METRICS AND METHODS TO
QUANTIFY AND COMMUNICATE
TROPICAL CYCLONE RAINFALL HAZARD

by

Christopher D. Bosma

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CHAPTER 1 | INTRODUCTION

1.1 | TROPICAL CYCLONE RAINFALL HAZARD

The intense rainfall associated with tropical cyclones (TC) is a significant hazard to human life and property. From 1963 to 2012, extreme rainfall was the most frequent cause of tropical cyclone-related fatalities in the United States (Rappaport 2014). Climate models have indicated, with high confidence, that TC rainfall rates in the North Atlantic will increase due the effects of global warming (Knutson et al. 2010; Wuebbles et al. 2017), with projected increases of 5%-20% (Walsh et al. 2016). Furthermore, the mean translational speed of North Atlantic TCs over land has decreased by 20% since the mid-20th century (Kossin 2018). These changes have important implications since more intense, slower-moving storms are more likely to linger for long durations and to generate extreme rainfall totals.

The widely-used Saffir-Simpson scale assigns TCs a hazard category from one to five based on maximum sustained wind speed, with “Category 5” being the most catastrophic. However, maximum wind speed is a not a reliable indicator of overall hazard. Six of the ten deadliest TCs in the U.S. in the fifty years from 1963 to 2012 were tropical storms or Category 1 hurricanes at landfall (Rappaport 2014), and the Saffir-Simpson scale does not provide an accurate estimate of potential damage for a TC post-landfall (Senkbeil and Sheridan 2006). While a TC’s wind speed over land is typically much weaker than over the ocean (Sparks 2003), the rainfall threat may still be high post-landfall. Additionally, the area most impacted by extreme rainfall during a particular TC may be both spatially and temporally distinct from the region with the highest winds. These factors point to the need for an alternative means of characterizing and communicating TC rainfall threats.
Hurricane Harvey (2017) and Hurricane Florence (2018) highlighted the hazard posed by TC rainfall and the challenge of effectively communicating this information to the public. Hurricane Florence, for example, approached the East Coast of the United States as a Category 4 hurricane, before weakening and making landfall as a Category 1 storm. The storm generated extreme rainfall and severe flooding throughout the Carolinas. Over 900 mm of rainfall was recorded in Elizabethtown, North Carolina, breaking the state’s record for TC rainfall. There is anecdotal evidence that the downgrade in Florence’s category as it approached the coast was perceived by members of the public as an indication of reduced hazard, resulting in some residents choosing not to evacuate (Achenbach and Wax-Thibodeaux 2018).

The previous year, in 2017, Hurricane Harvey stalled over southeastern Texas for several days, making landfall as a Category 4 hurricane and weakening to a tropical storm shortly thereafter. Over 1500 mm of rain fell in Nederland, Texas—the highest TC-related rainfall total ever recorded in the United States. Experts and the media attempted to use recurrence intervals to contextualize the associated rainfall and flooding, with some media outlets reporting that Harvey was a “500-year” or “1000-year” event (Ingraham 2017; Lind 2017; Samenow 2017), while some outlets noted the shortcomings of these claims (Koerth-Baker 2017; D’Angelo 2017; Bledsoe 2017).

1.2 | Recurrence Intervals

Recurrence interval (i.e. return period) estimates are critical to the fields of engineering design and probabilistic hazard and risk assessment. They are typically estimated by fitting a statistical distribution to a time series of observations (Coles 2001). A rainfall or flood event with a “500-year” recurrence interval has a 1 in 500 (0.2%) probability of being exceeded in
any year (i.e. annual exceedance probability); such an event will occur, on average, once every 500 years in a stationary (i.e. unchanging) climate. The usage of these statistical measures is complicated by the fact that storm duration is a critical component in determining the impacts of an extreme rainfall event. A one-day, 500-year rainfall event could generate localized flash flooding, for example, while a three-day, 500-year event could cause widespread flooding in large watersheds. Previous attempts to develop TC classification systems have highlighted how differences in storm duration result in different magnitudes of TC impacts (Senkbeil and Sheridan 2006).

Rainfall records are rarely longer than 75 years in the United States and are considerably shorter in many other parts of the world. Thus, rainfall recurrence interval estimates tend to be subject to substantial sampling uncertainty because the period of record is often substantially shorter than the desired quantile. Rainfall distributions are typically derived from point-scale observations (such as rain gauges), describing the distribution of extreme rainfall at a specific location, but with a limited ability to describe distributions at larger spatial scales. Additionally, when new events occur that lie outside the range of previously observed rainfalls, recurrence interval estimates should, in principle, be updated to reflect these new records. These changes can be quite large, as seen in the revised “Atlas 14” precipitation frequency estimates from the National Oceanic and Atmospheric Administration (NOAA) for the state of Texas, released in September 2018. An earlier estimate of the 100-year rainfall in Houston, based on rainfall records up to the 1960s, was approximately 330 mm (13 inches) in 24 hours (Hershfield 1961); this was updated to 457 mm (18 inches) in Atlas 14 using the most up-to-date data for the region, including observations of rainfall from Harvey (Perica et al. 2018).
In addition to these statistical challenges, recurrence intervals can be confusing and misleading to the public (Keller et al. 2006). Probabilities and frequencies are abstract concepts, creating room for misinterpretation (Schneider 2016). For example, there is a common misperception that multiple “100-year” events cannot occur within a short timeframe. Statistically, however, there is a 26.4% chance of two or more “100-year” events of the same duration occurring at a particular location within any century-long period; this issue is complicated even further when events of varying durations are considered. Additionally, the understanding of probabilistic metrics is highly individual—the same metric can have different meanings for different users based on their own perception of risk (Schneider 2016).

A growing number of studies highlight the importance of “experiential processing” in everyday decision-making – the idea that decisions are often made by relating current situations to events that individuals can recall from prior personal experience or recent media reports and images (Marx et al. 2007). Investigations into how individuals process information related to weather hazards have shown some shortcomings of current approaches, including recurrence intervals, and some have proposed alternatives that could convey this information more effectively (Schroeder et al. 2016; Lave and Lave 1991; Wachinger et al. 2013). A survey of residents in a flood-prone community in Texas in the United States, for example, highlighted how residents were more concerned about a potential flooding hazard when concrete information about the nature of flooding was provided, as opposed to abstract probabilities (Bell and Tobin 2007). Preparedness ahead of high-impact floods in 2015 and 2016 in the United Kingdom may have been reduced because residents had trouble adequately conceptualizing the magnitude of the flooding, which exceeded any that had occurred in recent memory (Cologna et al. 2017).
1.3 | OUTLINE

Given the well-documented shortcomings of recurrence intervals in the context of communicating the hazard associated with extreme rainfall events (including tropical cyclones), this paper seeks to devise an alternative metric to more effectively quantify and communicate rainfall hazard. This metric – the Extreme Rainfall Multiplier (ERM) – expresses the magnitude of extreme rainfall as a multiple of the climatologically derived 2-yr rainfall value and is derived in Chapter 2. The ERM metric is applied retrospectively to historical TCs from 1948 to 2017 in Chapter 3, highlighting both the most extreme TC rainfall events (including Hurricane Harvey, which had the highest ERM value during this period) and the wide geographical distribution of these events in the eastern and southern United States. This analysis also allows for the development of regional-scale (rather than local-scale) recurrence interval estimates for extreme TC rainfall. Chapter 4 explores the potential utility of ERM to characterize extreme rainfall hazard in a forecast context, as well as other ways to improve the public’s general understanding using informal science communication methods. Future applications of the ERM metric and general conclusions are presented in Chapter 5.
CHAPTER 2 | THE “EXTREME RAINFALL MULTIPLIER” (ERM)

2.1 | DERIVATION AND EQUATION

With a goal of developing an ideal “scale” to quantify and communicate TC rainfall hazard that would meaningfully improve upon existing methods, four key requirements were identified:

1. The scale must accurately characterize TC rainfall hazard.
2. The scale should identify “locally extreme” rainfall events, based on the recognition that local negative impacts increase in conjunction with increasing positive deviations from the local rainfall climatology.
3. The scale should succinctly describe TC rainfall hazards of various durations by identifying the threats posed by extreme rainfall at a range of time scales up to the lifetime of the storm system.
4. The scale should have an easy-to-understand meaning rooted in experiential processing to ensure efficacy in communicating the TC rainfall hazard to the public.

The “extreme rainfall multiplier” (ERM) is presented here as a metric for TC rainfall hazard that can satisfy these requirements. For storm $s$ and location $x$, the rainfall depth over duration $t$ can be written as $R_{s,x,t}$ and

$$\text{ERM}_{s,x,t} = \frac{R_{s,x,t}}{R_{x,t}^{T-year}}$$

The denominator ($R_{x,t}^{T-year}$) is the rainfall depth for the $T$-year average recurrence interval for the same location and duration. This concept was first applied to river flood peaks instead of
rainfall extremes in Smith et al. (2018), using the name “upper-tail ratio”, though the practice of normalizing extreme rainfall and flood observations by a more frequent quantile has longstanding precedent in hydrologic practice, including so-called “index flood”-based estimation of rainfall and flood quantiles using regional observations (e.g. Stedinger 1993). Other metrics, such as the “wet-millimeter day” (Shepherd et al. 2007), have attempted to quantify extreme TC rainfall via quantitative comparison to a reference value.

In this study, the 2-year rainfall event is used as the denominator in the above equation, to represent a baseline “heavy” rainstorm that would occur relatively frequently. The 2-year rainfall represents the median annual maximum rainfall – the median value in a timeseries of the largest rain events per year, based on recent climatology – and, statistically has a 50% chance of being exceeded in any given year. In hydrologic engineering, the 2-year flood event is often considered a reasonable approximation of the threshold above which floodwaters overflow stream banks and negative impacts begin (Leopold 1968). This “rule of thumb” suggests that events below the 2-year (e.g. ERM < 1.0) generally will not produce negative impacts, while those above the 2-year (e.g. ERM > 1.0) may. The 2-year rainfall has the added statistical advantage that, unlike more extreme quantiles, it is easier to estimate accurately and is less prone to fluctuate as additional extreme events are added to the observational record, making it a more “stable” normalization factor with less need for frequent updating.

An individual may struggle to understand the event magnitude associated with a rare event (such as a 500-year rainfall), particularly if a such an event has not occurred recently in their location. However, it is likely that an individual has experienced a more typical rainstorm (similar to the 2-year storm) in the relatively recent past. Intuitive understanding of one’s local climatology can therefore serve as an “anchor,” which, in cognitive psychology research, is an
initial piece of information upon which subsequent judgements are based (Tversky and Kahneman 1974). Expressing the magnitude of rare events as multiples of this anchor, which is derived from local climatology rather than abstract probabilities, can help the public utilize their own experiences to conceptualize the magnitude of extreme events.

2.2 | DEFINING A “TYPICAL” HEAVY RAINFALL EVENT

The ERM metric is useful because it normalizes extreme rainfall events in the context of the rainfall climatology at particular locations. Compared to using event total rainfall, ERM allows for a more detailed comparison of the relative severity of rainfall events between locations, focusing not solely on the sheer magnitude of the event, but on how much it deviates from typical rainfall events. Compared to other metrics of precipitation climatology – such as daily precipitation records or monthly or seasonal climate normals – ERM is calculated independent of date of occurrence, allowing for events from different times of the year to be compared.

However, selecting the appropriate value for the normalizing factor (the denominator of the ERM equation) involves several important considerations, particularly in terms of the time period used to estimate the 2-year rainfall. Statistically, it is generally desirable to use the longest data record possible when generating recurrence interval estimates; the uncertainty of recurrence interval estimates typically decreases as the period of record increases. However, this is not necessarily true when nonstationarity exists within the data. Based on CPC-Unified rainfall data, there are statistically significant positive linear trends (p-values much less than 0.05) for the mean 2-year rainfall amount across much of the United States and within the geographic regions considered in this study, for all rainfall durations between one and seven
days. This implies that rainfall observations from earlier in the CPC-Unified record may be less representative of present-day “typical” heavy rainfall events.

To solve this issue, it is recommended that ERM be calculated similarly to the well-known concept of “climate normals,” as defined by the World Meteorological Organization (World Meteorological Organization 2017). Climate normals for ERM were calculated by determining the median (i.e. 2-year) annual maximum rainfall for each grid cell for the thirty-year period ending from 1981 to 2010. This has the added advantage of making ERM similar to other climate normals the general public may already familiar with; for instance, current normal high and low temperatures are also based on the 1981-2010 reference time period. Additionally, using of the median, rather than the mean, of annual maximum rainfall minimizes the impact of outlier events in determining the climate normals (e.g. Arguez and Vose 2011).
CHAPTER 3 | ANALYSIS OF HISTORICAL TROPICAL CYCLONE ERMS

3.1 | METHODS

A total of 385 North Atlantic TCs that made landfall or passed within 500 km of the eastern United States between 1948 and 2017 were analyzed for this study. NOAA’s gridded, gauge-based CPC-Unified dataset (Xie et al. 2007; Xie 2010; Chen et al. 2008) was the source of precipitation data for this analysis. The CPC-Unified dataset contains precipitation information for the continental United States (CONUS) at a spatial resolution of 0.25° by 0.25° (approximately 600 km²) and a temporal resolution of one day.

The CONNECT algorithm was used to convert NOAA’s gridded, gauge-based CPC-Unified precipitation data into precipitation objects (Sellars et al. 2015). The algorithm connects the precipitation data based on the underlying relationships within individual data observations in four dimensions: latitude, longitude, time, and rainfall intensity. To minimize spurious connectivity from the object generation process, observations of rainfall intensity less than 10 mm/day were not included in the connectivity analysis. Observations that are connected in at least one dimension of the analysis (i.e. that are connected spatially and/or temporally) are joined together to create a precipitation object, which depicts the evolution of precipitation over space and time (Sellars et al. 2013). Applying this algorithm to the CPC-Unified dataset created over 12,000 unique precipitation objects for the period 1948-2017, each representing a historical rainfall event.

The complete precipitation object database generated from the CONNECT algorithm contains historical rainfall events of multiple types, throughout each year. To narrow this database, historical TC tracks were used to identify the objects associated with North Atlantic
TCs that made landfall (or passed near) the continental United States. Hurricane storm track data were obtained via NOAA’s HURDAT-2 Atlantic hurricane database, which reports the six-hour position (latitude and longitude) of North Atlantic TCs, as well as maximum wind speed and central barometric pressure (Landsea and Franklin 2013). TC tracks that made landfall or passed within 500 km of the continental United States were used in subsequent analyses. (Distances of 500 km have been used in previous studies to identify rainfall and flooding associated with TCs, see Hart and Evans 2001; Lonfat et al. 2004; Zhou and Matyas 2017.) Precipitation objects that pass concurrently within 500 km of one of these storm tracks were identified. A total of 385 storm tracks were associated with one (or more) rainfall precipitation object(s) in the eastern United States from 1948 to 2017.

CPC-Unified was also used to estimate the 2-year rainfall for each grid cell. Using these 2-year rainfall values, daily and multi-day rainfall totals, up to the lifetime of each TC, were converted into their corresponding ERM value. The single grid cell from each cyclone with the highest ERM (regardless of duration) was selected for additional analysis (referred to hereafter as “single-cell storm maximum ERM”). Single-cell ERMs were used here for simplicity and because of their resemblance to how TCs are currently classified by maximum sustained wind speed (which usually exists over a relatively small region of a TC) using the Saffir-Simpson scale. A possible alternative to this approach would be an analysis of the area (or the number of grid cells) exceeding certain ERM thresholds during extreme TC rainfall events, which often produce spatially-extensive rainfall (Stevenson and Schumacher 2014).
3.2 | Analysis of Historical Tropical Cyclone ERMs

The overall distribution of single-cell storm maximum ERM is shown in Figure 1, along with distributions of these values by the associated rainfall duration and TC strength based on the Saffir-Simpson scale. While the mean single-cell storm maximum ERM is approximately 2.0, the distribution features multiple high-impact TC rainfall events. Nineteen TCs (4.8%) have ERM values greater than four, including Hurricane Harvey (2017), which has an ERM maxima of 6.4—the highest value found within the TC database. This indicates that the rainfall from Hurricane Harvey was more than six times greater than the typical “heavy” (2-year) rainfall event at that location (Fig. 2).

The large majority (74.0%) of single-cell storm maximum ERM values are associated with rainfall durations of one day, highlighting how TCs only occasionally become long-lived rainfall events. The distribution of these ERM values by duration highlights that high ERM events occur at both daily and multi-day timescales (Fig. 1B). There is a weak but statistically significant correlation between storm maximum ERM and event duration (Kendall’s tau rank correlation of 0.125; \( p = 0.002 \)). When classified by peak Saffir-Simpson category at (or near) initial U.S. landfall, there is a positive relationship between Saffir-Simpson wind speed categories and single-cell storm maximum ERM (Fig 1C; Kendall’s tau rank correlation of 0.324; \( p < 10^{-5} \)).

Deeper examination of three TCs with the highest ERM values in three regions of the United States highlights some of ERM’s properties. As mentioned previously, Hurricane Harvey produced the largest ERM (6.4) since 1948, near Giddings, Texas. This ERM was the result of 565 mm of rainfall over a 3-day period, a value 6.4 times greater than the 3-day, 2-year rainfall (88 mm) in that grid cell. Because CPC-Unified data represents a spatial average
over a 0.25º grid cell and is interpolated from rain gages, the rainfall total for this grid cell is lower than some individual gauge measurements from Hurricane Harvey. Additionally, this grid cell represents the location where Harvey’s rainfall deviated most from the local rainfall climatology, which is not always co-located with the place of highest rainfall. (An ERM value above 6.0 was also found near Houston, Texas associated with CPC-Unified rainfall of 787 mm.)

Hurricane Georges made its final landfall near Biloxi, Mississippi on 28 September 1998 as a Category 2 storm. Within twenty-four hours, the system weakened to a tropical depression and became nearly stationary. Georges generated 561 mm of rain in two days near Andalusia, Alabama, resulting in a single-cell maximum ERM of 5.5. Hurricane Floyd first came ashore in North Carolina as a Category 2 storm on 16 September 1999. A particularly large storm, Floyd left 415 mm of rainfall in one day near Bald Head Island, North Carolina, producing a single-cell maximum ERM of 5.7. These results highlight that very high ERM values can occur at a range of rainfall durations and geographic locations.

ERMs were computed for durations ranging from one to three days to further demonstrate the relationship between ERM and rainfall duration. At the 1-day duration, the ERM for Hurricane Harvey near Giddings, Texas is less than 4.0, climbing to over 5.0 at the 2-day duration before reaching its maximum of 6.4 at 3 days (Fig. 3A). The ERM for Georges, in contrast, peaks at 2 days but remains above 5.0 for the 3-day duration (Fig. 3B). As a system that quickly moved up the East Coast of the United States, the ERM for Floyd peaks at 1-day and declines slightly at the 2-day duration (Fig. 3C).

These three storms generated significant impacts in the continental United States. Hurricane Harvey caused $125 billion in damages (second only to Hurricane Katrina) and 68
deaths in Texas; sixty-five of these deaths were attributed to freshwater flooding (Blake and Zelinsky 2018). Hurricane Georges was responsible for $3.8 billion in damages and one direct death in the United States, which was linked to freshwater flooding (Guiney 1999). Hurricane Floyd caused $9.6 billion in damages and 56 direct deaths in the United States, most of which were caused by freshwater flooding (Pasch et al. 1999). (All TC damage figures are inflation-adjusted to 2017 and are from the National Hurricane Center’s 2018 update of estimates from Blake et al. 2011.) The correspondence between high ERM and high storm impacts for these three TCs, despite their relatively low Saffir-Simpson categories at the time of rainfall impact, lends support to the suitability of ERM as a metric for characterizing TC rainfall hazard.
**Figure 1.** Overall distribution of single-cell maximum ERM (A), distribution of ERM based on rainfall duration associated with ERM maxima (B), and distribution of ERM based on peak TC strength (based on Saffir-Simpson scale) within 500 km of location of initial TC landfall in the continental United States (C). Blue lines indicate the mean for each distribution.
Figure 2. (A) Storm total precipitation, based on CPC-Unified data and CONNECT precipitation objects, for Harvey (2017). (B) Maximum ERM values for locations with rainfall associated with Harvey (2017). Black lines show the HURDAT-2 storm track. Black circles highlight the 1200 UTC position of Harvey. Characters inside black circles represent 1200 UTC intensity of Harvey (D: tropical depression, S: tropical storm, 1-5: hurricane, with Saffir-Simpson category).
Figure 3. (A-C) Comparison of location-specific ERM values (on y-axis), rainfall (gray isolines and gray markers) and associated single-cell TC ERM values (green diamonds; red diamonds show the ERM-maximizing duration) for varying durations for Harvey (2017), Georges (1998), and Floyd (1999), respectively. Rainfall for Floyd did not last beyond 2 days at that location, and thus the 3-day ERM for that storm is omitted.
3.3 | **REGIONAL DISTRIBUTION OF TROPICAL CYCLONE ERMs**

Fig. 4 shows the single highest ERM for each 0.25° grid cell in the eastern and southern United States that has experienced at least one TC rainfall event from 1948-2017. While ERM values generally decrease with distance from the coast, there is a wide geographic distribution of high ERM values throughout the analyzed region.

Empirical probability density functions (Fig. 5A) and inverse cumulative distribution functions (Fig. 5B-D) of single-cell storm maximum ERM were constructed to compare the historical distributions of this metric in three regions of the United States subject to TC rainfall extremes: the Texas/Louisiana area of the Gulf Coast, the rest of the Gulf Coast and the inland southeast (including Florida and Georgia), and the remaining states along the Atlantic Coast. Due to topographic and climatic features, these three regions differ in terms of the types and paths of TCs that make landfall (Elsner et al. 2000; Matyas 2013). Despite such differences, the distributions of single-cell storm maximum ERMs for the regions shown in Figure 5 are remarkably similar. These results suggest that the distribution of ERM maxima is relatively invariant to geographic location. This property would allow for hazard communication to be placed within the context of the local rainfall hydroclimate, despite significant differences in the extreme rainfall hydroclimatology throughout the eastern United States. This property also facilitates estimation of ERM annual exceedance probabilities, described in Section 3.4.
Figure 4. Map of maximum ERM for grid cells in coastal regions of the United States experiencing rainfall from at least one North Atlantic TC; locations of single-cell storm maximum ERM values are marked by black dots.
Figure 5. (A) Empirical probability density functions of regional distributions of single-cell storm maximum ERM for North Atlantic TCs, based on Gaussian kernel density estimates. (B-D) Empirical inverse cumulative distribution functions of single-cell storm maximum ERM by region; some TCs produced maxima in multiple regions. Colored shading represents 95% confidence intervals derived via nonparametric bootstrapping. Regional means are also displayed as inset text; values in parentheses represent 95% confidence intervals of these means, also derived via nonparametric bootstrapping. Inset map identifies regions used for subsequent analysis.
3.4 Estimating the Climatological Frequency of High ERM Events

As shown above, the distribution of single-cell storm maximum ERM is practically invariant to geographic location (Figs. 4 and 5) and only moderately sensitive to duration (Fig. 1B). These properties imply that a single statistical distribution can approximate ERM over the eastern and southern United States for all storm durations. Such a distribution could be useful to the hydrologic hazard and risk assessment communities since it could yield estimates of the recurrence intervals of past or future TC rainfall events. In addition, if recurrence intervals are to be used in public communication, estimates derived from this ERM distribution may prove more effective.

A peaks-over-threshold (POT) extreme value model was fitted using the 385 single-cell storm maximum ERM values in order to estimate the frequency of TC rainfall events that exceed a range of ERM values within the eastern and southern United States (Fig. 6; see Fig. 4 for the regions of analysis). The peaks-over-threshold (POT) Generalized Pareto (GP) Distribution extreme value model was fitted using maximum likelihood estimation via the `fevd` function from the “extRemes” R package (Gilleland and Katz 2016). This GP model was then used to estimate ERM recurrence intervals. A threshold level of ERM = 3.0 was used, based on visual assessment of diagnostic plots provided by the “extRemes” package.

In developing this model, normalizing TC rainfall totals by the 2-year rainfall is statistically beneficial since it reduces the variance and skewness of ERM relative to “raw” (i.e. non-normalized) rainfall values. For example, the coefficient of variation (skewness) reduces from 0.68 (1.50) for the rainfall time series to 0.58 (0.78) for the ERM time series (Fig. 7). (Coefficient of variation is the sample standard deviation divided by the sample mean).
Lower values of these higher-order statistical moments generally lead to more robust parameter estimates and inferences.

Based on this model, a TC rainfall event with an ERM of 4.0 or higher would be expected to occur approximately once every three years somewhere within the study region. Events with ERMs exceeding 5.0 and 6.0 have recurrence intervals of roughly 13 and 57 years, respectively. A TC with an ERM magnitude equal or greater to Hurricane Harvey (ERM ≥ 6.4) has an estimated recurrence interval of approximately 102 years.

It is important to note, however, that the model shown in Fig. 6 provides the recurrence intervals or annual exceedance probabilities of events occurring anywhere within the study region shown in Fig. 4. This is in contrast with the common usage of recurrence intervals to describe event likelihood at a specific location. While the likelihood of an extreme event like Hurricane Harvey occurring at any specific location—such as the Houston metropolitan area—is very low, the probability of an event of this magnitude occurring somewhere within the eastern United States may be considerably higher. This distinction is probably lost on many members of the public, which may contribute to further confusion when recurrence interval terminology is used in the popular media. If recurrence intervals are to be used to contextualize individual events (as they were in the popular media during and after Hurricane Harvey), it may be more appropriate to report them based on “regional recurrence” estimates like those presented in Fig. 6.

In contrast, it is not defensible to compute regional recurrence estimates based on rainfall observations themselves, since the rainfall distributions at individual locations in the study region—for instance, Texas and New Jersey—differ substantially. Meanwhile, the regional invariance of ERM demonstrated in Section 3.3 means that it is defensible to consider
all ERM events as belonging to a single population, thus increasing sample size and permitting robust regional recurrence estimation.

Using this property of regional invariance, it may also be possible to develop models to estimate the recurrence interval of high-ERM events with extensive geographic footprints; the large spatial extent of Hurricane Harvey’s extreme rainfall was major contributor to its catastrophic impacts. With this information, recurrence interval estimates of ERM extent could be derived, which may have utility in specific forecasting or risk assessment applications.
Figure 6. Plot of recurrence intervals for the fitted POT extreme value model. Red diamond indicates the recurrence interval corresponding to the storm maximum ERM of 6.4 from Hurricane Harvey. White diamonds indicate the recurrence interval of TC rainfall events with storm maximum ERMs greater than or equal to listed thresholds within the United States. Green lines indicate the 90% confidence interval of ERM as a function of recurrence interval.
Figure 7. Timeseries of maximum single-cell ERM and rainfall for all TCs, 1948-2017. Highest values per year indicated with colored markers. Colored lines represent linear regression fit for annual maxima timeseries. A Mann-Kendall test for monotonic trends in annual maxima values did not reveal significant changes over time for either ERM ($z = 0.441, n = 70, p = 0.659$) or rainfall ($z = 0.203, n = 70, p = 0.839$).
CHAPTER 4 | COMMUNICATING RAINFALL HAZARD

4.1 | USING ERM TO COMMUNICATE TC RAINFALL FORECASTS

To demonstrate how ERM could be used in a forecast setting during a landfalling tropical cyclone, forecast ERM values were generated for two separate systems: Hurricane Florence (2018) and Hurricane Isaias (2020). In each case, forecast ERMs were calculated from quantitative precipitation forecasts (QPFs) issued by NOAA’s National Weather Service Weather Prediction Center (WPC) in the time before landfall. QPF data was obtained as shapefiles, which saved the forecast precipitation data as contours; these contours were transformed to match the 0.25º grid resolution of the CPC-Unified precipitation data. Each 0.25º grid cell was assigned the rainfall forecast value equal to the highest contour that was found within (or surrounding) it. These QPFs totals were then converted into ERM forecasts by dividing by the two-year rainfall (based on CPC-Unified) for the appropriate duration.

In the case of Hurricane Florence, forecasts issued by the National Hurricane Center called for the system to approach the North Carolina coast as a major hurricane. However, Florence weakened more rapidly than expected, ultimately making landfall as a Category 1 system. The resulting wind-related impacts, while severe, were less than originally anticipated.

In contrast to the wind hazard, forecast ERM for Hurricane Florence indicates that the expected rainfall hazard was very high, and increasing, as the storm neared the United States. Estimates of the peak, single-cell, 5-day ERM for Hurricane Florence increased from 4.2 on 12 September (Fig. 8A) to 5.0 on September 14 (Fig. 8B). The estimated 3-day ERM on the day of Florence’s landfall was even higher at 5.7 (not shown). Not only did these forecast ERM values remain elevated amid Florence’s weakening winds, the magnitude of these forecast
ERM values is extremely high. A value of 5.7 would equal Hurricane Floyd (1999) as the highest ERM value ever seen on the Atlantic coast, and the second-highest ERM value anywhere since 1948 (after Hurricane Harvey). Additionally, while this study has focused primarily on the single-cell storm maximum ERM, the forecast maps (Fig. 8A and 8B) show how the spatial extent of rainfall hazard could be communicated to the public using ERM. Areas of 19,700 km² and 33,700 km² have forecast ERMs greater than 3.0 on 12 September and 14 September, respectively.

These forecast ERM values were validated using post-storm CPC-Unified rainfall observations. The single-cell storm maximum ERM based on CPC-Unified was found near Lumberton, North Carolina, where a 2-day rainfall total of 472 mm generated an ERM value of 5.8. Throughout the Carolinas, a region of 36,900 km² experienced an ERM above 3.0. Verification of the original rainfall forecast from the National Weather Service (and the ERM values derived from it) for the three-day period after the landfall of Hurricane Florence can be seen in Fig. 9. It should be noted, however, that the utility of any ERM forecast in this context is dependent on the accuracy of the rainfall forecast used to generate ERM values.

After the initial publication of the details of the ERM metric (Bosma et al. 2020), a follow-up analysis was conducted, evaluating the forecast ERM of Hurricane Isaias in near real-time before it made landfall. A fast-moving system, Isaias made landfall near Ocean Isle Beach, North Carolina around 0300 UTC on 4 Aug 2020 as a Category 1 hurricane. Just before landfall (at 0000 UTC), QPF data estimated a peak rainfall of 152 mm from Isaias, at a location just south of the Washington, DC metropolitan area, which translated into a peak, single-cell, 1-day ERM of 2.9 (Fig. 10). While this value is appreciably lower than the ERMs associated with the extreme rainfalls from Harvey and Florence, the forecast rainfall from Isaias is still
nearly three times higher than the local 2-year rainfall, highlighting Isaias’s flooding potential. Due to inland flooding, as well as wind and tornado damage, Isaias was ultimately classified by NOAA’s National Centers for Environmental Information as a “billion-dollar weather disaster”, responsible for an estimated $4.8 billion in damages throughout the eastern United States (NOAA NCEI 2020).

The forecast analysis for Hurricane Isaias also included the identification of a historical analogue event: Hurricane Isabel (2003). Similar to Isaias, Hurricane Isabel made landfall in North Carolina and quickly moved up the east coast of the United States. The storm’s peak, single-cell ERM, based on CPC-Unified rainfall data, was 2.8 (Fig. 11), close to the forecast ERM value for Isaias. Hurricane Isabel resulted in damages of approximately $7.8 billion due to wind damage and flooding in the mid-Atlantic states. This ERM forecast comparison was published on “The Front Page”, the official blog of the American Meteorological Society (Capella 2020), allowing members of the public to directly associate the rainfall hazard from the impending Hurricane Isaias with a historical TC event that local residents in the path of Hurricane Isaias might be familiar with.

More broadly, when compared to current forecast products and to recurrence interval estimates, ERM forecast values can contextualize extreme QPF values and potentially provide a more tangible meaning to the public. Similar to the pre-landfall analysis of Isaias, forecast ERM values can be compared to past rainfall events to find similarly extreme historical analogues; doing so might allow communicators to develop appropriate “indexical images”—real-world depictions of possible damages. This type of imagery has been shown to lead to higher risk perception (Rickard et al. 2017) and highlight another way ERM could be used to identify and communicate potential rainfall hazard in the days before TC landfall. At least one
existing rainfall hazard product utilized during TC events—the Excessive Rainfall Outlook (ERO) issued by the WPC—focuses on the probability of rainfall exceeding flash flood thresholds, emphasizing the likelihood rather than the magnitude of the rainfall threat. ERM could be used as a complement or alternative to these outlooks.
Figure 8. 5-day ERM forecasts based on QPF estimates issued at 1200 UTC 12 Sep 2018 (A) and 1200 UTC 14 Sep 2018 (B). Peak forecast ERM values are 4.2 (A) and 5.0 (B). White circles indicate National Hurricane Center forecast TC track positions on date of rainfall forecast. Characters inside white circles represent NHC forecast intensity of Florence (D: tropical depression, S: tropical storm, 1-5: hurricane, with Saffir-Simpson category).
Figure 9. Three-day forecast rainfall based on QPF estimates issued at 1200 UTC 14 Sep 2018 (A) and actual rainfall based on CPC-Unified data (C). ERM forecasts derived from QPF estimates (B) and ERM based on post-storm CPC-Unified data (D) is also shown.
Figure 10. Forecast three-day rainfall (A) and peak ERM (B) associated with Hurricane Isaias based on WPC QPF estimates issued at 0000 UTC 4 Aug 2020. The ERM-maximizing rainfall duration (from one to three days) is also shown (C).

Figure 11. Cumulative three-day rainfall (A) and peak ERM (B) associated with Hurricane Isabel based on CPC-Unified gridded data from 1200 UTC 17 Sep 2003 to 1200 UTC 20 Sep 2003. The ERM-maximizing rainfall duration (from one to three days) is also shown (C).
4.2 | INFORMAL COMMUNICATION OF RAINFALL HAZARD METRICS

As mentioned above, recurrence intervals—despite being commonly used by engineers, climate scientists, and others—confuse and potentially misinform members of the general public due to the abstract nature of the statistical concepts involved (Keller et al. 2006, Schneider 2016). While “experiential processing”, relating current events to situations that individuals can recall from personal experience (Marx et al. 2007), can be useful, it is likely true that many people have not experienced an extreme rainfall event in their recent past. Rather than waiting for tragedies to befall everyone in society, there could be value in utilizing various informal science communication techniques to provide individuals with the empirical evidence needed to understand the relative frequency and magnitude of extreme hydrological events. Two such methods are presented here: a board game and a podcast.

Short-duration, high-impact rainfall events (i.e. the “100-year flood”) represent only one portion of the hydrologic cycle that can cause substantial human impacts. Other significant components include total seasonal precipitation (which is important for agriculture), the El Niño-Southern Oscillation (ENSO; which can amplify or suppress regional precipitation) and the impacts of global climate change on precipitation (which can result in changes in total precipitation or the frequency of wet or dry extremes). For instance, an effect called “precipitation whiplash” has been found in model simulations of precipitation in California; throughout the 21st century, regional precipitation regimes are projected to become more intense and more variable, even while mean annual precipitation amounts remain relatively static (Swain et al. 2018).

The Hydro-Chance board game (highlights shown in Fig. 12) was developed to explore these components and give players a sense of the real trade-offs decision makers have to
balance when dealing with various hydrological challenges. In the game, each player is given a “town property board” they can use to build and develop a wide array of properties featured on individual cards. Each property card can generate economic benefits or losses based on the precipitation the town receives. For instance, the “golf course” property card loses money when rainfall is low, when the business will likely need to spend more money on watering the grass to keep the course in top shape.

Precipitation amounts are determined by a deck of one hundred cards. Each card has a specific precipitation value, based on a rough sampling of the historical distribution of annual precipitation throughout coastal California. Some precipitation cards also feature major flooding events that have the power to destroy a player’s property cards. One card out of the deck of 100 precipitation cards features the “100-year flood”, which has the ability to wipe out all of player’s property cards. With a draw probability of 1% (1/100), the frequency of this card’s appearance in the game should roughly approximate the frequency of real-world “100-year” rainfall events. Assuming the deck is sufficiently shuffled after each turn, it is possible (just as in the real world) that this “100-year” event could occur multiple times.

Other major features of the game include forecast cards (which provide information to the players about what the precipitation might be in subsequent turns and which can also be set up to feature either a dry or wet bias), mitigation cards (where players take actions like purchasing insurance or building reservoirs to mitigate the effects of negative events), ENSO impacts (which can increase or decrease the value of precipitation cards), and climate change cards (where properties with blue (or red) backgrounds can reduce (or increase) the carbon footprint of their town). The climate change mechanism introduces a communal aspect to the game. If the total carbon footprint across all of the towns in the game exceeds a certain level,
climate change becomes unavoidable and a new precipitation regime (with a new set of precipitation cards) is established, increasing both the uncertainty of precipitation forecasts and the likelihood of high-impact events.

Players can track how all of these hydrologic events unfold in several ways. Each player’s final score is reflective of the net economic productivity of their selected properties over time and the impacts of the adaptation decisions they made. Additionally, players can track the distribution of precipitation over time using an included blank histogram chart. They can also track the accuracy (and possible bias) of the precipitation forecasts using a blank contingency table (also included). This game gives players a chance to experience a wide array of high-impact situations, potentially increasing the amount of information available for “experiential processing” of future hydrologic events in their own lives. Additionally, the game familiarizes players with key concepts in statistics and probability. While the game has not been explicitly tested in a classroom environment, many of the game components align with the practices and disciplinary core ideas of the Next Generation Science Standards in the fields of Earth’s Systems and Earth and Human Activity (Council 2011).

Another informal science communication technique available to introduce general audiences to concepts related to rainfall hazard is podcasting. Using the flooding associated with Hurricane Harvey as an entry point, a short podcast (approximately 7 minutes in duration) was created to explain the concept of return periods to those with limited experience with statistics or hydrology. A full transcript of this podcast appears in Appendix A. Rather than surplanting the real-time forecast and hazard information provided by weather forecasters and the media, the goal of a podcast like this is to provide experiential learning that individuals can recall back to during future flooding events.
Figure 12. Highlighted game elements from the Hydro-Chance board game. Players select properties to put on their town property board, with varying benefits (or costs) based on the local precipitation. Players can use forecasts to make planning decisions and utilize various mitigation strategies to avoid costs of high-impact events, such as major floods.
CHAPTER 5 | SUMMARY AND CONCLUSIONS

5.1 | SUMMARY AND CONCLUSIONS

This study demonstrates that the Extreme Rainfall Multiplier (ERM) framework to quantify TC rainfall offers several useful properties. When applied retrospectively, it produces values that correspond with observed TC rainfall impacts for several high-impact events, confirming that it can depict hazard. ERM values reflect geographic differences in the climatology of rainfall extremes and can succinctly describe TC rainfall hazard of varying durations using a single scale. Furthermore, an ERM value has an intuitive interpretation that leverages individuals’ conceptions and prior experiences of rainfall magnitudes, lending itself to communicating TC rainfall hazard and contextualizing recent and imminent TC rainfall extremes for the public. The ERM framework could be applied to rainfall extremes produced by TCs in other basins (particularly eastern Pacific TCs, which can cause high impacts from extreme rainfall in the southwestern United States), to other types of rainfall-producing storm systems, and, in principle, to other types of natural hazards.

Despite observational evidence for increasing TC intensity (Emanuel et al. 2006) and decreases in translational speed (Kossin 2018), relatively less work has been done to assess changes in TC rainfall hazards (Emanuel et al. 2006; Langousis and Veneziano 2009; Kunkel et al. 2010). Challenges facing TC rainfall trend studies are the limited observations available at any particular location as well as the influences of geographically-varying rainfall hydroclimate and storm lifetime. The relative invariance of ERM to geographic location is a potentially useful property for investigation of TC rainfall nonstationarity, allowing for the construction of time series using all TCs within an entire region, rather than only those at
particular locations. However, no evidence of nonstationarity was found in either ERM and the underlying rainfall totals used to compute it (Fig. 7); more work is needed.

Additionally, the record-breaking 2020 Atlantic hurricane season, with a record thirty named storms and a record twelve storms that made landfall in the United States, merits further evaluation in future studies of both TC precipitation magnitude and frequency. While the magnitude of the rainfall associated with landfalling 2020 Atlantic TCs in the United States did not approach the totals experienced during Hurricane Harvey in 2017, there were several notable events. Tropical Storm Cristobal brought heavy precipitation all the way to the Upper Midwest, providing Minnesota with its first known instance of a direct impact from a tropical cyclone (Minnesota DNR 2020). The slow-moving Hurricane Sally brought up to 762 mm of precipitation (measured by rain gauges) in the Florida Panhandle (Livingston 2020).

A number of issues must be resolved before ERM could be suitable as an operational forecast communication product. These include the differences in the resolution and coverage of gridded rainfall products and precipitation forecasts, how and whether to communicate a range of forecast lead-times or durations, and what graphical and verbal techniques should be used to communicate it most effectively. Nonetheless, our Hurricane Florence ERM “hindcast” demonstration showed that the method is able to accurately characterize the rainfall hazard of a significant TC event several days before the impacts were realized, in a way that could be readily communicated to, and interpreted by, the public.
WORKS CITED


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APPENDIX A | TEXT OF RAINFALL HAZARD PODCAST

“...Hurricane Harvey barreling into the Texas coastline as a Category 4 storm with 130 mph winds...”

“...the system continues to weaken in terms of its wind speed, but not at all in terms of what it is going to pump in moisture-wise, still tapping into the Gulf of Mexico...”

“...breaking news...Harvey is provoking an unfolding flooding disaster in America’s 4th largest city: Houston, Texas...”

“...I’m walking in downtown Houston and I’m surrounded by water...”

“...and the situation is unfortunately dire, people trapped in their flooded-out homes...”

“...the flooding Hurricane Harvey left behind in Houston was deadly and devastating. After rainfall exceeded ‘500 year’ levels...”

In August 2017, Hurricane Harvey slammed into the coasts of Texas and Louisiana, leaving a path of destruction and extensive flooding behind its path. In portions of southwest Texas, over 60 inches of rain fell, shattering the all-time record for rainfall from a tropical cyclone in the United States.

As a graduate student in civil engineering at the University of Wisconsin-Madison, I investigate to better understand where and when they might happen next.

By almost any metric, the rainfall from Hurricane Harvey was historically significant. For instance, The Washington Post called Hurricane Harvey “a one-thousand-year flood unprecedented in scale”.

But what does that mean? In this brief podcast, I will break down what a “1000 year” flood really is and highlight some surprising reasons why these so-called “rare” rainfall events, like Hurricane Harvey, might be more common than they seem.

So, let’s get the definitions out of the way. A value like the “1000 flood” represents the “return period” of that particular event. Return period is a concept used by engineers, climate scientists, and the media to describe how often they expect an event of a similar magnitude to occur at a certain location. In a different context, return periods are also used by agencies like FEMA to map locations that might be susceptible to flooding.

The return period value is directly related to the probability of an event occurring. An event with a 2-year return period has a 50% (or one divided by two) probability. An event with a one-thousand year has a 0.1% (or one divided by one thousand) probability.
Thus, for Hurricane Harvey, the estimate probability of a rainfall event of that magnitude occurring in Houston, Texas was approximately 0.1%.

For a demonstration of these probabilities in action, we can play a little game. If you have a deck of playing cards, feel free to play along. To simplify the math a bit, take two cards out of your deck, leaving you with a total of 50 cards. Keep the Ace of Spades inside your deck of 50; we’ll use this card to represent a major flood occurring.

Now, let’s shuffle the cards.

One card in our deck of 50 – the Ace of Spades – represents the major flood. Thus, the return period of that flood is 50 years and the probability of the flood is one divided by 50 (or 2%).

So, let’s get to the game. We’ll keep the deck of cards face down. On each turn of the game, we’ll draw one card randomly from the deck. If we draw the Ace of Spades, unfortunately, that means we’ve been flooded. If we draw any card but the Ace of Spades, that means we’re safe…for now.

Regardless of what the card was, we’ll put it back into our deck. If you want to play the game again, just make sure you shuffle the cards and then take another turn.

You can play this game for as many turns as you dare. When I played the game, it took 17 turns to draw the Ace of Spades. Then, just six turns later, I drew the Ace of Spades again. That’s pretty bad luck, but it’s not impossible.

This unlucky draw represents some key facts about return periods. A “50-year” flood doesn’t necessarily happen exactly once every fifty years. Some cities, including Houston, have experienced multiple major flood events in a short amount of time, while some locations may go even longer than 50 years (or the equivalent of 50 turns in the game) before seeing a flood event.

This simple game represents the true probability of a flood because we shuffle the deck of cards after every turn. The risk of experience of a flood (or drawing the Ace of Spades) does not depend on what happened in a previous year or turn.

A more challenging version of the game would involve playing with multiple, but separate, decks. For instance, if both you and I were playing the game at the same time, on some turns we might both draw the Ace of Spades. If we were playing the game with 100 people at once, some turns could have several major floods drawn at the same time.

If we imagine different locations in the United States (or in the world) as consisting of thousands of individual decks of cards, drawing at the same time, it is hopefully possible to imagine how any particular year could contain multiple major flooding events, including some that could reach the scale of the flooding associated with Hurricane Harvey.
Analyzing the connections between different locations and the probabilities associated with their unique “deck of cards” is one way engineers and scientists, including myself, try to develop a broader picture of flood risk.

For more information about Hurricane Harvey, flood risk, and the music and audio used in this podcast, please visit: go.wisc.edu/04t39t.