Advances in Water Resources 32 (2009) 986–1002

Contents lists available at ScienceDirect

Advances in Water Resources

journal homepage: www.elsevier.com/locate/advwatres

A non-parametric automatic blending methodology to estimate rainfall fields from rain gauge and radar data

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ARTICLE INFO

Article history:
Received 10 February 2008
Received in revised form 8 October 2008
Accepted 12 October 2008
Available online 18 October 2008

Keywords:
Radar rainfall
Rainfall estimation
Rain gauges
Merging
Blending
Geostatistics

ABSTRACT

Quantitative estimation of rainfall fields has been a crucial objective from early studies of the hydrological applications of weather radar. Previous studies have suggested that flow estimations are improved when radar and rain gauge data are combined to estimate input rainfall fields. This paper reports new research carried out in this field. Classical approaches for the selection and fitting of a theoretical correlogram (or semivariogram) model (needed to apply geostatistical estimators) are avoided in this study. Instead, a non-parametric technique based on FFT is used to obtain two-dimensional positive-definite correlograms directly from radar observations, dealing with both the natural anisotropy and the temporal variation of the spatial structure of the rainfall in the estimated fields. Because these correlation maps can be automatically obtained at each time step of a given rainfall event, this technique might easily be used in operational (real-time) applications. This paper describes the development of the non-parametric estimator exploiting the advantages of FFT for the automatic computation of correlograms and provides examples of its application on a case study using six rainfall events. This methodology is applied to three different alternatives to incorporate the radar information (as a secondary variable), and a comparison of performances is provided. In particular, their ability to reproduce in estimated rainfall fields (i) the rain gauge observations (in a cross-validation analysis) and (ii) the spatial patterns of radar fields are analyzed. Results seem to indicate that the methodology of kriging with external drift [KED], in combination with the technique of automatically computing 2-D spatial correlograms, provides merged rainfall fields with good agreement with rain gauges and with the most accurate approach to the spatial tendencies observed in the radar rainfall fields, when compared with other alternatives analyzed.

1. Introduction

Rainfall is one of the most important inputs in hydrological models. Rain gauges and weather radars are probably the two sensors that are most widely used in rainfall measurement. Unfortunately, typical densities of operational rain gauge networks are usually unable to fulfill the requirements for real-time hydrological modelling. Weather radar helps to improve our knowledge of rainfall fields, but radar rainfall fields are affected by systematic and local errors that should be corrected, in order to use these fields directly for hydrological purposes. Previous works have suggested that radar data are essential information in providing accurate flow estimates using a rainfall runoff model, even when a dense rain gauge network exists [1–3]. These results have led to the development of diverse methodologies for estimating rainfall fields by merging radar and rain gauge data.

These merging techniques range from the simplest formulation, i.e. finding a constant multiplicative calibration factor [4–6], to statistical approaches based on multivariate analysis [7,8], radar–rain gauge probability distribution analysis [9–12], geostatistical estimators [2,13–18], and Bayesian methods (see e.g. [19]).

The aim of this study is to define a methodology to estimate rainfall fields that fit locally with direct (but scarce) rain gauge measurements and spatially with the shapes of highly detailed (but indirect) radar fields in a real-time combination of radar and rain gauge data using geostatistical approaches.

The methodology proposed here introduces two main advances over classical approaches.

(i) The use of a non-parametric automatic procedure for estimating valid spatial variability models, firstly proposed in [20], and applied for the first time to rainfall estimation by the authors [21,22] and fully described and developed in this paper. This automatic procedure uses FFT for estimating valid spatial variability models for rainfall fields that can

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doi:10.1016/j.advwatres.2008.10.004

be used to estimate rainfall fields merging radar and rain gauge data. The main advantages of this automatic technique are that:

- o it does not require the prior selection of an analytical model (i.e. covariance values do not need to be related by any analytical formulae and there are no parameters that must be adjusted),
- o it includes the observed anisotropy of rainfall fields in the estimation because it is possible to compute two- or three-dimensional correlation maps,
- o the spatial variability model can be changed for each time step of an event because this technique provides fast, automatic definitions and
- o it guarantees a single, valid solution for the kriging equations system by definition.

(ii) The second advance is the use of the radar data field to infer the spatial structure of the rainfall field. Thus, the high spatial and temporal resolutions of radar data are used to compute the correlogram (or variogram if desired), allowing a better definition of the high variability in space and time of the rainfall.

The incorporation of these two new advances into geostatistical techniques for blending radar and gauge data is the main originality of the methodology proposed here.

The goal of the paper is to show how this methodology can be used to improve selected geostatistical estimators of rainfall fields and to compare the performances of three alternative approaches that use the radar field data as supporting information. All three alternatives use rain gauge data to estimate rainfall fields, but supplementing these estimates with radar data in different ways: (1) using radar fields only to define the spatial variability models of rainfall (i.e., an ordinary kriging estimator), (2) using radar fields as in (1) but also driving rainfall estimation using the observed trends in radar fields (i.e., via kriging with external drift), and (3) using radar fields as in (1) but also including the radar observations at the target point in the estimation equations (i.e., via collocated cokriging). It is noted that in all these alternatives radar fields are used to infer the spatial variability model (as correlation maps) of true rainfall through the non-parametric automatic methodology based on FFT introduced in this paper. Finally, a fourth (reference) technique is used in the comparisons: classical ordinary kriging using only information from rain gauges (i.e., with correlation maps obtained directly from the rain gauge data), which serve to assess the improvements introduced by the use of radar data. The performance of each one of these estimators was analyzed, compared and discussed using several events observed in Catalonia (Spain).

The description of the automatic modelling technique used to automatically define spatial variability models for rainfall fields is presented in Section 2. A brief description of each blending alternative, as well as some examples showing how they are implemented, is included in Section 3. The case study is described in Section 4. Finally, Section 5 describes the analysis and the comparisons and discusses the results and performance of the proposed methodology and its different alternatives.

2. Automatic modelling of the spatial variability of rainfall

The traditional (parametric) modelling approach for determining valid spatial models (to be used in kriging) considers only positive, linear combinations of basic covariance or semivariogram models known to be positive definite under very restrictive conditions. All previous radar–rain gauge (co-)kriging applications have used this parametric modelling of the spatial covariance of experimental radar and rain gauge data. Each author defined different spatial models appropriate to the specific data used. Krajewski [13] worked with simulated fields and defined an exponential covariance model for a radar–rain gauge cokriging system. Creutin et al. [14] defined three different variograms from radar and rain gauge data for each analyzed day. Seo [2] employed isotropic exponential models with a nugget effect to model both indicator and conditional correlation functions in his estimations of real-time rainfall fields. Sun et al. [3] worked on an Australian case study and defined a Gaussian model for both auto- and cross-covariance from radar and gauge data. Nicolau et al. [23] mapped the spatial distribution of rainfall in Portugal, interpolating rain gauge data using a spherical semivariogram model. Seo et al. [16] merged radar and rain gauge data by cokriging using a least squares criterion to find the best-fit empirical combination for defining the semivariogram model, choosing between spherical, exponential and Gaussian models. Germann and Joss [24] reported the effects of precipitation type on the spatial patterns of rainfall in various Swiss Alpine regions using semivariograms. Berne et al. [25] used spherical semivariograms to analyze the temporal and spatial correlation of Mediterranean rainfall events. Due to this diversity of results, and the difficulty of adjusting the covariance (correlation) models, it has not been possible to establish, until now, a reference methodology for the operational combination of radar and rain gauge data.

As an alternative, some authors have proposed non-parametric methodologies for finding valid spatial covariance (correlation) models [26,27]. Generally, non-parametric techniques look for covariance values that do not need to be related by any analytical formulae via numerical approaches. Nevertheless, all values must be consistent with each other and provide a good fit for the corresponding experimental covariance. The principal advantages of non-parametric techniques are that they: do not require the prior selection of an analytical model; free the modelling of coregionalization models when several variables are involved in the estimation process; and guarantee a single, valid solution for the kriging equations system. To our knowledge, there are no previous studies in which these non-parametric techniques were applied to the estimation of rainfall fields with a combination of radar and rain gauge data. Only preliminary results have previously been reported by the authors [21,22,28]. In this paper, we propose using a non-parametric technique based on FFT firstly proposed by Yao and Journel [20] (from now as YJ) for the fast and automatic definition of valid, two-dimensional correlograms from radar or rain gauge data. With this methodology it is possible to progressively compute valid, two-dimensional spatial correlograms for each time step in operational applications of the radar–rain gauge merging process.

The technique proposed by YJ consists of transforming the experimental (cross-)covariance values into spectral density maps in the frequency domain using FFT. Following Bochner's theorem [29], the spectral density maps are smoothed in the frequency domain under positivity constraints. Then, the inverse FFT transform of the smoothed spectral density provides (jointly) positive-definite (cross-)covariance matrices. This technique can be applied to define intrinsic cross-covariance models and to find valid variability models in one, two, or three dimensions.

YJ's algorithm proceeds as follows:

1. *Calculate the experimental covariance (correlation) maps from the sample data.* This original sample covariance matrix is generally not positive definite.
2. *Because not all covariance values are experimentally available, the sample covariance values must be interpolated to fill it up.* This preliminary smoothing of the experimental covariance maps fills in all missing entries of the covariance matrix and filters