700 km radius impacts the calculation of instantaneous rainfall volume ($R_{vi}$), which is defined as the rainfall rate multiplied by the storm area obtained using 500 km, 600km, 700km or any desired radius. As Figure 5.1 and Figure 5.3 illustrate, 500 km radius is sufficient for most time-steps, but for some time-steps it is necessary to use a 700 km radius.

To overcome these limitations, this study defines the rain field extent as the radius which contains a certain percentage ($P_{rf}$ %) of the total instantaneous rainfall volume enclosed by a radius of 700 km from the storm center. That is, instead of using a single radius, this study uses several distances to describe the extent of rain field. These distances are the radii that enclose 25 %, 50 %, 75% and 95 % of the $R_{vi}$. The rain field extents are denoted by $R_{EP}$. For instance, $R_{E50}$ (referred to as ‘50-percentile rain field extent’) denotes the rain field extent that encloses 50 % of the total rainfall volume within the 700 km radius from the storm center. Using several radii to describe the rain field extent has the advantage of partially describing the spatial distribution of rainfall volume. Moreover, using the 95 percentile radii to represent the overall shape of the rain field offers a quantitative criterion for distinguishing the hurricane rain field from surrounding rain field.
Figure 5.1: High rainfall rate in outer rain band far away from storm center in Hurricane Isabel (2003)

Figure 5.2: Hurricane rain field merging with atmospheric rain field in Hurricane Isabel (2003)
Figure 5.3: Impact of considering various radii to define rain field extent demonstrated by instantaneous rainfall volume time history of Hurricane Floyd (1999).

5.5. Factors affecting rainfall volume and extent

This section examines the correlation between $R_v$, $R_E$ and various environmental parameters to identify the parameters that may be used as predictors during stochastic simulation. Figure 5.4 and Figure 5.5 show that both $R_v$ and $R_E$ have strong correlation with their previous time-steps, indicating a gradual evolution. $R_v$ has correlation coefficients of 0.66, 0.46, -0.37, 0.42 and 0.25 with respect to vorticity ($\nabla \times \vec{V}$), precipitable water ($W_P$), central pressure ($P_c$), relative humidity ($H_r$) and Reynold’s sea surface
temperature (RSST). On the other hand, $R_{E50}$ has correlation coefficients of 0.29, 0.13, 0.26, 0.32 and -0.01 with respect to $V_o$, $W_P$, $P_c$, $H_r$ and RSST.

This shows that in comparison to the $R_{E50}$, $R_{vl}$ demonstrates better correlation with atmospheric parameters. Therefore, in the next section simulation equations are first developed for $R_{vl}$.

Figure 5.4: Correlation between 50% rain field extents in current vs previous two time-steps
Figure 5.5: Correlation between $R_{vl}$ in current vs previous two time-steps

Figure 5.6: Correlation between $R_{vl}$, $R_{E50}$ and central pressure
Figure 5.7: Correlation between $R_{vi}, R_{E50}$ and vorticity

Figure 5.8: Correlation between $R_{vi}, R_{E50}$ and precipitable water
Figure 5.9: Correlation between $R_{vl}$, $R_{E50}$ and relative humidity

Figure 5.10: Correlation between $R_{vl}$, $R_{E50}$ and Reynold's sea surface temperature (RSST)
5.6. Stochastic simulation of instantaneous rainfall volume

This section describes a stochastic model used to simulate the time-history of \( R_{vl} \) which is developed based on the correlations described in previous section. A total of 6937 time-steps (including those on land as well as ocean) are available for the stochastic simulation of \( R_{vl} \) and \( R_{ep} \).

A set of candidate equations for \( R_{vl} \) are presented as follows.

\[
R_{vi,i} = a_0 + a_1 \Delta P_c + a_2 W_p + a_3 V_o + a_4 R_{vl,i-1} + a_5 R_{vl,i-2} + \varepsilon \tag{5.2a}
\]

\[
R_{vi,i} = a_0 + a_1 \Delta P_c + a_2 H_r + a_3 V_o + a_4 R_{vl,i-1} + a_5 R_{vl,i-2} + \varepsilon \tag{5.2b}
\]

\[
R_{vi,i} = a_0 + a_1 \Delta P_c + a_2 W_p + a_3 V_o + a_4 R_{vl,i-1} + a_5 R_{vl,i-2} + a_6 H_r + \varepsilon \tag{5.2c}
\]

\[
R_{vi,i} = a_0 + a_1 \Delta P_c + a_2 R_{vl,i-1} + a_3 R_{vl,i-2} + \varepsilon \tag{5.2d}
\]

\[
R_{vi,i} = a_0 + a_1 \Delta P_c + a_2 W_p + a_3 R_{vl,i-1} + a_4 R_{vl,i-2} + \varepsilon \tag{5.2e}
\]

\[
R_{vi,i} = a_0 + a_1 \Delta P_c + a_2 V_o + a_3 R_{vl,i-1} + a_4 R_{vl,i-2} + \varepsilon \tag{5.2f}
\]

\[
R_{vi,i} = a_0 + a_1 \Delta P_c + a_2 W_p + a_3 V_o + a_4 R_{vl,i-1} + a_5 R_{vl,i-2} + a_6 D_L + \varepsilon \tag{5.2g}
\]

\[
R_{vi,i} = a_0 + a_1 \Delta P_c + a_2 W_p + a_3 V_o + a_4 R_{vl,i-1} + a_5 R_{vl,i-2} + a_6 R_{SSL} + \varepsilon \tag{5.2h}
\]

Equations 5.2a to 5.2f can be applied for time-steps on land as well as ocean, whereas, 5.2g applies only to points on land and 5.2h applies only to points on ocean.
It is necessary to have a quantitative approach to decide which of the candidate equations represents a better model. The various quantitative parameters used to check the skill of a model are $R^2$, standard deviation of error, square root of sum of square of error (SRSSE), sum of signed square of errors (SSSE), scatter plot between error vs predicted quantity (i.e. $R_{vt}$) and histogram of errors. The residual analysis for Equations 5.2 are shown in Table 5.1. Since Equations 5.2g and 5.2h do not offer any significant improvement over equations 5.2a to 5.2f, the results corresponding to them are not shown in the following tables. Table 5.2 presents the fitted coefficients for equations 5.2a to 5.2f.

<table>
<thead>
<tr>
<th>Equation</th>
<th>Data location</th>
<th>$R^2$</th>
<th>St. deviation ($\frac{km^3}{hr}$)</th>
<th>SRSSE</th>
<th>SSSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>5.2a</td>
<td>Land &amp; Ocean</td>
<td>0.77</td>
<td>0.29</td>
<td>24.40</td>
<td>107.39</td>
</tr>
<tr>
<td>5.2b</td>
<td>Land &amp; Ocean</td>
<td>0.77</td>
<td>0.29</td>
<td>24.40</td>
<td>109.85</td>
</tr>
<tr>
<td>5.2c</td>
<td>Land &amp; Ocean</td>
<td>0.77</td>
<td>0.29</td>
<td>24.36</td>
<td>108.41</td>
</tr>
<tr>
<td>5.2d</td>
<td>Land &amp; Ocean</td>
<td>0.76</td>
<td>0.30</td>
<td>24.91</td>
<td>111.82</td>
</tr>
<tr>
<td>5.2e</td>
<td>Land &amp; Ocean</td>
<td>0.76</td>
<td>0.30</td>
<td>24.70</td>
<td>109.06</td>
</tr>
<tr>
<td>5.2f</td>
<td>Land &amp; Ocean</td>
<td>0.76</td>
<td>0.29</td>
<td>24.54</td>
<td>110.02</td>
</tr>
</tbody>
</table>
Table 5.2: Regression coefficients for selected equations to estimate instantaneous rainfall volume using data on land and ocean

<table>
<thead>
<tr>
<th>Equation</th>
<th>$a_0$</th>
<th>$a_1$</th>
<th>$a_2$</th>
<th>$a_3$</th>
<th>$a_4$</th>
<th>$a_5$</th>
<th>$a_6$</th>
</tr>
</thead>
<tbody>
<tr>
<td>5.2a</td>
<td>-0.1555</td>
<td>0.0019</td>
<td>0.0050</td>
<td>0.0016</td>
<td>0.6346</td>
<td>0.1095</td>
<td>NA</td>
</tr>
<tr>
<td>5.2b</td>
<td>-0.2459</td>
<td>0.0022</td>
<td>0.0051</td>
<td>0.0015</td>
<td>0.6349</td>
<td>0.1127</td>
<td>NA</td>
</tr>
<tr>
<td>5.2c</td>
<td>-0.2847</td>
<td>0.0021</td>
<td>0.0032</td>
<td>0.0015</td>
<td>0.6319</td>
<td>0.1087</td>
<td>0.0034</td>
</tr>
<tr>
<td>5.2d</td>
<td>0.0656</td>
<td>0.0019</td>
<td>0.6936</td>
<td>0.1563</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>5.2e</td>
<td>-0.2270</td>
<td>0.0019</td>
<td>0.0062</td>
<td>0.6754</td>
<td>0.1394</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>5.2f</td>
<td>0.0841</td>
<td>0.0019</td>
<td>0.0018</td>
<td>0.6446</td>
<td>0.1196</td>
<td>NA</td>
<td>NA</td>
</tr>
</tbody>
</table>
Figure 5.11: Scatter plot and histogram for the error (residuals) corresponding to Equation 5.2a

Figure 5.12: CDF of error: Empirical vs Normal distributed with mean = 0, standard deviation = 0.29 km$^3$/hr for Equation 5.2a
Figure 5.12 and Figure 5.13 shown the error histogram and cumulative distribution function (CDF) for Equation 5.2a. Since the mean of the error is very close to 0, and the error is symmetrically distributed about 0, the model can be considered unbiased and acceptable.

The residual analysis results shown in Table 5.1 suggest that the predictor equations do not get significantly better with the addition of more terms such as $V_o$, $W_p$ and $H_r$, although the bias in the residual versus predicted value scatter plot does reduce slightly with the inclusion of more predictors.

5.7. Stochastic simulation of rain field extents

The hurricane rainfall simulation framework developed in this study requires the 99-percentile rain field extent ($R_{E99}$). Due to poor correlation between the rain field extents and potential predictors as described in Section 5.5, it is not feasible to obtain an equation for $R_{E99}$ based on multiple linear regression in a manner similar to $R_{vl}$. Instead, after the $R_{vl}$ has been simulated using the procedure described in Section 5.6, it is possible to estimate the $R_{E99}$ using the relationship between $P_c$, $R_{vl}$ and $R_{E99}$ shown in Figure 5.14 to Figure 5.16. These figures indicate that for events with higher $R_{vl}$ and greater intensity (i.e. lower $P_c$), $R_{E99}$ tends to be greater.

The complete set of data shown in Figure 5.13 is divided into 3 sub-datasets based on which central pressure the points correspond to:

i. $P_c \geq 980$ mbar (Figure 5.14)
ii. \[ 950 \leq P_c < 980 \text{ mbar} \] (Figure 5.15)

iii. \[ <950 \text{ mbar} \] (Figure 5.16)

Knowing the values of \( P_c \) and \( R_{vl} \), the \( R_{E99} \) can be simulated by the following steps:

i. For the given \( P_c \), select the appropriate scatter plot. For example, if \( P_c = 960 \) mbar, select the data represented by red circles in Figure 5.15.

ii. In the selected scatter plot, there will be several values of \( R_{E99} \) corresponding to a value of \( R_{vl} \), especially for \( R_{vl} < 2.5 \text{ km}^3/\text{hr} \).

iii. Select all points within \( R_{vl} \pm 0.2 \text{ km}^3/\text{hr} \), (or \( R_{vl} + 0.4 \text{ km}^3/\text{hr} \) for points on extreme end of \( R_{vl} \) axis) and randomly sample any one value from these selected points. This represents the randomly simulated value of \( R_{E99} \) corresponding to the given \( R_{vl} \) and \( P_c \).
Figure 5.13: Relationship between $R_{E99}$ and $R_{vi}$ showing all data points

Figure 5.14: Relationship between $R_{E99}$ and $R_{vi}$ showing all time-steps and those with $P_c \geq 980$ mbar
Figure 5.15: Relationship between $R_{E99}$ and $R_{vl}$ showing all time-steps and those with $950 \leq P_c < 980$ mbar

Figure 5.16: Relationship between $R_{E99}$ and $R_{vl}$ showing all time-steps and those with $P_c < 950$ mbar
Figure 5.17: Empirical cumulative distribution function for $R_{E99}$ corresponding to various bins of central pressure $P_c$. This curve indicates that $R_{E99}$ tends to increase as $P_c$ decreases.

5.8. Evolution of rainfall volume and extent after landfall

In a manner similar to the study of post-landfall radius to maximum winds and Holland $B$ parameter as described in Section 3.8, this section describes the post-landfall evolution of normalized instantaneous rainfall volume ($R_{vl}$) and normalized 50-percentile rain field extent ($R_{E50}$) after landfall. In this context, normalized $R_{vl}$ and $R_{E50}$ refer to the values of these parameters on land divided by the values just prior to landfall.

In case of normalized $R_{vl}$ (Figure 5.18), out of 1764 landfalling time-steps in total, 1235 time-steps (70% of total) are below 1 and 529 (30% of total) are greater than 1. On the other hand, in case of normalized $R_{E50}$ (Figure 5.19), out of 1764 landfalling time-steps in total, 511 time-steps
(29% of total) are below 1 and 1253 (71% of total) are greater than 1. This indicates that in most cases after landfall, the rainfall volume gradually diminishes, whereas, the rain field extent gradually increases. That is, as a storm moves farther inland and loses its intensity, the rain field tends to scatter over a wider area while the rainfall intensity gradually diminishes. This is analogous to the post-landfall increase in the storm wind field size (i.e. radius to maximum wind speeds), while the storm intensity (central pressure and maximum wind speeds) gradually decays.

The simulation methods for $R_{vl}$ and $R_{E99}$ described in Sections 5.6 and 5.7 do not explicitly consider the post-landfall decay or increase, but instead, these methods indirectly account for the post-landfall behavior by using central pressure as a simulation parameter. Future investigation can be done to check if the simulation of $R_{vl}$ and $R_{E99}$ can be improved by separately simulating the portion after landfall.
5.9 Discussion

Assessing the long-term hurricane rainfall hazard or determining the rainfall rates corresponding to large return periods directly would require hundreds of years of data. But since such kind of data is unavailable, various statistical methods are used to assess the long-term hazard. One method of overcoming the limitation posed by lack of many years of data is to create such data via stochastic simulation, which is the purpose of this study. Any method used to simulate many of years of data should require less computation time and resources, which is why researchers have devoted considerable efforts towards
developing relatively simple statistical models instead of using pre-existing complex physical models.

Existing statistical hurricane rainfall models simulate the variation of rain fall rate with respect to storm center, and in doing so, implicitly assume that the rainfall volume and extent will automatically be modelled realistically as long as the rainfall rates are reasonably modelled. However, such models cannot always capture the high localized rainfall rates which can be several times larger than the mean rain fall rates, and therefore, they can significantly underestimate the total rainfall volume. It is for this reason, this study takes a different and novel approach, and models the rainfall volume and extent before considering the spatial distribution of rainfall rates. The $R_{vl}$ is simulated using a multiple linear regression based equation derived using parameters such as vorticity, precipitable water, storm intensity ad $R_{vl}$ at earlier timesteps. However, $R_{E99}$ cannot be simulated with this approach and therefore, it is simulated by randomly sampling from the scatter plot relationship between $R_{E99}$ and $R_{vl}$ depending on what value the central pressure of the storm is at that time-step.

After the hurricane rainfall extent and volume have been simulated using the method explained in this chapter, it is necessary to determine the rainfall rates associated with the rainfall volume, and where these rates are likely to occur within the rain field extent. This process is described in the next chapter.
5.10. References


Tropical Rainfall Measuring Mission (TRMM). (2011). TRMM (TMPA) Rainfall Estimate L3 3 hour 0.25 degree x 0.25 degree V7, Greenbelt, MD, Goddard Earth Sciences Data and Information Services Center (GES DISC).

CHAPTER 6. SIMULATION OF HURRICANE RAIN FIELD SHAPE AND RAINFALL RATE DISTRIBUTION: THE ‘NORMRAIN’ MODEL

6.1. Introduction

The shape of a hurricane rain field is irregular due to factors such as wind shear and interaction with land. When a hurricane rain field is observed in a two-dimensional view, it is noticed that there are certain regions where heavy localized rainfall occurs. For example, Figure 6.1. shows Hurricane Harvey (2017) at landfall, where high rainfall rates are clearly seen to be concentrated over small regions away from the storm center.

Figure 6.1: The asymmetric rain field of Hurricane Harvey (2017) at landfall as seen in NCEP Stage IV data (Lin 2011).
The irregularity and asymmetry in rain field shape is too complex to be described accurately by statistical equations. Therefore, this study takes a different approach and instead of exclusively using equations, introduces the use of normalized rain field shapes (NRFS) from historical events to describe the rain field shape of simulated events. This chapter describes the process of normalizing the rain fields of historical storms and simulating a rain field using this normalized field.

Since the concept of rain field normalization is central to this study, the stochastic hurricane rainfall simulation model developed here (Chapters 5 and 6) is named the ‘NormRain’ model.

6.2. Wind shear and other hurricane parameters

Wind shear, which represents the difference in wind speed and direction between various layers of the atmospheric wind, is one of the main factors causing rainfall asymmetry in hurricanes (Chen et al. 2006; Corbosiero et al. 2003; Ueno 2007). Figure 6.2 to Figure 6.5 describe the nature of wind shear values impacting the North Atlantic hurricanes. These plots are generated using the data in the hurricane time-steps in the SHIPS dataset from 1982-2017. These plots reveal that in most of the time-steps of hurricanes, the magnitude of wind shear is between 5 to 10 m/s and its direction is around 180°, indicating that most of the hurricane time-steps in the database experience Westerly shear. Figure 6.4 shows that all the of intense time-steps occur below a wind shear magnitude of 10m/s, whereas Figure 6.5 indicates the large wind shear values (>15m/s) tend to occur above 20° latitude. Due to the critical role of wind shear in determining
hurricane genesis as well as rain field asymmetry, wind shear is included as one of the
decisive parameters in the Normalized rain field shape database (NRFSD), which is
described in the next section.

![Wind shear magnitude distribution in SHIPS data (all points)](image)

**Figure 6.2:** Wind shear magnitude distribution in SHIPS data (all points)
Figure 6.3: Wind shear direction (Westerly shear measured 90° clockwise from North) distribution in SHIPS data (all points)

Figure 6.4: Wind shear magnitude vs central pressure
6.3. Normalization of historical rain fields

The term ‘normalize’ means to scale the data in such a way that all the data points get mapped to a desired range of numbers. The rain field shape of any tropical cyclone or a hurricane is described using the distance and azimuth to various rainfall rates with respect to storm center. Therefore, to obtain a normalized rain field shape (NRFS) at any time-step, the following three quantities need to be normalized in the manner described below:

i. The azimuth from the storm center to each of the rainfall grid point ($\theta_{rg}$):

Since an azimuth always ranges between $0^\circ$ to $360^\circ$, it is already normalized by default.

ii. The distance from the storm center to each of the rainfall rate grid point ($D_{rg}$):
Normalizing $D_{rg}$ is not as straightforward as in case of $\theta_{rg}$. It is first necessary to define the 99-percentile rain field extent ($R_{E99}$) as described in Chapter 5. Then, the normalized distance from the storm center to each of the rainfall rate grid point ($D_{rgN}$) is obtained by dividing $D_{rg}$ by $R_{E99}$. After normalization, the distance $D_{rg}$ ranges from 0 at the storm center to 1 at the $R_{E99}$, as illustrated in Figure 6.10.

iii. The rainfall rates ($R_R$) in the rain field:

Since the distribution of $R_R$ is different in each time-step and in each storm, $R_R$ is normalized using its empirical cumulative distribution function (CDF), denoted by $F_{RR}$. The probability or percentile corresponding to each rainfall rate is denoted by $P_{RR}$. If $R_R$ is a vector of all rainfall rates contained in the hurricane rain field extent then,

$$P_{RR} = F_{RR}(R_R) \quad (6.1)$$

Conversely, if the probability is known, and the rainfall rate is needed,

$$R_R = F_{RR}^{-1}(P_{RR}) \quad (6.2)$$

After normalization the largest value of $R_R$ in the entire rain field will be denoted by 1, and the smallest one will be denoted by zero.

This process is illustrated in Figure 6.9.
6.4 Normalized rain field shape database (NRFSD)

Using the procedure discussed in Section 6.2, a Normalized rain field shape database (NRFSD) can be derived by combining TRMM and SHIPS dataset. The SHIPS data contains event from 1982 to 2017, at 6-hourly time-steps, whereas the TRMM data contains events from 1998 to 2017 at 3-hourly time-steps. Interpolating the wind shear data in SHIPS dataset from 6-hourly to 3-hourly could create unrealistic values. Therefore, only the time-steps that are present in both TRMM and SHIPS data are retained in the NRFSD. This includes a total of 6779 points corresponding to 304 events from 1998 to 2017. Out of these 6779 points, 649 are located on land and the remaining 6130 points are on ocean. Thus, NRFSD contains 6779 different shapes for hurricane or tropical cyclone rain field shape.

Figure 6.6 and Figure 6.7 show the distribution of the number of time-steps in the NRFSD on land and on the ocean with respect to wind shear and central pressure values. These distributions look like the actual distribution of wind shear (Figure 6.2) and central pressure (Figure 2.9), which indicates that the NRFSD is a good representative subset of the entire historical hurricane catalog.

The NRFSD contains the following fields for each of the 6779 time-steps belonging to 304 events from 1998 to 2017:

1) Central Pressure ($P_c$)

2) Latitude ($Lat$)
3) Land or sea identifier (LSI)

4) Wind shear magnitude and direction (WSMD)

5) Rainfall rate empirical cumulative distribution function (F_{RR})

6) Normalized distance (D_{rgN}) Vs rainfall rate percentile (P_{RR}) plot

7) Azimuth (\theta_{rg}) Vs rainfall rate percentile (P_{RR}) plot

The first four fields i.e. P_c, Lat, LSI and WSMD are referred to as ‘NRFSD input fields’ whereas the last three are referred to a ‘NRFSD output fields’.

Figure 6.6: Distribution of points on land in NRFSD
6.5. **Stochastic simulation of hurricane rain field shape**

Using the NRFSD, the hurricane rain field shape can be simulated through the following steps:

1. Simulate the translational speed, heading angle, central pressure, radius to maximum winds and Holland $B$ parameters using methods described in Chapters 2 and 3.

2. Simulate the instantaneous rainfall volume ($R_{vl}$) and the 99-percentile rain field extent ($R_{E99}$) using the method described in Chapter 5.

3. Simulate the value of wind shear using historical data.
4. For the given NRFSD input fields (i.e. central pressure, latitude, land or sea identifier, wind shear magnitude and direction) select the NRFSD output fields (i.e. $F_{RR}$, $D_{rgN}$ Vs $P_{RR}$ and $\theta_{rg}$ Vs $P_{RR}$).

5. Keep generating random sample of simulated rainfall rates ($R_{R,sim}$) from the $F_{RR}$ until total $R_{vl}$ is achieved.

$$R_{R,sim} = F_{RR}^{-1}(P_{RR,sim})$$

Where, $P_{RR,sim}$ is a vector of random numbers between 0 and 1, which represents the vector of rainfall rate percentile for the simulated rainfall rates ($R_{r,sim}$).

At the end of this step, a vector of rainfall rates has been simulated (as shown in the $R_{r,sim}$ histogram in Figure 6.9), but the distance and azimuth from the storm center to those rainfall rates ($R_{r,sim}$) is still unknown, which will be determined in the next step.

6. Using $P_{RR,sim}$ from step 5, and $D_{rgN}$ Vs $P_{RR}$ scatter plot from step 4, interpolate to obtain the simulated normalized distance from storm center ($D_{rgN,sim}$) corresponding to $P_{RR,sim}$, as illustrated in Figure 6.10.

7. Multiply the $D_{rgN,sim}$ from step 6 by $R_{E99}$ from step 2 to get the actual distance from storm center to the simulated rainfall rate grid points ($D_{rg,sim}$).
\[ D_{rg, sim} = D_{rg, sim} \times R_{E99} \]

8. Using \( P_{RR, sim} \) from step 5, and \( \theta_{r_g} \) Vs \( P_{RR} \) scatter plot from step 4, interpolate to obtain the simulated azimuth from storm center \((\theta_{r_g, sim})\) corresponding to \( P_{RR, sim} \) as shown in Figure 6.11. The example in Figure 6.11 uses a nearest neighborhood interpolation, but the proper method of interpolating azimuth to create randomness in the simulation output is a subject for further study.

Thus, step 5 generates a vector of rainfall rates to achieve the simulated \( R_{vl} \), steps 6 and 7 generate the distance from the storm center to the rainfall rates for the simulated \( R_{E99} \) and finally step 8 generates the azimuth for these rainfall rates.

Figure 6.12 presents an example of original footprint compared to its simulated version. Figure 6.13 represents the simulation of the same time-step as in Figure 6.12, but shows six simulations. Since NormRain is a stochastic model, the rain field pattern will be slightly different each time, but it is expected to preserve the rain field shape of the original rain field shape.
Figure 6.8: Hurricane Isabel (2003-09-12-18) time-step shown with annuli spaced at 25 km from the storm center up to 700 km. This time-step is used as an example to illustrate the rainfall simulation process.

Figure 6.9: The rainfall rate ($R_R$) histogram (for the time-step in Figure 6.8) from TRMM observation is used to obtain the rainfall rate CDF ($F_{RR}$), using which the simulated rainfall rate histogram $R_{R,sim}$ is obtained. The CDF ($F_{RR}$) is obtained from NRFSD.
Figure 6.10: (For the time-step in Figure 6.8) The first plot shows the mean rainfall rate at each annulus and the second plot illustrates the distribution of all rainfall rates without averaging. The third plot shows $D_{rgN} \text{ vs } P_{RR}$ obtained from second plot and retrieved from NRFSD (blue dot) and the $D_{rgN, sim} \text{ vs } P_{RR, sim}$ (red circle).
Figure 6.11: (For the time-step in Figure 6.8) The blue dots show the azimuth vs probability ($\theta_{rg}$ Vs $P_{RR}$) retrieved from NRFSD and the red circles show the simulated azimuth vs probability ($\theta_{rg,\text{sim}}$ Vs $P_{RR,\text{sim}}$). Each of the blue dots correspond to the blue dots shown in the $D_{rgN}$ vs $P_{RR}$ plot in Figure 6.10.

Figure 6.12: Hurricane Isabel (2003-09-12-18) (Figure 6.8), original rain field (left), simulated rain field (right). The legend shows rainfall rate in mm/hr.
Figure 6.13: Six simulation realizations for Isabel (2003-09-12-18) (Figure 6.8) show random behavior at each simulation while preserving original shape.

6.6. Discussion

This chapter explained the working method of the ‘NormRain’ model. The model is able to replicate the irregular rain field shape of historical hurricanes reasonably well. This indicates that NormRain can also be applied on simulated hurricanes to get realistic rain field shapes. This model still needs to undergo more rigorous testing and refinement, but the model performance indicates that the model development is proceeding in the right track, and more effort in the improvement of this model is worthwhile.
6.7. References


CHAPTER 7. CONCLUSION

7.1. Summary of objectives

The main objective of this study was to create an integrated framework for simulating hurricane wind and rain hazard. To achieve this prime objective, the study was further divided into three objectives:

1) To select a hurricane track and intensity simulation method suitable for integration with rain simulation model, identify its limitations, and improve upon it.

2) Develop a method to calculate hurricane wind speed, and use it to: (i) Develop a new equation to simulate the radius to maximum winds \( R_{max} \) and Holland B parameter \( B \), which can better represent the correlation between successive time-steps, (ii) Develop a hurricane wind hazard curve database for the 30 Eastern US states and find a suitable probability distribution to represent this data.

3) Develop a model to simulate hurricane rain field that directly models the total rainfall volume and extent (i.e. the radius) at each time-step and can simulate the irregular and asymmetric shape as seen in actual hurricane rain fields.

7.2. Findings and contribution

The major contribution and findings of this study are as follows:
1) The major contribution of this study is the development of NormRain model, a novel approach to perform stochastic simulation of hurricane rainfall, which is based on the concept of using normalized rain field shapes from historical storms to replicate the irregular and asymmetric shape of hurricane rainfall. This model also explicitly models hurricane rainfall volume and extent, so that its output may be more useful for flood hazard analysis over a catchment area.

2) New equations to simulate radius to maximum wind speed ($R_{max}$) and Holland $B$ parameter were developed, which can better replicate the temporal correlation with previous timesteps. Since hurricane wind footprint estimate is very sensitive to $R_{max}$ and $B$ parameters, improved method of $R_{max}$ and $B$ simulation can improve wind speed estimation.

3) If the lower and upper limits of hurricane parameter are not properly constrained during simulation, this can result in an unrealistically high concentration in the extreme value of the parameter.

For instance, if 860 mbar is set as the lower limit of central pressure ($P_c$), during the simulation each time the simulated value drops below 860 mbar, the simulation program outputs 860 mbar. If the histogram of $P_c$ is viewed, a sharp spike will be seen at 860 mbar. Its implication is that 860 mbar value can occur at any latitude in the Atlantic basin, which is physically impossible, and can result in incorrect estimation of wind hazard. This issue can be solved if the
lower limit of central pressure is set to be the minimum sustainable central pressure corresponding to the sea surface temperature of storm’s location.

4) The simulated hurricane wind speed hazard is best represented by generalized extreme value distribution, among the 11 different continuous probability distributions considered (Section 4.3).

5) The database of hurricane wind hazard curves for the 30 Eastern US states is expected to aid further research into performance based wind engineering (PBWE), since hazard curve is one of the essential inputs to several PBWE frameworks.

7.3. Future research and improvements

During this study, several research topics were identified which have the potential for being practically useful. Some of these topics which may be of interest to future researchers are listed below:

**Hurricane track simulation genesis model:**

1. Consider the seasonality effect in the selection of hurricane genesis points.

2. Incorporate kernel density estimation so that the selection of genesis points as well as initial hurricane parameters will be spatially continuous instead of being limited to discrete historical genesis locations.
Wind speed algorithm:

1. Research to identify fetch distance where most of the transition between wind speeds of two different roughness is completed. This could probably be performed in a wind tunnel setup.

2. Develop a method of calculating average roughness values over a larger area which includes a wide variety of surface roughness types.

3. Incorporate the effect of topography on gust factor.

Rainfall simulation:

1. Use the NormRain model to perform a simulation run using at least 10,000 years simulated catalog in order to assess the long-term hurricane rainfall hazard. Since the currently used hydrologic design maps in the US were mostly developed around the 80s, newer studies have the potential to help revise hydrologic design maps.

2. Test the capability of NormRain model to assess hurricane flooding risk assessment.

3. The NormRain model can also be adapted to other ocean basin such as West Pacific or Indian Ocean.
4. Use of NCEP Stage IV precipitation data, which has a finer resolution than the currently used TRMM 3B42 dataset to better capture the localized rainfall effects over land.
APPENDICES
Appendix A  Additional validation plots for stochastic simulation program

Figure A.1: Mileposts along the US Atlantic coastline

Figure A.2: The data within 250 km radius of mileposts from simulation as well as HURDAT have been selected for comparison
Figure A.3: Occurrence rates at Mileposts

Figure A.4: HURDAT2 tracks (1851-2015), i.e. a total of 165 years
Figure A.5: Simulated tracks (165 years)
Figure A.6: Translational speed around mileposts (Simulation vs HURDAT2)

Figure A.7: Heading directions around mileposts (Simulated vs HURDAT2)
Figure A.8: Central pressure distribution around mileposts (Simulated vs HURDAT2)

Figure A.9: Regions used for the validation of central pressures
Figure A.10: Central pressure at different return periods (Simulated vs HURDAT) for regions shown in <Figure Previous>
Table B.1: Roughness values corresponding to various land-use

<table>
<thead>
<tr>
<th>Land cover type</th>
<th>$z_0 , (m)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Evergreen Needleleaf Forest</td>
<td>0.5</td>
</tr>
<tr>
<td>Evergreen Broadleaf Forest</td>
<td>0.5</td>
</tr>
<tr>
<td>Deciduous Needleleaf Forest</td>
<td>0.5</td>
</tr>
<tr>
<td>Deciduous Broadleaf Forest</td>
<td>0.5</td>
</tr>
<tr>
<td>Mixed Forests</td>
<td>0.5</td>
</tr>
<tr>
<td>Closed Shrublands</td>
<td>0.05</td>
</tr>
<tr>
<td>Open Shrublands</td>
<td>0.06</td>
</tr>
<tr>
<td>Woody Savannas</td>
<td>0.05</td>
</tr>
<tr>
<td>Savannas</td>
<td>0.15</td>
</tr>
<tr>
<td>Grasslands</td>
<td>0.12</td>
</tr>
<tr>
<td>Permanent wetlands</td>
<td>0.3</td>
</tr>
<tr>
<td>Croplands</td>
<td>0.15</td>
</tr>
<tr>
<td>Urban and Built-Up</td>
<td>0.8</td>
</tr>
<tr>
<td>Cropland/natural vegetation mosaic</td>
<td>0.14</td>
</tr>
<tr>
<td>Snow and Ice</td>
<td>0.001</td>
</tr>
<tr>
<td>Barren or Sparsely Vegetated</td>
<td>0.01</td>
</tr>
<tr>
<td>Water</td>
<td>0.0001</td>
</tr>
<tr>
<td>Wooded Tundra</td>
<td>0.3</td>
</tr>
<tr>
<td>Mixed Tundra</td>
<td>0.15</td>
</tr>
<tr>
<td>Barren Tundra</td>
<td>0.1</td>
</tr>
<tr>
<td>Water</td>
<td>0.0001</td>
</tr>
</tbody>
</table>
Appendix C  WMO Gust factors

The World Meteorological Organization (WMO) has published a guideline (Harper et al. 2010) to aid the conversion between various wind averaging periods in tropical cyclones. This document describes a method to perform such type of conversion based on empirical gust factor, referred to as ‘WMO gust factor’ herein. These gust factors are applicable over open terrain, but if applied over non-open terrain, they can still give reasonable approximation of the wind speeds as compared to meteorological observations.

The gust factor computation method in Section 3.2.4 can also be replaced by the WMO gust factor method for computing wind speed on open terrain.

Since Georgiou’s gradient wind field equation (Equation 3.1) provides a wind speed of averaging duration of 10 min (or 600 s), the gust factors to convert 10 min wind to other durations will be necessary. Accordingly, the following table enlists the relevant gust factors from Harper et al. (2010).

Table C.1: WMO Gust Factors

<table>
<thead>
<tr>
<th>Exposure at 10m above the ground</th>
<th>Reference period (s)</th>
<th>Gust factor for:</th>
<th>3</th>
<th>60</th>
<th>120</th>
<th>180</th>
<th>600</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class</td>
<td>Description</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>In-land</td>
<td>Roughly open terrain</td>
<td>600</td>
<td>1.66</td>
<td>1.21</td>
<td>1.12</td>
<td>1.09</td>
<td>1.00</td>
</tr>
<tr>
<td>Off-land</td>
<td>Offshore winds at coastline</td>
<td>600</td>
<td>1.52</td>
<td>1.16</td>
<td>1.09</td>
<td>1.06</td>
<td>1.00</td>
</tr>
<tr>
<td>At-sea</td>
<td>&gt;20 km offshore</td>
<td>600</td>
<td>1.23</td>
<td>1.05</td>
<td>1.02</td>
<td>1.00</td>
<td>1.00</td>
</tr>
</tbody>
</table>

The ‘In-land’ class is used for locations on land which are greater than or equal to 1 mile distance from the coastline, whereas the ‘Off-land’ class is used for locations right at the coastline. For points on land located between the coastline and 1 mile, the gust factor
can be determined by linear interpolation between ‘In-land’ and ‘Off-land’ class. The ‘At-sea’ class can be applied to all points over the ocean.

As an example, if the 10 min wind speed is to be converted to 1 min gust for a point located 0.5 mile inland from the coastline, the gust factor would be $1.16 + (1.21 - 1.16) \times 0.5 = 1.19$. For all the locations beyond 1 mile inland, the gust factor would be 1.21 in the same scenario.
Appendix D  Wind speed time history plots

Station: CHS

Station: NBC

HUGO (1989)
Station: ALI

Wind speed (2-min, 10m) mph

08-23-2017,00:00:00 to 09-02-2017,00:00:00

Observation
Calculated

Station: BEA

Wind speed (2-min, 10m) mph

08-23-2017,00:00:00 to 09-02-2017,00:00:00

Observation
Calculated

HARVEY (2017)
Figure D.1: The data within 250 km radius of mileposts from simulation as well as HURDAT have been selected for comparison.
Appendix E  Wind speed footprints

Charley (2004)
Ivan (2004)
Dennis (2005)
Rita (2005)
Wilma (2005)
Gustav (2008)
Ike (2008)
Irma (2017)

Wind footprint, 10m-3s, IRMA (2017)
Appendix F  Wind speed comparison with H*wind

The following plots show comparison between calculated wind speeds (without exposure correction) with H*Wind data. The wind contour plot to the left shows H*wind results and that to the right shows calculated footprint.

Two scatter plots are shown:

1) Using data points from entire footprint,

2) Using data points close to eyewall only.
Charley (2004)
Frances (2004)

FRANCES2004 (all), Correlation Coeff. = 0.94

FRANCES2004 (inner), Correlation Coeff. = 0.94
Gustav (2008)
Irene (2011)
Isaac (2012)
Appendix G  Wind speed comparison with ASCE 7-10 at mileposts

This section presents a comparison between simulated wind speeds and the design wind speeds given in ASCE 7-10 for selected return periods for the mileposts shown in Figure A.1. A few points to be noted in this context:

1) ASCE 7 includes both hurricane and non-hurricane winds, but the simulated database generated by this study as described in Chapter 4 only contains hurricane winds and does not account for extratropical transition.

2) Since the milepost points are located right at the coastline, the application of over-water gust factor could be the reason behind higher values seen in Figure G.2 and Figure G.3.

Figure G.1: Wind speed at mileposts for 50 years return period (Simulated vs ASCE 7-10)
Figure G.2: Wind speed at mileposts for 300 years return period (Simulated vs ASCE 7-10)

Figure G.3: Wind speed at mileposts for 1700 years return period (Simulated vs ASCE 7-10)