Table 1. Trend test results. Significant test statistic values (at 5% significance level) and related p-values in bracket are marked in italic.

Rain gauge	Observation period	t_S	MK	Variation [mm/years]
Trapani	1881-2010	*-2.931* (*0.004*)	*-2.733* (*0.006*)	-0.903
Agrigento	1886-2009	0.008 (0.994)	-0.389 (0.698)	0.003
Petralia Sottana	1881-2010	*2.115* (*0.036*)	*1.972* (*0.05*)	0.900
Caltanissetta	1879-2010	*-2.074* (*0.040*)	*-2.060* (*0.040*)	-0.744

Furthermore the probabilities of drought of given length l have been computed using Eq. (4). The results are shown in Figure 2, where for each rain gauge, the probabilities of deficit p_t and the probabilities of drought length l=1, l=3 and l=5 years are plotted as a function of time.

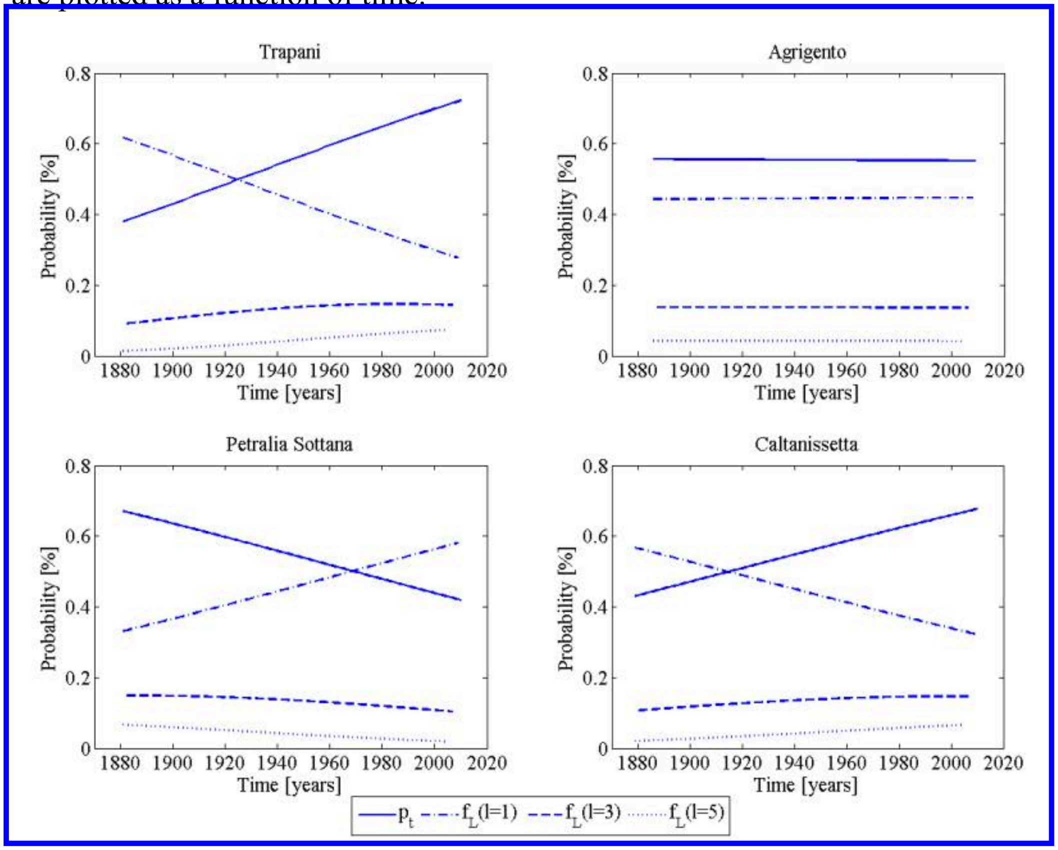

Figure 2. Probabilities of single deficit (p_t) and probabilities of a drought length equal to 1 year (f_L(1)), 3 years (f_L(3) and 5 years (f_L(5)) vs. time for the 4 investigated series.

Inspection of the figure reveals that, as expected, the probability of deficit increases in the cases of decreasing trends of precipitation (Trapani and Caltanissetta), decreases for increasing trend (Petralia Sottana) while is constant for Agrigento, which does not exhibit trend. This is consistent with the fact that as the series tends to exhibit smaller values, the probability of observing values below a fixed threshold increases, vice versa for the opposite case. From the figure it can also be inferred that in the case of decreasing trend (Trapani and Caltanissetta), the probability of drought length l=1 exhibits a decreasing pattern with time, whereas the probabilities of longer droughts (l=3 and l=5), show an increasing shape. Such apparent contrasting behaviour finds an explanation in the fact that as the values tend to be smaller, short droughts tends to be less frequent, while more longer droughts are to be expected.

Finally the expected value of drought duration *E[L]* has been computed with reference to different years, namely 1900, 1950 and 1990 by means of Eq. (11). The results are reported in Table 2, from which it can be inferred that, as expected, the mean value of drought length tends to increase with time for series exhibiting decreasing trend (Trapani and Caltanissetta). Conversely, series with increasing trend (Petralia Sottana), tends to exhibit shorter droughts as time progresses. On the other hand, Agrigento does not exhibit any significant changes in mean drought length.

Table 2. Non-stationary expected values E[L] of drought length (years) computed with reference to different years

Rain gauge	year 1900	year 1950	year 1990
Trapani	1.771	2.352	3.102
Agrigento	2.252	2.243	2.235
Petralia Sottana	2.705	2.146	1.841
Caltanissetta	1.903	2.332	2.808

CONCLUSIVE REMARKS

Probabilistic characterization of droughts in a non-stationary setting requires the development of specific method and tools. In the paper, a methodology for characterizing drought length assuming non-stationarity either in the hydrological variable or in the demand level (threshold) has been proposed.

The derived pdf's enable to compute the probability of a drought of length l starting at time t under the assumption that the probability of observing a deficit p_t varies with time t. Furthermore, the expected value of the duration of a drought starting at a given time t has also been derived.

Application of the methodology to four long annual precipitation series in Sicily exhibiting different degrees of trend in the mean has highlighted the feasibility of the derived expression to characterize drought length in the presence of non-stationarity. Further, the derived methodology is flexible enough to accommodate for virtually any type of non-stationarity in the series and the demand, provided it is modeled adequately.

Ongoing research is oriented to extend the results to other drought characteristics (e.g. severity, intensity), as well as to better take into account the inevitable uncertainty related to the assessment of non-stationarity in hydrological series.

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Analysing the Performance of Various Radar-Rain Gauge Merging Methods for Modelling the Hydrologic Response of Upper Thames River Basin, Canada

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Abstract

Accurate estimate of precipitation is of paramount importance for assessing the hydrologic response of a river basin. Weather radar data integrated with rain gauge measurements are applied to characterize the spatial feature of the storm event producing precipitation over the basin. Ordinary kriging of rain gauge data, mean field bias, Brandes spatial adjustment, conditional merging (CM), and local bias techniques are applied in this study to evaluate the performance of these radar-rain gauge merging methods for hydrologic modelling of the Upper Thames River basin (UTRb), south-western Ontario, Canada. Singularity-sensitive Bayesian merging method (SSBM) with a fine spatial resolution was also applied to retain the singularity character of the rainfall event. Rainfall–runoff simulations were carried out for three major storm events recorded in the UTRb using the HEC-HMS 4.0 hydrologic model. River flow analysis was performed for the comparison of results of HEC-RAS 4.1 hydraulic model with the observed rating curve. A novel methodology involving a dual-storage system is proposed to model three sub-basins of UTRb which displayed skewed and spiked observed runoff hydrographs. Using this dual-storage system for the three sub-basins it is found that CM and SSBM merging methods yielded optimal Nash-Sutcliffe efficiency coefficients for the prediction of runoff from these sub-basins.

Keywords: Modelling; Rainfall-runoff; Radar; Merging methods; Calibration; Validation.

INTRODUCTION

Assessment of the hydrologic response of a river basin is essential to evaluate characteristics of floods that may arise as a result of rainfall events over the basin. It requires quantitative estimation of precipitation over the basin at high spatial and temporal resolutions. Rainfall measurements obtained by rain gauge or radar measurements alone do not precisely qualify for direct application in hydrologic analysis due to their inherent weaknesses in terms of spatial and temporal uncertainties (McMillan et al., 2011). Rain-gauge networks provide reasonable temporal characteristics of rainfall with a rough estimate of the spatial variability. Systematic and calibration errors associated with rain gauges add further to the uncertainty of this measurement technique. However, measurements obtained by weather radar display better spatial and temporal resolution (Wilson and Brandes, 1979) but electronic instability, mis-calibration of the radar system, erroneous beam geometry, non-uniform vertical profile of reflectivity (VPR), and erroneous Z-R (reflectivity-rainfall) relationship are additional sources of uncertainty in estimates from radar (Ciach et al., 2007).

Rain-gauge networks integrated with weather radar are widely applied to capture the real-time data pertaining to rainfall characteristics. Several radar-rain gauge merging methods are available to reduce or eliminate the inherent weaknesses of these techniques. Previous research in this area (see, e.g., Kalinga and Gan, 2006; Kim et al., 2008; Looper and Vieux, 2012; Wang et al., 2013; etc.) has shown that rainfall estimates obtained by merging radar observations with rain gauge data could significantly improve the accuracy of hydrologic modelling. However, rain-gauge network density, wind drift and storm characteristics may introduce additional uncertainty in precipitation estimates, thus affecting the performance of the merging methods. Goudenhoofdt and Delobbe (2009) determined the optimal merging method for a particular rain gauge network density in a watershed in Belgium. McKee (2015) investigated the effect of rain-gauge density and other location-specific factors on the performance of radar-rain gauge merging methods for prediction of rainfall accumulations and hydrological flows in southwestern Ontario, Canada. Resolving radar reflectivity into convective and stratiform components, Chumchean et al. (2013) proposed a storm classification method for rainfall estimation, however limited studies were performed to assess the effect of types of storms on the suitability of merging methods.

The goal of the present study is to evaluate the performances of six radar-rain gauge merging methods, including singularity-sensitive Bayesian merging method proposed by Wang and Onof (2015), on the prediction of hydrologic response. The Upper Thames River basin (UTRb), located in southwestern Ontario, Canada, is used as a case study. In order to capture the skewed and spiked character of the observed hydrographs from select sub-basins, a novel methodology is proposed to predict the runoff hydrograph of those sub-basins.

RADAR-RAIN GAUGE MERGING METHODS

Radar-rain gauge merging methods are classified according to two categories (Wang et al., 2013): bias reduction and error variance minimization techniques. Rain-gauge ordinary kriged, mean field bias correction, Brandes spatial adjustment, local bias correction with ordinary kriging, and range dependent adjustments are bias-reduction techniques, whereas error-variance minimization comprises conditional merging and Bayesian data combination. A brief overview of these methods is given in the sub-sections below:

Rain-gauge ordinary kriged (RGOK)

Rain gauge data is interpolated across the spatial field. Variograms and covariance functions are created to estimate the statistical dependence (called spatial autocorrelation) based on the autocorrelation model for predicting precipitation.

Mean field bias correction (MFBC)

The MFBC method applies a single correction factor (Hitschfeld and Bordan, 1954) across the entire radar field to remove bias, according to the following relation:

$$C = \frac{\sum_{j=1}^{N} G_j}{\sum_{j=1}^{N} R_j}$$

where C is a correction factor, G_j and R_j are the associated gauge and radar observations at gauge j, respectively, and N is the number of valid radar-rain gauge pairs.

Brandes spatial adjustment (BSA)

In contrast to the MFBC, BSA method (Brandes, 1975) assumes biases to be spatially variant and applies a spectrum of corrections across the radar field. A correction factor for each rain gauge location j is calculated initially as:

$$C_j = \frac{G_j}{R_j}.$$

Further, a weight (w_i) for each radar bin i for each gauge location is determined as:

$$w_i = \exp\left(\frac{-d_{ji}^2}{k}\right)$$

where d_{ji} is the distance between the gauge j and the centroid of bin i, and k is a smoothing factor based on rain gauge network density. The correction factors are then interpolated across the radar grid using two passes of the multi-pass Barnes interpolation scheme (Barnes, 1964):

$$F_{1,i} = \frac{\sum_{i=1}^{N} (w_i \times G_i)}{\sum_{i=1}^{N} w_i} \quad \text{and} \quad F_{2,i} = F_{1,i} + \frac{\sum_{i=1}^{N} (w_i \times D_i)}{\sum_{i=1}^{N} w_i}$$

where $D_i = G_i - F_{1,i}$. The corrected precipitation at bin i is then obtained by multiplying the correction factors with radar observations.

Local bias correction with ordinary kriging (LBOK)

Kriging is an optimal interpolation technique that applies a weighted moving average to produce the local estimate of a regionalized variable (correction factor in the present context). The correction factors are determined for each gauge location to find the semivariance to produce variograms. Kriging weights are then calculated from these variograms to obtain correction factors for interpolated locations.

Range dependent adjustments (RDA)

RDA assumes radar bias to be a function of distance from the radar tower. Uncertainties in radar estimates accumulates with distance from the radar tower due to the overshooting of the beam, beam broadening, VPR and beam attenuation (Creutin et al., 2000). The correction factor is expressed on a log-scale and the range is approximated by a second order polynomial whose coefficients are determined by a least square fit method, following the relation:

$$\log C = ar^2 + br + c$$

where r is the distance from radar tower to radar bin i, and a, b and c are coefficients determined by least square method.

Conditional merging (CM)

CM assumes radar observation produce a true field of unknown values, while rain gauges produce an unknown field of true values (Sinclair and Pegram, 2005). This technique works in three steps: 1) radar values are interpolated for gauge locations to create the radar kriged field; 2) the correction field is determined as the difference of the kriged and original radar field data; and 3) the correction is added to the kriged rain gauge surface to obtain corrected rainfall estimates.

Bayesian data combination (BDC)

BDC assumes the difference between the radar and interpolated rain gauge estimates to be an intrinsic random field characterized by an experimental variogram (Todini, 2001). It involves: 1) block-kriging of the rain gauge estimates to fit the radar grid and to obtain the difference between the two measurements at each grid location; 2) fitting the error field with an experimental variogram to develop a smooth error field; and 3) applying a Kalman filter to combine the kriged gauge estimates with the modelled error variogram.

Singularity–sensitive Bayesian merging method (SSBM)

Wang et al. (2013) found peak runoff from a small drainage area to be significantly underestimated by several merging methods. They inferred that first or second order statistical moment approximations upon which most of the techniques are based cannot capture non-normalities in precipitation estimates. To preserve such local extremes, Wang and Onof (2015) integrated BDC with local singularity analysis (Cheng et al., 1994; Schertzer and Lovejoy, 1987) and proposed SSBM that involves separation of singularity indices from the radar rainfall image, merging of non-singular radar image with block-kriged rain gauge field, application of a Kalman filter on the resulting field to give non-singular Bayesian merged rainfall field and addition of singularity indices to obtain the final singularity-sensitive Bayesian merged rainfall field. This technique was found effective in capturing the non-normalities or singularities in runoff from the small-scale urban area of London, England.

HYDROLOGIC DATA

Basin characteristics

The Upper Thames River basin (UTRb) in south-western Ontario, Canada, constitutes the study area in the present research. The Upper Thames River Conservation Authority

(UTRCA) has divided basin (3,482 km^2) into 28 sub-watersheds, as shown in Fig 1a. Three flood control reservoirs at Pittock, Woodstock and Fanshawe serve as buffers to minimize the risk of flooding in prominent urban centres of the UTRb. With the exception of a few large urban centres of London, Stratford and Woodstock, a large portion of watershed covers agricultural farms. Approximately 75% land is in agricultural use, 14% is covered with natural vegetation and 10% is urban or built-up. The soil in the UTRb is composed of silty loam (36%), clay load (26%), sandy loam (10%) and silty clay loam (6%).

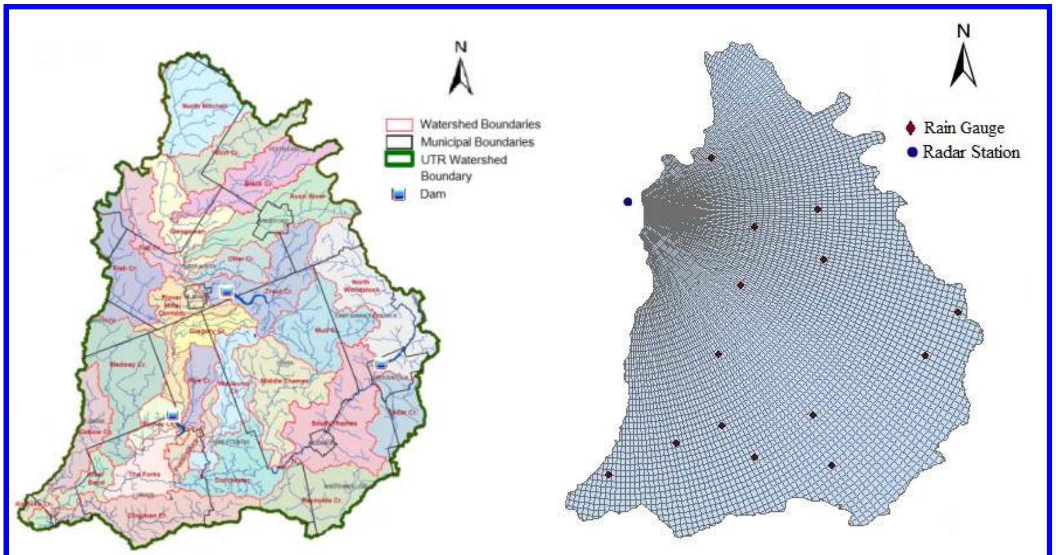

Fig.1. **a)** Upper Thames River basin (UTRb) and associated sub-basins (source UTRCA, 2012); and **b)** Radar and rain gauge locations

Data source

UTRCA and Environment Canada (EC) monitors water levels at 23 locations along the main channel of the Thames River to determine hourly variation in flow rates. The locations of 14 rain gauges representing optimal rain gauge density are shown in Fig. 1b. Radar data, provided by EC's Meteorological Research Division for the Exeter radar station, is used in this study. The technical specifications for the weather radar system are: Range-120 km, Theta-360°, Bin Resolution-1.000 km, Azimuthal Resolution-1.000°, Bits 8, Site ID WSO, Site name EXETER, Latitude 43.37°and Longitude -81.38°.

Rainfall events

Table 1 presents the characteristics of three major rainfall events that occurred on July 8, September 5-6, and September 10-11, 2014. Rain events 1 and 2 were high intensity localised rainfall, whereas Rain event 3 was relatively uniform in nature across the

UTRb. Event 2 occurred after a long dry period, whereas Events 1 and 3 had wet antecedent soil moisture conditions.

Rain gauge network

The density of rain gauge network affects the accuracy of estimated rainfall therefore, in conformance to the earlier study of McKee (2015), a network of 14 rain gauges was adopted to analyse the hydrologic response of the UTRb.

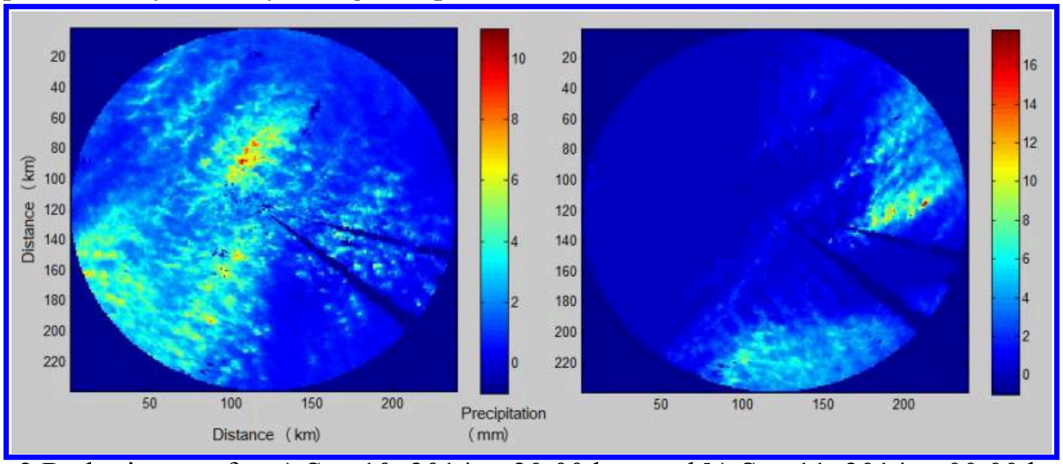

Fig. 2 Radar images for **a)** Sep 10, 2014 at 20:00 hrs; and **b)** Sep 11, 2014 at 00:00 hrs

Table 1: Characteristics of three major rainfall events

Rain event	Date	Time (UTC)	Duration (hr)	Intensity (mm/hr)	Peak Flow (m^3/s)	Antecedent soil condition
1	July 8, 2014	16:00-01:00	11	15.5	138.5	Wet
2	Sept. 5-6, 2014	23:00-10:00	12	43.25	120.0	Dry
3	Sept. 10 -11, 2014	19:00-08:00	14	30.6	240.6	Wet

HYDROLOGIC SIMULATION

HEC-HMS 4.0 developed by the U.S. Army Corps of Engineers, was applied to determine the hydrologic response of the UTRb. A moving patch of 20×20 km^2 was applied to calculate the rainfall using SSBM (see Fig. 3). Another moving patch of 42 x 42 km^2 was also applied but no significant improvement was observed in two different calculated precipitation estimates.

Accounting losses and transform method

'Initial and constant' loss method and 'Clark's Unit Hydrograph (CUH)', that considers the duration of excess precipitation to be infinitesimally small, were applied. The two parameters of the CUH, time of concentration (T_c) and storage coefficient (S_c), represent the time for water to travel from the hydraulically farthest point in the basin to the outlet and temporary storage of excess precipitation in the basin as it moves down towards the outlet (USACE, 2000), respectively.