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Effects of radar data improvements on hydrological modelling

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Abstract. The aim of presented work is to investigate the impact of proposed corrections in radar rainfall estimates on the accuracy of runoff simulations. The study area consisted of a few catchments (both mountainous and lowland) located at different catchment-to-radar distances. The rainfall data were provided by C-band Doppler radar and raingauge network. MFB correction and Bayesian adjustment were applied to radar data independently. Effects of radar data improvements were assessed from hydrological point of view. The hydrologic response of catchments was modelled by a conceptual rainfall-runoff model.

1 Introduction

Progress in quantitative precipitation estimation (QPE) from radar data resulted in considering weather radar to be a promising tool for hydrological modelling. Weather radar is capable of providing surface precipitation estimates over a large area with high spatial and temporal resolution almost in real-time. On the other hand radar data is burdened with errors of different sources. A lot of papers have been devoted to evaluate impact of radar errors on radar estimates of precipitation (e.g. Salek et al., 2004). Some studies analyse these errors from an hydrological point of view (Borga, 2002; Sanchez-Diezma et al., 2001).

In this paper two corrections are proposed, Mean Field Bias (MFB) and based on Bayesian technique, in order to improve radar data. Next their effectivness was investigated in terms of both radar rainfall estimates and radar related hydrographs.

2 Case Studies

The study area comprises a few catchments within the southern Poland, which is the source region of the biggest Polish rivers: Wisla and Odra. Catchments Klodnica, Mala Wisla and Przemsza are located above 100 km basin-to-radar distance and cover an area from 300 to 2000 km^2. Investigations are performed on different catchment types both mountainous and lowland ones. Antropogenic influence is observed on some of them. Catchment characteristics are reported in Table 1.

The rainfall data were provided by raingauge network (36 raingauges) and C-band Doppler radar (Skalky, Czech Republic) as 1-hour accumulations from MAX products. Precipitation field was limited to computation domain of size 190×160 km with 1-km resolution.

Hydrological data were collected from 3 level gauges. Five flood events were selected for each catchment.

3 Interpolation of raingauge data

The point raingauge measurements were interpolated on a pixel lattice of computation domain by means of weighted mean method. For each domain pixel, the precipitation amount was calculated as a weighted mean from three nearest raingauges:

$$G_{MW} = \frac{\sum_{i=1}^{3} G(i) \cdot w(i)}{\sum_{i=1}^{3} w(i)} \tag{1}$$

where $w(i)$ is the weight defined as reverse distance from domain pixel to the raingauge $G(i)$.

4 Radar rainfall correction

Radar data are subject to non-negligible errors: non-meteorological (related to the instrument characteristics and the sampling strategy) and meteorological (e.g. Z-R relationship, variability in vertical profile of reflectivity, bright band, orographic enhancement). There are a lot of methods to correct radar rainfall estimates (e.g. Meischner, 2004). In this study the following procedures: MFB correction and adjustment based on Bayesian approach were applied.

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Table 1. Catchment characteristics.

Catchment	Level gauge	Area	n	Altitude	Description
		km^2		m a.s.l.	
Klodnica	Gliwice	444	1	211-329	urban, lowland
Mala Wisla	Skoczow	297	5	471–1220	rural, mountainous
Przemsza	Jelen	1996	8	233–500	rural/urban, highland

n – the number of raingauges inside the catchment

4.1 Mean Field Bias (MFB)

Radar rainfall estimates were compared against raingauge data at 1-hour accumulation time-step using 6-hours time moving window to compute a *MFB* coefficient.

$$MFB = \frac{\sum_{j=1}^{N} G(i)}{\sum_{j=1}^{N} R(i)} \tag{2}$$

where $G(i)$ and $R(i)$ are corresponding raingauge and radar rainfall values.

To avoid sampling errors *MFB* is calculated if more than 20% of raingauges measured no-zero precipitation. Otherwise *MFB* was set to historical *MFB* previously evaluated for the whole data period. Historical *MFB* equals 1.68, which means that radar data were underestimated. Consequently *MFB* coefficient calculated in this way was applied uniformly to the whole radar rainfall field.

4.2 Bayesian approach

Radar data adjustment with Bayesian approach, proposed by Moszkowicz (2001), is aimed at obtaining information determining what rainfall would be measured by a raingauge if it was placed in some location. Using all the available information (a priori), a posteriori probabilities for different rainfall intervals can be found. In the same way a posteriori expectations of the rainfall can be estimated.

Not only is radar measurement R taken under consideration but 2-dimensional vector **R** (ln R, ln d^2) which consists of radar data R and d – distance from radar site.

Let the variable G (rainfall measured by gauge) has n classes (rain intervals) and in our case n=10 classes with upper limits (mm): 0.1, 0.2, 0.4, 0.6, 1.0, 1.5, 2.0, 3.0, 4.5 and above 4.5. For each class a priori probability P_j is calculated. According to the Bayes theorem a posteriori probability of each class can be determined as:

$$P(j|\boldsymbol{R}) = \frac{p(\boldsymbol{R}|j)P_j}{p(\boldsymbol{R})} \tag{3}$$

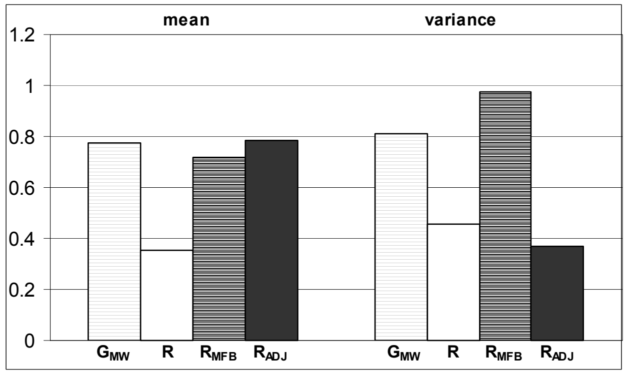

Fig. 1. Characteristics of precipitation fields.

where $p(\mathbf{R})$ is calculated from the following formula:

$$p(\boldsymbol{R}) = \sum_{i=1}^{n} p(\boldsymbol{R}|i)\, P_i \tag{4}$$

and also the a posteriori expectation:

$$R_{adj} = E\{G\} = \sum_{j=1}^{n} G_j P(j|\boldsymbol{R}) \tag{5}$$

where G_j is the mean value of G in j class (e.g. central value of a rainfall interval).

Assuming that **R** has normal distribution conditional probability density $p(\mathbf{R}|j)$ can be estimated as follows:

$$p(\boldsymbol{R}|j) = \frac{1}{(2\pi)^{k/2}\sqrt{|\boldsymbol{\Sigma}_j|}} \exp\left(-\frac{(\boldsymbol{R}-\boldsymbol{\mu}_j)^T \boldsymbol{\Sigma}_j^{-1}(\boldsymbol{R}-\boldsymbol{\mu}_j)}{2}\right) \tag{6}$$

where k is the size of vector **R**. Both the vector of mean values μ and the covariance matrix Σ of **R** are determined on the whole data period.

This procedure was adapted to 6 h running temporal window similarly to aforementioned MFB correction. In this case both the vector of mean values μ and the covariance matrix Σ of **R** are calculated on the basis of moving window.

5 Statistical characteristics of rainfall estimates

Analysis of rainfall estimates after MFB and Bayesian correction was conducted by means of statistical characteristics taking into account mean from all catchments and all events. In comparison the following data were included: G – raingauge network (point), G_{MW} – spatially interpolated raingauge data using weighted mean method, R – raw radar data, R_{MFB} – radar data after MFB correction, R_{ADJ} – adjusted radar data using Bayesian approach.

Radar data was significantly underestimated. Mean of radar data equalled 0.35 whereas for raingauges 0.78 (Fig. 1). After both corrections statistical characteristics of radar data were improved. Bias reduced from −0.42 to −0.02 and 0.03 after MFB and Bayesian correction respectively (Fig. 2).

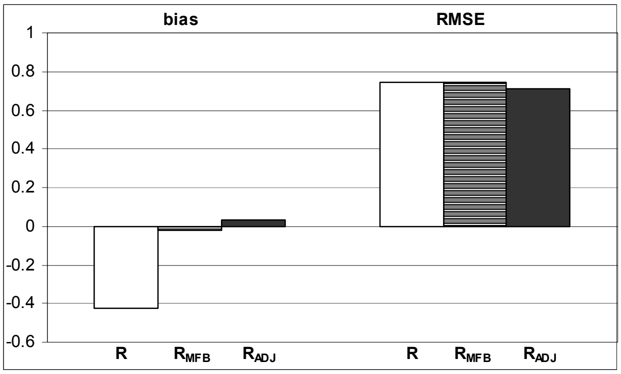

Fig. 2. Comparison of precipitation fields to interpolated raingauges data.

6 Rainfall-runoff model

In order to evaluate effect of radar data improvements on hydrological modelling simple rainfall-runoff conceptual model was applied. It is based on a parametrical equation expressing a relationship between the outflow from a river basin, so called the direct runoff $Q(t)$, and the excess rainfall $R_e(t)$:

$$Q(t) = \int_0^t h(t-\tau) R_e(\tau) d\tau \tag{7}$$

The response function $h(t)$ used in this paper is well known in hydrology as the Nash model (Nash, 1958):

$$h(t) = \frac{1}{k\Gamma(n)} \left(\frac{t}{k}\right)^{n-1} e^{-\frac{t}{k}} \tag{8}$$

where $\Gamma(n)$ is the gamma function, and n, k are the model parameters.

The excess rainfall has been estimated basing on SCS formula (SCS, 1986) with parameters calculated from total direct runoff.

7 Statistical characteristics of simulated hydrographs

Analysis of runoff sensitivity to radar rainfall correction was assessed by comparing simulated hydrographs obtained using radar data (raw and corrected) with those derived from raingauges as input. These simulations were evaluated and compared with corresponding observed flows.

For a statistical evaluation of the hydrological model output, two criteria were selected: coefficient of determination R^2 and integrated square error *ISE* defined as:

$$AAPE = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(Q_{Oi} - Q_{Si})^2}}{\overline{Q_O}} \tag{9}$$

where Q_O – observed discharge, Q_S – simulated discharge, i – time step, N – number of time-steps.

Table 2. Statistical characteristics of simulated hydrographs using different precipitation inputs.

Input	G_{MW}	R	R_{MFB}	R_{ADJ}
R^2	0.69	0.46	0.57	0.53
ISE	28.7	46.6	30.3	29.7

Radar rainfall corrections, both MFB and Bayesian, improved statistical characteristics of simulated runoff. Coefficient of determination increased from 0.46 to 0.57 and 0.53 after MFB and Bayesian correction respectively. By analogy *ISE* was reduced from 46.6 to 30.3 and 29.7 (Table 2). Results of hydrological modelling with corrected radar estimates as input turned out to be close to those derived from raingauges.

8 Conclusions

This study was focused on analysis of impact of two proposed radar data corrections: MFB and Bayesian technique on radar rainfall estimates and their hydrological consequences.

Applied corrections resulted in improvements in radar rainfall estimates and radar-derived hydrographs. However none of them turned out to be significantly better, both in terms of statistical characteristics of rainfall estimates and hydrological simulations.

Achieved results might be conditioned on the use of rainfall-runoff model with uniform model parameters. In future works the effect of proposed corrections will be investigated employing model with spatially distributed parameters.

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