P4C.2

COMBINATION OF WEATHER RADAR AND RAINGAUGES DATA FOR SMALL MOUNTAINOUS CATCHMENT

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1. INTRODUCTION

The presented work is aimed at getting estimated precipitation field as close as possible to the "true" field combining raingauge and weather radar data. Raingauges measure rainfall with good accuracy but only in given points. For that reason the first step consisted in interpolation of raingauges data on a lattice with spatial resolution 1-km.

The investigations are performed on small mountainous catchment of Vistula River up to Skoczów covering an area of about 300 km^2. The specific feature of such a catchment is very variable precipitation in spatial scale but only few raingauges are available. Therefore the problem of precipitation field estimation is very difficult.

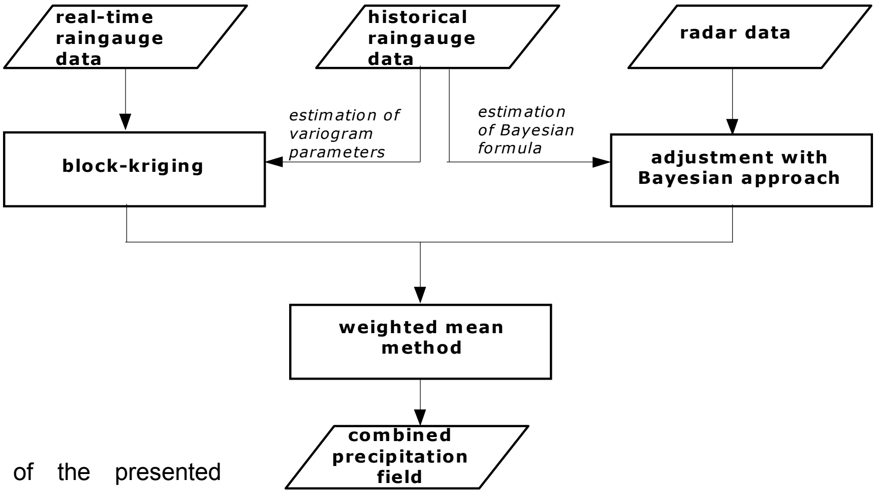

Fig. 1. Scheme of the presented method

of radar pixels. It was achieved by means of block Kriging method developed in the frame of the MUSIC project. On the other hand radar provides rainfall field with high spatial resolution however suffering from errors of different sources. Therefore it was adjusted with Bayesian technique proposed by Moszkowicz (2001). Finally the two sets of data were combined with simple procedure based on weighted mean method.

Radar data was provided by Skalky radar (in Czech Republic) – Gematronik Meteor 360AC, C-Band Doppler radar. The precipitation was measured with MAX method

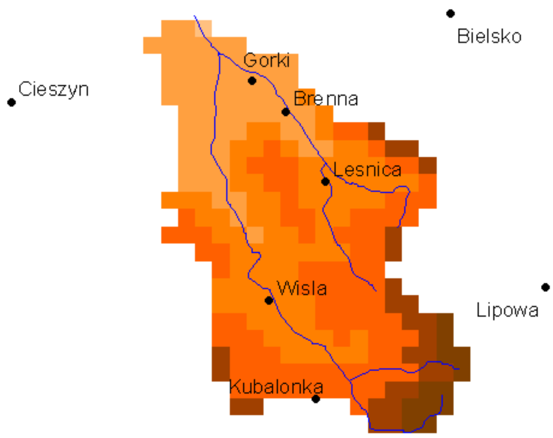

Fig. 2. The Vistula River catchment up to Skoczów – DEM with river network and raingauges map. The spatial resolution (a pixel size) is 1 km.

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2. SPATIAL INTERPOLATION OF RAINGAUGES DATA: BLOCK-KRIGING

Kriging algorithm consists of two steps: first a spatial structure of precipitation is investigated as a function called variogram, then interpolation is performed. The software delivered by University of Bologna developed in the frame of the MUSIC (*The block Kriging*…, 2003) project was applied.

2.1. Variogram

Variogram describes the spatial dependence between the estimation points and the measurement points in function of distance *h*. In the presented work a Gaussian Variogram with the following equation was used for the variogram estimation:

$$\gamma(h) = p + \omega\left(1 - e^{-\left(\frac{h}{\alpha}\right)^2}\right)$$

where *h* is the distance between two raingauges; *p*, ω, α are the parameters of variogram.

Parameters of variogram can be estimated applying Maximum Likelihood method (Todini, 2001) or in traditional way on historical data using least squares method.

2.2. Kriging

The kriging allows interpolation of point measurements from network of *n* raingauges into map consisting of *m* pixels:

$$G^i \ (i = 1, ..., n) \quad \rightarrow \quad G^x{}_{BK} \ (x = 1, ..., m)$$

Estimation of R^x_G for each *x*-pixel is calculated from equation:

$$G^x{}_{BK} = \sum_{i=1}^{n} \lambda_{xi} G^i$$

Weights values λ_{xi} can be estimated using previously calculated variogram on assumption that weights sum for each *x* should equal 1.

For each *x*-pixel of map *n*+1 equations are solved:

$$\sum_{i=1}^{n} \lambda_{xi}\gamma(h_{ij}) + \mu = \gamma(h_{xj}) \quad j = 1,...,n$$

$$\sum_{i=1}^{n} \lambda_{xi} = 1$$

where h_{ij} is the distance between *i*- and *j*-raingauges; h_{xj} is the distance between *x*-pixel and *j*-raingauge; μ is the Lagrange multiplier.

2.3. Block-kriging

Using block-kriging instead of standard kriging results in more smoothed precipitation field (Whelan et al., 2001). Precipitation field G_{BK} is estimated taking into account grid of *s* pixels around the *x*-pixel.

Modification consists in calculation of variogram as the average variogram between *x*-pixel and the area *S*:

$$\bar{\gamma}(x_i, S) = \frac{1}{S}\int_S \gamma(x_i - x)dx$$

where $\bar{\gamma}(x_i, S)$ is the average variogram between the measured point x_i and the area *S*.

3. RADAR DATA ADJUSTMENT

Radar data adjustment with Bayesian approach is aimed to obtain 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 *k*-dimensional vector **R** which consists of radar data *R* and other variables which may significantly impact on the measured precipitation *R*. In this paper one additional parameter *d* – distance from radar site was introduced. Finally the two-dimensional vector **R** = (ln *R*, ln d^2) is used.

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:

$$P(j \mid \mathbf{R}) = \frac{p(\mathbf{R} \mid j)P_j}{p(\mathbf{R})}$$

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

$$p(\mathbf{R}) = \sum_{i=1}^{n} p(\mathbf{R} \mid i) P_i$$

and also the *a posteriori* expectation:

$$R_{adj} = E\{G\} = \sum_{j=1}^{n} G_j P(j \mid \mathbf{R})$$

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:

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

where k is the size of vector **R** (in our case k = 2). Both the vector of mean values μ and the covariance matrix Σ of **R** are determined on historical data.

The constructive sample was composed of 1-hour rainfall accumulations from both radar data and 8 raingauges for the summer (May-October) seasons 1998-2001.

The above adjustment consists in correction of radar precipitation data according to its historical relationship with raingauges data and some other parameters that impact on precipitation using Bayesian approach. This is a correction in statistical meaning because does not take real-time raingauge data into account.

4. RAINGAUGES – RADAR DATA COMBINATION: WEIGHTED MEAN APPROACH

The last step is merging the corrected radar data R_{adj} with interpolated raingauges data G_{BK} by weighted mean method:

$$R_{comb} = R_{adj} w_R + G_{BK} w_G$$

on the assumption that:

$$w_R + w_G = 1$$

where w_R and w_G are radar and raingauges data weights respectively.

Estimation of w_R and w_G values is a critical point in the method. A simple procedure was applied where the weights were assumed as $w_G = w_R = 0.5$.

5. RESULTS

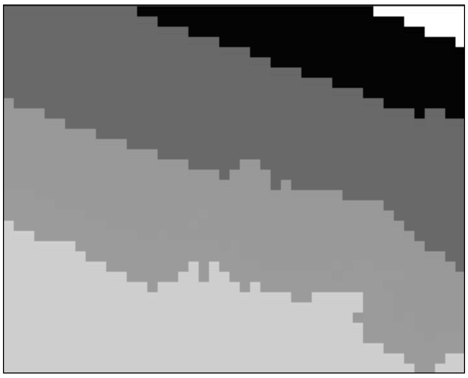
A method for combination of radar and raingauges data was presented. The technique was tested on 1-hour accumulations of precipitation provided by radar and 8 raingauges from the summer season 1997. Raingauge data was spatially interpolated using block Kriging before entering the merging step whereas radar data was adjusted with Bayesian approach. Statistical analysis of obtained results is shown in the Table 1.

Table 1. Statistical analysis of precipitation fields

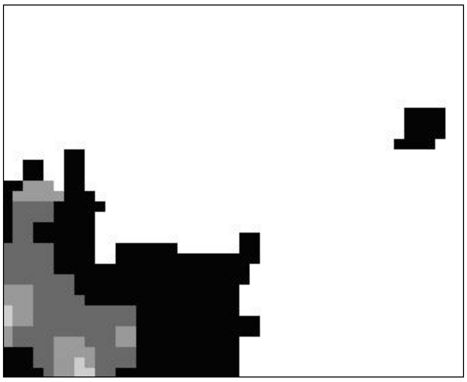
Results of precipitation field estimation	**Mean value μ *(mm)***	**Variance**
G	0.21	0.84
G_{BK}	0.22	0.78
R	0.05	0.07
R_{adj}	0.14	0.30
R_{comb}	0.19	0.45
	Bias	**Covariance**
$R – G$	-0.16	0.10
$R_{adj} – G$	-0.07	0.31
$R_{comb} – G$	-0.02	0.55

Radar data was significantly underestimated and its variance was smaller in comparison with raingauges data. Adjustment based on Bayesian approach improved statistical characteristics of radar data. Bias between radar and raingauge data diminished from -0.16 to -0.07 and covariance increased from 0.10 to 0.31. Merging pre-processed radar and raingauge data resulted in further improvement in bias and covariance in spite of applying simple combination method. Finally bias was reduced to -0.02 and covariance rose to 0.55.

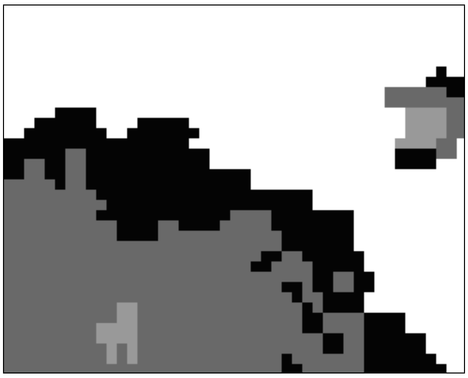
Example of described method performance is shown in Figure 3.



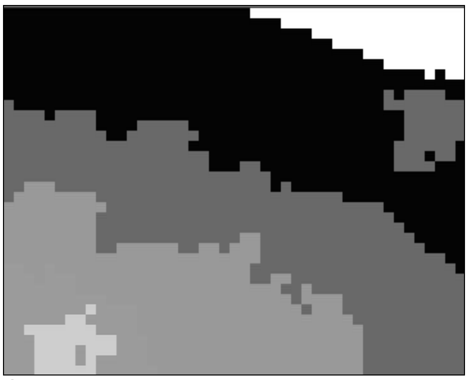
Block Kriging



Radar



Adjusted radar



Combination

Fig. 3. Example of precipitation fields.

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