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Short Contribution

The Extreme Precipitation Forecast Table: Improving Situational Awareness When Heavy Rain is a Threat

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ABSTRACT

A collaborative team of Science and Operations Officers from the National Weather Service (NWS) Weather Forecast Offices (WFOs), hydrologists from the Lower Mississippi River Forecast Center (LMRFC), and management from the Weather Prediction Center (WPC) worked together to develop and transition a tool into NWS operations called the Extreme Precipitation Forecast Table (EPFT). The EPFT was designed to help NWS forecasters improve their situational awareness (SA) when heavy rainfall threatens their county warning area. The EPFT compares Quantitative Precipitation Forecasts (QPF) to Average Recurrence Intervals (ARIs) from the NOAA Atlas-14 to alert forecasters to the potential for climatologically significant and extreme rainfall. A counterpart to the EPFT, called the Extreme Precipitation Assessment Table (EPAT), compares observed precipitation (i.e., Quantitative Precipitation Estimates [QPE]) to inform forecasters as to the climatological significance of impactful rain events. This paper presents cases demonstrating the usefulness of the EPFT and EPAT in helping forecasters improve their SA in real-time operational settings when heavy rain was a threat.

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1. Introduction

When extreme rainfall is a threat, National Weather Service (NWS) forecasters are faced with both scientific and societal challenges when creating a forecast for public dissemination. Many of the scientific challenges arise prior to the event when the forecaster is sifting through large quantities of atmospheric data

to make an accurate assessment of where, when, and how much precipitation is expected to fall. At any given moment, they have multiple numerical weather prediction models (NWP; see Appendix A for a list of key acronyms used in this paper) providing quantitative precipitation forecasts (QPF) down to hourly resolution in the short-term forecast (i.e., ≤1 day), 3-hourly in the extended short-term forecast (1-2 days) and 6-hourly in the long-term forecast, (3-7 days), which in some models can be available in the extended long-term forecast (8-10 days). Each NWP model contains additional information on the atmospheric ingredients that are known to initiate or enhance extreme rainfall including: the presence of a mid-tropospheric potential vorticity anomaly or meso-α trough, weak-to-moderate vertical wind shear, strong warm-air advection, high precipitable water, high surface dew points, high values of low- to mid-level equivalent potential temperature, moderate convective available potential energy, and low convective inhibition (Maddox et al. 1979; Doswell et al. 1996; Davis 2001; Trier et al. 2006; Jessup and DeGaetano 2008; Schumacher and Johnson, 2008, 2009; Graham and Grumm 2010; Schumacher et al. 2011; Stevenson and Schumacher 2014). Assessing a large volume of data while often under strict time constraints is a challenge that can easily be exacerbated when NWP models are in substantial disagreement with one another. This is usually the case when the forecasted rainfall is on the extreme end of the spectrum and when models with significant differences in resolution are being compared (Herman and Schumacher 2016). In addition, the full potential for flooding cannot be assessed without further considering the characteristics of the watershed and antecedent conditions, such as soil moisture and vegetation coverage (e.g., Jessup and DeGaetano 2008).

Despite the abundance of data available, several NWS service assessments from impactful hydrometeorological events have highlighted that there are a lack of datasets to help forecasters recognize the potential for extreme events. Furthermore, there are even fewer products that help forecasters place the magnitude of the situation into a meaningful context for decision makers. For example, the Southeast United States Floods 2009 service assessment found that forecasters, emergency managers (EMs), and residents did not recognize the magnitude or severity of the forecast until the flood event was well underway (NWS 2010). Another finding that came from this service assessment is that despite the use of Flash Flood Guidance

(FFG), the Flash Flood Monitoring Prediction System (FFMP), and radar precipitation estimates, forecasters had limited historical context or tools to utilize that would help put this information into a climatological perspective. Prior to the South Carolina 2015 floods, when the forecast called for 20+ in of rain, residents could not comprehend what this meant specifically to them because they lacked a point of reference to compare with this event or a way to visualize it (NWS 2016). In this case, there were no analogs or tools to place the forecast within a historical context that the public could understand. These examples illustrate where the scientific challenges (e.g., model uncertainty or model performance during extreme events) start to blend in with the societal challenges (e.g., decision support messaging or difficulty of communicating extreme events) when extreme hydrometeorological events occur. Once the forecaster has determined where, when, and how much rain is expected, they then have to figure out how to effectively convey the magnitude of the event as well as the potential impacts to their core partners.

Within the last few years, addressing the societal challenges has become the forefront of the forecaster's job duties in the NWS as the agency has started to focus on Impact-Based Decision Support Services (IDSS). The concept of IDSS allows the forecaster to give advice and interpretative services to help core partners, such as emergency personnel and public safety officials, make decisions when weather, water, and climate impacts the lives and livelihoods of the American people (NOAA 2018). Among the most common hazards from extreme rainfall is flooding. Long-term flooding from multi-day storms can lead to massive infrastructure damage and billions of dollars in costs (NCEI 2019). Flash-flooding from a rapid onset of extreme rainfall can result in fatalities due to the more unpredictable nature in both the meteorological processes and hydrologic response (Ashley and Ashley 2008; Gourley and Clark 2018). FFG, which is commonly used in NWS operations, takes into account soil characteristics but has deficiencies that have been well documented. FFG is only valid for 24 hrs or less (Reed et al. 2007; Clark et al. 2014; Gourley and Clark 2018) and has significant spatial discontinuities that exist on River Forecast Center (RFC) boundaries resulting from different methods used in the NWS to derive gridded FFG values (Ortega et al. 2009). Some RFC boundaries divide county warning areas so that a Weather Forecast Office (WFO) could be covered by very different FFG values and very different methods

of FFG generation (Gourley and Clark 2018). FFG also does not necessarily help convey the full magnitude of a hydrometeorological event (NWS 2016), because it only represents the amount of rainfall needed to reach bankfull conditions. If forecasters are to improve their situational awareness (SA) for effective decision support when extreme rainfall is a threat, they need to have tools that can leverage large amounts of data, facilitate the identification of extreme rainfall in the forecast, and help them convey the information within a meaningful context that their core partners can understand. This is necessary so that in spite of uncertainty in the models and underlying ground conditions, they can still properly inform decision makers on the risks and impacts.

The Extreme Precipitation Forecast Improvement Project was established in 2015 to help provide a solution to remediate some of the issues highlighted in the NWS service assessments mentioned above. The project was pursued by a regionally diverse team of science and operations officers from local WFOs, forecast managers from the Weather Prediction Center (WPC), and hydrologists from the Lower-Mississippi River Forecast Center (LMRFC). The main objective of the project was to integrate new datasets and tools into NWS operations that can help forecasters identify climatologically significant and/or extreme rainfall in the forecast for improved SA and IDSS.

This paper will describe the efforts made by the team to fulfill the objective outlined above, which largely consisted of providing tools called the Extreme Precipitation Forecast Table (EPFT) and Extreme Precipitation Assessment Table (EPAT) to forecasters and hydrologists in the NWS. The EPFT and EPAT are situational awareness tables designed to help forecasters identify climatologically significant and extreme rainfall using Average Recurrence Interval (ARI) data from the NOAA Atlas-14. Section 2 describes the NOAA Atlas-14 dataset and methods used to design and implement the EPFT and EPAT in NWS operations. Cases where these tools provided enhanced SA in real-time forecast settings are presented in section 3. The paper concludes with a discussion in section 4.

2. Data and method

It has been shown that SA tables that highlight important threshold exceedances can facilitate the identification of significant features and hazards in the forecast (Graham et al. 2013). SA tables organize weather data into 2-D matrices, usually with forecast time in one direction and either forecast model or parameter in the other. Values are generally color-coded to alert forecasters when significant thresholds are reached. The Ensemble Situational Awareness Table (ESAT), originally developed at WFO Salt Lake City and now hosted by WPC (satable.ncep.noaa.gov), is an SA table that has been proven effective at highlighting extreme events in the forecast (Graham et al. 2013). Following the success of the ESAT, the EPFT was designed to facilitate detection of extreme precipitation events by comparing QPF from NWP models and other sources of guidance to ARIs from the NOAA Atlas-14. The EPAT is designed similarly to the EPFT but instead compares quantitative precipitation estimates (QPE) to ARIs to indicate when a climatologically significant rainfall event has been observed.

An ARI represents the average amount of years between precipitation threshold exceedances over a specific duration, or accumulation period, at a given location. The NOAA Atlas-14 contains precipitation frequency estimates (PFEs) based on a 90% confidence interval for ARIs from 1 to 1000 yrs and durations of five minutes up to 60 days (Bonnin et al. 2004). Gridded PFEs spanning the entire Continental United States (CONUS) for ARIs of 1-, 2-, 5-, 10-, 25-, 50-, and 100-yrs for rainfall durations of six and 24 hrs are incorporated into the EPFT and EPAT. The grids are filled with NOAA Atlas-14 where complete, which include all United States regions except for Texas and the Pacific Northwest (i.e., Washington, Oregon, Idaho, Montana, and Wyoming). Texas and the Pacific Northwest are supplemented with estimates from NOAA Technical Paper 40 (Hershfield 1961) and NOAA Atlas-2 (Miller et al. 1973). Details on how the nationally mosaiced ARI grids were constructed are contained in Herman and Schumacher (2016). It is important to note, however, that the ARI datasets incorporated into each national mosaic are developed with many decades of gauge data based on the availability and density of historical data in each region and may be subject to under-sampling from the use of gauge data alone. This is more likely to occur in rural areas, areas of complex terrain, and within the older ARI datasets. For example, Herman and Schumacher (2018) pointed out that ARI thresholds in Wyoming are likely too low from the NOAA Atlas-2 when compared with the updated NOAA Atlas-14 values in bordering states. They speculated that some areas of Wyoming are likely inaccurate and highly uncertain due to this region being historically rural, especially at the time the threshold estimates were derived. The ARI

thresholds in Texas obtained from Technical Paper 40 are also considerably more uncertain than the recently updated NOAA Atlas-14 grids released in 2018. Although the updated ARI thresholds contain data from recent landfalling tropical cyclones, there are several precipitation bullseyes along the Texas Gulf coast that are not apparent in the Technical Paper 40 datasets. Thresholds from the NOAA Atlas-14 for ARIs greater than 100 yrs are also highly uncertain because there are little reliable gauge data going back more than 100 yrs. In the EPFT and EPAT, rainfall comparisons are limited to the 100-yr ARI due to the uncertainty in higher ARI thresholds.

For more than half a century, ARIs for specific durations of rainfall have been used in the hydrologic design of flood-prevention systems in the United States (Hershfield 1961; Lopez-Cantu and Samaras 2018). The ARI thresholds significant in this respect are associated with PFEs that when integrated within hydrologic models that consider the characteristics of a watershed, would lead to hydrographs and peak discharges that would result in runoff and inundation of water-control structures (Merkel et al. 2015). ARI thresholds used to define hydrologic design standards can vary across cities and municipalities and depend on the type of structure, drainage area, and risk of failure. In general, larger structures that pose a loss of life, like dams and levees in urban areas, are designed to withstand peak flows associated with at least the 100-yr ARI for a 24-hr duration event (Mays 2011; USDA 2020). The merit in using ARIs for IDSS is that forecasters can get a sense of potential impacts if they have knowledge of the ARI thresholds used in the design of hydrologic structures in their county warning area (CWA). Although research is limited, some studies have linked certain ARI threshold exceedances to reports of flash flooding and resulting impacts (e.g., Lincoln and Thomason 2018; Herman and Schumacher 2018).

The default configuration of the EPFT and EPAT compares the precipitation to the 100-yr ARI, which is an operationally acceptable threshold to define an extreme precipitation event. The values within the EPFT represent the maximum ratio of QPF to the 100-yr ARI threshold (QPF/ARI_{100}) for a user-specified duration and area of interest. The ratio is converted to a percentage and color-coded in the table based on the level of QPF/ARI exceedance (or non-exceedance). The EPFT in Fig. 1a shows QPF/ARI_{100} for a 24-hr duration rainfall capturing the QPF forecast from Hurricane Harvey, initialized at 2200 UTC 26 August 2017. When

QPF from models with temporal resolutions less than six hrs are compared, the EPFT will sum the values to create 6- and 24-hr accumulations for a proper QPF/ARI comparison. If 24 hrs of QPF data are not available, the table will not display results. The user can select a cell within the table, which then displays the grid of QPF/ARI_{100} percentages (or QPE/ARI_{100} within the EPAT) to allow for further investigation into the location(s) at risk. They can view QPF guidance contoured in the context of ARIs from 1 to 100 yrs, as well as the QPF and ARI grids used to calculate the ratios from the EPFT's user interface.

A key for interpreting the EPFT with the default configuration (i.e., 100-yr ARI) was provided to NWS forecasters to facilitate analysis of the results (Fig. 1b). The key was designed based on several post-storm event analyses conducted out of the State College, Pennsylvania WFO (Grumm 2016a, 2016b). A case study of the southern United States heavy rain and floods of March 2016 found that the GFS (see Appendix B for a list of model abbreviations) produced QPF/ARI_{100} ratios between 75% and 100% of the 100-yr ARI for 24-hr duration rainfall, with nearly all 24-hr forecasts, initialized starting at 0000 UTC 7 March and valid for the period ending 1800 UTC 9 March, capturing at least 50% of the 100-yr ARI. According to QPE from the NCEP Stage IV Precipitation Analysis product (Stage IV; Lin and Mitchell 2005), QPE/ARI_{100} ratios were between 125 and 150% for the 24-hr observed rainfall ending 1800 UTC 9 March. An analysis of the historic West Virginia floods of June 2016 (Grumm 2016b) showed similar results, with the wettest runs of the GFS barely exceeding 75% of the 100-yr ARI for 24-hr duration rainfall, whereas QPE comparisons verified with ratios closer to 125%. A main finding uncovered from both studies is that the GFS, like many other models that use cumulus parameterization schemes rather than explicitly solving for convection, has difficulty producing extreme QPF amounts in localized, strongly forced events. Herman and Schumacher (2016) similarly found that the GEFS mean QPF rarely predicts 100-yr events, whereas QPF from the HRRR and WRF-NSSL verify much better with observed 100-yr exceedances of 6-hr duration rainfall. It follows that the forecaster should have heightened awareness to the potential for an extreme event, and thus damaging impacts to life and property, when QPF/ARI_{100} values within the table start to near or exceed 75%. The key does not account for the areal extent of the precipitation system or the antecedent conditions, which are both
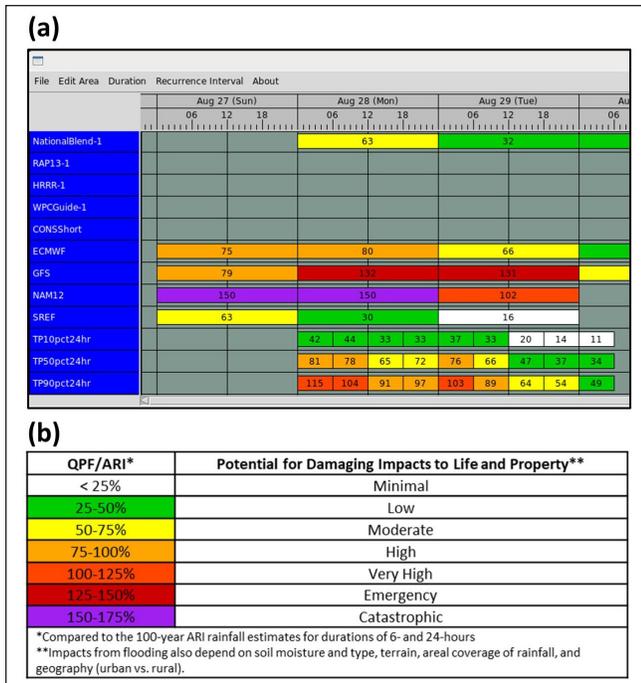
Figure 1. a) EPFT Initialized at 2200 UTC 26 August 2017 showing the max QPF/ARI$_{100}$ ratio associated with the QPF forecasts from Hurricane Harvey (i.e., TX/LA domain). See Appendix B for a list of model abbreviations and descriptions. b) The following key was provided to NWS forecasters to help identify significant values in the table. *Click image for an external version; this applies to all figures and hereafter.*

important aspects that need to be considered when determining potential impacts from extreme rainfall. In addition, the key is only applicable to QPF comparisons with the 100-yr ARI. Although there is the ability in the EPFT to compare QPF with lower ARI thresholds, additional studies would need to be completed to refine the key and facilitate analysis of the results.

The EPFT and EPAT are available to NWS forecasters at all CONUS-wide WFOs, RFCs, and the Weather Prediction Center via the Advanced Weather Interactive Processing System (AWIPS). The value in using AWIPS to host the EPFT is that it allows NWS forecasters and hydrologists to take advantage of the maximum amount of QPF guidance available for a streamlined assessment of when and where extreme precipitation could be a threat. AWIPS has the unique ability for tools to be created that can leverage large amounts of model data as well as guidance from nearby WFOs, RFCs, and WPC for enhanced collaboration and coordination during the forecast generation process.

In the next section, we will demonstrate cases where the EPFT and EPAT enhanced situational awareness in real-time operational settings.

3. Operational use-cases

a. Anticipating an atmospheric river event

An atmospheric river impacted southern California during 21–23 March 2018. The NWS San Joaquin Valley/Hanford Office (HNX) was at risk for heavy rainfall from this event, and with the prevalence of burn scars in their CWA, was concerned about the possibility of mudslides and flood impacts. A forecaster at HNX initialized the EPFT on 1900 UTC 20 March 2018, comparing 6-hr QPF from 20 different sources of guidance to the 100-yr ARI (Fig. 2a). Using the metric that QPF/ARI$_{100}$ ratios exceeding 75% are indicative that an extreme rainfall event is possible, the EPFT allowed the forecaster to key in on the timeframe 0000–0600 UTC 22 March 2018, corresponding to Wednesday afternoon/evening. Several models forecasted 6-hr rainfall exceeding 75% of the 100-yr ARI, including the HIRESWarw, HIRESWnmm, NAM12, and GFS1hr. The 24-hr comparison showed five QPF sources, including WPCGuide, exceeding 75% of the 100-yr ARI (Fig. 2b). A plot of the ratios generated from the HIRESWnmm valid at 0000 UTC 22 March shows an example of where some of the higher values were located (Fig. 3a). The HNX forecaster indicated that flood impacts (e.g., road wash-outs, mudslides) could have been possible if the storm cell in the HIRESWnmm moved over one of the many burn scars in the CWA. The burn scar from the 2017 Detwiler fire was of particular concern, and the grid generated from the CMCnh during 0000 UTC

Figure 2. EPFT initialized at 1900 UTC 20 March 2018 showing QPF/ARI$_{100}$ over the HNX CWA for a) 6-hr and b) 24-hr duration rainfall.
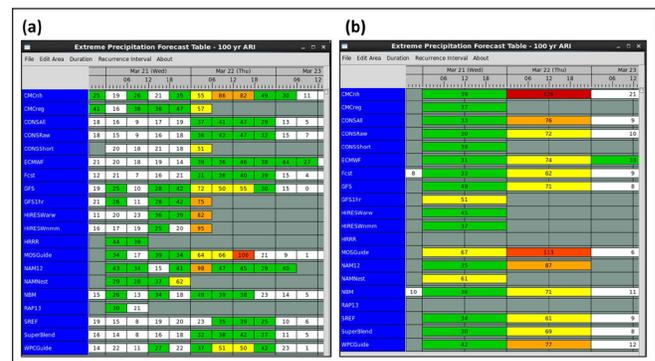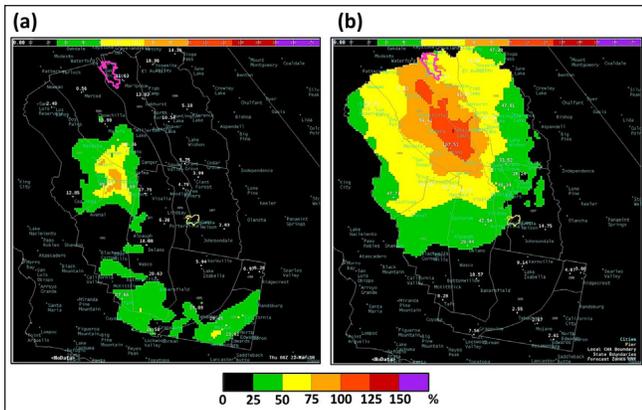
Figure 3. Select images generated from the EPFT in Fig. 2 displaying the spatial extent of the QPF/ARI$_{100}$ values from the a) 6-hr HIRESWRFnmm valid starting at 0000 UTC 22 March 2018 (max=95%) and b) 24-hr CMCnh valid starting 0000 UTC 22 March 2018 (max=126%). The magenta outline depicts the bounds of the Detwiler burn scar.

22 March to 0000 UTC 23 March shows QPF/ARI$_{100}$ values exceeding 75% in and around the area (Fig. 3b).

This information consolidated in the EPFT helped the forecaster to craft their message when informing core partners of the risk imposed by the atmospheric river event in their CWA. Here is a quote from the forecaster regarding the event:

> The EPFT showed the potential for heavy rainfall and sufficient rainfall rates to produce flooding over the Detwiler Burn Scar, associated with a narrow cold frontal rainband that was fed by an atmospheric river on March 22, 2018. The enhanced situational awareness provided by the tool helped the NWS Hanford office communicate potential flood impacts with several hours of lead time for Mariposa County emergency managers. This allowed an elementary school to be evacuated in a timely manner. Potential flood impacts were also conveyed to the NWS Western Region Regional Operations Center and the California Governor's Office of Emergency Services, which ultimately aided decision making on a state-wide scale.

Through personal communication, the forecaster indicated that it was a wet year, so that antecedent conditions lowered the ARI thresholds they considered important while assessing the EPFT values.

SA was additionally enhanced due to the forecaster's previous use of the EPFT to self-calibrate their own awareness toward the values in the EPFT that are significant for impacts. During the 2017 wet season, the forecaster ran the EPFT at 2200 UTC 6 February 2017, comparing QPF to the 50-yr ARI (QPF/ARI$_{50}$) for a 6-hr duration rainfall (Fig. 4a). Several pieces of guidance (i.e., GFS, HIRESWarw, HIRESWnmm, MOSGuide) had indicated that there was potential for a 50-yr ARI event to occur somewhere within the HNX CWA between 1200 UTC 7 February and 0000 UTC 8 February 2017. The event verified with 6-hr rainfall closer to a 25-yr ARI according to Stage IV QPE (Fig. 4b), which had led to local storm reports of flooded roadways and roads blocked from rockslides and landslides during the same period.

Regarding the 21–23 March 2018 atmospheric river event, knowledge of other risk factors like high
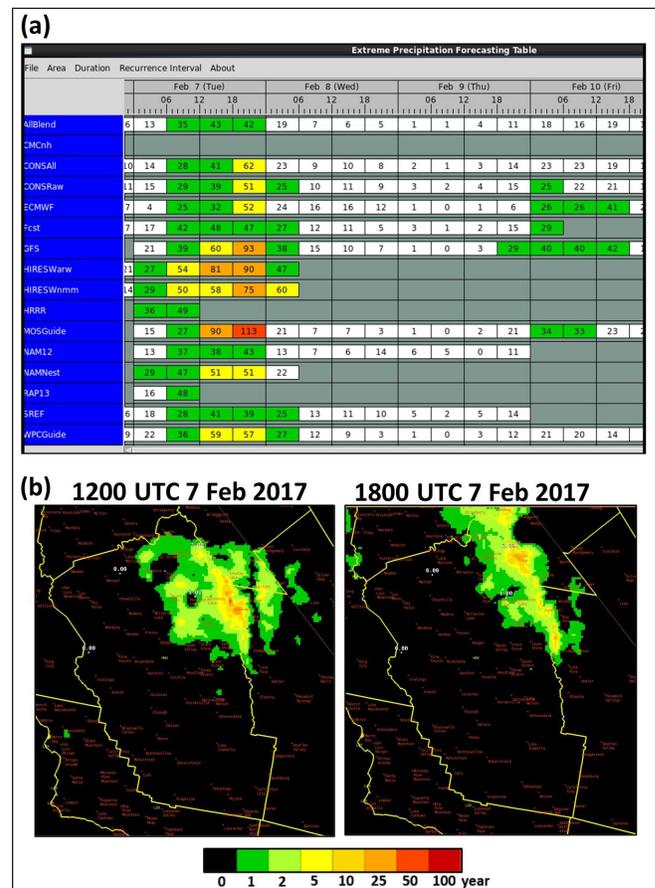
Figure 4. a) The EPFT initialized at 2200 UTC 6 February 2017 showing the max QPF/ARI$_{50}$ over the HNX CWA. b) Observed 6-hr ARI threshold exceedances according to Stage IV QPE valid starting at 1200 UTC and 1800 UTC 7 February 2017.

soil moisture and burn scars and previous experience correlating specific ARI thresholds with impacts in the HNX CWA were all necessary so that the forecaster could deliver effective decision support in a timely manner.

b. Enhanced situational awareness at LMRFC

On 22 October 2017, a slow-moving mesoscale convective system (MCS) fed by anomalously moist, low-level confluent flow had impacted south-central Louisiana and southern Mississippi with heavy rain and flash flooding. An LMRFC hydrologist ran the EPAT and EPFT during the event to assess how each tool could be used to enhance situational awareness for this particular event. Prior to running the EPAT, the hydrologist was aware that 8–11 in of rain fell overnight (in about six hrs), which caused a major highway to flood. A social media post from the Louisiana State Police was provided showing a picture of a flooded road and detour information (Fig. 5a). Consequently, by running the EPAT the hydrologist was able to identify the ARI-equivalent rainfall amounts that corresponded to the impacts shown in Fig. 5a. During the 0000–0600 UTC and 0600–1200 UTC periods on 22 October, several QPE observing sources within the EPAT (Fig. 5b) indicated that rainfall had exceeded the 10-yr ARI from the MCS that had anchored itself over south-central Louisiana (Fig. 5c).

In regard to the values in the EPAT, the hydrologist stated:

> Given the impacts from the previous 12 hours, the EPAT had provided guidance for what impacts could be expected if convection associated with this system continued to produce 10-yr ARI threshold exceedances, let alone 100-yr ARI exceedances.

The hydrologist initialized the EPFT at 1700 UTC 22 October, which had shown the HRRR and HIRESWnmm forecasting rainfall exceeding the 100-yr ARI over the next 6-hr period (Fig. 6a). The hydrologist noted that both models depicted a band of 100-yr ARI rainfall moving into southern Mississippi (e.g., Fig. 6b), which include drainages that feed the Biloxi and Wolf Rivers. Given the additional situational awareness provided by the EPFT and EPAT, the hydrologist was confident in their decision to put out forecast hydrographs for gauges on the Biloxi and Wolf
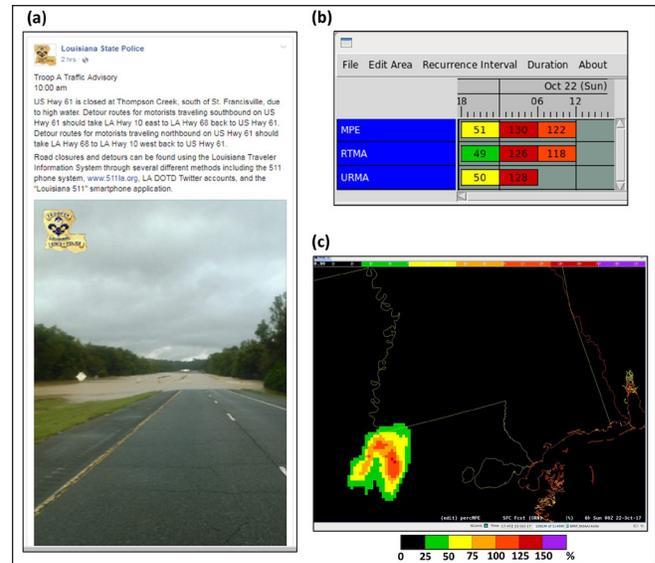
Figure 5. From an MCS-driven heavy-rain event that occurred 22 October 2017: a) LA state police reported road closures from a flash flood on social media. b) The EPAT corresponding to the event had shown 6-hr QPE exceeding the 10-yr ARI threshold according to 3 QPE observing sources starting at 00 UTC and 2 QPE sources starting at 06 UTC. Shown in c) are the 6-hr QPE/ARI$_{10}$ gridded ratios from the MPE valid starting at 00 UTC 22 October.

Rivers that are shown reaching Flood stage (Fig. 7a) and Action stage (Fig. 7b), respectively.

The hydrologist further commented that except in areas of steep terrain, the 10-yr ARI threshold is often defaulted to when using the EPFT. With the exception of land-falling tropical cyclones, higher ARI threshold exceedances are rarely observed within their forecast area. From using EPAT, they found that the 10-yr ARI has the most benefit in capturing flood impacts, especially in areas less than 200 mi from the Gulf of Mexico coast. In this area, the terrain is flatter, leading to poor drainage and ponding of water. In areas of steeper terrain, they look for 25-yr ARI exceedances within the EPFT. Because of the terrain changes within their forecast area of responsibility, the rainfall durations used are dependent on the response of local creeks, streams and tributaries. In steeper terrain, ARIs associated with shorter durations of rainfall (i.e., <6 hrs) are a better indicator of flooding, whereas ARIs associated with longer durations (i.e., ≥6 hrs) are more widely used along the coast and locations just inland.
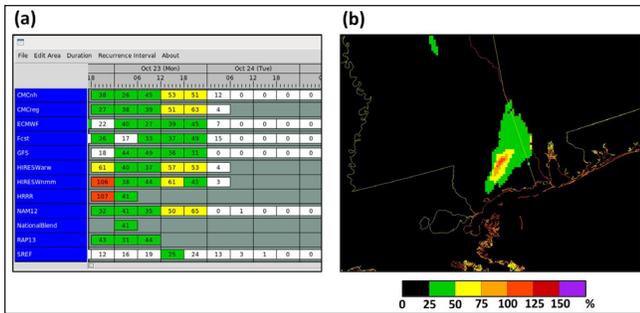
Figure 6. a) The EPFT initialized around 1700 UTC 22 October 2018. b) An EPFT-generated grid showing the spatial extent of the 6-hr QPF/ARI$_{100}$ values from the HRRR (max=107%) valid starting at 1800 UTC 22 October 2018.
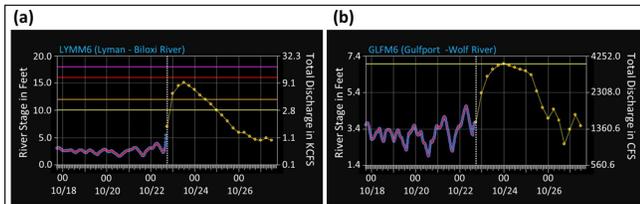
Figure 7. The updated river stage forecast (yellow-dotted line) for the a) Biloxi River (flood stage = 12 ft) and b) Wolf River (flood stage = 8 ft). The horizontal lines represent flood categories: Action Stage (Yellow), Flood Stage (Orange), Moderate Flood Stage (Red) and Major Flood Stage (Purple).

4. Summary and discussion

The Extreme Precipitation Forecast Improvement Project developed and transitioned situational awareness tools into NWS operations for the purpose of improving situational awareness and IDSS for impactful hydrometeorological events. The EPFT allows forecasters to compare multiple sources of QPF guidance to ARI threshold exceedances to alert them to when the models are predicting an extreme or climatologically significant precipitation event, whereas the EPAT helps them to identify when a climatologically significant precipitation event has been observed. Continual use of the EPAT will allow offices to calibrate their ARIs to impacts and enhance the use of the EPFT as an effective SA Tool.

Two use-cases are presented where the EPFT and EPAT helped improve situational awareness and had implications to IDSS during heavy rain events associated with an atmospheric river in California and an MCS in the southeastern United States. There were key similarities between how the tools were used in

each event that made it effective: 1) Previous use of the EPFT and/or EPAT was necessary to get a sense of the impacts that can result when different ARI thresholds are exceeded; 2) Recognition of multiple sources of guidance nearing or exceeding the ARI threshold of interest helped increase confidence in the message; 3) Use of the EPFT in conjunction with products that depict antecedent conditions helped to provide a full assessment of flood potential.

We should note here that there are some regions in the United States where the EPFT and EPAT may be more unreliable due to the combined poor performance of the inputs, particularly in the intermountain West. Here, there are significant gaps in both gauge data and radar coverage so that both the ARI and QPE inputs could be unreliable and have high uncertainty (Cocks et al. 2016; Herman and Schumacher, 2018). Confidence limits associated with the ARI thresholds are provided through NOAA's Hydrometeorological Design Studies Center, but they have not been incorporated into either tool. Forecasters should also be aware that the performance of the EPFT depends on the model QPF going into it, to which no additional bias-correction is applied before the values in the table are calculated. Thus, depending on the type of weather system being forecasted, high-resolution models can have a high-QPF bias and display high ARI exceedances, while low-resolution models can have a low-QPF bias and thus low-ARI exceedances.

Feedback from NWS forecasters reveal that they still view ARIs as a relatively new and advanced statistical concept. If they have not had enough experience or training with ARIs themselves, they have trouble relating them to on-the-ground impacts. If these challenges are to be remedied, more locally conducted research is necessary into the impacts that can be expected when certain ARI thresholds are forecasted. The EPFT could benefit from the inclusion of more probabilistic information to help forecasters identify the likelihood of a certain ARI event occurring. Probabilistic QPF (PQPF) from WPC has been incorporated into the EPFT, but additional PQPF from the National Blend of Models, which has been released in version 3.2, will also add substantial value. There are plans to work NBM's calibrated probabilistic QPF into the EPFT so that the information can be recast in the context of ARIs by percentile, which will help forecasters identify the probability of a specific ARI threshold being exceeded. The value here, as noted in Craven et al. 2020, is that forecasters can use this information to convey the most

likely scenario and potential alternative outcomes when extreme rainfall is a threat. The use of these datasets will allow forecasters a larger toolset to build effective IDSS messaging for extreme rainfall events.

APPENDIX A

Key Acronyms

AARI - Average Recurrence Interval
AWIPS - Advanced Weather Interactive Processing System
CONUS - Continental United States
CWA - County Warning Area
EM - Emergency Manager
EPAT - Extreme Precipitation Assessment Table
EPFT - Extreme Precipitation Forecasting Table
ESAT - Ensemble Situational Awareness Table
FFG - Flash Flood Guidance
FFMP - Flash-Flood Monitoring and Prediction system
HNX - San Joaquin San Joaquin Valley/Hanford Office
IDSS - Impact-based Decision Support Services
LMRFC - Lower Mississippi River Forecast Center
MCS - Mesoscale Convective System
NCEP - National Centers for Environmental Prediction
NOAA - National Oceanic and Atmospheric Administration
NWP - Numerical Weather Prediction
NWS - National Weather Service
PFE - Precipitation Frequency Estimate
PQPF - Probabilistic QPF
QPE - Quantitative Precipitation Estimate
QPF - Quantitative Precipitation Forecast
RFC - River Forecast Center
SA - Situational Awareness
WFO - Weather Forecast Office
WPC - Weather Prediction Center
WRF-NSSL – Weather Research Forecast National Severe Storms Laboratory

APPENDIX B

Model Abbreviations and Descriptions

AAllBlend - Average of CONSAll and previous forecast
CMC - Canadian Meteorological Center model
CMCreg - CMC regional model
CMCnh - CMC global model
CONSAll - a consensus blend of all MOS type models and all deterministic models.
CONSRaw - a consensus blend of all deterministic models
CONSShort - a consensus blend of short-term, hourly model guidance.
ECMWF - European Center for Medium Range Weather Forecasting model
Fcst - The WFO's QPF
GEFS - Global Ensemble Forecasting System
GEFS/R - Global Ensemble Forecast System Reforecast climatology
GEFSMEAN - Ensemble mean of the GEFS
GFS - Global Forecast System
GFS1hr - GFS interpolated to a 1-hr temporal resolution
HREF - High-Resolution Ensemble Forecast system
HIRESWarw - NCEP version of the Weather Research and Forecast model - Advanced Research WRF
HIRESWnmm - NCEP version of the Weather Research and Forecast model - Nonhydrostatic Mesoscale Model
HRRR - High-Resolution Rapid Refresh model
MOS - Model Output Statistics
MOSGuide - MOS gridded QPF guidance
MRMS - Multi-Radar/Multi-Sensor System
MPE - Multi-sensor Precipitation Estimate
NAM - North American Model
NAM12 - NAM produced at a12-km grid spacing
NAMNest - NAM 3-km nest
NationalBlend - National Blend of Models
NBM - National Blend of Models
NDFD - National Digital Forecast Database
RAP13 - Rapid Refresh model (13-km grid spacing)
RTMA - Real-Time Mesoscale Analysis QPE
SREF - Short-Range Ensemble Forecast model
TP10pct24hr - 10th percentile QPF from WPC's 46-member ensemble
TP50pct24hr - 50th percentile QPF from WPC's 46-member ensemble
TP90pct24hr - 90th percentile QPF from WPC's 46-member ensemble
URMA - Unrestricted Mesoscale Analysis QPE
WPCGuide - Weather Prediction Center deterministic QPF Guidance

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