

# Sensitivity analysis of a distributed hydrological model for the Upper Medway catchment using point and radar-based rainfall data

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## Abstract

The application of quantitative weather radar in hydrological models has long promised the prospect of improvements in the accuracy of rainfall inputs and hydrological models used in real-time flood forecasting. To investigate the impact of temporal and spatial resolution of radar rainfall, a fully physically-based distributed model has been built for the Upper Medway basin (220 km<sup>2</sup>) using MIKE SHE/MIKE 11. The model was calibrated and validated using 15-minute raingauge data with a 100×100 m model grid size. Sensitivity analysis has been carried out using raingauge data with different resolutions and radar data (1km and 5km). The uncertainty of radar-rainfall estimation, scale effects and extreme rainfall and flooding issues are discussed in this context, and the quantitative performance of the radar is addressed; comments are made on the problems associated with characterizing the uncertainties of space–time hydrological processes. This paper presents a preliminary analysis of the sensitivity of radar rainfall with different spatial and temporal resolutions in a distributed hydrological model.

## Introduction

Considering the accuracy of the real-time flood forecasting system, meteorological data — especially precipitation, which has high spatial and temporal resolution — is one of the most critical input variables. Recently, the applications of weather radar in hydrological modelling have demonstrated the prospect of improving the accuracy of rainfall inputs on which the accuracy of streamflow prediction through hydrological models depends. Many studies have focused on using radar rainfall in hydrological models in order to assess the application of weather radar in flood forecasting (Bell and Moore, 1998; Carpenter *et al.*, 2001; Hossain *et al.*, 2004).

However, the estimation of precipitation using radar has many different sources of uncertainty. Some of the factors that affect radar measurements are radar calibration, signal attenuation, clutter and anomalous propagation, variation of the vertical reflectivity profile, extrapolation of the measurements to the ground, variation of the drop size distribution, the selection of the proper Z-R relationship, sampling effects and beam overshooting the shallow precipitation (Rico-Ramirez *et al.*, 2007). Nevertheless, correction techniques can be applied to improve the quality of the radar rainfall estimation (Harrison *et al.*, 2000; Fulton *et al.*, 1998).

This paper presents a preliminary analysis of the sensitivity of radar rainfall with different spatial and temporal resolutions in a distributed hydrological model.

To achieve this, a fully physically-based distributed model was developed using MIKE SHE/ MIKE 11 in the Upper Medway Catchment in Kent, in south-east England. This model was used to represent the rainfall-runoff process in the catchment.

## Methodology

### *Physically-based distributed model: MIKE SHE/ MIKE 11*

Physically-based distributed models take explicit account of the spatial variability of processes, inputs, boundary conditions, and watershed characteristics (Abbott *et al.*, 1986a,b; Refsgaard, 1997; Park, 2007). In particular, distributed physical models are able to represent the spatial variations in catchment characteristics by providing spatial data (Refsgaard and Storm, 1996; Refsgaard, 1997). MIKE SHE was originally developed as the SHE (Système Hydrologique Européen) model by three European organizations: the UK Institute of Hydrology, the Danish Hydraulic Institute and the French consulting company SOGREAH (Abbott *et al.*, 1986a,b; Refsgaard and Storm, 1996; Park, 2007).

In this study, MIKE SHE was applied to build a physically-based distributed model including the following procedures: overland flow, unsaturated and saturated flow, evapotranspiration, and their interaction in the processes of the hydrological cycle. Also each component has several approaches, ranging from simple, lumped, conceptual

methods to complex, distributed and physically-based solutions.

**Study area and parameterization**

The study area was the Upper Medway Catchment with an area of 220 km<sup>2</sup> shown in Figure 1. The Weir Wood Reservoir (capacity 1237 million gallons) influenced base flow with its daily compensation flow and was set as the upstream boundary condition for the hydrodynamic river channel model (MIKE 11), which was converted from the existing hydrodynamic model using ISIS developed by Mott MacDonald (Mott MacDonald, 2003) led by the Environment Agency (EA). The main river channel (about 22 km) was modelled using surveyed river cross-sections obtained through the previous project.

The grid size of the computational model was 100 m. The average annual rainfall and annual potential evapotranspiration was around 729 mm and 663 mm, respectively. The hydrological data were obtained from nine real-time TBRs (tipping-bucket raingauge), which were operated by the EA. As in Figure 1, Chafford flow gauge data were used to compare the simulated results for the model evaluations. The daily potential evapotranspiration data were provided by UK Meteorological Office (Met Office) and the actual evapotranspiration was calculated by the Kristensen and Jensen (1975) method in MIKE SHE.

Land use in the Upper Medway was provided by National Soil Resources Institute (NSRI) and it was simplified to *permanent grass* as this was dominant over the catchment (NSRI, 2006). The roughness of the overland flow was described by Manning’s n and it was converted into Manning’s M in MIKE SHE. The value of roughness for permanent grass was taken from Chow (1959).

The simplified two-layers water balance method was used to compute unsaturated and saturated zone. The soil

data obtained from NSRI were updated and were roughly equivalent to 10 m resolution with 1:250,000 scales and consisted of attribute information for soil properties linked by a soil series code. The soil properties (field capacity, wilting point, water content and infiltration rate) were calculated from volumetric water content at 5 KPa tension, volumetric water content at 1500 KPa suction, water content at quasi-saturation and saturated hydraulic conductivity (sub-vertical), respectively (NSRI, 2006).

The conceptual ground water model, Linear Reservoir Method (DHI, volume 2, 2007) was employed to calculate the saturated flow in this study due to the soil data availability. Based on the flood plain map drawn by the EA and the characteristics of the topography of the catchment, the flood plain area and the hill side area were developed for building the linear reservoir model.

**Model calibration and validation**

The model calibration and validation was carried out using 15-minute raingauge measurements and the calibration was performed to account for changes in the base flow and peak flow. Firstly, calibration was focused on getting base flow through the simulation period and then hydrodynamics were adjusted through the rest of calibration procedures. Therefore, the results through validation could be less accurate than calibration, as the validation period has different base flow from the calibration period. Four assessment criteria were employed in this study as below:

(i) MAE (Mean Absolute Error) = 
$$\frac{\sum_{i=1}^n |o_i - m_i|}{n}$$

(ii) RMSE (Root Mean Square Error) = 
$$\sqrt{\frac{\sum_{i=1}^n (o_i - m_i)^2}{n}}$$

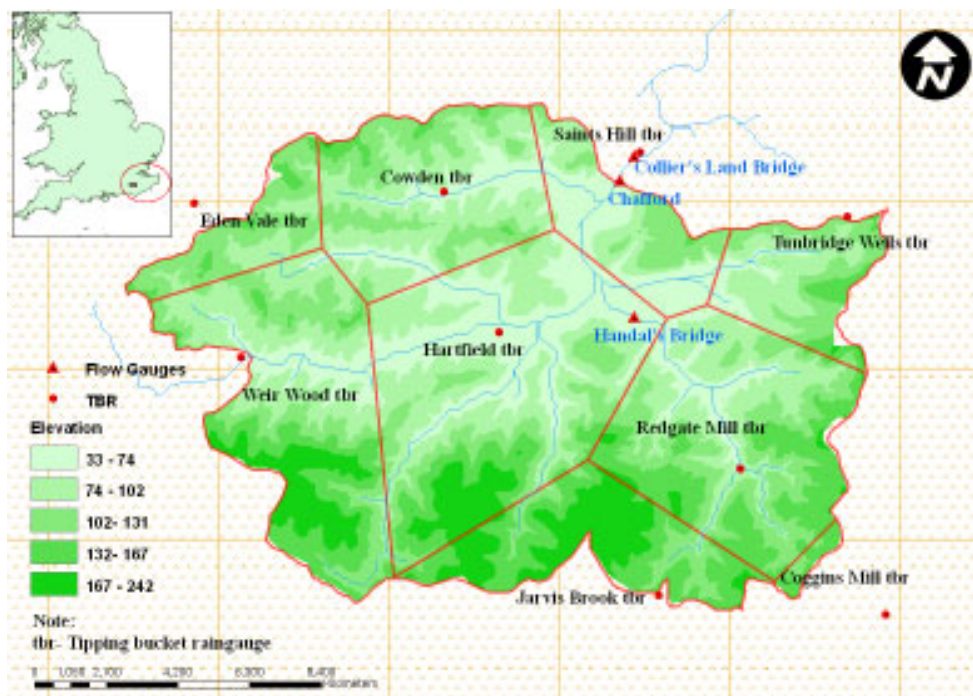


Figure 1 Gauges Network and River Channel in Upper Medway Catchment

$$(iii) \text{ Correlation} = \frac{\sum_{i=1}^n (o_i - \bar{o})(m_i - \bar{m})}{\sqrt{\sum_{i=1}^n (o_i - \bar{o})^2 \sum_{i=1}^n (m_i - \bar{m})^2}}$$

(iv) Nash-Sutcliffe (Nash and Sutcliffe, 1970)

$$= 1 - \frac{\sum_{i=1}^n (o_i - m_i)^2}{\sum_{i=1}^n (o_i - \bar{o})^2} \quad (-\infty \text{ to } 1)$$

where  $o_i$  is the observed discharge, and  $m_i$  is the modeled discharge.

Nash-Sutcliffe criteria (1970) were used to assess the model efficiency, hence the closer the value is to 1 the more accurate the model is. The value 1 indicates a perfect match of modelled discharge to the observed data and the value 0 means that the model predictions are as accurate as the mean of the observed data, whereas an efficiency less than zero occurs when the observed mean is better than the modelled data.

Through the model calibration, as shown in Figure 2, it was limited to get precise regression due to the conceptual groundwater method applied. The performance of model validation was not as good as model calibration in terms of

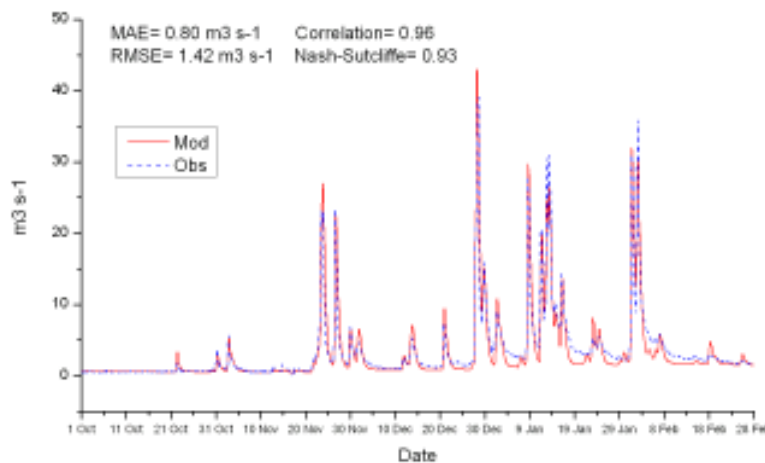
MAE and RMSE, as the model under-estimates the peak flows, but the correlation and Nash Sutcliffe indicate that it still has good performance.

Based on the overall performance of calibration and validation, the model was accepted to carry out sensitivity analysis of radar rainfall with different spatial and temporal resolutions.

### Model sensitivity analysis to distributed rainfall

Radar rainfall data were used to test the sensitivity of the MIKE SHE model to distributed rainfall with different spatial and temporal scales. The radar data set comprised data with 5 km spatial resolution (15-min interval) and data with 1 km resolution (5-min interval). This data set was provided and quality controlled by the UK Meteorological Office through the British Atmospheric Data Centre (BADC). This high-resolution radar composite 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). The nearest radar to the Upper Medway catchment is the Thurnham radar, which is about 50 km away from the catchment. Table 1

#### Model Calibration (01/10/2003-28/02/2004)



#### Model Validation (01/11/2006-28/02/2007)

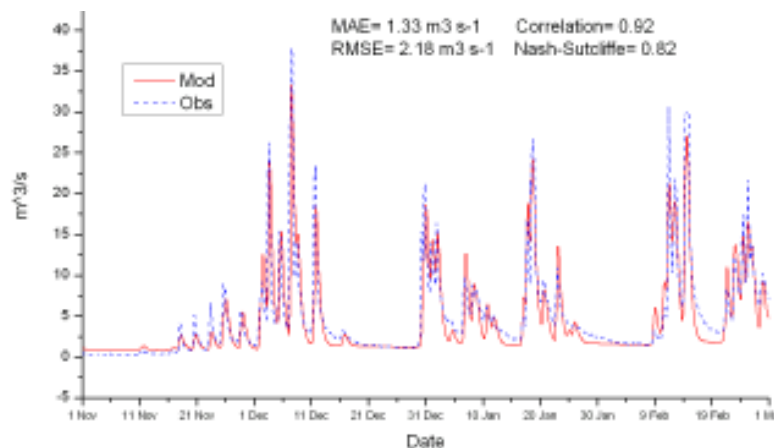


Figure 2 Model calibration and validation results

**Table 1** Characteristics of different rainfall input

Rainfall type	Spatial resolution	Time interval
Radar data	1 km	5 minute
Radar data	5 km	15 minute
Accumulated TBR	point	5 minute
Accumulated TBR	point	15 minute

summarises the characteristics of radar and raingauge rainfalls.

There were some intervals of missing radar data, which were replaced with raingauge measurements. Due to the data availability of radar rainfall, the period from July 2006 to December 2007 was selected. However, before the rainfall data were fed into the model, the following analysis was carried out to assess the quality of the radar rainfall when compared to raingauge measurements.

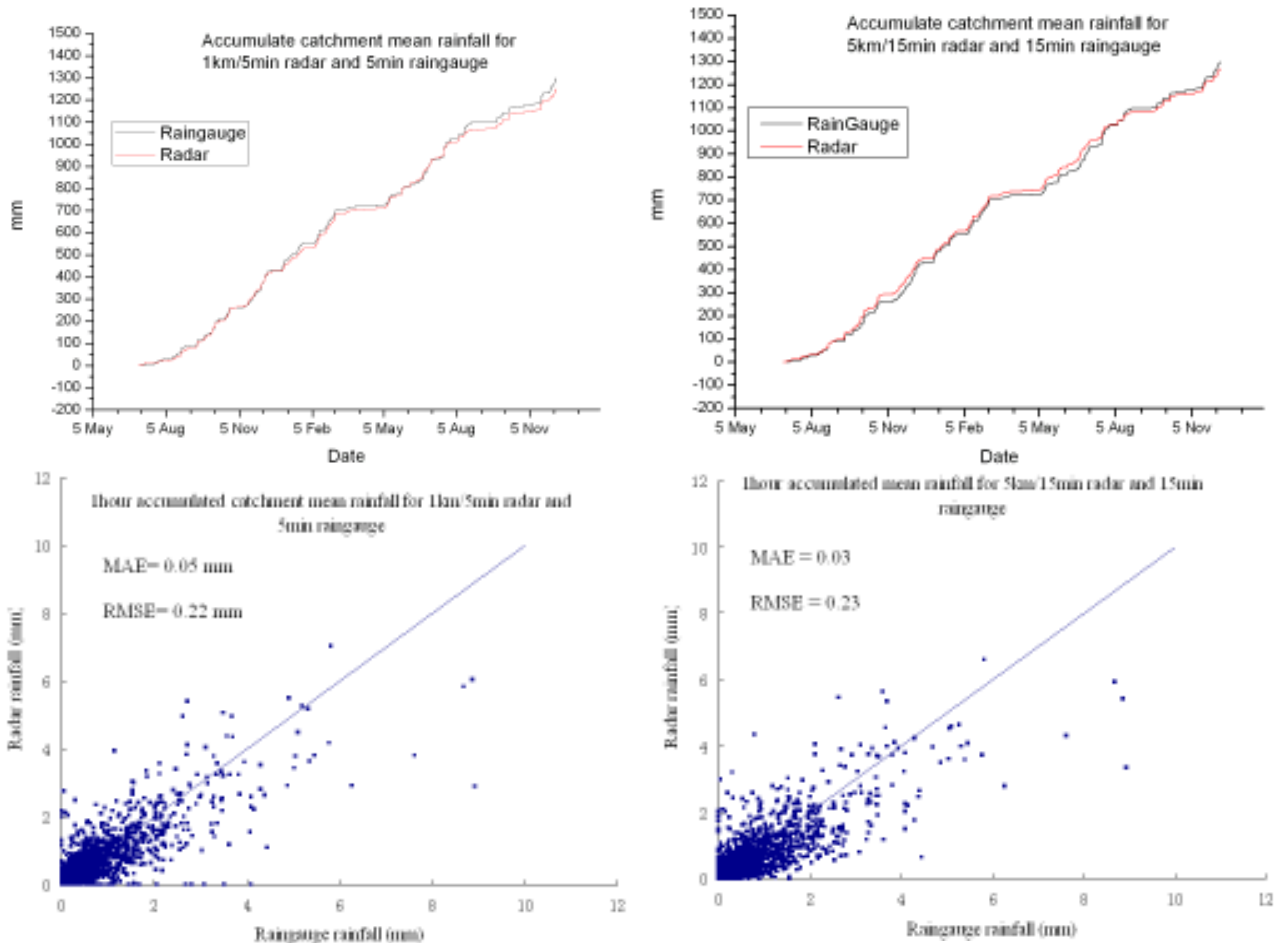
The rainfall measurements from raingauges were averaged, based on the area weighting of relative Thiessen polygons, while the mean radar rainfalls over the catchment were calculated based on the different spatial resolutions (1 km and 5 km). The 1 km resolution radar rainfall was then compared to 5-min raingauge rainfall and 5 km resolution radar rainfall was assessed with 15-min raingauge rainfall, respectively.

Figure 3 shows the comparisons of the rainfall measurements from weather radar and raingauges; the accumulated mean catchment rainfall from raingauges and radar are illustrated in (a) and (b) while mean catchment rainfall with hourly accumulation scatter maps are provided in (c) and (d).

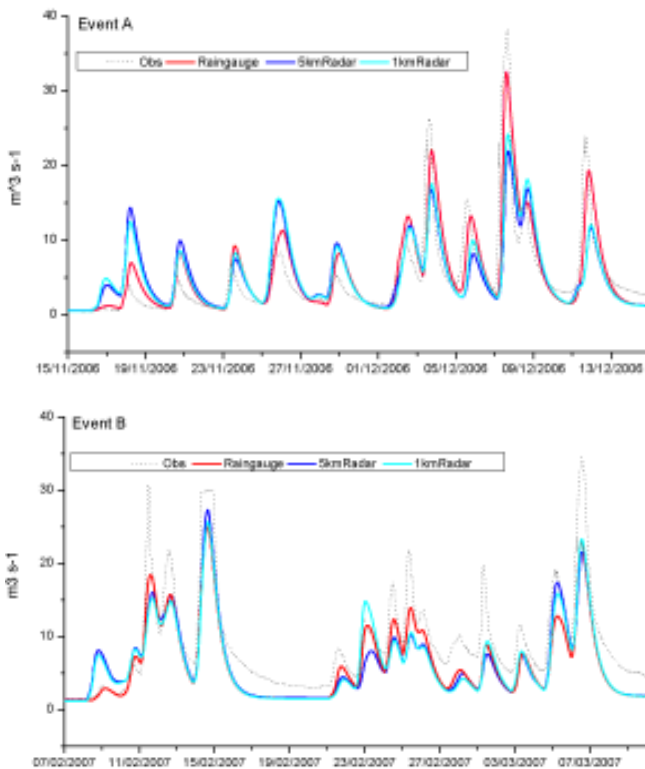
The accumulated mean catchment rainfall maps indicate that the 5km/15min resolution radar rainfall was closer to the raingauge measurements than the 1km/5min radar resolution, when accumulating rainfall for 18 months. The scatter plots show that the radar often underestimated rainfall when compared to the raingauge, especially on events which had a high rainfall rate. However, the 5km/15min radar data have a slightly better performance than the 1km/5min data

Two flood events are employed to assess the radar rainfall data through the distributed model. Firstly, the performance of radar rainfall data was discussed according to the comparisons between radar rainfall data and raingauge data which have the same time interval. Secondly, the differences between radar data with different resolutions was analyzed in order to address the efficiency issue of adoption of radar data with different spatial resolutions.

Figure 4 indicates that the simulated flows when using raingauge measurements as input are closer to the measured flows, and there is little difference on the modelled flows when using 5-min raingauge data and 15-min data as input.



**Figure 3** Comparisons of mean rainfall



**Figure 4** Flood Events A and B simulations

On the other hand, the simulated flows using radar data as input are much lower than the measured discharge (especially the high peaks which are over  $20 \text{ m}^3 \text{ s}^{-1}$ ) in Event A. The reason is that the high rainfall intensities estimated from radar are generally smaller than raingauge measurements (see Figure 4(c) and 4(d)). But contrarily, for the relative smaller peaks (less than  $20 \text{ m}^3 \text{ s}^{-1}$ ), the outcomes from the radar are over-estimated compared to using raingauge data.

However, Event B shows less heterogeneity among radar data and raingauge data as input in the model, especially for the high peaks (except the peaks around 26<sup>th</sup> February 2007 which show some differences among radar rainfall and raingauge rainfall).

Table 2 demonstrates the statistics for these simulations. It is clear that the raingauge measurements gave a better performance in the model than the radar rainfall, but the advantages of raingauge data are not as significant as was expected originally. The spatial and temporal resolution of the radar data had little effect in the simulated flows. To some extent this reflects the

integrating nature of a model structure (even a distributed structure) that in effect averages the distributed effects.

## Conclusions

The physically-based, fully-distributed hydrological model of the Upper Medway Catchment had a good performance in both calibration and validation results. It could simulate the rainfall–runoff process of the catchment and it was good enough to be used for flood forecasting.

More importantly, this distributed model proved to be feasible and reliable with grid-based radar rainfall data input and produced comparable simulation results, which is a crucial quality for radar data.

The two flood events with different rainfall inputs indicated that precipitation data from radar gave high reliability and good performance in the distributed model. However, the weather radar had difficulty in measuring high rainfall rates accurately and, as the model advises, the simulated flows with radar rainfall input could not cope with the high peaks when compared to the modelled flow with raingauge measurements. Although the precipitation data from the radar could not satisfy the peak flow on the quantity issue, the timing on the peak was well matched with the simulation results from raingauge rainfall input and observations. Radar has already shown its potential in flood forecasting and weather radar can be used in catchments without sufficient raingauges or in ungauged basins.

Due to the similarity of the model results with different radar rainfall inputs, 5 km resolution rainfall radar data showed little difference with 1 km resolution rainfall radar data, which suggests that the large spatial radar data have the same performance as the smaller in the distributed model for this particular catchment ( $220 \text{ km}^2$ ). Considering the effort required in processing the 1 km resolution data, (which has 271 grids in this case study compared to only 17 grids of 5 km resolution data) and the time consumed in the data processing and the model calculation, it is not worth applying high resolution radar data in this middle sized catchment. However, the 1 km resolution radar data may be extremely useful for small catchments.

## Acknowledgment

The authors acknowledge the financial support provided by the FRMRC (Flood Risk Management Research Consortium). We also thank the support of the Environment Agency, Danish Hydraulic Institute (DHI), Met Office and we acknowledge BADC and OS/EDINA.

**Table 2** Statistics for different flood event simulations

Event	Model Input	MAE ( $\text{m}^3 \text{ s}^{-1}$ )	RMSE ( $\text{m}^3 \text{ s}^{-1}$ )	Correlation	Nash Sutcliffe
<b>A</b>	Raingauge	1.52	2.56	0.88	0.76
	Radar (1km)	1.96	3.53	0.75	0.55
	Radar (5km)	1.95	3.68	0.72	0.51
<b>B</b>	Raingauge	2.54	3.35	0.96	0.73
	Radar (1km)	2.83	3.69	0.91	0.66
	Radar (5km)	2.83	3.71	0.91	0.67

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