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A surge response function approach to coastal hazard assessment – part 1: basic concepts

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Abstract This paper reviews historical methods for estimating surge hazards and concludes that the class of solutions produced with Joint Probability Method (JPM) solutions provides a much more stable estimate of hazard levels than alternative methods. We proceed to describe changes in our understanding of the winds in hurricanes approaching a coast and the physics of surge generation that have required recent modifications to procedures utilized in earlier JPM studies. Of critical importance to the accuracy of hazard estimates is the ability to maintain a high level of fidelity in the numerical simulations while allowing for a sufficient number of simulations to populate the joint probability matrices for the surges. To accomplish this, it is important to maximize the information content in the sample storm set to be simulated. This paper introduces the fundamentals of a method based on the functional specification of the surge response for this purpose, along with an example of its application in the New Orleans area. A companion paper in this special issue (Irish et al. 2009) provides details of the portion of this new method related to interpolating/extrapolating along spatial dimensions.

Keywords Natural hazards · Storm surge · Hurricane

1 Introduction

Prompted at least in part by the devastation wreaked by Hurricane Katrina and the potential for increased risks due to rising sea levels and global climate change, considerable national and international interest has been focused on the evaluation of future hurricane hazards along coasts. We begin here with an examination of past methods utilized for hurricane

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surge hazard estimation. Next, we discuss the implications of improved modeling concepts and technologies. The rest of the paper is focused on a new approach being introduced here—the development of scaling laws for coastal surge response and their incorporations into a statistical methodology for coastal surge hazards.

2 Surge hazard assessment: historical perspective

At least four methods have been applied in past studies of hurricane (typhoon, tropical cyclone) surge extremes around the world:

1. Design storm events,
2. Analysis of historical storms: Parametric
3. Analysis of historical storms: Non-Parametric, and
4. The joint probability method (JPM).

Due to the fact that little or no long term historical measurements of surge levels exist anywhere in the world today, essentially all of these methods involve the application of numerical wind, wave, and surge models to one extent or another. Since this same paucity of data limits the degree to which a model can be locally tuned, it is imperative to use the best possible physics-based models to ensure accurate surge estimates for hazard estimation (Resio and Westerink 2008). However, even with these best possible models and inputs, one must recognize that there are accumulated errors in models and modeling assumptions, which translate into uncertainty in the hazard estimates. In addition to this source of uncertainty, there are at least three other sources of uncertainty that should be understood and evaluated. First, there is the uncertainty in the characterization of all statistical information utilized in each of these methods due to the limited historical samples upon which they are based. Classically, this source of uncertainty has been evaluated by assuming that the parent statistical population is known and that the parameter uncertainty can be estimated from sampling theory. Second, there is uncertainty in what can happen in any future random sample, even if the population remains constant. Typically, this source of uncertainty is evaluated via the application of “re-sampling” or “boot-strap” methods. Third, there is the uncertainty associated with potential changes in existing conditions from the present (climatic variability, sea-level rise, etc.). This uncertainty is usually treated through the examination of various scenarios to examine the sensitivity to potential changes in future conditions. All of the methods referenced above have different strengths and weaknesses relative to these statistical characteristics for various applications. To help understand these, a brief discussion of conventional applications of these methods in the past will be given before moving on to a discussion of the approach developed herein.

2.1 Design storm events

An example of this approach is the Standard Project Hurricane (SPH), as adopted by the Corp of Engineers in the 1960s to estimate potential surge hazards along the U.S. Gulf coast (U.S. Department of Commerce 1959; U.S. Weather Bureau 1965). Due to the paucity of data, it would have been very difficult, if indeed possible, to specify detailed, site-specific characteristics of landfalling hurricanes prior to 1960; consequently, the Corps requested that NOAA prepare an estimate of a storm with characteristics that were expected to occur relatively infrequently within some stretch of coastline. Unfortunately, the period of record prior to 1960 (the input to the statistical analyses performed by NOAA) was a period of relatively low hurricane activity in the Gulf of Mexico (GOM); consequently, the SPH, as specified in those earlier studies, does not appear to be representative of the characteristics of extreme storms that have occurred in the central Gulf since 1960. An update to the hurricane characteristics for a design storm approach was issued in 1979 in an attempt to adjust to these recognized changes (U.S. Department of Commerce 1979).

The design storm approach has typically used a single storm to characterize environmental factors for design at a given location. This effectively reduces the number of degrees of freedom in storm behavior to one parameter, typically the intensity of the storm. All other storm parameters (e.g., storm size, forward storm speed, and track location) are deterministically related to storm intensity. The major problem with this is that, if one or more additional factors significantly affect surge levels, the design storm approach suppresses this variability. An extrapolation of the single design storm concept is to define a small set of storms with some range of additional parameters considered. This yields a set of storms that can be used in a preliminary fashion to examine various design alternatives efficiently. Given their frequent use in this context, these storms are often termed "screening storms" rather than design storms.

Since the "design storm concept" was initially intended to serve as somewhat of an upper limit for storm surges, the effects of uncertainty in future samples was not considered in applications of this methodology. In retrospect, the neglect of the uncertainty in the probabilities of hurricane parameters can be seen as a significant problem, because the years since 1960 contained storms that were much more intense than those included in the initial sample.

2.2 The analysis of historical storms: parametric

In the 1960s and 1970s, it became increasingly clear that a single (design) storm could not provide an appropriate characterization of extreme conditions at a site for design purposes. Following the study of Gumbel (1959) and others in the estimation of extremes, many researchers began to examine the application of various extremal distributions for the estimation of surge levels based on surges from historical storms. However, since hurricanes are both relatively infrequent and small in terms of the amount of coastline affected by these storms each year, the frequency of storms affecting a site is significantly less than 1 storm per year within the GOM. Consequently, a potentially serious problem with the reliance on historical storms for estimating coastal inundation is the small sample of storms at a site, coupled with the relatively small spatial extent of high surge levels. For example, in the vicinity of New Orleans, Louisiana, the frequency of major landfalling storms within a given 60 nautical mile region (1-degree) is only about once every 25–50 years. Since we have limited records before the middle of the 20th century and since the frequency and intensity of storms in the latter half of the century may be markedly different than the frequency and intensity of storms in the early part of the century, the resulting sample size can lead to very unrealistic variations in storm frequency and intensities along the coast.

In the historical storm method, the sample Cumulative Distribution Function (CDF)of x, denoted here as $F(x)$, is usually fit by some theoretical distribution using Maximum Likelihood Method, the Method of Moments, or some other regression-based fitting algorithm. For example, if one assumes that the distribution is reasonably fit by a Gumbel distribution, a simple approximation for the CDF is given by

$$F(x) = \frac{m}{N+1} \tag{1}$$

where m is the rank of the storm (with m = 1 as the smallest) and N is the total sample number. In most hurricane applications, the number of storms is substantially less than one per year, and so it is not possible to construct a useful estimate based on a set of annual maxima. In this case, one can estimate the return period via the use of a Poisson frequency parameter, λ(which is typically given in units of storms per year),

$$T(x) = \frac{1}{\lambda[1 - F(x)]} \tag{2}$$

where $T(x)$ is the expected return period for x. For example, for a sample size of 43 storms drawn from an interval of 100 years, the value of λ would be 0.43.

A more subtle sampling problem is the tendency for intense storms to sometimes behave differently than weaker storms. Since derivations of most extreme distributions rely on the assumption that the storms are all drawn from a homogeneous population, magnitude-related influences on storm characteristics can create a "mixed population" problem. In order to compensate for such potential sampling inhomogeneity, many oil-industry groups have adopted the "Peaks Over Threshold," or POT method, for estimating extremes. In this approach, only storms above some threshold value are considered within a statistical analysis of extremes. By screening small storms from the analyzed sample, the effect of small storms on the parameters of fitted distributions (e.g., the parameters of the Gumbel, Frechet, Weibull, Lognormal, Log Pearson, or other distributions of choice) is minimized. This approach is inherently parametric due to the need to assume/specify a distribution (or class of distributions such as the Generalized Extreme Value method).

2.3 The analysis of historical storms: non-parametric

In the early 1990s, Borgman et al. (1992) and Scheffner et al. (1993) introduced an approach (termed the Empirical Simulation Technique or EST) for estimating the expected extremal distribution of surges based on a variation of the "historical record" approach. In contrast to the conventional parametric historical storm method, in the EST sample, CDF estimates are not fit by a prescribed extremal distribution in the interior portion of the distribution. Instead, the actual CDF estimates are used directly. Thus, in the interior of the ranked points, the EST assumes that the best estimate of the expected distribution is the sample itself and does not fit any parametric distribution to the central distribution to obtain a "smoothed" distribution. Consequently, within this interior range, the distribution is nonparametric. However, extrapolation to return periods that exceed the period of record is still accomplished via fitting a subset of the total points in the distribution by some parametric (typically spline-based) form. Since such a procedure reduces the number of degrees of freedom to some small, pre-set number, such an extrapolation is inherently parametric, even if the parameterization is not based on a given theoretical equation.

In several hurricane surge studies with the EST (similar to situations arising in applications of parametric methods), it has been observed that a single intense storm could introduce an anomalously large value in a small spatial region, while other areas had much lower maximum surge values. For example, Fig. 1 shows results from an EST study

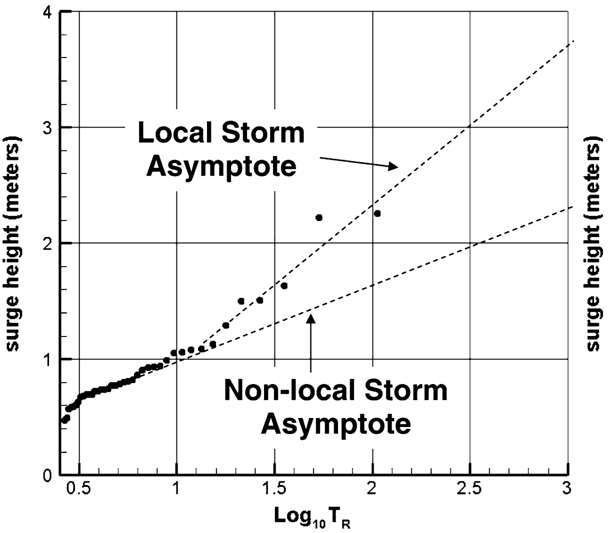

Fig. 1 Example of EST application for a point along the south shore of Lake Pontchartrain. In this figure, T_R is the return period for the surge level estimated from Eq. 1. The two asymptotic lines show that the response of surges to storms which are very close to a given site cannot be estimated by including many storms, which strike the coast greater than about two times the radius to maximum wind speeds from the storm into the sample

conducted in 2004, using a calibrated version of ADCIRC with no wave coupling for a point in Lake Pontchartrain. These results represent the maximum surges for a set of more than 40 historical storms over the interval from 1895 to 2004. In this figure, we see that, even though our sample covers an interval of over 100 years, only six storms contribute to the asymptotic form for the locally generated surges. Although the other storms contribute numbers to the sample, they contain little if any useful information for extrapolation. None of the storms in the historical sample contained Katrina's combined attributes of intensity and size. Thus, Katrina's surge of about 3.7 m would appear around a 1000-year event. In contrast, if we include Katrina in the historical storm population in the EST analysis, Katrina's surge levels become the 111-year event, certainly a huge difference in the two estimates. Recently, Agbley and Basco (2008) have provided information from numerical experiments, which corroborates the potential for unstable estimates from the EST method when applied to hurricanes.

Since there is no reason to believe that all future hurricanes would make landfall at exactly the same points as represented in the historical dataset, some applications of the EST have introduced a set of hypothetical storms intended to distribute the effects of large storms throughout the region being studied. In this approach, the largest storm is usually assigned a number of offset tracks and the probability of that storm is distributed over that set of tracks. However, in this procedure, additional storms retained exactly the same characteristics, other than track, as the original storm. The rules for this re-distribution of tracks still remain somewhat ill-defined and tend to rely heavily on the judgment of the individual performing the application, making it difficult to express the probability laws for this type of storm "cloning" very precisely.

2.4 The joint probability method (jpm)

The JPM was developed in the 1970s (Myers 1975; Ho and Myers 1975) and subsequently extended by a number of investigators (Schwerdt et al. 1979; Ho et al. 1987) in an attempt to circumvent problems related to limited historical records. In this approach, information characterizing a small set of storm parameters was analyzed from a relatively broad geographic area. Initial applications of the JPM used a set of four parameters, including (1) central pressure, (2) radius of maximum wind speed, (3) storm forward speed, and (4) the angle of the storm track relative to the coast, to generate parametric wind fields at landfall. Furthermore, initial applications of the JPM assumed that the values of these four parameters varied only slowly in storms approaching the coast; therefore, the values of these parameters at landfall could be used to estimate the surge at the coast. As will be discussed subsequently, recent data shows that this is not a good assumption. Neglect of these evolutionary features in hurricane wind fields leads to an inevitable bias within the simulated data. In fact, since the storms tend to be stronger off the coast, the use of landfall pressures in these earlier applications of the JPM tended to significantly underestimate storm intensities that existed offshore and the surges generated by these storms.

For a given storm, we can define a maximum surge value for that storm, $\eta_{\max}(x,t)$ for either storms remaining constant along a transect across the coast or storms, which are allowed to evolve during its approach to the coast. The probability for each event simulated can be associated with the probability of the 5 parameters (central pressure, storm size, storm forward velocity, angle of storm track at the coast, and landfall location) used to drive the simulations

$$\Delta p(\eta_{\max}) = p(c_{\mathrm{p}}, R_{\max}, v_{\mathrm{f}}, \theta_{\mathrm{l}}, x_0)\delta(c_{\mathrm{p}})\delta R_{\max}\delta v_{\mathrm{f}}\delta\theta_{\mathrm{l}}\delta x_0 \tag{3}$$

where δ denotes the incremental size of the parameter element, c_{p} is the central pressure, $R_{\max}$ is the radius to maximum wind speed from the center of the storm, v_{f} is the forward velocity of the storm, θ_{l} is the angle of the track relative to the cost at landfall, and x_0 is the distance between the point of interest and the land fall location.

In this form, it is evident that the size of the discrete probability elements plays a potentially important role in estimating surge probabilities. An example of the potential computational burden associated with the JPM can be seen if one assumes that one might simulate 3 storm intensities, 3 storm sizes, 3 storm speeds, and 3 angles for hurricanes (81 storm simulations) along each track covering the area of interest. It was typically assumed that one had to use a track spacing no larger than the smallest storm size (about 15 km) considered in the study to resolve the spatial gradients in hazards along the coast within the simulations. Thus, in a simplistic application of this method, about 810 complete storm simulations might be used to cover a 150-km section of coast. Although some gains in efficiency were used to lower this number a bit, the storm count remained quite high in these older studies (300–600 storms for even a relatively small length of coast).

Besides problems with computational burdens, considerable controversy in JPM applications arose during the 1970s and 1980s related to the definition of this 5-dimension joint-probability function. The lack of reliable data in the dataset available at that time made it very difficult to derive representative distributions, even for extended sections of coast. For example, consistent information on storm size (as required in JPM applications) was lacking for the vast majority of hurricanes in the available dataset.

A particular deficiency of the JPM as it was initially applied was that little or no attention was paid to the impact of various sources of uncertainty on the results. As noted in Sect. 2, all present-day methods for estimating surge probabilities rely heavily on numerical models. Assumptions, simplifications, and omissions in such models can produce very significant error contributions to the estimated hazard levels. In addition, earlier JPM studies did not consider either uncertainty in estimation of the joint probability distributions or the effects of factors that could vary through time. It is clear today that careful attention to all potential sources of uncertainty is essential in order to properly characterize surge hazards in critical areas of the world.

3 Theoretical and modeling advances in coastal surge prediction and their implications for hazard assessment

In 1980, Holland (1980) provided evidence that hurricanes (tropical cyclones/typhoons) exhibited considerably more variability in the peakedness of the pressure distribution along a radial than could be explained by the simple exponential models available at that time (for example: Collins and Viehmann 1971). He introduced a new parameter, now known as the Holland B term, which significantly enhanced the ability of parameterized pressures to match observations. The importance of this parameter can be seen in its role in determining the maximum wind speed in hurricanes

$$U_{\max} = \left(\frac{B}{\rho_a e}\right)^{1/2} (p_n - p_c)^{1/2} \tag{4}$$

where $U_{\max}$ is the maximum velocity in the storm, B is the Holland B parameter, ρ_a is the density of air, p_c is the (surface) central pressure in the storm; p_n is the ambient surface pressure at the periphery of the storm, and e is the base of natural logarithms (equal to 2.718). Considerable evidence suggests that surge levels are related to the square of the wind speed (Irish et al. 2008); thus, it is expected that surge levels will depend approximately linearly on the Holland B value of the storms. Unfortunately, this also introduces potentially yet another dimension into the JPM.

More recently, it has been noted that the assumption of constant parameters during approach to the coast is often violated by major storms. For example, both Katrina and Rita exhibited significant modifications in their intensity and structure during its approach to the coast—well before landfall. In the old JPM, which used central pressures at the time of landfall to characterize storm intensity, the offshore power of storms such as Katrina and Rita would have been very significantly underestimated (Fig. 2).

During forensics studies of surges during Katrina and Rita, it became extremely clear that waves contributed significantly to coastal surges. Previously, most model studies just "nudged" coefficients (such as the coefficient of drag or the bottom friction coefficient) until they approximately matched the peak surges in the storm. During the forensics studies, it was found that the best results were obtained via a coupled model approach that combined the contributions of direct wind-driven surge with radiation stresses from wave fields. Since wave fields evolve over time intervals that are much slower than those of coastal surges (10s of hours compared to hours), storm tracks cannot be treated as straight line segments over short distances near landfall for wave generation. Instead, physically consistent tracks must be defined over the typical distances which are involved in the development of the wave fields expected to accompany a hurricane.

Recent numerical studies have made it very clear that it is essential to resolve coastal bathymetry and landforms far more precisely than they were resolved in earlier studies

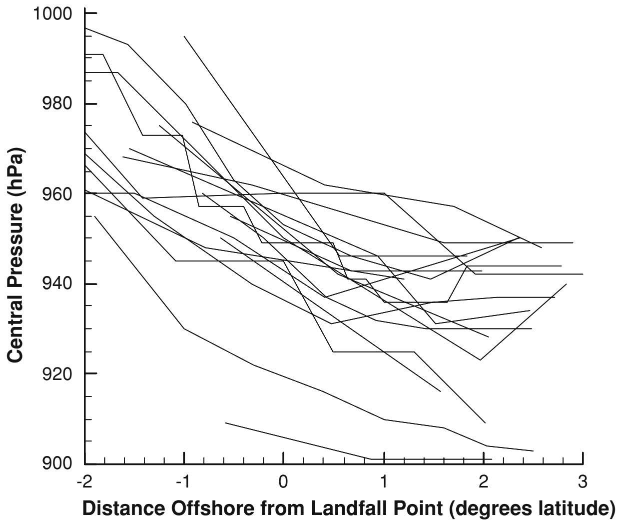

Fig. 2 Variation in central pressures in storms approaching the coast along the northern Gulf of Mexico. Each line in this figure represents the central pressures in a particular hurricane. For example, the bottom line provides information on Hurricane Camille and the line immediately above this provides information on Hurricane Katrina. One degree latitude equals approximately 111 km

(Resio and Westerink 2008). This includes not only the need to resolve various small-scale features (such as roads, culverts, and levee crests), to reliably assess impacts to these small-scale features, but also the need to resolve regions where physical processes (such as wave current interactions) occur on a relatively small scale. As an example of this, the ADCIRC model domain used in current hazard estimates for the New Orleans contains over 2,000,000 computational nodes.

4 Optimal sampling methods for the JPM

All of these complications noted in the previous section, the non-stationarity of hurricane wind characteristics, the need to couple wave radiation stresses into the model forcing, and the need for highly resolved grids, create significant problems with attempts to use the original JPM for estimating hurricane surge hazards. Consequently, considerable effort has now been expended on developing improved variants of the JPM method that could incorporate uncertainty into the hazard estimates for modern applications. These efforts, as described in Niedoroda et al. (2008), have focused on the need for increased efficiency in the sampling methods used in forming the JPM sample to be simulated.

From the previous discussions, it is apparent that the computational burden to simulate an individual storm accurately is quite large. One option would be to simplify the grid and some of the modeling complexity; however, it is very hard to estimate the types and magnitudes of errors that would result from such simplifications—other than to say that, in the New Orleans area, such simplifications would lead to serious misestimates for recent major storms. An alternative method is to develop an approach that reduces the number of sample storms that have to be simulated to provide a reasonable statistical characterization of the storm population. The overall approach to accomplish this optimization within the context of the JPM has now been termed the JPM-Optimal Sampling or the JPM-OS. Two different approaches to this optimization have been considered to date (Niedoroda et al. 2008), one based on an optimization of the sample set to match the parent distribution and a second that uses locally tuned interpolations to construct a detailed response function within the multi-dimensional parameter space. There are advantages and disadvantages to both optimization approaches, and it is likely that the two methods might be merged into a single approach at some point in the future. The latter of these two methods is the topic of the remainder of this paper and the accompanying paper by Irish et al. (2009) in this special issue.

At this point, let us introduce a concept for the definition of continuous (rather than discrete) surge probabilities via numerical storm surge models for an arbitrary number of parameters

$$p(\eta) = \int \ldots \int p(x_1, x_2, \ldots, x_n)\delta[\Psi(x_1, x_2, \ldots, x_n) - \eta]dx_1 dx_2 \ldots dx_n \tag{5}$$

where $\eta(\eta_{\max}$ for each individual storm at a fixed spatial location) is the storm surge level, is$\delta[.]$ the Dirac delta function and$\Psi(x_1, x_2, \ldots, x_n)$ is a numerical model or system of models that operate on the set of parameters $(x_1, x_2, \ldots, x_n)$ to provide an estimate of the surge level at a fixed location. This can be directly integrated to yield the CDF for surge levels

$$F(\eta) = \int \ldots \int p(x_1, x_2, \ldots, x_n)H[\eta - \Psi(x_1, x_2, \ldots, x_n)]dx_1 dx_2 \ldots dx_n \tag{6}$$

where $H[.]$ is the Heaviside function. If we retained a sufficient number of degrees of freedom to resolve the wind fields exactly, if our numerical codes were also “exact,” and if our specification of the joint probability function $p(x_1, x_2, \ldots, x_n)$was known exactly, we could treat this equation as an exact integral for the CDF, with no uncertainty in its expected value. The sampling variability could then be estimated by re-sampling methods along the lines of the EST.

The CDF integral (Eq. 6) shows that the number of dimensions required for an exact representation of the surge CDF must equal the number of degrees of freedom contained within the system (for practical purposes determined by the number of degrees of freedom contained in the wind fields). Since we recognize that all wind fields, wave models, and surge models remain inexact and that our estimates of joint probabilities are greatly hampered by the small sample size, it is clear that the actual representation of this integral should be written as

$$F(\eta) = \int \ldots \int p(x_1, x_2, \ldots, x_n, \varepsilon)H[\eta - \Psi(x_1, x_2, \ldots, x_n) + \varepsilon]dx_1 dx_2 \ldots dx_n d\varepsilon \tag{7}$$

where ε is an “error” term due to wind field deficiencies, ocean response model deficiencies, unresolved scales, etc. In this form, we see that there is a trade-off between modeling accuracy and the magnitude of the error term, ε. There is also a similar trade-off between errors/uncertainties in the probability estimates and the overall accuracy in estimates of the surge CDF. These errors will increase substantially if we attempt to split a small sample (for example, the historical hurricane record in the Gulf of Mexico) into information for too many dimensions. Following this reasoning, it seems advisable to limit the number of parameters considered in the JPM probability integral to those which most impact the surge response and to include an approximation for all of the neglected terms within the error term, ε. As noted previously, PBL models provide a relatively accurate representation of the broad-scale structure within hurricanes. Furthermore, wind fields from PBL models have a very long history of providing accurate ocean response estimates in the Gulf of Mexico hurricanes (Cardone et al. 1976). Consequently, the logical choice appears to be to limit the number of dimensions in the JPM integral to the number of parameters contained within such PBL models

$$F(\eta) = \int \ldots \int p(c_{\mathrm{p}}, R_{\mathrm{p}}, v_{\mathrm{f}}, \theta_1, x, B) p(\varepsilon) H[\eta - \Psi(\vec{X}) + \varepsilon] dx_1 dx_2 \ldots dx_n d\varepsilon \quad (8)$$

where the error term has been separated from the rest of the probability distribution and with the vector set of parameters reduced to

$$\Psi(\vec{X}) = \Psi(c_{\mathrm{p}}, R_{\mathrm{p}}, \theta_1, v_{\mathrm{f}}, B)$$

In this form, the "error" term allows us to include additional effects on water levels, such as tides (albeit in an uncoupled, linear fashion). Also, in this equation, we have replaced$R_{\max}$ withR_{p} (a pressure field scaling term rather than a wind speed scaling term), since the latter term is used in the PBL model that is used in the actual wind field construction here (Thompson and Cardone 1996).

Considerable effort has gone into re-analyzing hurricane characteristics and hurricane wind fields in terms of their impacts on coastal surges. One of the significant findings of this effort is that the Holland B parameter in mature storms within the Gulf of Mexico tended to fall into a fairly small range of 0.9 to 1.6. Furthermore, numerical sensitivity tests of both wind fields and coastal surges driven with the PBL winds generated with the Thompson and Cardone (1996) model suggest that the adoption of a constant value of 1.27 for storms centered more than 90 nm from the coast provided a reasonable first approximation to both the wind fields and the surges. Thus, if we add the effects of B-variations into the "error" term, we can reduce the CDF equation to

$$F(\eta) = \int \ldots \int p(c_{\mathrm{p}}, R_{\mathrm{p}}, v_{\mathrm{f}}, \theta_1, x) p(\varepsilon|\eta) H[\eta - \Psi(\vec{X}) + \varepsilon] dx_1 dx_2 \ldots dx_n d\varepsilon \quad (9)$$

with

$$\Psi(\vec{X}) = \Psi(c_{\mathrm{p}}, R_{\mathrm{p}}, \theta_1, v_{\mathrm{f}}, \bar{B})$$

where $\bar{B}$ is the mean value of $\bar{B}$

4.1 Construction of extended storm tracks for wave predictions

In order to obtain realistic wave fields for the wave component of the surge, it is essential to have representative tracks defined over the tracks that extend across the entire wave-generation region. For the Gulf of Mexico, it was found that the most intense storms tended to follow tracks that could be represented by the set of tracks of the type shown in Fig. 3.

4.2 The effect of time variations in the parameter set

As noted previously, considerable evidence has emerged in recent years that the wind fields in hurricanes vary considerably during their approach to shore. One approach to characterize this in a statistical context is to discretize the rate of change of each of the four wind

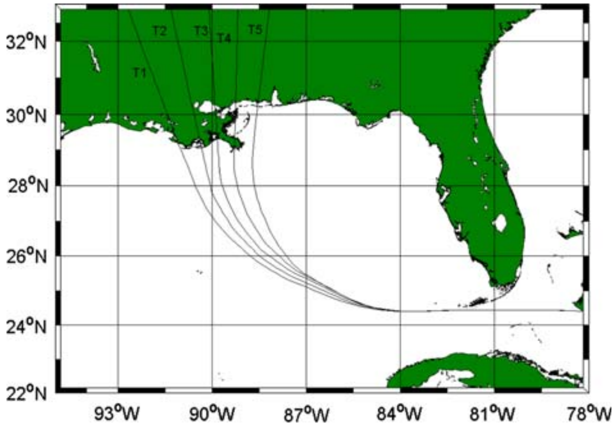

Fig. 3 Example of extended tracks used in wave modeling for coastal surges representing the tracks followed by the most intense storms on record. These tracks were developed by a team of meteorologists from the track characteristics of major storms within the Gulf of Mexico

field parameters and consider this within the scope of the simulations. Unfortunately, this would increase the computational burden by a large factor (typically at least by a factor of 3^4). Sensitivity studies have shown that the typical range of variations in storm angle and storm speed during approach to land is fairly small and does not appear to affect estimated surge values significantly. Thus, it is primarily variations in storm intensity and storm size (and to a lesser extent the variation in the mean value of the Holland B term) that are important to capture during approach to land. This would change the form of Eq. 3 to

$$\Delta p(\eta_{\max}) = p(c_{\mathrm{p}}, R_{\max}, v_{\mathrm{f}}, \theta_{\mathrm{l}}, x_0, \Delta c_{\mathrm{p}}, \Delta R_{\max})\delta c_{\mathrm{p}}\delta R_{\max}\delta v_{\mathrm{f}}\delta\theta_{\mathrm{l}}\delta x_0\delta(\Delta c_{\mathrm{p}})\delta(\Delta R_{\max}) \quad (10)$$

where Δc_{p} is the change in the central pressure during its approach to land and $\Delta R_{\max}$ is the change in storm size during its approach to land and would increase the total degrees of freedom in the simulation by two (from 5 to 7). However, even if we used only three categories to represent variations in both of these parameters, it would still increase the computational burden by a factor of 9. An alternative to this is to use a deterministic function to capture the mean values of Δc_{p} and $\Delta R_{\max}$much in the manner that was used for the Holland B term.

Based on an analysis of all data for hurricanes within the Gulf of Mexico that attained central pressure less than or equal to 955 mb at some time during their passage through the Gulf, we found the following equation provided a reasonable fit to the rate of change over the last 90 nautical miles of approach to the coast

$$< \Delta c_{\mathrm{p}} > \ = R_{\max} - 6$$

where c_p is in millibars and $R_{\max}$ is in nautical miles. Here, the $< >$ brackets denote the averaging over the entire sample.

This form for the rate of change in central pressure assumes that it is linearly dependent on storm size. Although this has not yet been clearly demonstrated, a number of historical storms clearly support this hypothesis. The finding of an average storm de-intensification during approach to shore is consistent with the findings of Rappaport (2007, personal communication). Kimball (2006) has shown that such decay is consistent with the intrusion of dry air into a hurricane during its approach to land. Other mechanisms for decay might include lack of energy production from parts of the hurricane already over land and increased drag in these areas. In any event, the evidence appears rather convincing that major hurricanes begin to decay before they make landfall, rather than only after landfall as previously assumed. Since the empirical basis for this decay is drawn only from data in the northern Gulf of Mexico, these results should be treated as site specific to that area.

During this study, it was also found that the mean variation in storm size could be represented by a simple multiplicative factor, independent of storm intensity, with storms increasing their size by about 30% over the last 90 nautical miles of approach to the coast. It was also determined that the Holland B term decreased from its average value of 1.27 off the coast to a value of about 1 at the coast. Thus, the final form for the continuous probability is

$$F(\eta) = \int \ldots \int p(c_{\mathrm{p}}, R_{\mathrm{p}}, v_{\mathrm{f}}, \theta_{\mathrm{l}}, x) p(\varepsilon|\eta) H[\eta - \Psi(X) + \varepsilon] dx_1 dx_2 \ldots dx_n d\varepsilon \tag{11}$$

with

$$\Psi(\vec{X}) = \Psi(c_{\mathrm{p}}, R_{\mathrm{p}}, \theta_{\mathrm{l}}, v_{\mathrm{f}}, \bar{B}, <\Delta c_{\mathrm{p}}>, <\Delta R_{\mathrm{p}}>)$$

5 The application of a surge response approach to estimating surge probabilities

If one makes assumptions concerning the relative magnitudes of the surge response to different parameters, it is possible to form a set of points with associated probability masses (i.e., the $\delta c_{\mathrm{p}} \delta R_{\mathrm{p}} \delta v_{\mathrm{f}} \delta \theta_{\mathrm{l}}$ term in the probability integral) that approximates, to some extent, the overall integral. Instead of using this approach, it is also possible to use information from surge responses in a more general way. Extensive numerical studies using ADCIRC and SLOSH have shown that coastal surge levels are very dependent on storm intensity, typically categorized by pressure differential defined as the peripheral pressure minus central pressure (i.e., $\Delta p = p_0 - c_{\mathrm{p}}$, where p_0 is the peripheral pressure), storm size ($R_{\max}$ or R_{p}), and storm location relative to a site. Storm surge is less sensitive to forward storm speed and angle of the storm relative to the coast. Figure 4 shows the

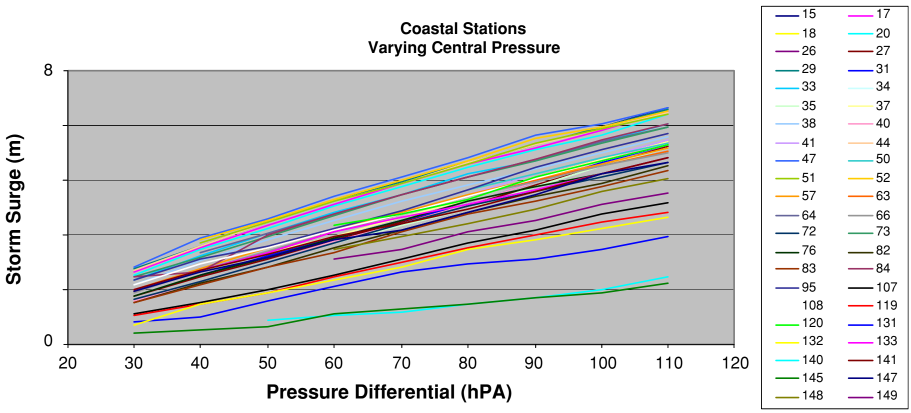

Fig. 4 Variation in surge levels (meters) at coastal stations (station numbers denoted on right hand side of chart) along Mississippi coast as a function of pressure differential (mb). Surge levels based on SLOSH model

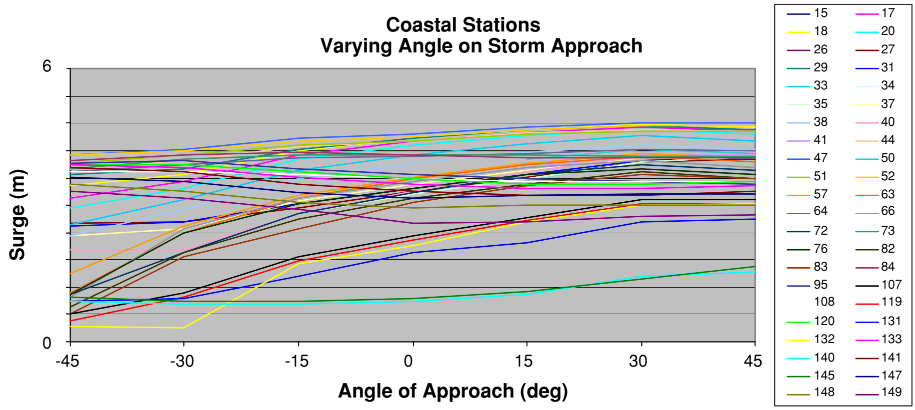

Fig. 5 Variation of surge levels (meters) at coastal stations (station numbers denoted on right hand side of chart) along Mississippi coast as a function of angle of storm approach to land. Surge levels based on SLOSH model

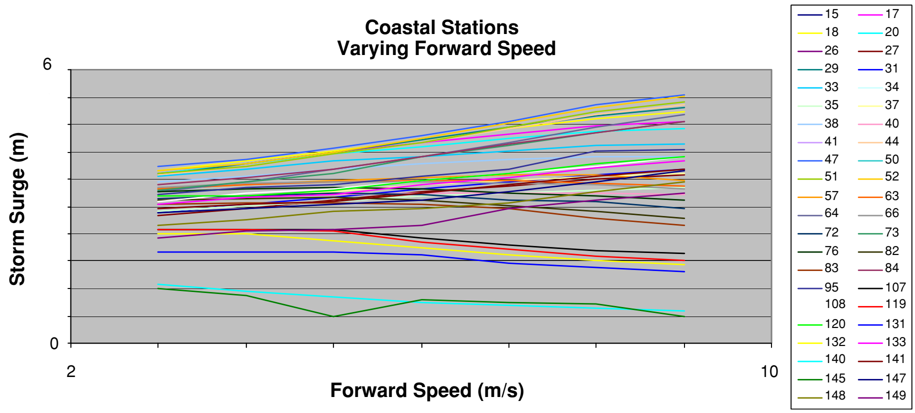

Fig. 6 Variation of surge levels (meters) at coastal stations (station numbers denoted on right hand side of chart) along Mississippi coast as a function of forward speed of storm (mph). Surge levels based on SLOSH model

characteristic variation of surge elevations at coastal stations as a function of variations in pressure differential $(p_0 - c_p)$, based on SLOSH tests along the coast of Mississippi. Figures 5 and 6 show the characteristic variations of coastal surges as a function of storm angle relative to the coast (θ_l) and forward storm speed (v_f), respectively. As can be seen here, surge variations as a function of these three parameters tend to be quite smooth with either linear or slightly curved slopes in these figures.

For a given location, a major portion of the surge response to hurricanes has been shown to be captured by the variation of Δp and R_p (Irish et al. 2008). Because of this, the surge response integration method uses $\Delta p - R_p$planes as the primary variables within the five-dimensional parameter space used in the JPM. Thus, for a fixed value of storm landfall location (x), storm track angle at the coast(θ_l), and storm speed (v_f), we can define a response function at location (x, y) as

$$\eta_{\max}(x, y) = \phi_{\text{kmn}}(\Delta p, R_{\text{p}}, x, y) \tag{12}$$

where $\phi_{\text{kmn}}$is the surge response function and the subscripts “k, m, and n” denote a specific track angle, storm speed, and landfall location, respectively. This notation reflects the fact that this response function must be defined for each spatial (x, y) point in the computations.

The effect of variations in storm speed has been found to be fairly small and tends to have fairly linear slopes that are roughly independent of $R_{\max}$and Δp; consequently, only a small number of storms is required to represent the variation in surge levels as a function of forward storm speed. This retains the overall structure of the response function for the initial forward speed values used in Eq. 12. In general, within this approach, the value of $[\phi_{\text{kmn}}(\Delta P, R_{\text{p}}, x, y)]$for different forward speeds is obtained from the relationship

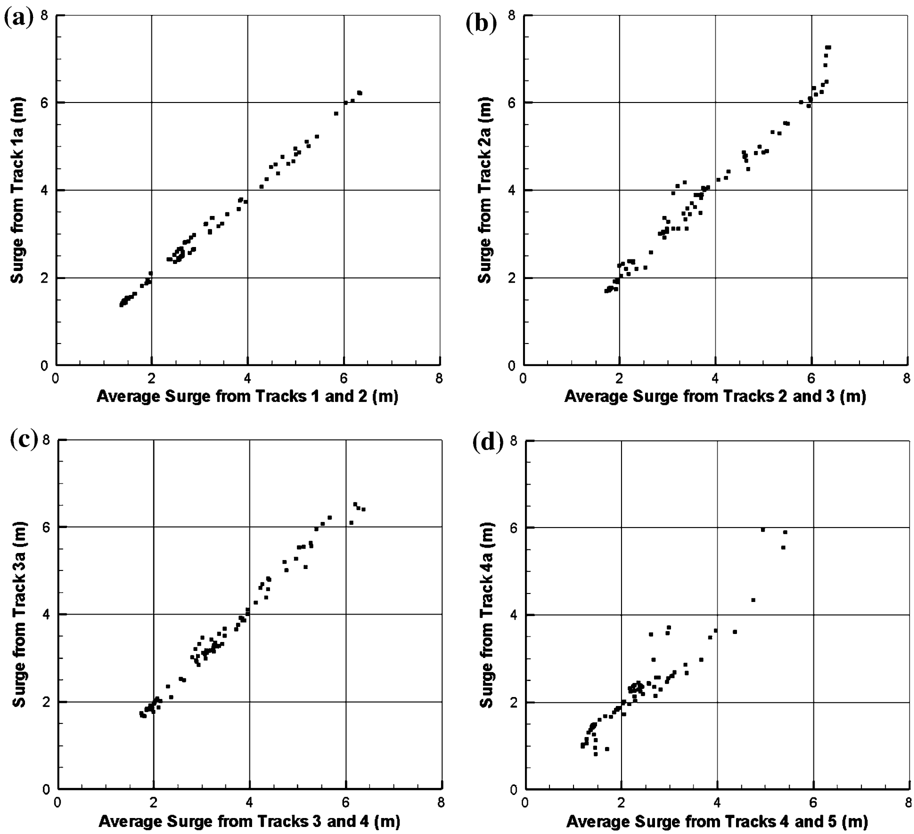

Fig. 7 a-d. **a** Comparison of results from Track 1a (midway between Tracks T1 and T2 in Fig. 3) to interpolated values using information from Tracks T1 and T2 for a set of points spread throughout the entire New Orleans region. **b** Comparison of results from Track 2a (midway between Tracks T2 and T3 in Fig. 3) to interpolated values using information from Tracks 2 and 3 for a set of points spread throughout the entire New Orleans region. **c** Comparison of results from Track 3a (midway between Tracks T3 and T4 in Fig. 3) to interpolated values using information from Tracks 3 and 4 for a set of points spread throughout the entire New Orleans region. **d** Comparison of results from Track 4a (midway between Tracks T4 and T5 in Fig. 3) to interpolated values using information from Tracks 4 and 5 for a set of points spread throughout the entire New Orleans region. Surge levels in all panels based on ADCIRC model results

$$\phi_{\mathrm{kmn}}(\Delta P, R_{\mathrm{p}}, x, y) = \phi_{\mathrm{k_0m_0n}}(\Delta P, R_{\mathrm{p}}, x, y) + \Psi_{\mathrm{kmn}} \tag{13}$$

where the subcript "0"refers to the central speed and angle categories for specific land full location and

$$\Psi_{\mathrm{kmn}} = \frac{\partial \phi_{\mathrm{kmn}}(\Delta P, R_{\mathrm{p}}, x, y)}{\partial v_{\mathrm{f}}} \delta v_{\mathrm{f}} + \frac{\partial \phi_{\mathrm{kmn}}(\Delta P, R_{\mathrm{p}}, x, y)}{\partial \theta_{\mathrm{l}}} \delta \theta_{\mathrm{l}}$$

For the cases in which a single storm is used to infer the variation with forward speed Ψ_{kmn}reduces to a constant.

One concern that should be addressed here is the sensitivity of the probability estimates to storm track spacing. In the study of the New Orleans area, two sets of tracks were investigated: primary tracks with a spacing of about 40 km and secondary tracks midway between the primary tracks. The sufficiency of the spacing of the primary tracks to represent the surge response in this area can be investigated by comparing results from the secondary tracks to results of interpolations between primary tracks. Figure 7 shows the results of these comparisons. In general, little or no bias is introduced into the probability integration by using only results from the primary tracks.

6 Estimation of surge hazards for the New Orleans area

One of the major impediments to developing the JPM sample has been the lack of guidance on the spatial domain size appropriate for sample selection. Chouinard et al. (1997) developed a method for determining an optimal spatial sample size based on consideration of both the errors due to limited sample size and the errors due to inhomogeneity in the sample. Using this method, it can be shown that the optimal spatial sampling size for developing hurricane occurrence frequency statistics in the central Gulf of Mexico lies in the neighborhood of ±160 km, or a total of 320 km. For storm intensity, this window was found to be even larger—around 660 km.

Putting all of the pieces of information together, for any point in our five-dimensional parameter space (retaining appropriate interrelationships among parameters), we see that the final estimates of joint probability densities can be written as

$$\begin{aligned}
p(c_{\mathrm{p}}, R_{\mathrm{p}}, v_{\mathrm{f}}, \theta_{\mathrm{l}}, x) &= \Lambda_1 \cdot \Lambda_2 \cdot \Lambda_3 \cdot \Lambda_4 \cdot \Lambda_5 \\
\Lambda_1 &= p(c_{\mathrm{p}}|x) = \frac{\partial F[a_0(x), a_1(x)]}{\partial(\Delta p|c_{\mathrm{p}})} \\
&= \frac{\partial}{\partial x}\left\{\exp\left\{-\exp-\left[\frac{\Delta p - a_0(x)}{a_1(x)}\right]\right\}\right\} \text{ (Gumbel Distribution)} \\
\Lambda_2 &= p(R_{\mathrm{p}}|c_{\mathrm{p}}) = \frac{1}{\sigma(\Delta P)\sqrt{2\pi}} e^{-\frac{(\bar{R}_{\mathrm{p}}(\Delta P) - R_{\mathrm{p}})^2}{2\sigma^2(\Delta P)}} \\
\Lambda_3 &= p(v_{\mathrm{f}}|\theta_l) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(\bar{v}_{\mathrm{f}}(\theta_{\mathrm{l}}) - v_{\mathrm{f}})^2}{2\sigma^2}} \\
\Lambda_4 &= p(\theta_{\mathrm{l}}|x) = \frac{1}{\sigma(x)\sqrt{2\pi}} e^{-\frac{(\bar{\theta}_{\mathrm{l}}(x) - \theta_{\mathrm{l}})^2}{2\sigma^2(x)}} \\
\Lambda_5 &= \Phi(x)
\end{aligned} \tag{14}$$

where the overbars denote average values of the dependent variable for a specified value of an independent variable in a regression equation, $a_0(x)$ and $a_1(x)$ are the Gumbel coefficients for the assumed Gumbel form of the central pressures, and $\Phi(x)$ is the frequency of storms per year per specified distance along the coast.

6.1 Estimation of the ε term for the New Orleans area

The uncertainty term is estimated as the sum of a series of independent error terms

$$\sigma^2_{\text{total}} = \sigma^2_{\text{tide}} + \sigma^2_{\text{model}} + \sigma^2_{\text{B}} + \sigma^2_{\text{waves}} + \sigma^2_{\text{winds}} + \sigma^2_{\text{residual}} \tag{15}$$

where the subscripts denote the contribution to a Gaussian error due to a specific type of variation not contained within the simulations, i.e., tidal variations, the presence of modeling errors, variations in the Holland B term, variations in the wave contributions to surges related to deviations between actual extended tracks and the assumed extended track, variations in wind fields not captured by the parameter-driven PBL model, and residual variations due to suppression of variations around the mean functions during approach to land,.

Although there may be some degree of nonlinearity in the superposition of tides and storm surges, numerical experiments have shown that for the most part, linear superposition provides a reasonable estimate of the (nonlinearly) combined effects of tides and surges. Thus, the tidal component of the ϵ term represents the percentage of time occupied by a given tidal stage and can be directly derived from available tidal information along the coast.

Model errors combined in calibration/verification runs of ADCIRC have shown that this combination of model and forcing in the Louisiana–Mississippi coastal area provides relatively unbiased results with a standard deviation in the range of 0.5 to 0.75 m. Relative errors associated with the use of PBL winds increase the value of the standard deviation to 0.6 to 1.1 m. This is not surprising, since the accuracy of HWMs (the primary measurements to which the model results are compared) are quite variable in and of itself. In the actual application shown here, a value of 0.75 m was used.

For the Gulf of Mexico hurricanes, a standard deviation of 0.15 in the Holland B term was found. Via numerical experiments, the maximum storm surge generated by a hurricane has been found to vary approximately linearly with variations in the Holland B parameter, at least for changes of the Holland B parameter in the range of 10 to 20%.

Sufficient information to separate the effects of each of the remaining terms in Eq. 15 is not available. Given the expected magnitudes of the contributions involved in these terms, the sum $\sigma^2_{\text{waves}} + \sigma^2_{\text{winds}} + \sigma^2_{\text{residual}}$was assumed to equal 0.46 m for the New Orleans area.

Table 1 shows an example of the effect of adding this term on expected surge levels for selected return periods. In this example, a Poisson frequency of 1/16 was used in combination with a Gumbel distribution for the pressure differential (peripheral storm pressure minus central pressure),

$$F(\Delta P) = \exp -\left\{\exp -\left[\frac{\Delta P - a_0(x)}{a_1(x)}\right]\right\}$$

with parameters$a_0 = 9.855$ and $a_1 = 3.63$. For this example, the effect of adding theε-term is about 0.3 m for return periods up to 175 years and only exceeds 0.4 m at return periods approaching 300 years. However, for risk-based calculations, which often include very large return periods (1000–10000 years), this term can become as large as 0.6–0.9 m, even for the

Table 1 Example of expected surge values as a function of return period with and without ε-term

Return period (years)	Without ε-term (m)	With ε-term (m)
50	3.65	3.95
100	4.52	4.70
150	5.03	5.26
200	5.39	5.66
250	5.67	5.96
300	5.89	6.21
350	6.08	6.43
400	6.26	6.61
450	6.40	6.77
500	6.53	6.92

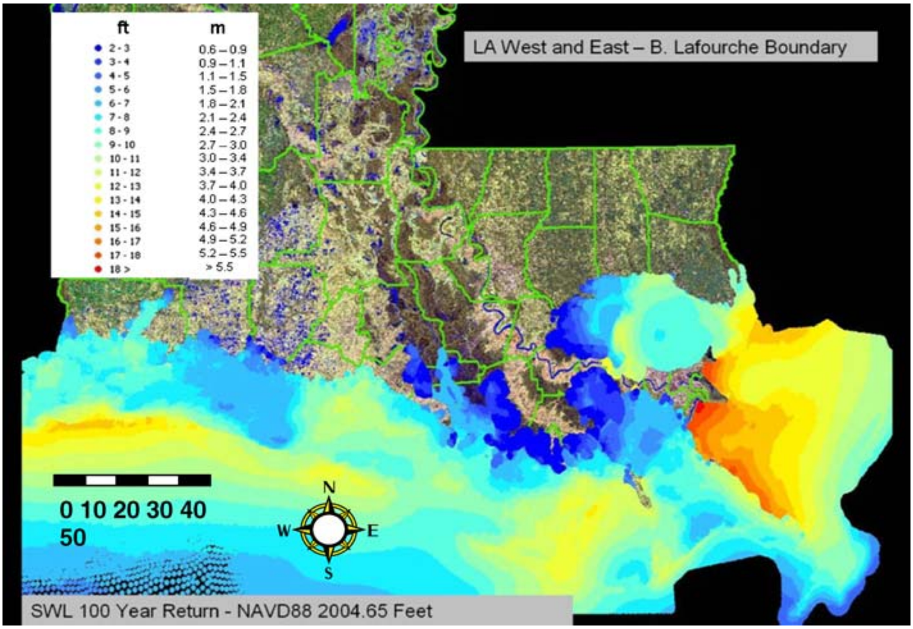

Fig. 8 Preliminary 100-year surge values for Southeast Louisiana. Surge levels (in feet and meters) based on ADCIRC model results and JPM-OS method

case where the effects of all neglected factors are assumed to be distributed around a mean deviation of zero. The effect would of course be larger if the deviations were biased. Figure 8 shows the distribution of estimated 100-year surge values for the Southeast Louisiana area, derived from the JPM-OS method using the surge response approach.

7 Discussion of uncertainty in New Orleans surge estimates

In addition to the uncertainty discussed in the previous section, it is important to assess the uncertainty associated with our limited sample size. This cannot be estimated using re-sampling techniques, since these techniques use the initial sample as the basis for their re-sampling and implicitly assume that the initial sample exactly represents the actual population characteristics. Thus, some parametric method must be used to obtain this information. There are many classes of distributions which can be used to fit the data. Since we are only using the parametric fits to estimate uncertainty and not to replace the non-parametric estimates obtained from the JPM, we are somewhat free to use any distribution for which the sampling uncertainty is known. Gringorten (1962, 1963) has shown that the expected root-mean-square (rms) error of an estimated return period in a two-parameter Fisher-Tippett Type I (Gumbel 1959) distribution is given by

$$\sigma_T = \sigma\sqrt{\frac{1.1000y^2 + 1.1396y + 1}{N}} \tag{16}$$

where σ is the distribution standard deviation, σ_T is the rms error at return period,T, N is the number of samples used to estimate the distribution parameters, and Y is the reduced Gumbel variate given by $y = (\eta - a_0)/a_1$; η is the variate of interest (surge level in this case), and a_0 and a_1 are the parameters of the Gumbel distribution

The reduced variate and return period are related by

$$y = -\ln\left[\ln\left(\frac{T}{T-1}\right)\right] \tag{17}$$

which for $T > 7$ years approaches an exponential form given by

$$\left(T - \frac{1}{2}\right) \rightarrow e^y \tag{18}$$

Equation 16 shows that the rms error at a fixed return period is related to the distribution standard deviation and the square root of a nondimensional factor involving the ratio of different powers of y $(y^2, y^1,$ and $y^0)$to the number of samples used to define the parameters. By the method of moments, the Gumbel parameters can be shown to be given by

$$a_0 = \gamma a_1 - \mu a_1 = \frac{\sqrt{6}}{\pi}\sigma \tag{19}$$

where γ is Euler's content (= 0.57721…) and μ is the distribution mean

Thus, the distribution standard deviation is related to the slope of the line represented by Eq. 18.

Although Eq. 16 was initially derived for applications to annual maxima, it can be adapted to any time interval for data sampling in a straightforward manner. For the case of hurricanes, the average interval between storms (the inverse of the Poisson frequency used in the compound Gumbel-Poisson distribution) can be used to transform Eq. 16 into the form

$$\sigma'_T = \sigma\sqrt{\frac{1.1000y'^2 + 1.1396y' + 1}{N'}} \tag{20}$$

where σ is the distribution standard deviation, σ'_T is the rms error at return period,$T'(T/\widehat{T}$, where T' is the average years between hurricanes), and N' is the number of samples used to estimate the distribution parameters $(N/\widehat{T})$

Since the form of Eq. 18 is logarithmic, the slope is not affected by a multiplicative factor, and thus, the distribution standard deviation remains the same. N'in Eq. 20 can be estimated from the equivalent total number of years in the sample divided by $\widehat{T}$. The total number of years for this case is 65 (1941–2005, inclusive) times a factor, Z, which relates the spatial area covered by the sample used to the spatial extent of a hurricane surge. For the sample used here, the effective number of years is estimated to be approximately 400.

Based on the discussions here, it is apparent that simulations of future storm sets should include both the random sampling variability that is typically captured by re-sampling methods as well as the sampling variability of the type described here. Present re-sampling methods consider only the first of these sources of variation.

8 Summary and conclusions

Resio and Westerink (2008) provide a good review of the hurricane processes and recent advances relevant to the physics of storm surge modeling. Unfortunately, a side effect of our improved understanding of hurricane surges is the requirement for a significant increase in computational burdens to obtain accurate surge hazard estimates in coastal areas. In order to maximize the computational accuracy of the modeled storms in a framework that utilizes an optimally small set of simulations, we are developing a "response function" approach for estimating surge probabilities in coastal areas. The fundamentals of this approach, treating the incorporation of physical scaling into the storm and the treatment of uncertainty, are presented in this paper, while the details of the characterization of the spatial scaling are presented in Part II (Irish et al. 2009). This new approach reduces the number of runs required by a factor of 3 to 10 over older methods. The new values produced by this new approach appear much more consistent with our present understanding of surge levels for Louisiana–Mississippi coastal areas with estimated surges for the "100-year" (0.01 annual expected values) about 1 to 1.5 m higher than previous estimates in this area.

It should be noted that we do not include an estimate for subsidence and sea-level rise within our analysis here. These effects must be included in a separate analysis at this stage of our understanding of these processes, since there is considerable controversy surrounding quantitative estimates of these terms.

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