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Statistical analysis of error propagation from radar rainfall to hydrological models

D. H. Zhu¹, D. Z. Peng², and I. D. Cluckie¹

¹Department of Civil Engineering, Swansea University, Swansea, UK ²College of Water Sciences, Beijing Normal University, Beijing, China

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Correspondence to: D. Z. Peng (dzpeng@bnu.edu.cn)

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Abstract

This study attempts to characterize the manner with which inherent error in radar rainfall estimates input influence the character of the stream flow simulation uncertainty in validated hydrological modelling. An artificial statistical error model described by

- Gaussian distribution was developed to generate realizations of possible combinations of normalized errors and normalized bias to reflect the identified radar error and temporal dependence. These realizations were embedded in the 5 km/15 min UK Nimrod radar rainfall data and used to generate ensembles of stream flow simulations using three different hydrological models with varying degrees of complexity, which consists
- of a fully distributed physically-based model MIKE SHE, a semi-distributed model TOP-MODEL and a lumped model PRTF. These models were built for this purpose and applied to the Upper Medway Catchment (220 km²) in South-East England. The results show that the normalized bias of the radar rainfall estimates was enhanced in the simulated stream flow and also the dominate factor that had a significant impact
- ¹⁵ on stream flow simulations. This preliminary radar-error-generation model could be developed more rigorously and comprehensively for the error characteristics of weather radars for quantitative measurement of rainfall.

1 Introduction

Recently, the advances of radar rainfall estimates with high spatial and temporal reso lution have demonstrated the prospect of improving the accuracy of rainfall inputs on which the accuracy of stream flow simulation and real-time flood forecasting through hydrological models depends. There is a wide range of studies have focused on using weather radars for quantitative measurement of rainfall in various hydrological models in order to evaluate the radar performance in different hydrological applications,
 especially in flood forecasting (Collier and Knowles, 1986; Owens, 1986; Cluckie and Owens, 1987; Cluckie et al., 1989; Bell and Moore, 1998; Borga, 2001; Carpenter





et al., 2001; Tachikawa et al., 2003; Hossain et al., 2004; Reichel et al., 2008; Zhu and Cluckie, 2011). And particularly the value of radar-based data from the UK Nimrod system has been highlighted repeatedly, for example, in two severe flooding events during 1998 (at Easter over the Midlands and in late October over Wales), estimates of surface rainfall derived from radar data provided evidence of the extent and severity of the rainfall events.

However, the advantage of the weather radar rainfall estimates has been limited by a variety of sources of uncertainty exists in radar reflectivity process, including random and systematic errors, such as the hardware calibration, which acquires accurate measurements of transmitted power, bandwidth, antenna gain, wavelength and pulse width (Probert-Jones, 1962; Battan, 1973), the deflection of the radar beam (anomalous propagation), non-meteorological echoes (clutter), signal attenuation, orographic enhancement, radar beam overshooting, variation of the vertical profile of reflectivity (VPR), extrapolation of the measurements to the ground, drop size distribution, *Z-R*

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relationship, sampling effects and bright band, all of which can be referred to the numerous of discussions of radar rainfall estimation errors (Harrold et al., 1974; Browning, 1978; Wilson and Brandes, 1979; Duncan et al., 1993; Fabry et al., 1992, 1994; Kitchen, 1997; Krajewski and Smith, 2002; Rico-Ramirez et al., 2007).

More importantly, all these radar-related errors cannot be separated from the model

errors when radar rainfall estimates are inputted to the hydrological models, and therefore the added benefit of radar rainfall data was devalued. Although corresponding correction techniques can be applied to improve the quality of the radar rainfall estimation (Collier et al., 1983; Hardaker et al., 1995; Collier, 1996; Fulton et al., 1998; Harrison et al., 2000), the radar rainfall estimates are always at risk of being contaminated by
 the error from different sources due to a great deal of uncertainty.

Therefore, some studies have been conducted to analyze the impact of radar rainfall estimation errors on hydrological applications. Collier and Knowles (1986) suggested that the impact of the errors in the precipitation estimation on the rainfall-runoff process varies, in specific circumstances, the errors will be less in the flow simulation,





but in other circumstances, the error will be magnified. In addition, Wyss et al. (1990) argued that the errors in runoff predictions are more significantly caused by the errors introduced in the transformation of rainfall to runoff than the errors of radar-estimated precipitation input. Winchell et al. (1998) concluded that the errors in radar rainfall es-

- timates can be separated into two categories: the errors come from the conversion of reflectivity to rainfall and the errors due to the misrepresentation of rainfall field in spatial and temporal domain. And he pointed out that infiltration-excess runoff generation is much more sensitive than saturation-excess runoff generation to both types of precipitation uncertainty, and the decrease of spatial and temporal resolution will result
- in the significant reduction of predicted flow in infiltration-excess runoff model. Pessoa et al. (1993), Vieux and Bedient (1998) and Morin et al. (2005) analyzed influence of various *Z-R* relationship upon simulated hydrographs and indicated that the differences can be significant. Borga (2002) selected different elevation scan angles to evaluate the impact of VPR on the catchment stream flow through a lumped hydrological model. Vivoni et al. (2007) presented the propagation of radar rainfall nowcasting error
- to flood forecasts in the context of distributed hydrological simulations over a range of catchment size or scales.

The above mentioned studies have only focused on individual sources of the radar error. However, in practical applications, separating and estimating the different sources of radar errors is not possible. Therefore, several researchers employed physically based simulators of radar observations to study the radar-based rainfall error structure and focused on the estimation of total radar uncertainties (Ciach et al., 2007; Habib et al., 2008). Krajewski et al. (1993) and Anagnostou and Krajewski (1997) proposed and extended a physically based simulator of radar observations accord-

²⁵ ing to a two-dimensional time-space stochastic modeling of radar errors, combined with a vertical structure of hydrometeors and a statistically generated drop-size distribution. Sharif et al. (2002, 2004) coupled a physics-based mesoscale atmospheric model, a three-dimensional radar simulator, and a two-dimensional infiltration-excess hydrological model to analyze the radar beam geometric and sampling-related effects.





It showed that radar-watershed-storm orientation-related errors in Horton runoff predictions increase significantly due to range effects, particularly beyond about 80 km. However, the main limitation on the implementation of this approach is the requirement to have access to a dense raingauge network that can be used to approximate "true" 5 surface rainfall (Habib et al., 2008).

In this study, a simplified statistical error model based on empirical random error distribution was constructed to define and quantitative the errors in the radar rainfall estimates through hydrological models with different rainfall-runoff mechanisms. The propagation of radar rainfall estimation errors was assessed by different hydrological models, ranging from fully distributed through semi-distributed to lumped models in the Upper Medway Catchment in Kent, UK. The implication of hydrological model structures on radar errors propagation is illustrated by different integrative nature of the hydrological simulations. Despite its importance, error propagation from national radarbased rainfall data (Nimrod radar rainfall data) to various hydrological simulations has

not been previously addressed in a quantitative mode, which differs from prior studies 15 on the propagation of radar estimation errors. In order to quantify the impact from the radar errors on the stream flow, an ensemble test using 5 km resolution radar rainfall was carried out to measure the influence by adding the artificial noise to the radar measurement data and propagate those perturbed rainfall through the calibrated hy-

drological models, then the characteristic of the radar error can be identified. 20

Study area and experimental data 2

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This hydrological experiment for radar rainfall estimation error propagation was taken place in the Upper Medway Catchment, which is around 220 km² and located south of London; 50 km from the Thurnham Weather Radar site (see Fig. 1). The average annual rainfall and potential evapotranspiration is around 729 mm and 663 mm, respectively. The catchment elevation varies between 30 m and 220 m above mean sea level and the majority of slope ranges from 2 degrees to 8 degrees, which makes up



around 70 % of the whole catchment and it suggests that the main scenery of the Upper Medway Catchment is small hills surrounding the flat, little relief low-lying area without much variation of elevation. The land use in the catchment can be simplified and described as permanent grass (over 95 %). The major soil types can be classified into two

- ⁵ main types: silt loam and clayey silt, according to the National Soil Resources Institute (NSRI, 2006) data. The catchment is characterized by a mixture of permeable (chalk) and impermeable (clay) geologies and the dominant aquifers consist of the Ashdown Formation and the Tunbridge Wells Formation. The saturation-excess mechanism is the major runoff generation process in the catchment.
- The radar rainfall estimates used in this study is extracted from the UK Nimrod composite data set, which was provided and quality controlled by the UK Met Office using the lowest available scan, and has been adjusted by available raingauge measurement and undergone extensive processing to correct for various sources of radar error including noise, clutter, anomalous propagation, attenuation, occultation, "bright band"
- and orographic enhancement, etc. Therefore, this high-resolution radar composite rainfall estimates incorporates the latest UK Met Office processing algorithms to account for the different sources of errors in the estimation of precipitation using weather radars (Harrison et al., 2000), which implies that this data set is the best possible estimate of rainfall at the ground in the UK and can be regarded to be the error-free data. The
- ²⁰ hydrological data was obtained from 9 real-time TBRs (Tipping-bucket raingauge) and resampled to 15 min interval. The Nimrod radar rainfall data was provided by the British Atmospheric Data Centre (BADC) with 5 km/15 min resolution. Figure 1 shows the locations of the raingauges (circles) and the discharge gauges (triangles), the rectangular grid represents the 5 × 5 km² Cartesian national grid of the Nimrod radar data. Due
- to the data availability of radar rainfall, the period from July 2006 to December 2007 (18 months in total) was selected for radar-based rainfall error propagation analysis.





3 Methodology

3.1 Rainfall-runoff models and parameterization

Three hydrological models with different mathematical structures and hydrological mechanisms were selected and constructed on the Upper Medway Catchment, includ-

- ⁵ ing the physically based, fully distributed model: MIKE SHE (Abbott et al., 1986; Refsgaard and Storm, 1995); the semi-distributed model: TOPMODEL (Beven and Kirkby, 1979; Beven and Freer, 2001) and lumped the unit hydrograph model: PRTF model (Han, 1991). All the models chosen have been widely used across the world and are representative of a set of mathematical structures that span from complex to simple
- and reflect a decreasing ability to specifically represent the distributed (spatial) nature of the rainfall-runoff process. The only objective of the Upper Medway models is in constructing a surrogate of the catchment that can be used to study the error propagation from the radar rainfall estimation to the stream flow simulation by different rainfall-runoff procedures, thus the model errors were not taken into account in the comparisons. The
- ¹⁵ purpose of this work is to gain further insight into the interaction between radar-rainfall estimation and corresponding hydrological simulations by considering and evaluating the impact of radar rainfall estimation errors on a set of different rainfall-runoff model structures, instead of inter-comparing a set of hydrological models for a specific flood event or comparing the simulation results from different radar-rainfall processing sce-
- narios. Consequently, all the model errors are assumed to be free so that the uncertainty analysis can be constrained to the quantitative comparison among various radar rainfall estimation error ensembles, the reliability of radar rainfall detection and the model capability of simulation for radar-based rainfall storms.

MIKE SHE is a further developed hydrological modelling system based on the SHE concept, which was introduced in 1976 by three collaborating European organizations (Abbott et al., 1986). MIKE SHE is a complex deterministic model, which covers the entire hydrological system on a catchment scale (Refsgaard and Storm, 1995). The overland flow module in MIKE SHE employs a two-dimensional Saint-Venant equation





to describe the water movement on the surface, and the finite difference method is used to solve this equation. The water movement through the soil profile, along with the evapotranspiration is modelled by a simplified Two-Layer ET/UZ model, which is suited to be applied to the catchment that has a shallow groundwater table and used

- ⁵ in the unsaturated zone to calculate the actual evapotranspiration and the amount of water that recharges the saturated zone. The ground water flow is calculated using the linear reservoir method and this method can be regarded as the balance of the data availability of the geology, the complexity of the groundwater simulation and the benefit from the model simplicity.
- ¹⁰ TOPMODEL (TOPographic Model) developed a topographic index to represent a dynamic saturated area of a basin (Beven and Kirkby, 1979; Beven and Freer, 2001). Since the early 1990s, TOPMODEL has been widely used because it can provide spatially distributed hydrologic information with available input requirements (e.g. DEM data). For a DEM data grid cell, *i*, its topographic index, TI_{*i*}, is calculated as follows:

¹⁵
$$\mathsf{TI}_{i} = \ln \frac{a_{i}}{\tan \beta_{i}}$$

where a_i and $\tan \beta_i$ are the upstream contributing area per unit contour length and the local slope at grid cell *i*, respectively. The model simulates the variable source areas of the catchment, which assumes that overland flow is produced only over a small fraction of the total catchment area. The source areas that produce overland flow are those that become saturated during precipitation events. The dynamics of the saturated source areas is controlled by catchment topographical and subsurface hydraulic characteristics and the state of the catchment wetness.

By contrast to the MIKE and TOPMODEL model, the PRTF model was a pure mathematical model of a dynamic system, which was constructed from the observation data ²⁵ and prior knowledge. PRTF model is an advanced form of rainfall-runoff Transfer Function (TF) model and is unconditionally stable which means the adjustment of any of the model parameters cannot result in model instability or fluctuations in model output



(1)



(Han, 1991). PRTF model is a unit hydrographs type, black-box model which empirically relates rainfall and flow, which can be subject to conceptual interpretation as forms of routing function. Mathematically it represents the simplest structure chosen to transfer the precipitation information to stream flow by replicating the non-linear and time variant nature of the rainfall-runoff process and matching the model response as closely as possible to the catchment response in terms of three real-time adjustment factors (shape, volume and timing). The typical rainfall runoff transfer function model TF can be described by the following formula:

 $y_t = a_1 y_{t-1} + a_2 y_{t-2} + \dots + a_p y_{t-p} + b_0 u_t + b_1 u_{t-1} + b_2 u_{t-2} + \dots + b_q u_{t-q}.$

¹⁰ where a_i , b_i are the model parameters, y_t and u_t are river flow and rainfall rate at t time respectively, and the percentage runoff of the process can be represented by Eq. (2). Due to the lack of availability of radar rainfall data during the model calibration period, the model calibration and validation was carried out using 15 min rain gauge measurements and compared with 15 min observations of discharge at the catchment outlet at ¹⁵ Chafford. This process were performed for a 6 months period (from September 2003 to February 2004), using the first 2 months as a warm-up period, and the remaining 4 months were used to evaluate model outputs.

MIKE SHE was set up using a grid size of 100 m × 100 m. The trial-and-error minimization was employed to calibrate the model. Firstly, the base flow was the main target, the relative base flow controlling parameter, was set in a range and the parameters adjusted by validating the model iteratively. Secondly, the peak flow was taken

- into account and several sensitive parameters are selected in the calibration due to the contribution of the variability of parameters in relation to the peaks (Zhu and Cluckie, 2011). The final calibrated model parameters can be found in Table 1.
- Based on the DEM data, the topography index curve for the basin was calculated. Using TOPMODEL and the topography index curve to the Upper Medway Catchment, the overland flow and base flow was simulated (Beven and Kirkby, 1979; Beven and



(2)



Freer, 2001; Peng and Xu, 2010), and the main parameters of TOPMODEL were listed in Table 2.

The auto calibration function was employed and the identified PRTF model for the Upper Medway Catchment using effective rainfall can be written in the formation of Eq. (3) as below:

$$y_t = 2.866626y_{t-1} - 2.739182y_{t-2} + 0.872468y_{t-3} + 0.0083970u_t.$$
 (3)

with time lag = 15 min and time to peak = 10.799 h where y_t and u_t are recorded river flow and precipitation rate at *t* time, respectively.

Figures 2 and 3 show the comparisons of model performance among MIKE SHE, 10 TOPMODEL and PRTF in model calibration and validation period against the observation stream flow at the catchment outlet (Peng and Du, 2010; Zhu and Cluckie, 2011). And the corresponding statistics for all the models was listed in Table 3.

3.2 Radar rainfall error-ensemble-generation model

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As the noise in radar signals can result in normalized errors, normalized bias or both in the estimated rainfall, a statistical error model was constructed in order to analyze how those errors in the radar based rainfall are transmitted to the stream flow through the rainfall-runoff models.

Two criterions (normalized errors and normalized bias, see Eqs. 4 and 5) were employed to evaluate the impact on the stream flow. In this study, the "true" rainfall was assumed to be the original 5 km radar rainfall data provided by BADC, the "observed" flow was that simulated from the rainfall-runoff models in the Upper Medway Catchment using "true" rainfall as the precipitation input. The normalized error and normalized bias were defined by:





$$\sigma = \frac{\overline{\sum |Q_{\rm O} - Q_{\rm S}|}}{\overline{Q_{\rm O}}}$$

$$\phi = \frac{\overline{\sum (Q_{\rm O} - Q_{\rm S})}}{\overline{Q_{\rm O}}}$$

5

where Q_0 is the observed rainfall or stream flow, Q_S is the simulated measurement.

A simple radar error model (see Eq. 6) was assumed to take account of the normalized error and normalized bias in the original 5 km radar rainfall:

 $R_{\rm P} = \phi R(1 + \sigma).$

where R_{p} is the perturbed radar data, R is the unperturbed radar data.

4 Results and discussion

- The radar error model was set to generate 3 different normalized biases, which was –0.3, 0 (no bias) and 0.3 with various normalized errors (from 0 to 1.0) from a Gaussian distribution (Lukacs and King, 1954). Additionally, this artificial noise was added to radar rainfall for all the radar grids and they varied randomly for each time step during the simulation. Each combined ensemble (one normalized bias and one normalized ¹⁵ error) was repeated 10 times, which produced 157 radar rainfall ensemble members in this study. Therefore, the impact on rainfall and flow from model error and model bias can be seen in Figs. 4 and 5 contour maps, which indicate how the statistical error model affects the normalized errors in rainfall and stream flow and normalized bias in rainfall and stream flow respectively.
- In Fig. 4, the ensemble normalized error in rainfall has different distribution with the normalized error in the stream flows simulated in three models. It shows that the rainfall normalized error can trigger a range of possible corresponding normalized errors in



(4)

(5)

(6)



stream flow. Although the maximum values of the range are quite close to the rainfall normalized error, the minimum values of the range increase along with the enhancement of the rainfall normalized error. Figure 4 also demonstrates the different performance of ensemble simulation in three hydrological models, even though they share the similar error distribution. The propagated normalized errors in distributed model (MIKE SHE) are slightly smaller than the errors produced in the lumped model, TOP-MODEL. However, the normalized errors were constrained more in the unit hydrograph model PRTF than the other two models.

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Contrast to the normalized error distribution showed in Fig. 4, the ensemble nor-¹⁰ malized bias in rainfall has similar distribution with the normalized bias in the stream flows simulated in three models (see Fig. 5). It shows that if the normalized bias of the rainfall raise, the normalized bias of the stream flow would not only follow but also be enhanced, especially when the rainfall normalized bias was above zero. However, this enhancement was relatively smaller when the rainfall normalized bias was below zero.

¹⁵ And similar to the Fig. 4, the propagated bias varies among three hydrological models, the bias enhancement in MIKE SHE distributed model has less than the lumped model, TOPMODEL, but still the PRTF unit hydrograph model has best performance on the bias control, the value of which is almost the same as the bias in the rainfall.

Additionally, the normalized errors in the stream flow; it was mainly influenced by the normalized bias in the rainfall as well. Generally, it was less than the normalized errors in the rainfall, when the normalized bias of the rainfall was not too high, and its value would be very similar to the absolute value of the normalized bias in the stream flow. However, when the normalized bias of the rainfall decreases below zero, the normalized errors in the stream flow would be narrowed, compared to the rainfall paralized errors but its value was bigger than the absolute value of the stream flow.

²⁵ normalized errors, but its value was bigger than the absolute value of the steam flow normalized bias.

Regarding the different error propagation through hydrological models, the distributed model MIKE SHE slightly outperformed the lumped model TOPMODEL in terms of the value of normalized error and normalized bias in stream flow. However,





these two criterions are more considerably constrained in unit hydrograph model PRTF. This is initially seem as a controversial conclusion but after reflection is completely justified by the analysis presented. This study also proved that the hydrological models, especially for the distributed and lumped hydrological models, which constructed based

- on physical rainfall-runoff mechanism, act like a low-pass filter and smooth the noise of rainfall by averaging. Therefore, the ensemble perturbed rainfall data has similar error propagation through the MIKE SHE and TOPMODEL. However, the unit hydrograph model PRTF is based on transfer function, which was a pure mathematical model of a dynamic system. The connection between rainfall and runoff in this model is non-
- ¹⁰ linear and time variant. Hence, the PRTF model is only sensitive to the three real-time adjustment factors (shape, volume and timing), which matching the model response as closely as possible to the catchment response. Therefore, the rainfall perturbation has less effect in this process, compared to the other two hydrological models.

5 Conclusions

- A simplified statistical error model based on empirical random error distribution was constructed to define and quantitative the errors in the radar rainfall estimates through hydrological models with different rainfall-runoff mechanisms. The propagation of radar rainfall estimation errors was assessed by different hydrological models, ranging from fully distributed through semi-distributed to lumped models in the Upper Medway Catchment in Kent, UK. The implication of hydrological model structures on radar errors propagation is illustrated by different integrative nature of the hydrological simulations. Overall, the conclusions made in this study are summarized as follows:
 - 1. The normalized bias of the radar rainfall was the dominate factor that had a significant impact and would be enhanced by the stream flow bias.
- 25 2. The distributed model MIKE SHE and the lumped model TOPMODEL selected in this study have similar performance on the rainfall error propagation.





3. The unit hydrograph model PRTF was good at constraining the rainfall error on the stream flow because of the simplicity of transfer function mechanism.

The radar precipitation error ensemble analysis was a preliminary experiment regarding the issue of how much impact on simulated flow could be caused by a distributed hydrological model if the error of radar rainfall data is identified.

More effort could be made to further research on this issue and one of the alternatives is to add the noise to the radar signals in a "radar" way, which means not every radar grid has the same error, but it depends on the source of the noise during the forecasting. An example is clutter that could be added into the radar image to see the distribution of the error in the forecast rainfall or attenuation could be used to examine the influence under different error magnitudes. The model could then tell how much influence the error acues to the flow which could give come indication on how to deal

influence the error caused to the flow, which could give some indication on how to deal with the radar rainfall data errors, especially when some of these errors are inevitable.

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20 References

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- Abbott, M. B., Bathurst, J. C., Cunge, J. A., O'Connell, P. E., and Rasmussen, J.: An introduction to the European Hydrological System Système Hydrologique Européen, "SHE", 1: History and philosophy of a physically-based, distributed modeling system, J. Hydrol., 87, 45–59, 1986a.
- Abbott, M. B., Bathurst, J. C., Cunge, J. A., O'Connell, P. E., and Rasmussen, J.: An introduction to the European Hydrological System – Système Hydrologique Européen, "SHE", 2: Structure of a physically-based, distributed modeling system, J. Hydrol., 87, 61–77, 1986b.



Anagnostou, E. N. and Krajewski, W. F.: Simulation of radar reflectivity fields: algorithm formulation and evaluation, Water Resour. Res., 33, 1419–1429, 1997.

Battan, L. J.: Radar Observation of the Atmosphere, The University of Chicago Press, 1973.

Bell, V. A. and Moore, R. J.: A grid-based distributed flood forecasting model for use with weather radar data: Part 1. Formulation, Hydrol. Earth Syst. Sci., 2, 265–281, doi:10.5194/hess-2-265-1998. 1998a.

5

15

- Bell, V. A. and Moore, R. J.: A grid-based distributed flood forecasting model for use with weather radar data: Part 2. Case studies, Hydrol. Earth Syst. Sci., 2, 283–298, doi:10.5194/hess-2-283-1998, 1998b.
- Beven, K. J. and Freer, J.: A dynamic TOPMODEL, Hydrol. Process., 15, 1993–2011, 2001. Beven, K. J. and Kirkby, M. J.: A physically based variable contributing area model of basin hydrology, Hydrological Science Bulletin, 24, 43–69, 1979.
 - Borga, M.: Use of radar rainfall estimates in rainfall-runoff modeling: an assessment of predictive uncertainty, Fifth International Symposium on Hydrological Applications of Weather Radar-Radar Hydrology, Japan, 451–456, 2001.
 - Borga, M.: Accuracy of radar rainfall estimates for stream flow simulation, J. Hydrol., 267, 26– 39, 2002.

Browning, K. A.: Meteorological applications of radar, Rep. Prog. Phys., 41, 763–801, 1978. Carpenter, T. M., Georgakakos, K. P., and Sperfslagea, J. A.: On the parametric and nexrad-

- 20 radar sensitivities of a distributed hydrologic model suitable for operational use, J. Hydrol., 253, 169–193, 2001.
 - Ciach, G. J., Krajewski, W. F., and Villarini, G.: Product-error-driven uncertainty model for probabilistic quantitative precipitation estimation with NEXRAD data, J. Hydrometeorol., 8, 1325– 1347, 2007.
- ²⁵ Cluckie, I. D. and Owens, M. D.: Real-time rainfall-runoff models and use of weather radar information, in: Weather Radar and Flood Forecasting, John Wiley & Sons, 1987.
 - Cluckie, I. D., Yu, P., and Tilford, K.: Real-time forecasting: model structure and data resolution, in: Weather Radar Networking, Brussels, Belgium, 1989.

Collier, C. G.: Applications of Weather Radar Systems, Praxis Publishing Ltd., 1996.

- ³⁰ Collier, C. G. and Knowles, J. M.: Accuracy of rainfall estimates by radar, part iii: application for short-term flood forecasting, J. Hydrol., 83, 237–249, 1986.
 - Collier, C. G., Larke, P. R., and May, B. R.: A weather radar correction procedure for real-time estimation of surface rainfall, Q. J. Roy. Meteorol. Soc., 109, 589–608, 1983.





Duncan, M. R., Austin, B., Fabry, F., and Austin, G. L.: The effect of gauge sampling density on the accuracy of streamflow prediction for rural catchments, J. Hydrol., 142, 445–476, 1993.

- Fabry, F., Austin, G. L., and Tees, D.: The accuracy of rainfall estimates by radar as a function of range, Q. J. Roy. Meteorol. Soc., 118, 435–453, 1992.
- Fabry, F., Bellon, A., Duncan, M. R., and Austin, G. L.: High resolution rainfall measurements by radar for very small basins: the sampling problem re-examined, J. Hydrol., 161, 415–428, 1994.

Fulton, R. A., Breidenbach, J. P., Seo, D. J., Miller, D. A., and Bannon, T.: The wsr-88d rainfall algorithm, Weather Forecast., 13, 377–395, 1998.

- ¹⁰ Habib, E., Aduvala, A. V., and Meselhe, E. A.: Analysis of radar-rainfall error characteristics and implications for streamflow simulation uncertainty, Hydrolog. Sci. J., 53, 568–587, 2008.
 - Han, D.: Weather radar information processing and real-time flood forecasting, Ph.D. thesis, University of Salford, UK, 1991.

Hardaker, P. J., Holt, A. R., and Collier, C. G.: A melting-layer model and its use in correcting for

- the bright band in single-polarization radar echoes, Q. J. Roy. Meteorol. Soc., 121, 495–525, 1995.
 - Harrison, D. L., Driscoll, S. J., and Kitchen, M.: Improving precipitation estimates from weather radar using quality control and correction techniques, Meteorol. Appl., 7, 135–144, 2000.
 Harrold, T. W., English, E. J., and Nicholass, C. A.: The accuracy of radar derived rainfall mea-
- ²⁰ surements in hilly terrain, Q. J. Roy. Meteorol. Soc., 100, 331–350, 1974.
 Hossain, F., Anagnostou, E. N., Dinku, T., and Borga, M.: Hydrological model sensitivity to parameter and radar rainfall estimation uncertainty, Hydrol. Process., 18, 3277–3291, 2004.
 Kitchen, M.: Towards improved radar estimates of surface precipitation rate at long range, Q. J.
 - Roy. Meteorol. Soc., 123, 145–163, 1997.

30

- ²⁵ Krajewski, W. F. and Smith, J. A.: Radar hydrology: rainfall estimation, Adv. Water. Resour., 25, 1387–1394, 2002.
 - Krajewski, W. F., Raghavan, R., and Chandrasekar, V.: Physically based simulation of radar rainfall data using a space-time rainfall model, J. Appl. Meteor., 32, 268–283, 1993.

Lukacs, E. and King, E. P.: A property of normal distribution, Ann. Math. Stat., 25, 389–394, 1954.

Morin, E., Maddox, R. A., Goodrich, D., and Sorooshian, S.: Radar *Z-R* relationship for summer monsoon storms in Arizona, Weather Forecast., 20, 672–679, 2005.





National Soil Resources Institute: NSRI soil data structures and relationships, Cranfield University, 2006.

- Owens, M. D.: Real-time flood forecasting using weather radar data, Ph.D. thesis, University of Salford, UK, 1986.
- ⁵ Peng, D. Z. and Du, Y.: Comparative analysis of several Lhasa River basin flood forecast models in Yarlung Zangbo River, iCBBE 2010, Chengdu, China, 2010.
 - Peng, D. Z. and Xu, Z. X.: Simulating the impact of climate change on stream flow in the Tarim River basin by using a modified semi-distributed monthly water balance model, Hydrol. Process., 24, 209–216, 2010.
- ¹⁰ Pessoa, M. L., Bras, R. L., and Williams, E. R.: Use of weather radar for flood forecasting in the Sieve River basin: a sensitivity analysis, J. Appl. Meteor., 32, 462–475, 1993.
 - Probert-Jones, J. R.: The radar equation in meteorology, Q. J. Roy. Meteorol. Soc., 88, 485–495, 1962.

Refsgaard, J. C. and Storm, B.: MIKE SHE, in: Computer Models of Watershed Hydrology,

edited by: Singh, V. P., Water Resources Publications, Highlands Ranch, 809–846, 1995. Reichel, F. V., Hans-Reinard, S. K., Cluckie, I. D., and Rico-Ramirez, M. A.: Radar-based flood forecasting for the Upper Medway Catchment in the UK, in: Proceedings of the Institution of Civil Engineers-Water Management, 2008.

Rico-Ramirez, M. A., Cluckie, I. D., Shepherd, G., and Pallot, A.: A high-resolution radar experiment on the island of Jersey, Meteorol. Appl., 14, 117–129, 2007.

Sharif, H. O., Ogden, F. L., Krajewski, W. F., and Xue, M.: Numerical simulations of radar rainfall error propagation, Water Resour. Res., 38, 1140–1153, doi:10.1029/2001WR000525, 2002.

20

- Sharif, H. O., Ogden, F. L., Krajewski, W. F., and Xue, M.: Statistical analysis of radar rainfall error propagation, J. Hydrometeorol., 5, 199–212, 2004.
- Tachikawa, Y., Vieux, B. E., Georgakakos, K. P., and Nakakita, E.: Weather Radar Information and Distributed Hydrological Model, IAHS-AISH P., 282, 30–34, 2003.
 - Vieux, B. E. and Bedient, P. B.: Estimation of rainfall for flood prediction from WRS-88D reflectivity: a case study, 17–18 October 1994, Weather Forecast., 13, 407–415, 1998.
 - Vivoni, E. R., Entekhabi, D., and Hoffman, R. N.: Error propagation of radar rainfall nowcasting
- fields through a fully distributed flood forecasting model, J. Appl. Meteorol. Clim., 46, 932– 940, 2007.
 - Wilson, J. W. and Brandes, E. A.: Radar measurement of rainfall a summary, B. Am. Meteorol. Soc., 60, 1048–1058, 1979.





Winchell, M., Gupta, H. V., and Sorooshian, S.: On the simulation of infiltration and saturationexcess runoff using radar-based rainfall estimates: effects of algorithm uncertainty and pixel aggregation, Water Resour. Res., 34, 2655–2670, 1998.

Wyss, J., Williams, E. R., and Bras, R. L.: Hydrologic modeling of New England basins using radar rainfall data, J. Geophys. Res., 95, 2143–2152, 1990.

5

Zhu, D. and Cluckie, I. D.: A preliminary appraisal of Thurnham Dual Polarisation Radar in the context of hydrological modelling structure, Hydrol. Res., 43, 736–752, doi:10.2166/nh.2012.023, 2011.





Table 1.	. Initial	parameter	values ar	nd expected	ranges fo	r MIKE SH	IE model.
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Parameters for calibration	Unit	Initial	Selected
Overland flow			
Surface manning's number M	$m^{1/3} s^{-1}$	6	5
Unsaturated zone			
Infiltration rate (HOST 9)	$m s^{-1}$	3×10^{-6}	3.4×10^{-6}
Infiltration rate (HOST 18)	ms^{-1}	5×10^{-6}	5.2×10^{-6}
Infiltration rate (HOST 24)	ms^{-1}	4×10^{-6}	5.2×10^{-6}
Infiltration rate (HOST 25)	ms^{-1}	6×10^{-8}	6.9×10^{-8}
Saturated zone			
Time constant of 1st interflow reservoir	day	6	2
Time constant of 2nd interflow reservoir	day	3	1
1st interflow reservoir time constant of percolation	day	10	5
2nd interflow reservoir time constant of percolation	day	15	5
Initial depth in base flow reservoir	m	0.3	0.5
Manning's number <i>m</i> in river channel	s m ^{-1/3}	0.05	0.03





 Table 2. Main parameter values for TOPMODEL.

Parameters for calibration	Unit	Value
Maximum moisture deficit SZM	m	9.01×10^{-3}
Lateral transmissivity when the soil is just saturated T0	$m^2 h^{-1}$	3.44×10^{-4}
Time delay per unit of deficit in the unsaturated zone T_{d}	h	2.93 × 10 ⁻³
Maximum allowable storage deficit SR _{max}	m	0.63

HESSD 9, 10277-10302, 2012 **Statistical analysis** of error propagation from radar rainfall to hydrological models D. H. Zhu et al. Title Page Abstract Introduction Conclusions References Tables Figures 14 Back Close Full Screen / Esc **Printer-friendly Version** Interactive Discussion

Discussion Paper

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Table 3. Model performances in calibration and validation for the Upper Medway Catchment

	Calibration			Validation			
	SHE	TOPMODEL	PRTF	SHE	TOPMODEL	PRTF	
MAE	0.80	1.86	2.00	1.08	2.35	2.27	
RMSE	1.42	2.98	3.49	1.60	2.59	3.08	
Correlation	0.96	0.75	0.78	0.96	0.78	0.84	
Nash-Sutcliffe	0.93	0.71	0.70	0.91	0.66	0.67	



Fig. 1. Topographic and the river network map of the Upper Medway Catchment.









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Fig. 3. Model validation performance among MIKE SHE, TOPMODEL and PRTF.







Fig. 4. Normalized errors distribution of perturbed rainfall and stream flow (red solid line: rainfall, orange dot line: MIKE SHE, green dot line: TOPMODEL, blue dot line: PRTF).







Fig. 5. Normalized bias distribution of perturbed rainfall and stream flow (red solid line: rainfall, orange dot line: MIKE SHE, green dot line: TOPMODEL, blue dot line: PRTF).



