Environment Protection Engineering

Vol. 40 2014 No. 2

DOI: 10.5277/epe140212

BOGUMIŁ JAKUBIAK[1], PAWEŁ LICZNAR[2], SZYMON P. MALINOWSKI[3]

RAINFALL ESTIMATES FROM RADAR VS. RAINGAUGE MEASUREMENTS. WARSAW CASE STUDY

Contemporary models of urban hydrology and especially hydrodynamic models of stormwater systems demand on supply with high resolution spatial and temporal precipitation information. A plausible solution of precipitation information acquiring over urban catchments is seen in coupling of radar signals and raingauge networks measurements. Suitability of this approach is tested in the case of standard C-band weather radar and the dense network of fast-response raingauges. Rainfall rate estimated based on dependence on the reflectivity factor (*Z–R* relationship) in single pixels of the radar image are compared to rainfall rates measured by 25 raingauges located in Warsaw, Poland. In the analyzed period, 23 precipitation days with rain from convective clouds and cloud systems are detected. The main conclusion is that despite the fact that adopted *Z–R* relationship holds well in statistical sense (i.e. the whole period long empirical probability distribution functions (PDFs) of estimated and measured rainfall rates are in good agreement), instantaneous measurements and estimates as well as short-term (one day) PDFs differ remarkably. These differences are not systematic, they vary from the raingauge to raingauge and from day to day. Moreover, the most remarkable differences are associated with the highest rainrates which should be carefully considered prior radar data use as input for urban hydrology modelling.

1. INTRODUCTION

Intermittent and highly intensity variable characteristics of rainfalls, interesting from the scientific perspective, are simultaneously awkward issues to be solved on daily basis of environmental engineering practice. Assessment of these characteristics at scales of urbanized catchments is prerequisite to accurate predict or assess urban drainage systems rainfall-runoff response. In urban environments, rainfall-runoff re-

[1]Interdisciplinary Centre for Mathematical and Computational Modelling, University of Warsaw, Warsaw, Poland.

[2]Institute of Environment Protection Engineering, Wroclaw University of Technology, Wrocław, Poland, e-mail: pawel.licznar@pwr.edu.pl

[3]Institute of Geophysics, Faculty of Physics, University of Warsaw, Warsaw, Poland.

sponse is additionally complicated by the patchwork pattern of developed, undeveloped and impervious and previous lands, crossing catchment boundaries [1]. Distribution of numerous impervious surfaces and construction of artificial drainage results in reduction of catchment response times on sudden bursts of intense storms and manifests itself in increased magnitude and frequency of urban floods as well as in increased pollution loads entering water recipients with stormwater. Thus, it is inevitable for urban hydrology to have access to information on rainfall at temporal scales of even single minutes and with spatial resolution ranging up to 100 m. Even for typically small domains of urban catchments, not exceeding 20×20 km, monitoring of precipitation fields with such precise temporal and spatial resolutions still remains challenging task.

Despite continuous progress in rainfall measuring in former decades, the past observation of Niemczynowicz [2] that rainfall input was one of weak points in the urban hydrology, remains still valid. Severity of this limitation is additionally amplified by the current common trend of using spatially distributed approaches in urban runoff modeling. High costs of computer models of drainage systems development could be considered remunerative only if models are supplied with decently accurate rainfall inputs to produce reliable predictions. With regard to current engineering standards [3], flow predictions generated by hydrodynamic models based on local historical time series, preferably exceeding 30 years of continuous record are necessary for deliver probabilistic assessment of drainage performance. Despite ambitious goal of drainage system probabilistic assessment, it is realized, in practice, based on single gauge time series, utterly rejecting natural effects of inherent rainfall field spatial variability. The obvious excuse for this practice is the spatial rainfall data shortage.

Spatial rainfall measurements over urban areas were first addressed through the installation of rain gauge networks [1]. This solution remains popular even currently. However, as the installation of gauges is problematic over highly developed urban areas and simultaneously dense networks of fast-response, synchronized instruments are indispensable for rainfall fields monitoring, very early urban hydrologists showed interest in weather radars, as promising solution of rainfall mapping with excellent temporal and spatial resolution [1]. For example, Quirmbach and Schultz [4] estimated the density of one gauge per 16 km^2 as a limit value legitimizing use or radar data for urban runoff modeling. Pioneering experiences with radars implementations for specific needs of urban hydrology and their measuring errors reduction were reported by Einfalt et al. [5]. Delrieu and Creutin [6] were probably first to promote use of X-band radars. Lower costs, greater installation and operational flexibility and reduced sensitivity to ground clutter were found as promising advantages of X-band light configuration radar. Simultaneously, severe operation limitations due to attenuation by heavy rainfalls were also found. In consequence, the X-band light configuration of conventional radar does not overcome the drawbacks of rainfall monitoring by radar over urban areas [1].

Attempts of remote rainfalls measurements uncertainty reduction over urban catchments are made most of all calibrating radar signal by the use of rain gauges. Value of this approach for X-band radar was confirmed for example by Thorndahl and Rasmussen [7]. Rendon et al. [8] were using rain gauges for verification of the derived local *Z–R* relationships for NEXRAD high-resolution S-band Doppler weather radars. Intercomparison of single- and dual-polarization NEXRAD radar rainfall fields based on two overlapping radars and a dense rain gauge network in Kansas City was presented by Cunha et al. [9]. Finally coupling of radar and rain gauge networks signals is a common practice in case of Real Time Control (RTC) systems of urban drainage, where the control of stormwater outflows from different conduits is based on spatial information on rain intensities. Examples of such RTC systems could be found for Marseille where the radar images of Météo-France and a network of 24 rain gauges spread throughout the town and Vienna where point and areal rainfall is monitored by 25 stations and rainfall radar [10].

Why so many studies and difficulties? Radar provides information on radar reflectivity, power of scattered back part of the radar signal. For raindrops, scatters of sizes much smaller than radar wavelengths (Rayleigh scattering), distributed uniformly (in statistical sense) within the radar sampling volume, reflectivity can be expressed after [11] as:

$$Z = \frac{\pi^5}{\lambda^4} \frac{m^2 - 1}{m^2 + 1} \sum_i D_i^6 \tag{1}$$

where λ is the radar wavelength, m is the refraction coefficient of water and D is droplet diameter, summation is over all droplets within the sampling volume.

Interpretation of Eq. (1) is that radar signal Z is proportional to the 6th moment of droplet size distribution. On the other hand, mass of precipitating water is proportional to the 3rd moment of droplet size distribution. Since there is no direct relationship between the 3rd and 6th moment of droplet size distribution, uncertainty in quantitative precipitation estimate from radar signal is inherent. Other major uncertainties include inhomogeneous distribution of scatterers in radar beam (e.g. only a part of radar beam is filled with precipitating particles), attenuation of the radar signal along the beam, presence of ice phase in precipitation [11].

Relation between droplet size distribution and rainrate is also uncertain [12]. For long-term averages, sizes of precipitation droplets follow exponential distribution, which allows to formulate *Z–R* relationships in terms of power laws. However, different factors and powers are needed to provide *Z–R* relationships to various types of precipitation, there are also differences between precipitation events.

Having above in mind, we explore the potential of the Polish POLRAD radar system for urban hydrology in the example of Warsaw, capital city of Poland and present practical problem of coupling radar and gauges signals. In Section 2, we briefly describe raingauge and radar data used in our study and discuss differences between high-resolution rainfall series from both types of measurements. Section 3 contains comparisons of rain gauge data and quantitative estimates of precipitation based on radar reflectivity. Linear regressions are discussed and attempts to improve results with the Bayesian regression models are presented. Summary and conclusions are presented in Section 4.

2. DATA SPECIFICATION

Rainfall in August 2010 over Warsaw has been investigated, as reflected by two data sets:

- surface rainfall observations on network of 25 fast-response (with a temporal resolution of 1 min) weighing-type raingauges (for location and spatial distribution see Fig. 1 in [13]);
- radar reflectivities at 1 km constant altitude level (CAPPI) of 15 min temporal resolution recorded by the nearby Legionowo C-band radar.

Only a subset of reflectivity maps 128×128 pixels centered on the middle of area covered by rain-gauges is selected for the purpose of the analysis (Fig. 1).

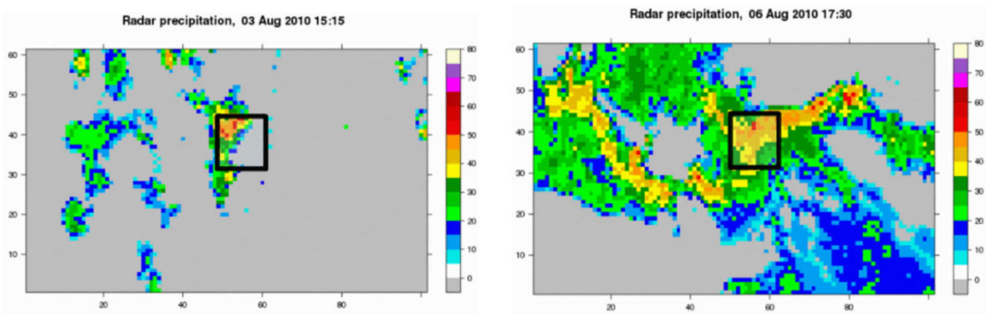

Fig. 1. Examples of radar maps of investigated precipitation events, the squares mark the area of interest

In the analyzed period, there were 23 days with precipitation. Vast majority of precipitation events was related to deep convection. They were characterized by limited spatial and temporal extension and high variability of rainfall rate. The maximum 1 min precipitation rates recorded by rain gauges exceeded 100 mm/h, being typical of intensive convective precipitation events.

Radar reflectivity maps were converted to Lambert equal area projection and each pixel was covering the area of 2×2 km^2 square. Localizations of point (gauge) measurements were converted to the same reference frame, in effect both data sets were available on a common grid. A typical distance between rain gauges slightly exceeds resolution of the radar data, in effect there are no raingauges which correspond to the same pixel.

The focus of the study was not aimed at establishing the new Z–R relationship. Instead, we used a formula typically adopted to convective precipitation to estimate rainfall from reflectivity [14]:

$$Z = 300R^{1.5} \tag{2}$$

where R is the rainfall rate (mm/h) and Z is the reflectivity factor (mm^6/m^3) in dBZ scale.

Comparisons of single, instantaneous, coincident observations by radar (each pixel refreshed by scan every 15 min) and point time series from raingauges (integrated to 15 min periods) are still problematic. The reason is different sampling characteristics of both types of instruments. Radar reflectivities and corresponding quantitative precipitation estimates are averages over a sampling volume of the radar (segment of the beam) ca. 1 km above ground, afterwards recalculated to the volume of 2×2 km^2 in horizontal and hundreds meters of depth in vertical. In contrary, rain gauge data are point time series collected on the ground. Radar data are grab samples taken with the frequency corresponding to repetition rate of radar scans, while raingauge data are integrals over specified periods. All these differences cause discrepances, which usually cannot be represented by a constant bias but vary with the type of precipitation and other factors.

In our research, we focus our attention on daily and monthly time series, comparing rainrates, expressed in mm/h, estimated from 15 min sums of precipitation from raingauges (R_g) to their radar counterparts – rainfall rates estimated from radar reflectivities (R_r) using Eq. (2).

3. DATA ANALYSIS

In this section we analyze experimental probability distribution functions (PDFs) of rainfall in locations of raingauges. From the total set of 25 PDFs of 15 min rainfall sums 4 randomly selected cases are presented in Fig. 2 on order to illustrate similarities and most important differences in these PDFs.

In general, there is a very good agreement in the shape of all PDFs of measured and estimated 15 min precipitation sums, disappearances can only be noticed for rainrates exceeding 2 mm/h. This means that Z–R relationship (2) works very well in statistical sense for 2 km pixel size and 15 min period. Also shapes of PDFs from all locations are similar, except for large variability in distribution tails. Even in nearby location gauges intense precipitation rates varied significantly within the period of analysis.

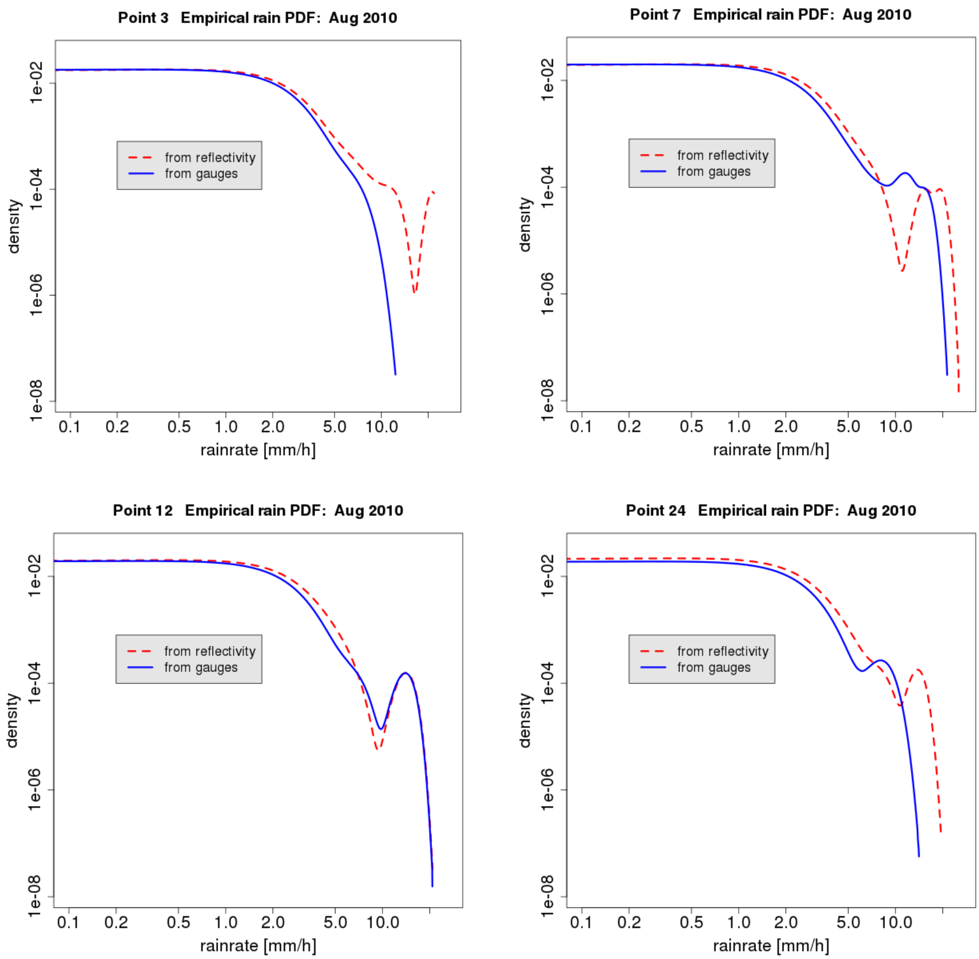

Fig. 2. Example PDFs of rainrates estimated from 15 min sums of precipitation recorded by raingauges and their radar counterparts for August 2010 (the whole month)

Short-period PDFs (example for randomly selected raingauges and a single precipitation day – August 6th is shown in Fig. 3) exhibit substantial differences between measurements and radar counterparts. Tails of the distributions, representing high rainfall sums, differ significantly. In some locations radar significantly overestimates intensive rainfall, in other locations situation is opposite. This is even better seen on a scatter plots combining information on rainfall rates from all 25 locations presented in Fig. 4 for the whole month (left panel) and selected day (right panel).

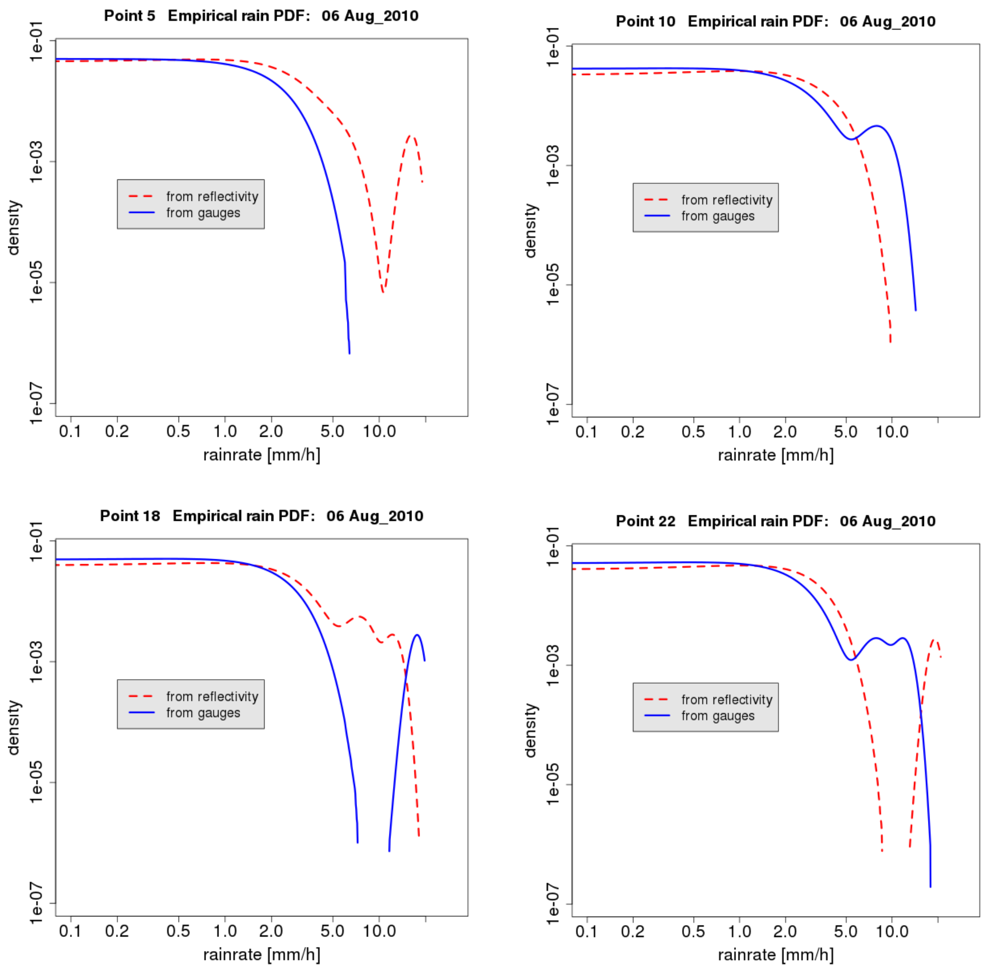

Fig. 3. Example PDFs of rainrates estimated similarly as in Fig. 2 but for a single day Aug. 6th, 2010

Inspection of Fig. 4 indicates that in statistical sense there is a general agreement between both data sets (measured and estimated rainfall rates). There is no obvious bias in monthly and daily plots, which indicates that Eq. (2) works well in a statistical sense. On the other hand, a considerable scatter of points around the diagonal is observed. To be more precise, for rainrates below 2 mm/h majority of the points groups around the diagonal. Above 2 mm/h, for strong and extreme rainfall events (either measured or estimated), points are scattered suggesting no functional relationship.

A question arises: how reliable are instantaneous local estimates of rainfall rate from radar for strong and extreme convective rainfall events? Can simple statistical models be applied to R_r in order to reduce the scatter and provide a reliable relationship? To answer this question, we applied selected statistical models to one day precipitation series in all locations. We tested four different Bayesian nonparametric regression models based on stationary Gaussian processes (GPs), GPs with jumps to the limiting linear model (LLM) and treed partitioning for nonstationary models (T). All these models are easily available in R open source programming package [15] and allow estimation the posterior values of number of parameters due to implementation of MCMC (Markov chain Monte Carlo) approach with ALM (active learning & maximize) algorithm [16]. The norm of predictive quantiles is computed sampled from the normal distribution given by kriging equations [17]. Exemplary results of selected tests for several raingauges and a single day are presented in Fig. 5.

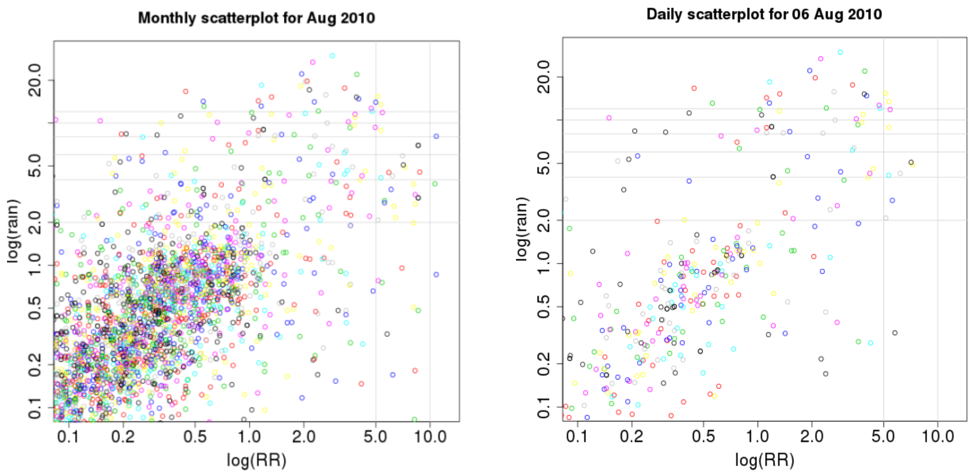

Fig. 4. Scatterplots of rainrates (in mm/h) estimated from radar pixels R_r (horizontal axis) and measured by corresponding raingauges R_g (vertical axis)

A general principle of using the above regression models is as follows: empirical PDFs for each point and day (Fig. 3) are randomly sampled (according to various rules – specific for each model) in order to generate larger data sets, from which functional relations specific for each model and uncertainty parameters (in our case 5–95% probability range) are estimated. In the present study we selected four models: Bayesian linear model (BLM), Bayesian treed linear model (BTLM), Bayesian treed Gaussian process model (BTGP) and Bayesian treed Gaussian processes limited linear model (BTGPLLM). BLM is a stationary model, while others – treed models – are nonstationary, allowing treed partitioning of the data, with different background statistical processes in each partition. In our case, all partitions occur at very small rainrates, distinguishing between (almost) no rain – rain situations. Linear models differ with respect to Gaussian process models in such a way, that they remember the previous step of the Markov chain process which may lead to jumps in regression line.

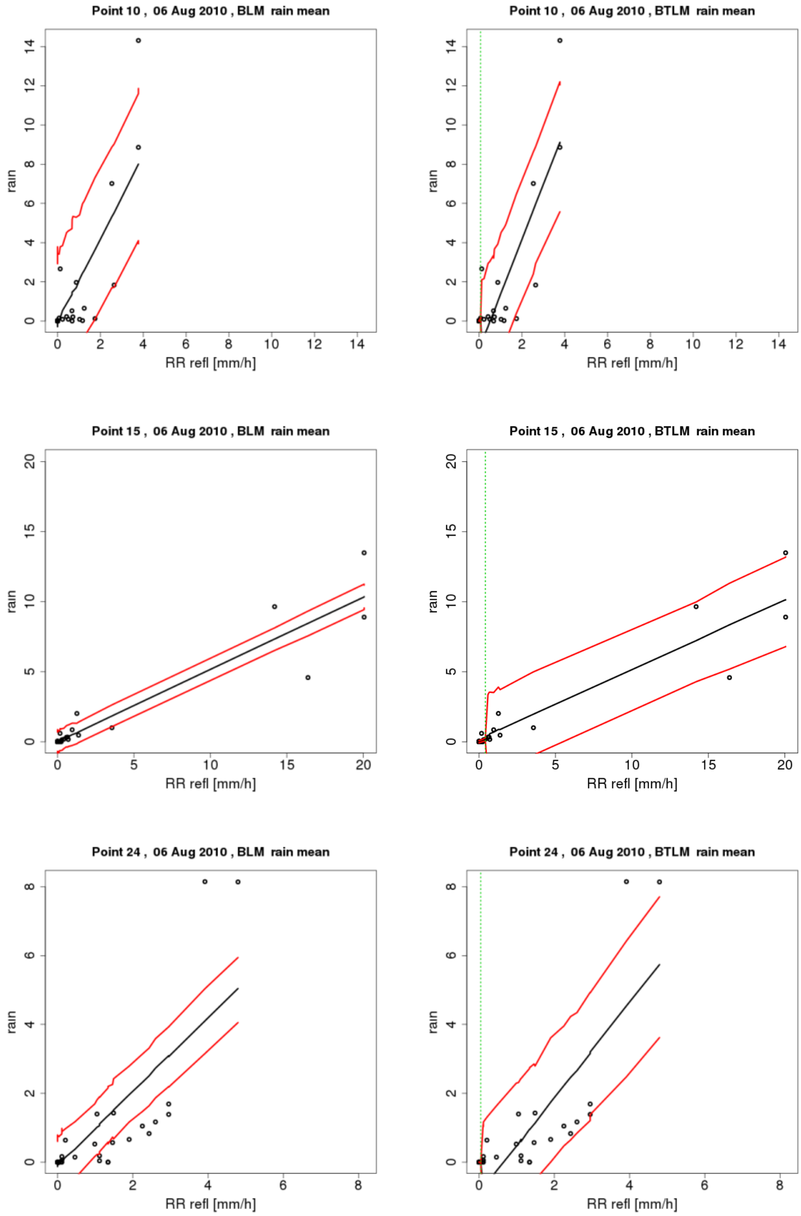

Fig. 5. Examples of application of various statistical models
to rainfall rates recorded during a single day (Aug. 6th, 2010).
Values estimated from radar reflectivity (horizontal axis)
and measured by raingauges (vertical axis) are marked with circles.
Bayesian linear model (BLM) and Bayesian treed linear model (BTLM)

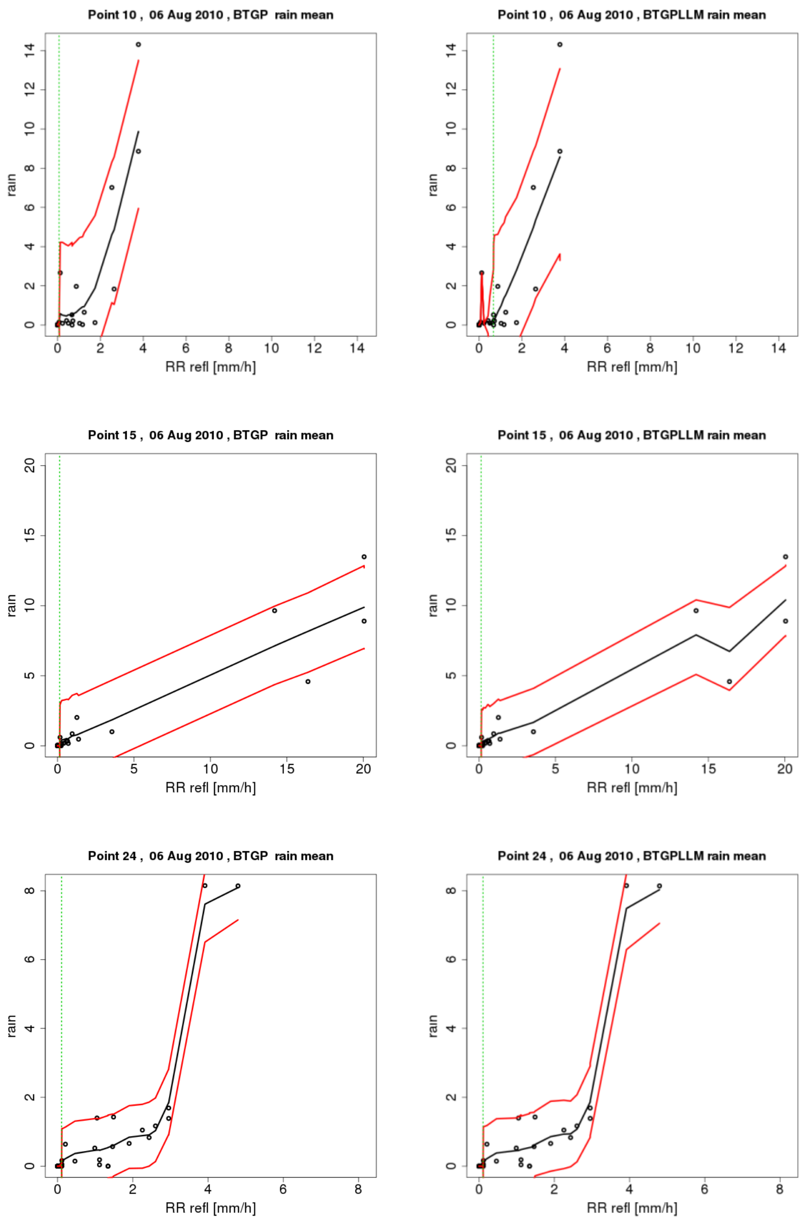

Fig. 6. Examples of application of various statistical models
to rainfall rates recorded during a single day (Aug. 6th, 2010).
Values estimated from radar reflectivity (horizontal axis)
and measured by raingauges (vertical axis) are marked with circles.
Bayesian treed Gaussian process model (BTGP)
and Bayesian treed Gaussian processes limited linear model (BTGPLLM)

Figures 5 and 6 clearly show that for a given location and day different models of the same type (linear and Gaussian process) result in similar regression characteristics, as expected. There are, however, substantial differences in regression curves for various locations. The same is true for various precipitation days and the same locations (not shown for brevity). We did not find a simple statistical model leading to improvement of local rainrate prediction from radar data for high rainrates in convective rainfalls.

4. CONCLUSIONS

Preliminary results from the short case study performed in the months of active convective precipitation over Warsaw suggests that PDFs of rainfall rates estimated from radar by a simple *Z–R* relationship (2) based on a sufficiently long period (at least one month, in our case 23 convective precipitation events) match reasonably the observed rainfall rates calculated based on short-term (15 min) precipitation sums on ground measured by raingauges. This result suggests that in statistical sense, for convective precipitation Eq. (2) works well in Warsaw and, presumably in central Poland. This is not surprising, since *Z–R* relationship is derived from long statistics of observations.

However, fact that *Z–R* relationship works in statistical sense does not mean that it is a reliable tool to estimate actual precipitation sum or rainrate in potentially interesting cases of intense or very intense precipitation. In such cases local estimates are highly uncertain. For radar pixels with high reflectivity indicating very intensive rainfall we find often a weak rainrate measured on ground and vice versa. This suggests that the most extreme events are highly localized and both in space and time in such a way that insufficient temporal resolution of radar scans and insufficient spatial resolution of raingauge network might miss them.

There is no simple way to correct this deficiency of the observation system: we have not found a stochastic model able to significantly improve estimates of actual rainfall from the radar pixel. This result may have practical consequences for urban hydrology applications. Radar estimates of rainfall rate based on *Z–R* relationship can be used to feed hydrodynamic models of catchments for the purpose of drainage systems general planning. It is, however unlikely to obtain reasonable estimates of flow in the existing drainage system in the course of actual precipitating event using rainrate estimates from radar as the only input data.

ACKNOWLEDGMENTS

This project was financed by the Polish National Science Centre (NCN) funds allocated based on decision No. 2011/03/B/ST10/06338. It was realized as a part of scientific project: *Spatio-temporal analysis and modeling of urban precipitation field*. We used radar reflectivity composites from BALTEX Radar Data Centre, Norrkoeping, Sweden.

REFERENCES

[1] FLETCHER T.D., ANDRIEU H., HAMEL P., *Understanding, management and modelling of urban hydrology and its consequences for receiving waters. A state of the art*, Adv. Water Resour., 2013, 51, 261.

[2] NIEMCZYNOWICZ J., *Urban hydrology and water management: present and future challenges*, Urban Water, 1999, 1, 1.

[3] SCHMITT T.G., *ATV-DVWK Kommentar, ATV-A 118 Hydraulische Berechnung von Entwässerungs-systemen*, DWA, Hennef 2000.

[4] QUIRMBACH M., SCHULTZ G.A., *Comparison of rain gauge and radar data as input to an urban rain-fall-runoff model*, Water Sci. Technol., 2002, 45, 27.

[5] EINFALT T., ARNBJERG-NIELSEN K., GOLZ C., JENSEN N.E., QUIRMBACH M., VAES G., VIEUX B., *Towards a roadmap for use of radar rainfall data in urban drainage*, J. Hydrol., 2004, 299, 186.

[6] DELRIEU G., CREUTIN J.D., *Weather radar and urban hydrology. Advantages and limitations of X-band light configuration systems*, Atmos. Res., 1991, 27, 159.

[7] THORNDAHL S., RASMUSSEN M.R., *Marine X-band weather radar data calibration*, Atmos. Res., 2011, 103, 33.

[8] RENDON S., VIEUX B., PATHAK C., *Continuous forecasting and evaluation of derived Z–R relation-ships in a sparse rain gauge network using NEXRAD*, J. Hydrol. Eng., 2013, 18 (2), 175.

[9] CUNHA L.K., SMITH J.A., BAECK L.M., KRAJEWSKI W.F., *An early performance evaluation of the nexrad dual-polarization radar rainfall estimates for urban flood applications*, Weather Forecasting, 2013, 28, 1478.

[10] *Appendix B. Report on Approaches to UWWTD Compliance in Relation to CSO's in major cities across the EU*, Thames Tunnel Needs Report, 2010.

[11] SAUVAGEOT H., *Radar meteorology*, Artech House Publishers, Norwood, MA, 1992.

[12] CAMPOS E., ZAWADZKI I., *Instrumental uncertainties in Z–R relations*, J. Applied Meteorol., 2000, 39, 1088.

[13] RUPP D.E., LICZNAR P., ADAMOWSKI W., LEŚNIEWSKI M., *Multiplicative cascade models for fine spatial downscaling of rainfall: parameterization with rain gauge data*, Hydrol. Earth Syst. Sci., 2012, 16, 671.

[14] JOSS J., WALDVOGEL A., *A method to improve the accuracy of radar-measured amounts of precipita-tion*, Prepr., Radar Meteorol. Conf., 1970, 14, 237.

[15] GRAMACY R., tgp: *An R package for Bayesian Nonstationary, Semiparametric Nonlinear Regression and design by treed Gaussian process models*, J. Stat. Soft., 2007, 19 (9), 1.

[16] MACKAY G.J.C., *Bayesian computation*, Neural Comput., 1992, 4, 415.

[17] MATHERTON G., *Principles of geostatics*, Econ. Geol., 1963, 58, 1246.