**Toward high-resolution flash flood prediction in large urban areas – Analysis of sensitivity
to spatiotemporal resolution of rainfall input and hydrologic modeling**

by

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25 Urban flash flooding is a serious problem in large, highly populated areas such as the Dallas-Fort
26 Worth Metroplex (DFW). Being able to monitor and predict flash flooding at a high
27 spatiotemporal resolution is critical to providing location-specific early warnings and cost-
28 effective emergency management in such areas. Under the idealized conditions of perfect models
29 and precipitation input, one may expect that spatiotemporal specificity and accuracy of the model
30 output improve as the resolution of the models and precipitation input increases. In reality,
31 however, due to the errors in the precipitation input, and in the structures, parameters and states
32 of the models, there are practical limits to the model resolution. In this work, we assess the
33 sensitivity of streamflow simulation in urban catchments to the spatiotemporal resolution of
34 precipitation input and hydrologic modeling to identify the resolution at which the simulation
35 errors may be at minimum given the quality of the precipitation input and hydrologic models
36 used, and the response time of the catchment. The hydrologic modeling system used in this work
37 is the National Weather Service (NWS) Hydrology Laboratory's Research Distributed
38 Hydrologic Model (HLRDHM) applied at spatiotemporal resolutions ranging from 250 m to 2 km
39 and from 1 min to 1 hour applied over the Cities of Fort Worth, Arlington and Grand Prairie in
40 DFW. The high-resolution precipitation input is from the DFW Demonstration Network of the
41 Collaborative Adaptive Sensing of the Atmosphere (CASA) radars. For comparison, the NWS
42 Multisensor Precipitation Estimator (MPE) product, which is available at a 4-km 1-hr resolution,
43 was also used. The streamflow simulation results are evaluated for 5 urban catchments ranging in
44 size from 3.4 to 54.6 km² and from about 45 min to 3 hrs in time-to-peak in the Cities of Fort
45 Worth, Arlington and Grand Prairie. The streamflow observations used in evaluation were
46 obtained from water level measurements via rating curves derived from 1-D steady-state non-

uniform hydraulic modeling. The results indicate that a spatiotemporal resolution of 500 m and 15 min or higher is a good choice for streamflow prediction using HLRDHM and CASA QPE in the study area, but that, due to the nonlinear accretion of random errors in QPE and imperfect model dynamics, there are trade-offs to consider among resolution, timeliness of prediction and prediction accuracy.

Key words: distributed hydrologic modeling, radar-based quantitative precipitation estimates, space-time resolution, sensitivity

1 Introduction

To take full advantage of high-resolution quantitative precipitation information (QPI) from weather radars, it is necessary to operate hydrologic models at a resolution that is commensurate with the effective resolution of QPI. Conceptually, variability in runoff and streamflow for urban flash flood forecasting can be captured by employing hydrologic and hydraulic models and precipitation input at a sufficiently high resolution. In reality, however, all models and precipitation input have errors of varying nature and magnitude. Because the errors are nonlinearly transformed by the models in a scale-dependent way, the accuracy of simulated runoff and flow is generally not proportional to the resolution of modeling (Smith et al. 2004b, Berne and Krajewski 2013). To illustrate, Fig 1 shows the relative error in runoff simulation as a function of the scale of subcatchment delineation and the magnitude of errors in precipitation input under the assumption of a perfect hydrologic model (Koren et al. 2003, Smith et al. 2004b). If the precipitation input is perfect, delineating subcatchments at a higher resolution would yield more accurate simulation of areal runoff. If there are large errors in the precipitation input, however, the accuracy of areal runoff simulation may deteriorate as the resolution of modeling

increases due to the nonlinear growth of error. For skillful flash flood prediction at a high resolution, it is therefore necessary to identify the effective resolution at which the relative errors may be at minimum, given the quality of radar quantitative precipitation estimates (QPE) and the hydrologic models used (Vieux and Imgarten, 2012, Berne and Krajewski 2013, Bruni et al. 2015).

In this work, to infer the above accuracy-vs.-resolution relationships, we test and ascertain the limits of high-resolution hydrologic modeling using the QPEs available in the DFW area. Specifically, we seek to identify the optimal spatiotemporal resolution for flash flood prediction for large urban areas such as DFW. The results characterize the incremental value of high resolution precipitation input and hydrologic modeling for streamflow prediction in urban catchments (see, e.g., Finnerty et al. 1997 for analysis for non-urban catchments). The spatial resolution considered in this work ranges from 1 to 1/16 HRAP (Hydrologic Rainfall Analysis Projection, Greene and Hudlow 1982) where 1 HRAP is approximately $4 \times 4 \text{ km}^2$ in the study area. The temporal resolution considered ranges from 60 min to 1 min. The 1 HRAP-60 min resolution corresponds to that of the Multisensor Precipitation Estimator (MPE) product (Fulton et al. 1998; Seo et al. 2010; Kitzmiller et al. 2011). The 1/8 HRAP-1 min resolution corresponds to that of the Collaborative Adaptive Sensing of the Atmosphere (CASA) QPE product (Wang and Chandrasekar 2010, Chandrasekar et al. 2012, Chen and Chandrasekar 2012, Chandrasekar et al. 2013). The 1/16 HRAP resolution corresponds to the highest spatial resolution for impervious cover in rainfall-runoff modeling and for hillslope and channel routing considered in this work. The new contributions of this work include: 1) assessment of sensitivity of streamflow simulation in urban catchments to spatiotemporal resolution of precipitation input, impervious cover, and hillslope and channel routing, 2) comparative analysis of sensitivity of streamflow simulation to different radar-based QPEs of different resolutions, 3) assessment of sensitivity of

temporal variability in simulated streamflow to spatiotemporal resolution of precipitation input and hydrologic modeling, and 4) guidance on planning, design and implementation of high-resolution flash flood prediction capabilities for large urban areas. The paper is organized as follows. Section 2 describes the study area and precipitation data used. Section 3 describes the models used. Section 4 describes derivation of rating curves. Section 5 describes calibration and initialization of the models. Section 6 presents the results. Section 7 provides the conclusions and future research commendations.

2 Study area and precipitation data used

The modeling domain is a rectangular area encompassing the Cities of Fort Worth, Arlington and Grand Prairie, which have a combined area and population (as of 2013) of 1,378 km² and 1,355,676, respectively, in the Dallas-Fort Worth Metroplex area (DFW) in north central Texas (Fig 2). It is expected that the domain will be expanded in the very near future to include the City of Dallas to the east. The primary rainfall data is the CASA QPE. Currently, a network of CASA X-band radars, referred to as the DFW Demonstration Network, is being deployed in the area (Chen and Chandrasekar 2012, Chandrasekar et al. 2013). One of the limitations with the WSR-88D network, or NEXRAD, is that they do not observe the lower atmosphere at locations distant from the radar, which also causes degradation of spatial resolution at far ranges. Also, the temporal resolution is constrained by a fixed set of volume coverage patterns (VCP, Brown et al. 2005, Klazura and Imy 1993). A contributing factor to the lack of resolution in NEXRAD is that the radar operation is independent of the weather conditions. To maximize its utility, radar may adapt to the time-varying needs of the users (Junyent et al. 2010). To address the above gaps and needs, the National Science Foundation

(NSF) Engineering Research Center (ERC) for CASA developed a new weather warning system based on dense networks of small radars (McLaughlin et al. 2005) with adaptive scanning strategy (Junyent et al. 2010). The first testbed of a networked CASA radar system was the CASA Integrated Project composed of four X-band radars in Oklahoma (for details, see Junyent et al. 2010). For precipitation estimation using X-band radars, attenuation is a well-known issue (Seo et al. 2010, Berne and Krajewski 2013, Anagnostou et al. 2004). To mitigate its effects, the CASA system uses the network reflectivity retrieval (Chandrasekar and Lim 2008) and network-based attenuation correction (Lim et al. 2011) techniques. Lim et al. (2011) showed that the techniques work robustly in real time in retrieving attenuation-corrected reflectivity. CASA QPE is based on specific differential propagation phase, which makes it immune to absolute calibration errors (Bringi and Chandrasekar 2001). The Oklahoma network was evaluated using rain gauge observations for a five-year period, which showed a good agreement between radar QPE and rain gauge observations with a standard deviation of 25% and a bias of 3.7% (Chandrasekar et al. 2012). After the successful testbed demonstration in Oklahoma, the CASA system was moved to DFW in late 2012. In this work, the 1-min 500-m QPE product from the CASA radar installed at the University of Texas at Arlington, XUTA, was used along with the MPE product from the NWS West Gulf River Forecast Center (WGRFC). Fig 2 shows the coverage of XUTA together with the city limits of Fort Worth, Arlington and Grand Prairie. The location of the nearest WSR-88D in Burleson, TX (KFWS), is also shown. The historical CASA QPE is available only for significant events as the radar has been operating only in times of severe weather or precipitation. The period of record for the CASA QPE used in this work is from Jan 2013 to Dec 2013. While 2013 was not a wet year for north central Texas, there were a number of significant flash flooding events in the study area in the months of Apr, Jun and Sep.

The largest occurred on Sep 20 due to a slow-moving system which dumped over 120 mm of rainfall over parts of the City of Arlington.

3 Hydrologic models used

For hydrologic modeling, we used the NWS distributed hydrologic modeling system, Hydrology Laboratory Research Distributed Hydrologic Model (HLRDHM, Cui et al. 2011). HLRDHM has been used in a wide range of applications. Reed et al. (2007) used the threshold frequency (TF) approach with HLRDHM for flash flood forecasting. Yilmaz et al. (2008) evaluated HLRDHM using the hydrological “signature measures” to quantify the performance of the model at the watershed outlet. Mejia and Reed (2010) used HLRDHM to evaluate parameterization of channel cross sections. Lee et al. (2011) assimilated streamflow observations and in-situ soil moisture data into HLRDHM to improve streamflow prediction. Fares et al. (2014) applied HLRDHM in a flashy tropical watershed in Hanalei Bay, HI. HLRDHM coupled to a TF post-processor, or DHM-TF, has been applied to urban catchments in the Baltimore/Washington (LWX), Binghamton (BGM), and Pittsburgh (PBZ) Weather Forecast Office (WFO) domains to produce gridded forecasts of return periods for flash flood forecasting (Cosgrove et al. 2012). HLRDHM can be configured in many different ways. In this work, we used the Sacramento Soil Moisture Accounting model (SAC, Burnash et al. 1979) with heat transfer, or SAC-HT (Koren et al. 2014), for rainfall-runoff and the kinematic wave model for routing (Koren et al. 2004). HLRDHM has been used to generate routine analysis and forecast products within the NWS on the HRAP grid (~4 km) forced by hourly precipitation, but not as fine a spatiotemporal resolution as 250 m and 1 min as used in this work.

HLRDHM is recognized as one of the best performing distributed hydrologic modeling systems as demonstrated in the Distributed Model Intercomparison Projects (Reed et al. 2004, Smith et al. 2012). It is used routinely at the NWS at the River Forecast Centers (RFC) and WFOs. The core modeling components of HLRDHM are used at the National Centers for Environmental Prediction (NCEP) for continental-scale land surface modeling (Mitchell et al. 2004, Xia et al. 2012). Within HLRDHM, SAC is capable of simulating both saturation- and infiltration excess runoff. For the upper-layer storages, saturation excess is assumed; no surface runoff occurs before the upper-zone tension and free water capacities are filled. Once the upper layers are filled, surface runoff occurs from infiltration excess as a function of percolation (Koren et al. 2004).

Hydrologically, the urban environment differs most significantly from others in that it has large impervious areas and storm drains. Within a large urban area such as DFW, spatial variability of imperviousness may vary greatly. In this work, we used the a priori estimates of the SAC parameters available from NWS for the continental US on the HRAP grid (Koren et al. 2000, Anderson et al. 2006, Zhang et al. 2012) by uniformly disaggregating them onto finer grids, but re-derived the Permanent Impervious Area (PCTIM) at higher resolutions from the GIS layers that contribute to imperviousness (see Table 1). The layers were obtained from the Cities of Fort Worth, Arlington and Grand Prairie. Note that PCTIM in SAC refers to areas in the watershed that are impervious and are directly connected to the channel system. All available layers were combined and the percent impervious cover, defined as the percentage of the impervious area within a grid box, was calculated for each pixel ranging from 1/16 HRAP (~250 m) to 1/2 HRAP (~2 km). Fig 3 shows the resulting PCTIM at a 1/16 HRAP resolution, which shows very large spatial variability across the model domain. The upper bound of 1/16 HRAP is

based on extensive visual examination of the land cover images in various parts of DFW. It was observed that most large features associated with imperviousness may be resolved on a 1/16HRAP grid. Because the GIS layers used in this work do not account for all sources of imperviousness, however, the PCTIM field is likely to be an underestimate.

Hillslope and channel routing in HLRDHM is performed using kinematic-wave routing (Chow et al. 1988, Koren et al. 2004).HLRDHM routes runoff through the natural channels identifiable from the digital elevation model (DEM) by the Cell Outlet Tracing with an Area Threshold (COTAT) algorithm (Reed 2003).Within each cell, fast runoff is first routed over conceptual hillslopes, and then the combination of channel inflow from hillslope routing, slow (i.e. subsurface or ground) runoff and inflow from upstream cells is routed via channel routing (Koren et al. 2004). A conceptual hillslope consists of multiple uniform hillslopes, the number of which depends on the stream channel density specified for the cell. The conceptual channel that transfers water from one cell to another usually represents the highest order stream in the cell selected. The cell-to-cell connectivity is used to transfer water from upstream to downstream cells and to the basin outlets. For hillslope routing, discharge per unit area of hillslope (q_h) is given by (Koren et al. 2004):

$$q_h = 2k_q D \frac{\sqrt{S_h}}{n_h} h^{5/3} \quad (1)$$

where k_q denotes the unit transformation coefficient, D denotes the stream channel density in km^{-1} , S_h denotes the hillslope slope, n_h denotes the hillslope roughness coefficient, and h denotes the average depth of water on the hillslope. For channel routing, the discharge for each cell, Q_c , is a power function of the wetted cross sectional area, A :

$$Q_c = q_0 A^{q_m} \quad (2)$$

where q_0 denotes the specific discharge, i.e., discharge per unit channel cross section area, and q_m denotes the exponent in the power-law relationship. The specific discharge may be evaluated if A and Q_c are known. Mean annual flow may be derived from the mean average annual runoff data over the continental US available from the United States Geological Survey (USGS, Slack and Landwehr 1992). The wetted channel cross section, A , may be obtained from $A=Q/V$ where V denotes the mean velocity, which may be evaluated using the empirical equation developed by Jobson (1996):

$$V = 0.094 + 0.0143 \left(\frac{D_a^{1.25} \sqrt{g}}{Q} \right)^{0.919} S^{0.159} \frac{Q}{D_a} \quad (3)$$

where D_a denotes the upstream drainage area calculated using the flow direction and cell size grids, g denotes the gravitational acceleration and S denotes the channel slope. The two kinematic-wave channel routing parameters, q_0 and q_m , were derived using the above relationships and the National Elevation Dataset (NED) with 30 meter resolution from NHDPlus Version 2 dataset (David et al. 2014). Fig 4 shows the derived flow directions at different resolutions over the model domain.

4 Evaluation and estimation of rating curves

For hydrologic evaluation, we used the water level observations available from the Cities of Fort Worth, Arlington and Grand Prairie; they have been operating the so-called High Water Warning Systems (HWWS) at 19,5 and 21 locations throughout the cities since 2007, 2013 and 2009, respectively. Recently, Fort Worth has added 38 such systems throughout the city. The HWWS observes precipitation, water level and, if equipped, a set of meteorological variables in real time. The rain gauge observations have been used to validate the radar-based QPEs (Rafieeinassab et al. 2014a,b). The water level observations at most locations are based on

pressure transducers located at the channel bottom. Though the real-time observations from the HWWS have been being archived, the historical data have not been studied prior to this work. To quality-control the data, we visually examined the historical time series of all available water level observations and selected 5 locations in the City of Grand Prairie for evaluation (see Fig 5). They represent the outlets of Catchments 6033, 6043, 6103, 6133 and 6363, denoted hereafter as C6033, C6043, C6103, C6133 and C6363, whose drainage areas are 40.2, 3.4, 32.0, 54.6 and 14.4 km², respectively. Figs 6 and 7 show the terrain and PCTIM maps for the 5 catchments. Also shown in Fig 6 are the storm drain networks in the area.

Because HLRDHM does not model storm drains explicitly, the simulation results may not be realistic if the collective capacity of the storm drain network is large. Compared to the conveyance capacity of open channels, that of storm drainage pipes is significantly smaller in the study area as explained below. Fig 8 shows the empirical cumulative probability distribution functions (ECDF) of bankfull flow in the storm drainage open channels (in blue, see also Fig 6) and fully-charged flow in the storm drainage pipes (in green, see also Fig 6). Also shown in the figure for reference is the ECDF of HLRDHM-simulated flow in the natural channels in the Johnson Creek Catchment (see Fig 5) due to remnants of Tropical Storm (TS) Hermine in Sep 2010 (in black) which flooded many areas and roadways throughout the City of Arlington, TX. In south Arlington, the rainfall total exceeded 250 mm. In the figure, we used model-simulated flow only at the outlet locations of the storm drainage pipes and open channels to facilitate comparison. There are about 3,300 and 300 storm drainage pipes and open channels in the catchment. Due to lack of complete dimensional information, only about a half of each type could be represented in Fig 8. Because storm drainage open channels are generally built on the natural channels, it is very likely that the latter, which is modeled by HLRDHM, reflect the

former whereas the storm drainage pipes are not accounted for in the routing process. The figure indicates that the full-capacity storm drainage open channels can convey several times as much flow as fully-charged storm drainage pipes at the 95th percentile level, and that, for remnants of TS Hermine, the natural channels conveyed about 3 and 15 times as much flow as the full-capacity storm drainage open channels and pipes, respectively, at the same level. For hydrologic modeling of large areas, explicit modeling of storm drains is a large challenge. In the City of Fort Worth, there are well over 30,000 storm drains within the 904.4 km² area, many of which lack complete hydraulic information necessary for modeling. In the 5-catchment study area, there are close to 10,000 storm drains of different cross-sectional shapes and dimensions (see Fig 6). For example, the diameter of the round storm drains varies between 76 mm to 2,440 mm. It is expected that explicit modeling of storm drains will occur incrementally over time. Currently, we are modeling storm drains explicitly only in two of the inundation-prone catchments in the City of Fort Worth (Nazari et al. 2014) and in the Johnson Creek Catchment in the City of Arlington. In this work, the effects of storm drains were aggregated into channel routing by multiplicatively adjusting the parameters, q_0 and q_m (see Eq.(2)), spatially uniformly for each catchment, as described in the next section.

There are no rating curves available for the HWWS locations to estimate flow from the stage observations. In this work, we derived rating curves using the numerical modeling approach of Kean and Smith (2004, 2005, 2010) which was also used by Nathanson et al. (2012). The approach is applicable to geomorphically stable channels and consists of two parts: 1) procedures for quantifying various contributions to the total flow resistance in the channel and 2) a flow model that incorporates the results from the above procedures. The technique models streamflow in a channel reach by solving the Saint-Venant equation (Chow et al. 1988) for steady non-

uniform flow in one dimension. The mass and momentum balance equations are given by (Kean and Smith 2005):

$$\frac{\partial Q}{\partial x} = 0 \quad (4)$$

$$\frac{1}{2} \frac{\partial (u^2)_{av}}{\partial x} + g \frac{\partial E}{\partial x} + \frac{1}{\rho} \frac{(\tau_b)_{av}}{R} = 0 \quad (5)$$

where Q denotes the channel flow, x denotes the direction of flow, $(u^2)_{av}$ denotes the square of the downstream velocity averaged over the cross section, $(\tau_b)_{av}$ denotes the perimeter-averaged shear stress (N/m^2), E denotes the elevation of the water surface (m), and R denotes the hydraulic radius (m). The physical roughness of the channel bed is related to the particle size of the bed material via $z_o = 0.1D_{84}$ (m), where D_{84} denotes the 84th percentile of the grain size distribution. The channel roughness is estimated from the channel geometry, the physical roughness of the channel bed, banks, and floodplain, and the vegetation density on the banks and floodplain. To determine D_{84} and the relative bed roughness, z_o , we used the grain size distributions available from the City of Grand Prairie (see Table 2). To delineate the channel shape and to derive the river cross sections, we used the 0.7 m-resolution LiDAR data from the Texas Natural Resources Information System (2015). The derived channel cross sections were transferred to the river flow and riverbed variation analysis solver, Flow and Sediment Transport with Morphological Evolution of Channels (FastMECH, Nelson and McDonald 1996, Nelson et al. 2003), to construct a mesh. The resulting mesh was then used to calculate the bed slope of the channel, velocity field for a given cross section, stage, and water surface slope using the ray-isovel approach of Kean and Smith (2004). Given the water level, Eq.(5) is solved iteratively to estimate the discharge, which is repeated over the desired range of water level.

Once the rating curves for different grain sizes were derived, they were compared with those derived using HLRDHM as described below. Streamflow was simulated using the MPE estimates at 1/8-HRAP and 15-min resolution in which the 1-HRAP 1-hr MPE estimates were uniformly disaggregated onto the 1/8-HRAP grid and into 15-min subintervals. The 15-min subinterval corresponds to the sampling interval of stage observations. The 1/8 HRAP subgrid is chosen to avoid favoring simulations at either end of the range of resolutions considered. The MPE data was used to avoid favoring simulations forced by the higher-resolution CASA QPE. We then fitted the following stage-discharge relationship (Herschy 1993):

$$Q = c (h + a)^n \quad (6)$$

where Q denotes the discharge (m^3/s), h denotes the stage (m), c and n denote the parameters to be estimated, and a denote the stage (m) at zero flow. The datum correction, a , represents the stage corresponding to zero discharge. To minimize the effects of resolution-dependent timing errors in estimating the parameters in Eq.(6), we considered only the marginal statistics of mean, variance and maximum flow in the curve fitting. Fig 9 shows an example of the resulting observed stage vs. simulated discharge relationships from HLRDHM. The black line denotes the rating curve obtained via the Kean and Smith method (2004, 2005, 2010) for different values of the roughness height, z_0 (mm), within the observed range shown in Table 2. As seen in the figure, the two independently-derived rating curves agree well. The results presented below are based on the rating curves estimated using Kean and Smith (2004, 2005, 2010).

5 Calibration and initialization

There are multiple sources of error in simulating streamflow. In addition to the errors in the forcing input, model states, model parameters and model structure, there may also be human

control of water that is not modeled. Ideally, one may assess the sensitivity to the resolution of precipitation input and hydrologic modeling in an ensemble framework such that the uncertainties due to all significant errors may be considered. Such an endeavor, however, was beyond the scope of this work. Instead, we carried out conditional analysis in which the sensitivity of streamflow simulation at the catchment outlet is assessed to the resolution of the precipitation input, PCTIM and the channel routing parameters only, given that all other initial, and observed and fixed boundary conditions are perfectly known. The three variables above represent the most significant hydrometeorological, hydrologic and hydraulic controls in the study area that are considered resolution-sensitive. The above approach of carrying out only limited calibration to reduce the most important input and parametric uncertainties is commonly practiced in the real world in lieu of exhaustive calibration. Timing errors are very often a large contributing factor to errors in streamflow simulation. They may originate from different sources: errors in capturing the spatiotemporal distribution of precipitation, errors in soil moisture accounting, and/or errors in routing. In this work, we carried out bias correction of the precipitation input and calibration of the channel routing parameters to reduce volume and timing errors, respectively. Calibration of distributed parameters of complex rainfall-runoff models such as SAC at a high resolution is an ongoing area of research (Beven and Binley 1992, Pokhrel and Gupta 2010, Li et al. 2012, Ragetti and Pellicciotti 2012) and is left as a future endeavor.

As noted above, in addition to applying a multiplicative adjustment factor to the precipitation input, β_p , to reduce streamflow volume errors, we applied uniform multiplicative adjustment factors, β_{q_o} and β_{q_m} , to the channel routing parameters of specific discharge, q_0 , and the exponent, q_m (see Eq.(2)), respectively, to reduce timing errors and to account for the effects

of the storm drains which were not modeled explicitly (see Table 3). In this way, the errors in streamflow simulation are reflective of the effects of the varying resolution of precipitation and hydrologic modeling rather than those of volume and/or timing errors. Fig 10 shows how the uniform adjustment of q_0 and q_m may impact both the timing and magnitude of peak flow at the outlet of C6133. Note in Fig. 10 that increasing β_{q_o} or β_{q_m} increases peak flow and reduces time to peak, and that β_{q_m} has a larger impact than β_{q_o} . The above approach amounts to adjusting the hydraulic properties of the open channel system to account for the storm drains based on the observed flow at the outlet. While an oversimplification, the above approach is reasonable for outlet simulation because the storm drains discharge into the natural open channels thereby modifying the hydraulics of the flow through the latter.

Admittedly, such spatially uniform adjustment is less likely to yield skillful simulations at interior locations than at the outlet. Spatially nonuniform adjustment (see, e.g., Seo et al. 2003), however, was not considered in this work because streamflow observations are available only at the outlet and hence evaluation at interior locations is not possible.

To optimize the adjustment factors at the 1/8 HRAP and 15 min resolution, we considered the root mean square error (RMSE) and mean error (ME) of simulated streamflow, correlation between simulated and observed flows, and timing error in peak simulated flow as a function of the observed peak flow, and probability of detection (POD) and false alarm rate (FAR). All statistics were calculated only for the significant events for which the CASA QPE was available. A significant event was defined as the streamflow response to a precipitation event resulting in the peak flow exceeding a preset threshold for each catchment. There were 16, 13, 15, 12 and 14 such events for C6033, C6043, C6103, C6133 and C6363, respectively. POD and FAR, which are widely used in forecast verification (Brown et al. 2010), are particularly important for flash

flood forecasting in urban areas (Li and Lai 2004, Barnes et al. 2007, Calianno et al. 2013, Fares et al. 2014). We used the 99th percentile and higher flows as estimated from the observed flow within the period of record for thresholds for POD and FAR. The above threshold was chosen to assess sensitivity in the high-flow regime with at least a dozen or so significant events to work with for each catchment. The final adjustment factors estimated in this way for each catchment are listed in Table 3. That the estimates of β_{q_o} and β_{q_m} are larger than unity for all catchments (see Table 3 and explanations for Fig 10) suggests that the storm drains increase peak flow and reduce time to peak. The estimates of β_p suggest dry biases in the CASA QPE for all catchments. To warm up the model states, the SAC and kinematic wave routing models were run from 1996 to 2013 using the historical data from a combination of Stage 3, which preceded MPE, and MPE. It is well known that the Stage 3 products have significant low biases (Seo et al. 1999, Seo and Breidenbach 2000, Seo et al. 2011). Given the long warmup period, however, the effects of the low bias are expected to be very small for the simulations carried out in this work. For the warmup, the SAC was run at a spatiotemporal resolution of 1/8 HRAP and 15 min for which the MPE estimates were uniformly disaggregated from the native 1-HRAP and 1-hour space and time resolutions.

6 Results

To assess the sensitivity of streamflow simulation to the resolution of precipitation input and hydrologic modeling given the a priori SAC parameters, initial SAC and kinematic wave routing states, we compared streamflow simulations from HLRDHM over a range of spatiotemporal resolutions. Because we are using streamflow observations at the catchment outlet only for evaluation, it is important that the characteristic response time of each catchment be identified so

that the smoothing effects due to spatiotemporal integration of fast runoff may be assessed in interpreting the results. To that end, we derived empirical unit hydrographs (UHG) for the 5 catchments in Fig 5 using the lumped modeling tool for SAC and UHG, the Adjoint-Based OPTimizer (AB_OPT, Seo et al. 2009). AB_OPT estimates the multiplicative adjustment factors to mean areal precipitation (MAP) and mean areal potential evaporation (MAPE), derives empirical UHG, and locally optimizes the SAC parameters. The first two operations are based on variational assimilation (Seo et al. 2003) and the last uses the Sequential Line Search (SLS, Kuzmin et al. 2008). For further details, the reader is referred to Seo et al. (2009). Fig 11 shows the resulting UHGs for the 5 catchments. The figure indicates that C6033, C6043, C6103, C6133 and C6363 have time-to-peaks of 0.75, 0.75, 3, 2.75 and 1.5 hours, respectively. Note also that C6033 and C6103 have bimodal UHGs due to the elongated shape of the catchment and the two tributaries having different concentration times, respectively (see Figs 5 and 6). C6033 (40.2 km²) has the fastest rising limb due presumably to a combination of large slopes and large impervious areas particularly near the catchment outlet (see Fig 7). While smaller and more impervious, C6043 (3.4 km²) does not exhibit as fast a rising limb as C6033 due presumably to significantly lower slopes. While much larger in size, C6033 has a time-to-peak of only about 45 min, which is comparable to that of much smaller C6043. It is evident from the UHG analysis that, even for streamflow predictions only at the outlets of relatively large catchments, high temporal resolution modeling is necessary in the study area due to the fast response and small time-to-peak.

6.1 Sensitivity to spatial resolution

To assess the sensitivity of streamflow simulation to the spatial resolution of precipitation input and hydrologic modeling, simulations were carried out at resolutions of 1/2, 1/4, 1/8 and 1/16 HRAP, corresponding to 2 km, 1 km, 500 m and 250 m, respectively. The temporal resolution was fixed at 15 min, which corresponds to the resolution of streamflow observations. To assess the sensitivity of the peak flow, the timing of peak flow, and the runoff volume to spatial resolution, we examined the peak flow simulation error (=simulated peak flow - observed peak flow) as a function of the observed peak flow, timing error (=simulated time-to-peak - observed time-to-peak) as a function of the observed peak flow, and volume error (=simulated flow volume - observed flow volume) as a function of the observed flow volume, respectively, at different spatial resolutions for all significant events in the simulation period. Fig 12 shows examples of the peak flow simulation error as a function of the observed peak flow for the CASA QPE- (left) and MPE-forced (right) simulation results for C6103 (32.0 km²). The CASA QPE-forced simulations show somewhat larger sensitivity to spatial resolution. The magnitude and direction of sensitivity, however, vary among the 5 catchments with little or no pattern. The timing and volume errors show little sensitivity to spatial resolution for all 5 catchments. Fig 13 shows the cross correlation between the observed and simulated flows, and RMSE and ME of simulated flows forced by CASA QPE (in black) and MPE (in red) as a function of spatial resolution for all catchments. In general, the MPE-forced simulations show somewhat higher correlation than the CASA QPE-forced. Note that the CASA QPE-forced simulations show much lower correlation at 1/2 HRAP than at higher resolutions. This is because, at a very coarse resolution, the number of grid boxes in the catchment area is very small and the large grid boxes cannot accurately delineate the catchment. The small sample size (i.e. the number of grid boxes)

over a highly erroneous support (i.e. the catchment area) results in large errors in estimation of catchment-wide precipitation, and hence produces large errors in runoff and streamflow. The MPE-forced simulation, on the other hand, is not very susceptible to such errors because MPE precipitation is spatially uniform at the HRAP scale and, as such, its estimation of catchment-wide precipitation is largely immune to the sample size or goodness of catchment delineation. At resolutions higher than $\frac{1}{2}$ HRAP, the quality of CASA QPE-forced simulations increases greatly due to improved sampling and catchment delineation, and shows only modest sensitivity to spatial resolution. That the MPE-forced simulations have higher correlation than the CASA QPE-forced is probably aided by that fact that the routing parameters of HLRDHM were calibrated using the MPE-forced simulations (see Table 3). The CASA QPE-forced simulations, on the other hand, have somewhat smaller ME than the MPE-forced, which is probably aided by the bias adjustment applied to the CASA QPE (see Table 3). Recall that the MPE product already reflects rain gauge-based bias correction (Seo et al. 1999) as well as radar-gauge merging (Seo 1998) and does not have significant mean field bias in the study area (Rafieeiniasab et al. 2014b). In Fig 13, the differences in correlation between the CASA QPE- and MPE-forced simulations are negligible to marginal at resolutions higher than $\frac{1}{2}$ HRAP. That the correlation of the CASA QPE-forced simulations are lower than that of the MPE-forced nevertheless supports the hypothesis that the random errors in CASA QPE are nonlinearly transformed at the resolution of modeling and accrue spatiotemporally to result in reduced skill in areal runoff and streamflow (see Fig 1). The RMSE results, which collectively reflect correlation, ME and bias in variability (Nelson et al. 2010), indicate that a spatial resolution of $\frac{1}{8}$ HRAP is a good choice for hydrologic modeling using HLRDHM and CASA QPE in the study area. To relate the above observations to hydrograph simulations, we show in Fig 14 the scatter plots of simulated flow at

spatial scales of 1/2, 1/4, 1/8 and 1/16 HRAP forced by the CASA QPE and MPE for C6363 (14.4 km²), respectively, vs. the observed flow. Note the very poor result for the CASA QPE-forced simulation at 1/2 HRAP, and the generally reduced scatter associated with the MPE-forced simulations except for the largest event, for which the CASA QPE-forced simulation is somewhat better than the MPE-forced at resolutions of 1/8 and 1/16 HRAP. The latter observation may be explained by the magnitude-dependent accuracy of the CASA QPE and MPE; Rafieeiniasab et al. (2014b) showed that, in general, the CASA QPE is more accurate for larger precipitation amounts whereas the MPE estimates are more accurate for smaller amounts in the study area.

The results above pertain to the accuracy of streamflow simulation in the temporally univariate sense only. To assess how closely the simulated streamflow may capture the temporal variability of observed streamflow (and hence time-integrated flow), we estimated and examined the semi-variograms of observed and simulated streamflows. If the simulated streamflow mimics the temporal variability of observed streamflow closely, their semi-variograms would be similar. Fig 15 shows the semi-variograms of the observed (in black) and simulated (in color) streamflow at the outlet of C6043 and C6103 (see Fig 5) forced by the CASA QPE and MPE at all spatial resolutions. The results for other catchments are, in general, qualitatively similar to those for C6103 and are not shown. The temporal resolution used in these simulations is 15 min which corresponds to the resolution of the observed streamflow. C6043 is by far the smallest (3.4 km²) and contributes to C6103 (32.0 km²) through one of the two main tributaries of the latter. With reduced smoothing effects, C6103 offers a tough test for reproducing temporal variability. Fig 15 indicates that the simulated streamflow for C6043 does not very well capture the temporal variability of the observed streamflow at any resolution. Note that the semi-variograms of the

471 simulated streamflows are too regular near the origin (Journel and Huijbregts 1978) compared to
472 that of the observed streamflow which quickly loses temporal correlation. Nonetheless, the
473 CASA QPE-forced simulations at higher than $\frac{1}{2}$ HRAP resolution show temporal correlation
474 structure that is significantly closer to that of the observed at time scales of less than a few to
475 several hours. The above observations indicate that streamflow simulations forced by the high-
476 resolution CASA QPE are able to represent the temporal variability of observed streamflow
477 significantly better than the MPE-forced simulations, but that both are too smooth at the time
478 scale of the fast response of the basin while over-simulating variability at larger time scales.
479 Possible explanations for the second observation may include underestimation of PCTIM and
480 less than accurate modeling of infiltration excess by SAC, and lack of explicit storm drain
481 modeling. Modeling and field work are continuing in the study area and elsewhere in DFW to
482 address the above questions and the findings will be reported in the near future. The results for
483 C6103 indicate that the CASA QPE-forced simulations exhibit larger sensitivity to spatial
484 resolution than the MPE-forced, and that the former closely reproduces the temporal variability
485 of the observed streamflow at $\frac{1}{8}$ HRAP or higher resolution whereas the latter does not,
486 regardless of the spatial resolution of hydrologic modeling. Note also that the variability of the
487 CASA QPE-forced simulations approaches that of the observed streamflow increasingly closely
488 as the spatial resolution increases from $\frac{1}{2}$ to $\frac{1}{8}$ HRAP, but that there is little difference in
489 variability between $\frac{1}{8}$ and $\frac{1}{16}$ HRAP. The latter observation supports the earlier finding that
490 $\frac{1}{8}$ HRAP is a good choice in the modeling and prediction framework of this work.

6.2 Sensitivity to temporal resolution

Analysis for sensitivity to temporal resolution was performed for 60, 30, 15, 5 and 1 min. Spatial resolution was fixed at 1/8 HRAP throughout. To render sampling and sample size identical for all simulations, we primarily considered the streamflow results valid at the top of the hour for all cases. To aid interpretation at smaller time scales, however, we also examined the semi-variograms at 15 min scale at temporal resolutions of 1, 5 and 15 min. Fig 16 shows the peak streamflow simulation error (=simulated peak flow – observed peak flow) for C6103 as a function of the observed peak flow for significant events at different temporal resolutions. The timing and volume errors in flow simulation show little sensitivity to temporal resolution and are not shown. Fig 16 indicates that, the higher the temporal resolution is, the larger the simulated peak flow is, and that the sensitivity is somewhat larger for the CASA QPE-forced simulations of streamflow than for the MPE-forced, a reflection of the fact that the former has a larger dynamic range due to the added spatiotemporal variability in precipitation forcing. Fig 17 is the same as Fig 13 but at temporal resolutions of 60, 30, 15, 5 and 1 min. As in Fig 13, the MPE-forced simulations show marginally higher correlation with the observed than the CASA QPE-forced. Unlike the sensitivity to spatial resolution, however, both the correlation and RMSE deteriorate as the temporal resolution increases past 15 min for both the CASA QPE- and MPE-forced simulations. This probably reflects reduced effects of averaging of random errors, or smoothing, as the temporal resolution increases. It is possible, however, that the above may also be an indication that the SAC model dynamics do not scale well at temporal resolutions higher than 15 min. We note here that high-resolution soil moisture and water level sensors are being deployed in the study area for investigation and the results will be reported in the near future. Fig 17 also shows that, for the fast-responding C6033, the maximum correlation occurs at a temporal

resolution of 15 to 30 min for both the CASA QPE- and MPE-forced simulations. For the smallest C6043, the maximum correlation occurs at a temporal resolution of 30 min for the CASA QPE-forced simulation. The above results are consistent with the UHG results and support the hydrologic characterization of the catchments described at the beginning of this section. For C6043, the increasing correlation for the MPE-forced simulations for increasing time resolution is unexpected and is likely to be an artifact of sampling. For the more slowly responding C6103, C6133 and C6363, the maximum correlation occurs at a temporal resolution of 60 min and decreases as the temporal resolution increases. This is due to the fact that the time-to-peak for these catchments is larger than an hour (see Fig 9), and that the smoothing effect of routing is larger at lower temporal resolutions. To resolve and ascertain sensitivity to temporal resolution for these catchments, it is necessary to observe streamflow at subcatchment scales. Work is under way to deploy additional hydrologic sensors in the area and elsewhere in DFW to address the above and related questions.

Similar to Fig 15, Fig 18 shows the semi-variograms of the observed (in black) and simulated (in color) streamflow at the outlets of C6043 and C6103 at different temporal resolutions. Being a very small basin (3.4 km^2), C6043 shows little structure in temporal variability at the hourly scale. Fig 18 indicates that, for C6043, neither the CASA QPE- nor MPE-forced simulations are able to capture the observed variability very well. Nevertheless, it is readily seen that the CASA QPE-forced simulations at temporal resolutions of 1- to 15-min represent the observed variability significantly better than the MPE-forced, and that the former exhibit larger sensitivity to temporal resolution. For C6103, the CASA QPE-forced simulation at temporal resolution of 15 min captures the temporal variability of observed streamflow very well at time scales of a few hours or less. The MPE-forced simulations, on the other hand, are not able

to capture the observed variability regardless of the temporal resolution. Collectively, the above observations indicate that a resolution of about 15 min is necessary to capture the temporal variability in observed streamflow for the catchments studied in this work but that, to resolve fast-rising streamflow, a higher temporal resolution is necessary. It was also observed that, due to the nonlinear transformation of errors in QPE and in hydrologic models, a higher temporal resolution may not translate into improved accuracy, and that there are trade-offs to consider for flash flood forecasting in large urban areas among resolution, timeliness of prediction and prediction accuracy.

7 Conclusions and future research recommendations

To assess the sensitivity of streamflow simulation to the spatiotemporal resolution of precipitation input and hydrologic modeling, a conditional sensitivity analysis was carried out. Streamflow was simulated for 5 urban catchments (3.4 to 54.6 km²) in the Cities of Fort Worth, Arlington and Grand Prairie in the DFW area using HLRDHM. The spatiotemporal resolution of precipitation ranged from 1/16 HRAP (~250 m) and 1 min to 1/2 HRAP (~2 km) and 60 min, and the spatial resolution of the Permanent Impervious Area (PCTIM) and two kinematic routing model parameters varied from 1/16 HRAP to 1/2 HRAP. The precipitation data used are the quantitative precipitation estimates (QPE) from the Collaborative Adaptive Sensing of the Atmosphere (CASA) X-band radar deployed at the University of Texas at Arlington and the Multisensor Precipitation Estimator (MPE, Fulton et al. 1998, Seo et al. 2010, Kitzmiller et al. 2011) operated by the NWS West Gulf River Forecast Center (WGRFC) in Fort Worth, TX. The CASA QPE and MPE have resolutions of 500 m-1min and 4 km and 1 hr, respectively. HLRDHM was executed with the SAC-HT and kinematic wave routing model and initialized

559 using the historical Stage 3 and MPE data with a warm-up period of 16 years. The streamflow
560 simulation results were evaluated using streamflow observations derived from the water level
561 measurements made by the High Water Warning Systems (HWWS) of the City of Grand Prairie.
562 The rating curves used were derived from the one-dimensional steady-state non-uniform
563 hydraulic modeling method of Kean and Smith (2004, 2005, 2010).

564 The unit hydrograph analysis using the Adjoint-Based OPTimizer (AB_OPT, Seo et al. 2009)
565 indicated that the 5 catchments have time-to-peaks of approximately 0.75 to 3 hrs. The smallest
566 time-to-peak of 0.75 hrs was associated with the smallest (3.4 km^2) and the second-largest (40.2
567 km^2) catchment, the latter of which responds very quickly due to large slope and imperviousness.
568 The UHG results illustrate the importance of high temporal resolution modeling in large urban
569 areas due to the fast response and small time-to-peak even for relatively large basins. The
570 analysis of sensitivity to spatial resolution indicates that the CASA QPE-forced flow simulations
571 are more sensitive to variations in spatial resolution than the MPE-forced. The magnitude and
572 direction of sensitivity, however, vary significantly among the catchments with little or no
573 pattern. The timing and volume errors show little sensitivity to spatial resolution for all 5
574 catchments. The MPE-forced simulations show generally higher correlation, albeit only
575 marginally, than the CASA QPE-forced. This is likely due to nonlinear transformation of the
576 random errors in the high-resolution CASA QPE and the accretion of resulting non-cancelling
577 errors under spatiotemporal integration which reduces skill in prediction of areal runoff and
578 streamflow.

579 The semi-variogram analysis for the smallest catchment (3.4 km^2) indicates that the
580 streamflow simulations forced by the high-resolution CASA QPE represent the temporal
581 variability of observed streamflow significantly better than the MPE-forced, but that both are too

smooth at the time scale of the fast response of the basin while over-predicting variability at larger time scales. Possible reasons for the above may include less-than-accurate modeling of PCTIM and infiltration excess in SAC, and lack of explicit storm drain modeling. The results for the larger catchments show that the CASA QPE-forced flow simulations exhibit larger sensitivity to spatial resolution than the MPE-forced, and that the former closely reproduces the temporal variability of the observed streamflow at resolutions of 1/8 HRAP or higher whereas the latter does not, regardless of the spatial resolution of hydrologic modeling. The variability of the CASA QPE-forced simulations closely approaches that of the observed streamflow as the spatial resolution increases from 1/2 to 1/8 HRAP, but that there is little difference between 1/8 to 1/16 HRAP for the basins studied. The above results suggest that a spatial resolution of 1/8 HRAP is a good choice for the study area using the modeling and prediction framework described in this work.

Analysis of sensitivity to temporal resolution indicates that, the higher the temporal resolution is, the larger the simulated peak flow is, and that the sensitivity is larger for the CASA QPE-forced flow simulations than for the MPE-forced, a reflection that the former has a larger dynamic range due to the added spatiotemporal variability in precipitation forcing. The timing and volume errors in simulated flow, on the other hand, show little sensitivity to temporal resolution. Both the correlation and RMSE of simulated streamflow deteriorate as the temporal resolution increases past 15 min for both the CASA QPE- and MPE-forced simulations due presumably to reduced averaging of random errors. The above finding, however, may also be an indication that the SAC model dynamics does not scale well at temporal resolutions higher than 15 min. For fast-responding catchments, maximum correlation occurs at temporal resolutions of 15 and 30 min. For more slowly responding catchments, maximum correlation occurs at a

temporal resolution of 60 min and decreases as the temporal resolution increases. The latter observation is due to the fact that the time-to-peak for the more slowly-responding catchments is larger than an hour, and that the smoothing effect of routing is larger at lower temporal resolutions.

The semi-variogram analysis at different temporal resolutions indicates that, for the smallest catchment (3.4 km²), neither the CASA QPE- nor MPE-forced flow simulations reproduce the observed variability very well, but that the CASA QPE-forced simulations at temporal resolutions of 1- to 15-min represent the observed variability much more closely than the MPE-forced. For the larger catchments, the CASA QPE-forced simulations at temporal resolution of 15 min capture the temporal variability of observed streamflow well at time scales of a few hours or less. The MPE-forced simulations, on the other hand, are not able to capture the observed variability at any temporal resolution. The above observations indicate that a temporal resolution of at least 15 min is necessary to capture the temporal variability of observed streamflow but that, for fast-responding basins, a higher resolution is necessary to resolve fast-rising hydrographs. Due to the nonlinear accretion of random errors in QPE and imperfect model dynamics, however, there are trade-offs to consider among resolution, timeliness of prediction, and prediction accuracy in flash flood forecasting in large urban areas. It is important to point out that the above results are based on minor to moderate flash flooding events that are usually associated with flooded roads and/or isolated highwater rescues. They do not, however, reflect extreme events. The forecast system described in this work operated in real time in May 2015 during which record-breaking rainfall events caused extreme flooding in DFW. We plan to carry out performance evaluation for the extreme events and the results will be reported in the near future.

To further resolve and ascertain the sensitivity of temporal resolution for the catchments in the study area, it is necessary to observe streamflow at subcatchment scales. We note here that work is underway to deploy additional water level sensors in selected catchments in the study area and elsewhere in DFW to address the above and related questions. To explain and address the relatively poor prediction of temporal variability in streamflow simulation for the smallest catchment, it is necessary to examine the realism of infiltration-excess modeling in SAC, accuracy of impervious cover, and impact of storm drains. We note here that, in addition to water level sensors, high-resolution soil moisture sensors are being deployed in the study area to investigate the above questions, and that hydraulic modeling of storm drains is being carried out in selected catchments. Finally, the findings from this work are conditional on the particular choice of the models, catchments and data sets used. Given that every model or basin is unique (Beven 2000) and that each model is subject to structural uncertainties of varying nature and magnitude in addition to the parametric and input uncertainties partially considered in this work, one may expect the optimum resolution to vary depending on the choice of the models as well as the choice of the basins. To ascertain such variations, multi-model analysis (Georgakakos et al. 2004) using more diverse urban catchments is necessary.

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Fig. 1. Relative error in streamflow simulation at the catchment outlet as a function of the scale of subbasin delineation and the magnitude of error in precipitation input.

Fig. 2. Model domain encompassing the Cities of Fort Worth, Arlington and Grand Prairie in north Texas, the coverage area of XUTA and the nominal range of KFWS.

Fig. 3. PCTIM at 1/16 HRAP resolution in the study area.

Fig. 4. Derived flow directions at different resolutions over the model domain.

Fig. 5. Catchments used in the evaluation in the Cities of Arlington and Grand Prairie.

Fig. 6. Terrain and storm drain networks (in green) in the study basins.

Fig. 7. PCTIM in the study basins.

Fig. 8. The empirical cumulative probability distribution functions (ECDF) of bankfull flow in the storm drainage open channels (blue), fully-charged flow in the storm drainage pipes (green), and HLRDHM-simulated flow in the natural channels in the Johnson Creek Catchment due to remnants of Tropical Storm (TS) Hermine in Sep 2010 (black).

Fig. 9. Rating curves derived via the Kean and Smith method (black) and HLRDHM (red). The empty circles plot observed stage vs. HLRDHM-simulated flow.

Fig. 10. Impact of uniformly adjusting q_0 and q_m on timing and magnitude of peak flow at the outlet of C6133 for the June 16-19, 2013, event.

Fig. 11. AB_OPT-derived empirical unit hydrographs (UHG) of the study catchments.

Fig. 12a. Peak flow simulation error for C6103 as a function of observed peak flow for CASA QPE-forced simulations at different spatial resolutions.

Fig. 12b. Same as Fig 12a but for MPE-forced simulations.

Fig. 13. Cross correlation between observed and simulated flows (left), and RMSE (middle) and ME (right) of simulated flows forced by CASA QPE (black) and MPE (red) as a function of spatial resolution for all catchments.

Fig 14a. Scatter plots of simulated flow forced by CASA QPE vs. observed for C6363 at spatial resolutions of $\frac{1}{2}$ (upper-left), $\frac{1}{4}$ (upper-right), $\frac{1}{8}$ (lower-left) and $\frac{1}{16}$ (lower-right) HRAP.

Fig 14b. Same as Fig 14a but for MPE-forced simulations.

Fig 15a. Semi-variograms of observed (black) and simulated (color) streamflow at the outlet of C6043 forced by CASA QPE at all spatial resolutions.

Fig 15b. Same as Fig 15a but for MPE-forced simulations.

Fig 15c. Same as Fig 15a but for C6103.

Fig 15d. Same as Fig 15b but for C6103.

Fig 16a. Same as Fig 12a but for different temporal resolutions.

Fig 16b. Same as Fig 12b but for different temporal resolutions.

Fig 17. Same as Fig 13 but for temporal resolutions of 60, 30, 15, 5 and 1 min.

Fig 18a. Same as Fig 15a but for different temporal resolutions.

Fig 18b. Same as Fig 15b but for different temporal resolutions.

Fig 18c. Same as Fig 15c but for different temporal resolutions.

Fig 18d. Same as Fig 15d but for different temporal resolutions.

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Table 1. GIS layers used in estimation of PCTIM for the Cities of Fort Worth, Arlington, and Grand Prairie.

Layer	Fort Worth	Arlington	Grand Prairie
Building footprint	Included	included	Included
Impervious cover, commercial	Included (parking lots for commercial buildings)	Not included	Included (parking lots for commercial buildings)
Pavement	Included (streets only)	Included (all streets and parking lots)	Not included
Centerline of sidewalks	Included (width of 6.5 ft assumed)	Not included	Not included
Centerline of streets	Not included	Not included	Included (width of 12 ft assumed)

Table 2. D_{84} at different locations in the study area.

D_{84} (mm)	Location	Water level sensors
15.0	Arbor Creek, Grand Prairie, TX	6043
15.0	Cotton Wood Creek, Grand Prairie, TX	6103, 6363
20.0	Warrior Creek, Grand Prairie, TX	
30.0	Fish Creek, Grand Prairie, TX	6133

Table 3. Multiplicative adjustment factors for precipitation (P), specific discharge (q_o) and exponent (q_m).

Catchment	β_P	β_{q_o}	β_{q_m}
6033	1.3	1.1	1.5
6133	1.1	1.1	1.1
6103	1.3	1.0	1.1

Table-Marked

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Response to Reviewer 1's comments on "Toward high-resolution flash flood prediction in large urban areas - Analysis of sensitivity to spatiotemporal resolution of rainfall input and hydrologic modeling" by Arezoo Rafieeiniasab et al.

Reviewer 1's Comment 1: More specifically, this study showed an existence of an optimal spatial and temporal resolution of radar rainfall based on one model and five test catchments. The basic question goes like this. Will the optimum be changed if we use a different model applied to a different catchment with different catchment scale? It is quite reasonable to expect an appropriate modeling resolution that reproduce hydrographs depending on the catchment scale. What if pursuing a relative modeling resolution compared to catchment scale and model complexity?

Authors' Response: We very much appreciate the reviewer's careful reading of the manuscript and the very helpful comments.

The "optimal" resolution necessarily depends on the scale of the contributing area at the outlet where streamflow prediction is desired. If the contributing area is very large such that the model may not have to resolve smaller-scale processes (i.e., variations due to certain smaller-scale processes may average out over some larger scale), the optimal resolution could be lower. If, on the other hand, the contributing area is very small, the optimal resolution would be higher, assuming that the model is capable of resolving the processes that are important at that scale. The results presented and the conclusions drawn in this work are necessarily limited to the 5 urban catchments in the study area and the particular choices of model and data used, which is now clearly stated in the revised manuscript.

Regarding the Reviewer's 2nd question, we would like to distinguish "model complexity" from modeling resolution. A model can be complex but may lack skill, or it may be simple but skillful over a range of resolutions. For example, visual examination of the physiography of the study area suggests that, to resolve the spatial variability of impervious cover, a spatial resolution of about 250 m or higher is necessary. Because runoff generation is highly nonlinear, one may not expect lower- and higher-resolution modeling to produce comparable results. As such, we do not consider the relative modeling resolution concept readily viable in a physically-based modeling approach.

It is well known that, in addition to the spatial resolution of the physiographic controls, the spatiotemporal resolution of the forcings, in particular, that of precipitation determines the optimal resolution of modeling. For example, Berne et al. (2004) investigated rainfall resolutions required for urban hydrological applications and concluded that urban basins of the order of 1000 ha (10 km²) require a resolution of 5 min and 3 km for rainfall and those of the order of 100 ha (1 km²) requires a resolution of 3 min and 2 km. More recently, Bruni et al. (2015) studied sensitivity of urban hydrodynamic modeling on spatiotemporal resolution of rainfall, and found that time to maximum water depth at the outlet varies with changes in the spatiotemporal resolution of rainfall. As noted in the manuscript, the work presented is "conditional" on the choice of the particular models, catchments and data sets used. Given that every model and basin

are unique (Beven 2000) and that, in addition to the parametric and input uncertainties described above, each model is subject to structural uncertainties of varying nature and magnitude, one may expect the optimum resolution to vary according to the choice of model as well as to the choice of the basin. As the Reviewer is hinting at, a worthy topic for future research would be multi-model analysis (Georgakakos et al. 2004) using more diverse urban catchments. This is now mentioned in the revised manuscript for future research.

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Reviewer 1's Comment 2: Second, this study looked into an urban catchment which has storm drains from 76 mm to 2,440 mm in size. However, are they well represented in the distributed model, this study based on? That is the second question. As shown in lines 227-229, and 301-305, this study adopts uniform multiplicative adjustment factors to minimize modeling errors and, in this manner, the performance of storm drain network was aggregated into channel routing, which is based on kinematic wave routing. However, it should be noted that the urban drainage networks has complex nonlinear characteristics in terms of hydrologic response. It would be better to suggest any hydrographs that show the effect of the uniform adjustment and also suggest prior examples of application of HLRDHM to urban catchments.

Authors' Response: We have added two figures and a significant amount of text in the revised version of the manuscript to address the reviewer's comments. HLRDHM does not model storm drains explicitly. It does reflect, however, storm drainage open channels that can be resolved in kinematic wave modeling of open channels. In the study area, storm drainage open channels, which are generally built on the natural open channels, are much more important for flood prediction than storm drainage pipes. We have newly added Fig 8 in the revised manuscript to assess the relative importance between the two and to provide a reference frame on how the conveyance capacity of the storm drains may compare with flow in natural channels for a very significant flooding event.

We agree with the reviewer's comment that the urban drainage networks have complex nonlinear characteristics in terms of hydrologic response. In our opinion, however, the gain from a very detailed modeling of storm drains is relatively modest for flash flood

forecasting in large urban areas as may be inferred from the newly added Fig 8. Also, for slope-dominated flows, the gain from dynamic wave modeling may not justify the additional complexity and computational cost, except in specific areas where the additional nonlinear effects may be important. Note that the widely used HEC1 program, which is based on kinematic wave modeling, has been successfully applied to many urban areas (HEC 1993). As the reviewer suggested, we have newly added Fig 10 to illustrate how the uniform adjustment factors, β_{q_o} and β_{q_m} , may be used in lieu of more detailed and complex modeling to modify the hydrograph response at the catchment outlet. We have also added Cosgrove et al. (2012) as a reference for application of HLRDHM in urban areas.

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Reviewer 1's Comment 3: Figures should have titles.

Authors' Response: According to the Journal of Hydrology's author information pack (<http://www.elsevier.com/journals/journal-of-hydrology/0022-1694?generatepdf=true>), the figures are not to include titles.

Reviewer 1's Comment 4: Please plot lines distinguishable (Figure 9, 16; now Figs 11 and 18).

Authors' Response: The plots have been improved as suggested.

Reviewer 1's Comment 5: Please include legends (Figure 11, 15; now Figs 13 and 17).

Authors' Response: The figures are explained in the figure captions. Please note that the plots are too small to include legends.

Reviewer 1's Comment 6: Figure 11, 15 (now Figs 13 and 17) is hard to read.

Authors' Response: The figures will be enlarged in the production stage without loss of resolution.

Response to Reviewer 2's comments on "Toward high-resolution flash flood prediction in large urban areas - Analysis of sensitivity to spatiotemporal resolution of rainfall input and hydrologic modeling" by Arezoo Rafieeinasab et al.

Reviewer 2's Comment 1: I understand it as the urban drainage runoff is neglected in the hydrological modeling approach. This is rather critical considering that the scope of the study is predicting flash flooding in urban areas and that the studied urban area is densely populated. The urban catchments have significantly different runoff response than rural areas and its functionality often relies on its ability to release water to receiving streams. I fully understand the complications of including a fully distributed urban drainage model system into the modeling approach, but as it is now, it is rather unclear to what extent the urban drainage response is accounted for.

Authors' Response: We recognize that the original version of the manuscript did not fully explain to what extent the urban drainage response is accounted for. To address the reviewer's comments, we have added two figures (Figs 8 and 10) and a significant amount of text in the revised manuscript (pages 12 and 16 in particular) as summarized below.

HLRDHM does not model storm drains explicitly. It does reflect, however, storm drainage open channels that can be resolved in kinematic wave modeling of open channels. In the study area, storm drainage open channels, which are generally built on the natural open channels, are much more important for flood prediction than storm drainage pipes. We have newly added Fig 8 in the revised manuscript to assess the relative importance between the two and to provide a reference frame on how the conveyance capacity of the storm drains may compare with flow in natural channels for a very significant flooding event.

Even though storm drains are not explicitly modeled, their effects are accounted for in this work to the extent that uniform multiplicative adjustment of the two spatially-varying kinematic channel routing parameters, q_0 and q_m , may allow. Note that the storm drains discharge into the natural channels and hence modify the flows therein. We used the adjustment factors, β_{q_0} and β_{q_m} , in lieu of more detailed and complex modeling, to reflect bulk modifications to the hydrograph response at the catchment outlet due to storm drains. In the revised manuscript, we have newly added Fig 10 which illustrates how the application of the adjustment factors may change the timing and magnitude of peak flow in one of the catchments studied. Admittedly, such spatially uniform adjustment is less likely to yield skillful simulations at interior locations than at the outlet. This is now acknowledged in the revised manuscript (page 17) along with the additional explanations.

Reviewer 2' Comment 2: It is also unclear to the reader if any of the measured and modelled streamflows are causing flooding. I hope that flooding of the study area is rare and that it is only occurring under extreme conditions with intense and long lasting rainfall. However, is the input and model sensitivity under flooding events similar to daily events? Or could decisions on input and model resolution that are based on the

'normal' occurring event be a problems under extreme flooding events? It is difficult for the reader to assess whether the conclusions is fully valid for extreme events as well.

Authors' Response: We very much appreciate this very important comment. The study area in the Dallas-Fort Worth Metroplex (DFW) is within the so-called Flash Flood Alley and flash flooding is fairly common. The focus of our study was on being able to predict flash flooding events with a return period of 2 years or larger. Recall that the Flash Flood Guidance (FFG) produced by NWS uses the 2-yr return period as a nominal threshold for flash flooding.

While 2013 was not a wet year for north central Texas, there were a number of significant flash flooding events in the study area in the months of Apr, Jun and Sep that are usually associated with flooded roads and isolated high water rescues. The largest, which was estimated by DHM-TF to have produced streamflow of up to a 10-yr return period within the study area, occurred on Sep 20 due to a slow-moving system which dumped over 120 mm of rainfall over parts of the City of Arlington. There were, however, no “extreme” events in 2013 and, as such, it was not possible to assess performance for such events in this work. During the record-breaking rainfall period of May 2015, the forecast system operated in real time. Once the verifying ground observations are collected from various sources, we plan to assess performance for the multiple extreme flooding events occurred in that period. We have added in the revised manuscript the above comments to qualify our conclusions and to describe the plan for performance evaluation for extreme events.