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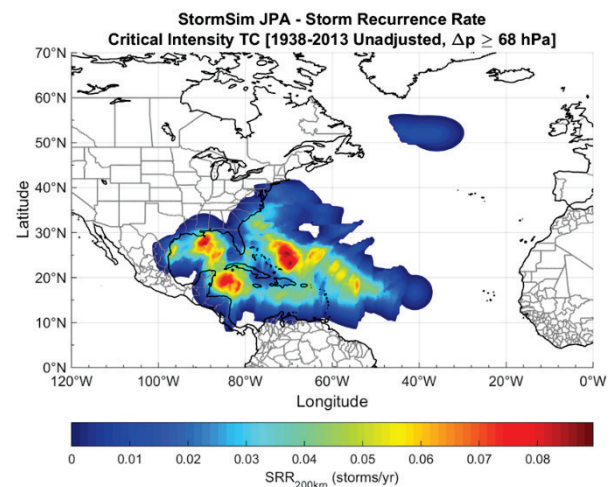
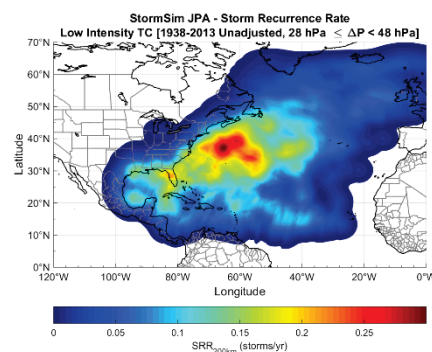
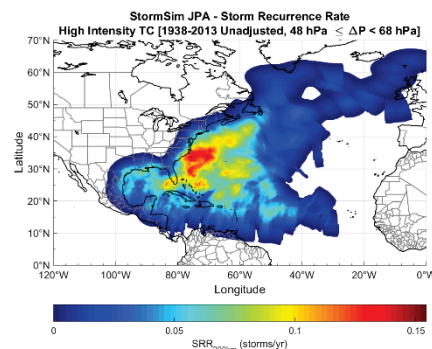
Quantification of Uncertainties in Probabilistic Storm Surge Models

Storm Recurrence Rate Models for Tropical Cyclones

Report 1

Norberto C. Nadal-Caraballo, Victor M. Gonzalez,
and Luc Chouinard

May 2019



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Storm Recurrence Rate Models for Tropical Cyclones

Report 1

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Report 1 of a series

Approved for public release; distribution is unlimited.

Prepared for U.S. Nuclear Regulatory Commission
One White Flint North
11555 Rockville Pike
Mail Stop CSB C2 A7
Rockville, MD 20852-2738

Under Contract no. NRC-HQ-60-14-I-0019

Abstract

Quantification of the storm surge hazard is an integral part of the probabilistic flood hazard assessment of structures and facilities located in coastal areas. The U.S. Army Engineer Research and Development Center, Coastal and Hydraulics Laboratory (ERDC-CHL), performed a comprehensive assessment of uncertainties in probabilistic storm surge models for the U.S. Nuclear Regulatory Commission (USNRC) as part of its efforts to develop a framework for probabilistic storm surge hazard assessment for nuclear power plants. State-of-the-art statistical assessment of coastal storm hazards in hurricane-prone coastal areas requires the development of a joint probability model of tropical cyclone (TC) forcing parameters. The task summarized in this technical report focused on the quantification of epistemic uncertainties in storm recurrence rate (SRR) models and associated data sources. SRR is an estimate of the expected annual rate of occurrence of TCs within a given region. Numerical experiments were performed to quantify SRR uncertainty associated with data sampling, observational data quality, selection of kernel function and kernel size, period of record, quality of observational data, and partition of TCs according to their intensity. This technical report is the first of a series covering the USNRC-sponsored study “Quantification of Uncertainties in Probabilistic Storm Surge Models performed by the ERDC CHL.”

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Preface

This study was conducted as a task within the U.S. Nuclear Regulatory Commission (USNRC) sponsored study “Quantification of Uncertainties in Probabilistic Storm Surge Models,” under contract number NRC-HQ-60-14-I-0019. Dr. Joseph Kanney (Fire and External Hazards Assessment Branch, Division of Risk Analysis, Office of Nuclear Regulatory Research) was the Project Manager and primary point of contact for the USNRC. The study was funded by the USNRC and conducted at the U.S. Army Engineer Research and Development Center (ERDC), Coastal and Hydraulics Laboratory (CHL), Vicksburg, MS, during the period January 2015–July 2017.

General supervision was provided by Mr. James D. Gutshall, Chief, Harbors, Entrances, and Structures Branch; Dr. Jackie Pettway was Chief, Navigation Division. At the time of publication of this report, Dr. Ty V. Wamsley was Director, CHL, and Mr. Jeffrey R. Eckstein was Deputy Director, CHL.

Ms. Amanda B. Lewis and Mr. Efrain Ramos-Santiago, Harbors, Entrances, and Structures Branch, are acknowledged for their contributions to this report.

COL Ivan P. Beckman was Commander of ERDC, and the Director of ERDC was Dr. David W. Pittman.

Unit Conversion Factors

Most measurements and calculations referenced in this technical report are in SI units. The following table can be used to convert SI units to English customary units.

Multiply	By	To Obtain
m	3.28084	ft
km	0.621371	mi
km	0.539957	nmi
km/h	0.621371	mph
km/h	0.539957	kt
hPa	1	mb

1 Introduction

Quantification of the storm surge hazard is an integral part of the probabilistic flood hazard assessment (PFHA) of structures and facilities located in coastal areas. The U.S. Army Engineer Research and Development Center, Coastal and Hydraulics Laboratory, performed a comprehensive assessment of uncertainties in probabilistic storm surge models for the U.S. Nuclear Regulatory Commission (USNRC) as part of its efforts to develop a framework for probabilistic storm surge hazard assessment for nuclear power plants.

1.1 Background

Modern statistical assessment of coastal storm hazards in hurricane-prone coastal areas requires the development of a joint probability analysis (JPA) model of tropical cyclone (TC) forcing parameters. After Hurricane Katrina, the joint probability method with optimal sampling (JPM-OS) became the standard JPA model for the assessment of coastal storm hazards for hurricane-prone U.S. coastlines. Other recently developed probabilistic storm surge modeling approaches include the use of global climate models with downscaling to generate synthetic TCs and employ Monte Carlo simulation methods for the computation of hazard curves in lieu of the standard JPM-OS integration approach. The TC forcing parameters typically used in the development of the JPM-OS and other JPA models, including the traditional Joint Probability Method (JPM), are the following:

- landfalling or bypassing reference location (x_0)
- central pressure deficit (Δp)
- radius of maximum winds (R_{max})
- translational speed (V_f)
- heading direction (θ).

1.2 Objectives

The storm recurrence rate (SRR) is the component of the joint probability model that ties the frequency of occurrence of a TC to a geographical location based on the historical record of storms within a given area of influence. The task summarized in this technical report focused on the

quantification of uncertainties in SRR models (e.g., kernel functions) and associated data sources. The quantification of uncertainty associated with the SRR included the characterization of epistemic uncertainty arising from the selection of kernel size, period of historical record considered, quality of observational data, and data resampling. The quantification of uncertainty related to the SRR is the second task of the USNRC sponsored study “Quantification of Uncertainties in Probabilistic Storm Surge Models.”

1.3 Study approach

The present study is part of an initiative by the USNRC to implement a PFHA research plan to inform the development of regulatory guidance for nuclear power plant facilities that incorporates the latest developments in quantitative risk assessment. These developments represent a shift from deterministic to probabilistic methods that allow for the explicit consideration of uncertainties. Two distinct types of uncertainty are generally recognized. The first type, called *aleatory uncertainty*, consists of the natural randomness of a process and is inherent in nondeterministic modeling. It is often called stochastic or irreducible uncertainty, or aleatory variability. The second type, known as *epistemic uncertainty*, is associated with a lack of knowledge about the validity of models and data used to represent real systems; it is also called subjective or reducible uncertainty. Unlike aleatory uncertainty, epistemic uncertainty can potentially be reduced by collecting more data or performing additional research.

The categorization of a source of uncertainty as aleatory or epistemic is often subject to interpretation and may vary according to whether or not the uncertainty is regarded as reducible. The treatment of uncertainties in past JPM studies has typically been related to the specific approach used in each study and limited to the inclusion of uncertainty as an error term in the JPM integral (Gonzalez et al. 2019). Traditionally, this error term has incorporated the uncertainty arising from sources of error such as meteorological modeling, hydrodynamic modeling, TC track variation, and insufficient variation in wind and pressure profiles. These errors have been regarded as epistemic uncertainties because, theoretically, they could be reduced by collecting additional data, refining the numerical models, and constructing more efficient synthetic storm suites, among other improvements. The approach chosen for conducting a particular JPM study (e.g., data sources, computation of SRR, univariate distributions, distribution discretization method, development of synthetic storm suites)

is maintained throughout the entire study, and the uncertainties resulting from the choice of specific data, models, and methods are not considered.

The USNRC, in its guidance on probabilistic seismic hazard analysis (PSHA), has adopted an approach for the quantification and propagation of aleatory and epistemic uncertainties that can be adapted for performing probabilistic storm surge hazard assessment and PFHA. The treatment of uncertainties proposed in the present study, based on PSHA guidance, differs from past JPM efforts in that it considers a wide range of data sources, models, and methods that could be applied at each step of the joint probability analysis. In this paradigm, differences between a given model and the natural phenomenon being simulated are prevalent and thus this uncertainty is deemed to be irreducible or aleatory. It is in the selection and application of alternative data, methods, and models that the uncertainty can be reduced and is therefore considered to be epistemic. In PSHA, epistemic uncertainty is quantified and propagated through the use of logic trees. This scheme can also rely on expert elicitation (Kammerer and Ake 2012). This PSHA process allows capturing a wider range of possible seismic hazard estimates at a site through representation of the *center, body, and range* of technically defensible data, models, and methods relevant to the hazard analysis and proposed by the larger technical community.

The larger USNRC-sponsored study had the objective of establishing the data, models, and methods that should be evaluated and carried forward to quantify the epistemic uncertainty associated with the estimation of storm surge hazard. The classification of uncertainty adopted herein follows the USNRC convention. Errors considered in the JPM integral are regarded as aleatory while the epistemic uncertainty will emerge from the consideration of alternative data, models, and methods used for estimating the storm surge hazard. These data models and methods were explored through the execution of five technical tasks:

Task 1: *Literature review* of previous probabilistic storm surge studies.

Task 2: *Investigation of epistemic uncertainties in storm recurrence rate models*. The purpose of this task is to examine and evaluate the data sources and methods used for the computation of site-specific SRRs.

Task 3: *Explore technically defensible data, models, and methods for defining joint probability of storm parameters.* The objective of this task includes assessing the different models for characterizing and quantifying the site-specific joint probability of storm parameters and identifying the center, body, and range of technically defensible data and methods.

Task 4: *Explore technically defensible models and methods for generating synthetic storm simulation sets.* The objective of this task is to capture the full range of technically defensible data and methods for generating synthetic storm sets required to fully characterize and propagate uncertainties in storm surge estimates.

Task 5: *Investigate approaches for probabilistic modeling of numerical surge simulation errors.* The goal of this task is to investigate approaches for characterizing and modeling errors within the probabilistic framework constituted by modeling of storm surge.

1.3.1 Storm Recurrence Rate (SRR) in Joint Probability Methods (JPMs)

The standard of practice for quantifying the storm surge hazard in hurricane-prone coastal sites is to develop probabilistic models employing some variant of the JPM. In this method, the annual exceedance probability (AEP) of coastal storm hazards at a given site is a function of three main components: the SRR, the joint probability of characteristic TC forcing parameters (i.e., x_o , θ , Δp , R_{max} , and V_t), and the TC responses (e.g., storm surge, wave height). The TC forcing parameters are used to generate the wind and pressure fields, which in turn are used as input to hydrodynamic numerical models that simulates storm surge, still water level (SWL), and wave climate. The AEP of storm surge or SWL (i.e., hazard curve) is calculated by integrating the probability masses over the range of SWL. This JPM integral has the form

$$\lambda_{r(\hat{x}) > r} = \lambda \int P[r(\hat{x}) + \varepsilon > r | \hat{x}, \varepsilon] f_{\hat{x}}(\hat{x}) f_{\varepsilon}(\varepsilon) d\hat{x} d\varepsilon \quad (1-1a)$$

$$\approx \sum_i^n \hat{\lambda}_i P[r(\hat{x}_i) + \varepsilon > r | \hat{x}_i, \varepsilon] \quad (1-1b)$$

where $\lambda_{r(\hat{x}) > r}$ = AEP of TC response r due to forcing vector $\hat{x} = f(x_o, \theta, \Delta p, R_{max}, V_t)$; λ = SRR (storms/year/kilometer) at site of interest; $\hat{\lambda}_i$ = probability mass (storms/year) of synthetic storm i ; $P[r(\hat{x}_i) + \varepsilon > r | \hat{x}_i, \varepsilon]$ = conditional probability that storm i with parameters $\hat{x}_i$ generates a

response larger than r ; ε = unbiased error or aleatory uncertainty of the storm response.

In the discrete integral (Equation 1-1b), the probability mass of a given storm ($\hat{\lambda}_i$) is defined as $\hat{\lambda}_i = \lambda p_i$, where p_i is the product of its discrete joint probability and the TC track spacing (in kilometers). Otherwise stated, each storm's probability mass is computed as the product between its SRR, the discrete probability (or weight) determined from the joint probability model of TC parameters, and the TC track spacing.

The SRR is a measure of the annual frequency with which a particular area is expected to be affected by TCs. It typically is expressed in units of storms per year per unit distance along the shoreline (e.g., storms/year/kilometer). The SRR (λ in Equation 1-1a) is the most significant quantity in the JPM integral. The objective of the process of developing univariate distributions (i.e., marginal or conditional) of TC parameters, and subsequently generating a synthetic storm suite, is to discretize the joint probability distribution and compute unique probability masses for the synthetic storms in equation 1-1b. The present study aims to quantify the epistemic uncertainty associated with data, models, and methods for estimating SRR.

1.3.2 Estimation of SRR

For the North Atlantic and Gulf of Mexico basins, the National Oceanic and Atmospheric Administration (NOAA), National Hurricane Center's (NHC) hurricane database (HURDAT) (Jarvinen et al. 1984) has historically served as the principal source of TC track and parameter information used for the computation of the SRR. The current NOAA database is known as HURDAT2 (second generation) (Landsea and Franklin 2013). Several approaches have been developed for determining the SRR from the TC data contained in HURDAT2, with the main ones being the capture zone approach and the Gaussian kernel function (GKF) (Chouinard and Liu 1997). The capture zone approach consists of counting the number of TCs that are either making landfall along an idealized segment of coast line (line-crossing) or passing through a predefined area. The GKF, conversely, considers historical data by assigning weights to the TCs based on the distance to the study site or to a coastal reference location (CRL). The distance-adjusted weights are computed using a Gaussian probability density function (PDF) with user-defined kernel size. Hybrid methods have been used where the capture zone approach is used

to preselect the tracks that will be considered for the SRR calculation using the GKF. Several methods have been proposed for estimating the GKF optimal kernel size. Chouinard and Liu (1997) describe the cross-validated square error and the cross-validated likelihood as examples. In this study, the capture zone approach was considered as a special case of the uniform kernel function (UKF). This facilitates having a consistent framework for comparison between different kernel estimators used to calculate SRR.

1.3.3 Quantification of SRR uncertainty

The primary sources of uncertainty typically associated with SRR estimation methods are the selection of the capture zone size and the selection of the kernel size in the case of kernel functions. The proper selection of these parameters is necessary to balance the statistical uncertainty of a small sampling area and the potential spatial bias caused by an excessively large sampling area that may capture a heterogeneous population of TCs.

Multiple aspects involved in the estimation of SRR were examined to quantify the uncertainty associated with these processes. The study specifically examined the following:

- Uncertainty emerging from the selection of kernel function. The UKF and GKF have been widely used in previous studies for the computation of SRR. Other nonparametric models, such as the Epanechnikov kernel function (EKF), could also be applied for this purpose. Each kernel function (i.e., UKF, GKF, and EKF) will be described, and their respective SRR estimates will be compared as part of this study.
- Uncertainty arising from the selection of kernel function size or bandwidth. The technical literature shows that there is no consensus approach for the selection of kernel size. Since previous JPM studies have used a wide range of values for the kernel size, it is of interest to quantify the uncertainty associated with the selection of specific values for this parameter.
- Uncertainty arising from the selection of historical period of record. Estimation of SRR is sensitive to the number of TCs captured in the historical record. Since the methods of recording TCs have not been homogeneous throughout the time period for which there is formally documented data, the selection of a specific period of record represents a significant source of uncertainty in the computation of SRR.

- Uncertainty associated with TC sampling. From a stochastic perspective, the data recorded in HURDAT2 are fundamentally a single sample out of an infinite number of possible outcomes that constitute the physically plausible TC population. As such, a bootstrapping technique can be used for the estimation of confidence limits and quantification of TC sampling uncertainty.
- Uncertainty arising from observational TC data, as recorded in the HURDAT2 best track dataset. The hurricane information in HURDAT2 is based on measurements and observations, which inherently introduces uncertainty as a result of the accuracy of the methods and instruments used to collect the data. The methods for collecting TC data have evolved significantly over time.
- Uncertainty arising from the partitioning of data by TC intensity. Intense TCs can behave differently than weaker ones; therefore, a comprehensive analysis of uncertainty requires partitioning the historical TC population according to their intensity. It is also important to isolate the very high intensity TCs to determine their SRR and associated uncertainty since these events are critical for the estimation of the range of AEP of interest for nuclear power plants.

In this technical report, uncertainty will be expressed in terms of standard deviation (SD) and coefficients of variation (CV). The CV is the ratio of the SD to the sample mean; it is a normalized measure of the variability of a distribution. These analyses were replicated at different geographical locations along the U.S. Gulf of Mexico and Atlantic coasts, from Galveston, TX, to Boston, MA. One test case or CRL was established outside of continental United States, on the southeastern coast of Puerto Rico. All CRLs considered in this study are shown in Figure 1-1 and listed in Table 1-1. The selection of CRLs sought to provide a representative selection of locations with particular emphasis on the Gulf of Mexico and the North Atlantic coasts. Uncertainty quantification results are only applicable to the specific CRL evaluated in this study. A reanalysis would be required to estimate SRR at new locations.

Figure 1-1. Study coastal reference locations (CRLs).

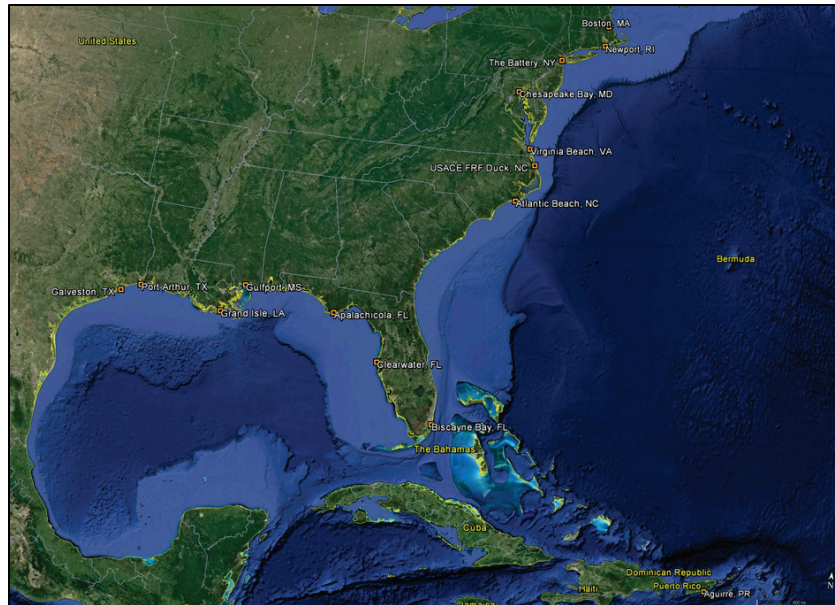


Table 1-1. Coordinates of CRLs used in this study.

CRL	Latitude (deg. N)	Longitude (deg. W)
Gulf of Mexico		
Galveston, TX	29.3324	94.7255
Port Arthur, TX	29.6794	93.8379
Grand Isle, LA	29.1988	90.041
Gulfport, MS	30.3476	89.0868
Apalachicola, FL	29.7239	84.9776
Clearwater, FL	27.9674	82.8316
North Atlantic		
Biscayne Bay, FL	25.6654	80.1581
Atlantic Beach, NC	34.6971	76.7394
Duck, NC	36.1837	75.7452
Virginia Beach, VA	36.8502	75.9723
Chesapeake Bay, MD	39.2147	76.5192
The Battery, NY	40.7001	74.0143
Newport, RI	41.4523	71.3266
Boston, MA	42.3445	70.9535
OCONUS		
Aguirre, PR	17.9477	66.2264

2 Tropical Cyclone (TC) Data Sources and Uncertainties

The computation of SRR at a given CRL requires historical TC data or synthetic TC data that adequately reproduce the historical occurrence and trends (i.e., frequencies and intensities) of TCs at the locations of interest. In the JPM methodology, the main TC parameters used in the analysis of SRR are the reference location (x_0) and central pressure deficit, Δp . The latter is used as a proxy for intensity for screening and partitioning TCs when specific SRR estimates are sought for different ranges of TC intensity. In the JPM, Δp has typically been computed as the difference between an assumed far-field atmospheric pressure of 1,013 hectopascals (hPa) and the minimum pressure measured at the center of the TC, and this definition has been adopted herein. Location is typically recorded in the form of latitude and longitude at specific time intervals over the duration of the event (e.g., 6 hours [hr]).

2.1 Hurricane data sources

The HURDAT2 format constitutes the official U.S. record for tropical and subtropical cyclones that have been observed within the Atlantic Ocean and Eastern Pacific Ocean. The Atlantic HURDAT2 specifically covers the North Atlantic Ocean, the Gulf of Mexico, and the Caribbean Sea, and goes back to 1851. The Eastern Pacific HURDAT2 currently covers the time period from 1949 to present; it is maintained and updated by the NHC over the region that extends from 140°W to the west coast of North and Central America, and by the Central Pacific Hurricane Center, which oversees the region extending from 140° to 180°W. HURDAT2 includes historical TC data, quality controlled through yearly post-season analyses of recent events, as well as reanalyses of past hurricane seasons that are performed to correct biases and random errors in the historical data (Landsea et al. 2004). The results of those analyses are called the *best tracks*, and each best track represents a subjectively smoothed representation of a TC's history (Landsea and Franklin 2013).

The original HURDAT (Jarvinen et al. 1984) was created per request of the NASA space program to provide tracks and forecasts of TCs. Prior to 1944, the principal sources of data were land stations and ship reports. The amount of data in the period from 1851 to the early 1940s was limited by the coincidental encounters between ships and weather

systems, and the quality of the data was affected by the limitations of the instrumentation. Storm positions were only recorded once or twice a day, making it necessary to interpolate intermediate positions. Even though wind speeds were recorded for each position, changes to the instrumentation, as well as height and location inconsistencies, introduced inaccuracies to the data set (Jarvinen et al. 1984). After 1944, when aircraft reconnaissance was initiated, an increase in available track information and pressure data over the ocean was observed. Weather satellites were introduced during the 1960s and were considered one of the major advances to TC tracking (Jarvinen et al. 1984). The combined use of satellites and aircraft reconnaissance resulted in great improvements to the consistency and quality of the HURDAT database. Differences in the frequency, instrumentation, and methods of data measurement and analysis, throughout the history of storm tracking, introduced errors and systematic biases to the database, which are the focus of the reanalyses periodically performed by NHC.

These reanalyses are performed according to the most recent analysis techniques by gathering all available meteorological data and are based on current understanding of TCs (Delgado 2014). Because of the extent of the database, the reanalysis project has been divided in various eras. The entire process has been completed for the period of 1851–1963 (Landsea et al. 2004, 2008, 2012, 2014; Hagen et al. 2012; Delgado et al. 2018). New reanalyses are submitted to the NHC Best Track Change Committee for approval and then incorporated into the HURDAT2 database.

The best track data in HURDAT2 include the maximum sustained surface winds in knots, the central pressure in millibars, location (latitude and longitude), and wind radii in nautical miles. The precision for these parameters is 5 knots, 1 millibar, 0.1° latitude/longitude, and 5 nautical miles, respectively, for each of the aforementioned categories (Landsea et al. 2013). Best track maximum sustained surface winds and position data are provided at 6 hr intervals (synoptic times), starting at 0000 hr, for cyclones recorded after 1956. Best track central pressure values are provided at the same time interval starting in 1979 while the recording of wind radii data starts in 2004.

2.2 Uncertainty associated with data sources

The uncertainty associated with HURDAT2 data (e.g., measurements and other observations) has long been recognized in the technical literature,

and efforts have been made towards its quantification. Uncertainties associated with the recorded TC parameters have been provided as part of the reanalysis projects for different eras (Landsea et al. 2014). Additional efforts can be attributed to separate independent efforts by Torn and Snyder (2012) and Landsea and Franklin (2013).

Torn and Snyder (2012) estimated the uncertainty for position and intensity of TCs for the period of 2000 to 2009. They first verified the satellite observations using reconnaissance data and then derived new estimates by comparing the ones provided by the NHC against the verified dataset. In a separate work, Landsea and Franklin (2013) estimated the best track uncertainties associated with each parameter (intensity, central pressure, position, and size) for the same period of record of 2000 to 2009. The intensity refers to wind speed and the position refers to the latitude and longitude of the center of closed circulation or center of the area of minimum central pressure. The study consisted of surveying 11 NHC hurricane specialists on their estimates of best track parameter uncertainties based on their individual experience and expertise. Uncertainty estimates were provided for three different sources: (1) satellite-only; (2) satellite and aircraft; and (3) U.S. landfalling TCs. Although the estimates were quantitative, these reflected the subjective interpretation of each of the participants. The results are shown in Table 2-1. The uncertainty estimates for intensity from Torn and Snyder (2012) and Landsea and Franklin (2013) were similar while the position uncertainty estimates for the former were larger. The mean uncertainty estimates reported in Table 2-1 were incorporated into the SRR analysis in Chapter 6 through a bootstrapping procedure to quantify the uncertainties produced in the SRR calculations. In addition to the mean value of each observed TC parameter, Table 2-1 provides the range of estimated values given by the participants for each of the parameters. The study showed the effect of type of data source on parameter uncertainty and interdependence. For example, TC position uncertainty decreased with aircraft reconnaissance and landfall over satellite-only monitoring. Also, an increase in TC intensity decreases the uncertainty of its position as the eye tends to be better defined.

Table 2-1. Average best track uncertainty estimates as provided by the NHC hurricane specialists in 2010. Ranges of the responses are given in parentheses (adapted from Landsea and Frankling [2013]).

Data Type	Tropical Storms	Category 1 and 2 Hurricanes	Major Hurricanes
Satellite Only			
Intensity (km/hr)	21.3 (17.6–27.8)	20.9 (18.5–27.8)	25 (13.9–33.3)
Central pressure (hPa)	5.8 (3–10)	7.7 (5–10)	9.5 (5–15)
Position (km)	63.9 (46.3–83.3)	43 (27.8–74.1)	22.8 (9.26–37)
Gale (63 km/hr) radii (km)	70.4 (37–111.1)	73 (46.3–111.1)	73.7 (46.3–111.1)
Storm (92.6 km/hr) radii (km)	51.3 (27.8–92.6)	56.5 (37–92.6)	59.8 (37–92.6)
Hurricane (118.5 km/hr) radii (km)	—	41.7 (13.9–92.6)	45.2 (13.9–92.6)
Satellite and Aircraft			
Intensity (km/hr)	15.2 (9.26–18.5)	16.85 (9.26–18.5)	19.6 (9.26–27.8)
Central pressure (hPa)	3.0 (2–5)	3.5 (2–8)	3.9 (2–10)
Position (km)	40.7 (23.15–64.8)	27.6 (13.9–46.3)	20.7 (9.26–37)
Gale (63 km/hr) radii (km)	54.6 (27.8–83.3)	54.6 (27.8–83.3)	54.6 (10–45)
Storm (92.6 km/hr) radii (km)	39.1 (18.5–74.1)	43.3 (27.8–74.1)	23.9 (10–40)
Hurricane (118.5 km/hr) radii (km)	—	29.4 (13.89–55.6)	32 (9.26–27.8)
U.S. Landfalls			
Intensity (km/hr)	15 (9.26–18.5)	15.9 (9.26–18.5)	18.1 (9.26–27.8)
Central pressure (hPa)	2.8 (2–5)	3.5 (1.5–8)	3.6 (1.5–10)
Position (km)	33.3 (18.5–64.8)	22.2 (9.26–46.3)	14.4 (9.26–27.8)
Gale (63 km/hr) radii (km)	44.6 (18.5–74.1)	44.1 (18.5–55.6)	45.4 (18.5–55.6)
Storm (92.6 km/hr) radii (km)	30.74 (18.5–55.6)	35.7 (18.5–55.6)	35.4 (18.5–55.6)
Hurricane (118.5 km/hr) radii (km)	—	23.9 (9.26–46.3)	24.8 (9.26–55.6)

2.3 Validity of the Poisson distribution assumption

Occurrence of TCs within the North Atlantic basin is often described as a Poisson process (e.g., Chouinard and Liu 1997; Elsner et al. 2001; Sommer 2003). The Poisson distribution is defined by the parameter λ , which is the recurrence rate of the TCs:

$$(2-1)$$

where X is a random variable representing number of TCs in a year; λ (lambda) is the rate of TCs per year at a CRL; and $P(X=x)$ is the probability that x number of TCs occur in a year given λ .

The validity of the Poisson assumption was tested at each of the 15 CRLs. The number of TC occurrences within a distance of 200 kilometers (km) and 400 km from each CRL were identified using a capture zone approach and fit with the Poisson distribution. A chi-square goodness of fit test was performed to test whether the TC count data follow a Poisson distribution. The Poisson distribution's lambda parameters and the results of chi-square goodness-of-fit tests at each CRL are presented in Table 2-2. The null hypothesis for the test is that the count data come from a historical TC population with a Poisson distribution. A test decision equal to zero indicates that the null hypothesis is not rejected at the selected 5% level of significance. For TC occurrences within 200 km of the CRLs, Table 2.2 shows that the null hypothesis is not rejected. Nevertheless, the chi-square goodness-of-fit test rejects the hypothesis for the four CRLs from Biscayne Bay, FL, to Virginia Beach, VA, when considering a distance of 400 km.

Table 2-2. Poisson distribution fit lambda parameter and chi-square goodness-of-fit results for TC counts at 200 and 400 km from the CRLs.

CRL	Lambda (storms/yr)		Chi-Square Goodness-of-Fit			
	200 km	400 km	200 km		400 km	
			Test Decision	p-value	Test Decision	p-value
Galveston, TX	0.78	1.45	0	0.397	0	0.890
Port Arthur, TX	0.79	1.49	0	0.304	0	0.825
Grand Isle, LA	1.00	1.99	0	0.210	0	0.695
Gulfport, MS	0.92	1.72	0	0.370	0	0.156
Apalachicola, FL	0.93	2.07	0	0.270	0	0.734
Clearwater, FL	1.00	2.38	0	0.964	0	0.142
Biscayne Bay, FL	1.00	2.13	0	0.057	1	0.039
Atlantic Beach, NC	1.41	2.42	0	0.156	1	0.028
Duck, NC	1.28	2.28	0	0.527	1	0.008
Virginia Beach, VA	1.08	2.13	0	0.707	1	0.006

CRL	Lambda (storms/yr)		Chi-Square Goodness-of-Fit			
	200 km	400 km	200 km		400 km	
			Test Decision	p-value	Test Decision	p-value
Chesapeake Bay, MD	0.43	1.34	0	0.827	0	0.417
The Battery, NY	0.43	1.17	0	0.827	0	0.191
Newport, RI	0.62	1.36	0	0.747	0	0.213
Boston, MA	0.53	1.17	0	0.230	0	0.474
Aguirre, PR	0.67	1.67	0	0.216	0	0.080

3 Uncertainty Due to Gaussian Kernel Size

The SRR has been calculated in several post-Katrina JPM studies using either using a capture zone approach (e.g., uniform kernel function [UKF]) or a Gaussian kernel function (GKF) model. Both approaches include the selection of parameters related to the establishment of an area of influence that represents relevant historical TC activity for a specific location. The selection of the size of this area of influence can be subjective in nature. The mathematical basis for these approaches relates to the kernel estimators used in density estimation, adapted for the development of intensity functions that describe the occurrence of storms. This chapter presents computational experiments performed to evaluate adequate distance ranges used for the estimation of SRR using the capture zone approach and the GKF, including the selection of Gaussian kernel size to quantify the associated SRR uncertainty. The application of the Epanechnikov kernel function (EKF) is also evaluated for SRR estimation. These experiments focused on TCs with $\Delta p \geq 28$ hPa, which are expected to be classified, on average, as category 1 hurricanes based on the Saffir-Simpson hurricane wind scale.

3.1 Estimation of SRR by uniform kernel function (UKF) approach

Capture zone approaches for defining the SRR of TCs include line-crossing and area-crossing methods. In the line-crossing method, the coastline is smoothed, and all TCs that make landfall are counted. All line-crossing storms are given uniform weight while all other storms are given a weight of zero since they are not considered. The number of storms is divided by the length of the line to calculate the rate. Note that the line-crossing approach can lead to underestimation of TC hazard because it excludes bypassing (alongshore) tracks. Capture zones can also be defined in other ways, such as a rectangular or circular window, or any other finite spatial region.

Resio et al. (2007) noted that capture zone approaches may be prone to sample size and heterogeneous population errors at the moment of defining the capture zone. The capture zone must be large enough to sample a sufficient number of TCs to allow the computation of robust storm recurrence statistics (sample size error) but small enough to minimize the chance of selecting TCs that belong to more than one population (population error). A significant shortcoming of the capture

zone approach is that all sampled TCs (included in the capture zone) are assigned the same weight, regardless of distance, while TCs outside of the capture zone are given a weight of zero. Therefore, the resulting SRR can be highly sensitive to the often-subjective process of establishing spatial limits of the capture zone.

3.1.1 UKF methodology

The capture zone approach adopted in this study consisted in estimating the SRR using circular capture zones with radii ranging from 10 km to 1,000 km at 10 km intervals. SRRs were calculated for each radius applying a UKF as follows:

$$\lambda = \frac{1}{T} \sum_i^n w(d_i) \quad (3-1)$$

$$w(d_i) = \frac{1}{h_d} \begin{cases} 0.5, & \text{if } \left| \frac{d_i}{h_d} \right| < 1 \\ 0, & \text{otherwise} \end{cases} \quad (3-2)$$

where λ = the SRR in storms/year/kilometer; T = record length (year); $w(d_i)$ = uniform weight (storms/kilometer); d_i = distance from location of interest to a storm data point (kilometer); h_d = optimal kernel size (kilometer).

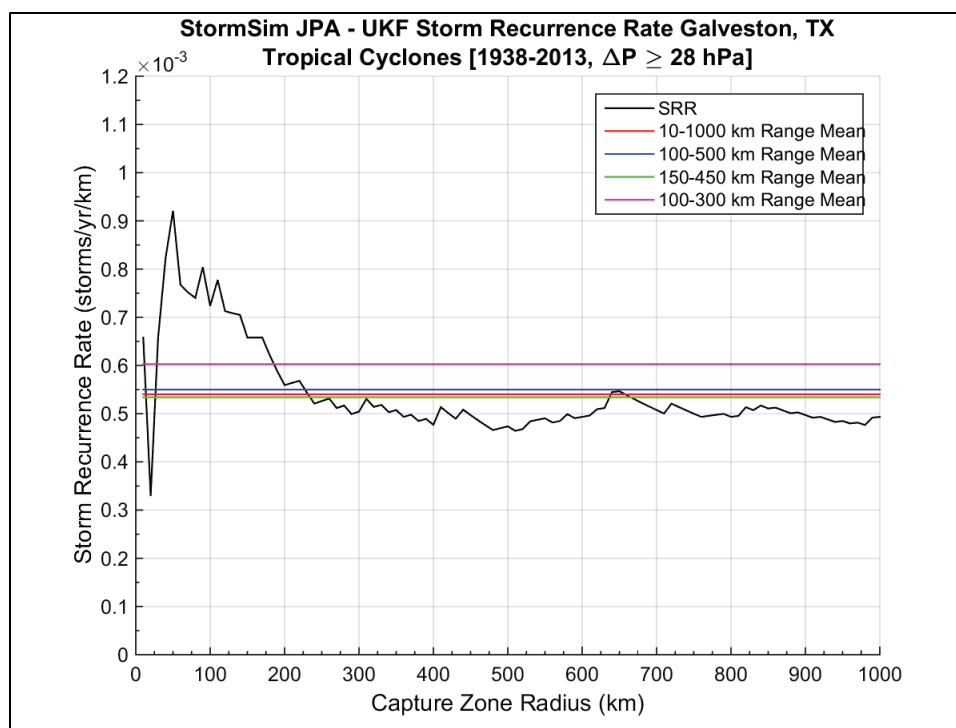
The optimal kernel size h_d is analogous to the capture zone extents, in particular the radius. The 0.5 weight reflects the consideration of hurricanes within a circle of diameter $2 \cdot h_d$ and center at the CRL.

3.1.2 UKF analysis results

A sensitivity analysis of the mean UKF SRR calculated over various kernel size ranges was performed. The mean SRR was computed for the full 10–1,000 km range, as well as 100–300 km, 100–500 km, and 150–450 km ranges. The latter three are meant to represent smaller ranges where the optimal kernel size would be expected to occur in order to achieve balance between TC sample size and statistical homogeneity. Figures 3-1 through 3-3 show the plotting of the SRR for the full range of evaluated capture zone sizes. The mean UKF SRR for each evaluated range is also plotted. The

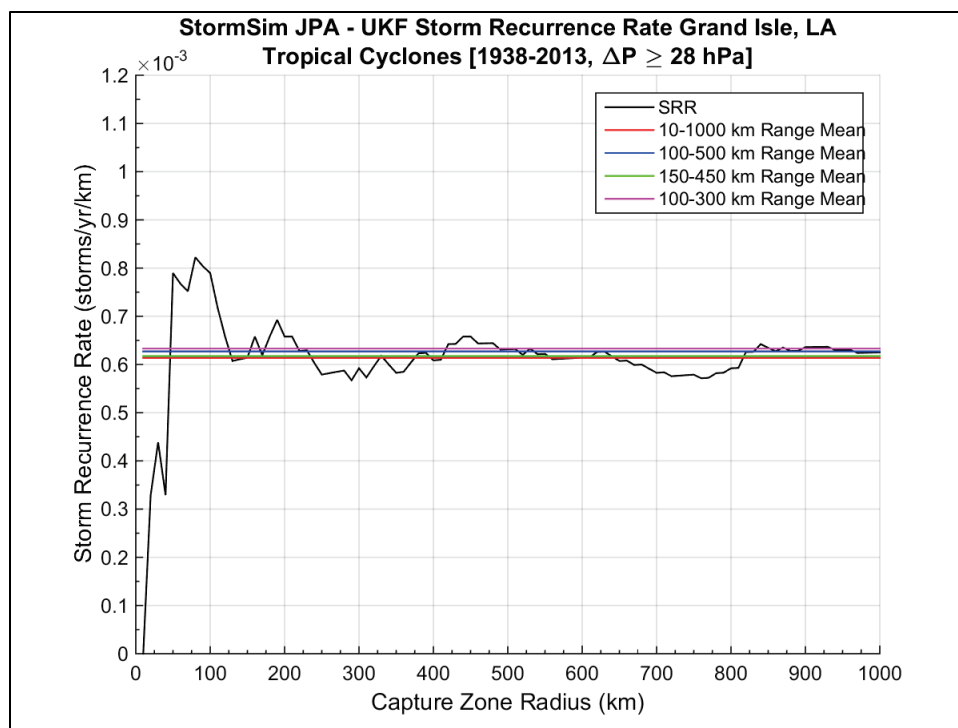
SDs of the UKF SRR for each range were also computed and are presented in Table 3-1 along with the mean SRR values.

Figure 3-1. SRR using UKF approach for Galveston, TX.



The evaluated UKF SRR, as seen in the adjacent figures, is sensitive to kernel size and demonstrates some volatility. Figure 3-1 shows the effect of the occurrence of historical TCs near Galveston, TX, on the SRR. A 50 km capture zone radius would result in an SRR of $9.2\text{E-}4$ while a capture zone of 200 km would result in an SRR of $5.59\text{E-}4$. The SRR for Grand Isle, LA, in Figure 3-2 shows the same general pattern but with a smaller difference in the SRR at 50 km and 200 km.

Figure 3-2. SRR using UKF approach for Grand Isle, LA.



In contrast, in Figure 3-3, The Battery, NY, location shows lower SRR within the first 100 km followed by some increased TC activity in the 100 to 150 km range. After 300 km, a steady increase in SRR can be observed as the kernel size increases and accounts for the effects of bypassing TCs farther away. This sensitivity to the capture zone radius can also be observed in the variability in the mean UKF SRR for the various evaluated ranges. Although at some CRLs these means may coincide, such as those shown in Figure 3-2, at others, as seen in Figure 3-3 and Table 3-1, the means may vary significantly. The mean UKF SRR considering the full range at The Battery, NY, is 4.33E-04 but only 3.04E-04 for the 100 to 300 km range.

Figure 3-3. SRR using UKF approach for The Battery, NY.

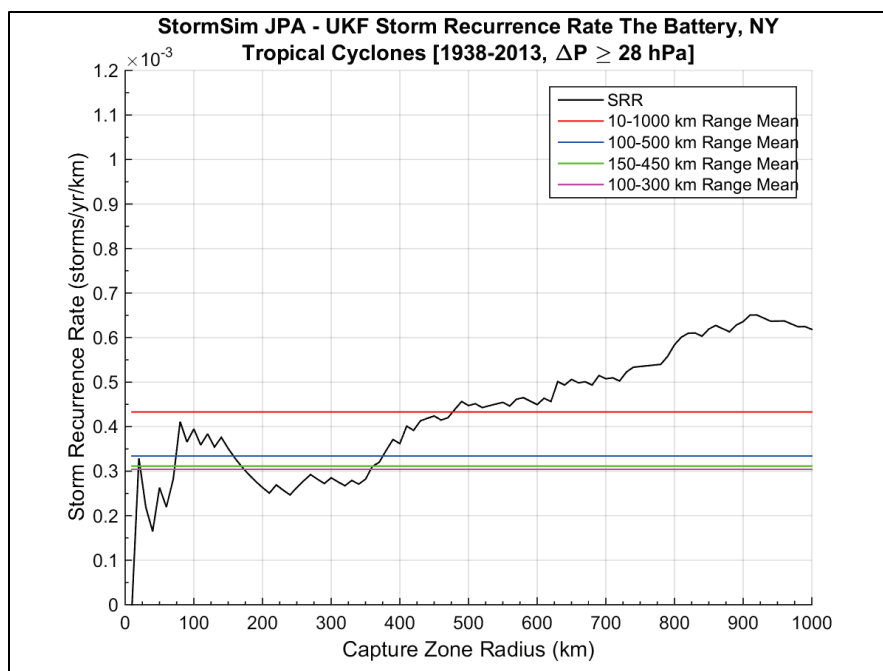


Table 3-1. UKF SRR mean and SD for different ranges of capture zone radii.

CRL	SRR (storms/yr/km)							
	All Ranges		100–300 km		100–500 km		150–450 km	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Galveston, TX	5.40E-04	6.03E-04	6.03E-04	8.67E-05	5.50E-04	8.30E-05	5.34E-04	5.20E-05
Port Arthur, TX	5.34E-04	5.80E-04	5.80E-04	3.49E-05	5.54E-04	4.09E-05	5.54E-04	3.80E-05
Grand Isle, LA	6.14E-04	6.33E-04	6.33E-04	5.33E-05	6.27E-04	4.20E-05	6.17E-04	3.19E-05
Gulfport, MS	5.66E-04	5.80E-04	5.80E-04	3.89E-05	5.67E-04	3.25E-05	5.73E-04	3.32E-05
Apalachicola, FL	6.03E-04	4.91E-04	4.91E-04	3.56E-05	5.46E-04	6.88E-05	5.48E-04	5.89E-05
Clearwater, FL	6.78E-04	5.84E-04	5.84E-04	4.85E-05	6.41E-04	7.32E-05	6.33E-04	7.18E-05
Biscayne Bay, FL	7.54E-04	6.84E-04	6.84E-04	3.98E-05	6.96E-04	3.41E-05	6.86E-04	2.77E-05
Atlantic Beach, NC	7.61E-04	8.85E-04	8.85E-04	9.32E-05	7.99E-04	1.14E-04	7.90E-04	1.19E-04
Duck, NC	6.52E-04	6.28E-04	6.28E-04	1.29E-04	6.84E-04	1.10E-04	7.20E-04	4.85E-05
Virginia Beach, VA	5.86E-04	4.36E-04	4.36E-04	1.72E-04	5.61E-04	1.80E-04	6.04E-04	1.29E-04
Chesapeake Bay, MD	3.83E-04	1.38E-04	1.38E-04	3.96E-05	2.42E-04	1.20E-04	2.31E-04	9.70E-05
The Battery, NY	4.33E-04	3.04E-04	3.04E-04	4.72E-05	3.34E-04	6.44E-05	3.11E-04	5.43E-05
Newport, RI	4.94E-04	3.52E-04	3.52E-04	6.56E-05	4.07E-04	8.25E-05	4.13E-04	6.41E-05
Boston, MA	4.06E-04	2.50E-04	2.50E-04	5.32E-05	3.25E-04	8.98E-05	3.30E-04	7.16E-05
Aguirre, PR	4.18E-04	2.95E-04	2.95E-04	1.08E-04	3.63E-04	1.05E-04	3.86E-04	5.97E-05

Based on the results for all CRLs, it is estimated that a range of 150 to 450 km represents a credible range for UKF kernel size since it resulted in more favorable uncertainties in terms of the standard deviation. Further examination of additional kernel size ranges and CRLs with 30 km spacing along the U.S. coast from the Gulf to the North Atlantic confirmed that compared to other evaluated ranges, the 150 km to 450 km range produced on average smaller uncertainties in terms of standard deviation. These results are included in Appendix A.

3.2 Gaussian kernel function (GKF)

The use of the GKF methodology for determining TC SRR, developed by Chouinard and Liu (1997) and Chouinard et al. (1997), can overcome the main limitations of the UKF approach. The standard application of the GKF consists in using a kernel estimator for describing the intensity function of hurricanes based on TC direction and distance from a CLR, or only on distance from a CRL (omnidirectional approach). The GKF methodology includes establishing a grid of nodes where estimates of the SRR are sought to develop a map of spatially varying SRR. All TCs within this gridded space can be counted at any given node, but the weight assigned to each TC decreases with increasing distance from TC to node. The distance-adjusted weights are computed using a Gaussian PDF with an optimal kernel size.

The omnidirectional SRR is calculated using equation 3-1 and the GKF equation:

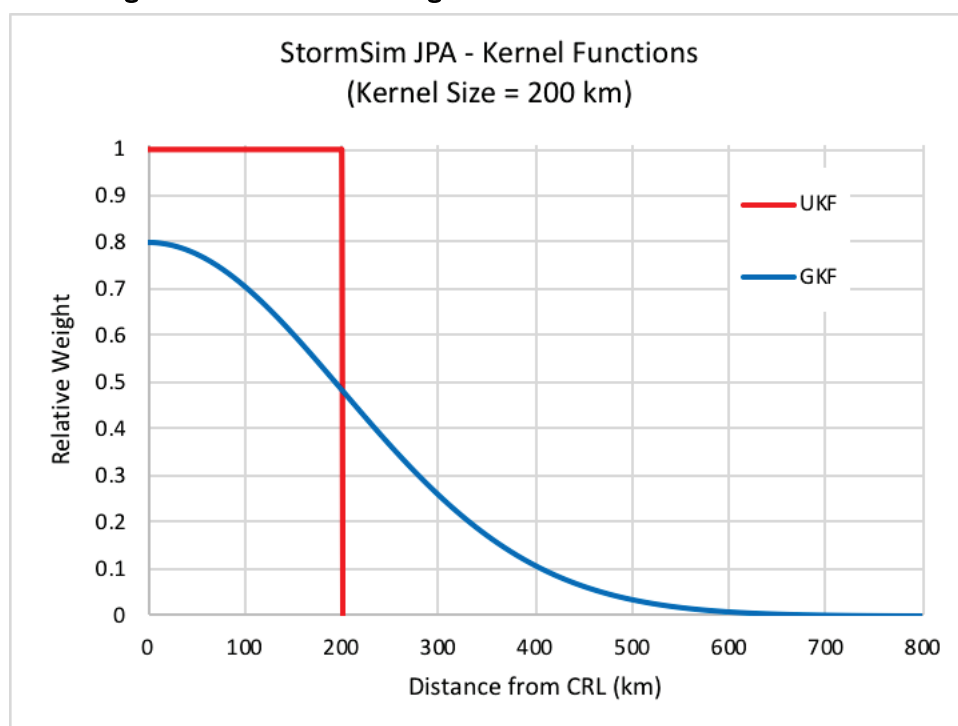
$$w(d_i) = \frac{1}{\sqrt{2\pi}h_d} \exp\left[-\frac{1}{2}\left(\frac{d_i}{h_d}\right)^2\right] \quad (3-3)$$

where $w(d_i)$ = distance-adjusted weights from the Gaussian PDF (storms/kilometer); d_i = distance from location of interest to a storm data point (kilometer); h_d = optimal kernel size (kilometer).

To illustrate the difference between the UKF approach and the GKF, the weights computed using the GKF with a kernel size of 200 km were compared to the weights of a 200 km UKF kernel size. Figure 3-4 shows UKF and GKF weights relative to the UKF weight of a TC track point located on the CRL (distance = 0 km); a storm track passing through the CRL has a relative weight of 1. This figure illustrates the point previously

discussed about the capture zone approach where all storms are assigned a weight of 1 if located within the capture zone radius and zero if located outside. It is also seen how the statistical model of the GKF SRR applies small weights to TCs that are much farther away than 200 km.

Figure 3-4. UKF and GKF weights as a function of distance from CRL.



3.2.1 GKF methodology

The sensitivity of SRR to changes in Gaussian kernel size was evaluated in a manner analogous to the capture zone (UKF) SRR. The GKF SRRs were calculated at all CRLs using the GKF equation by varying the kernel size from 10 km to 1000 km at 10 km intervals. The mean SRR was computed for the full 10 km to 1000 km range and for 100–300 km, 100–500 km, and 150–450 km ranges. Results were compared by plotting the calculated SRR curves with the observed curves.

Part of the objective of this analysis was also to determine a kernel size or bandwidth that can be applied uniformly in other experiments that examined additional aspects of the SRR uncertainty. There have been several proposed approaches that seek to achieve an objective selection process for determining the kernel size in the quantification of SRR:

- Chouinard and Liu (1997) cross-validated squared error (CVSE), resulting from least-squares cross validation (LSCV) method
- Chouinard and Liu (1997) cross-validated likelihood (CVL), resulting from the likelihood cross-validation (LCV) method
- Mississippi Coastal Analysis Project (FEMA 2008; Toro 2008) two-fold LSCV
- North Atlantic Coast Comprehensive Study (NACCS)(Nadal-Caraballo et al. 2015) SRR sensitivity analysis.

Three approaches were evaluated for the selection of GKF size for SRR uncertainty experiments. The first applied a leave-one-out LSCV similar to the Chouinard and Liu (1997) approach. The second method also applied LSCV but the data were partitioned into an estimation sample and a validation sampled, similar to the approach used in the Mississippi Coastal Analysis Project. Results for these two methods are presented in Appendix B. The third approach followed Nadal-Caraballo et al. (2015) and consisted of a sensitivity analysis of SRR based on the minimization of the squared error. A more detailed description of methods for optimizing kernel size for the computation of SRR and additional results is provided in Appendix C.

WHERE IS Likelihood Cross-Validation?

3.2.1.1 Leave-one-out LSCV method

The LSCV searches for a kernel size that balances the trade-off between statistical uncertainty and spatial bias in data (Silverman 1986). Consider a probability density function f and its estimator as $\hat{f}$. For a fixed bandwidth, the kernel estimator $\hat{f}$ is applied to yield a density estimate at each point in the data sample by excluding one of the data points. This process is referred as the leave-one-out method. The error is evaluated through the score

$$M_0(h) = \int \hat{f}^2(x)dx - 2n^{-1} \sum_i \hat{f}_{-i}(X_i) \quad (3-4)$$

where $\hat{f}_{-i}$ = the kernel estimator without one sample data point; h = the bandwidth; x = observations; X_i = observation that is left out; and n =sample size.

The score is evaluated for multiple bandwidths until a minimum error is achieved. This optimization procedure, therefore, yields a bandwidth value that balances the smoothing effect of the kernel estimator. A more detailed

description of LSCV is provided in Appendix C. This concept of the LSCV applies to the case of kernel intensity estimation, as is presented in Chouinard and Liu (1997). The LSCV method was applied to the study's CRLs using equation 3-4. The resulting kernel sizes that minimized the squared error ranged from 60 km to 130 km with a mean kernel size of 95 km. These values are below the typical values that have been used in previous JPM studies. The resulting kernel sizes and cross validated square error (CVSE) graphs are included in Appendix B.

3.2.1.2 Two-fold LSCV method

Toro (2008) and FEMA (2012) proposed a modified version of the Chouinard and Liu (1997) LSCV approach using two-fold cross validation to determine an optimal kernel size. In this approach, the data are partitioned in an estimation and validation sample, assigning each storm to a sample using a probability $p=0.90$ for the former and $p=0.10$ for the latter. The rate for the validation sample is determined using a UKF with a kernel sizes or bandwidth of 40 km. A modified version of this approach was tested. Bandwidth values of 40, 100, and 200 km were tested for the UKF validation sample. The CVSE graphs for 40 km for most CRLs did not produce local minimums. The lowest CVSE for most CRLs occurred to the left of the 50 km x -axis limit and continually increased past the graph's 500 km right-hand limit. The CVSE graphs for 100 km validation bandwidth showed better defined minimums compared to the 40 km graphs while the 200 km graphs showed more defined minimums than the 100 km graphs. These graphs are shown in Appendix B. This showed the sensitivity of the optimal kernel size to the selection of the UKF bandwidth for the validation sample. The choice of validation sample bandwidth introduces some subjectivity into the process of determining the optimal kernel size.

3.2.1.3 SRR sensitivity analysis

An alternate method was adopted herein to evaluate the stability of GKF by plotting the squared error of the calculated SRR with respect to the mean UKF SRR and determining the Gaussian kernel size for which this squared error is minimized. The squared error was calculated as the square of the difference between the SRR corresponding to each kernel size from 10 to 1000 km and the mean UKF SRR for the evaluated range. This eliminates the need for having to select a particular kernel size for a validation sample. In this case, the GKF kernel sizes are validated against a

baseline consisting of the mean UKF SRR for a particular range. In section 3.1 it was established that the UKF SRR range of 150–450 km yielded lower uncertainties than other ranges. The calculation of squared error was repeated using the mean UKF SRR for 100–300 km, 100–500 km, and 150–450 km ranges to evaluate sensitivity of the squared error to UKF kernel size range. The selection of a kernel size of application to all CRLs was based on an evaluation of these results and informed by previous JPM study estimates.

3.2.1.4 Additional comparisons of kernel size optimization techniques

In addition to the three methods evaluated for kernel size selection, other cross validation and plug-in approaches for the estimation of the GKF kernel size were documented and compared. The assessment included the variability of the kernel size due to each method's characteristics and sensitivity analyses of the GKF SRR due to data partitioning. Results for these analyses are presented for the U.S. East coast and Gulf of Mexico, and included consideration of spatial variability. This assessment is presented in Appendix C.

3.2.2 GKF analysis results

The SRR using the GKF was calculated by varying the Gaussian kernel size as previously described. Figure 3-5 shows the plot of SRR for all CRLs as a function of Gaussian kernel size. The curves at many CRLs seem to converge towards an SRR limit as the kernel size increases. Nevertheless, the SRR for the northernmost CRLs continues to increase over the range of evaluated kernel sizes. Given the reduced frequency of storms at these latitudes, the SRR increases at the larger kernel sizes are influenced by the inclusion of bypassing storms and particularly a large number of storms passing south of them. These results were subsequently compared with the variation of the UKF SRR with capture zone radius, as shown in Figures 3-6 to 3-8 for Galveston, TX, Grand Isle, LA, and The Battery, NY. The first thing that stands out in these figures is the smoothing effect of the GKF, which results in attenuated SRR at locations where the UKF SRR exhibits sharp peaks. Another effect of the application of the GKF, which can be observed in Figure 3-8 for The Battery, NY, is the increase in SRR over UKF SRR as a result of the GKF method considering storms that are farther away. This relates to the weight assignment described in Figure 3-4.

Figure 3-5. Plot of SRR versus Gaussian kernel size for all CRLs.

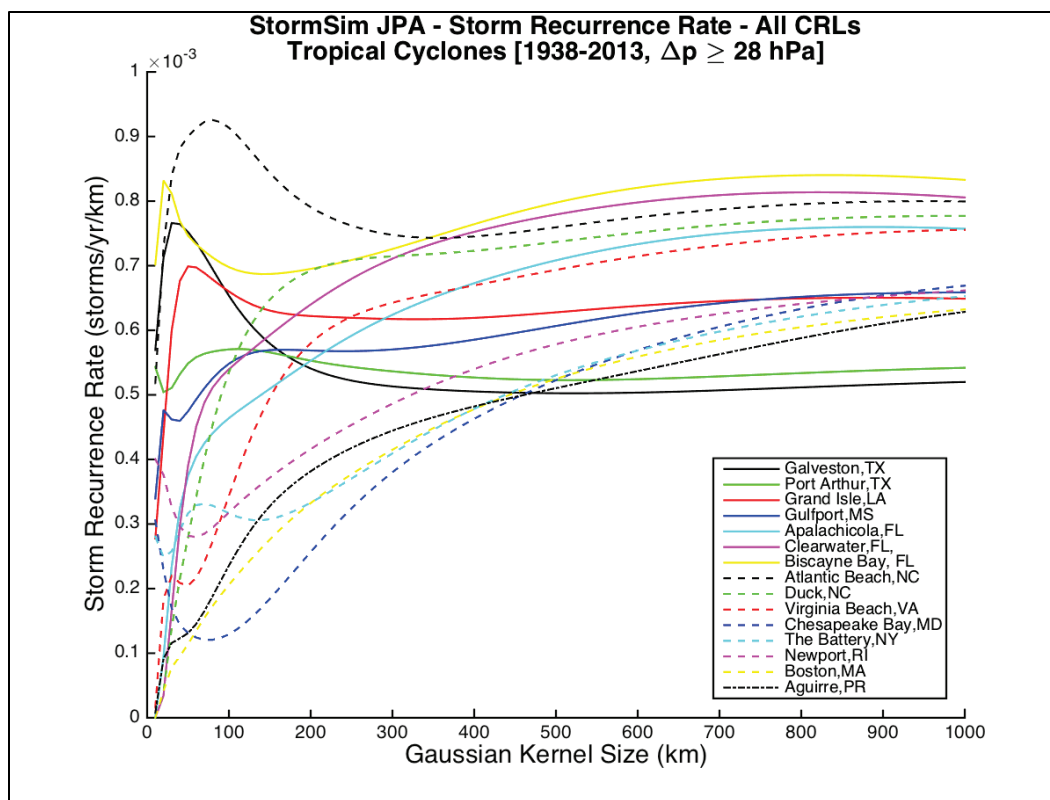


Figure 3-6. Comparison of UKF and GKF SRR at Galveston, TX.

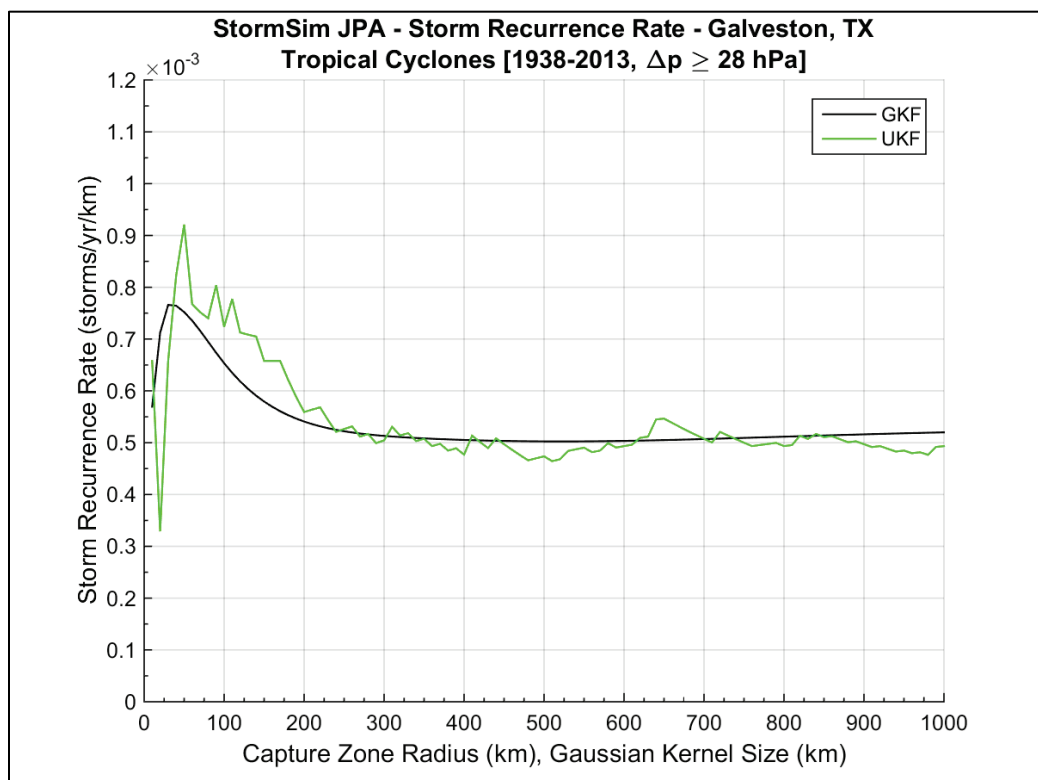


Figure 3-7. Comparison of UKF and GKF SRR at Grand Isle, LA.

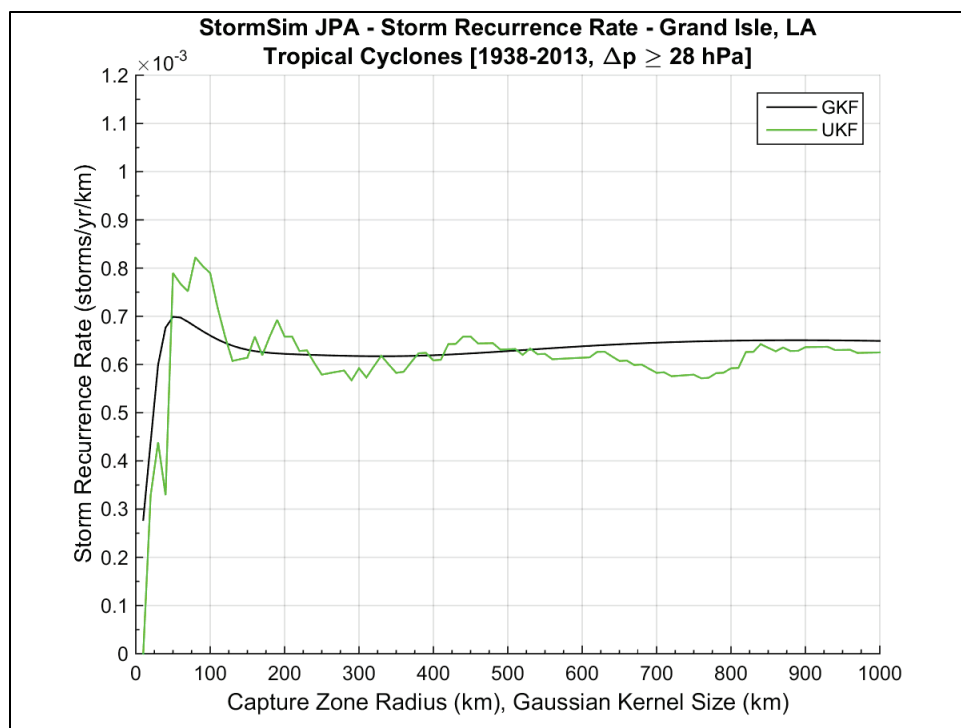
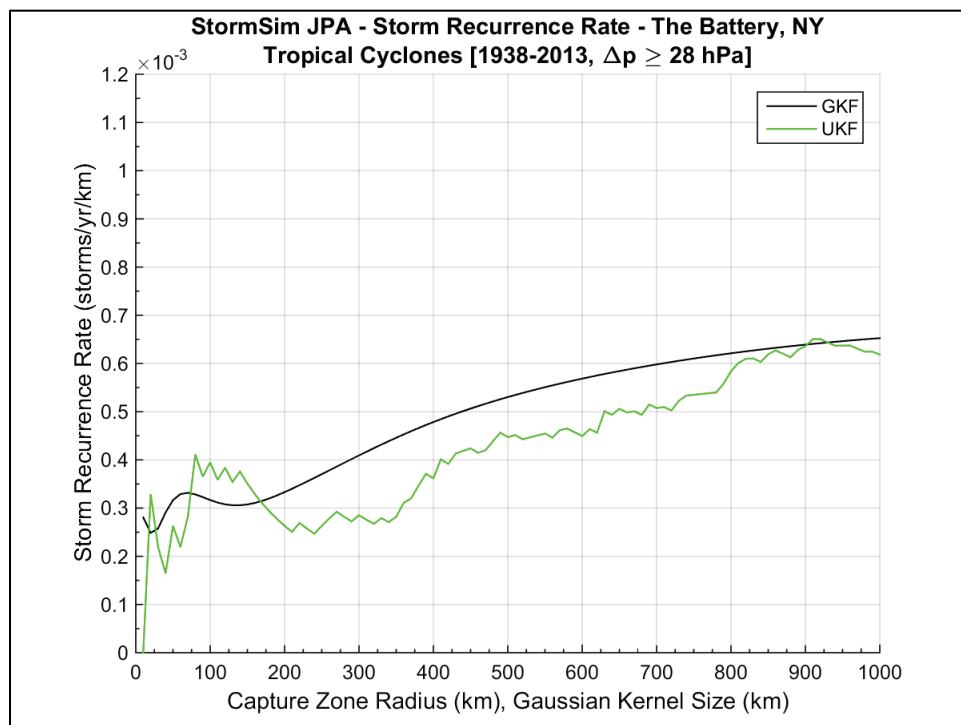


Figure 3-8. Comparison of UKF and GKF SRR at The Battery, NY.



The mean SRR was computed for the full 10 km–1000 km range and for 100–500 km, 150–450 km, and 100–300 km ranges. These means are

shown in Figures 3-9 through 3-11. It can be seen that similar to the UKF SRR, the range of mean SRR values for the ranges of evaluated Gaussian kernel sizes is small for Galveston, TX, and Grand Isle, LA, but larger for The Battery, NY. The mean SRR for the latter varies from $3.5\text{E-}4$ for the 100–300 km range to $4.98\text{E-}4$ for the full range of evaluated Gaussian kernel sizes. The means for the remaining CRLs are included in Table 3-2 along with their respective SDs. A comparison of these values with the results from Table 3-1 shows the mean GKF SRR values for the 100–300 km range are the closest to the UKF SRR results corresponding to the range of 100–500 km.

Figure 3-9. SRR versus Gaussian kernel size at Galveston, TX.

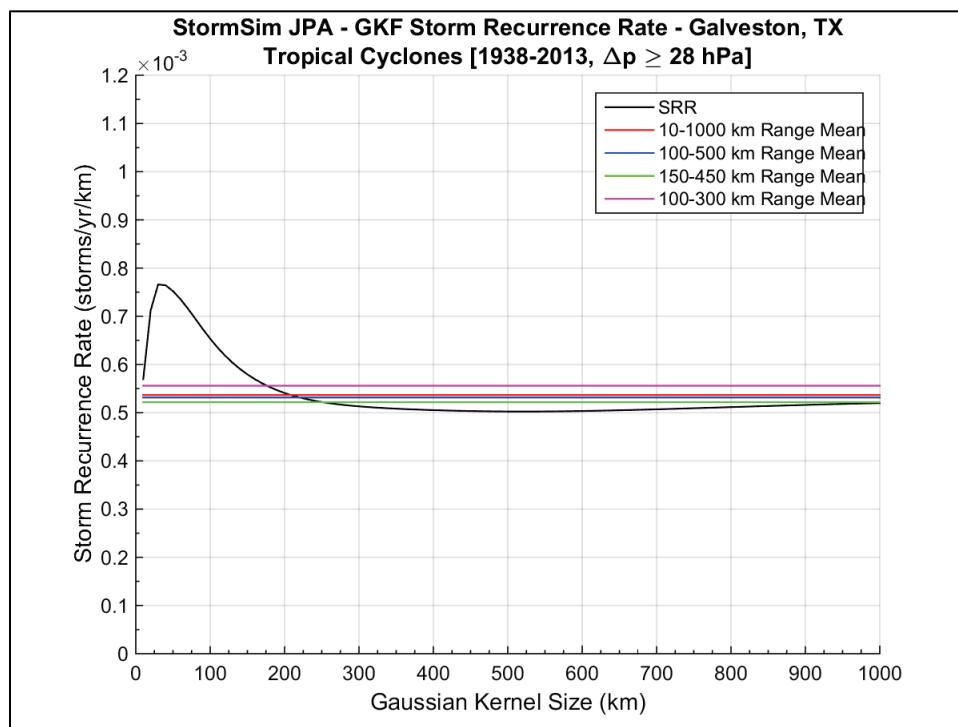


Figure 3-10. SRR versus Gaussian kernel size at Grand Isle, LA.

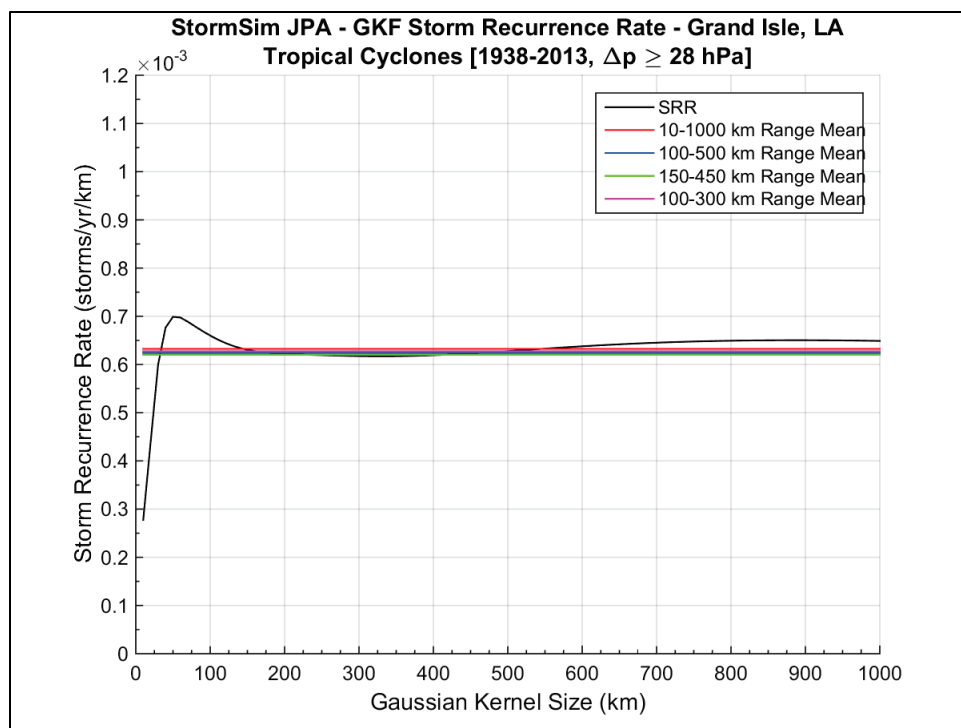


Figure 3-11. SRR versus Gaussian kernel size at The Battery, NY.

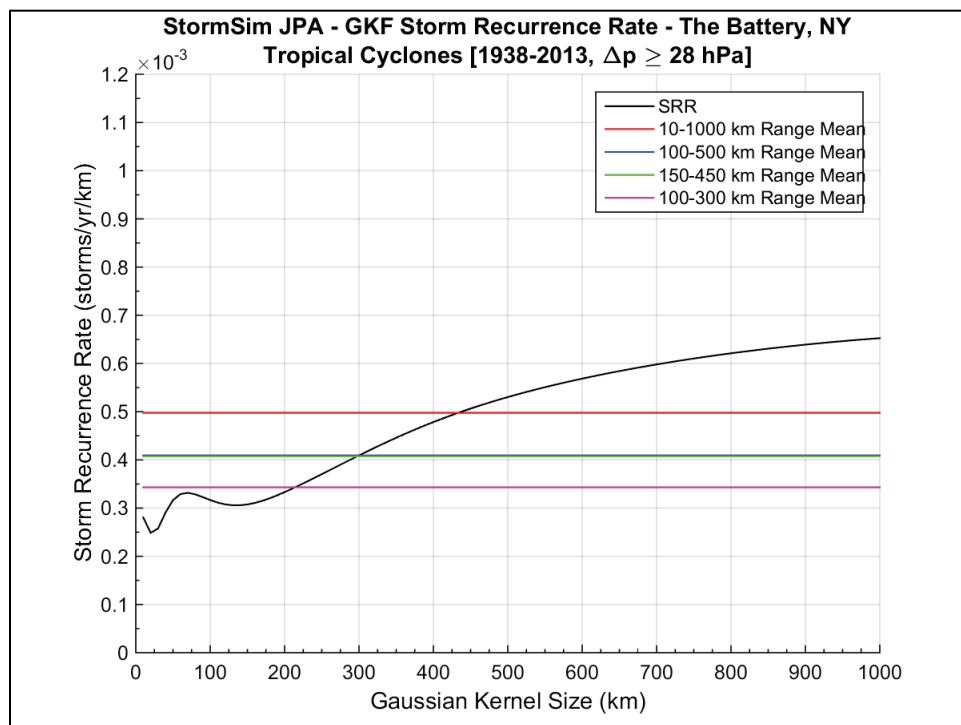


Table 3-2. Mean SRR and SDs for Gaussian kernel size ranges.

CRL	SRR (storms/yr/km)							
	All Ranges		100–500 km		150–450 km		100–300 km	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Galveston, TX	5.37E-04	6.34E-05	5.31E-04	3.93E-05	5.22E-04	2.09E-05	5.56E-04	4.24E-05
Port Arthur, TX	5.37E-04	1.41E-05	5.41E-04	1.62E-05	5.39E-04	1.25E-05	5.54E-04	1.22E-05
Grand Isle, LA	6.32E-04	4.46E-05	6.24E-04	9.50E-06	6.20E-04	3.28E-06	6.27E-04	1.21E-05
Gulfport, MS	6.01E-04	5.50E-05	5.77E-04	1.36E-05	5.75E-04	8.82E-06	5.67E-04	5.31E-06
Apalachicola, FL	6.51E-04	1.44E-04	6.10E-04	7.37E-05	6.15E-04	5.54E-05	5.50E-04	5.03E-05
Clearwater, FL	7.15E-04	1.56E-04	6.92E-04	7.17E-05	6.99E-04	5.27E-05	6.34E-04	5.38E-05
Biscayne Bay, FL	7.83E-04	5.60E-05	7.32E-04	3.70E-05	7.29E-04	3.07E-05	7.00E-04	1.24E-05
Atlantic Beach, NC	7.89E-04	5.28E-05	7.78E-04	4.83E-05	7.64E-04	2.84E-05	8.07E-04	5.36E-05
Duck, NC	6.91E-04	1.51E-04	6.96E-04	4.69E-05	7.08E-04	2.02E-05	6.69E-04	5.29E-05
Virginia Beach, VA	6.35E-04	1.61E-04	6.08E-04	9.01E-05	6.27E-04	4.98E-05	5.48E-04	9.14E-05
Chesapeake Bay, MD	4.68E-04	1.78E-04	3.56E-04	1.24E-04	3.65E-04	9.48E-05	2.55E-04	8.22E-05
The Battery, NY	4.98E-04	1.25E-04	4.09E-04	7.68E-05	4.07E-04	6.41E-05	3.43E-04	3.50E-05
Newport, RI	5.38E-04	1.15E-04	4.74E-04	7.69E-05	4.79E-04	5.71E-05	4.11E-04	5.17E-05
Boston, MA	4.69E-04	1.60E-04	3.99E-04	9.29E-05	4.07E-04	6.76E-05	3.24E-04	6.44E-05
Aguirre, PR	4.73E-04	1.41E-04	4.23E-04	7.42E-05	4.34E-04	4.87E-05	3.67E-04	6.25E-05

As discussed in section 3.2.1.3, the selection of Gaussian kernel size was established by plotting the squared error of the calculated SRR with respect to the mean UKF SRR and determining the Gaussian kernel size for which this squared error is minimized. The squared error of the difference between UKF and GKF SRR for Galveston, TX, Grand Isle, LA, and The Battery, NY, are presented in Figures 3-12 to 3-14. The squared error results are shown using mean UKF SRR for 100–300 km, 100–500 km, and 150–450 km ranges. In general, the squared error curves exhibit minima either with an asymmetric-parabolic shape, or they flatten for a range of Gaussian kernel sizes. For the latter, it may be difficult to visually discern the location of the minimum squared error, and the significance of the GK size corresponding to the minimum error could be reduced. As the curve flattens, local minimums may occur that may not be materially different from each other. Table 3-3 presents the Gaussian kernel sizes corresponding to the location of minimum squared error. Using the mean UKF SRR for the complete range of capture zone radii in the calculation of the squared error results in a mean Gaussian kernel size of 264. The mean

squared error for the 15 CRLs using the mean UKF SRR corresponding to the credible range of 150 km–450 km is 217 km. The mean square errors using the other ranges are 215 and 146.

Figure 3-12. SRR squared error for Galveston, TX.

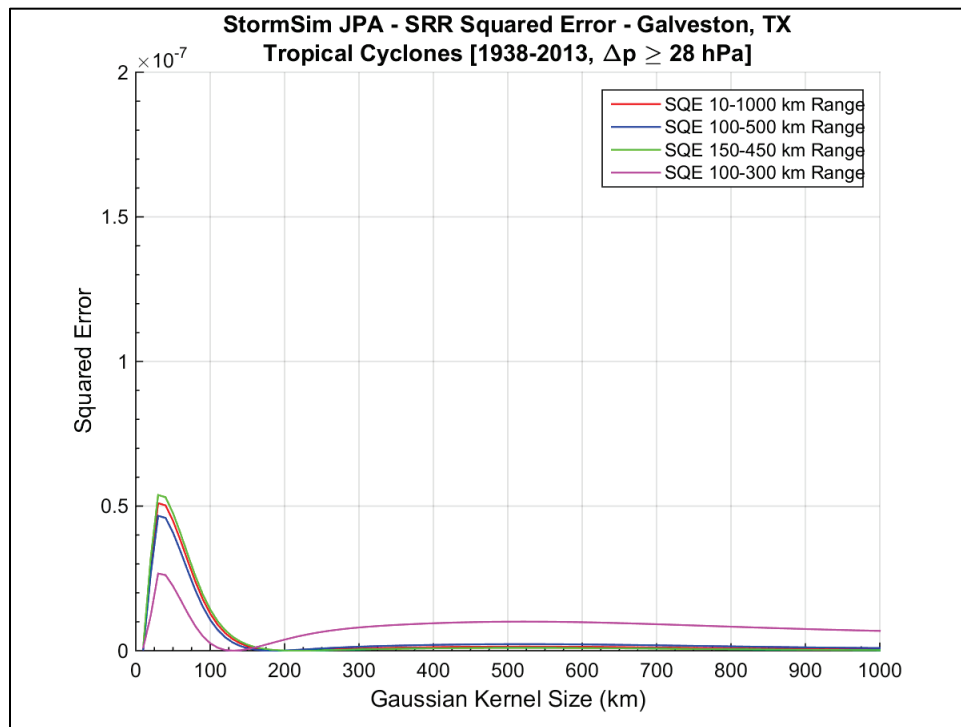


Figure 3-13. SRR squared error for Grand Isle, LA.

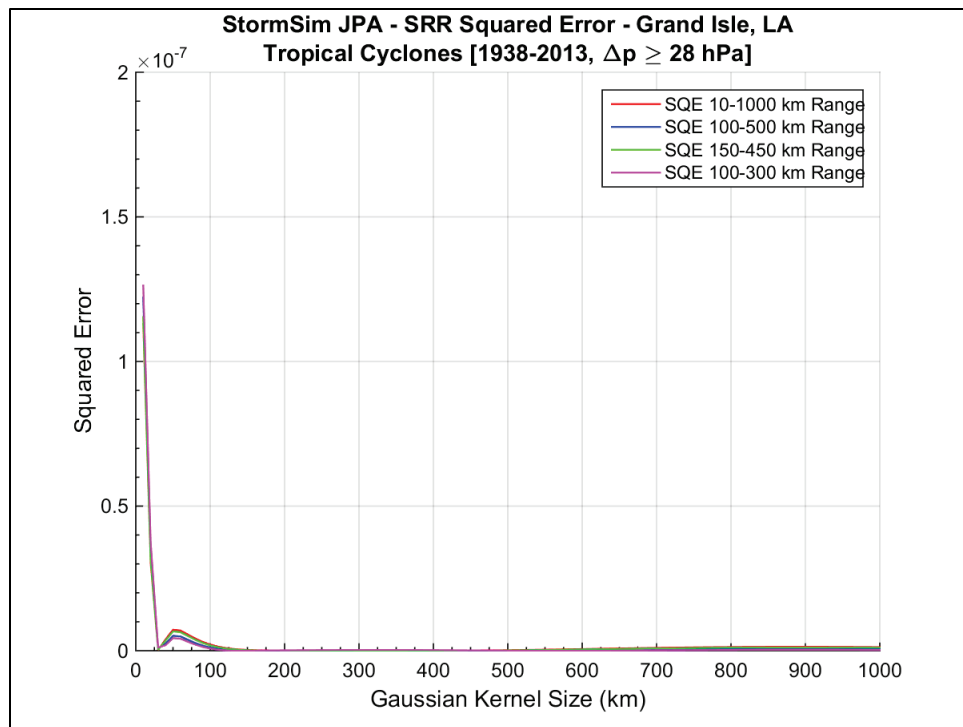


Figure 3-14. SRR squared error for The Battery, NY

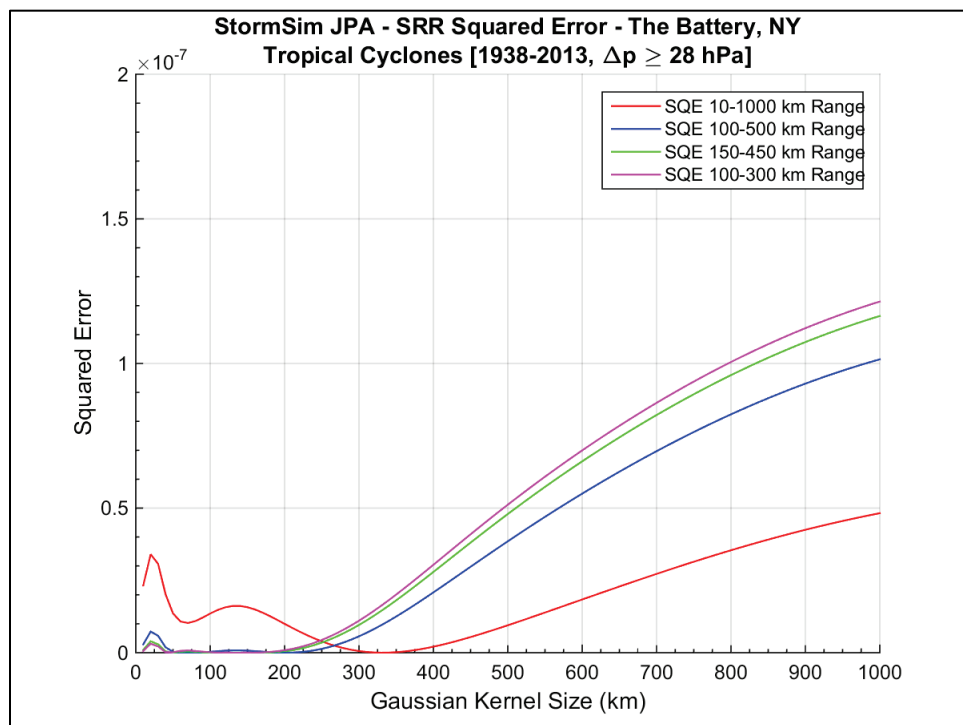


Table 3-3. Gaussian kernel sizes corresponding to the location of minimum squared error.

CRL	Capture Zone Radius Range (km)			
	All	100–300	100–500	150–450
Galveston, TX	200	130	180	210
Port Arthur, TX	320	110	200	200
Grand Isle, LA	330	140	490	310
Gulfport, MS	130	370	240	320
Apalachicola, FL	270	130	190	190
Clearwater, FL	250	140	200	190
Biscayne Bay, FL	370	140	210	140
Atlantic Beach, NC	250	120	190	200
Duck, NC	150	140	190	370
Virginia Beach, VA	210	130	190	230
Chesapeake Bay, MD	300	110	190	180
The Battery, NY	330	140	200	110
Newport, RI	310	130	190	200
Boston, MA	290	130	190	200
Aguirre, PR	250	130	180	210
Mean	264	146	215	217

This analysis was extended to additional CRLs covering the TC-exposed U.S. coast and the Caribbean. The mean Gaussian kernel size for the 150–450 km credible UKF or capture zone range using the additional CRLs was 214 km. The summary of these analyses for additional ranges and regions is shown in Table A-3 of Appendix A. A kernel size of 200 km was adopted based on these results. The kernel size needs to balance the need for the selection of an appropriate sample size versus the requirement to minimize the possibility of considering mixed TC populations. The selection of this value was also informed by the range of values used in previous JPM studies. The use of this Gaussian kernel size coincides with other recent studies such as the Federal Emergency Management Agency (FEMA) Coastal Mississippi study (FEMA 2008; Toro 2008), the latest FEMA Region II Risk MAP study (FEMA 2014), and the USACE North Atlantic Coast Comprehensive Study (NACCS) (Nadal-Caraballo et al. 2015). Subsequent study experiments herein adopted this Gaussian kernel size. In the following report chapters, many of the SRR results are presented as the recurrence rate associated with storms passing within

200 km of a given location, with units of storms per year. These are computed by multiplying the GKF SRR by 400 km. These results will be designated as SRR_{200km} .

Having established the Gaussian kernel size as 200 km, the corresponding GKF SRR was calculated for each of the 15 CRLs. This SRR was adopted as an assumed true value for the purpose of quantifying the uncertainty associated with the selection of the Gaussian kernel size. For these experiments, a credible range of 100–300 km was assumed for evaluating the GKF SRR. Overall, the mean of this range coincided with mean UKF SRR for the 100–500 km capture zone range. Although the use of a single kernel size is a typical approach in regional studies, the effect of using site-specific kernel sizes was examined. Table 3-4 shows the comparison between SRR calculated with a 200 km kernel size and site-specific kernel sizes based on location of the minimum squared error for the 150–450 km UK capture zone range. The percent difference in SRR varies from -1.5% to 0.7% in CRLs from Texas to Atlantic Beach, NC. The biggest differences can be observed on CRLs from Duck, NC, to Boston, MA, where the percent difference varies from 4.0% to -11.4 %. Even though the difference in kernel size is only 20 km, Chesapeake Bay, MD, shows the largest difference in SRR. Since this CRL is located in Chesapeake Bay, farther west than other CRLs, a small reduction in the kernel has a greater impact in reducing the influence of bypassing TCs in the Atlantic.

Table 3-4. SRR comparison between 200 km and site-specific kernel sizes.

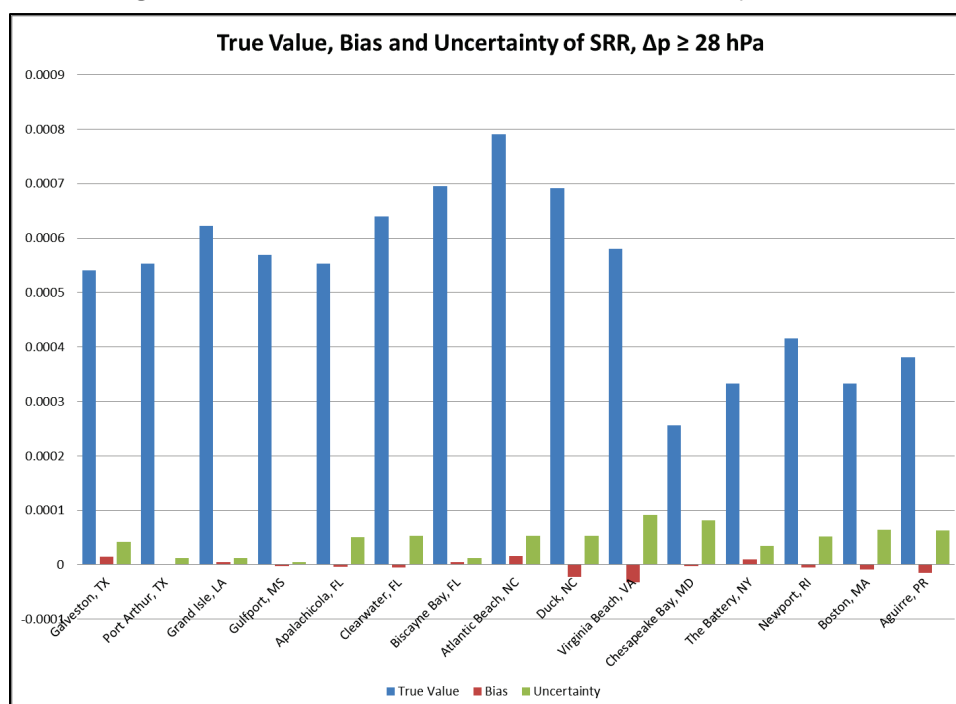
CRL	SRR [200 km] (storms/yr/km)	GK Size for Minimum SQE [150–450 km] (km)	SRR [site-specific] (storms/yr/km)	Percent Difference
Galveston, TX	5.41E-04	210	5.36E-04	-0.9
Port Arthur, TX	5.53E-04	200	5.53E-04	0.0
Grand Isle, LA	6.22E-04	310	6.17E-04	-0.8
Gulfport, MS	5.69E-04	320	5.72E-04	0.7
Apalachicola, FL	5.53E-04	190	5.44E-04	-1.5
Clearwater, FL	6.40E-04	190	6.31E-04	-1.4
Biscayne Bay, FL	6.95E-04	140	6.87E-04	-1.2
Atlantic Beach, NC	7.91E-04	200	7.91E-04	0.0
Duck, NC	6.92E-04	370	7.20E-04	4.0
Virginia Beach, VA	5.80E-04	230	6.08E-04	4.8
Chesapeake Bay, MD	2.57E-04	180	2.27E-04	-11.4
The Battery, NY	3.33E-04	110	3.11E-04	-6.5
Newport, RI	4.16E-04	200	4.16E-04	0.0
Boston, MA	3.32E-04	200	3.32E-04	0.0
Aguirre, PR	3.82E-04	210	3.90E-04	2.2

The uncertainty was calculated as the SD of the differences between the GKF SRR for kernel sizes over the 100–300 km range and the GKF SRR corresponding to a kernel size of 200 km. The SRR assumed true values, and Gaussian kernel size uncertainties and CV are presented in Table 3-5. True value, bias, and uncertainty are graphically depicted for the 15 CRLs on Figure 3-15. An examination of the uncertainty results for the CRLs reveals that three out of five of the largest uncertainty values correspond to CRLs on the U.S. Atlantic coast. The CV is comparatively a more adequate metric of SRR uncertainty than SD because it normalizes the dispersion using the mean SRR as a measure of scale. Making the comparison using the coefficient of variation, the CRLs from Virginia to Maine exhibit the five largest CV for the U.S. coast, excluding the Puerto Rico CRL. There is more uncertainty relative to the mean SRR at these CRLs, pointing to a larger uncertainty in this region.

Table 3-5. Gaussian kernel size uncertainty (100–300 km range).

CRL	SRR (storms/yr/km)	Uncertainty (storms/yr/km)	CV
Galveston, TX	5.41E-04	4.24E-05	7.64E-02
Port Arthur, TX	5.53E-04	1.22E-05	2.21E-02
Grand Isle, LA	6.22E-04	1.21E-05	1.92E-02
Gulfport, MS	5.69E-04	5.31E-06	9.38E-03
Apalachicola, FL	5.53E-04	5.03E-05	9.15E-02
Clearwater, FL	6.40E-04	5.38E-05	8.48E-02
Biscayne Bay, FL	6.95E-04	1.24E-05	1.77E-02
Atlantic Beach, NC	7.91E-04	5.36E-05	6.64E-02
Duck, NC	6.92E-04	5.29E-05	7.90E-02
Virginia Beach, VA	5.80E-04	9.14E-05	1.67E-01
Chesapeake Bay, MD	2.57E-04	8.22E-05	3.23E-01
The Battery, NY	3.33E-04	3.50E-05	1.02E-01
Newport, RI	4.16E-04	5.17E-05	1.26E-01
Boston, MA	3.32E-04	6.44E-05	1.99E-01
Aguirre, PR	3.82E-04	6.25E-05	1.70E-01

Figure 3-15. Gaussian kernel size true value, uncertainty, and bias.



3.3 Epanechnikov kernel function (EKF)

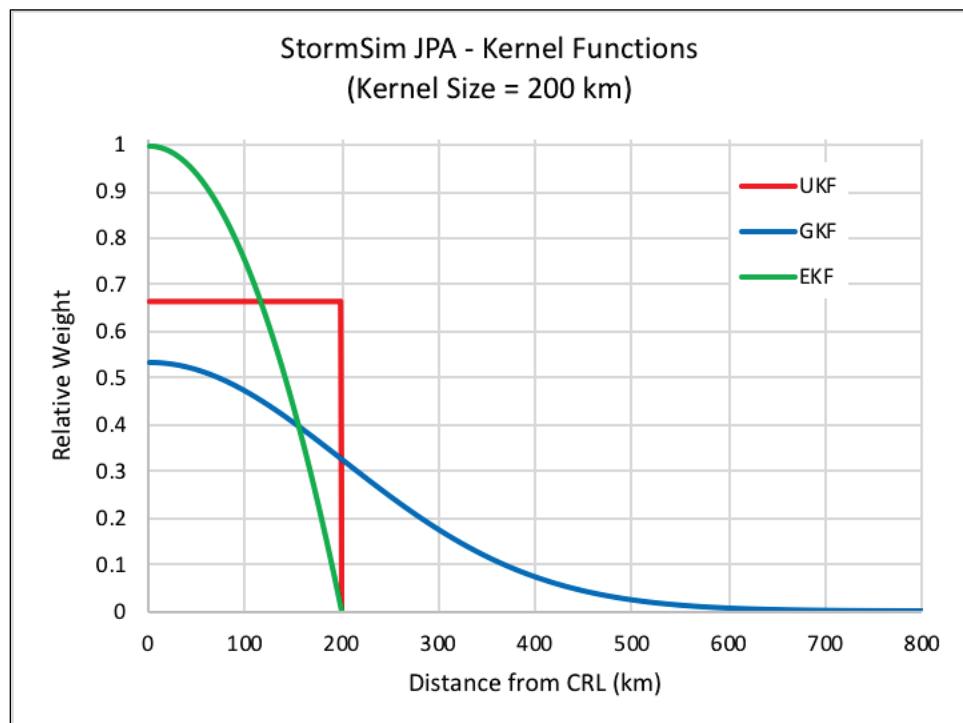
The EKF was also tested for the computation of SRR. The EKF has a parabolic form, and it is considered to be the optimal kernel shape for kernel density estimation (Silverman 1986). The EKF equation, as applied for intensity estimation, has the form

$$w(d_i) = \frac{1}{h_d} \begin{cases} \frac{3}{4} \left[1 - \left(\frac{d_i}{h_d} \right)^2 \right], & \text{if } \left| \frac{d_i}{h_d} \right| < 1 \\ 0, & \text{otherwise} \end{cases} \quad (3-5)$$

where $w(d_i)$ = distance-adjusted weights from the Epanechnikov kernel (storms/kilometer); d_i = distance from location of interest to a storm data point (kilometer); h_d = optimal kernel size (kilometer).

The curve of relative distance-adjusted weights for the EKF with a 200 km bandwidth is shown in Figure 3-16 along with the GKF. As in Figure 3-4, the weights are shown relative to the EKF weight of a TC track point located at the CRL (distance = 0 km). As in the case of the GKF, the EKF diminishes with distance from the CRL, but similar to UKF, the weight is zero after it reaches the selected kernel size.

Figure 3-16. UKF, GKF, and EKF weights as function of distance from CRL.



The SRR was calculated by applying the EKF shown in Equation 3-5 and Equation 3-1, analogous to the application of the GKF described in Section 3.2. The same experiments executed for UKF and GKF SRR were done using the EKF. Figure 3-17 shows the plot of SRR versus Epanechnikov kernel size for all CRLs. The plotted curves show that the use of the EKF results in curves that are less smooth than their GKF counterparts shown in Figure 3-5.

A comparison of the variation of UKF, GKF, and EKF SRR with kernel size is presented in Figures 3-18 through 3-20 for Galveston, TX, Grand Isle, LA, and The Battery, NY, CRLs. The figures show the smoothing effect of the EKF to be slightly less than the GKF smoothing, but it follows more closely the shape of the UKF SRR. As described in Section 3.3.2, the GKF method increases the GKF SRR over observed SRR for the larger kernel sizes at North Atlantic CRLs because fewer storms directly affect the area, and the GKF assigns weights to storms that are farther away than the kernel size distance. In contrast, for larger kernel sizes, the EKF produces lower SRR values than the UKF SRR.

Figure 3-17. Plot of SRR versus Epanechnikov kernel size for all CRLs.

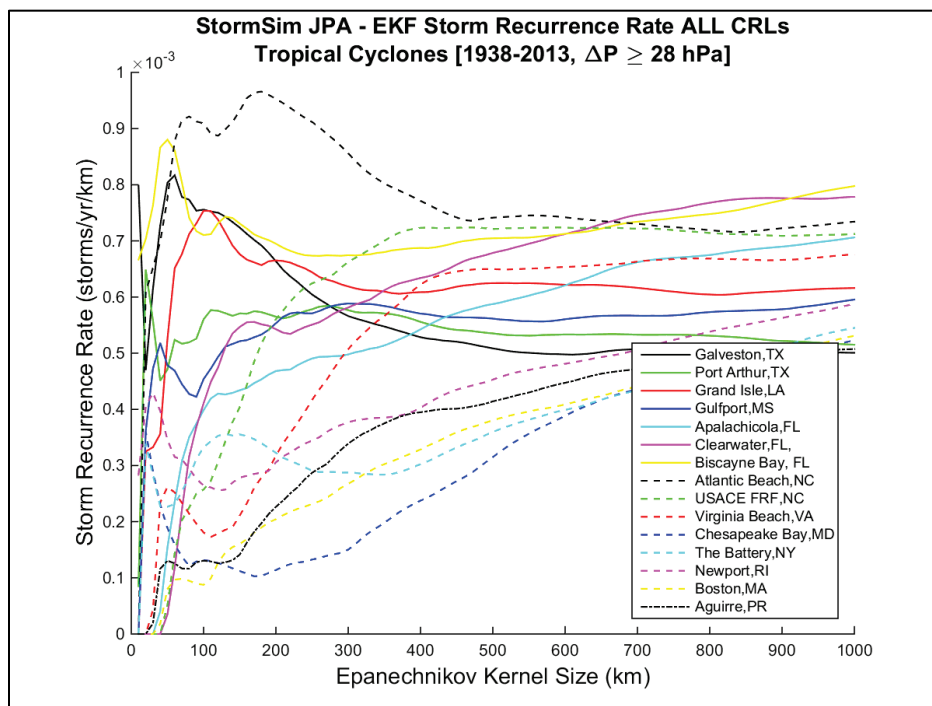


Figure 3-18. Comparison of capture zone, GKF, and EKF SRR at Galveston, TX.

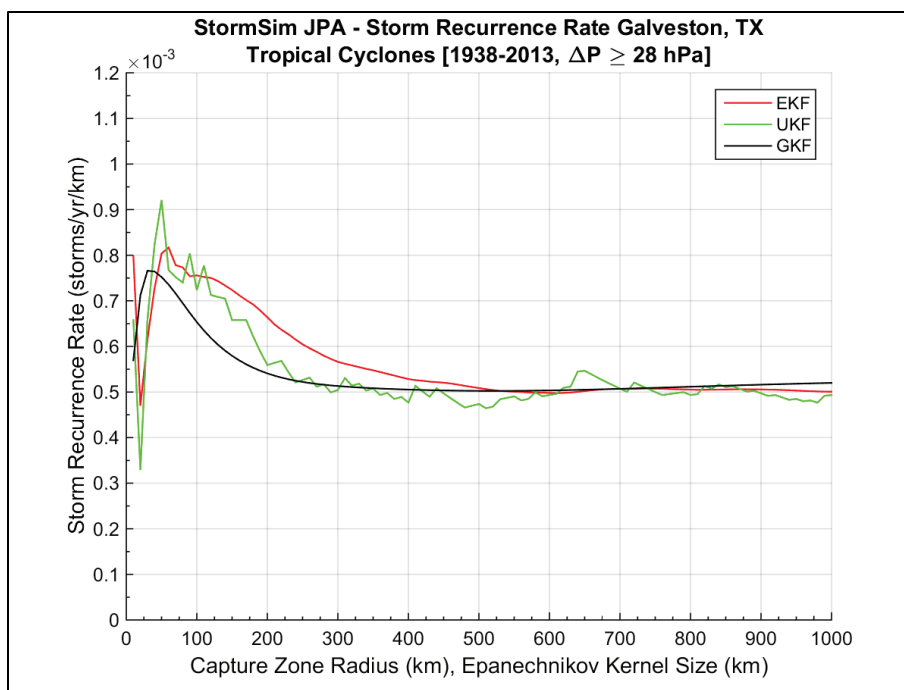


Figure 3-19. Comparison of capture zone, GKF, and EKF SRR at Grand Isle, LA.

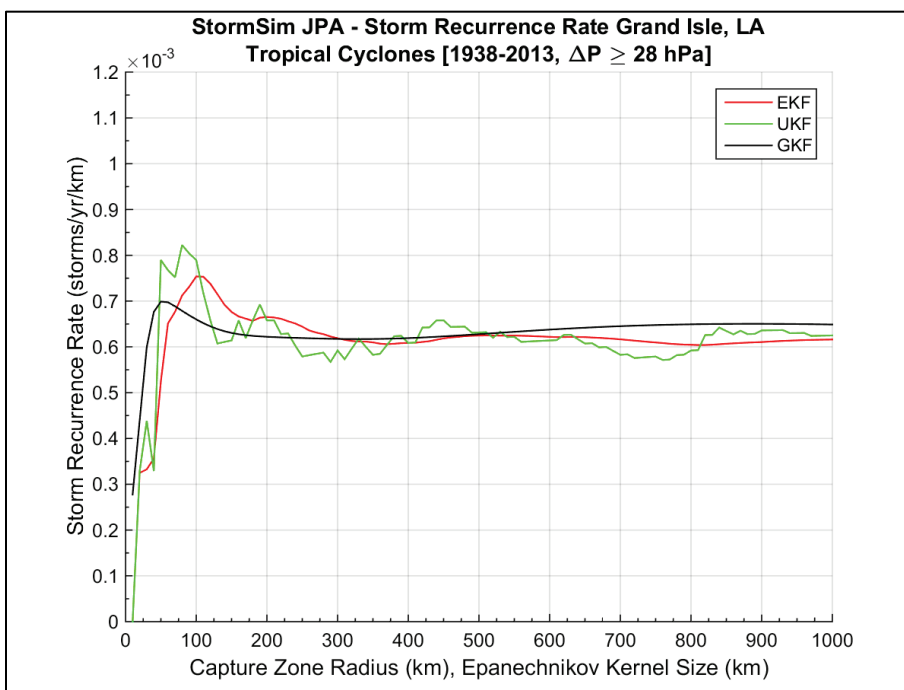
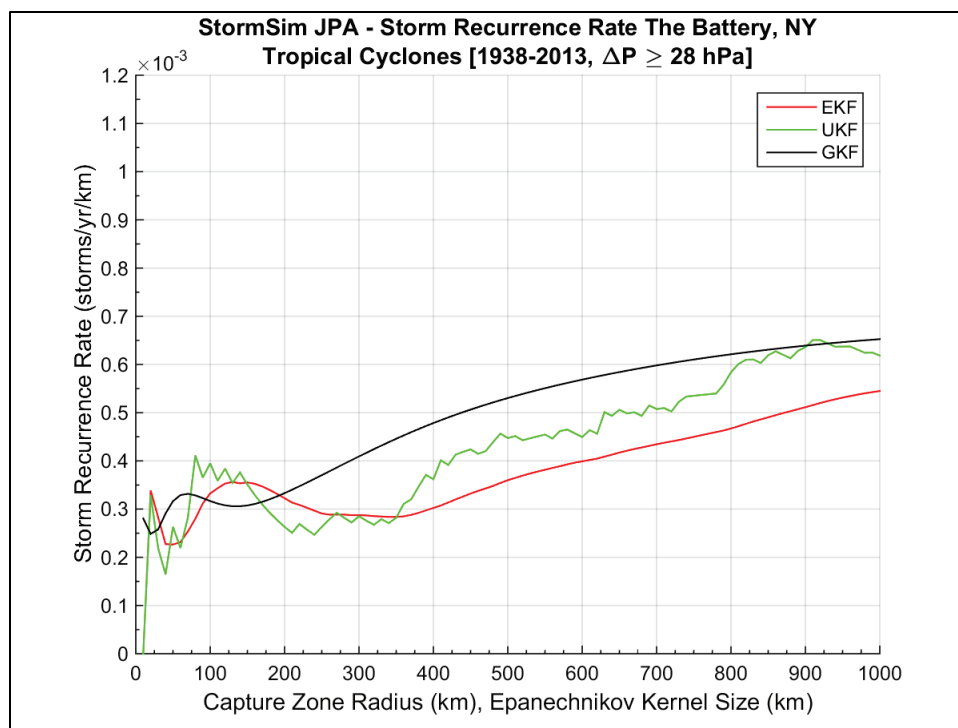


Figure 3-20. Comparison of capture zone, GKF, and EKF SRR at The Battery, NY.



The mean EKF SRR and SD were calculated for various ranges of kernel size as was done with UKF and GKF SRR. A comparison of the EKF SRR with the UKF SRR from Table 3-6 shows the mean EKF SRR values for the 100–500 km range are the closest overall to the UKF SRR results corresponding to the credible range of 100–500 km.

Table 3-6. Mean SRR and SDs for Epanechnikov kernel size ranges.

CRL	SRR (storms/yr/km)							
	All Ranges		100–500 km		150–450 km		100–300 km	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Galveston, TX	5.63E-04	9.23E-05	5.99E-04	8.22E-05	5.89E-04	6.36E-05	6.64E-04	6.59E-05
Port Arthur, TX	5.39E-04	5.25E-05	5.64E-04	1.42E-05	5.67E-04	1.15E-05	5.73E-04	6.85E-06
Grand Isle, LA	6.14E-04	8.66E-05	6.42E-04	4.00E-05	6.31E-04	2.37E-05	6.69E-04	4.00E-05
Gulfport, MS	5.50E-04	6.89E-05	5.58E-04	3.19E-05	5.68E-04	1.95E-05	5.44E-04	3.89E-05
Apalachicola, FL	5.51E-04	1.56E-04	5.02E-04	5.20E-05	5.02E-04	3.76E-05	4.61E-04	3.02E-05
Clearwater, FL	6.24E-04	1.88E-04	5.84E-04	6.21E-05	5.87E-04	3.99E-05	5.35E-04	4.20E-05
Biscayne Bay, FL	7.27E-04	4.35E-05	6.94E-04	1.93E-05	6.87E-04	1.46E-05	6.99E-04	2.45E-05
Atlantic Beach, NC	7.76E-04	1.14E-04	8.47E-04	7.96E-05	8.57E-04	7.69E-05	9.17E-04	3.24E-05
Duck, NC	6.17E-04	1.96E-04	6.09E-04	1.40E-04	6.39E-04	8.82E-05	5.12E-04	1.35E-04
Virginia Beach, VA	5.35E-04	1.89E-04	4.61E-04	1.69E-04	4.76E-04	1.37E-04	3.21E-04	1.14E-04
Chesapeake Bay, MD	3.13E-04	1.48E-04	1.81E-04	6.67E-05	1.71E-04	5.53E-05	1.25E-04	1.36E-05
The Battery, NY	3.79E-04	9.42E-05	3.16E-04	2.69E-05	3.06E-04	2.23E-05	3.21E-04	2.71E-05
Newport, RI	4.40E-04	9.83E-05	3.60E-04	6.15E-05	3.62E-04	4.68E-05	3.10E-04	4.10E-05
Boston, MA	3.41E-04	1.44E-04	2.61E-04	8.15E-05	2.66E-04	5.88E-05	1.94E-04	5.11E-05
Aguirre, PR	3.69E-04	1.40E-04	3.04E-04	1.01E-04	3.15E-04	8.05E-05	2.22E-04	7.45E-05

3.4 Comparison of kernel density estimators for estimation of TC genesis recurrence rates

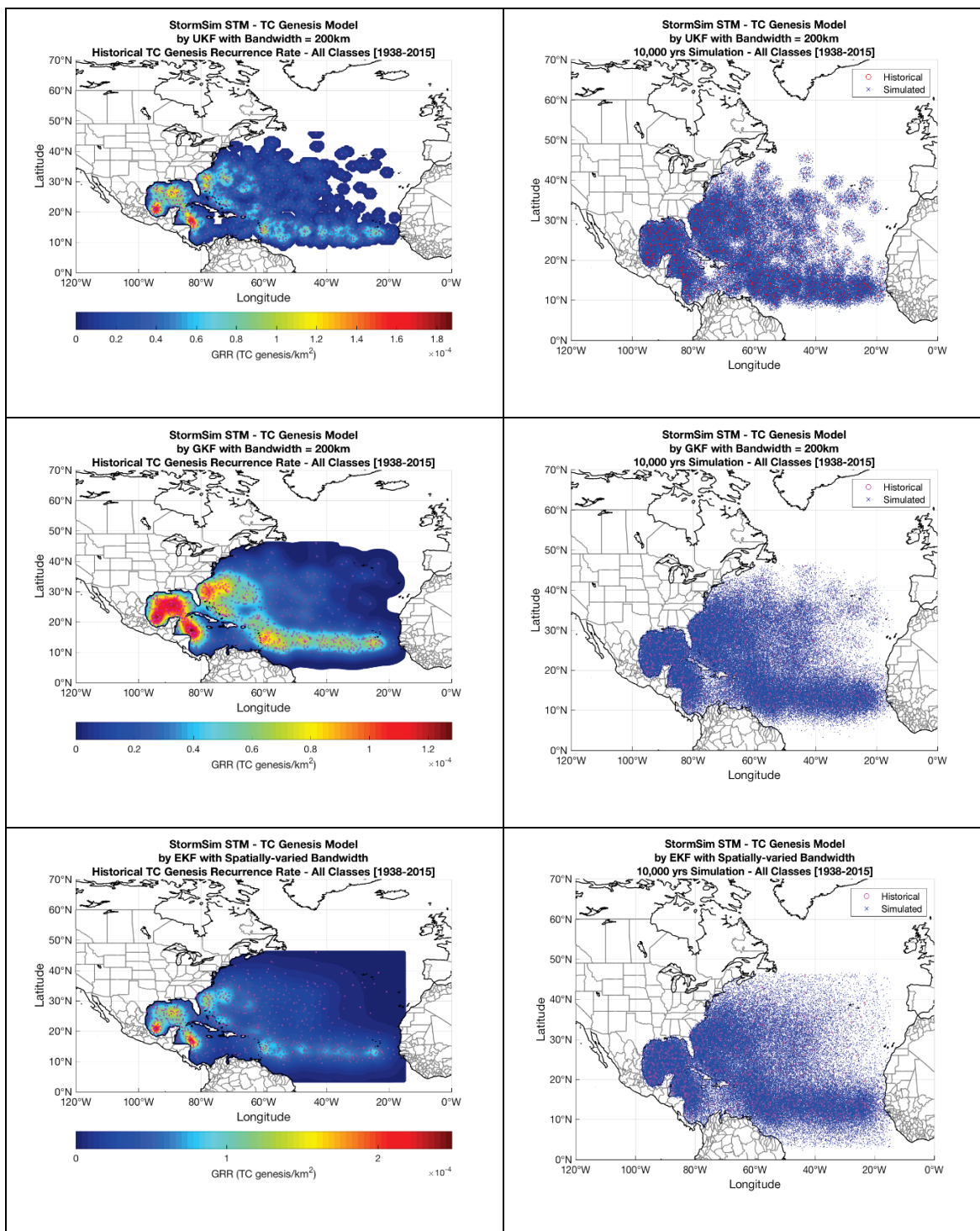
Several coastal hazard studies have applied approaches that model the entire TC track from formation to dissipation. Vickery et al. (2000) introduced a simulation approach that models the complete wind history of a TC along its track. Storm initiation was done by identifying the genesis points of historical TC tracks in HURDAT2 genesis data. Other applications of TC track simulation models sample TC genesis locations from the spatial probability distribution of TC genesis based on HURDAT2 data while others have developed random seeding genesis models that are not dependent on historical data (Emanuel et al. 2008). Rumpf et al. (2007) treated TC genesis as a spatial Poisson point process using nonparametric density estimation. Analogous to the application of kernel intensity estimation for the calculation of SRR, the genesis recurrence rate (GRR) can be calculated through kernel density estimators or generalized nearest-neighbor estimators. Wand and Jones (1994) discuss the main differences in the use of the kernel functions for the estimation of the

density and the intensity. This section presents an example application of the use of UKF, GKF, and EKF estimators for the development of TC genesis models.

TC genesis was modeled as a non-homogeneous Poisson point process where the Poisson parameter λ was characterized at each location within an area of interest as an annual rate or intensity of points of genesis. To compute this intensity surface, the bivariate GKF and the UKF were applied in the form of the kernel intensity estimator (KIE). Also, the bivariate EKF was tested in the form of the generalized nearest-neighbor estimator (GNE). Both non-parametric estimation approaches differ in the size of the bandwidth; while the KIE is applied with a constant bandwidth that can be determined through optimization techniques (e.g., a 200 km bandwidth for this application), the GNE's bandwidth varies spatially. More details on the main characteristics of these two non-parametric estimators can be found in Silverman (1986) and Wand and Jones (1994).

For this application, TC genesis was considered as the location where the system first achieved a wind speed of 60 km/hr, which corresponds to the threshold for tropical depression classification. The resulting intensity surfaces created using TC data for the time period of 1938–2015 and the previously mentioned estimators are shown in Figure 3-21. This figure also shows as example sampled TC genesis points using a 10,000-year Monte Carlo simulation. The smoothing effects of GKF and EKF in the generated intensity surface can be compared with the use of UKF. Since genesis points outside the 200 km bandwidth have a weight of zero, discontinuities are formed in the intensity map at locations with sparse historical data points.

Figure 3-21. Historical and simulated TC GRR for the 1938–2015 time period corresponding to the use of UKF, GKF, and EKF density estimators.



4 Uncertainty Associated with the Selection of Period of Record

The number of storms on record that are used for the computation of SRR can be influenced by undercount due to missing storms and by the effects of climatological trends that alter the average number of storms over different periods of time. These two factors can introduce bias into SRR computations. In this chapter, the uncertainty associated with period of record will be quantified.

4.1 TC counts and trends

Before proceeding with the evaluation of period of record uncertainty, TC counts were examined for the 15 CRLs to determine if any observed trends were statistically significant or if they could be explained by chance. Trends in TC counts were calculated at each CRL using the UKF with optimal kernel sizes of 200 km and 400 km and 5-year and 10-year moving averages. Since the main approach here consisted in counting the number of TC tracks particular radii to examine trends, the UKF approach was used instead of the GKF, which was used for testing uncertainty. A linear polynomial fit of TC counts was performed to test whether the resulting trend is statistically significant and whether this trend had to be considered. The null hypothesis was that the coefficient representing the slope of the line is zero. The p-values were calculated to determine statistical significance at the 5% level.

Positive linear trends were observed for 7 out of 15 CRLs using an optimal kernel size or capture zone radius of 200 km and 4 out of 15 when using a kernel size of 400 km. Figures 4-1 and 4-2 show the results of the linear trend analysis for Galveston, TX, for the 200 km and 400 km capture zone radii, respectively. The graphs reveal a positive linear trend that is higher for the 200 km capture radius than for the 400 km. These moving averages seem to show a cyclical behavior for the TC counts. As seen in Table 4-1, the large p-values for all CRL locations show that the null hypothesis of stationarity cannot be rejected.

Figure 4-1. Linear trend of moving averages of TC counts for 200 km radius.

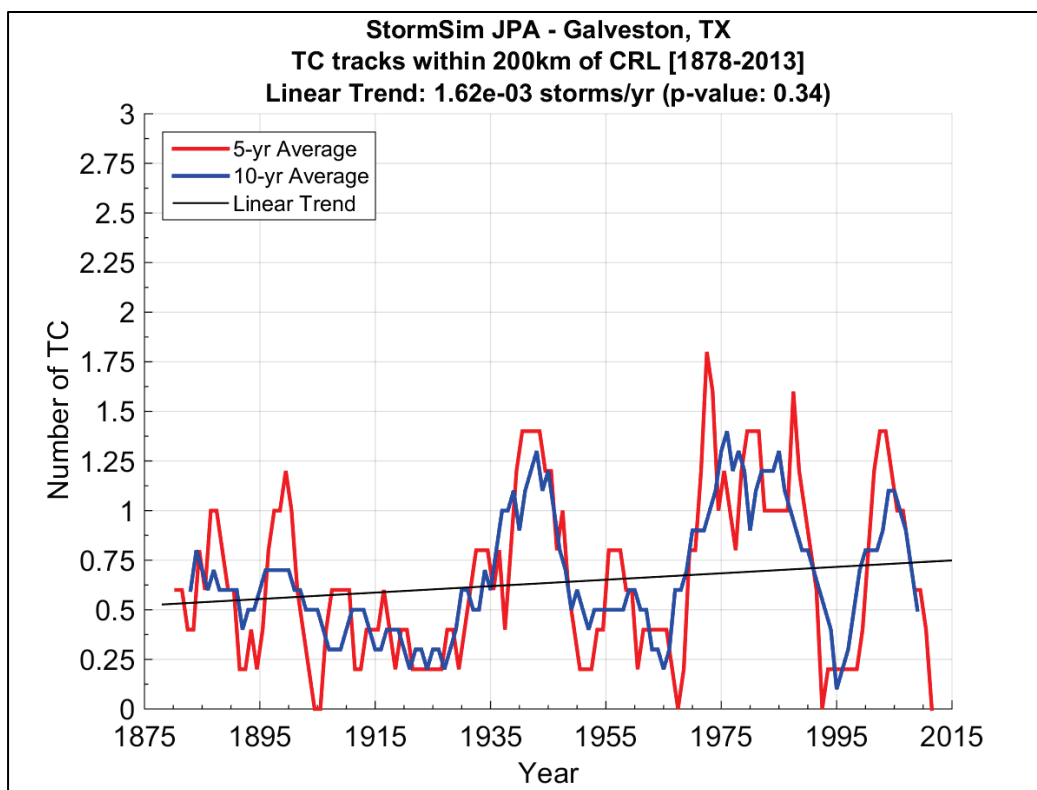


Figure 4-2. Linear trend of moving averages of TC counts for 400 km radius.

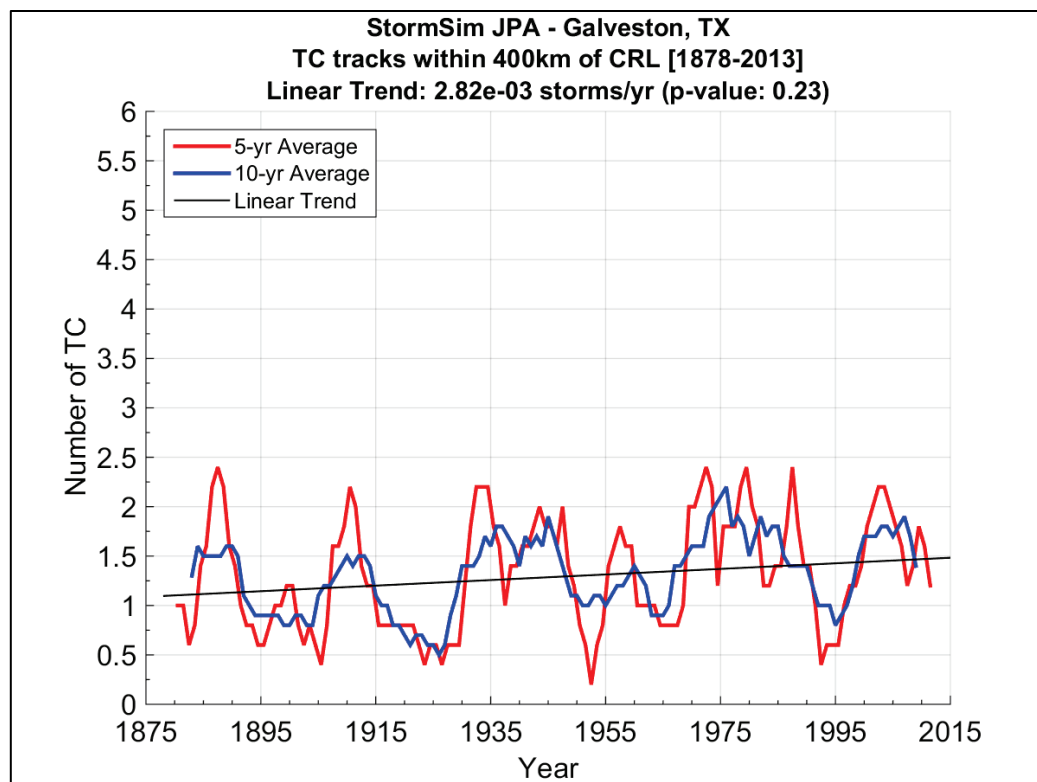


Table 4-1. Slopes of linear trends of TC counts and p-values.

CRL	Slope (storms/yr)		p-value	
	200 km	400 km	200 km	400 km
Galveston, TX	1.62e-03	2.82e-03	0.34	0.23
Port Arthur, TX	2.08e-03	2.54e-03	0.24	0.30
Grand Isle, LA	6.76e-04	3.01e-03	0.75	0.31
Gulfport, MS	8.49e-04	1.05e-03	0.68	0.72
Apalachicola, FL	7.53e-05	2.12e-04	0.97	0.94
Clearwater, FL	-9.00e-04	2.94e-03	0.65	0.38
Biscayne Bay, FL	-9.36e-04	8.77e-04	0.70	0.78
Atlantic Beach, NC	1.61e-03	-1.12e-04	0.50	0.97
Duck, NC	1.93e-03	1.03e-03	0.42	0.74
Virginia Beach, VA	2.19e-04	1.39e-03	0.92	0.64
Chesapeake Bay, MD	-5.14e-04	1.10e-03	0.73	0.66
The Battery, NY	-9.82e-05	-9.25e-04	0.94	0.70
Newport, RI	-8.79e-04	-1.48e-03	0.62	0.57
Boston, MA	-1.38e-03	-1.05e-03	0.38	0.66
Aguirre, PR	-2.40e-04	1.85e-03	0.89	0.48

The SRR is sensitive to the historical record length as it directly impacts the TC count. The completeness of the historical record also affects the SRR for the same reason. Therefore, SRR is susceptible to any bias present in the HURDAT2 data. As discussed in Chapter 2, before the era of air reconnaissance missions, which began in the 1940s, the TCs are underrepresented in the record. The high frequency of unsampled TCs prior to the 1940s has been well documented. Mann et al. (2007) estimated an undercount in the pre-aircraft reconnaissance era (1870–1943) ranging from 0.5 to 2.0 TC/year, with a mean of 1.2 TC/year. Landsea et al. (2010) discussed that the increase in reported TCs during the 1940s until approximately 1960 had been interpreted as a result of climate change. This increase, however, was likely to be the consequence of improved observing and recording of short-lived TCs coinciding with the advent of aircraft reconnaissance and satellite imagery.

Worley et al. (2005) identified the spikes in the number of unrecorded moderate to long-lived TCs during the 1910s and 1940s was due to reduced ship observations during World War I and World War II, respectively.

Vecchi and Knutson (2011), after adjusting HURDAT data for unrecorded TCs, concluded that the mid-twentieth century was a high-activity period that extended from the 1940s to the 1960s.

The review of technical literature evidences that, although the 1940s decade saw improvements in the observation and recording of TCs, there was still a significant undercount during this period. In recent flood hazard studies where the JPM methodology has been used, the analyzed period of record started in the early 1940s (FEMA 2008, 2012; Resio et al. 2007).

4.2 Period of record uncertainty analysis and results

The SRR was computed using GKF for sequential periods of record starting in 1851 through 2012. For example, the first SRR was calculated for the period corresponding to 1851–2013, the second for 1852–2013, the third for 1853–2013, and so on. Plots of the SRR against first year-of-record period were developed for each CRL. Assumed *true-value* SRR estimates were developed based on an evaluation of the plots and the documented uncertainties associated with the development of methods for measuring TC data. Various assumed true-value estimates were considered. The SD and CV were calculated for all CRL based on these values.

The SRR was calculated at each CRL for 162 periods of record with the first one starting in 1851 and the last starting in 2012. The SRR was calculated using a 200 km Gaussian kernel size. The SRR_{200km} plots for periods of record starting in 1851 to periods of record starting in 2000 are presented in Figure 4-3. Overall, the SRR_{200km} values show three general types of behaviors as the periods of record are shortened from 1850 to 2012 to 2000 to 2012. The $SRR_{200 km}$ values increase starting in 1850, and at some point in the middle part of the curves, for most of the CRLs, the values oscillate for a period of time without showing an increasing trend. Periods of record starting in 1970 show a rapid increase in SRR as the time periods of record are shortened and the era of satellite data collection increases the number of surveilled TCs. Some CRLs evidently exhibit different tendencies. Taking into account the beginning of aircraft reconnaissance missions in the mid-1940s and the start of satellite data collection in the 1960s, three ranges of dates were evaluated to establish true value. These ranges were 1935–1985, 1940–1980, and 1950–1970. These ranges of dates produce somewhat uniform SRR_{200km} based on

Figure 4-3. The mean SRR_{200km} , SD, and coefficient of variation were calculated for each of the three ranges of dates and are shown in Table 4-2. The range of time period from 1950–1970 resulted in the smallest coefficients of variation.

Figure 4-3. Variation of SRR_{200km} with start of record period.

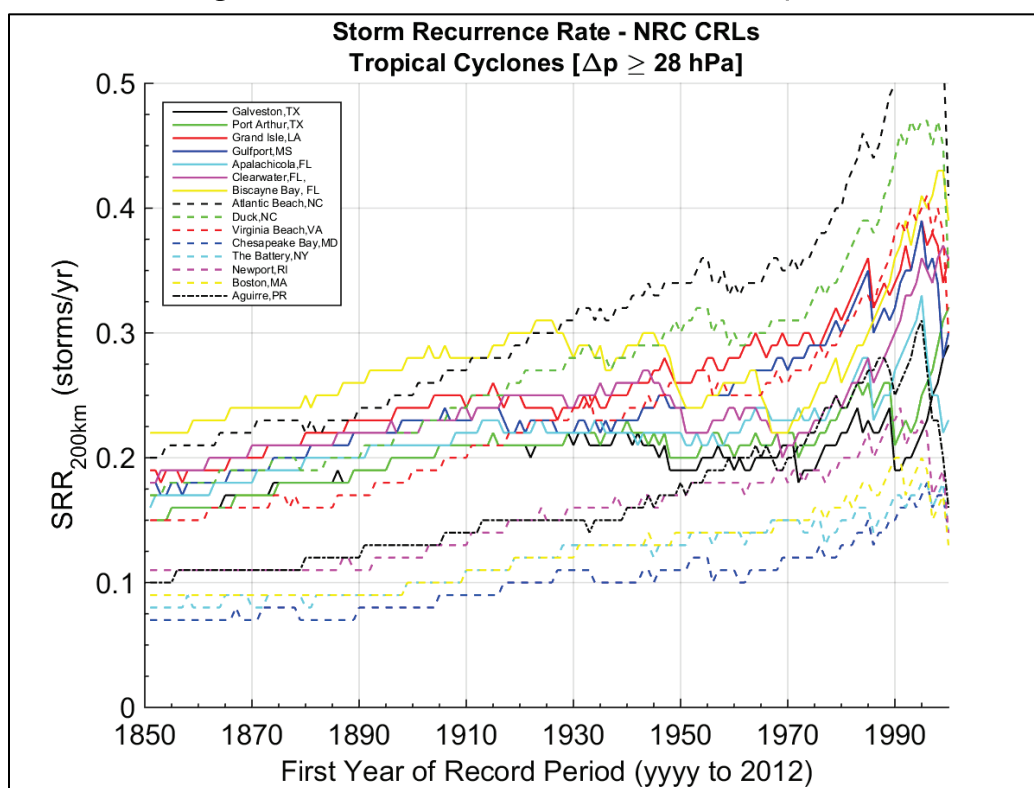


Table 4-2. Uncertainty for different period of record ranges for estimation of true value.

Coastal Reference Location	1935–1985			1940–1980			1950–1970		
	Mean SRR_{200km} (storms/yr)	SD (storms/yr)	CV	Mean SRR_{200km} (storms/yr)	SD (storms/yr)	CV	Mean SRR_{200km} (storms/yr)	SD (storms/yr)	CV
Galveston, TX	0.205	0.013	0.062	0.201	0.010	0.050	0.198	0.007	0.034
Port Arthur, TX	0.218	0.015	0.067	0.214	0.010	0.045	0.210	0.007	0.035
Grand Isle, LA	0.283	0.027	0.094	0.281	0.017	0.059	0.280	0.012	0.044
Gulfport, MS	0.265	0.032	0.119	0.261	0.022	0.084	0.258	0.014	0.053
Apalachicola, FL	0.229	0.017	0.072	0.225	0.011	0.047	0.223	0.011	0.047
Clearwater, FL	0.240	0.018	0.077	0.235	0.017	0.072	0.227	0.011	0.049
Biscayne Bay, FL	0.263	0.023	0.089	0.258	0.023	0.091	0.246	0.016	0.065

Coastal Reference Location	1935–1985			1940–1980			1950–1970		
	Mean SRR _{200km} (storms/yr)	SD (storms/yr)	CV	Mean SRR _{200km} (storms/yr)	SD (storms/yr)	CV	Mean SRR _{200km} (storms/yr)	SD (storms/yr)	CV
Atlantic Beach, NC	0.355	0.035	0.098	0.350	0.019	0.055	0.345	0.009	0.027
Duck, NC	0.312	0.028	0.091	0.308	0.017	0.054	0.305	0.009	0.030
Virginia Beach, VA	0.264	0.025	0.095	0.261	0.015	0.057	0.258	0.007	0.029
Chesapeake Bay, MD	0.114	0.012	0.102	0.113	0.008	0.072	0.111	0.007	0.059
The Battery, NY	0.139	0.010	0.069	0.138	0.008	0.058	0.140	0.006	0.045
Newport, RI	0.179	0.014	0.077	0.178	0.010	0.056	0.180	0.005	0.028
Boston, MA	0.144	0.013	0.091	0.142	0.009	0.064	0.141	0.004	0.025
Aguirre, PR	0.196	0.033	0.166	0.194	0.024	0.125	0.193	0.011	0.055

4.3 Effect of El Niño Southern Oscillation (ENSO) on SRR estimates

The effect of ENSO on TC activity has been widely documented in the scientific literature (Smith et. al 2007). ENSO describes fluctuations in temperatures in the eastern Pacific Ocean near the equator, in particular near the coasts of Ecuador and northern Peru. The sea surface temperature warm cycle is called El Niño while the cold cycle is called La Niña. El Niño's effect on TC frequency has been related to an increase in upper tropospheric westerly winds over the Caribbean and the equatorial Atlantic Ocean that create conditions less favorable for TC activity (Gray 1984). Conversely, La Niñas have been related to more favorable conditions for TC activity due to weaker upper tropospheric westerly winds.

The effect of ENSO on SRR was evaluated by estimating the SRR for time periods of El Niño, La Niña, and normal sea surface temperatures (SST). These periods were identified using the Oceanic Niño Index, which is determined by comparing the 3-month average SST in the east central-tropical Pacific with the 30-year average. El Niño cycles are identified as periods with temperatures 0.5 °C warmer than average while La Niña cycles are identified as periods with temperatures 0.5 °C colder than average. Table 4-3 shows the SRR_{200km} at the 15 CRLs for normal, El Niño, and La Niña time periods. The SRR at CRLs located on the Atlantic Ocean coast was higher for La Niña time periods, as it has been documented in

the scientific literature. The largest differences were observed at CRLs on the North Carolina coast and Aguirre, PR. The SRR at Gulf Coast CRLs from Grand Isle, LA, to Clearwater, FL, was slightly higher for El Niño time periods. This outcome may reflect a response to other factors that have been recognized to impact TCs but are beyond the scope of this work. These may include the North Atlantic Oscillation (Jagger and Elsner 2006; Villarini et al. 2010) or Gulf of Mexico warm-core eddies shed by the loop current (Chouinard et al. 1997; Hong et al. 2000; Jaimes and Shay 2009).

Table 4-3. SRR_{200km} for El Niño, La Niña, and normal time periods.

CRL	SRR _{200km} Normal Periods (storms/yr)	SRR _{200km} Niño Periods (storms/yr)	SRR _{200km} Niña Periods (storms/yr)
Galveston, TX	0.24	0.09	0.17
Port Arthur, TX	0.24	0.13	0.16
Grand Isle, LA	0.24	0.29	0.26
Gulfport, MS	0.18	0.31	0.27
Apalachicola, FL	0.19	0.25	0.23
Clearwater, FL	0.22	0.24	0.23
Biscayne Bay, FL	0.27	0.22	0.22
Atlantic Beach, NC	0.28	0.26	0.48
Duck, NC	0.26	0.21	0.45
Virginia Beach, VA	0.23	0.17	0.38
Chesapeake Bay, MD	0.10	0.05	0.19
The Battery, NY	0.10	0.10	0.21
Newport, RI	0.15	0.15	0.23
Boston, MA	0.10	0.11	0.21
Aguirre, PR	0.16	0.07	0.30

5 Sampling Uncertainty Associated with the Estimation of SRR

The GKF considers historical data by assigning weights to the TCs based on the distance to the coastal reference location. As such, and assuming that the sampled distances adequately represents the population, the statistical characteristics of the latter can be estimated through the use of a bootstrapping resampling procedure. An experiment was conducted where this distance was treated as a continuous random variable and its empirical distribution resampled to quantify the sampling uncertainty associated with the SRR. Resampling of the empirical cumulative distribution function of the distance (d_i) parameter of the GKF equation at each CRL (Equation 3-3) was performed 100,000 times. Distance adjusted weights were calculated for each of the resampled distances. An SRR was calculated for each resampling iteration. The SRR means and the 84%, 90%, 95%, and 98% confidence limits (CL) were calculated at each CRL.

Resampling results are presented in Table 5-1. The table shows the recurrence rate associated with storms passing within 200 km of each CRL for comparison with the mean SRR_{200km} calculated through resampling. It can be seen in the results that both values are similar. The effects of uncertainty expressed as 84%, 90%, 95%, and 98% CLs can also be seen. Table 5-2 shows the increases in confidence limits as percentage of mean SRR. The 98% confidence limit represents an increase over the mean SRR that varies from 31.6% for Duck, NC, to 47.1% in the Battery, NY. The margin of uncertainty increases the most towards the CRLs located in New England. The lowest margins of uncertainty for the 98% CL occur at CRLs located from Virginia to the Gulf coast of Florida. The SD and coefficient of variation of the sampled data are shown in Table 5-3. Overall, the largest sampling uncertainties appear to be found in the CRLs located north of Virginia.

Table 5-1. Mean SRR_{200km} and sampling confidence limits.

CRL	SRR _{200km} (storms/yr)	Mean (storms/ yr)	84% CL (storms/yr)	90% CL (storms/yr)	95% CL (storms/yr)	98% CL (storms/yr)
Galveston, TX	0.216	0.221	0.262	0.274	0.290	0.309
Port Arthur, TX	0.221	0.226	0.266	0.278	0.294	0.312
Grand Isle, LA	0.249	0.254	0.295	0.308	0.324	0.343
Gulfport, MS	0.227	0.232	0.272	0.284	0.300	0.318
Apalachicola, FL	0.221	0.226	0.263	0.274	0.290	0.307
Clearwater, FL	0.256	0.261	0.300	0.312	0.329	0.346
Biscayne Bay, FL	0.278	0.282	0.325	0.339	0.355	0.375
Atlantic Beach, NC	0.316	0.321	0.369	0.383	0.402	0.424
Duck, NC	0.277	0.281	0.322	0.335	0.352	0.370
Virginia Beach, VA	0.232	0.237	0.273	0.284	0.298	0.314
Chesapeake Bay, MD	0.103	0.108	0.130	0.138	0.147	0.158
The Battery, NY	0.133	0.138	0.168	0.177	0.190	0.203
Newport, RI	0.166	0.171	0.203	0.214	0.227	0.242
Boston, MA	0.133	0.138	0.166	0.175	0.186	0.199
Aguirre, PR	0.153	0.158	0.188	0.197	0.209	0.223

Table 5-2. Increase in confidence limits as percentage of mean SRR.

CRL	84% CL Percent Increase (%)	90% CL Percent Increase (%)	95% CL Percent Increase (%)	98%CL Percent Increase (%)
Galveston, TX	18.6	24.0	31.2	39.8
Port Arthur, TX	17.7	23.0	30.1	38.1
Grand Isle, LA	16.1	21.3	27.6	35.0
Gulfport, MS	17.2	22.4	29.3	37.1
Apalachicola, FL	16.4	21.2	28.3	35.8
Clearwater, FL	14.9	19.5	26.1	32.6
Biscayne Bay, FL	15.2	20.2	25.9	33.0
Atlantic Beach, NC	15.0	19.3	25.2	32.1
Duck, NC	14.6	19.2	25.3	31.7
Virginia Beach, VA	15.2	19.8	25.7	32.5
Chesapeake Bay, MD	20.4	27.8	36.1	46.3

CRL	84% CL Percent Increase (%)	90% CL Percent Increase (%)	95% CL Percent Increase (%)	98%CL Percent Increase (%)
The Battery, NY	21.7	28.3	37.7	47.1
Newport, RI	18.7	25.1	32.7	41.5
Boston, MA	20.3	26.8	34.8	44.2
Aguirre, PR	19.0	24.7	32.3	41.1

Table 5-3. SD and coefficient of variation of the resampled data.

CRL	SD (storms/yr)	CV
Galveston, TX	0.042	0.192
Port Arthur, TX	0.040	0.177
Grand Isle, LA	0.042	0.165
Gulfport, MS	0.040	0.172
Apalachicola, FL	0.037	0.166
Clearwater, FL	0.040	0.154
Biscayne Bay, FL	0.043	0.153
Atlantic Beach, NC	0.048	0.150
Duck, NC	0.041	0.147
Virginia Beach, VA	0.036	0.153
Chesapeake Bay, MD	0.028	0.263
The Battery, NY	0.030	0.217
Newport, RI	0.032	0.190
Boston, MA	0.028	0.204
Aguirre, PR	0.034	0.218

6 Uncertainty in TC Observational Data

TC data observations have uncertainties that are inherent to the methods used for their collection. As discussed in Section 2.2, several studies have attempted to quantify the uncertainty associated with the storm parameters recorded in HURDAT2. Landsea and Franklin (2013) provided uncertainty estimates based on the results of a survey of 11 subject matter experts. A method was developed to incorporate these estimates of parameter uncertainties into quantifiable SRR uncertainty. The parameter uncertainties evaluated were central pressure and position. Uncertainties for these two parameters were extracted from Table 2-1 for satellite and aircraft category 1 and 2 hurricanes and major hurricanes. The central pressure uncertainty was applied before the selection of TCs based on Δp threshold.

The overall procedure involved assigning a probability distribution to the reported uncertainty parameters and performing a random sampling from this distribution to assign a random uncertainty to the HURDAT2 parameters extracted for the computation of SRR using GKF. This process was repeated 100,000 times through a bootstrapping procedure. Two methods for assigning probability distributions to the parameters were evaluated. The first involved the development of triangular distributions with user-provided mean, and the second involved sampling from a normal distribution whose mean correspond to the reported parameter uncertainty.

Both methods yielded similar results. The results for the triangular distribution resampling are presented in Table 6-1. It can be seen that the mean SRR_{200km} compares favorably with the SRR_{200km} assumed true value calculated from the period of record uncertainty analysis. Table 6-2 shows the increases in confidence limits as percentage of mean SRR_{200km} . The 98% confidence limit represents an increase over the mean SRR that varies from 3.4% for Atlantic Beach, NC, to 7.9% in Chesapeake Bay, VA. These confidence limits are significantly narrower than the confidence limits resulting from the sampling uncertainty analysis.

Table 6-1. Measurement uncertainty from resampling triangular distribution.

CRL	SRR _{200km} (storms/yr)	Mean SRR _{200km} (storms/yr)	84% CL (storms/yr)	90% CL (storms/yr)	95% CL (storms/yr)	98% CL (storms/yr)
Galveston, TX	0.216	0.216	0.220	0.221	0.223	0.224
Port Arthur, TX	0.221	0.221	0.226	0.227	0.229	0.231
Grand Isle, LA	0.249	0.249	0.254	0.255	0.257	0.259
Gulfport, MS	0.227	0.228	0.233	0.234	0.236	0.238
Apalachicola, FL	0.221	0.222	0.227	0.229	0.231	0.233
Clearwater, FL	0.256	0.257	0.262	0.264	0.266	0.269
Biscayne Bay, FL	0.278	0.279	0.284	0.286	0.288	0.290
Atlantic Beach, NC	0.316	0.315	0.321	0.322	0.324	0.326
Duck, NC	0.277	0.278	0.284	0.286	0.288	0.290
Virginia Beach, VA	0.232	0.233	0.239	0.241	0.243	0.246
Chesapeake Bay, MD	0.103	0.104	0.108	0.110	0.111	0.113
The Battery, NY	0.133	0.134	0.138	0.139	0.141	0.142
Newport, RI	0.166	0.167	0.172	0.174	0.176	0.178
Boston, MA	0.133	0.134	0.139	0.140	0.142	0.144
Aguirre, PR	0.153	0.154	0.158	0.160	0.161	0.163

Table 6-2. Increases in confidence limits as percentage of mean SRR.

CRL	84% CL Percent Increase (%)	90% CL Percent Increase (%)	95% CL Percent Increase (%)	98%CL Percent Increase (%)
Galveston, TX	2.0	2.5	3.2	4.0
Port Arthur, TX	2.2	2.8	3.6	4.5
Grand Isle, LA	1.9	2.5	3.2	4.0
Gulfport, MS	2.2	2.8	3.6	4.5
Apalachicola, FL	2.4	3.0	3.9	4.9
Clearwater, FL	2.2	2.9	3.7	4.6
Biscayne Bay, FL	2.0	2.5	3.2	4.1
Atlantic Beach, NC	1.7	2.1	2.7	3.4
Duck, NC	2.2	2.8	3.6	4.5
Virginia Beach, VA	2.6	3.3	4.3	5.4
Chesapeake Bay, MD	3.8	4.9	6.3	7.9
The Battery, NY	2.9	3.7	4.8	6.1
Newport, RI	2.9	3.8	4.8	6.0
Boston, MA	3.4	4.4	5.7	7.1
Aguirre, PR	2.9	3.8	4.9	6.1

7 Discretization of TCs by Intensity

Probabilistic insight can be gained from grouping TCs according to their intensity, as intense TCs tend to behave differently than weaker ones. This study examined the GKF SRR uncertainty associated with different subsets of TCs. When partitioning TCs by storm intensity (e.g., Δp), the uncertainty associated with observed or measured intensity can cause TCs to be sampled as part of different populations. Particular interest was placed on very intense TCs that could provide a better understanding of flooding hazards with very low AEP, which can affect critical infrastructure such as nuclear power plants.

7.1 Selection of central pressure discretization bounds

Two discretization schemes based on TC intensity were adopted in this study. The first was to divide all TCs with central pressure deficits (Δp) larger than 28 hPa into low-intensity and high-intensity storms. Storms with $28 \leq \Delta p < 48$ hPa were classified as low-intensity storms, and storms with $\Delta p \geq 48$ were classified as high-intensity storms. The second consisted of dividing storms into three groups: low-intensity, high-intensity, and critical-intensity storms. Establishing the Δp lower threshold for critical-intensity storms was a trial and error process. A Δp of 88 hPa was first selected and discarded based on the calculated SRR_{200km} being zero for the U.S. North Atlantic Coast from central Florida all the way to Canada, as seen on Figure 7-1. A similar situation occurred when evaluating TCs with $\Delta p \geq 78$ hPa, although in this case SRR_{200km} values could be found farther north as shown in Figure 7-2. Finally, a Δp of 68 was selected as the lower threshold for critical-intensity storms. The intensities for discretization were $\Delta p \geq 68$ critical-intensity, $48 \leq \Delta p < 68$ hPa for high-intensity, and $28 \leq \Delta p < 48$ hPa for low-intensity. Figures 7-3 through 7-5 show the geographic distribution of SRR_{200km} values for the three groups.

Figure 7-1. SRR of critical-intensity TCs in the North Atlantic basin ($\Delta p \geq 88$ hPa).

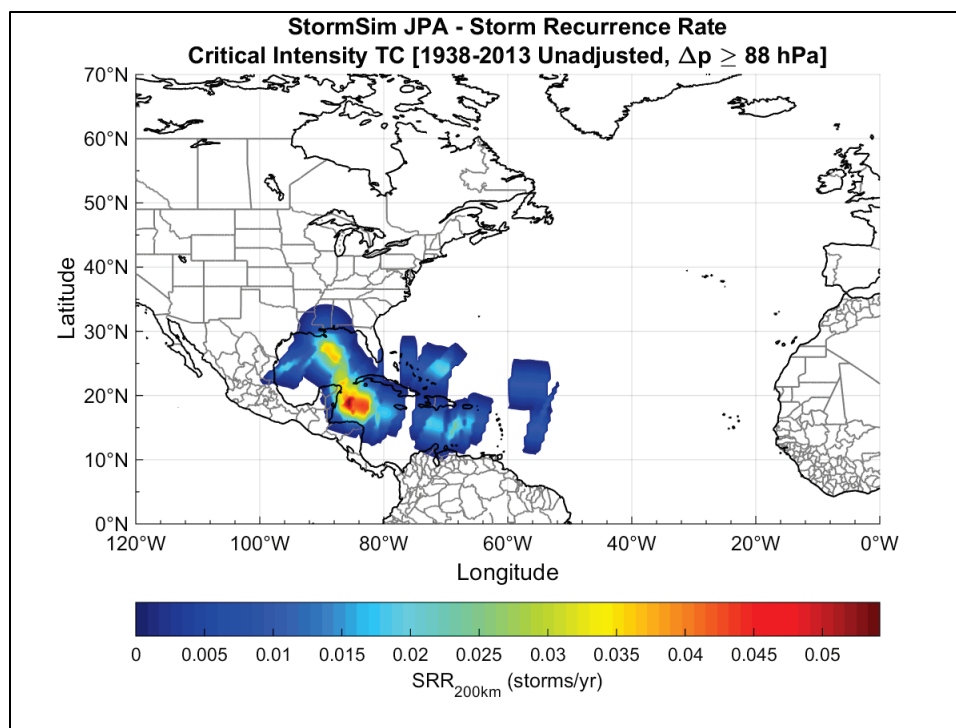


Figure 7-2. SRR of critical-intensity TCs in the North Atlantic basin ($\Delta p \geq 78$ hPa).

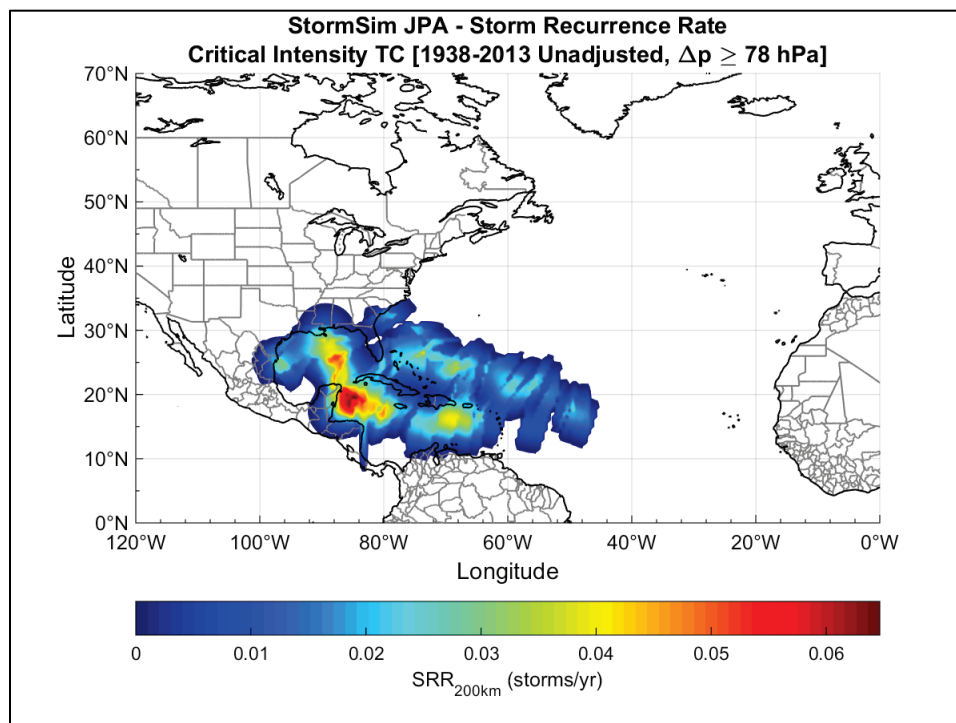


Figure 7-3. SRR of critical-intensity TCs in the North Atlantic basin ($\Delta p \geq 68$ hPa).

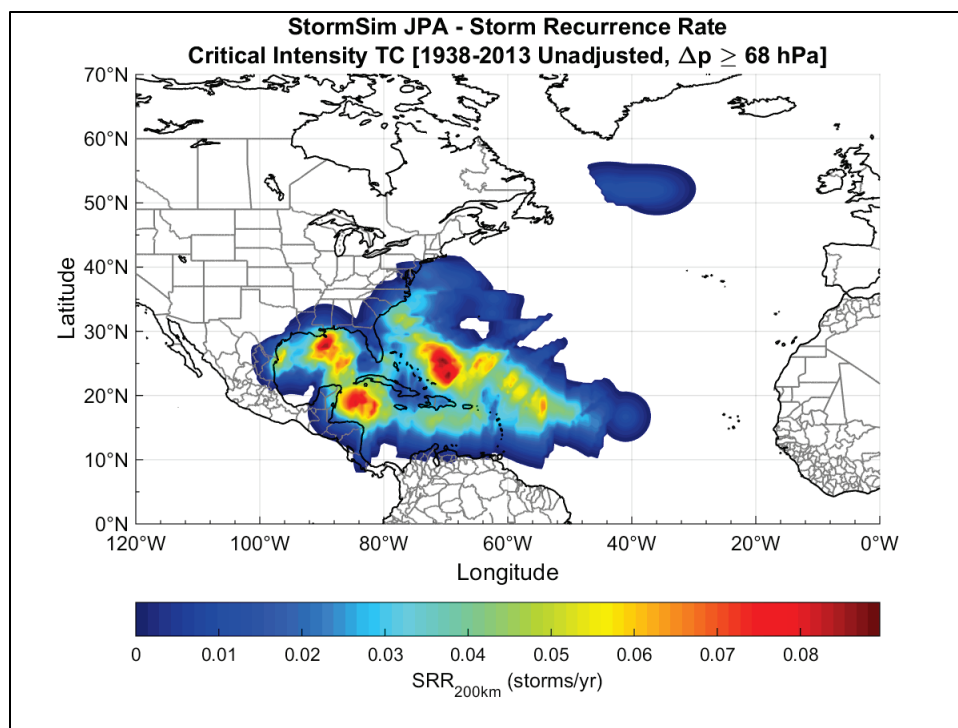


Figure 7-4. SRR of high-intensity TCs in the North Atlantic basin.

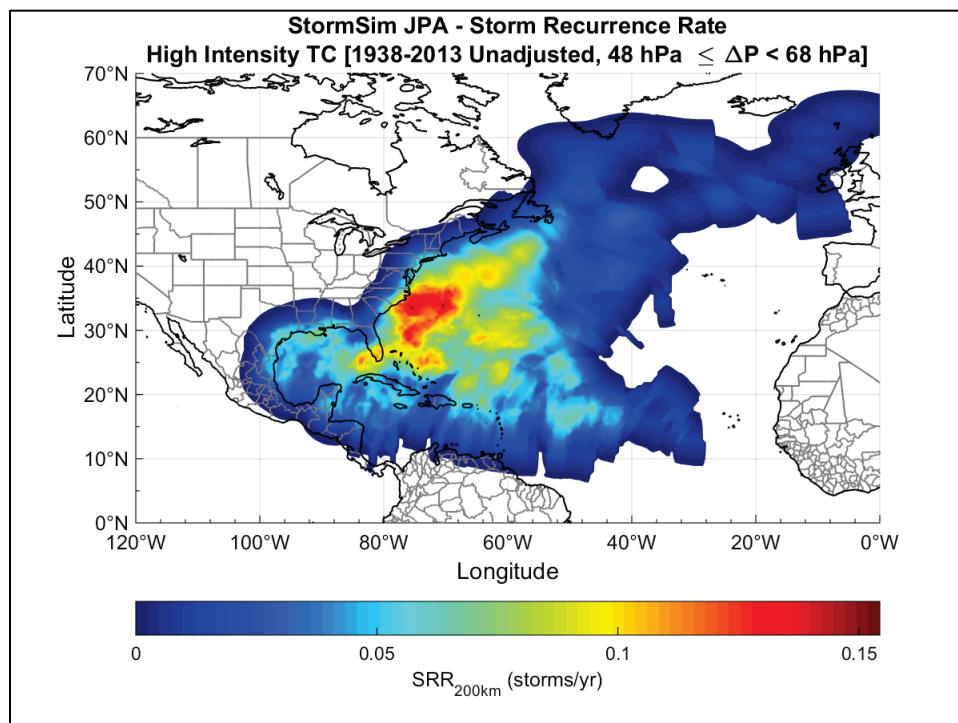
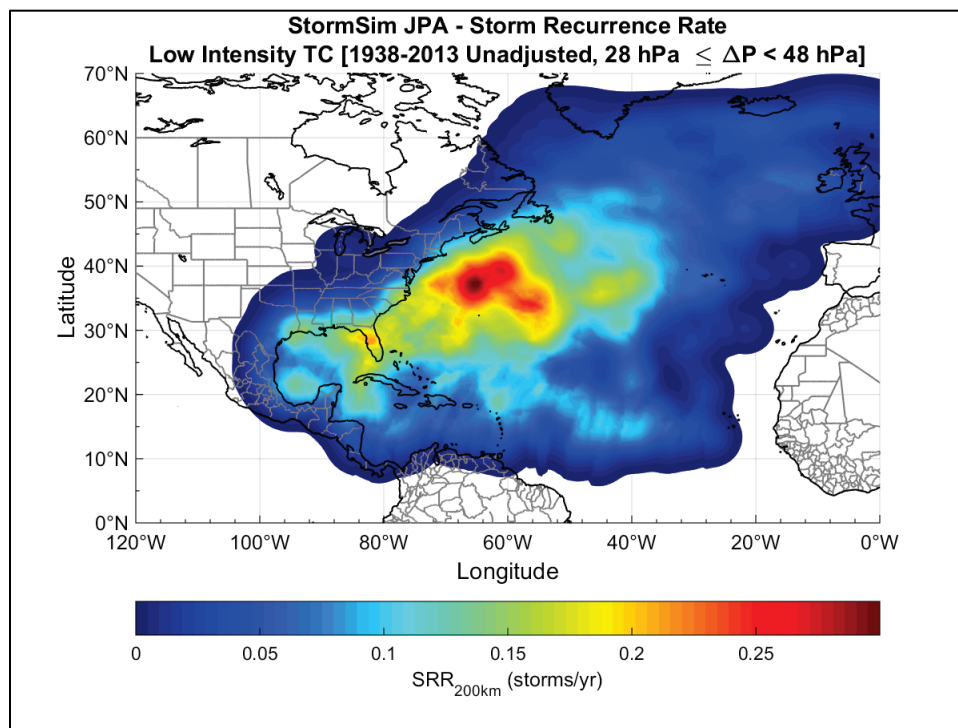


Figure 7-5. SRR of low-intensity TCs in the North Atlantic basin.



7.2 Effect of partitioning TCs by intensity

The immediate effect of separating TCs by intensity is the reduction of the sample. This reduction is particularly critical when evaluating events that are rare by their very nature (i.e., very intense TCs). The issue was observed when a higher threshold was established. TCs with central pressure deficits larger than 88 hPa are virtually nonexistent for the U.S. North Atlantic coast for purposes of computing SRR. Also, as the data are discretized into a greater number of groups, the sample is further reduced. It is expected that reducing the number of events in the sample will increase uncertainty. All the experiments in this study were re-executed for each grouping of TC intensity, with particular interest in quantifying the uncertainty of those TCs with central pressures deficits greater than 68 hPa, referred to here as critical-intensity storms. This section presents some of the results that better illustrate the effect of the groupings on uncertainty estimates. The main results for all experiments and intensity groups are presented in Chapter 8 in which the computed individual uncertainties are combined.

The first analysis performed was to illustrate the interaction between the three discretization groups for UKF SRR and for GKF SRR. The results of the analysis are shown Figures 7-6 to 7-9 for Galveston, TX, and The Battery, NY. The figures generally show, as expected, that low-intensity TCs have higher SRR than high-intensity TCs, and thus, high-intensity TCs have higher SRR than critical-intensity TCs. This also can be seen by comparing the UKF SRR means. Nevertheless, for The Battery, the high- and low-intensity storms UKF SRR are similar over the range of 50 km to 250 km capture-zone radius. This overlapping range is reduced for the GKF SRR in Figure 7-9. In general, the UKF SRR of low-intensity TCs is one order of magnitude larger than the critical-intensity SRR. This means that when all storms are combined under one classification, the probability masses of the critical storms could be overstated by using a single SRR and not segregating the computation of the storms' relative probabilities by intensity. In JPM analysis, the probability mass of each storm is calculated by the multiplication of the SRR by the relative probabilities of the storms determined from the joint probability of the storms parameters and the track spacing.

Figure 7-6. UKF SRR for critical-, high-, and low-intensity TCs at Galveston, TX.

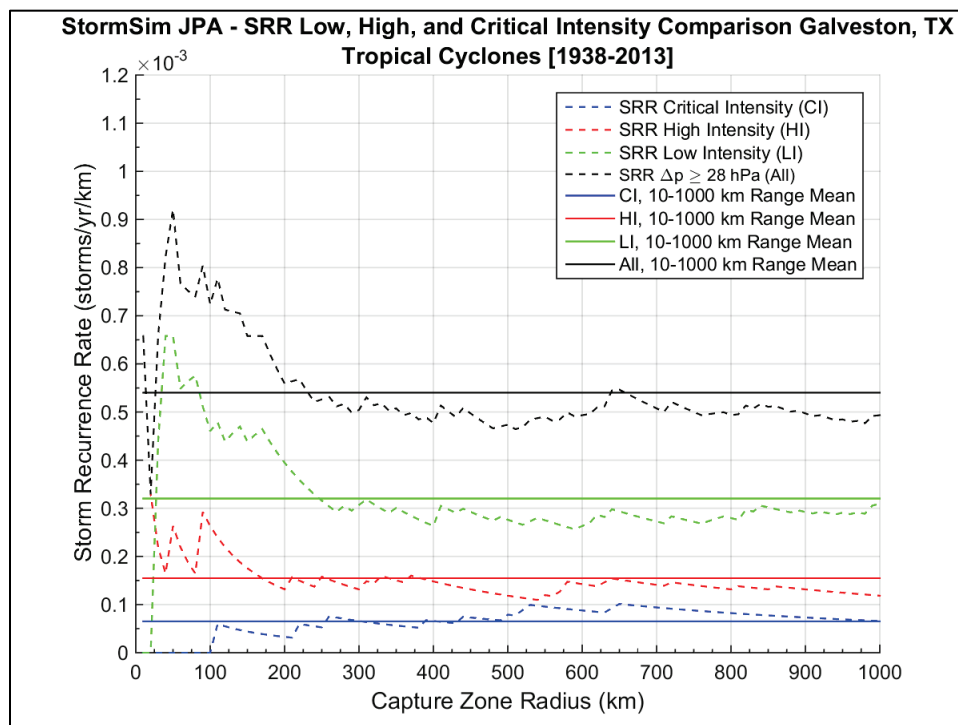


Figure 7-7. UKF SRR for critical-, high-, and low-intensity TCs at The Battery, NY.

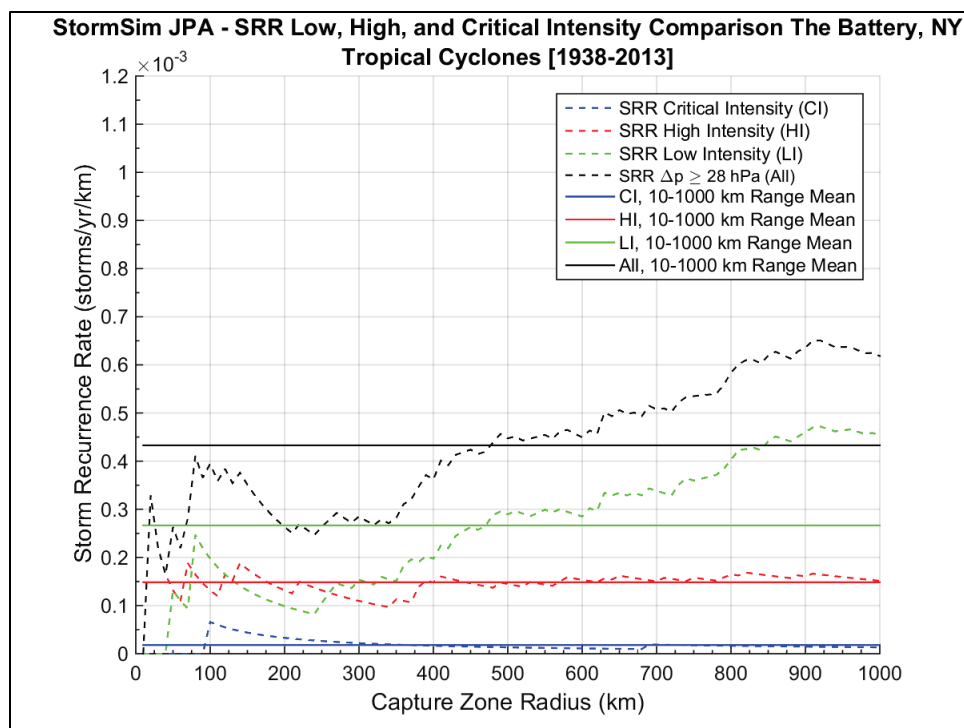


Figure 7-8. GKF SRR for critical-, high-, and low-intensity TCs at Galveston, TX.

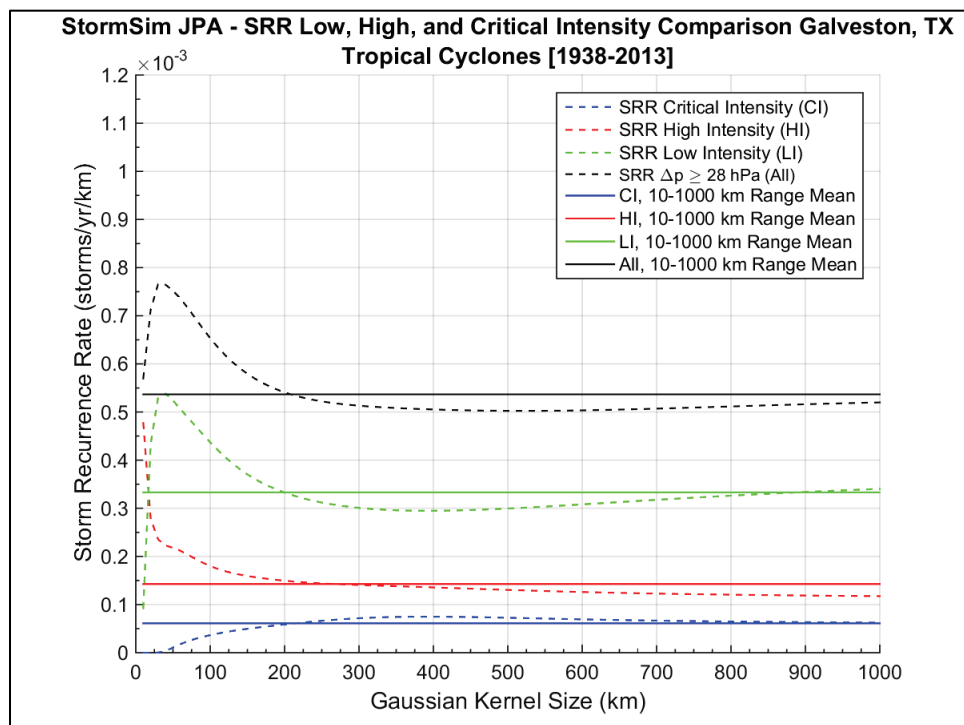
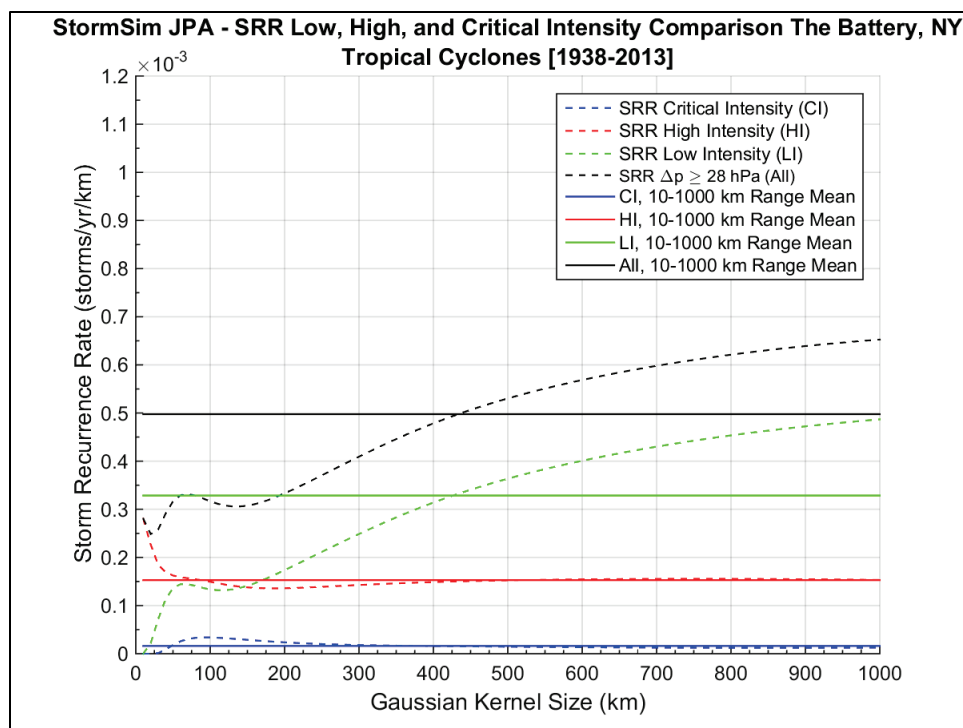


Figure 7-9. GKF SRR for critical-, high-, and low-intensity TCs at The Battery, NY.



The coefficient of variation was used in this study as measure of dispersion of the uncertainty and as such can be used to examine the effect of separating TCs by intensity. Figure 7-10 shows a comparison of coefficients of variation of low-, high-, and critical-intensity storms at each CRL. The coefficient of variation for the critical-intensity storms is largest in 10 of 15 CRLs. Figure 7-11 shows a comparison of coefficients of variation of critical-intensity storms and all storms. The coefficient of variation is greater for critical-intensity storms at 13 of 15 CRLs. The effect of separately analyzing TCs based on intensity on the uncertainty can also be seen in the sampling uncertainty. Tables 7-1 through 7-3 present the results of sampling uncertainty for low-, high-, and critical-intensity storms, respectively. It stands out that the critical intensities SRR for the northernmost CRLs of Newport, RI, and Boston, MA, reflects the absence of critical intensity TCs in their vicinity. The values are less than the three significant digits shown, and this can be contrasted with the Table 7-1 for low intensity TCs, which show values of 0.108 and 0.094 or Table 8-1 that shows values of 0.166 and 0.133 for all TC intensities. The coefficient of variation for critical-intensity storms is from 1.3 to 3.3 times higher than the coefficient of variation for the low-intensity storms.

Figure 7-10. Comparison of CV of low-, high-, and critical-intensity TCs.

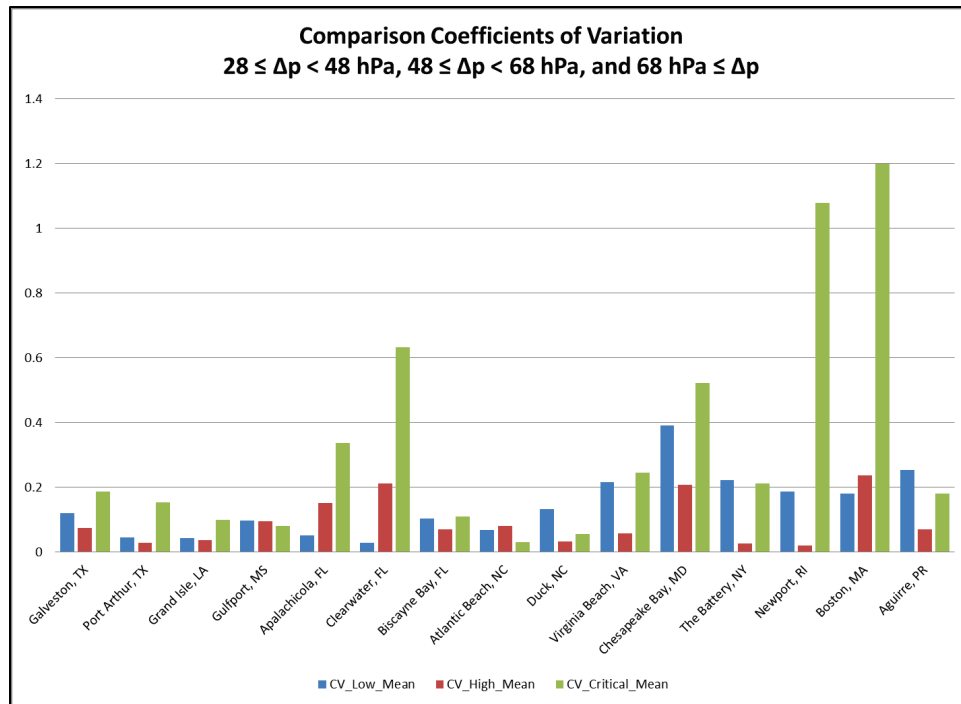


Figure 7-11. Comparison of CV between critical-intensity TCs and all TCs.

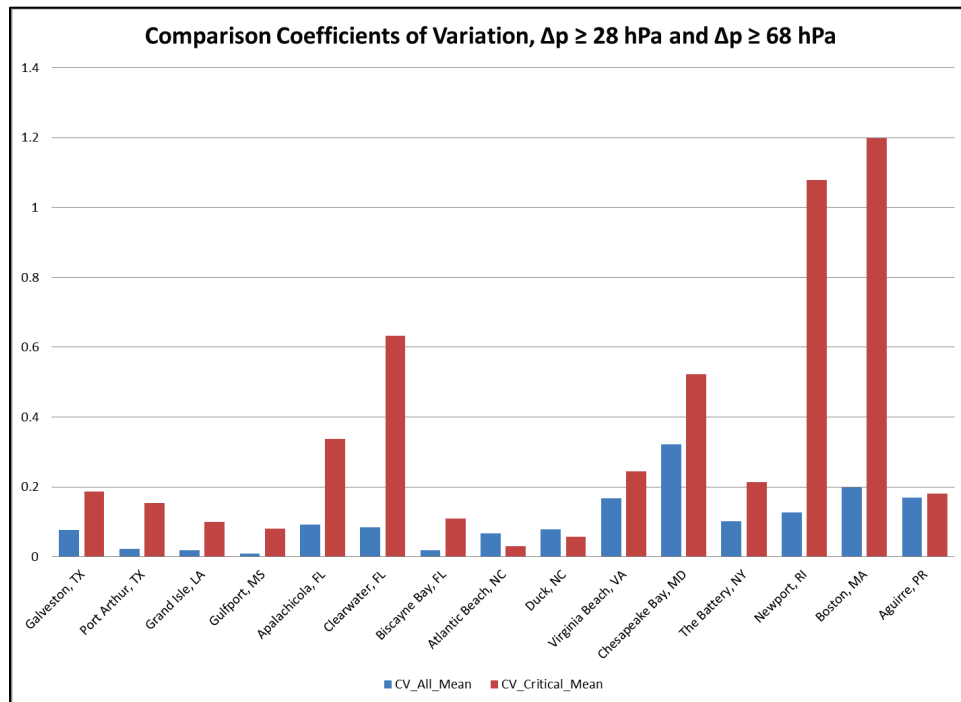


Table 7-1. Sampling uncertainty for low-intensity TCs.

CRL	SRR _{200km} (storms/yr)	Mean (storms/yr)	84% CL (storms/yr)	98% CL (storms/yr)	SD (storms/yr)	CV
Galveston, TX	0.133	0.182	0.219	0.309	0.037	0.201
Port Arthur, TX	0.148	0.186	0.222	0.312	0.038	0.203
Grand Isle, LA	0.127	0.168	0.200	0.343	0.032	0.194
Gulfport, MS	0.116	0.168	0.200	0.318	0.034	0.202
Apalachicola, FL	0.169	0.197	0.232	0.307	0.035	0.180
Clearwater, FL	0.202	0.227	0.266	0.346	0.039	0.171
Biscayne Bay, FL	0.149	0.187	0.220	0.375	0.033	0.176
Atlantic Beach, NC	0.179	0.220	0.259	0.424	0.039	0.179
Duck, NC	0.162	0.185	0.217	0.370	0.032	0.175
Virginia Beach, VA	0.142	0.158	0.186	0.314	0.028	0.180
Chesapeake Bay, MD	0.059	0.074	0.092	0.158	0.022	0.300
The Battery, NY	0.069	0.092	0.114	0.203	0.022	0.243
Newport, RI	0.108	0.134	0.162	0.242	0.028	0.210
Boston, MA	0.094	0.116	0.142	0.199	0.028	0.245
Aguirre, PR	0.065	0.082	0.103	0.223	0.021	0.253

Table 7-2. Sampling uncertainty for high-intensity TCs.

CRL	SRR _{200km} (storms/yr)	Mean (storms/yr)	84% CL (storms/yr)	98% CL (storms/yr)	SD (storms/yr)	CV
Galveston, TX	0.060	0.096	0.121	0.152	0.025	0.261
Port Arthur, TX	0.052	0.096	0.121	0.151	0.025	0.257
Grand Isle, LA	0.067	0.114	0.142	0.174	0.028	0.241
Gulfport, MS	0.073	0.109	0.137	0.170	0.028	0.253
Apalachicola, FL	0.033	0.073	0.092	0.116	0.019	0.260
Clearwater, FL	0.043	0.122	0.148	0.178	0.026	0.208
Biscayne Bay, FL	0.079	0.139	0.170	0.206	0.030	0.219
Atlantic Beach, NC	0.114	0.159	0.193	0.233	0.034	0.215
Duck, NC	0.091	0.137	0.166	0.201	0.029	0.214
Virginia Beach, VA	0.071	0.117	0.143	0.173	0.026	0.223
Chesapeake Bay, MD	0.041	0.053	0.070	0.091	0.017	0.319

CRL	SRR _{200km} (storms/yr)	Mean (storms/yr)	84% CL (storms/yr)	98% CL (storms/yr)	SD (storms/yr)	CV
The Battery, NY	0.054	0.070	0.092	0.120	0.023	0.327
Newport, RI	0.058	0.072	0.094	0.121	0.023	0.316
Boston, MA	0.038	0.056	0.074	0.096	0.018	0.322
Aguirre, PR	0.052	0.088	0.110	0.137	0.022	0.253

Table 7-3. Sampling uncertainty for critical-intensity TCs.

CRL	SRR _{200km} (storms/yr)	Mean (storms/yr)	84% CL (storms/yr)	98% CL (storms/yr)	SD (storms/yr)	CV
Galveston, TX	0.023	0.033	0.047	0.065	0.014	0.412
Port Arthur, TX	0.021	0.030	0.042	0.058	0.012	0.400
Grand Isle, LA	0.055	0.078	0.101	0.129	0.023	0.296
Gulfport, MS	0.038	0.065	0.086	0.112	0.021	0.322
Apalachicola, FL	0.020	0.030	0.041	0.056	0.011	0.377
Clearwater, FL	0.011	0.036	0.049	0.066	0.013	0.356
Biscayne Bay, FL	0.049	0.059	0.080	0.105	0.021	0.349
Atlantic Beach, NC	0.023	0.044	0.060	0.082	0.017	0.380
Duck, NC	0.024	0.034	0.049	0.069	0.015	0.433
Virginia Beach, VA	0.019	0.027	0.039	0.055	0.012	0.453
Chesapeake Bay, MD	0.003	0.016	0.026	0.041	0.010	0.619
The Battery, NY	0.009	0.021	0.035	0.053	0.013	0.633
Newport, RI	0.000	0.015	0.026	0.042	0.011	0.702
Boston, MA	0.000	0.011	0.019	0.032	0.008	0.779
Aguirre, PR	0.035	0.059	0.078	0.102	0.019	0.328

8 Comparison of SRR Sources of Uncertainty

The uncertainty associated with various aspects of the computation of SRR has been quantified. These uncertainties are related to the selection of Gaussian kernel size, selection of period of record, sampling uncertainty, and measurement uncertainty. The effect on SRR uncertainty of segregating TCs into groups according to their intensity was also examined. This chapter summarizes the sources of SRR uncertainties and presents combined uncertainty results by TC intensity category at all CRLs.

The JPM analysis allows for the consideration of uncertainty at the time of solving of the JPM integral. As seen in equation 1-1b, the SRR is incorporated into the JPM integration process as a component of the probability mass of each storm. In contrast with the uncertainty represented by the error term in the integral, the SRR uncertainty is associated with the storm forcing, not the response. The integration process typically consists of constructing the complementary cumulative density function (CCDF) by cumulative sum of the probability masses of storms sorted by their corresponding responses (e.g., storm surge, SWL) in descending order. The result of this integration is called a hazard curve and depicts the magnitude of the response as a function of annual exceedance probability (AEP). In the integration process, the uncertainty can be incorporated by discretizing the uncertainty (assumed to be a Gaussian or normal distribution with standard deviation equivalent to the estimated uncertainty) while creating as many replicates of each storm surge response as discrete uncertainty values and then adding the discrete uncertainty to the responses. The probability mass of each storm is evenly split among the replicates. In other words, the probability mass of each storm replicate is calculated as the quotient of the storm probability mass and the number of replicates.

The epistemic components of SRR uncertainty can be incorporated into the hazard quantification through the application of a logic tree approach where, for example, the effect of applying different kernel estimators would be represented by different branches of the tree. This can also apply to other SRR epistemic uncertainties such as kernel size, period of record, segregating by TC intensity, resampling uncertainty and observational uncertainty. Although resampling uncertainty and observational

uncertainty could be classified as aleatory variability, they can be considered epistemic from the point of view of reducibility. The sampling uncertainty will be reduced with the passage of time, as the sample size of TC occurrences in the vicinity of a CRL of interest increases with the advent of new TCs. In a similar manner, the uncertainty related to the measurement of TC parameters is expected to improve over time as new technologies are implemented for the observation of TCs. Note that these errors are assumed independent, but in practice there could be dependencies. Dependency can be present between the sampling uncertainty and the period of record. The spatial component of the computed sampling uncertainty can be affected by the temporal aspect of period of record. A reduction in the period of record will reduce sample size, therefore causing an increase the sampling uncertainty. In general, these types of dependencies need to be recognized since in JPM it is assumed that the error terms are independent, their effects can be combined by addition, and the combined error can be represented as a Gaussian distribution with mean zero. Herein, SRR uncertainty is being considered as epistemic, so it is not treated as a single quantity that is applied to the JPM integral.

Nevertheless, for purposes of comparing the relative contribution of the quantified uncertainties, these were combined by taking the square root of the sum of their squares. The relative contribution of each type of uncertainty was calculated by dividing the square of each contribution by the sum of the squares of all the uncertainties. The biggest contributor to uncertainty was the sampling uncertainty. The smallest contributor to overall uncertainty was the sampling intensity. This holds true for all storm group intensities. Tables 8-1 to 8-5 provide the summary of SRR uncertainties and total uncertainty for all storm intensities, as well as low, high, and critical intensity.

The CRLs with the lowest total uncertainty generally coincide with locations in North Carolina, Florida, and the Gulf of Mexico. An exception is Galveston, TX, which exhibits the fourth largest CV among the 15 CRLs. The Chesapeake Bay CRL exhibited the largest total uncertainty. This may be due to its inland location farther to the West of other North Atlantic coast CRLs. The effect of partitioning TCs by intensity can also be observed in the CV estimates. The uncertainty and CV increase as the intensity of the TCs also increases. This is because high-intensity TCs tend to occur less frequently than low-intensity TCs, and hence represent a

smaller subset of the historical record. On average, the CV of critical-intensity TCs ($\Delta p \geq 68$ hPa) was estimated to be 1.018 whereas the CV for low-intensity TCs ($28 \text{ hPa} \leq \Delta p < 48 \text{ hPa}$) was estimated at just 0.349. This represents a percent increase in uncertainty of 192%.

Table 8-1. Summary of SRR uncertainty for all sampled TCs.

TCs with $\Delta p \geq 28$ hPa (central pressure equal or lower than 985 hPa)							
CRL	SRR _{200km} (storms/yr)	SD (storms/yr)					CV
		Kernel Size	Period of Record	Sampling	Obs. Data	Total	
Galveston, TX	0.216	0.017	0.012	0.042	0.004	0.047	0.219
Port Arthur, TX	0.221	0.005	0.014	0.040	0.005	0.043	0.195
Grand Isle, LA	0.249	0.005	0.026	0.042	0.004	0.050	0.200
Gulfport, MS	0.227	0.002	0.031	0.040	0.005	0.051	0.223
Apalachicola, FL	0.221	0.020	0.016	0.037	0.005	0.046	0.206
Clearwater, FL	0.256	0.022	0.018	0.040	0.005	0.049	0.193
Biscayne Bay, FL	0.278	0.005	0.024	0.043	0.005	0.050	0.179
Atlantic Beach, NC	0.316	0.021	0.035	0.048	0.005	0.063	0.200
Duck, NC	0.277	0.021	0.028	0.041	0.006	0.055	0.198
Virginia Beach, VA	0.232	0.037	0.025	0.036	0.006	0.057	0.248
Chesapeake Bay, MD	0.103	0.033	0.011	0.028	0.004	0.045	0.436
The Battery, NY	0.133	0.014	0.009	0.030	0.004	0.035	0.259
Newport, RI	0.166	0.021	0.013	0.032	0.005	0.041	0.246
Boston, MA	0.133	0.026	0.013	0.028	0.004	0.041	0.305
Aguirre, PR	0.153	0.025	0.032	0.034	0.004	0.053	0.350
Mean	0.212	0.018	0.021	0.038	0.005	0.048	0.244
%	-	15.1	19.3	64.6	1.0	100	-

Table 8-2. Summary of SRR uncertainty for low-intensity TCs.

TCs with 28 hPa $\leq \Delta p < 48$ hPa (central pressures between 985 hPa and 965 hPa)							
CRL	SRR _{200km} (storms/yr)	SD (storms/yr)					CV
		Kernel Size	Period of Record	Sampling	Obs. Data	Total	
Galveston, TX	0.133	0.017	0.012	0.037	0.016	0.045	0.339
Port Arthur, TX	0.148	0.007	0.014	0.038	0.015	0.044	0.294
Grand Isle, LA	0.127	0.006	0.012	0.032	0.015	0.038	0.299
Gulfport, MS	0.116	0.011	0.016	0.034	0.015	0.042	0.362
Apalachicola, FL	0.169	0.009	0.012	0.035	0.015	0.041	0.244
Clearwater, FL	0.202	0.006	0.018	0.039	0.015	0.046	0.226
Biscayne Bay, FL	0.149	0.015	0.010	0.033	0.014	0.040	0.268
Atlantic Beach, NC	0.179	0.013	0.026	0.039	0.019	0.052	0.290
Duck, NC	0.162	0.021	0.017	0.032	0.016	0.045	0.276
Virginia Beach, VA	0.142	0.029	0.017	0.028	0.014	0.046	0.323
Chesapeake Bay, MD	0.059	0.023	0.004	0.022	0.008	0.034	0.570
The Battery, NY	0.069	0.016	0.011	0.022	0.011	0.031	0.452
Newport, RI	0.108	0.020	0.008	0.028	0.012	0.037	0.345
Boston, MA	0.094	0.017	0.005	0.028	0.012	0.035	0.373
Aguirre, PR	0.065	0.016	0.026	0.021	0.008	0.037	0.576
Mean	0.128	0.015	0.014	0.031	0.014	0.041	0.349
%	-	14.2	12.0	62.1	11.8	100	-

Table 8-3. Summary of SRR uncertainty for high-intensity TCs.

TCs with $\Delta p \geq 48$ hPa (central pressure equal or lower than 965 hPa)							
CRL	SRR _{200km} (storms/yr)	SD (storms/yr)					CV
		Kernel Size	Period of Record	Sampling	Obs. Data	Total	
Galveston, TX	0.083	0.001	0.005	0.027	0.010	0.029	0.351
Port Arthur, TX	0.073	0.002	0.007	0.025	0.009	0.028	0.383
Grand Isle, LA	0.121	0.007	0.022	0.032	0.010	0.040	0.332
Gulfport, MS	0.111	0.010	0.021	0.030	0.010	0.040	0.356
Apalachicola, FL	0.052	0.011	0.009	0.020	0.007	0.025	0.480
Clearwater, FL	0.054	0.016	0.004	0.026	0.010	0.032	0.605
Biscayne Bay, FL	0.129	0.011	0.017	0.033	0.009	0.040	0.308
Atlantic Beach, NC	0.137	0.009	0.016	0.036	0.013	0.042	0.308
Duck, NC	0.115	0.003	0.016	0.031	0.011	0.037	0.324
Virginia Beach, VA	0.090	0.008	0.013	0.027	0.010	0.032	0.359
Chesapeake Bay, MD	0.044	0.010	0.011	0.018	0.006	0.024	0.546
The Battery, NY	0.064	0.003	0.016	0.024	0.008	0.030	0.465
Newport, RI	0.058	0.002	0.012	0.023	0.009	0.028	0.477
Boston, MA	0.039	0.009	0.012	0.018	0.009	0.025	0.647
Aguirre, PR	0.088	0.009	0.009	0.025	0.006	0.029	0.332
Mean	0.084	0.007	0.013	0.026	0.009	0.032	0.418
%	-	5.5	16.1	70.2	8.2	100	-

Table 8-4. Summary of SRR uncertainty for high-intensity TCs with Δp up to 68 hPa.

TCs with 48 hPa $\leq \Delta p < 68$ hPa (central pressures between 965 hPa and 945 hPa)							
CRL	SRR _{200km} (storms/yr)	SD (storms/yr)					CV
		Kernel Size	Period of Record	Sampling	Obs. Data	Total	
Galveston, TX	0.060	0.005	0.006	0.025	0.012	0.029	0.481
Port Arthur, TX	0.052	0.001	0.005	0.025	0.011	0.028	0.531
Grand Isle, LA	0.067	0.002	0.011	0.028	0.012	0.032	0.483
Gulfport, MS	0.073	0.007	0.016	0.028	0.012	0.035	0.475
Apalachicola, FL	0.033	0.005	0.005	0.019	0.009	0.022	0.672
Clearwater, FL	0.043	0.009	0.004	0.026	0.011	0.029	0.685
Biscayne Bay, FL	0.079	0.006	0.010	0.030	0.012	0.035	0.439
Atlantic Beach, NC	0.114	0.010	0.014	0.034	0.015	0.041	0.358
Duck, NC	0.091	0.003	0.014	0.029	0.013	0.035	0.387
Virginia Beach, VA	0.071	0.004	0.011	0.026	0.012	0.031	0.433
Chesapeake Bay, MD	0.041	0.008	0.011	0.017	0.006	0.023	0.557
The Battery, NY	0.054	0.001	0.016	0.023	0.009	0.030	0.543
Newport, RI	0.058	0.001	0.012	0.023	0.010	0.028	0.476
Boston, MA	0.038	0.009	0.012	0.018	0.009	0.025	0.652
Aguirre, PR	0.052	0.004	0.006	0.022	0.010	0.025	0.481
Mean	0.062	0.005	0.010	0.025	0.011	0.030	0.510
%	-	2.9	12.0	71.4	13.7	100	-

Table 8-5. Summary of SRR uncertainty for critical-intensity TCs.

TCs with $\Delta p \geq 68$ hPa (central pressure equal or lower than 945 hPa)							
CRL	SRR _{200km} (storms/yr)	SD (storms/yr)					CV
		Kernel Size	Period of Record	Sampling	Obs. Data	Total	
Galveston, TX	0.023	0.004	0.003	0.014	0.007	0.016	0.696
Port Arthur, TX	0.021	0.003	0.004	0.012	0.007	0.015	0.705
Grand Isle, LA	0.055	0.005	0.012	0.023	0.008	0.028	0.503
Gulfport, MS	0.038	0.003	0.007	0.021	0.007	0.024	0.620
Apalachicola, FL	0.020	0.006	0.008	0.011	0.006	0.016	0.815
Clearwater, FL	0.011	0.007	0.002	0.013	0.004	0.015	1.418
Biscayne Bay, FL	0.049	0.006	0.008	0.021	0.009	0.024	0.496
Atlantic Beach, NC	0.023	0.001	0.004	0.017	0.008	0.019	0.835
Duck, NC	0.024	0.001	0.005	0.015	0.008	0.017	0.724
Virginia Beach, VA	0.019	0.004	0.005	0.012	0.006	0.015	0.786
Chesapeake Bay, MD	0.003	0.001	0.001	0.010	0.003	0.011	3.415
The Battery, NY	0.009	0.002	0.003	0.013	0.005	0.015	1.575
Newport, RI	0.000	0.000	0.000	0.011	0.005	0.012	-
Boston, MA	0.000	0.000	0.000	0.008	0.003	0.009	-
Aguirre, PR	0.035	0.006	0.007	0.019	0.008	0.023	0.645
Mean	0.022	0.003	0.005	0.015	0.006	0.017	1.018
%	-	3.7	7.4	75.1	13.8	100	-

9 Conclusions

Probabilistic storm surge model components for which uncertainties have been quantified in previous studies include hydrodynamic modeling, meteorological modeling, lack of storm track variation, storm track idealization, Holland B, and astronomical tide, among others. It has been recognized that the list of uncertainties typically considered is not exhaustive and that other sources of uncertainty can and should be incorporated into these probabilistic methodologies, like the joint probability method (JPM). The current standard of practice is for these uncertainties to be addressed through the inclusion of an error term (epsilon) in the integration leading up to the development of the hazard curve. The uncertainty included as an error term in the JPM integration is considered as aleatory variability in this study. In contrast, the epistemic uncertainty emerges from the consideration of alternative data, models, and methods used for estimating the storm hazard, which can lead to the development multiple hazard curves. This study focused on identifying and quantifying the uncertainty associated with data and methods involved in the computation of storm recurrence rate (SRR).

Different sources of epistemic uncertainty associated with the estimation of SRR were studied, including (1) uncertainty in the selection of kernel function and kernel size; (2) uncertainty arising from the selection of the period of record; (3) sampling uncertainty associated with the historical record; and (4) observation or measurement uncertainty in tropical cyclone (TC) parameter data. Another uncertainty assessment dealt with the partitioning or grouping of historical TCs by intensity and how this affected individual SRR uncertainty components. The center, body, and range of for these sources were evaluated.

Three methods for the estimation of SRR were considered: (1) the capture zone approach or uniform kernel function (UKF), the Gaussian kernel function (GKF), and the Epanechnikov kernel function (EKF). The capture zone approach includes line-crossing and area-crossing methods. The line-crossing approach can lead to underestimation of the hazard due to its exclusion of bypassing events. The area-crossing method was treated as a special case of the kernel approach through the application of the UKF. A significant advantage of the GKF is that it can consider a larger number of storms than the capture zone approach and the EKF. For the same ranges of optimal capture zone radii and Gaussian kernel sizes, the GKF SRR

estimates exhibited reduced coefficient of variation (CV) when compared to UKF estimates. The GKF was deemed to be the best method to be used for conducting the SRR computational experiments. Nevertheless, both the UKF and EKF could be carried forward for the computation of epistemic uncertainty.

Three methods were evaluated for the selection of kernel size for the GKF. Two of these methods were based on leave-one-out least squares cross-validation (LSCV) approaches that minimize cross-validation squared error (CVSE) and another on the minimization of the squared error. The LSCV approach produced overall kernel sizes smaller than the sizes typically used in previous JPM studies. The mean kernel size for all the considered CRLs was 95 km. The second LSCV approach, in which the data were partitioned in an estimation and a validation sample with UKF based rate, resulted in the location of the minimum CVSE being sensitive to the size of the validation sample's bandwidth. The third approach minimized the square of the difference between the SRR corresponding to each kernel size from 10 to 1000 km and the mean UKF SRR for a range of capture zone sizes. The range of 150 km–450 km was selected as a credible range for UKF since it had the lowest uncertainty values. The mean UKF SRR was assumed to be the reference true value in the minimization scheme. Based on this analysis, a kernel size of 200 km was selected to conduct the studies experiments. The use of site-specific kernel sizes resulted in SRR variations of -1.5% to 0.7% difference in CRLs from Texas to Atlantic Beach, NC, and 4.0% to -11.4 % in CRLs from Duck, NC, to Boston, MA.

Based on the evaluation of 15 CRLs, in general, the U.S. coast north of Virginia exhibited the largest uncertainties. The lowest uncertainties were observed in CRLs in North Carolina, Florida, Mississippi, and Louisiana. This is consistent with the expected negative correlation between uncertainty and TC activity. In other words, areas with higher TC recurrence rates produce larger sample sizes that, in general, exhibit lower uncertainties relative to areas with lower recurrence rates. Sampling uncertainty was the main contributor to total uncertainty followed by kernel size. Observational uncertainty was the lowest contributor to total SRR uncertainty.

The analysis of TCs partitioned by intensity resulted in increased uncertainty, in part, due to the reduced number of storms considered in

each partition. The lower limit for the critical intensity TCs was established at a central pressure deficit of 68 hPa. Partitions based on central pressure deficits higher than 68 hPa resulted in limited or nonexistent TC populations that precluded the computation of SRR in a large part of the U.S. North Atlantic Coast. It was found that the standard distribution (SD) decreased as the intensity of the TCs increased, but this occurrence is just because the SRR also decreases with intensity. The CV is comparatively a more adequate metric of SRR uncertainty than SD because it normalizes the dispersion using the mean SRR as a measure of scale. Regarding the CV, it was found that, as expected, it increased along with the intensity of the TCs. The CV increased by an average of 46% from low-intensity TCs ($28 \text{ hPa} \leq \Delta p < 48 \text{ hPa}$) to high-intensity TCs ($48 \text{ hPa} \leq \Delta p < 68 \text{ hPa}$), and by 99% from high-intensity to critical-intensity TCs ($\Delta p \geq 68 \text{ hPa}$). The CV increased by 192% from low- to critical-intensity TCs.

The comparison of the relative contribution of sources of SRR uncertainty focused on the characterization of the SRR variability arising from the selection of the Gaussian Kernel size and the period of record, the use of random subsets of data through bootstrap resampling, and the quality of the observational data. It was found that, on average, and without partitioning by storm intensity, sampling was the main contributor to the total uncertainty (65%), followed by period of record (19%), Gaussian kernel size (15%), and observational data errors (1%). This assessment assumed the different uncertainty components to be independent, but it is important to recognize that this may not always be the case. When TCs were partitioned based on their intensities, the mean contribution of the sampling uncertainty of the three intensity partitions increased to 70%, the period of record uncertainty decreased to 10%, the Gaussian kernel size uncertainty decreased to 7%, and the observational data uncertainty increased to 13%. Also, the average SRR CV of unpartitioned TCs was 0.244 while that of partitioned TCs was found to be 0.626. This constitutes a percent increase in uncertainty of 156%. Although partitioning TCs by storm intensity is inherently a source of uncertainty, the computation of a combined SRR, irrespective of intensity, significantly understates the uncertainty associated with high-intensity TCs and, especially, critical-intensity TCs. Therefore, it is recommended to do partitioning (grouping) by intensity to account for the uncertainty associated with the infrequent storms.

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Appendix A: Supplemental Analysis of UKF Capture Zone Ranges and GKF

A.1 UKF for additional capture zone ranges and CRLs

The examination of UKF capture zone ranges was expanded to include additional ranges and 224 CRLs encompassing the U.S. hurricane-exposed coast from the border with Mexico to Nova Scotia, Canada. The analysis was performed for the totality of CRLs divided into four regions: (1) the U.S. Gulf; (2) U.S. Southeast; (3) U.S. North Atlantic Coast; and (5) the Caribbean. These extents of these regions are shown in Figure A-1. The mean and standard deviation of UKF SRR estimates were calculated for 10 to 1000, 100 to 300, 100 to 500, 150 to 450, 100 to 400, and 150 to 500 km ranges for the 224 CRLs. The mean and standard deviation of the calculated means and standard deviations for all CRLs is shown in Table A-1 for each range. The corresponding coefficients of variation are shown in Table A-2.

Figure A-1. CRLs and regions for supplemental analysis of UKF capture zone ranges.

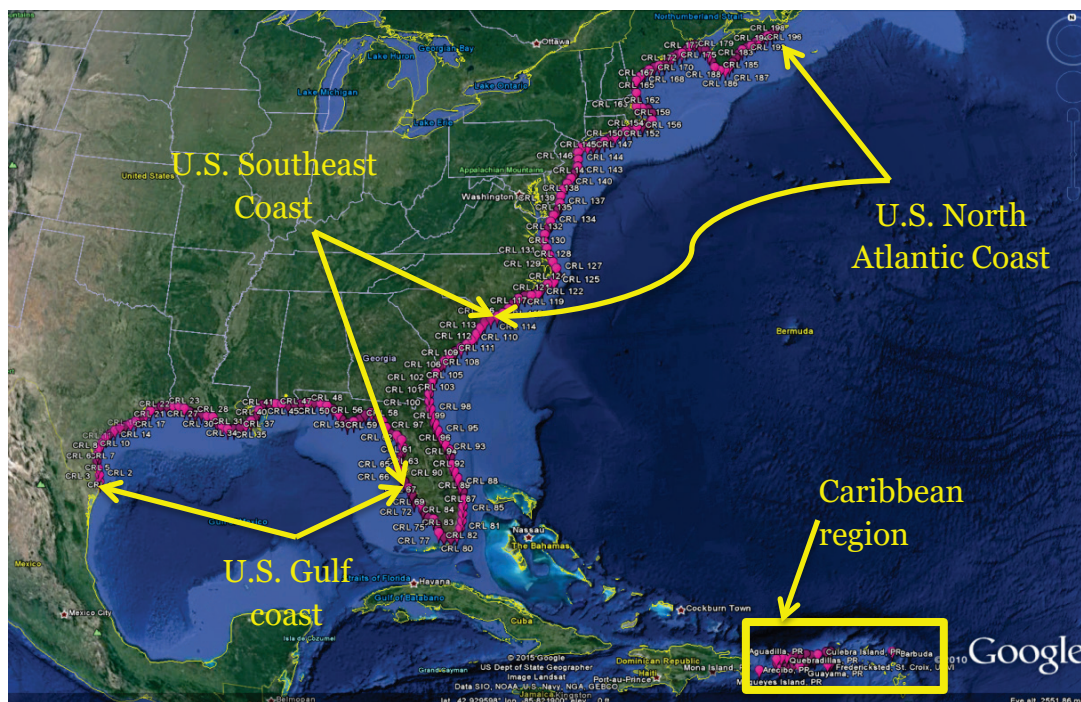


Table A-1. Means and standard deviations of SRR estimates for examined capture zone ranges and regions.

Range [km]	Statistic	Region					
		All	CONUS	U.S. Gulf	Southeast	North Atlantic Coast	Caribbean
10-1000	Mean	5.55E-04	5.56E-04	5.58E-04	5.59E-04	5.60E-04	5.61E-04
	SD	1.40E-04	1.40E-04	1.40E-04	1.40E-04	1.40E-04	1.40E-04
100-300	Mean	4.70E-04	4.72E-04	4.73E-04	4.75E-04	4.76E-04	4.78E-04
	SD	6.92E-05	6.91E-05	6.86E-05	6.85E-05	6.82E-05	6.82E-05
100-500	Mean	5.09E-04	5.10E-04	5.12E-04	5.13E-04	5.14E-04	5.15E-04
	SD	8.33E-05	8.31E-05	8.28E-05	8.26E-05	8.24E-05	8.24E-05
150-450	Mean	5.13E-04	5.14E-04	5.15E-04	5.17E-04	5.18E-04	5.19E-04
	SD	6.51E-05	6.50E-05	6.49E-05	6.47E-05	6.47E-05	6.48E-05
100-400	Mean	4.90E-04	4.92E-04	4.93E-04	4.95E-04	4.96E-04	4.97E-04
	SD	7.74E-05	7.72E-05	7.69E-05	7.68E-05	7.65E-05	7.65E-05
150-500	Mean	5.21E-04	5.22E-04	5.24E-04	5.25E-04	5.26E-04	5.27E-04
	SD	6.79E-05	6.78E-05	6.76E-05	6.75E-05	6.75E-05	6.75E-05

Table A-2. Coefficients of variation of mean SRR estimates for examined capture zone ranges and regions.

Range [km]	Statistic	Region					
		All	CONUS	U.S. Gulf	Southeast	North Atlantic Coast	Caribbean
10-1000	Coefficient of Variation	0.26	0.26	0.17	0.21	0.32	0.29
100-300		0.17	0.16	0.11	0.10	0.20	0.26
100-500		0.18	0.17	0.11	0.11	0.22	0.23
150-450		0.14	0.14	0.09	0.09	0.17	0.17
100-400		0.18	0.17	0.11	0.11	0.22	0.24
150-500		0.14	0.14	0.09	0.10	0.18	0.17

The means of the standard deviations presented in Table A-1 for the various regions show that the 150–450km range has the smallest values when compared to other regions, except for the U.S. Gulf. For this region the 150–500 km range produces a slightly lower standard deviation. This can also be observed in the coefficient of variation values in Table A-2. The 150 to 450 km range can be considered as a credible range for the UKF bandwidth or capture zone given its lower uncertainties.

A.2 Analysis of GK size for minimum squared error.

The method described in Section 3.3.1 of the main report for selecting the Gaussian kernel size by minimizing the squared error between the calculated SRR and the mean UKF SRR was expanded for additional CRLs and capture zone rages. These correspond to the 224 CRLs encompassing the U.S. hurricane-exposed coast from the border with Mexico to Nova Scotia, Canada, identified in Appendix section A-1. The mean Gaussian kernel size corresponding to the minimum squared error was computed for all the CRLs and by regions. The extents of these regions are also described in Appendix section A-1. Results are presented on Table A-3.

Table A-3. Mean Gaussian kernel sizes corresponding to the location of minimum squared error for various U.S. coastal regions.

Range [km]	Statistic	Region					
		All	CONUS	U.S. Gulf	Southeast	North Atlantic Coast	Caribbean
10-1000	Mean	279	280	268	287	282	270
100-300	Mean	151	154	174	177	137	126
100-500	Mean	194	195	208	189	192	185
150-450	Mean	214	216	244	206	210	196
100-400	Mean	178	180	211	186	166	156
150-500	Mean	227	229	250	212	227	211

Appendix B: Cross-Validation Tests Results

B.1 Least-squares cross validation

Table B-1. Kernel size corresponding to minimum CVSE.

CRL	Minimum CVSE Kernel Size	CRL	Minimum CVSE Kernel Size
Gulf of Mexico		North Atlantic	
Galveston, TX	60	Biscayne Bay, FL	120
Port Arthur, TX	90	Atlantic Beach, NC	70
Grand Isle, LA	70	Duck, NC	70
Gulfport, MS	100	Virginia Beach, VA	80
Apalachicola, FL	90	Chesapeake Bay, MD	130
Clearwater, FL	100	The Battery, NY	130
OCONUS		Newport, RI	120
Aguirre, PR	90	Boston, MA	110

Figure B-1. Least-squares cross validated squared error versus kernel size for Gulf coast CRLs.

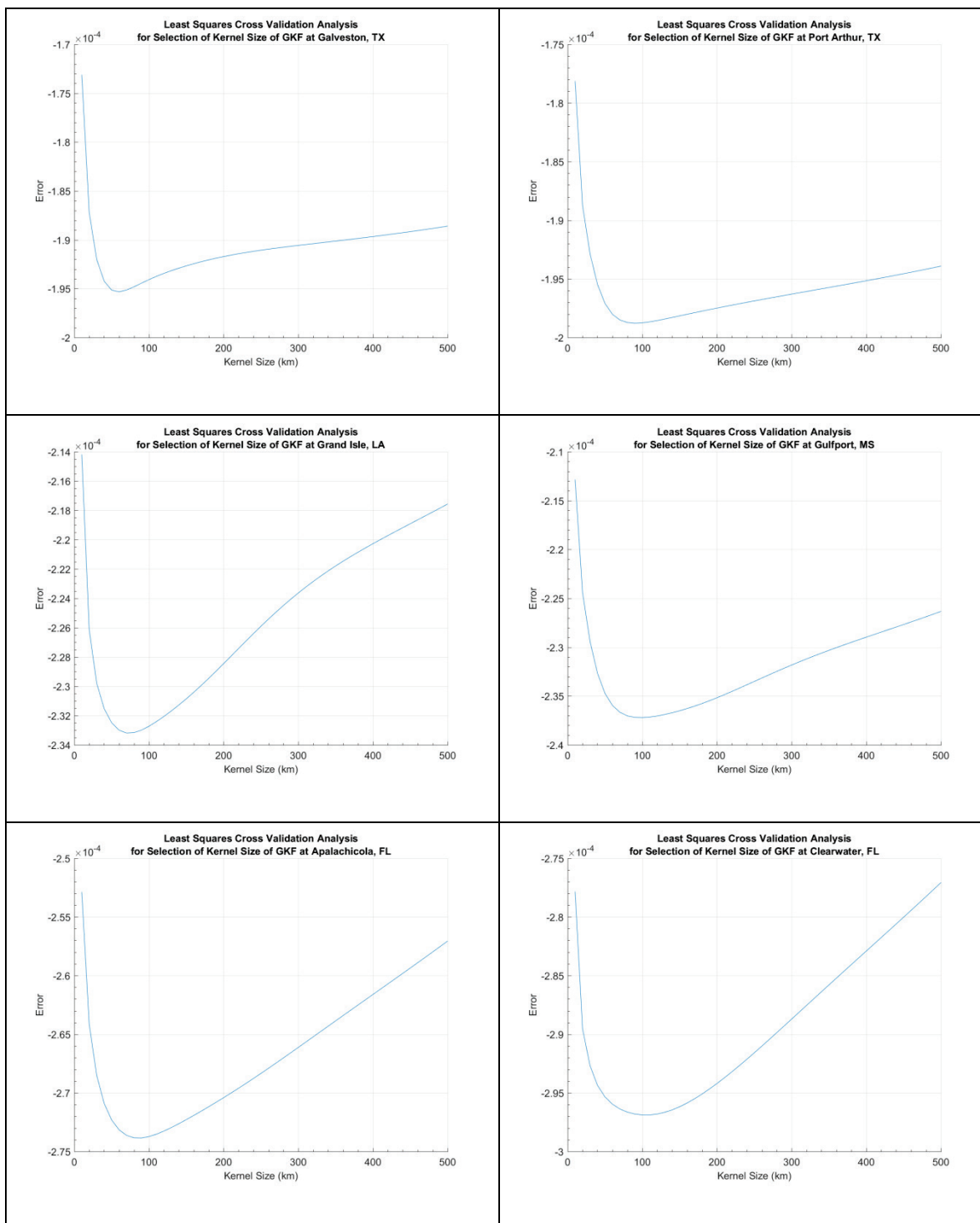


Figure B-2. Least-squares cross validated squared error versus kernel size for Atlantic coast CRLs from Biscayne Bay, FL, to The Battery, NY.

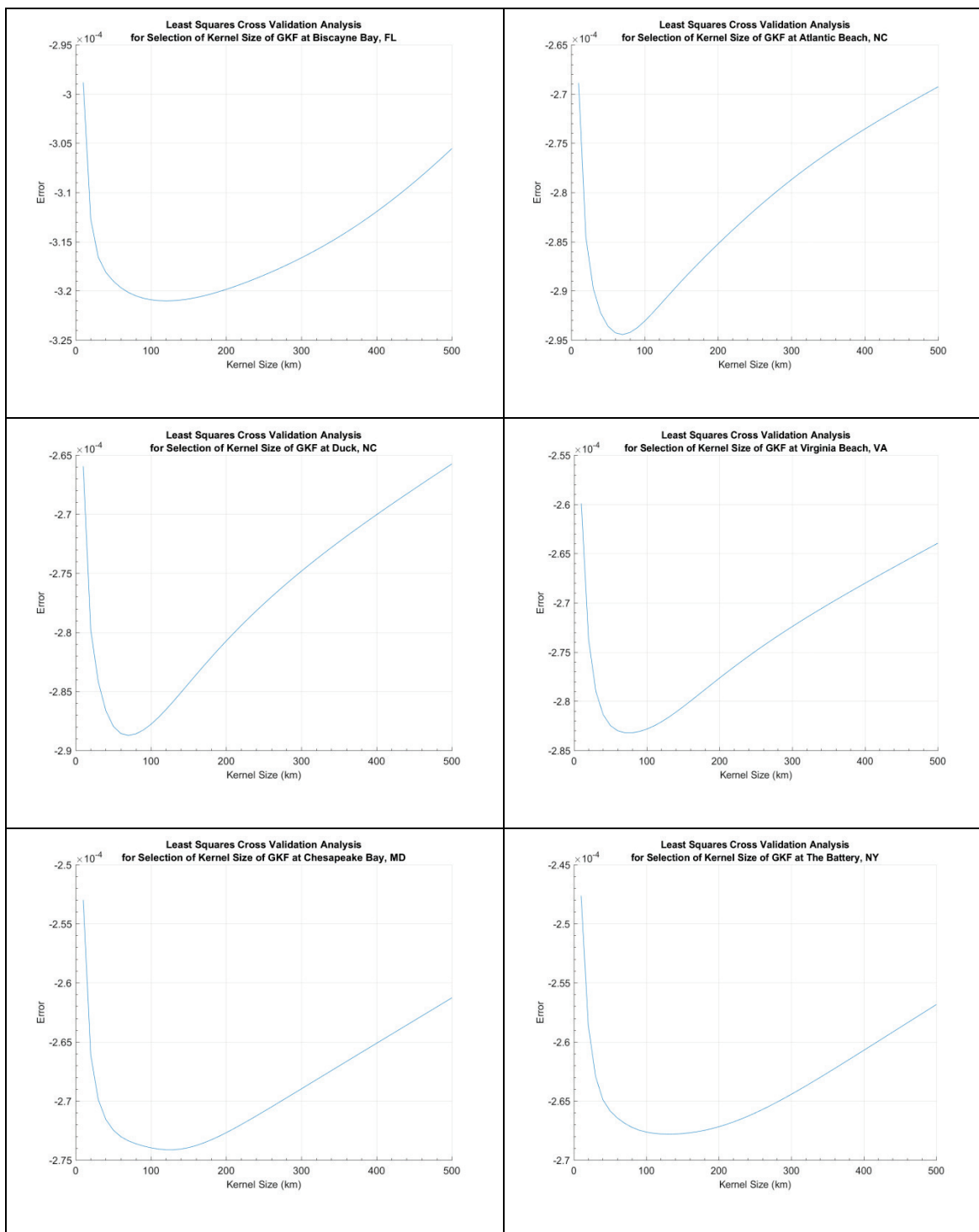


Figure B-3. Least-squares cross validated squared error versus kernel size for Newport, RI, and Boston, MA.

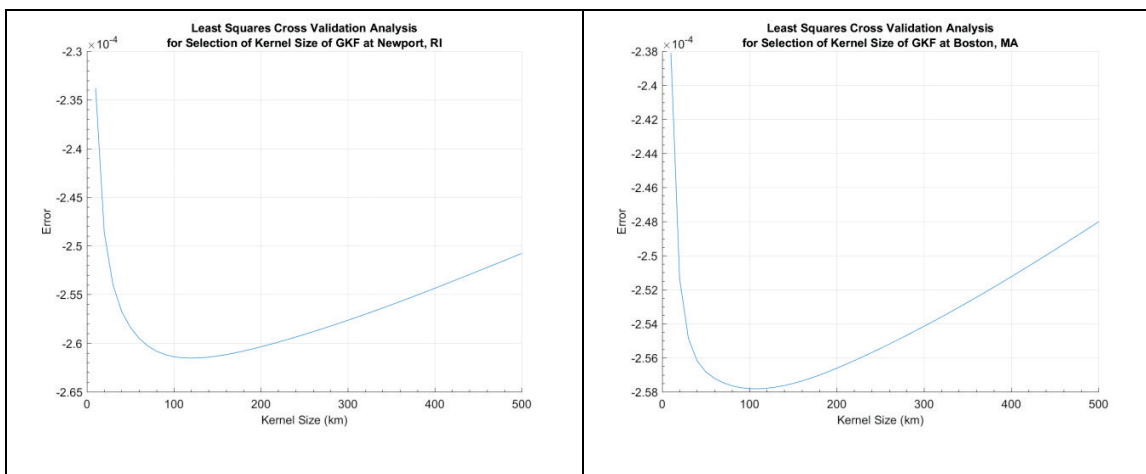
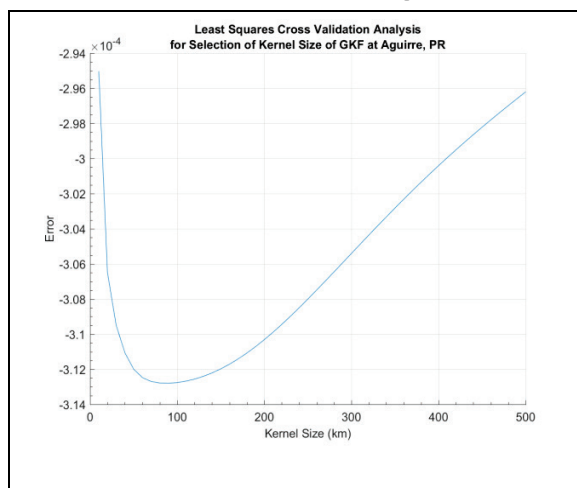


Figure B-4. Least-squares cross validated squared error versus kernel size for Aguirre, PR.



B.2 Modified least-square cross validation (leave-one-out) with UKF validation sample

Figure B-5. Least-squares cross validated squared error with 40 km UKF validation bandwidth for Gulf Coast CRLs.

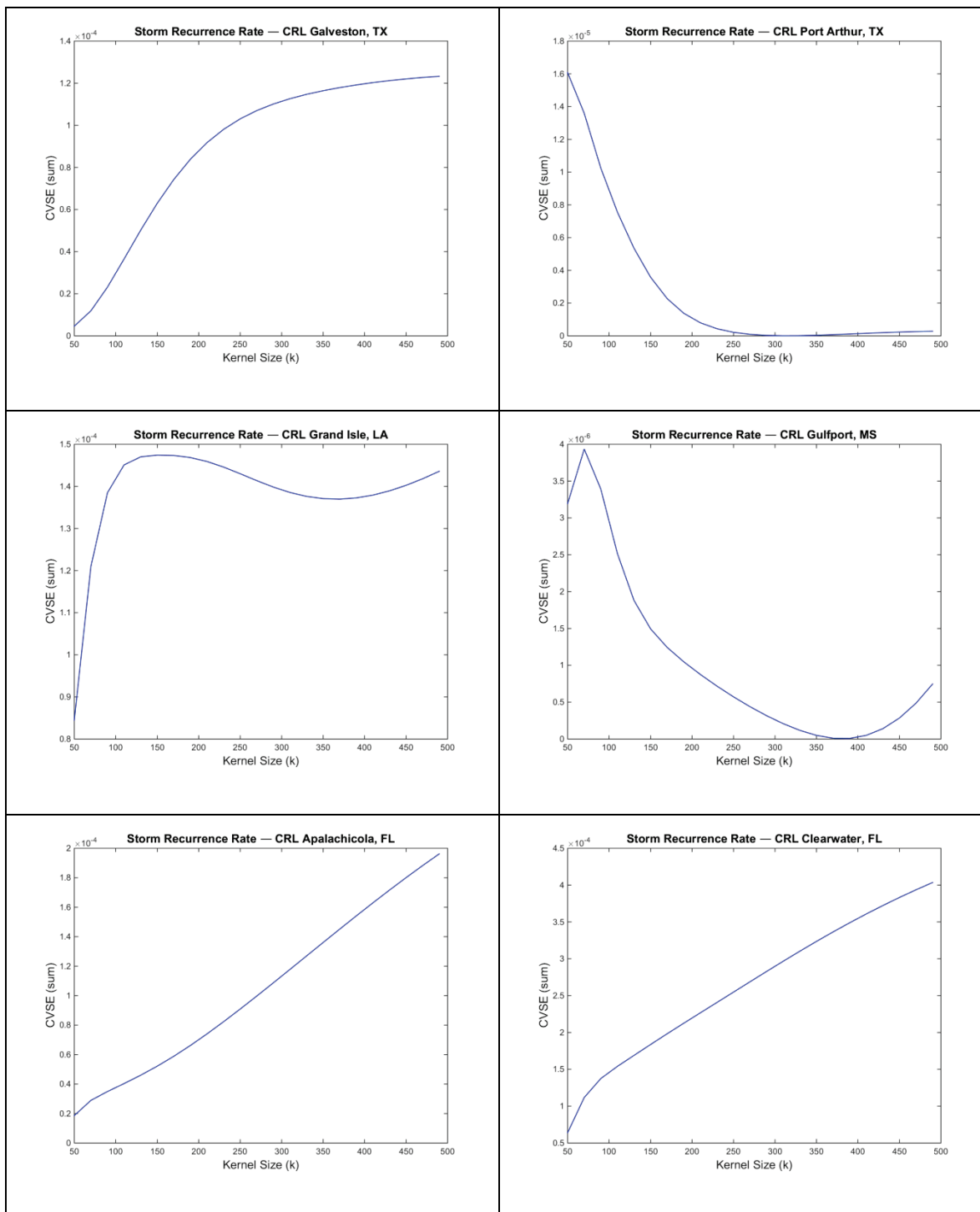


Figure B-6. Least-squares cross validated squared error with 40 km UKF validation bandwidth for Atlantic coast CRLs from Biscayne Bay, FL, to The Battery, NY.

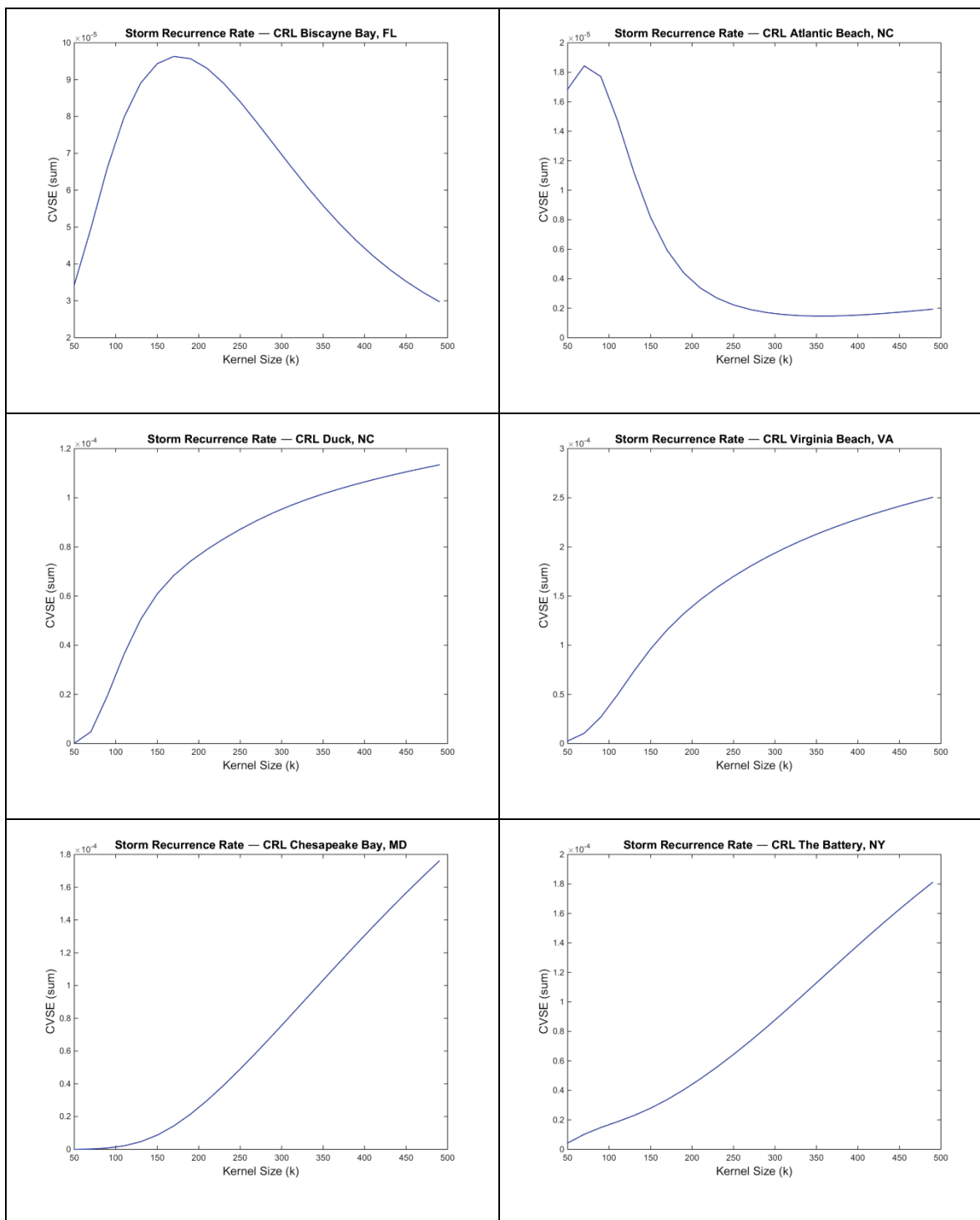


Figure B-7. Least-squares cross validated squared error with 40 km UKF validation bandwidth for Newport, RI, and Boston, MA.

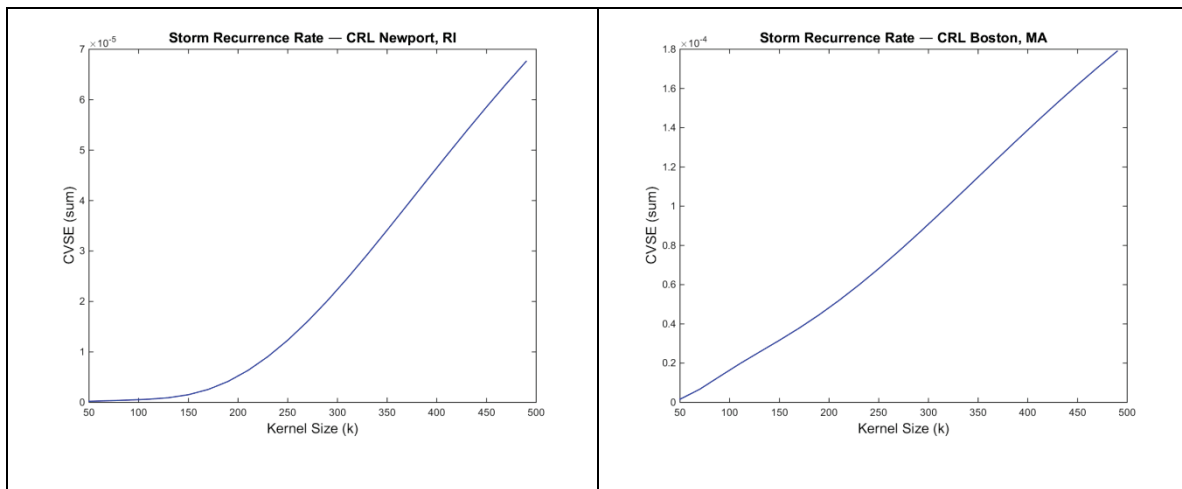


Figure B-8. Least-squares cross validated squared error with 40 km UKF validation bandwidth for Aguirre, PR.

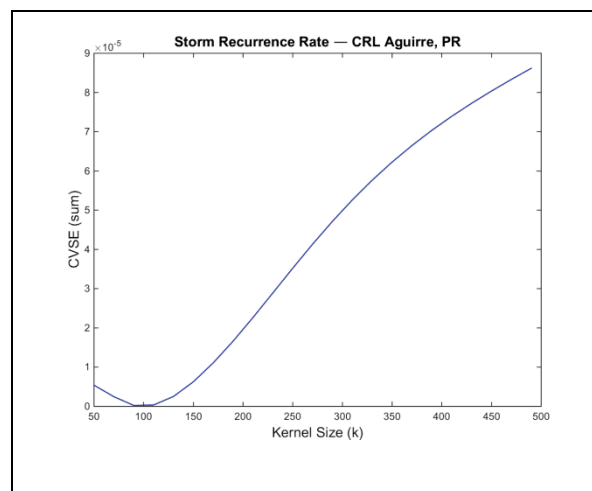


Figure B-9. Least-squares cross validated squared error with 100 and 200 km UKF validation bandwidth for Galveston, TX; Port Arthur, TX; and Grand Isles, LA.

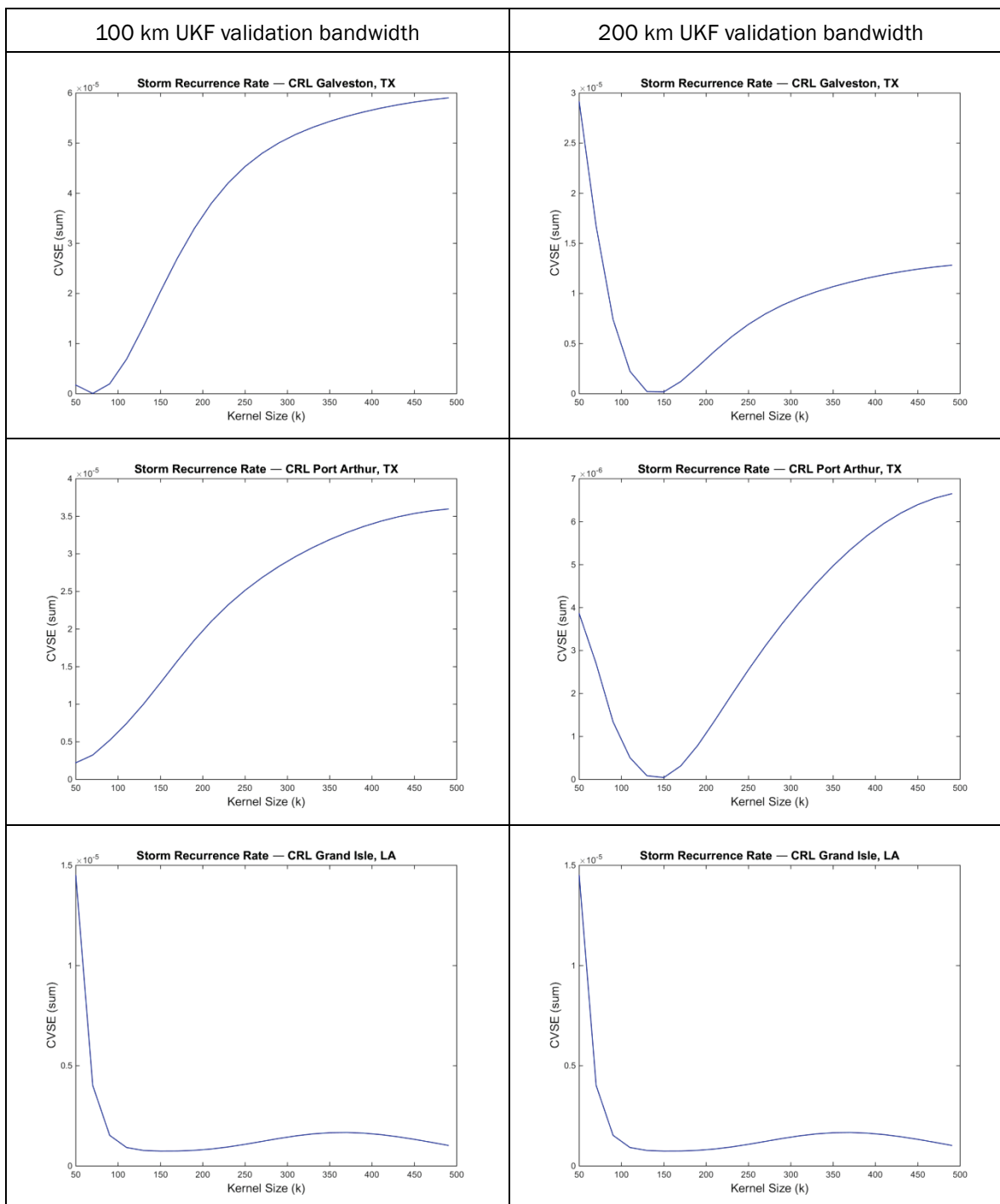


Figure B-10. Least-squares cross validated squared error with 100 and 200 km UKF validation bandwidth for Gulfport, MS; Apalachicola, FL; and Clearwater, FL.

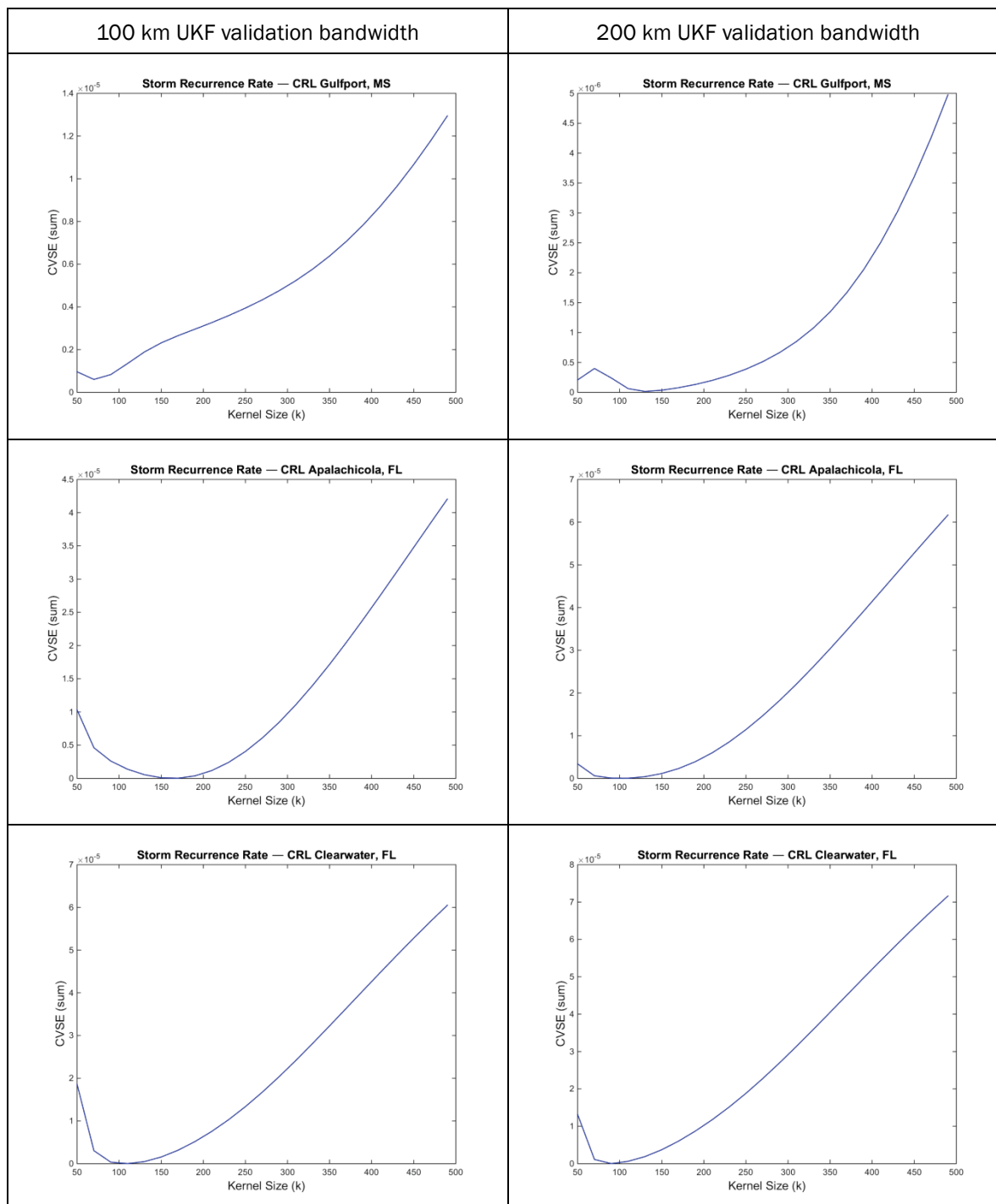


Figure B-11. Least-squares cross validated squared error with 100 and 200 km UKF validation bandwidth for Biscayne Bay, FL; Atlantic Beach, NC; and Duck, NC.

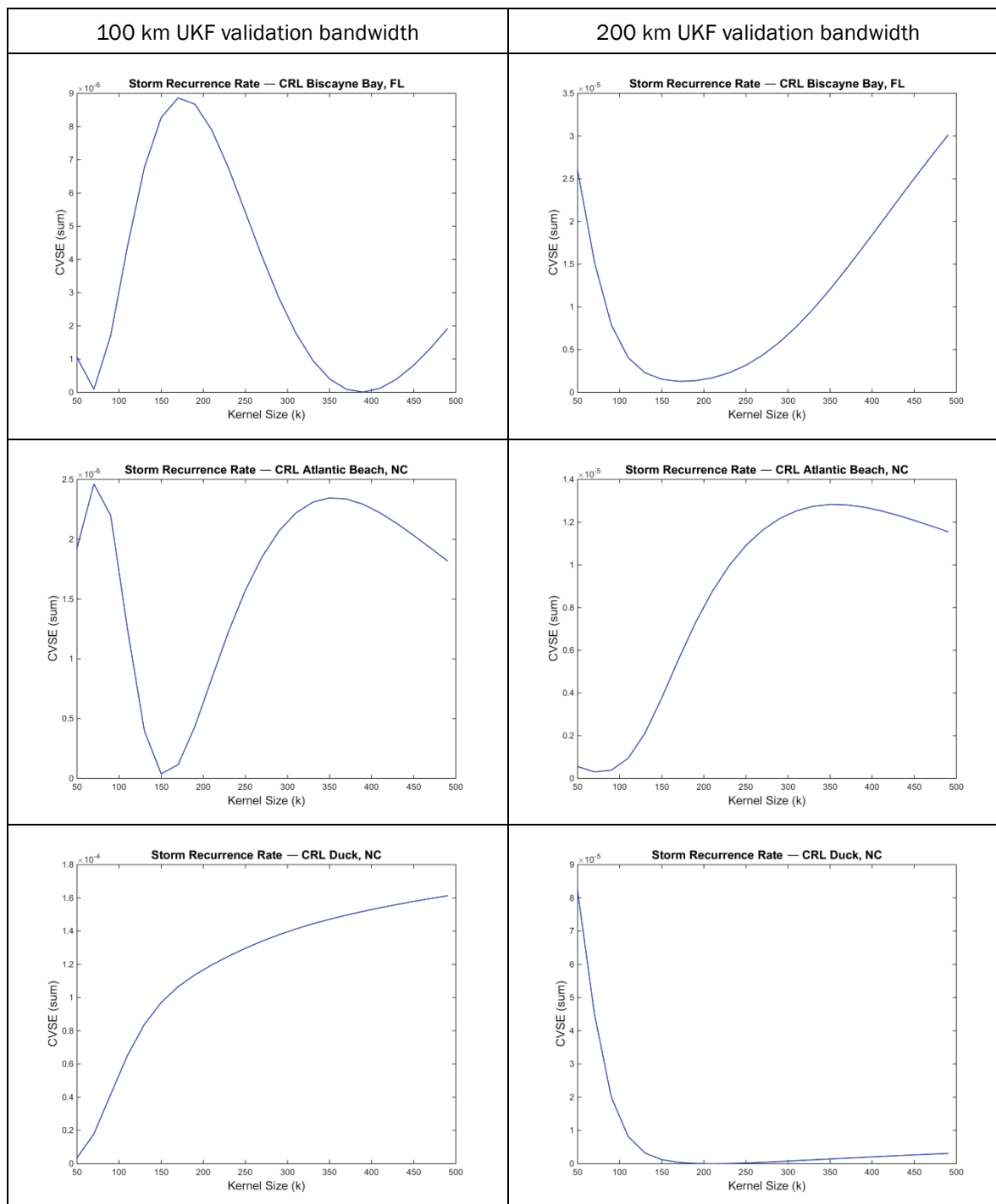


Figure B-12. Least-squares cross validated squared error with 100 and 200 km UKF validation bandwidth for Virginia Beach, VA; Chesapeake Bay, MD; and The Battery, NY.

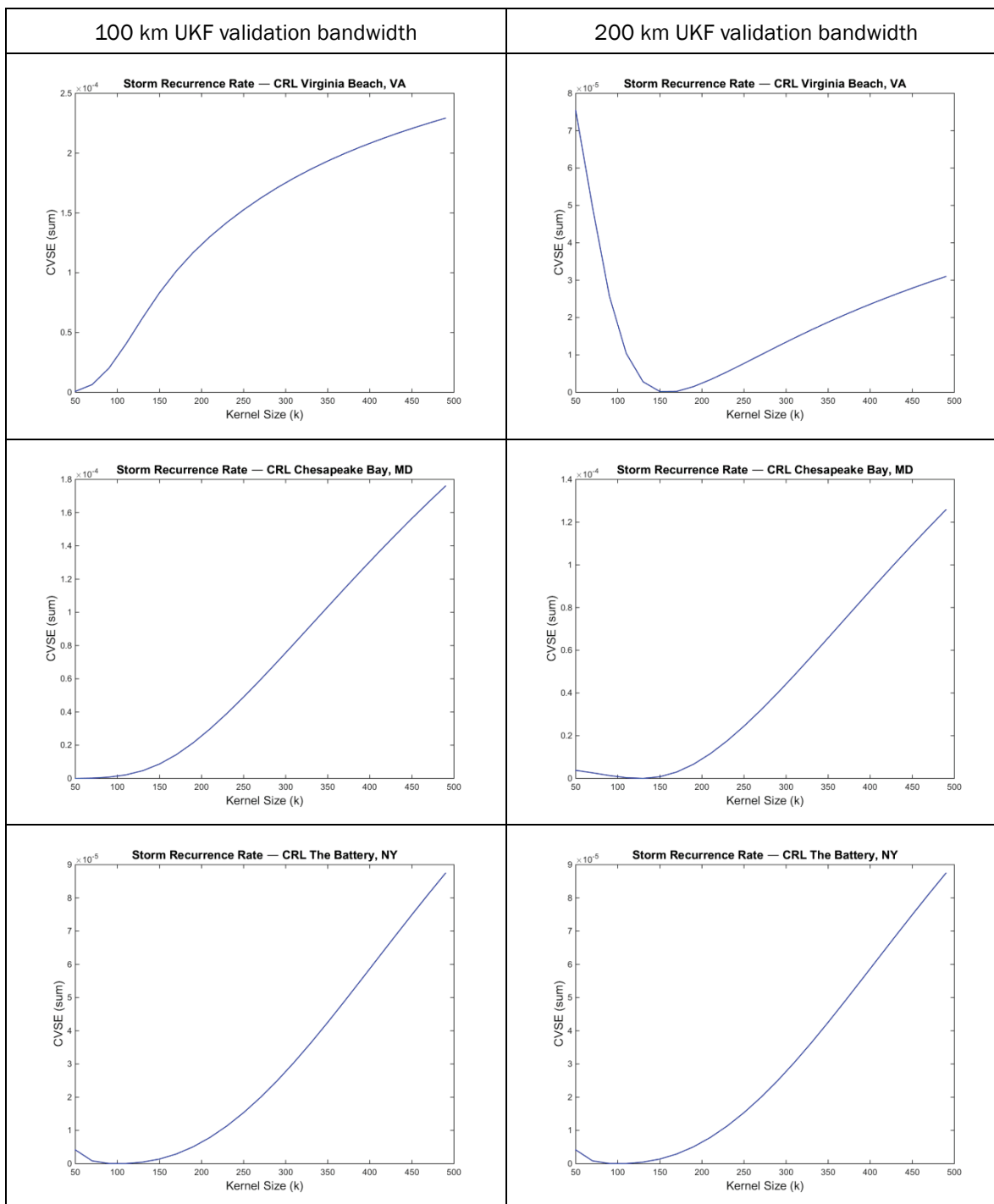
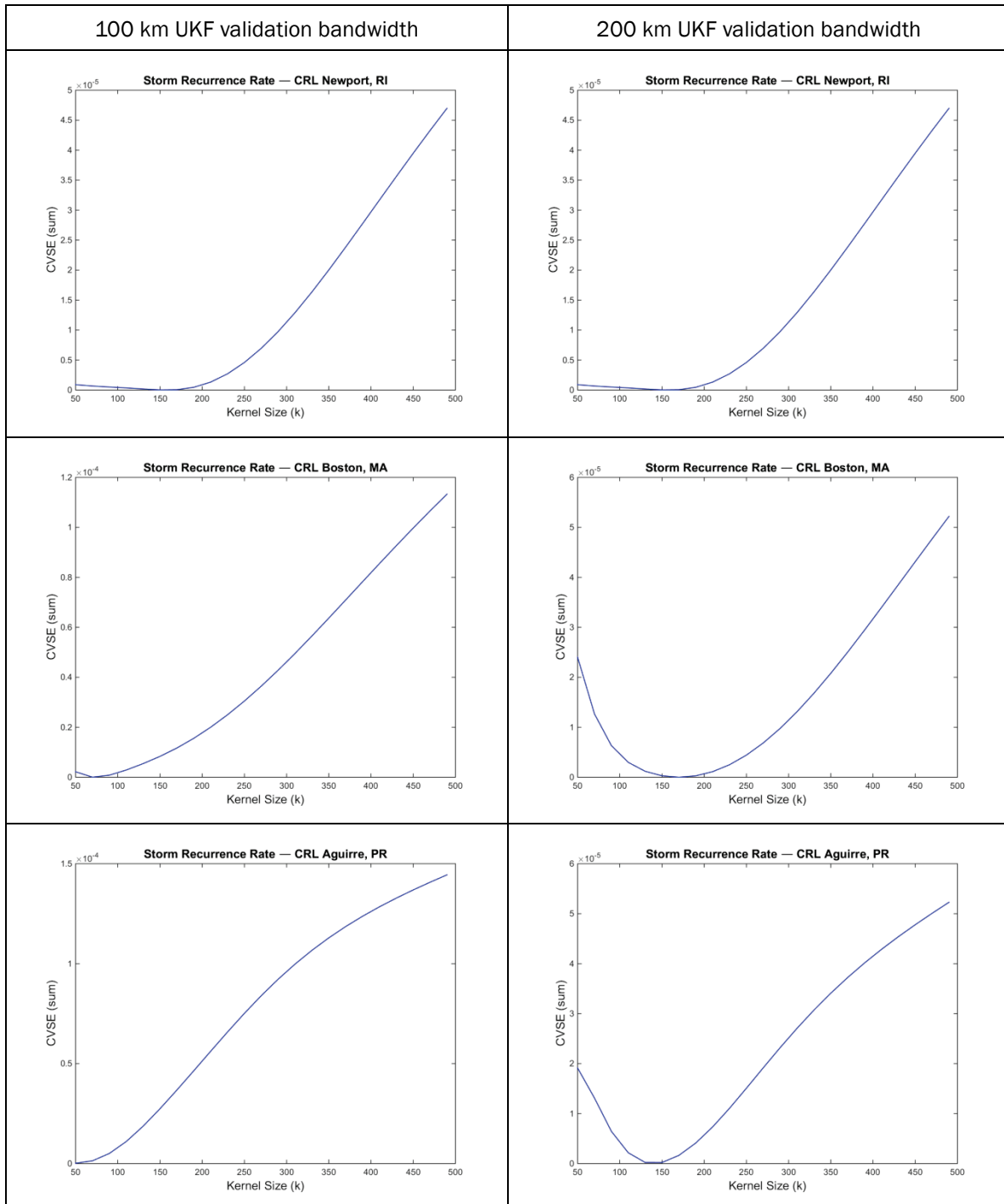


Figure B-13. Least-squares cross validated squared error with 100 and 200 km UKF validation bandwidth for Newport, RI; Boston, MA; and Aguirre, PR.



Appendix C: Kernel Size Optimization Techniques

Kernel density estimator (KDE) can be used to determine the storm recurrence rate for tropical cyclones. Four approaches for estimating the optimal smoothing parameter of a Gaussian kernel estimator for the storm recurrence rate of tropical cyclones were evaluated. The approaches investigated included cross-validated likelihood (CVL), cross-validated squared error, Silverman's rule of thumb plug-in method, and Botev's plug-in method. These procedures were evaluated separately for sites located along the U.S. East coast and the Gulf of Mexico. The analyses were performed for two categories of storms based on storm intensity, namely low and high intensity storms and high intensity storms.

C.1 Estimation of optimal kernel parameters

Among the criteria available to estimate the errors associated to the KDE method are the pointwise error, the uniform error, and the mean integrated square error (MISE) (Chen 2017). For instance, while the pointwise error relates to the confidence interval, the uniform error quantifies the uniform deviation. The MISE, on the other hand, has a straight relationship with the mean square error, and is the most common criterion used in practice to measure the average performance of the KDE and to aid in optimal bandwidth selection processes.

The MISE is defined as

$$MISE = \int E \left[\left(\hat{f}(x) - f(x) \right)^2 \right] dx$$

where $\hat{f}(x)$ is the density estimated using KDE and $f(x)$ is the true density. The MISE can be separated into contribution from bias and stochastic variation:

$$B_h(x) = E[\hat{f}(x) - f(x)]$$

$$\varepsilon(x) = \hat{f}(x) - E[\hat{f}(x)]$$

and

$$MISE = \int E \left[\left(\hat{f}(x) - f(x) \right)^2 \right] dx = \int B_h^2(x) dx + \int Var[\varepsilon(x)] dx$$

When h is too small, there are many local features in the density estimate. When h is too large, important features may be smoothed out. When h is at the optimal value, a clear picture of the underlying density is obtained. The optimal bandwidth from the above equation does not have a closed form, and an asymptotic approximation, known as the asymptotic mean integrated square error (AMISE), can be used. The AMISE is the dominating quantity in the MISE and is known to result in over smoothing.

The common idea behind most methods (except likelihood cross-validation) is to minimize the AMISE. Hence, bandwidth selection methods are also estimators to the AMISE. The details of the different methods and their comparison can be found in the literature (Jones et al. 1996; Sheather 2004; Scott 2015). Some of the common bandwidth selection methods include plug-in methods (Sheather and Jones 1991; Silverman 1986; Woodroffe 1970), likelihood cross-validation, least square cross-validation (Rudemo 1982; Bowman 1984; Bowman and Azzalini 1997; Stone 1984), and the biased cross-validation (Scott and Terrell 1987). Due to the lack of knowledge of the true underlying density function $f(x)$, the optimization problem leads to many theoretical approaches, where the plug-in and cross-validation techniques have demonstrated practical importance (Deng and Wickham 2011). Still, the sensitivity of the KDE method to differences in data density will require small bandwidths in data-crowded regions and vice-versa. This limitation of the KDE could be circumvented by the use of a spatially varied bandwidth (Terrell and Scott 1992), but is beyond the current scope of work. Note that this effect is probably not as significant when used for the recurrence rate since most of the storms considered in the analysis are located in proximity to the site where estimates are obtained.

In addition, plug-in methods minimize the AMISE of the KDE by first assuming a form of the unknown underlying probability distribution of the data (Chu et al. 2017). These methods are often used to obtain a preliminary estimate on the shape of a density function.

Several procedures for the optimal selection of smoothing parameter are investigated in this report. The CVL and CVSE methods used by Chouinard and Liu (1997) are investigated as well as other methods used

for non-parametric density estimation like the plugin methods known as Silverman's rule of thumb (Silverman 1986) and Botev's diffusion (Botev et al. 2010). MATLAB is used to implement the optimal selection procedures for the CVL, the CVSE, Silverman's rule of thumb rule and Botev's diffusion-based procedure.

C.1.1.1 Cross-validated likelihood (CVL)

Cross validation is a technique used to evaluate the predictive ability of models. The data set is partitioned into a number of non-overlapping estimation and validation data sets. The most commonly used cross-validation procedure is implemented by using the leave-one-out procedure. Using larger partitions (i.e., k-fold partitions) of the historical events produces slightly larger optimal smoothing parameters since binning reduces the influence of outliers and also accounts for the variability in the pattern of hurricane occurrences over time.

For a given the density function f and sample $X_1, X_2, \dots, X_n$ of random observations, each observation (or partition) can be removed sequentially from the sample before estimating the density function $\hat{f}_{-i}$. The log-likelihood of the observation $\log(\hat{f}_{-i}(X_i))$ that was removed is evaluated using the resulting density:

$$\hat{f}_{-i}(X_i) = \frac{1}{(n-1)} * \frac{1}{h} * \sum_{j \neq i} K\left\{\frac{1}{h} * (X_i - X_j)\right\}$$

$$CV(h) = n^{-1} * \sum_{i=1}^n \log(\hat{f}_{-i}(X_i))$$

The optimal model is identified as the one that has the greatest predictive ability considering all the partitions. Predictive ability can be measured through the CVSE or the CVL. The CVL choice of the smoothing parameter h is the one that maximizes $CV(h)$ (Silverman 1986). The CVL tends to produce parameters that under-smooth the density function.

For density estimation, the accuracy of the kernel density estimates is measured for the entire range of values of the variable. In the case of the CVL, the latter is most sensitive to outliers and observations in the tails of the distributions, which favors small optimal smoothing parameters. Note that when applied to the estimation of the recurrence rate of hurricanes at

a large distance from a site (i.e., in the tail of the distribution), estimates using the kernel function are not as important since they contribute less to the hazard function.

C.1.2 Cross-validated squared error (CVSE)

The least square cross-validation (LSCV) method considers a probability density function f and its estimator as $\hat{f}$. The optimal smoothing parameter using the CVSE criterion is obtained by minimizing the integrated squared error (Silverman 1986).

$$\int (\hat{f} - f)^2 = \int \hat{f}^2 - 2 \int \hat{f} \cdot f + \int f^2$$

In the above equation, the last term does not depend on f and can be ignored, such that

$$R(\hat{f}) = \int \hat{f}^2 - 2 \int \hat{f} \cdot f$$

Defining $\hat{f}_{-i}$ as an estimate of the density at $x = x_i$, when the i^{th} data point is removed from the data set,

$$\hat{f}_{-i}(X_i) = \frac{1}{(n-1)} * \frac{1}{h} * \sum_{j \neq i} K \left\{ \frac{1}{h} * (X_i - X_j) \right\}$$

where:

- n = number of observations
- h = smoothing parameter
- K = Gaussian Kernel density function
- x = observations
- X_j = observation that is left out

The optimal value of h is obtained by minimizing the following quantity:

$$M_0(h) = \int \hat{f}^2 - 2 * n^{-1} \sum_i \hat{f}_{-i}(X_i)$$

The terms of $M_0(h)$ can be expanded mathematically to the following forms:

$$\int \hat{f}(x)^2 dx = \frac{1}{(n^2 * h)} \sum_i \sum_j K^2 \left\{ \frac{1}{h} * (X_i - X_j) \right\}$$

$$n^{-1} \sum_i \hat{f}_{-i}(X_i) = \frac{1}{n * (n-1)} \sum_i \sum_j \frac{1}{h} * K \left\{ \frac{1}{h} * (X_i - X_j) \right\} - \frac{1}{(n-1)} * \frac{1}{h} * K(0)$$

Substituting the above two equations into the score function equation results in

$$M_1(h) = \frac{1}{(n^2 * h)} * \sum_i \sum_j K^2 \left\{ \frac{1}{h} * (X_i - X_j) \right\} + \frac{2K(0)}{nh}$$

where

$$K^*(t) = K^2(t) - 2K(t)$$

This form of the CVSE is also known as the unbiased cross-validation method. Many variants of the CVSE have been proposed in the literature. Examples of these variants are the biased (Scott and George 1987), modified Stute (1992), and trimmed cross-validation estimators (Feluch and Koronacki 1992).

C.1.3 Silverman's rule of thumb plug-in method

MATLAB (www.mathworks.com) provides a subroutine for the application of the KDE using a Gaussian kernel. The function is defined as follows:

$$[F, X, U] = ksdensity(yData)$$

where:

F = the vector of the probability density estimates

X = Vector of one hundred values where the density estimate is to be evaluated.

U = Bandwidth of the kernel smoothing window.

$y D a t a$ = Input data

The criteria for the selection of the optimal smoothing parameter is the MISE and is derived for the case when the density function can be

assumed to be approximately Gaussian. In that case, the optimal smoothing parameter is defined as

$$h_{opt} = k_2^{-\frac{2}{5}} * \left\{ \int K(t)^2 dt \right\}^{\frac{1}{5}} * \left\{ \int f''(x)^2 dx \right\}^{-\frac{1}{5}} * n^{-\frac{1}{5}}$$

For a normal distribution with a variance of σ^2 and sample size n ,

$h_{opt} = \left(\frac{4}{3}\right)^{\frac{1}{5}} \cdot \sigma \cdot n^{-\frac{1}{5}} = 1.06\sigma \cdot n^{-\frac{1}{5}}$ The above equation is also known as Silverman's rule of thumb (Bowman and Azzalini 1997). This method provides a simple procedure for selecting an approximate optimal smoothing parameter since only an estimate of the standard deviation is required. A drawback of this method is that a normal distribution is assumed, and over smoothing may occur for non-normal and multi-modal distributions.

C.1.4 Botev's diffusion plug-in method

Estimating the kernel density via diffusion is a method proposed by Botev et al. (2010) and implemented in the program KDE. This method has recently been used by Mudd and Vickery (2015) for estimating the optimal parameter of the kernel density for the recurrence rate of hurricanes. In this procedure, a linear diffusion process is used to obtain the optimal bandwidth for the kernel density. The optimal parameter is obtained from the properties of linear diffusion process and using the MISE of the estimate as a criterion. The Wiener Process (the standard Brownian motion) is a stochastic process that can be used to describe kernel density estimation by diffusion. The Gaussian kernel density satisfies the diffusion partial differential equation (also Kolmogorov backward equation):

$$\frac{\partial}{\partial t} K_t(x_i, x; t) = \frac{1}{2} \frac{\partial^2}{\partial x^2} K_t(x_i, x; t)$$

The above equation is also the Fourier heat equation (Chaudhuri and Marron 2000). In the heat equation, the Gaussian kernel is the Green's function for the diffusion partial differential equation (Larsson and Thomee 2003; Botev et al. 2010). Given a sample of N random observations from a Wiener process $\{W_t, t \geq 0\}$, then an estimate of the probability density function is

$$\hat{f}(x; t) = \frac{1}{N} \sum_{i=1}^N \frac{1}{(2\pi t)^{0.5}} e^{\frac{-(x-x_i)^2}{2t}} \stackrel{\text{def}}{=} \frac{1}{N} \sum_{i=1}^N \varphi(x, x_i; t)$$

$$\hat{f}(x; B) = \frac{1}{N} \sum_{i=1}^N K(x, x_i; B)$$

The criterion to determine the optimal bandwidth is the MISE:

$$MISE\{\hat{f}\}(B) = E_f \int [\hat{f}(x; B) - f(x)]^2 dx$$

The first order asymptotic approximation of the MISE is given as

$$AMISE\{\hat{f}\}(B) = \frac{1}{4} B^2 \|f''\|^2 + \frac{1}{2N(\pi B)^{0.5}}$$

The optimal value of B is minimal of the AMISE (Wand and Jones 1995) is

$$B_* = \left(\frac{1}{2N\pi^{0.5} \|f''\|^2} \right)^{\frac{2}{5}}$$

C.2 Analyses and results

The kernel estimation procedures are applied to different partitions of the hurricane catalog to investigate the selection of the optimal bandwidth as a function of the sample size and track distribution. The partitions are based on the minimum pressure reached by a hurricane:

- < 965 hPa
- < 985 hPa

Since the central pressure varies greatly as a function of location along the path of each hurricane, the minimum central pressure recorded for each hurricane is used for classification purposes. The first step is the identification of the set of points along hurricane paths that are closest to the site.

Analyses are performed for sites located along the East Coast and across the Gulf of Mexico. In all cases, the analyses are performed by only considering storms starting in 1938 since the data set seems incomplete prior to this date. The tracks of these hurricane tracks is seen in Figure C-1. Storm tracks divided by the two partitions evaluated are shown in Figure C-2. The number of storms in proximity to a site influences the selection of the optimal smoothing parameter. This effect is investigated by defining different partitions of the hurricane catalog but also by performing the analysis over a grid of multiple sites. In this analysis, the sites are located uniformly across a region and incorporate locations both offshore and near the coast. The number of storms considered for the analysis is truncated to those that are within 400 km of a given site. The distance considered is the shortest distance from the hurricane track to the site. The distance is considered positive if the hurricane passes to the right of the site (or if the moment vector defined as the product of distance vector from the site to the hurricane track and the forward velocity vector of the hurricane is counterclockwise).

Figure C-1. Hurricane tracks 1938–2014.

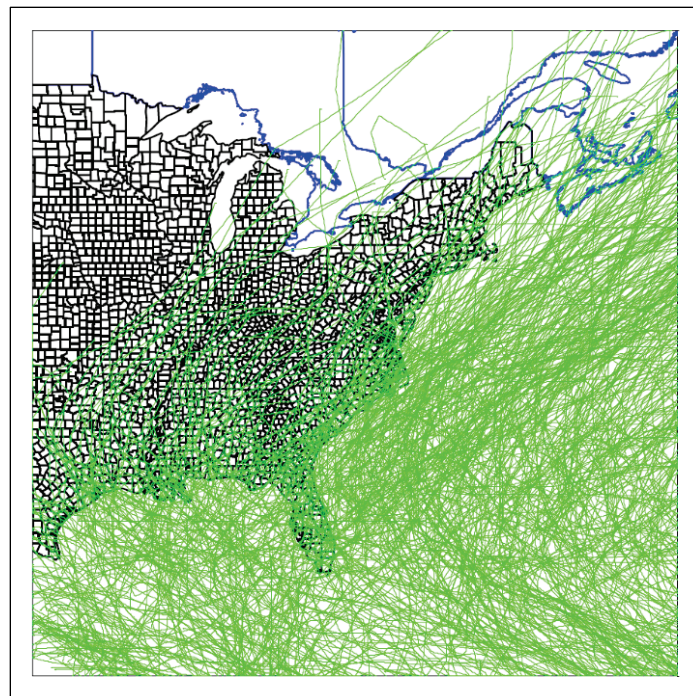
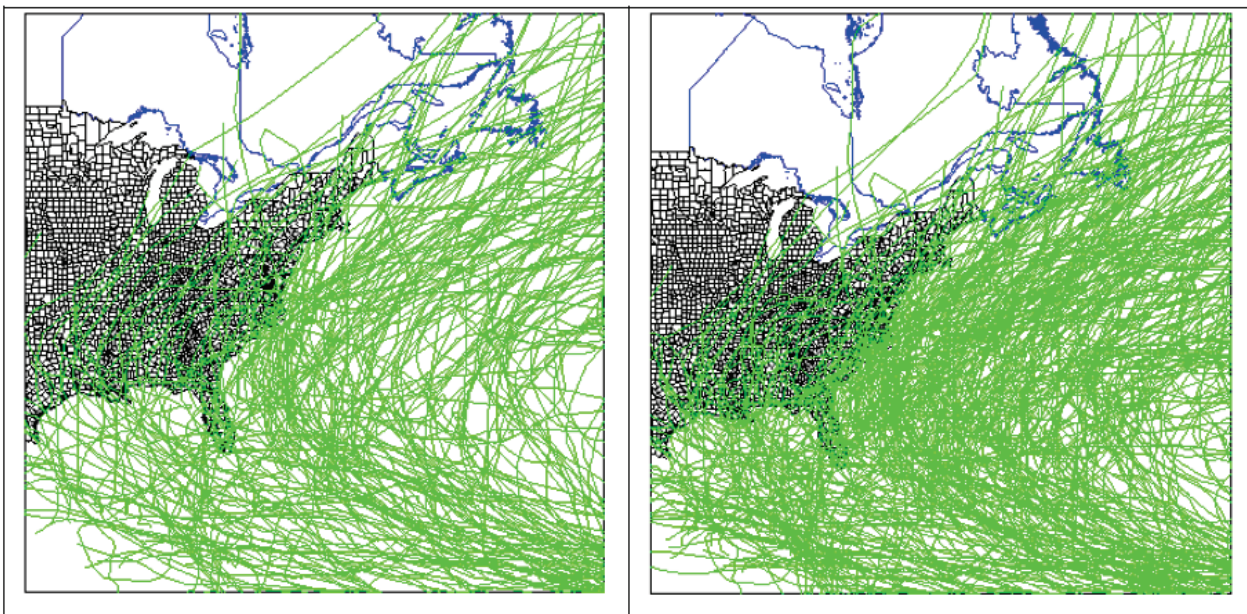


Figure C-2. Hurricane tracks 1938–2014: (1) central pressure < 965 hPa, (2) central pressure < 985 hPa.



C.2.1 Tests for algorithms

The main algorithms are first tested and demonstrated for a single site located along the East Coast. Figure C-3 shows the locations of the hurricanes at their closest point to the site located at (67°W, 39°N). The distance and bearing of the hurricane at the location of closest distance is used to define the point process in the space of (d, α) . For current purposes, the point process is defined as a function of the shortest distance from the hurricane track to the site. The distance is considered positive when the trajectory of the hurricane is counterclockwise in relation to the site, and negative otherwise. Refer to Figure C-4.

Figure C-3. Points indicating the location of hurricanes at their closest position to the site (67°W, 39°N) (blue cross).

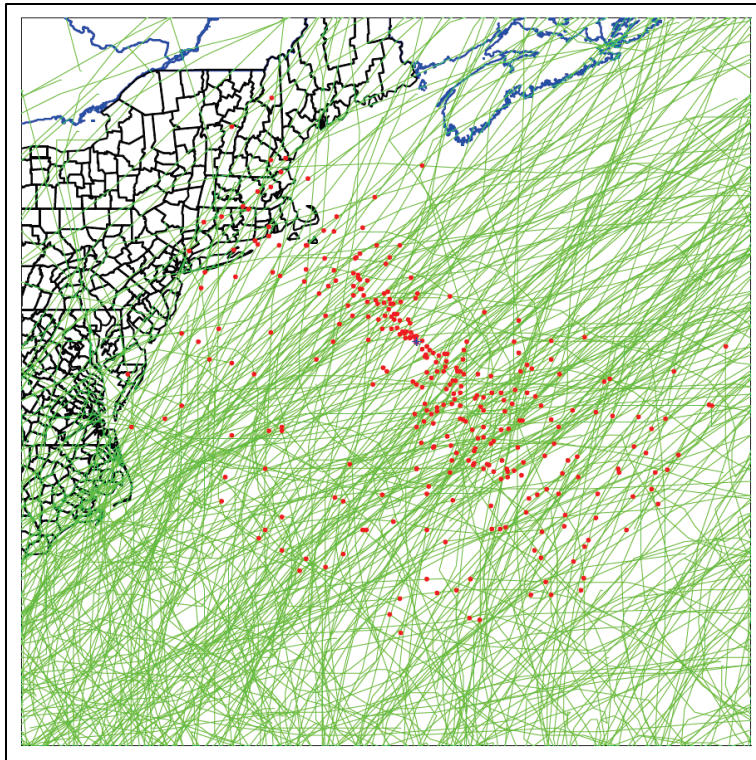


Figure C-4. Hurricanes as a function of distance and direction for site (67°W, 39°N).

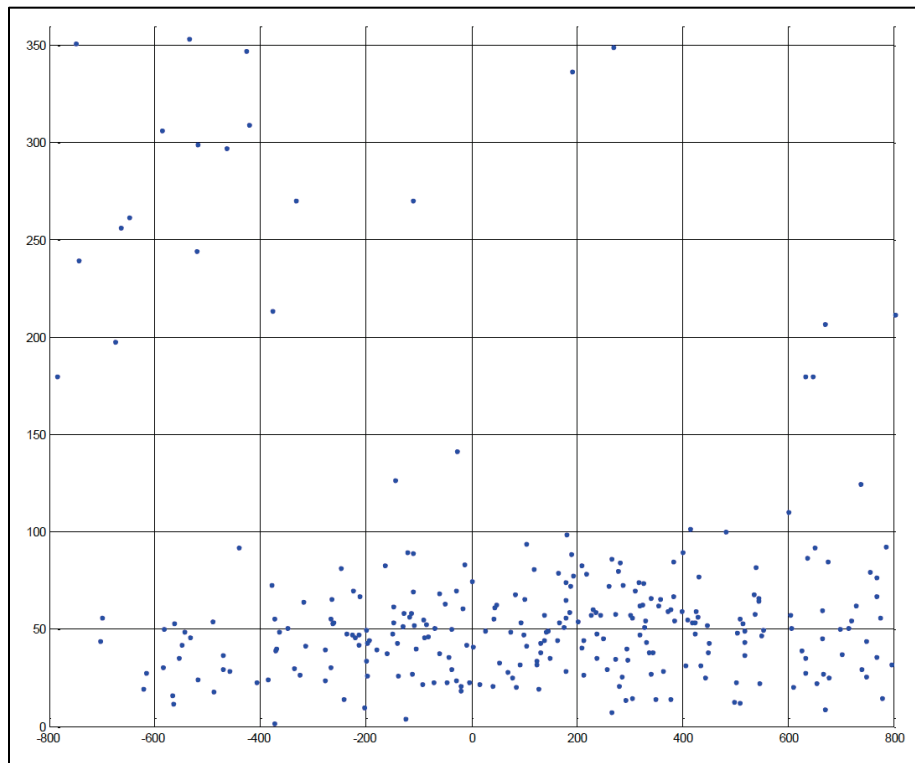


Figure C-5 compares estimates of the recurrence rate of hurricane as a function of the shortest distance to the hurricane track using the CVL and CVSE for the selection of the optimal smoothing parameter. The analysis considers all storms listed in HURDAT from 1938 to 2014 within 400 km of the site (Figure C-6; $N = 149$ storms). Optimal parameters are also obtained with Silverman's plug-in ($KS = 94$ km) and Botev's diffusion plug-in ($KDE = 86$ km). The optimal smoothing parameter using the CVL (30 km) is the smallest among the group and results in a recurrence rate that matches closely the histogram of observations. The cross-validation is performed using the leave-one-out procedure. This example illustrates the sensitivity of the CVL to the variability observed in the histogram. Figure C-7 shows the contribution of individual observations to the CVL as a function of the distance d and illustrates the variability of the optimal smoothness parameter to bumps in the empirical distribution. In this case, the optimal smoothing parameters are similar to those of CVSE (109 km) in the vicinity to the site (within 100 km). The CVSE is less sensitive to bumps in the empirical distribution and results in a larger optimal smoothing parameter.

Figure C-5. Histogram and kernel estimates using different methods for the optimal smoothing parameter (all storms, $N = 149$).

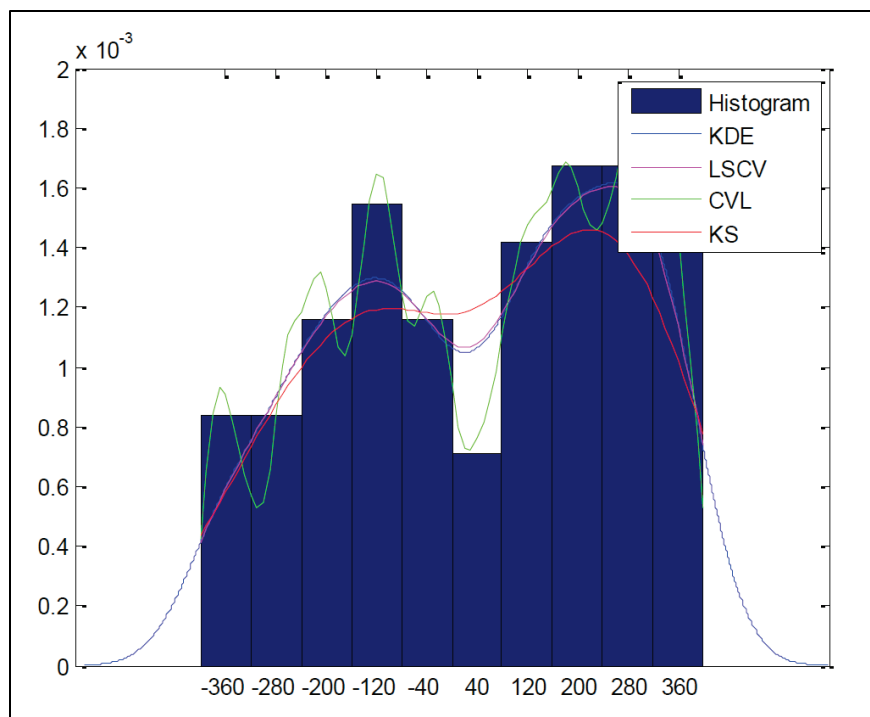


Figure C-6. CVL and CVSE for site (67°W, 39°N).

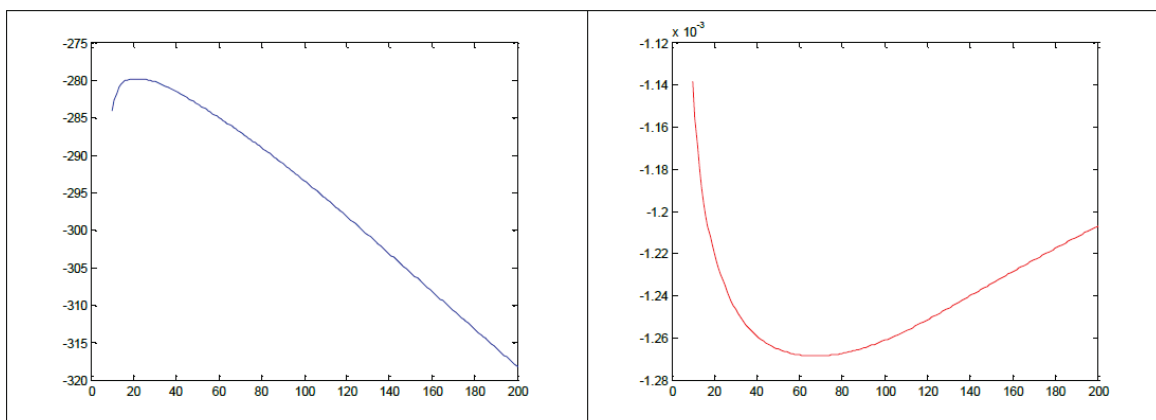
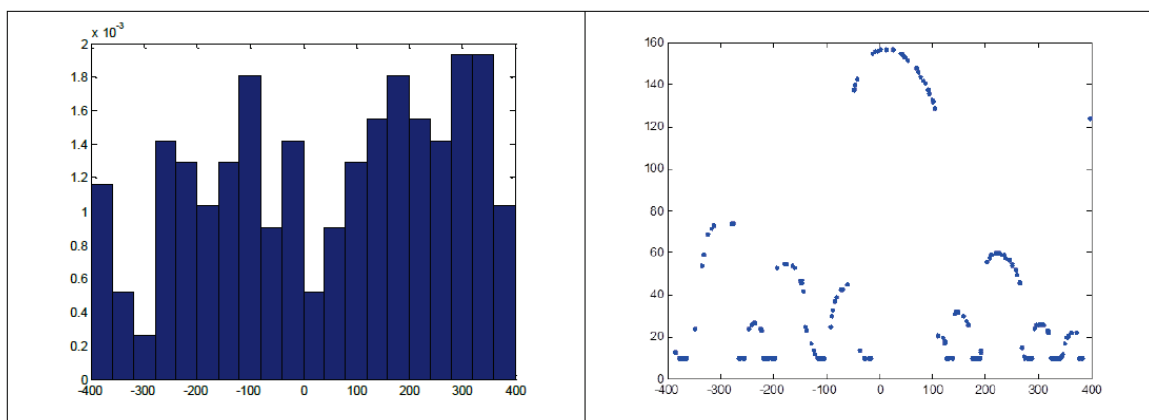


Figure C-7. Histogram and optimal smoothing parameter for each hurricane for CVL.

All storms (194 storms)



The CVL can vary greatly from one site to the next and can be dominated by a few individual points. In the case shown above, the peak is well defined for a smoothing parameter of 30 km. The optimal smoothing parameter as a function of position on the density function shows that the CVL is highly sensitive to bumps in the distribution. Figure C-8 shows the estimates obtained when the data set is restricted to storms with central pressure deficits below 985 hPa ($N = 94$, CVL = 39km, CVSE = 93 km, KS = 122 km, KDE = 94 km). In this case, the CVL exhibits less variability and is closer to the shape obtained with the other methods (Figure C-9). Reducing further the number of storms to those with central pressure below 965 hPa ($N = 49$) further improves the agreement between the various methods since the intensity function is less variable (Figure C-10) (CVL = 54km, CVSE = 188 km, KS = 142 km, KDE = 137 km).

Figure C-8. Histogram and kernel estimates using different methods for the optimal smoothing parameter for storms with central pressure < 985 hPa (N = 94 storms).

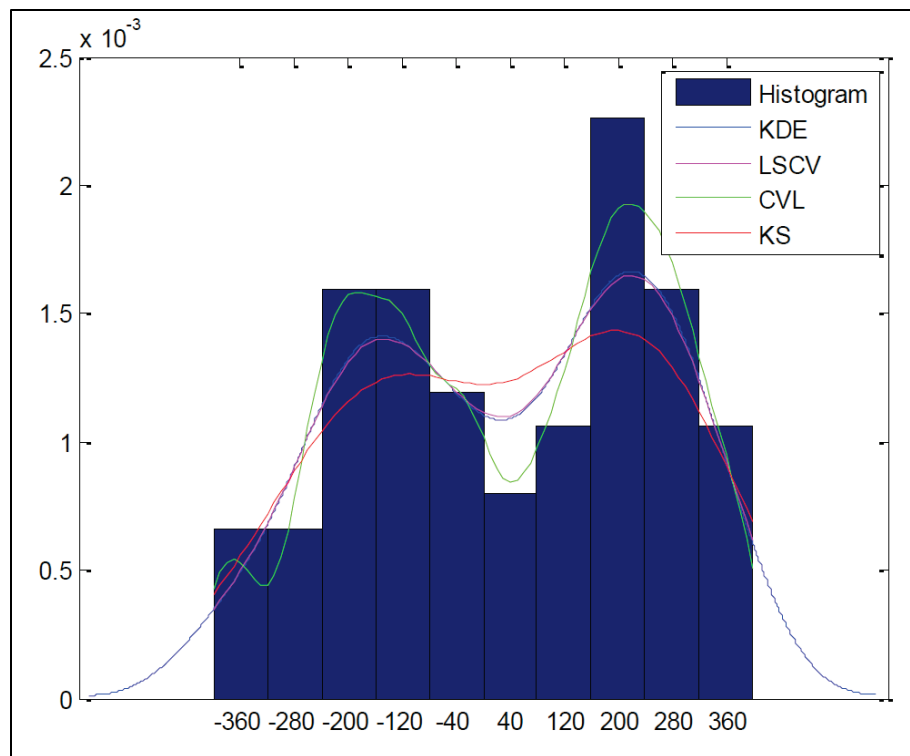


Figure C-9. (1) Contribution to the CVL by each storm; (2) optimal smoothing parameters for each storm using CVL.

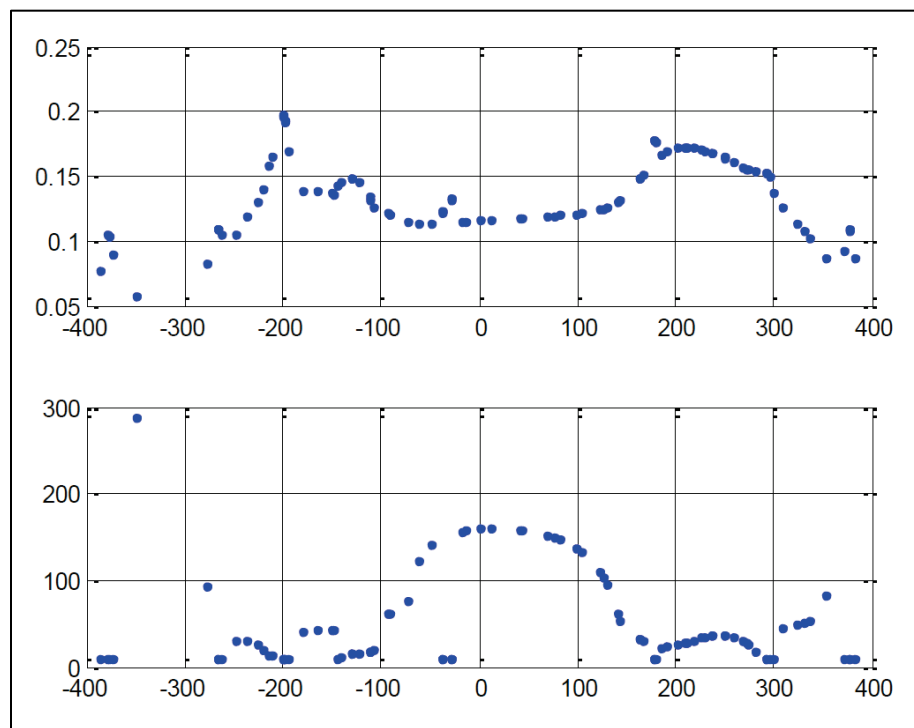
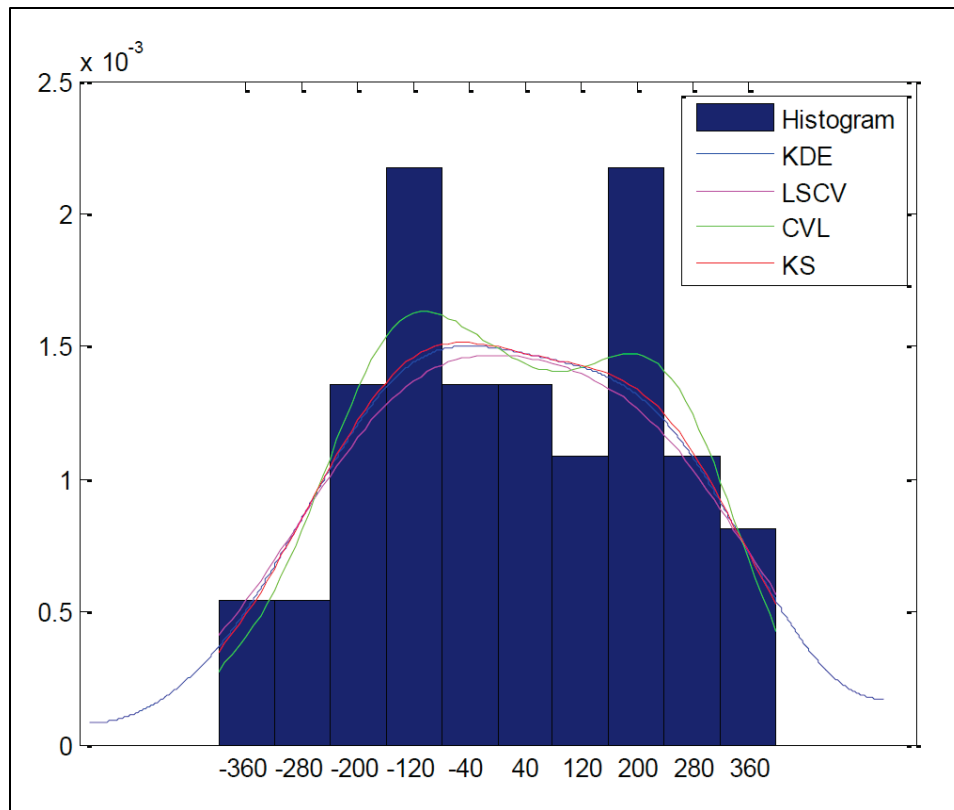


Figure C-10. Histogram and kernel estimates using different methods for the optimal smoothing parameter for storms with central pressure < 965 hPa (N = 49 storms).



The CVL provides estimates that are closer to the ones from the other procedures for a smaller sample size. This may be due to the fact that there is more uncertainty in the empirical density function and that the leave-one-out procedure requires more smoothing since there are fewer similar observations at proximity of the leave-out observation. The following illustrates that larger optimal smoothing is obtained when a three-fold partition (one-third of sample) of the data set used instead of the leave-one-out procedure. A similar procedure was used in Chouinard and Liu (1997). Both the CVL and CVSE are derived from the non-homogeneous Poisson distribution with parameter:

$$v(d) = \lambda(d)t = E[N_d^t]$$

$$E[N_d^t] = \frac{e^{-\lambda(d)t} (\lambda(d)t)^{N_d^t}}{N_d^t!}, N_d^t = 0, 1, 2, \dots$$

$$E[N_d^{-t}(h)] = \lambda_d^{-t} \Delta_t \Delta_d$$

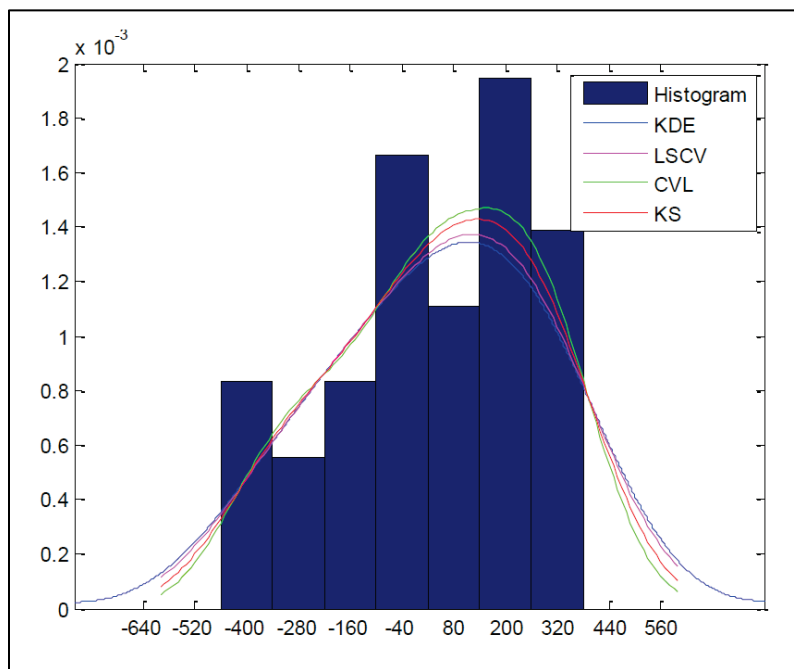
A justification for this approach is that it provides an estimator that has predictive optimal properties similar to those sought for the hazard function. The optimal smoothing parameter corresponds to the model that provides the highest predictive ability for a new set of independent observations (e.g., the model that best predicts 10 years of hurricane occurrences given that the process has been observed over a period of 90 years). The expressions for the CVL and CVSE are then

$$M_{CVL}(h) = \sum_t \sum_d (N_d^t \cdot \log(E[N_d^{-t}(h)]) - E[N_d^{-t}(h)])$$

$$M_{CVSE}(h) = \sum_t \sum_d (N_d^t - E[N_d^{-t}(h)])^2$$

The results obtained with the four methods are in close agreement for the recurrence rate for storms with central pressure below 965 hPa (Figure C-11) (CVL = 119 km, CVSE = 122 km, KS = 139 km, KDE = 137 km). In the following, the k-fold procedure was used to compute the optimal smoothing parameter for the CVL.

Figure C-11. Histogram and kernel estimates using different methods for the optimal smoothing parameter for storms with central pressure < 965 hPa (N = 49 storms) (k-fold procedure for CVL).



C.2.2 East Coast results

Figures C-12 through C-19, respectively, show the results for the optimal smoothing parameter for a grid of sites along the East Coast using the CVL, CVSE, Silverman's rule of thumb (KS) and the Botev's diffusion approach (KDE) for storms with central pressure deficits < 965 hPa and < 985 hPa respectively over the period from 1938 to 2014. In all cases, only storms within 400 km of a grid point are considered. The figures also show the recurrence rate of storms obtained with the corresponding optimal smoothing parameters.

The number of storms included in the analysis for storms with central pressure deficits < 965 hPa varies between 40 to 50 and between 70 to 90 for storms with central pressure deficits < 985 hPa. Because of the smaller number of storms, the optimal smoothing is generally larger for the first set of storms. The optimal smoothing parameters are smallest using CVL and are of the same order of magnitude using CVSE, KS, and KDE. The range of optimal parameters is largest for CVSE while the methods using CVL, KS, and KDE result in fairly uniform optimal parameters across the region.

The scatter plot of the optimal smoothing parameters show some correlation between CVL and CVSE estimates and very low correlations with KS and KDE estimates. The lack of correlation indicates that the optimal smoothing parameters are influenced by different characteristics of the data. For cross-validated procedures, the number of observations, the patterns of observations for different partitions, and the variability in hurricane tracks are important. In the case of KS and KDE, the results are mainly influenced by the variance in the distance distribution and by the assumption of an underlying Gaussian process.

The recurrence rates estimated using the optimal smoothing parameters from different methods give similar spatial trends, but the recurrence rates can vary by 30%. For storms < 965 hPa, the recurrence rate shows higher values offshore and south. For storms < 985 hPa, the recurrence rate shows higher spatial variability with two parallel preferential corridors offshore and parallel to the coast.

Figure C-12. Optimal smoothing parameters and estimate of storm recurrence rates using four different optimization procedures (East Coast < 965 hPa).

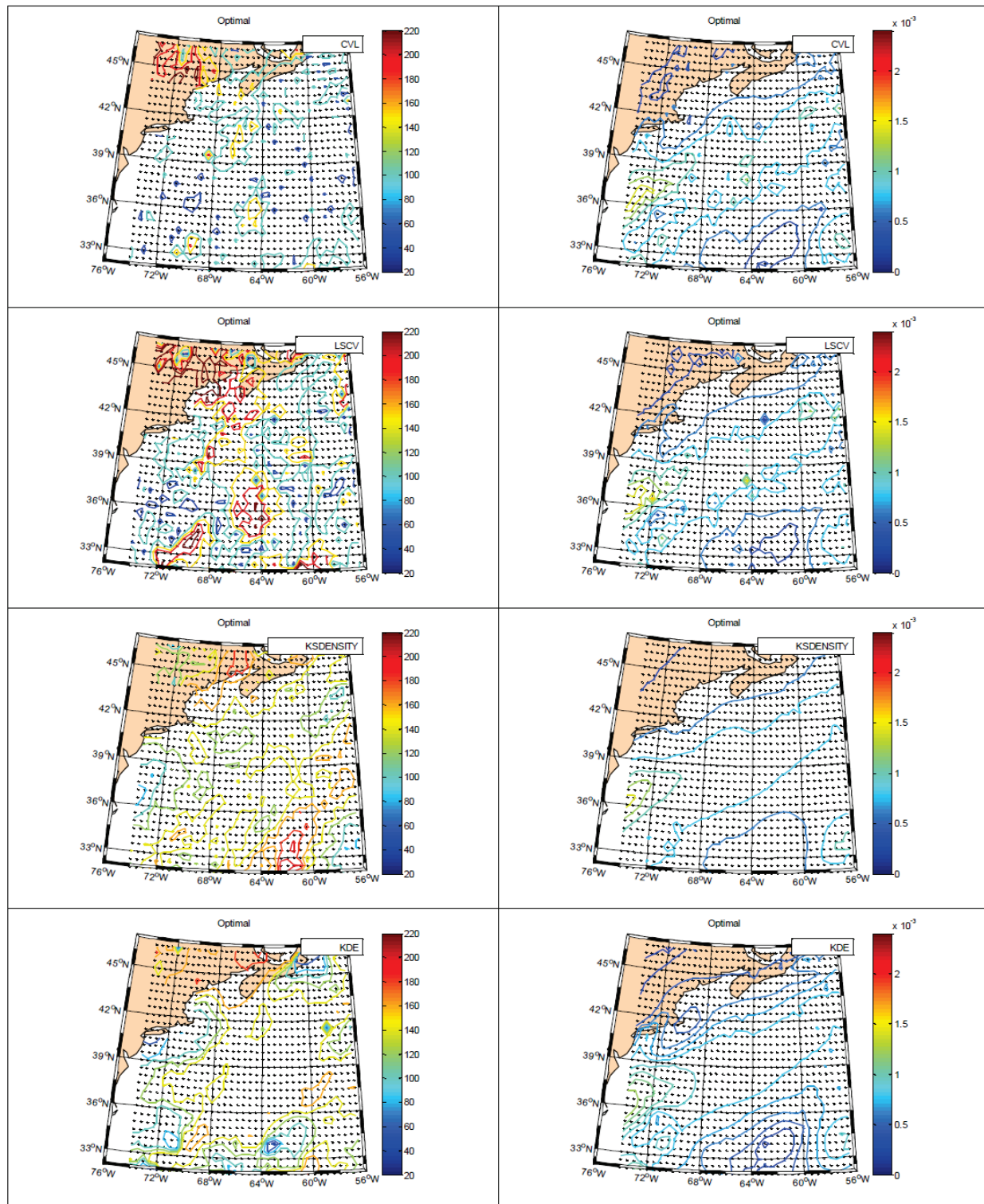


Figure C-13. Comparison of optimal smoothing parameters (East Coast < 965 hPa).

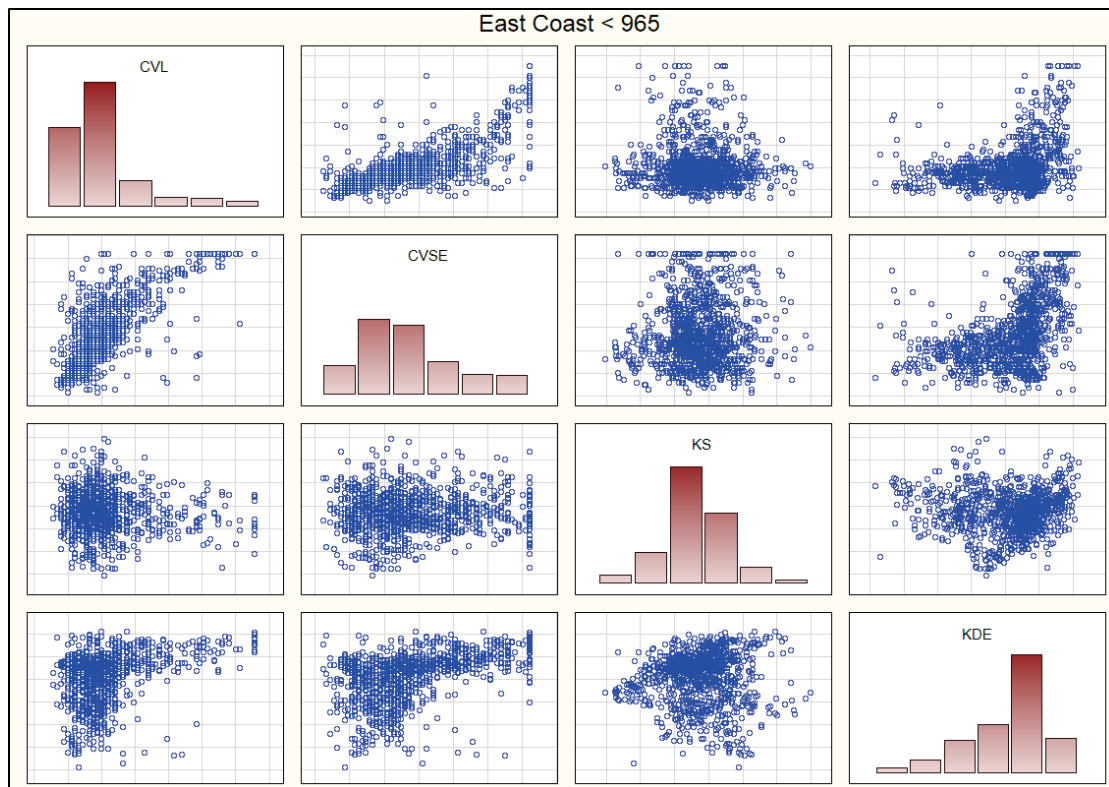


Figure C-14. Comparison of storm recurrence rate estimates (East Coast < 965 hPa).

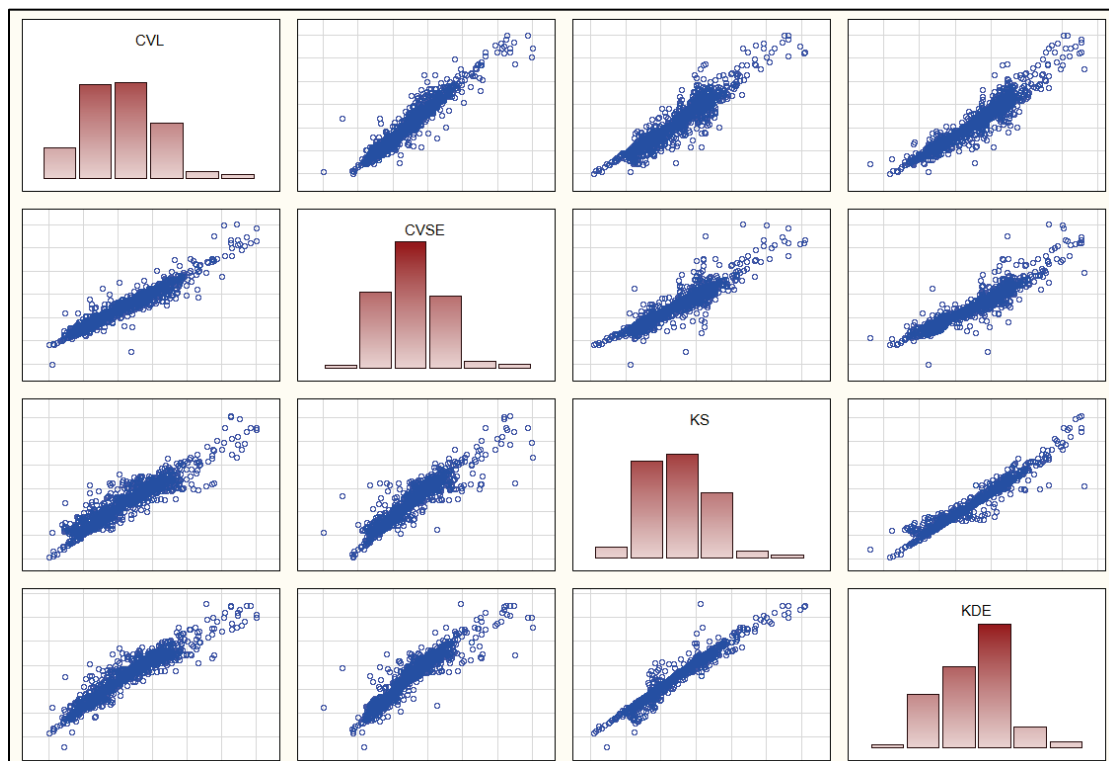


Figure C-15. Box and whiskers plot of optimal smoothing parameters (East Coast < 965 hPa).

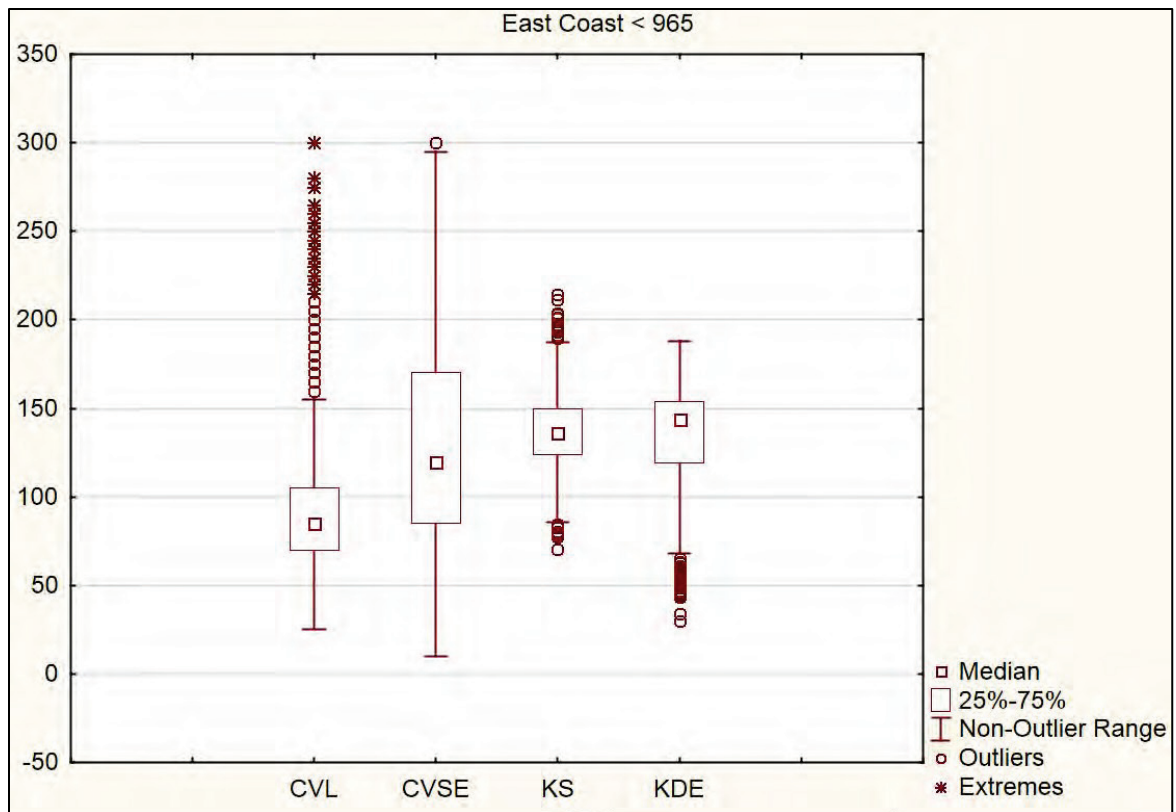


Figure C-16. Optimal smoothing parameters and estimate of storm recurrence rates using four different optimization procedures (East Coast < 985 hPa).

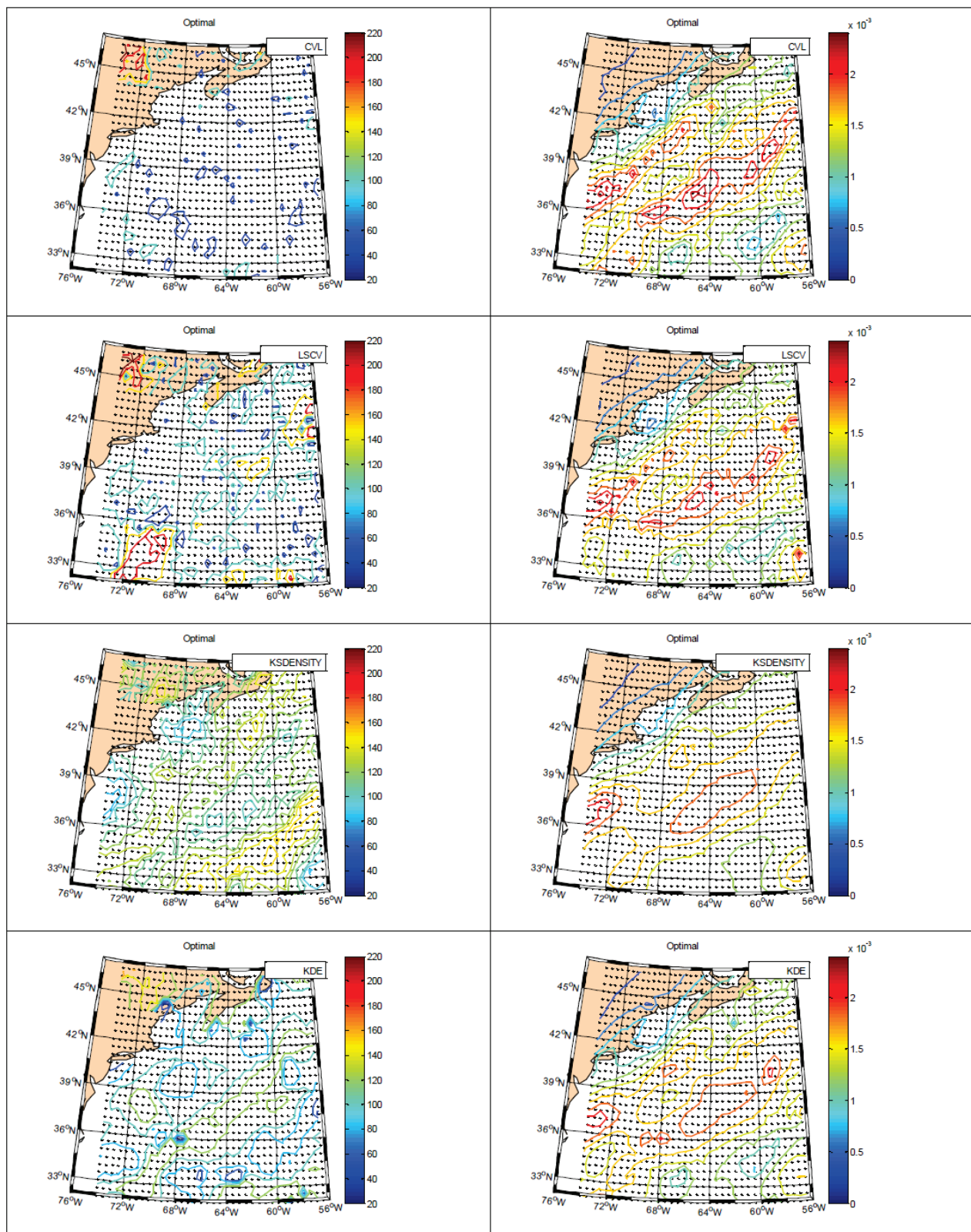


Figure C-17. Comparison of optimal smoothing parameters (East Coast < 985 hPa).

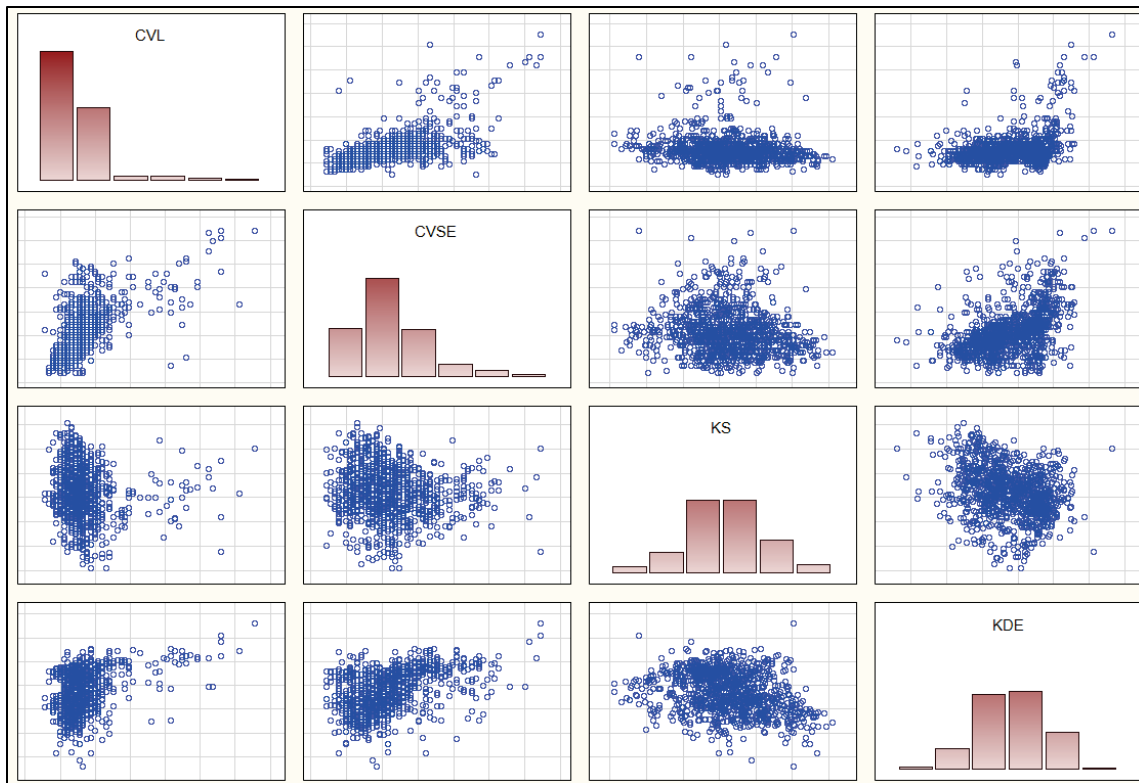


Figure C-18. Comparison of storm recurrence rate estimates (East Coast < 985 hPa).

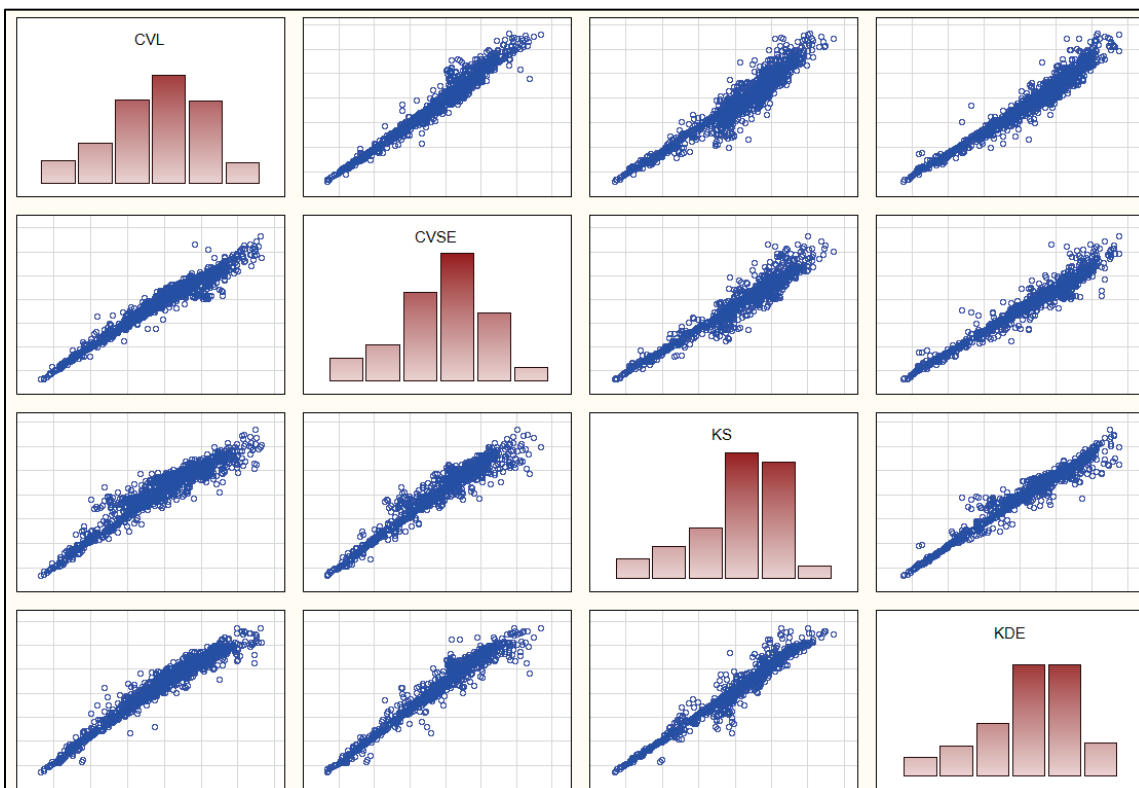
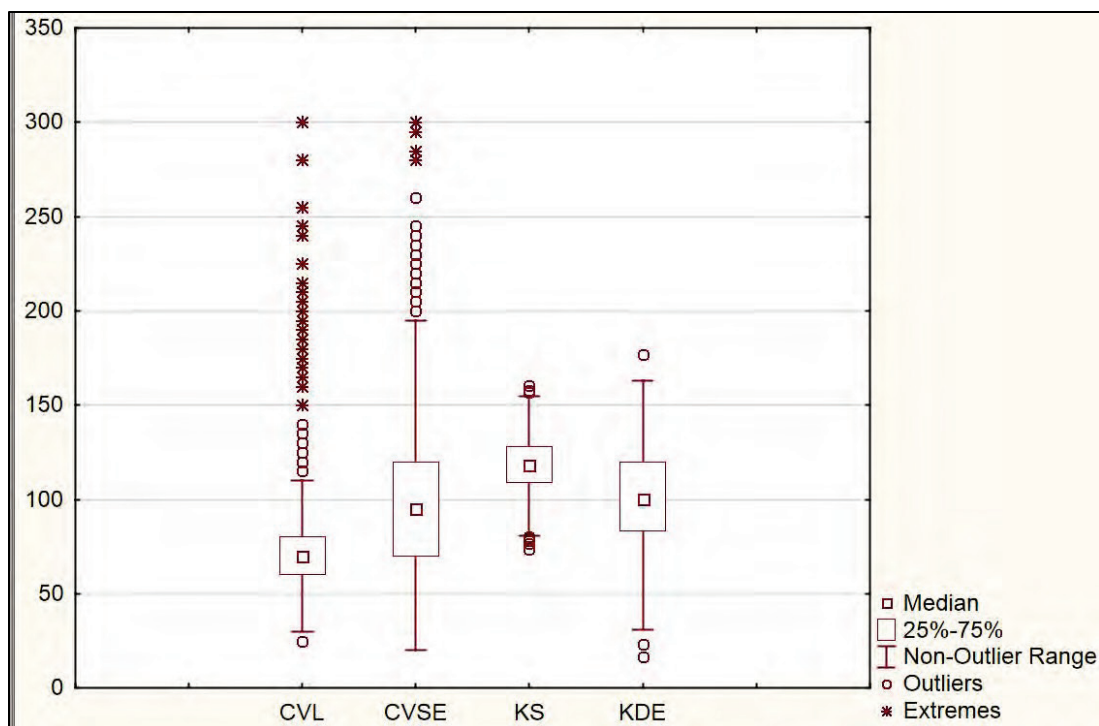


Figure C-19. Box and whiskers plot of optimal smoothing parameters (East Coast < 985 hPa).



C.2.3 Gulf of Mexico results

Figures C-20 through C-27, respectively, show the results for the optimal smoothing parameter for a grid of sites along the Gulf Coast. The number of storms included in the analyses varies between 20 and 30 for central pressure below 965 hPa and between 40 and 60 for central pressure below 985 hPa. The optimal smoothing parameters are generally higher than those for the East Coast due to the smaller number of storms and also due to more uniform shape of the intensity functions. Similarly to the results for the East Coast, the degree of correlation between optimal smoothing parameters using CVL and CVSE is highest with a lower degree of correlation between CVL and KDE. The criterion from KS shows that the variance in distances is smallest in the central Gulf region and highest for a corridor towards the western Gulf. The criterion from KDE is almost uniform across the Gulf and does not capture any of the detailed spatial features in the distribution of storm tracks. For storms < 965 hPa, the recurrence rate using CVL and CVSE detects two main paths across the Gulf while KS and KDE appear to over smooth the southernmost corridor.

For storms < 985 hPa, the recurrence rate is highest in the central Gulf area. The criterion from KDE exhibits spurious spatial variations not observed with the other methods in this last case.

Figure C-20. Optimal smoothing parameters and estimate of storm recurrence rates using four different optimization procedures (Gulf of Mexico < 965 hPa).

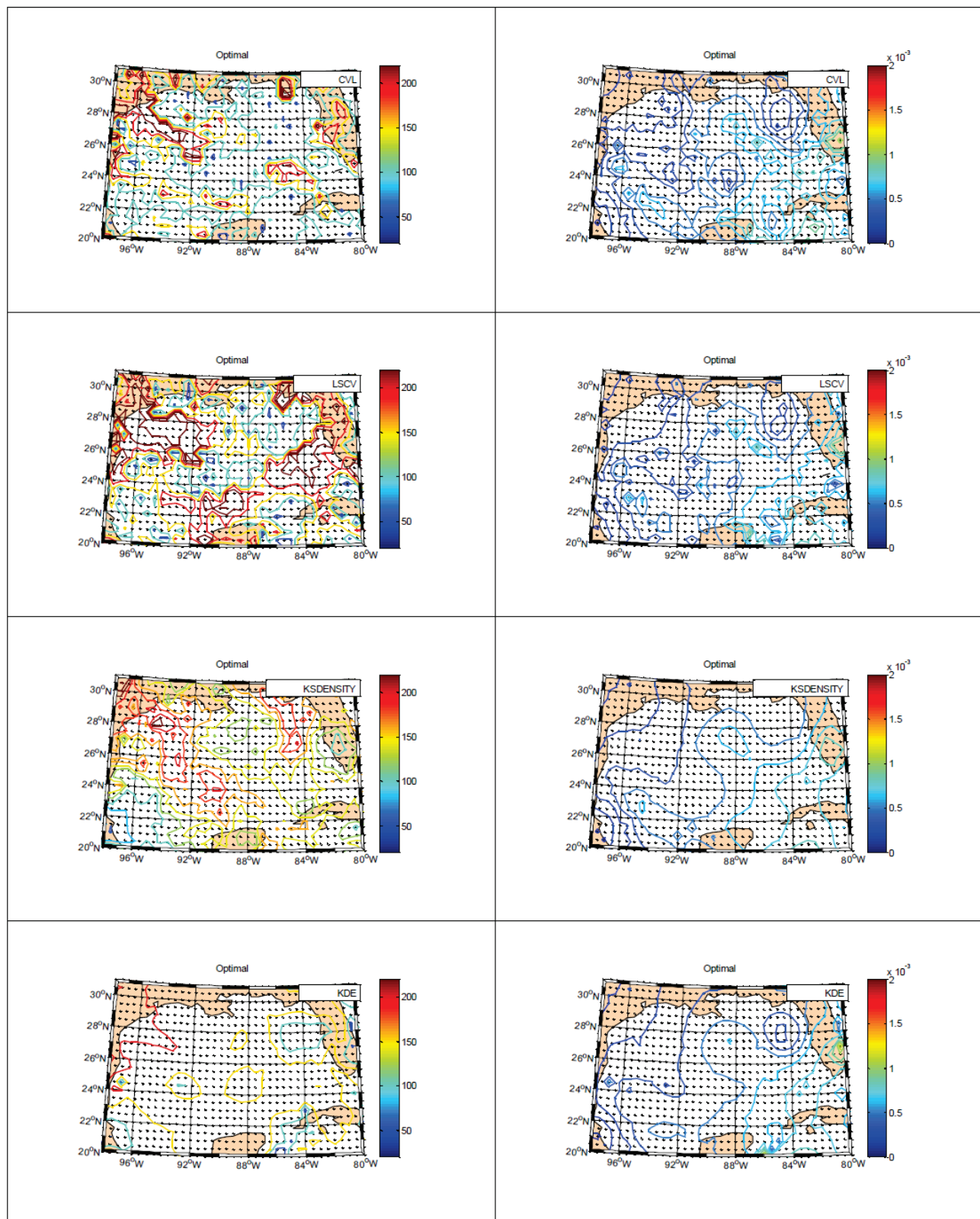


Figure C-21. Comparison of optimal smoothing parameters (Gulf of Mexico < 965 hPa).

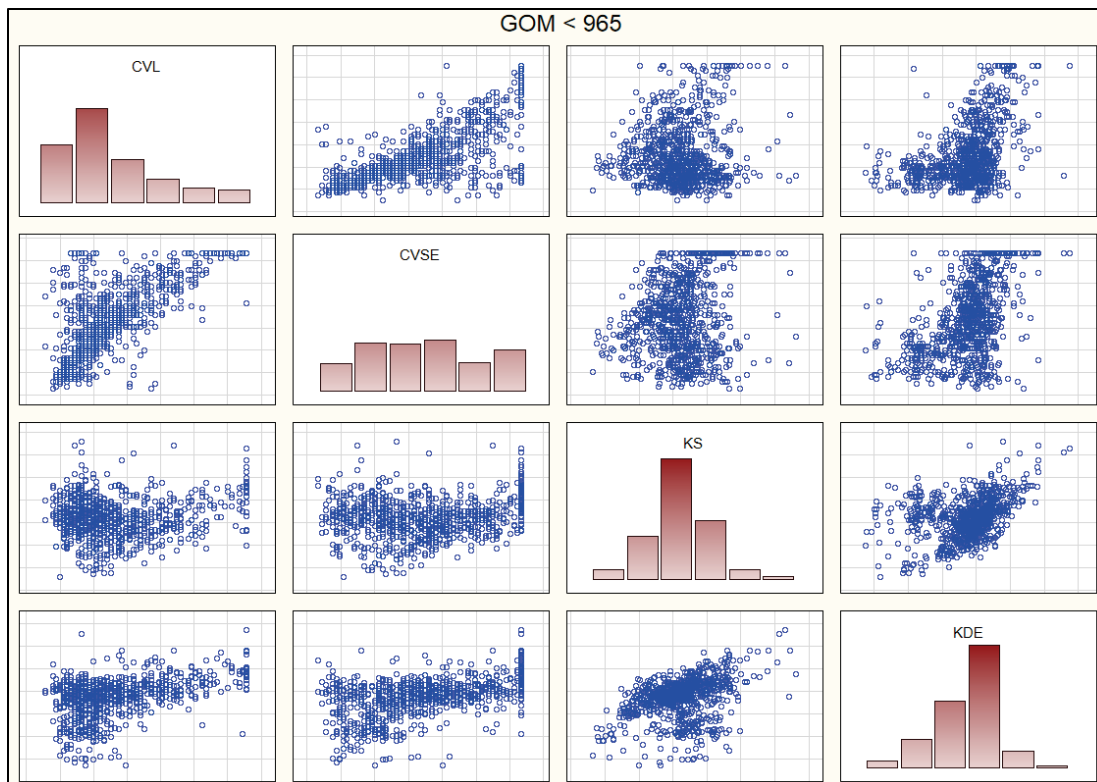


Figure C-22. Comparison of storm recurrence rate estimates (Gulf of Mexico < 965 hPa).

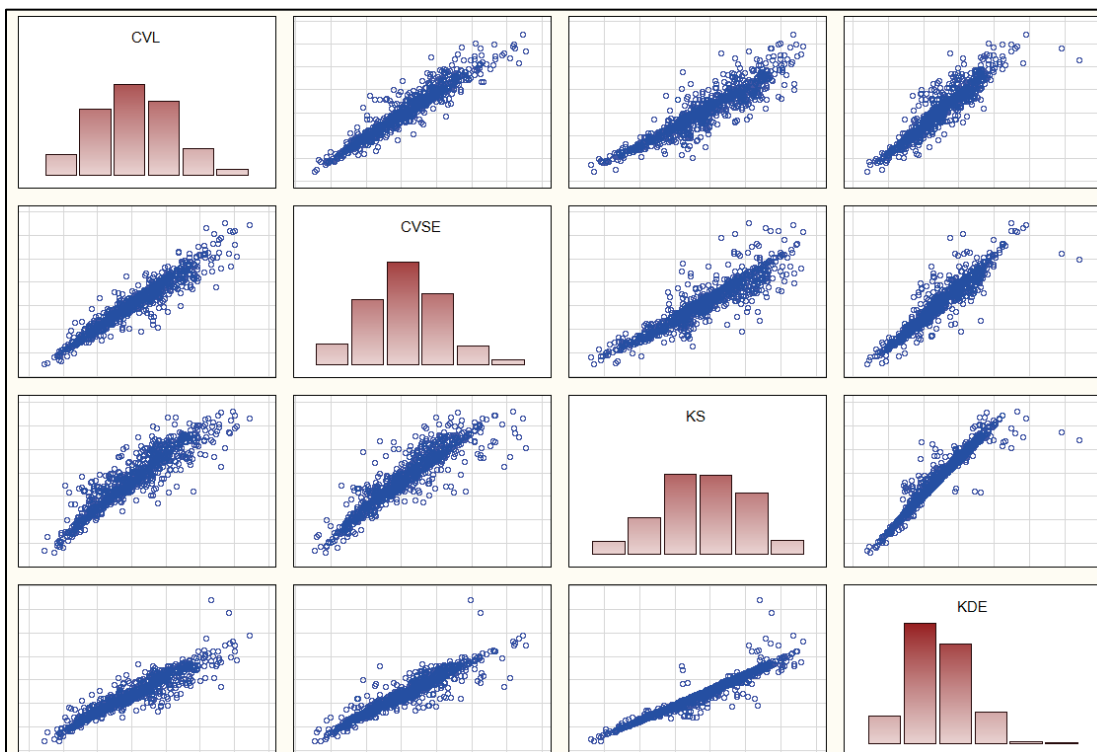


Figure C-23. Box and whiskers plot of optimal smoothing parameters (East Coast < 985 hPa).

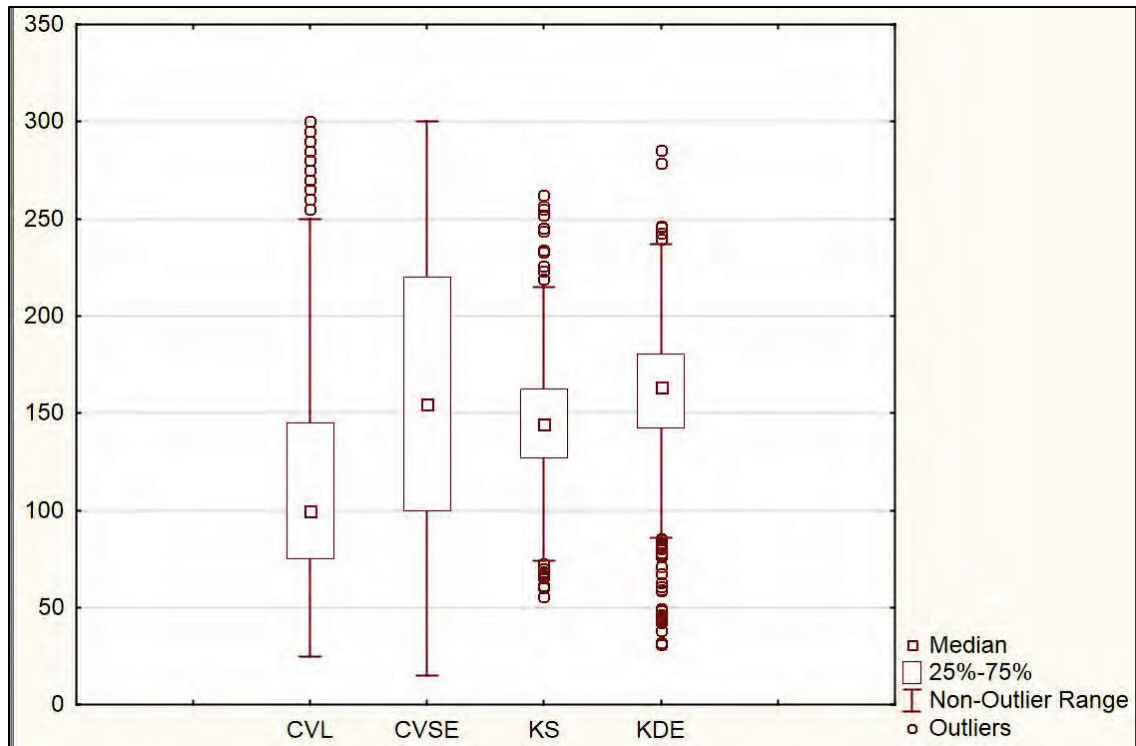


Figure C-24. Optimal smoothing parameters and estimate of storm recurrence rates using four different optimization procedures (Gulf of Mexico < 985 hPa).

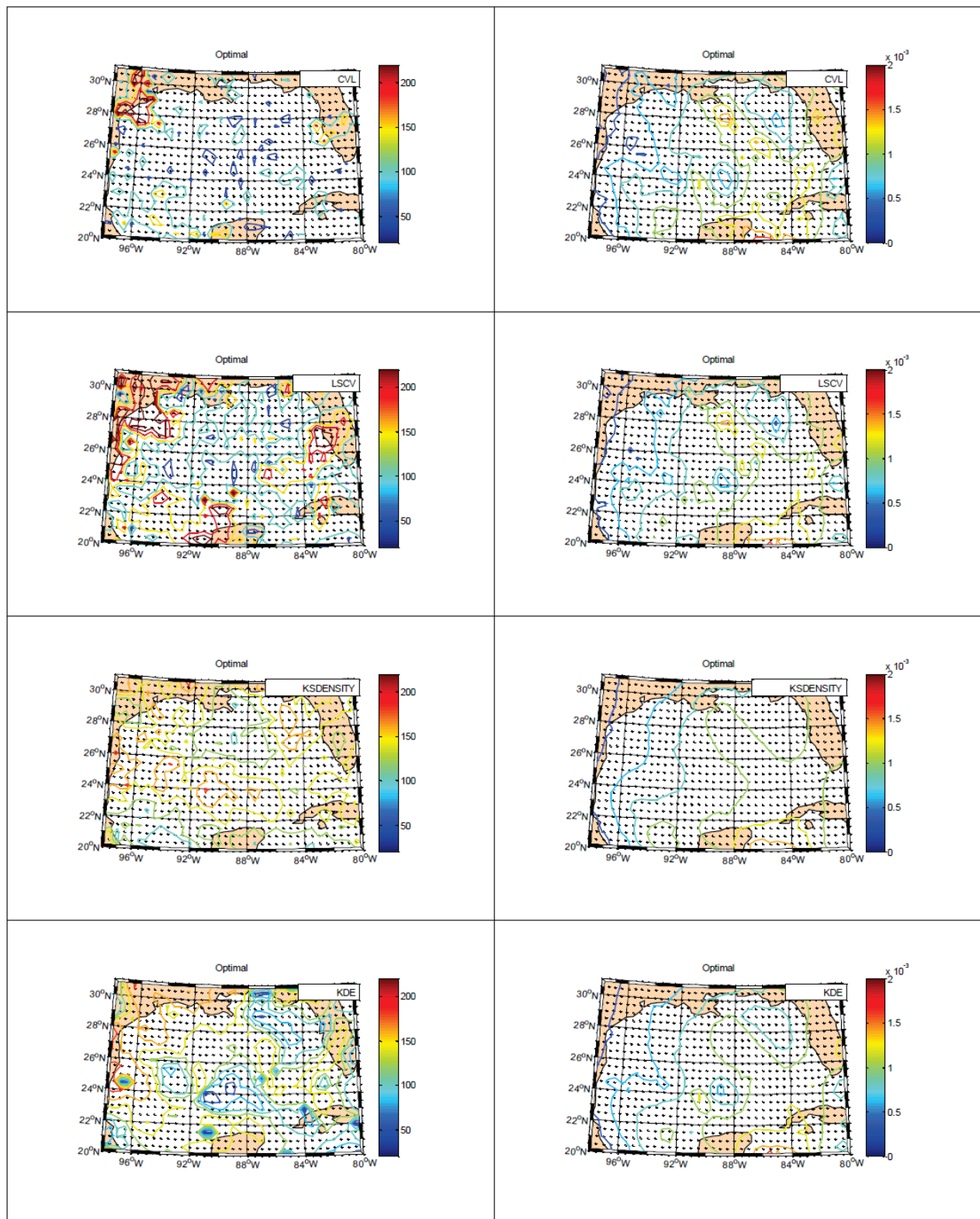


Figure C-25. Comparison of optimal smoothing parameters (Gulf of Mexico < 985 hPa).

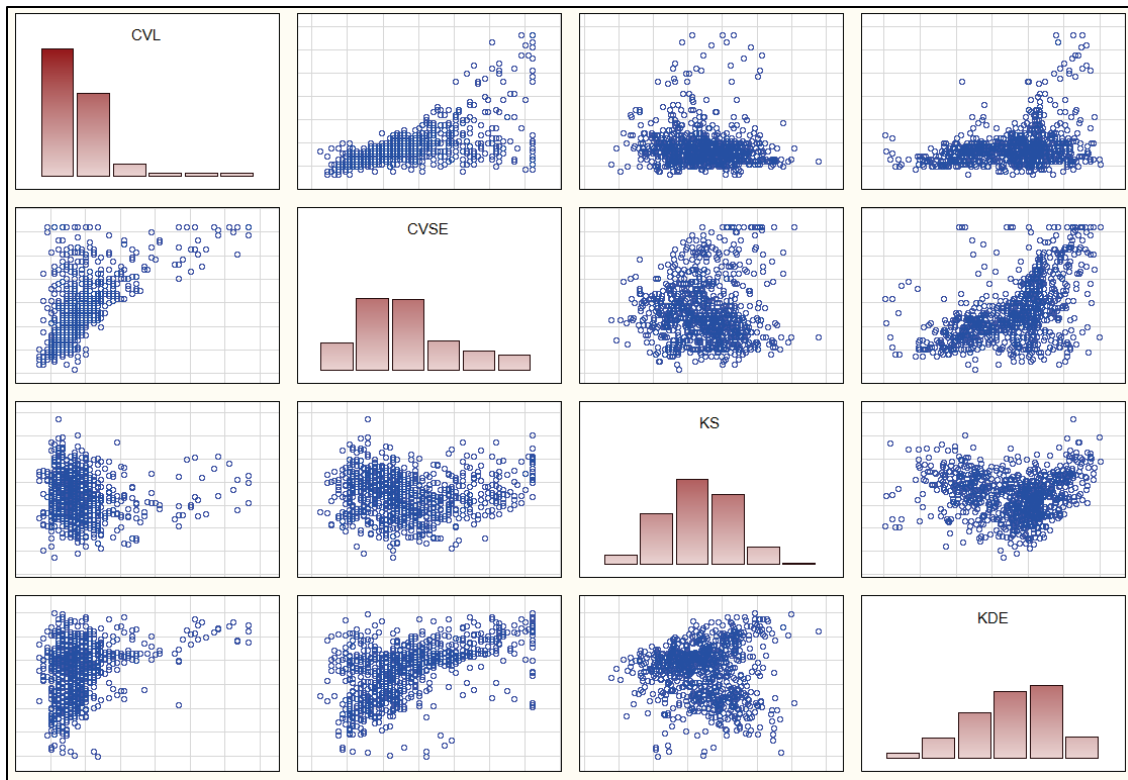


Figure C-26. Comparison of storm recurrence rate estimates (Gulf of Mexico < 985 hPa).

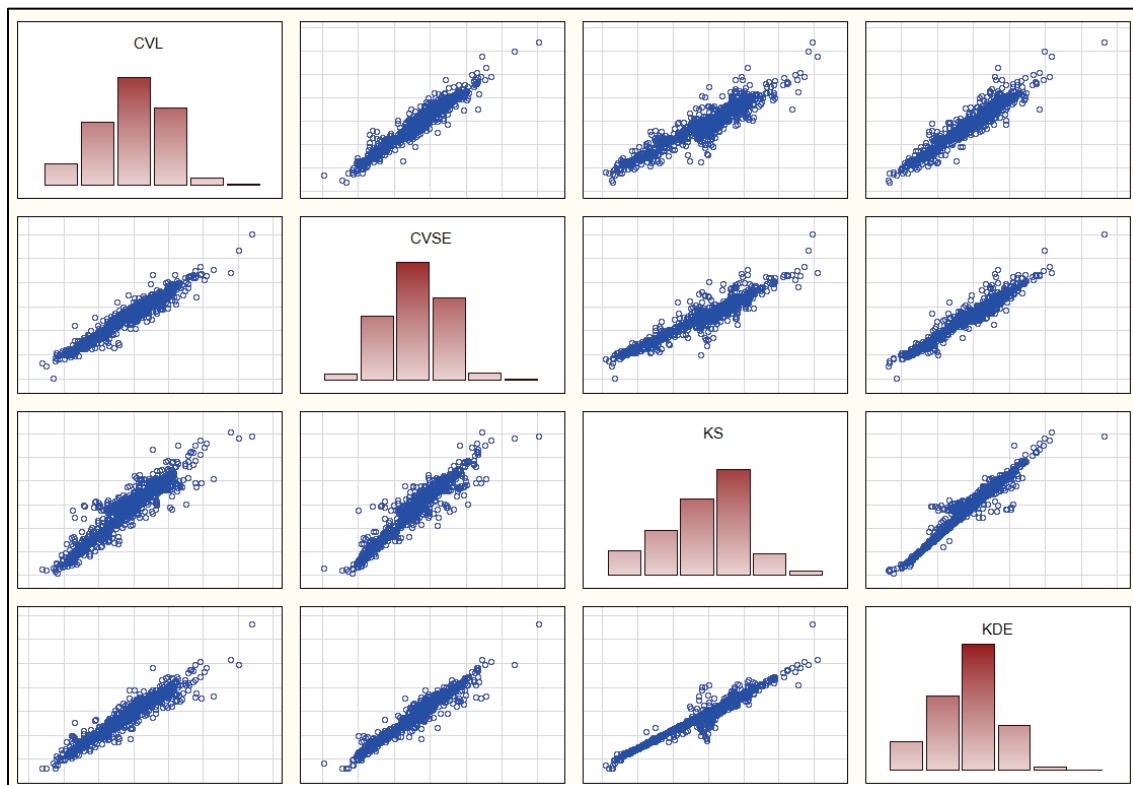
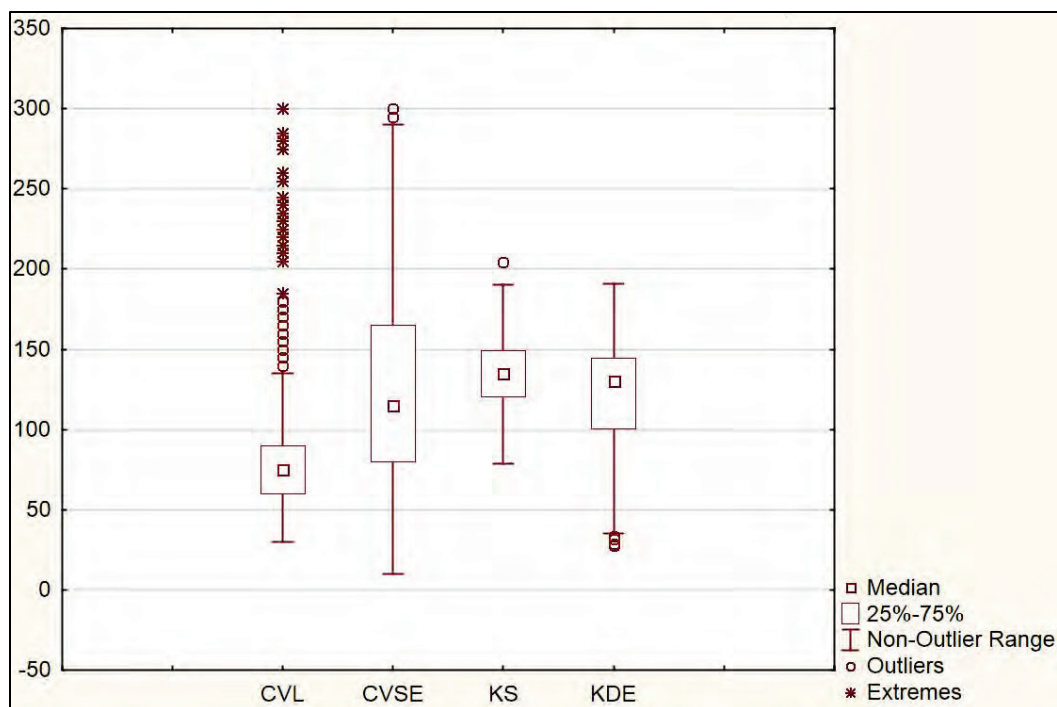


Figure C-27. Box and whiskers plot of optimal smoothing parameters (East Coast < 985 hPa).



C.3 Conclusions

Various procedures for estimating the optimal smoothing parameter of a Gaussian kernel estimator for the recurrence rate of hurricanes have been investigated. The characteristics and performance of these procedures are evaluated through a series of analyses for sites located along the East Coast and the Gulf of Mexico for two categories of storms. The set of storms from 1938 to 2014 is used for current purposes for cases when the maximum central pressure deficit is below 965 hPa and below 985 hPa.

The first set of procedures is based on cross validation, which consists in partitioning the data in non-overlapping intervals. Both the leave-one-out and k-fold partitions are investigated. The k-fold partition includes more events in each validation set and fewer events in the estimation set as compared to the leave-one-out option, which produces slightly larger optimal smoothing parameters. Advantages of the k-fold procedure are that they replicate the occurrence of storms over extended periods and can be used to analyze spatio-temporal changes in the recurrence rate of storms. Another advantage is that it reduces the influence of isolated occurrences and of storm tracks that are at large distance from the site. In the case of density estimation, the objective is to obtain a good fit for the full range of the variable including the tails while for the recurrence rate, the fit is more important in proximity to the site.

The cross-validation procedure is applied to compute the likelihood (CVL) as well as for the mean squared error (CVSE). Both can be interpreted as measures of the predictive skill of the estimator. The CVL tends to undersmooth the recurrence rate in comparison to the CVSE; however, in most cases the net effect on the estimation of the recurrence rate is at most on the order of 20% for the cases analyzed.

The other plug-in methods investigated (Silverman's rule of thumb and Botev's diffusion) are not based on cross validation and do not incorporate the notion of predictability. Both methods require assumptions of the form of the distribution (i.e., Gaussian) and do not account for the spatio-temporal variability in the recurrence rate. The two methods give generally similar results and are fairly constant over a large region with similar degrees of variability. Silverman's rule tends to over smooth the data whereas Botev's diffusion does not always provide stable bandwidths when the sample size is small and produces spurious results spatially.

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1. REPORT DATE May 2019		2. REPORT TYPE Report 1 of a series		3. DATES COVERED (From - To)	
4. TITLE AND SUBTITLE Storm Recurrence Rate Models for Tropical Cyclones: Report 1				5a. CONTRACT NUMBER NRC-HQ-60-14-I-0019	
				5b. GRANT NUMBER	
				5c. PROGRAM ELEMENT NUMBER	
6. AUTHOR(S) Norberto C. Nadal-Caraballo, Victor M. Gonzalez, and Luc Chouinard				5d. PROJECT NUMBER	
				5e. TASK NUMBER	
				5f. WORK UNIT NUMBER	
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Coastal and Hydraulics Laboratory U.S. Army Engineer Research and Development Center 3909 Halls Ferry Road Vicksburg, MS 39180-6199				8. PERFORMING ORGANIZATION REPORT NUMBER ERDC/CHL TR-19-4	
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES) U.S. Nuclear Regulatory Commission One White Flint North 11555 Rockville Pike Mail Stop CSB C2 A7 Rockville, MD 20852-2738				10. SPONSOR/MONITOR'S ACRONYM(S) USNRC	
				11. SPONSOR/MONITOR'S REPORT NUMBER(S)	
12. DISTRIBUTION/AVAILABILITY STATEMENT Approved for public release; distribution is unlimited.					
13. SUPPLEMENTARY NOTES					
14. ABSTRACT Quantification of the storm surge hazard is an integral part of the probabilistic flood hazard assessment of structures and facilities located in coastal areas. The U.S. Army Engineer Research and Development Center, Coastal and Hydraulics Laboratory (ERDC-CHL), performed a comprehensive assessment of uncertainties in probabilistic storm surge models for the U.S. Nuclear Regulatory Commission (USNRC) as part of its efforts to develop a framework for probabilistic storm surge hazard assessment for nuclear power plants. State-of-the-art statistical assessment of coastal storm hazards in hurricane-prone coastal areas requires the development of a joint probability model of tropical cyclone (TC) forcing parameters. The task summarized in this technical report focused on the quantification of epistemic uncertainties in storm recurrence rate (SRR) models and associated data sources. SRR is an estimate of the expected annual rate of occurrence of TCs within a given region. Numerical experiments were performed to quantify SRR uncertainty associated with data sampling, observational data quality, selection of kernel function and kernel size, period of record, quality of observational data, and partition of TCs according to their intensity. This technical report is the first of a series covering the USNRC-sponsored study "Quantification of Uncertainties in Probabilistic Storm Surge Models performed by the ERDC CHL."					
15. SUBJECT TERMS Cyclones—Tropics, Floods—Risk assessment, Hurricanes, Storm surges, Uncertainty—Mathematical models					
16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT	b. ABSTRACT	c. THIS PAGE			Victor M. Gonzalez
Unclassified	Unclassified	Unclassified	SAR	137	19b. TELEPHONE NUMBER (Include area code) 601-634-3006