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A method for probabilistic flash flood forecasting

Jill Hardy [a,*], Jonathan J. Gourley [b], Pierre-Emmanuel Kirstetter [c], Yang Hong [d], Fanyou Kong [e], Zachary L. Flamig [f]

[a] School of Meteorology, University of Oklahoma, 120 David L. Boren Blvd., Norman, OK 73072, USA
[b] NOAA/National Severe Storms Laboratory, 120 David L. Boren Blvd., Norman, OK 73072, USA
[c] Advanced Radar Research Center, University of Oklahoma, NOAA/National Severe Storms Laboratory, 120 David L. Boren Blvd., Norman, OK 73072, USA
[d] School of Civil Engineering and Environmental Science, Advanced Radar Research Center, University of Oklahoma, 120 David L. Boren Blvd., Norman, OK 73072, USA
[e] Center for Analysis and Prediction of Storms, University of Oklahoma, 120 David L. Boren Blvd., Norman, OK 73072, USA
[f] Cooperative Institute for Mesoscale Meteorological Studies, Advanced Radar Research Center, University of Oklahoma, NOAA/National Severe Storms Laboratory, 120 David L. Boren Blvd., Norman, OK 73072, USA

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SUMMARY

Flash flooding is one of the most costly and deadly natural hazards in the United States and across the globe. This study advances the use of high-resolution quantitative precipitation forecasts (QPFs) for flash flood forecasting. The QPFs are derived from a stormscale ensemble prediction system, and used within a distributed hydrological model framework to yield basin-specific, probabilistic flash flood forecasts (PFFFs). Before creating the PFFFs, it is important to characterize QPF uncertainty, particularly in terms of location which is the most problematic for hydrological use of QPFs. The SAL methodology (Wernli et al., 2008), which stands for structure, amplitude, and location, is used for this error quantification, with a focus on location. Finally, the PFFF methodology is proposed that produces probabilistic hydrological forecasts. The main advantages of this method are: (1) identifying specific basin scales that are forecast to be impacted by flash flooding; (2) yielding probabilistic information about the forecast hydrologic response that accounts for the locational uncertainties of the QPFs; (3) improving lead time by using stormscale NWP ensemble forecasts; and (4) not requiring multiple simulations, which are computationally demanding.

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1. Introduction

According to the U.S. Natural Hazard Statistics, flooding is the number one weather-related killer over a 30-year average (National Weather Service, 2014). In particular, flash flooding can be very dangerous due to its short timescales. Generally, flash floods are defined as flooding that occurs within six hours of a causative event (Hapuarachchi et al., 2011). They tend to occur in small headwater catchments, less than a few hundred square kilometers, due in part because these basins respond quickly to excessive rainfall amounts that fall in the short time periods characterized by flash flood-producing events (Kelsch, 2001). Unfortunately, these small basins can also be located in urban areas where the effects of flash flooding on society can be substantial.

In the simplest sense, as described by Doswell et al. (1996), "a flash flood event is the concatenation of a meteorological event with a particular hydrological situation." Meteorologically, it is crucial to properly predict not only the occurrence of a rain event, but more importantly, the intensity and movement of the rainfall to accurately depict the conditions of a flash flood event. However, the meteorological component is only half of the problem. Hydrologically, it is necessary to understand the antecedent soil conditions, land and soil characteristics, topography, and basin size to know how the rainfall will impact the basin response (Davis, 2001).

Therefore, this study focused on both sides of the problem: inputting high-resolution quantitative precipitation forecasts (QPFs), that attempt to capture the dynamics of heavy rainfall (e.g. cell motion, development, intensity, duration) into a distributed hydrological model, that will take into account the necessary hydrological factors. It should be noted that the focus of this paper will be on the meteorological component and its application in a hydrological framework.

In regards to the meteorological component, several studies have examined the accuracy of high-resolution,

* Corresponding author.
E-mail addresses: jill.hardy@ou.edu (J. Hardy), jj.gourley@noaa.gov (J.J. Gourley), pierre.kirstetter@noaa.gov (P.-E. Kirstetter), yanghong@ou.edu (Y. Hong), fkong@ou.edu (F. Kong), zac.flamig@noaa.gov (Z.L. Flamig).

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convection-allowing numerical weather prediction (NWP) models. Simply considering resolution, Roberts (2005) showed that higher resolution NWP models (1- or 4-km) have more reliable forecasts of flood-producing rainfall (up to 7 h ahead) as compared to lower resolution (12- or 60-km) models. Schwartz et al. (2009) delved into the issue of convection-allowing versus convection-parameterizing models; the difference being that convection-allowing models can generate and resolve convection, while the parameterizing models represent convective processes that occur at sub-pixel resolution using a statistical approach. They found that higher resolution (2- and 4-km), convection-allowing models were more skillful at predicting amplitude and location of heavy rainfall as compared to the 12-km, convection-parameterizing model. Furthermore, Clark et al. (2009) compared a high-resolution, convection-allowing ensemble with a coarser, parameterized-convection model. They found the ensemble to produce more skillful precipitation forecasts, even with a small number of members, thus showing the promise of such ensembles.

Particular to the use of high-resolution QPFs comes the issue of displacement errors of finescale features (Ebert, 2008). These small errors can have significant effects on flash flood prediction since flash flooding is very location-dependent. The smallest offset of heavy rainfall can make the difference between an event and non-event because basins prone to flash flooding are commonly quite small (Vincendon et al., 2011). Probabilistic forecasting offers the potential to quantify this locational uncertainty, thus it is the focus of our study.

In regards to the hydrological component, the use of hydrological models for flood forecasting has been commonplace for many years (Singh, 1995). However, their use for flash flood forecasting is at a relative infancy (Reed et al., 2007). More and more operational hydrological models incorporate radar-derived estimates of rainfall as their main precipitation input. These estimates can have resolutions as high as 1-km with a 2-min update cycle, and once input into the model, provide a good depiction of the present state of the hydrologic cycle. However, the radar estimates are also subject to uncertainties (Zhang et al., 2015), but more importantly, only allow for hydrological modeling once the water is already hitting the ground. The time interval between heavy rainfall observations and flash flooding can be on the order of minutes, especially for small (sometimes, urban) basins. This short lead time makes it imperative to receive information prior to radar measurements of rainfall.

Increasing the lead time for these events is necessary in order to better protect life and property (Stensrud et al., 2009; Hapuarachchi et al., 2011; Vincendon et al., 2011). The best way to do this is by improving guidance to hydrological models via inputting quantitative precipitation forecasts, derived from numerical weather prediction models, into the models (Collier, 2007). Fritsch and Carbone (2004) discussed the need to focus on warm-season QPF improvement, with one of the main purposes being the application to hydrological forecasting. They argued that a major research area needs to be determining whether QPFs are valuable to hydrological prediction, especially since hydrological predictions "are among the principal societal payoffs resulting from warm-season QPF improvement...". Our study assumes that QPFs on their own give an estimate of the relative location and intensity of future rainfall, however, giving them a hydrologic relevance is the only way they will be useful for flash flood forecasting.

In particular, the desire for ensembles of QPFs (no matter the resolution) as inputs for hydrological models is apparent in the field of flash flood forecasting (Cloke and Pappenberger, 2009). The methods thus far have been to: (1) input individual members of a QPF ensemble directly into a hydrological model to create an ensemble of hydrologic forecasts (Zappa et al., 2008; Verbunt et al., 2007), (2) perturb one deterministic QPF to create an ensemble for input into the hydrological model (Vincendon et al., 2011), or (3) perturb ensemble members and hydrologic model parameters. Our study is unique in that it creates a high-resolution deterministic representative of all ensemble members (via probability matching) for input into the hydrological model. This method cuts back the computational expense (compared to running multiple simulations), while still accounting for the optimal location defined by the ensemble mean, and the rainfall intensity represented by the entire QPF ensemble.

With such ensemble hydrologic outputs, probabilistic flash flood forecasting has been discussed in the above studies, and others (Krzysztofowicz, 2001; Drobinski et al., 2014). This study's method is novel in that it creates a final probabilistic product not from considering the fraction of hydrologic output members that exceeds a certain discharge threshold, but rather from the multiplication of meteorological and hydrological probabilistic products. In brief, the ultimate goal of this study is to derive basin-specific probabilistic flash flood forecasts (PFFFs) using an ensemble of forecast members (QPFs), combined with simulated basin responses (derived from a distributed hydrological model), in order to identify basin scales and lead times for flash flood prediction. It is noted that the proposed method deals with locational uncertainties in QPFs alone. Future methods should also consider additional errors in timing, storm structure, and amplitude. The rest of this paper is outlined as follows: Section 2 describes the two precipitation datasets and the distributed hydrological model used in this study; Section 3 explains the error quantification procedure that was done to find the biases related to the QPFs; Section 4 details the methodology conducted to create the PFFFs, and is followed by Section 5 discussing the results from the case study; and finally, Section 6 summarizes the conclusions from the study.

2. Datasets

2.1. Forecast rainfall

This study relies on the use of a NWP model that is capable of producing stormscale QPFs. These QPFs serve as the input precipitation field for the hydrological model. As part of the National Oceanic and Atmospheric Administration (NOAA) Hazardous Weather Testbed (HWT) Spring Experiment, the Center for Analysis and Prediction of Storms (CAPS) at the University of Oklahoma (OU) has developed a multi-model storm-scale ensemble forecast (SSEF) in real-time (Kong et al., 2011). Since the 2007 Spring Experiment, CAPS has been improving the SSEF each year to include such items as radar data assimilation, more members, larger domains, post-processed products, and longer forecasts.

QPFs produced during the 2010–2012 NOAA HWT Spring Experiments have a 4-km resolution, are produced hourly, and cover the entire continental U.S. (CONUS). Only ensemble members that included assimilated radar data into their initial conditions were used, since this information is useful in adjusting initial model states with the aim of improving rainfall forecasts. All members were initialized at 00Z and produced hourly QPFs up to 36 h ahead. Table 1 shows the overall details of each year's

Table 1
Details of the CAPS SSEF for the years 2010, 2011, and 2012.

Year	Number of members	Number of analysis days	Number of forecast hours
2010	24	36	30
2011	45	35	36
2012	24	35	36