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NOWCASTING OF RAINFALL BASED ON EXTRAPOLATION AND EVOLUTION ALGORITHMS. PRELIMINARY RESULTS

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ABSTRACT

Forecasts from nowcasting models are increasingly becoming a crucial input to the rainfall-runoff models. A basic approach to the nowcast generation is based on extrapolation (advection) of current precipitation field. The main limitation of such nowcasting is the rapid decrease in accuracy with forecasting lead time, due to dynamical evolution of precipitation, especially when convection appears, therefore recent studies are focused on taking into account also the evolution of precipitation. According to subject literature, the conceptual cell lifecycle models are not sufficient to significantly increase forecast accuracy, thus at present new approaches based on autoregressive models are investigated. This paper presents the SNAR (Spectral Nowcasting with Autoregression) nowcasting model developed at IMGW-PIB. The aim of the present research is to improve the nowcasting reliability, and to extend the lead time. The model proposes two innovative solutions: (I) decomposition of precipitation field to layers associated with their spatial scale, (II) forecasting based on autoregressive model. The paper gives an overview of algorithms used in the SNAR model and provides preliminary results.

Keywords: rainfall, nowcasting, forecasting, modelling

INTRODUCTION

The concept of nowcasting

Currently, the basic tool for generating short-term precipitation forecasts, up to 2 or 3 days, is the mesoscale numerical weather prediction (NWP). However, in the case of convective phenomena occurring at a very small spatial scale, and dependent on local meteorological conditions, these models fail short in their forecasting, due to their overly simplified physical description of the phenomena. In order to forecast such phenomena, nowcasting models are most often used which, for shorter lead times, have higher reliability than the NWP models (Pierce et al., 2012). "Nowcasting" is defined as forecasts with a very short lead time of up to 2–4 hours, based on the extrapolation (advection) of the precipitation field, often including also the evolution of the precipitation field. The initial conditions for nowcasting are defined by the "analysis" of the precipitation field.

Nowcasting of the precipitation field can be presented as a transformation carried out in accordance with the formula containing the sum of two components describing the advection and evolution of the precipitation field:

$$R(t_0 + \Delta t, x) = R(t_0, x - \Delta x) + \Delta R(t_0, x - \Delta x) \quad (1)$$

where:

- R – precipitation intensity;
- t_0 – time of generating the forecast (the analysis);
- Δt – lead time of the forecast;

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x – position of the pixel;
Δx – displacement of the pixel during the forecast lead time;
ΔR – change in the intensity of rainfall caused by the evolution of the precipitation field.

In most cases, the displacement (advection) vectors are determined by searching for such a shift between two successive fields of the precipitation analysis, at which the correlation coefficient will take the highest value. The field of displacement vectors is smoothed spatially by matching them with the surroundings or by imposing a constraint, for instance in the form of a field continuity equation.

Virtually all of the currently created models take into account the evolution of the precipitation field expressed as ΔR, which allows to extend the lead time of the forecasts while maintaining the verifiability at an appropriate level. In the TITAN model (Dixon, Wiener, 1993) a linear trend was used for this purpose, while in the British model GANDOLF, an empirical model of convective cell life cycle (Hand 1996; Pierce et al., 2000) was applied. Nevertheless, the GANDOLF model does not produce fully satisfactory results.

Therefore, other solutions are sought. One of those, used in the STEPS model developed in the Bureau of Meteorology in Australia, developed to the commercial version in the British Met Office, is the application of the autoregressive (AR) model to the field of precipitation. In the STEPS model, the field of precipitation is divided into layers related to the spatial scale of rainfall structures using the fast Fourier transform (Seed, 2003). Extrapolation and evolution algorithms are applied to individual layers, whereupon the predicted precipitation field layers are assembled into final forecasts for different lead times of the forecast (Bowler et al., 2006). A similar approach is being developed also in the Spanish SBMcast model (Berenguer et al., 2011).

OPERATIONAL NOWCASTING AT IMGW-PIB

Nowcasting methods using the assumption of extrapolation of the current precipitation field usually consist of modules, which are summarized in Table 1. At the Institute of Meteorology and Water Management – National Research Institute (IMGW-PIB), two models of this type are currently in operation: one, the INCA-PL2 – modernized at the IMGW-PIB the INCA (Integrated Nowcasting through Comprehensive Analysis) model of the Austrian meteorological service, forecasting precipitation and other meteorological fields (Haiden et al., 2011; Kann et al., 2012); and the other, the SCENE (Storm Cell Evolution and Nowcasting) – a model developed at the IMGW-PIB only for precipitation (Jurczyk et al., 2013). The initial conditions are generated by the RainGRS system (Szturc et al., 2014).

These models are important prognostic tools, however, the continuous development of algorithms requires the implementation of new techniques that improve the reliability of forecasts and increase their lead times.

Table 1. Comparison of main algorithms of rainfall nowcasting models: INCA-PL2, SCENE and SNAR

Algorithm	INCA-PL2 Model	SCENE Model	SNAR Model
Detecting convection	None	Based on a set of parameters (radar, lightning detection, mesoscale models) using the fuzzy logic technique	Decomposition of the precipitation field into levels associated with the spatial scale of precipitation using fast Fourier transform (FFT)
Extrapolating the field of precipitation	COTREC	TREC with own algorithm of vector control	Currently using an algorithm of the SCENE module, planned implementation of the optical flow algorithm
Evolution of the field of precipitation	None	None	Autoregressive model of AR(2)

The INCA-PL2 rainfall model is based on the widely used TREC extrapolation algorithm, applying its continuous version of COTREC, applied to the entire field of precipitation (Mecklenburg, 2000). This model does not detect convectional rainfall, therefore in the SCENE model their specificity is taken into account, and separate vector fields for non-convective and convective rainfall have been introduced. Different measurement and model data are used for the detection of convection (from POLRAD radar network, PERUN lightning detection system, Meteosat meteorological satellites, and from the mesoscale COSMO and AROME numerical models), and they are combined using the fuzzy logic technique (Jurczyk et al., 2012).

Attempts have been made to implement in the SCENE the forecasting module of the rainfall evolution in addition to the advection of the precipitation field. A conceptual model was applied, which determines, on the basis of measured convection parameters, the evolution of each convective cell for the next 2 hours, similar to the British GANDOLF model (Pierce et al., 2000). However, the validation of this version of the SCENE model did not show a significant improvement in the quality of forecasts.

PROPOSED MODEL FOR PRECIPITATION NOWCASTING: THE SNAR

Assumptions

Due to the need to extend the forecast lead time, other solutions were applied. In the proposed SNAR model (Spectral Nowcasting with Autoregressive model) assumptions similar to those used in the STEPS model were adopted.

The nowcasting model being developed is based on: (a) decamposition of the precipitation field into layers associated with the spatial scale of precipitation objects (using Fourier); (b) determining the extrapolation vectors; and (c) forecasting the precipitation field evolution using the second-order autoregressive model AR(2).

There are plans to create, on the basis of the SCENE and SNAR models, one nowcasting system within the more general SEiNO (precipitation estimation and nowcasting system) system (Szturc and in., 2018), (see: Table 1).

Decomposition of the precipitation field into layers corresponding to the spatial scale of the precipitation objects – fast Fourier transform

Spectral analysis of any given images, for instance of the precipitation field $R(x, y, t)$, makes it possible to reject the least significant part of the information without introducing significant distortions. In the Fourier transform, the separation of the precipitation field into size-dependent components is carried out. In the studies described, fast Fourier transform and Gaussian bandpass filter were used.

In the fast Fourier transform (FFT), a series of harmonic components is selected, related to the different spatial scale of rainfall objects equal to 2^p, where: p is the number of the level (that is, of the harmonic component).

The number of levels depends on the spatial resolution of the rainfall data, which limits the lower value of the spatial scale, and the size of the domain that determines the upper value. In this study a decomposition into 10 levels was applied. Spatial scales in the range from 2^m to 2 km are used, that is, for $m = 10$: 1024, 512, 256, …, 2 km.

An example of decomposition of the precipitation field presented in Figure 1a to individual levels is shown in Figure 2, while the result of their reassembly is presented in Figure 1b.

Forecasting the evolution of the precipitation field – autoregressive model AR(2)

Having generated the individual levels of the precipitation field, their evolution is predicted using the second-order autoregressive model AR(2). This is used to obtain forecasts for each level, and then adding them together to obtain the final forecast of the precipitation field. One of the advantages of this model is that it practically does not require calibration.

The precipitation field R is expressed in the units of R [dBR] $= 10 \cdot \log_{10}(c + R$ [mm]), g where constant $c = 1$ mm. The input to the model consists of three precipitation fields (pixels with x, y): $R_{raw}(x, y, t)$ for the current time step t; $R_{raw}(x, y, t-1)$ for the previous time step $t-1$; $R_{raw}(x, y, t-2)$ for time step $t-2$.

1) Decomposition of $R_{raw}(x, y, t)$ fields into m levels is performed using fast Fourier transform, as follows:

$$R_{raw}(x, y, t) \cong \sum_{p=1}^{m} R_{raw}(p, x, y, t) \tag{2}$$

Further calculations in points 2 to 7 are performed separately for each level of p.

2) The field of $R_{raw}(x, y, t)$ for the level p is normalized using the following formula:

$$R(p, x, y, t) = \frac{R_{raw}(p, x, y, t) - \mu(p, t)}{\sigma(p, t)} \tag{3}$$

where:
$\mu(p, t)$ – the average of z $R_{raw}(p, x, y, t)$ for the level of p;
$\sigma(p, t)$ – standard deviation of the values of $R_{raw}(p, x, y, t)$ for the level of p.

3) The advection is performed for each pixel (x, y) of the level p from the time step $t - 1$ and $t - 2$ into step t using the advection vectors of (v_x, v_y).

Currently, algorithms for determining the field of precipitation advection vectors from the SCENE model (Szturc et al, 2018) are used, but ultimately the model will be based on the optical flow method (for instance, Pierce et al., 2012). One common field of displacement vectors (v_x, v_y) is used, from the time step of $t - 1$ to t. A version allowing for the determination of vector fields for each level separetly is being developed.

The result is two fields: $R(p, x + v_x, y + v_y, t - 1)$ as the result of advecting the field $R(p, x, y, t - 1)$ to the time step t and $R(p, x + 2v_x, y + 2v_y, t - 2)$ as the result of advecting the field $R(p, x, y, t - 2)$ to the term of t.

4) For the above fields, correlation coefficients are calculated, with the analysis for the given time step of t:

$r_{raw1}(p, t)$ between the fields of $R(p, x + v_x, y + v_y, t - 1)$ and $R(p, x, y, t)$,

$r_{raw2}(p, t)$ between the fields of $R(p, x + 2v_x, y + 2v_y, t - 2)$ and $R(p, x, y, t)$.

These coefficients are smoothed to the value of $r_1(p, t)$ and $r_2(p, t)$ by averaging with the previous time step (which has a reduced weight).

If the process is non-stationary, that is if coefficients $r_{raw1}(p, t)$ and $r_{raw2}(p, t)$ differ significantly, then the weights are not determined, and only the extrapolation forecast is calculated: $R(p, x, y, t + 1) = R(p, x + v_x, y + v_y, t)$ and steps 5 and 6 are omitted.

5) The AR(2) model weights are determined based on the values of the above correlation coefficients (Wilks, 2011):

$$\phi_1(p, t) = \frac{r_1(p, t) \cdot (1 - r_2(p, t))}{1 - r_1^2(p, t)}, \qquad \phi_2(p, t) = \frac{r_2(p, t) - r_1^2(p, t)}{1 - r_1^2(p, t)} \tag{4}$$

or, in the simplified form:

$$\phi_1(p, t) = r_1(p, t), \;\; \phi_2(p, t) = r_2(p, t) \tag{5}$$

These weights are then normalized.

6) The forecast for the time step of $t + 1$ is obtained from the precipitation fields for steps t and $t - 1$, taking into account the weight of the model AR(2):

$$R(p, x, y, t+1) = \phi_1(p, t) \cdot R(p, x + v_x, y + v_y, t) + \\ + \phi_2(p, t) \cdot R(p, x + 2v_x, y + 2v_y, t - 1) \tag{6}$$

7) For lead times longer than one time step, the weight and forecast calculation (points 3 to 6) is repeated for every forecast time step using the same displacement vector field.

In the simplified version, the weights are determined only for the first lead time, after which they are applied to all subsequent lead times (Seed 2003).

8) Ultimately, for each lead time specified by time steps, all levels of p are denormalized, and then reassembled as follows:

$$R_{final}(x, y, t+n) = \sum_{p=1}^{m} (\sigma(p, t) \cdot \\ \cdot R(p, x, y, t+n) + \mu(p, t)) \tag{7}$$

A CASE EXAMPLE OF THE SNAR MODEL OPERATION

Tentatively, four versions of the precipitation field forecasting algorithm were tested, defined by: (a) the method of weighting – either according to Wilks (2011) (formula 4) or directly from correlation coefficients (formula 5); (b) the use of weights – for each lead time separately, or according to Seed (2003), that is using one common set of weights. The best results, that is such as the most correctly reproduce the evolution of the precipitation field, were obtained at the initial stage of the work by calculating the weights for each lead time separately from the formula 4. The following example was created for this particular version of the model.

Figure 1a shows the analysis of the precipitation field for June 29, 2017 at 12:00 UTC, when in large parts of Poland there was intense convective rainfall with intensities up to several dozen millimetres per hour. The RainGRS module provided precipitation analyses, whose time step is 10 minutes, and the precipitation fields are 10-minute accumulations. On the other hand, in Figure 1b we have presented a field of precipitation after reassembling the levels created as a result of decompositing the precipitation analysis by the FFT technique.

Figure 2 shows the analysis from Figure 1a after it has been decomposed into individual levels related to the spatial scale of rainfall objects, from the largest being 1024 km (that is, exceeding the 900 × 800 km domain size for which RainGRS rainfall is estimated), to the smallest being 2 km.

Figure 3 shows an example of a nowcasting forecast carried out with the model described above, where ultimately individual levels are reassembled into forecasted precipitation fields for subsequent lead times.

Figure 4 shows the behaviour of the model in the case example of convective rainfall discussed above. The charts show:

I coefficients of correlation between the precipitation field at the time of t, and rainfall fields at the t – 10 min and t – 20 min shifted with advection vectors to time t, which can be treated as measures of forecasts' autocorrelation,

II AR(2) model weights calculated based on these correlation coefficients (formula 4).

Figures 4a and 4b show the course of the correlation coefficient and the model weights depending on the lead times of the forecasts, for two different spatial scales of precipitation objects: 256 km – associated with non-convective rainfall, and 8 km – where the pronounced influence of convective phenomena is expected.

For large objects (see: Fig. 4a), the decorrelation, reflecting in the differences between the correlation coefficients for rainfall field at t and fields from time

a) b)

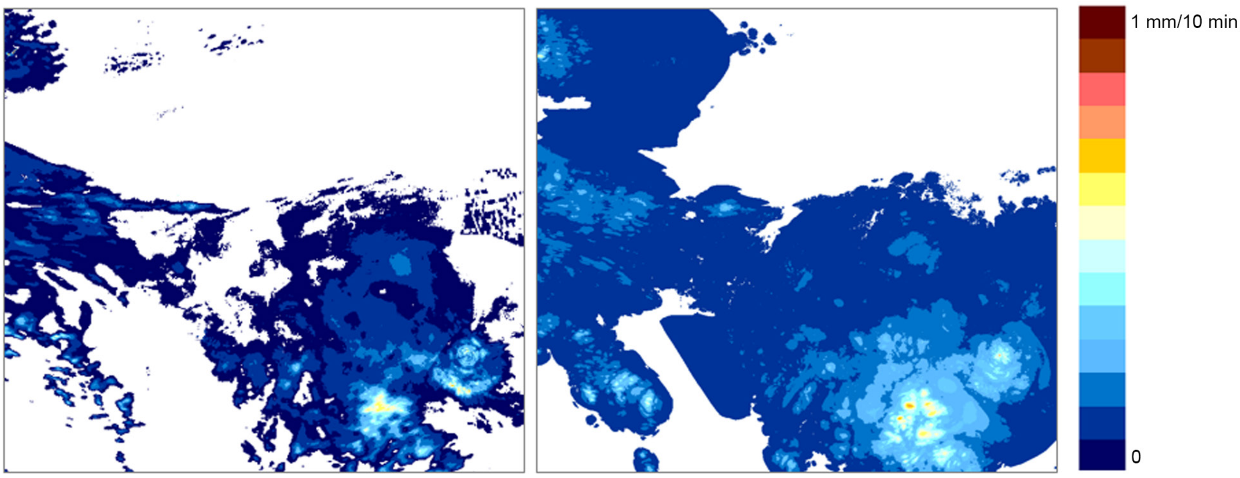

Fig. 1. Example of the (a) rainfall field analysis; and the (b) result of the accumulation of all layers decomposed using fast Fourier transform

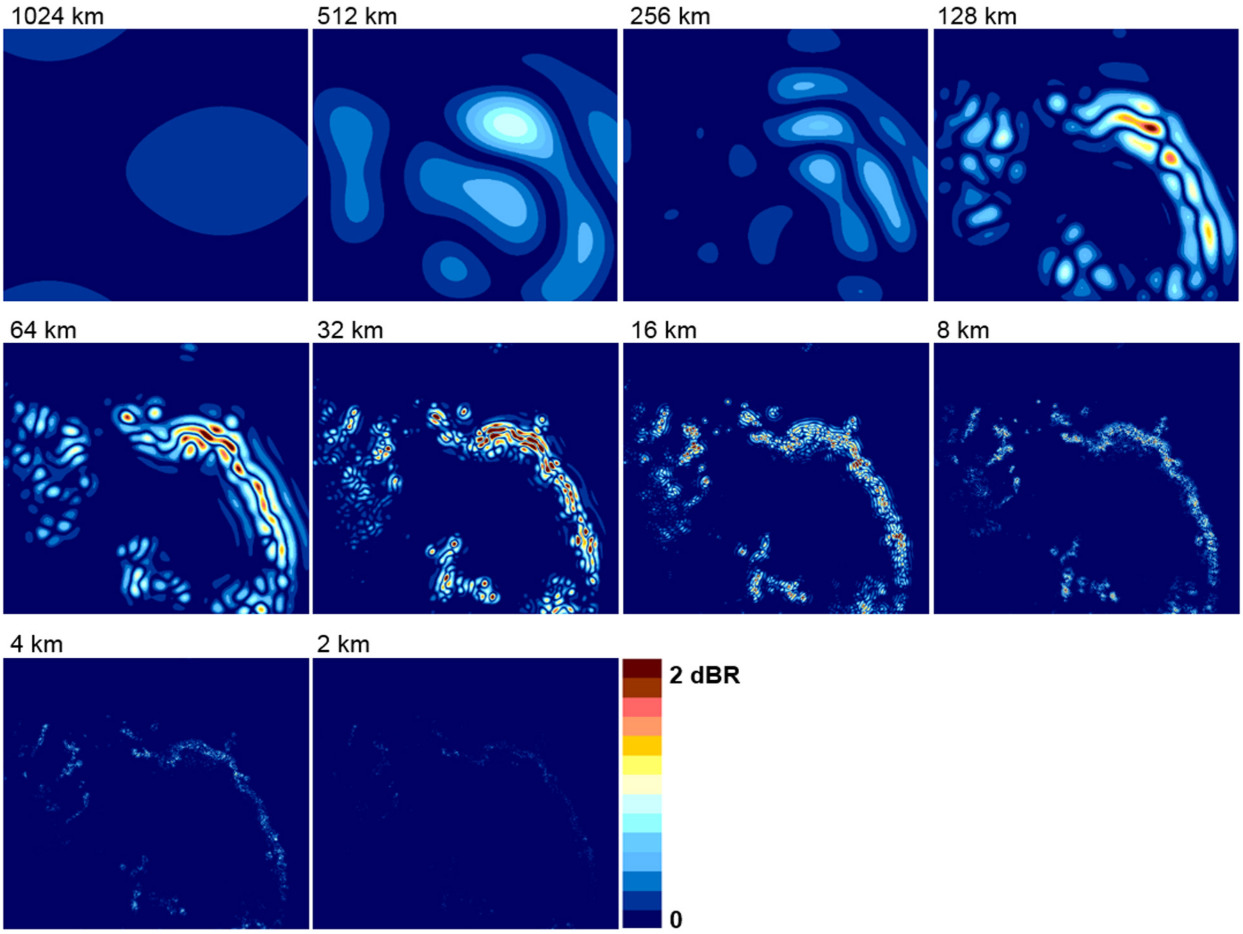

Fig. 2. Example of Fourier transformation of the rainfall field – decomposition into layers (harmonics) related to the spatial scale of precipitation objects

t – 10 min and *t* – 20 min advected to *t* is negligible, whereas more significant differences can be noticed only with shorter lead times. On the other hand, for smaller objects (see: Fig. 4b), these differences are clear for shorter lead times up to 90 minutes, and they reach 0.1 for the correlation coefficient, which also significantly affects the forecast weights depending on the lead time.

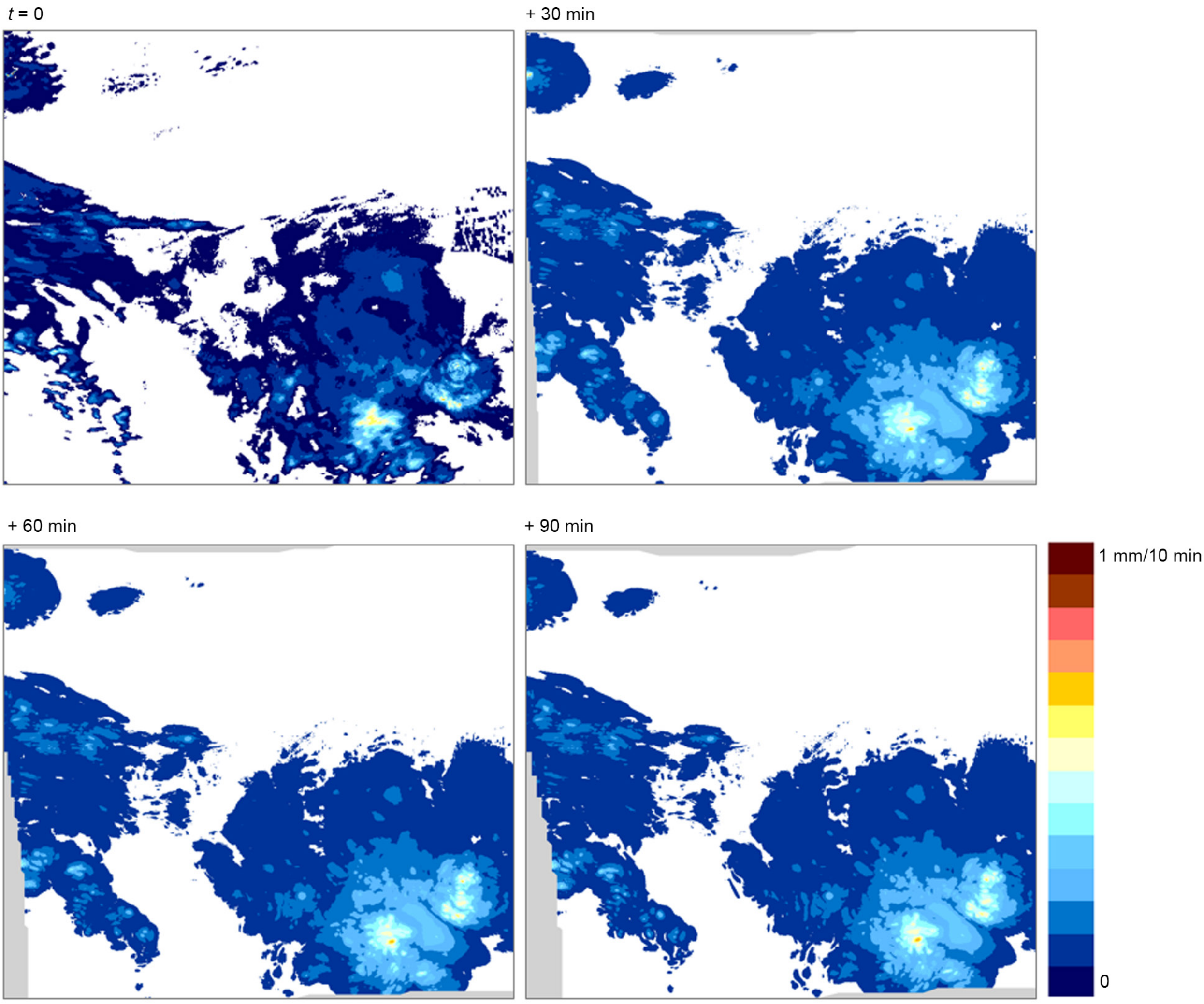

Fig. 3. Nowcasts generated from rainfall analysis from Figure 2 with lead time up to 90 min. The grey areas mainly in left parts of the fields are related to lack of data due to the field advection

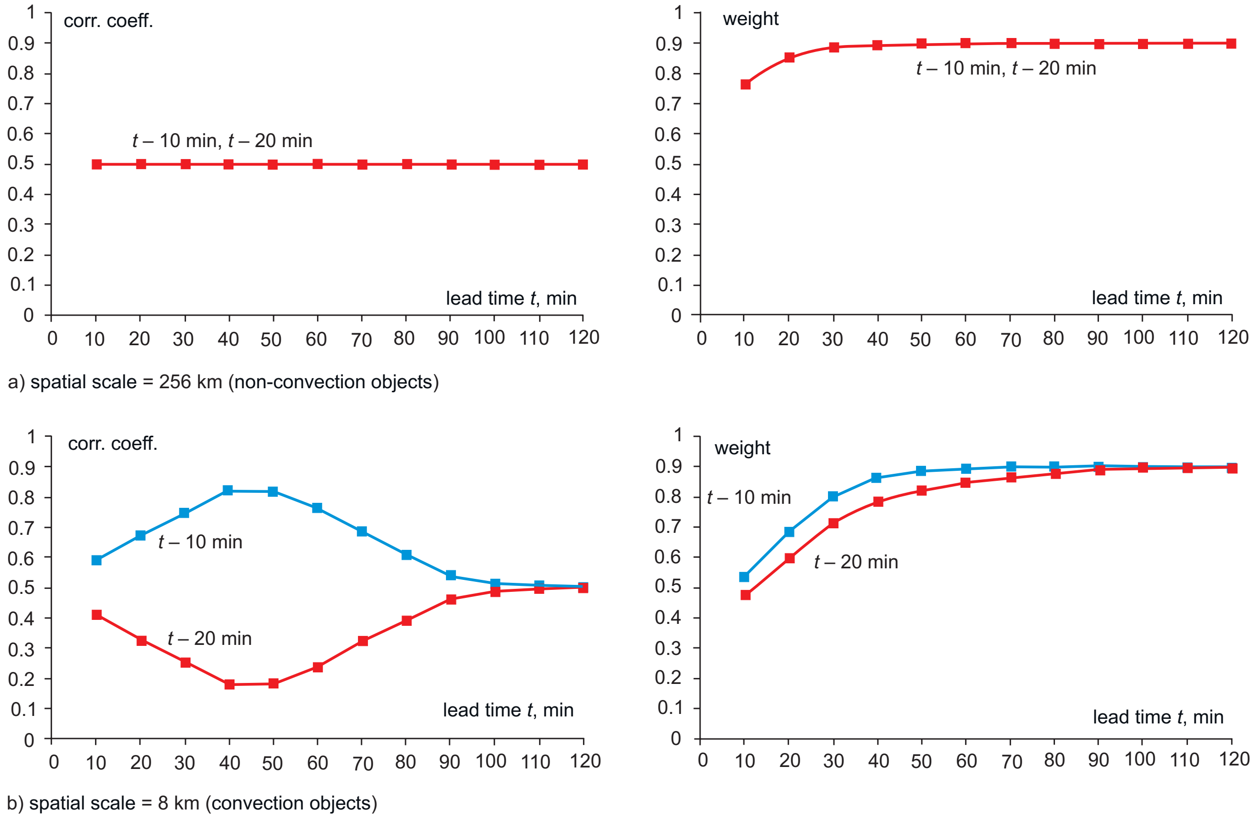

Fig. 4. Diagrams of correlation coefficients between rainfall field at time *t* and fields from *t* – 10 min and *t* – 20 min advected to *t* (on the left), and weights of input fields (on the right) depending on spatial scale of the precipitation objects and the nowcast lead times

CONCLUSIONS

The above observations confirm that the separation of rainfall into at least two classes – convective and non-convective – is necessary in order to improve the reliability of nowcasts. Furthermore, in the case of convective precipitation, it seems necessary to predict the evolution of the precipitation field. It can be concluded that the techniques described herein allow for some progress to be made in the nowcasting of the precipitation field. The pertinent algorithms require a detailed validation for various meteorological situations, using rainfall data available at the IMGW-PIB.

The developed algorithms will be implemented at the IMGW-PIB to the SEiNO system, and they will serve for the operational generation of nowcasting precipitation forecasts. These nowcasts constitute the input to hydrological rainfall-runoff models in the Hydrology System, in particular to the planned flash-flood models (caused by heavy rains), as a tool for meteorological and hydrological forecasting, and they are made available to external users, in particular to regional and district crisis management centres, etc.

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NOWCASTING OPADU OPARTY NA ALGORYTMACH EKSTRAPOLACJI I EWOLUCJI POLA OPADU. WSTĘPNE WYNIKI

ABSTRAKT

Prognozy modeli nowcastingowych coraz częściej są wykorzystywane jako wejście do modeli hydrologicznych typu opad-odpływ. Podstawowym sposobem ich obliczania jest ekstrapolacja (adwekcja) bieżącego pola opadu, zgodnie z wyznaczonymi wektorami przemieszczenia. Największym ograniczeniem tej metody jest brak uwzględnienia dynamiki (ewolucji) pola, co istotnie wypływa na dokładność prognoz. Spada ona szybko z wydłużaniem czasu wyprzedzenia, co widoczne jest szczególnie podczas sytuacji konwekcyjnych. Dlatego obecnie kładzie się nacisk na metody pozwalające uwzględnić ewolucję pola opadu.

Z analizy literatury wynika, że modele cyklu życia komórek nie są wystarczające do istotnej poprawy jakości prognoz, dlatego badane są inne podejścia. Niniejszy artykuł przedstawia zastosowanie modelu autoregresyjnego AR(2) do uwzględnienia zmienności pola. Prezentowany model SNAR (Spectral Nowcasting with Autoregression), rozwijany w IMGW ma na celu zwiększenie sprawdzalności prognoz nowcastingowych dla większych czasów wyprzedzenia.

Proponowane są dwa nowatorskie rozwiązania: I) rozkład pola na składowe zależne od skali przestrzennej, II) prognoza oparta na modelu autoregresyjnym rzędu drugiego. W artykule przedstawiamy opis algorytmów używanych w SNAR oraz pierwsze uzyskane rezultaty.

Słowa kluczowe: opad atmosferyczny, nowcasting, prognozowanie, modelowanie.