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Research Article

Comparing ALADIN-CZ and ALADIN-LAEF Precipitation Forecasts for Hydrological Modelling in the Czech Republic

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Precipitation forecasting has great significance for hydrological modelling, particularly for issuing flood alerts. This study assesses the high-resolution deterministic model ALADIN-CZ (Aire Limitée, Adaptation Dynamique, Development International–Czech Republic) and the ensemble model ALADIN-LAEF (Limited Area Ensemble Forecasting). Verified precipitation data were modified to the form in which they enter the hydrological model used for flood forecasting in the Czech Republic. ALADIN-LAEF, unlike ALADIN-CZ, is currently not considered to be of any value for hydrological predictions in the Czech Republic. In the present paper, we assess the added value of the ensemble model. The most significant rainfall events from the summer seasons during 2011–2015 were selected for the purpose of this study. The results show that ALADIN-LAEF does not have a lower success rate than ALADIN-CZ in predicting significant rainfall events. In fact, for the most verification scores and metrics, ALADIN-LAEF was assessed as more skilful. Surprisingly, the high-resolution ALADIN-CZ does not yield higher success rates than ALADIN-LAEF even at short prediction lead times. This is due to spatial aggregation into hydrological regions, with an area significantly larger than the resolution of the forecasting models. Furthermore, the relationship between synoptic weather types, hydrological regions, and predictability was considered. It was found that the worst prediction results are related to weather situation C (cyclone over central Europe), which dominantly affects Berounka and Lower Elbe catchments.

1. Introduction

Hydrological modelling in the Czech Republic has received increased attention since destructive floods occurred in the years 1997 and 2002. The hydrological prediction system is operated today by the Czech Hydrometeorological Institute (CHMI). Outflow predictions are based on simulations of the AquaLOG (Elbe River basin) and HYDROG (Morava and Oder river basins) models. The hydrological forecast is generated with a 54 h lead time for 111 river profiles. Precipitation input data are provided by the ALADIN-CZ (Aire Limitée, Adaptation Dynamique, Development International–Czech Republic) deterministic high-resolution regional model. Before entering the hydrological model, these data are aggregated into 37 regions over the Czech Republic (Figure 1). This preprocessing simplifies computation of the hydrological model and reduces uncertainty in the spatial distribution of rainfall [1]. Since 2011, the ESP (Ensemble Streamflow Prediction) system has been tested using the ALADIN-LAEF (Limited Area Ensemble Forecasting) ensemble precipitation forecast [2]. These ensemble outflow predictions are operatively simulated since 2012, but their practical implementation or public presentation is limited.

Despite improving hydrological forecasting methods, hydrological forecasts are still impaired by inaccuracies in the quantitative precipitation forecast (QPF) caused by initial conditions, boundary conditions, and model itself [3]. The possibility of determining the magnitude of forecast uncertainty is one of the reasons for the increasing popularity of ensemble prediction [4]. An ensemble forecast is

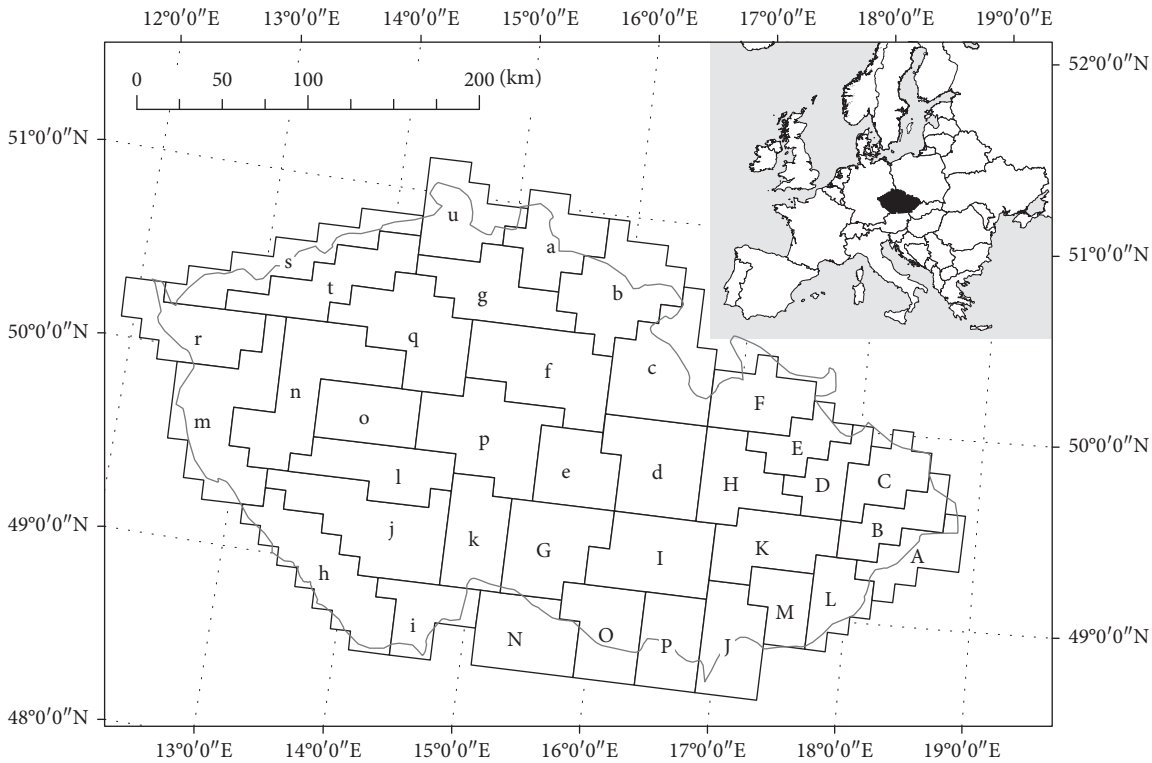

Figure 1: Study area. Hydrological regions for rainfall prediction averaging.

a valuable tool for decision making in hydrological prognostication, as stated, for example, by Cloke and Pappenberger [5] and Alfieri et al. [6]. Its growing popularity has led to the development of several international projects [7, 8]. On the other hand, due to the greater simplicity of their interpretation, deterministic forecasts are often more applicable for public users [9].

Verification of ALADIN-LAEF precipitation forecasts made on the 2010 data by CHMI provided unsatisfactory results and no significant benefit for hydroprognosis was found [10]. This verification used data for the whole year, not only for selected rainfall events, as is done in this work. For this reason, ensemble prediction was evaluated as a second-category product. The consequence of this is that until significant rain is predicted by deterministic ALADIN-CZ, the flood alert is not issued even if all ALADIN-LAEF members predict significant rain. The primary purpose of this work is not to assess the quality of each forecast but rather to assess the benefits of ALADIN-LAEF and its usefulness for hydrological prognosis during significant rainfall-runoff events. Of particular interest is the prediction skill in relation to forecast lead time, predicted total rainfall, and weather type during the event. Precipitation data are not verified in the format provided by forecast models, i.e., the original raster values are aggregated into hydrological regions with irregular shape, as is actually done during data preprocessing for hydrological model. This spatial treatment has a proven positive impact on the success [10].

The datasets and study area are introduced in Section 2. The forecast verification methodology for continuous values and binary events is explained in Section 3. This section also contains some brief description of uncertainties entering into this verification. Section 4 presents the verification results and the case study of extreme rainfall-runoff event on 3 July 2013. Finally, Section 5 summarizes and discusses the results. The weather types under consideration are described in the Appendix section at the end of this paper.

2. Data and Study Area

In the Czech Republic, significant rainfall causing flood events occur in most cases during the warmer part of the year. Therefore, this study is limited to the warm season (April–October). All datasets were available for the years 2011–2015 and were provided by CHMI.

2.1. Precipitation Forecasts. Two different data sources were used. The first model, ALADIN-CZ, is a deterministic model operated by CHMI. The second model, ALADIN-LAEF, is an ensemble forecast running operationally at the European Centre for Medium-Range Weather Forecasts (ECMWF) using the ALADIN-AUSTRIA model configuration. All models are developed within the framework of the LACE (Limited Area modelling Central Europe) international cooperation [11].

2.1.1. ALADIN-CZ Rainfall Data. ALADIN-CZ is a high-resolution hydrostatic spectral limited-area model (LAM). It produces a six-hour precipitation forecast four times daily (00 UTC, 06 UTC, 12 UTC, and 18 UTC) with a forecast range of 54 h (same as hydrological models). The horizontal

resolution is 4.7 km and number of levels used in vertical is 87. Only simulated rainfall amounts from 00 UTC and 12 UTC are postprocessed and used as inputs to the hydrological models. The domain of ALADIN-CZ covers the entire area of the Czech Republic, including the border areas [12, 13].

2.1.2. ALADIN-LAEF Rainfall Data. ALADIN-LAEF is a limited-area ensemble prediction system providing a variety of predictions with initial perturbations that are generated by a breeding-blending method, based on Wang et al. [14] and Wang et al. [11]. This method combines ECMWF-EPS large-scale perturbations and ALADIN-LAEF small-scale perturbations from previous runs using digital filtering. It also contains ARPEGE (Action de Recherche Petite Echelle Grande Echelle) analysis and multiphysics [15]. ALADIN-LAEF contains 17 members, consisting of 16 perturbations and 1 control forecast with horizontal grid spacing of 11 km and 60 levels of vertical resolution. Forecasts are initialized two times per day at 00 UTC and 12 UTC up to lead time 72 h. To match the ALADIN-CZ forecasts, the evaluation presented here was performed on a shorter forecast range of 54 h ahead, and the ALADIN-LAEF domain, covering the whole of Europe and part of the Atlantic [16], was limited to the Czech Republic.

2.2. Rainfall Observations. Adjusted radar rainfall estimates were used for the forecasts verification. One-hour quantitative precipitation estimates that were available for the study are the result of merging rain-gauge and radar measurements [17]. The Czech weather radar network (CZRAD) is operated by CHMI and consists of two C-band radars covering the entire area of the Czech Republic [13]. The rain-gauge network (CLIDATA database) is still growing and today encompasses approximately 500 rain gauges [18]. This gauge network density does not yet guarantee accurate rainfall estimates of convective events, and it provides only a partial view of precipitation's spatial variability. Therefore, conventional ground measurements are used to calibrate radar images, and radar measurements are used to estimate the spatial variability of the process [3]. Merging of radar estimates with rain-gauge measurements at CHMI is done using regression kriging [18, 19]. These data are also applied to several catchments as an alternative precipitation input for hydrological models and, with respect to verification results, they provide the most accurate estimation available of areal rainfall amounts [20]. For the purpose of this study, data were aggregated to 6 h accumulations in the time step corresponding to the forecasts.

2.3. Area of Interest. The area of interest consists of 37 hydrological regions. These regions were proposed by CHMI and are routinely used in operational hydrology. The outer boundary approximately corresponds to the Czech Republic's natural river basins. For this reason, the area of interest extends beyond the Czech boundaries. The shapes of individual areas partly respect the borders of subbasins and at the same time the landscape orography. These hydrological regions are divided into two groups. The first group, shown in Figure 1, is labelled by lowercase letters (areas covered by the AquaLog hydrological model) and the second group by capital letters (areas covered by the HYDROG hydrologic model) [10]. Sizes of the individual areas vary between 1338.6 km^2 (region "M") and 4041.3 km^2 (region "m"), while the average area of a region is 2503.8 km^2. The rainfall data entering the hydrological model for each region are aggregated, meaning that in each time step, each region has only one input rainfall value.

2.4. Synoptic Weather Types. A calendar of synoptic weather types (SWT) has been continually updated for the territory of the Czech Republic since 1946. These data are freely available on the CHMI webpage (http://portal.chmi.cz/historicka-data/pocasi/typizace-povetrnostnich-situaci). From the catalogue of 25 synoptic situations [21], exactly one type describing weather over the Czech Republic with respect to the situation over the whole of Europe and part of the Atlantic is determined for each day. For verification of the precipitation predictability depending on the actual synoptic situation, 6 SWTs occurring most frequently during rainfall events in the warm seasons of 2011–2015 were selected (from the total number of 19 SWTs occurring during the events). These 6 types are B—trough of low pressure over central Europe, Bp—trough moving over central Europe, C—cyclone over central Europe, Ec—eastern cyclonic situation, NEc—northeastern cyclonic situation, and SWc2—southwestern cyclonic situation 2. Characteristics of the synoptic weather types are described in detail in the Appendix section.

2.5. Rainfall Events. Based on the measured data, rainfall events with following characteristics were selected. The total number of determined events in individual regions is 824. The highest number of those events (35) was observed in the "h" region, while the lowest number (14) was in the "r" region. The average event duration was 28.5 h. The largest rainfall amount was 145.3 mm, which occurred with 72 h duration in the "a" region on 22 July 2011. This event occurred during a "C" weather type. The smallest rainfall amount from the evaluated events was 15 mm and the average event rainfall was 26 mm. The greatest event length of 96 h was observed from 13 to 17 May 2014 in the "C" region during a "Bp" weather type. The most significant flood occurred on 3 June 2013 and affected the entire river basin of the Vltava and northern part of Bohemia. Some flow rates gained values of 100-year flood. For the verification purpose, all 54 h forecasts overlapping time range of defined events were evaluated.

3. Verification Methodology

3.1. Data Preprocessing. All data were aggregated to 37 regions in the same way as is done for hydrological prediction purposes. This study assesses the performance of ALADIN-CZ and ALADIN-LAEF during events causing significant

rainfall-runoff response. The event selection was performed by applying the USLE definition in a similar way as was done by Hanel and Maca [22] and by Svoboda et al. [23], which means that only events with total depth greater than 12.7 mm and separated by at least a 6 h period without rain or events with maximum intensity greater than 6.35 mm/15 min are considered. Exceeding these thresholds potentially leads to soil erosion and surface runoff [24].

3.2. Verification Scores and Methodology. Given the focus of this work on precipitation data for hydrological modelling in the CHMI with its primary focus on the deterministic forecast, it was necessary to verify the ensemble data expressed as both probabilistic and deterministic forecasts.

ALADIN-CZ and ALADIN-LAEF forecasts were evaluated by verification methods for continuous variables as well as for binary (dichotomous) events (methods are described in the following paragraphs). Within the ensemble verification, all 16 + 1 members were evaluated individually. Moreover, ensemble mean (hereafter referred to as MEAN) and ensemble median (hereafter referred to as MEDIAN) were evaluated as well. Both MEAN and MEDIAN are calculated from 16 ensemble members. The seventeenth member is the control forecast (hereafter referred to as CF), and it is separated from the ensemble because the initial conditions for perturbations are centred around the control analysis, thereby generating the positive and negative perturbations [15, 25]. Forecast results similar to the MEAN can therefore be expected. When deterministic and probabilistic forecasts are compared, it is necessary to transform the probabilistic forecast to deterministic or the deterministic forecast to probabilistic using binary values [26]. With respect to the purpose of this work, MEAN and ALADIN-CZ are the pairs most often compared here as two deterministic predictions.

Verification methods recommended by Jolliffe and Stephenson [27], Wilks [28], and WMO [29] were used in this study. The correspondence between observations and predictions in the form of continuous values was assessed using mean error (ME), mean absolute error (MAE), and root mean squared error (RMSE). The association between observations and predictions was evaluated by Pearson correlation (COR). A verification approach based on binary events was chosen. Continuous values were transformed to binary by setting the probability of the deterministic forecast to 1 if the predicted event will occur and otherwise to set the probability to 0 [4]. Verification of binary events provides an extensive range of binary scores based on a contingency table summarizing the frequency of "yes" (1) and "no" (0) forecasts and occurrences, where rainfalls equal to or greater than a predefined threshold are set to "yes" and smaller rainfalls to "no" (nonevent). The contingency table provides four possible pair combinations of the counted absolute frequencies of yes/no forecasts and observations and is termed joint distribution. These pairs are usually referred to as hits, misses, false alarms, and correct rejections [28, 29]. Because performance was evaluated only for substantial rainfall events, only those scores were selected not focusing on correct rejections.

Binary scores were calculated for the same data as in the case of continuous values. The following binary measures were used: frequency bias (B); threat score (TS); probability of detection (POD), also known as hit rate (H); false alarm ratio (FAR); probability of false detection (POFD), also known as false alarm rate (F); proportion correct (PC); Heidke skill score (HSS); odds ratio (OR); odds ratio skill score (ORSS); Pierce skill score (PSS); Brier score (BS); and ranked probability score (RPS). The latter two are applicable also for probabilistic forecasts [26, 29]. The scores along with the range of possible values and the perfect score are shown in Table 1.

Unlike deterministic forecasts of binary events and continuous values, a probabilistic forecast is expressed as the probability of an event's occurrence having a value between 0 and 1, inclusive. Common summary measures of ensemble (ALADIN-LAEF) forecast skill, Brier skill score (BSS), and ranked probability skill score (RPSS) were calculated [30]. These scores assess the ensemble skill against the reference forecast. The reference forecast is usually obtained from climatology. It is also possible to use a deterministic forecast as a reference forecast. For the purpose of this work, the ALADIN-LAEF probabilistic forecast was compared to the reference forecasts given by ALADIN-CZ, MEAN, MEDIAN, and CF. A different approach to evaluating the ensemble forecast provides a rank histogram (also known as the Talagrand diagram). This graphical method tests ensemble reliability by ranking the observed outcomes with respect to the corresponding ensemble members [30, 31]. In accordance with the histogram's shape, a rank histogram provides information about an ensemble's bias and spread. The best result is indicated by a flat histogram, i.e., by uniform distribution of ranks. A lack of variability (underdispersion) is represented by a U-shaped histogram, a dome-shaped histogram means too large ensemble spread (overdispersion), and an asymmetric histogram indicates underforecasting or overforecasting bias [28, 32].

4. Results

All forecasts were verified from the perspective of dependence on time-ahead and rainfall thresholds. Thresholds were defined with respect to the measured 6 h rainfall accumulations at 1, 2.5, 5, and 10 mm. Calculations of these characteristics were related to the individual hydrological regions and, for the sake of clarity, were averaged to a single value representing all regions. Another perspective was provided by evaluation of forecast accuracy during the weather types occurring most frequently during the selected events. The 6 h precipitation totals were verified for all 16,938 forecast-observation pairs. In the following figures, ALADIN-CZ is referred to as ALADIN, ALADIN-LAEF ensemble mean as MEAN, ALADIN-LAEF ensemble median as MEDIAN, and ALADIN-LAEF ensemble control forecast as CF.

4.1. Continuous Variables. This section compares the dependence of forecasts accuracy on lead time (for a 6 h time

Table 1: Comparison of ALADIN and MEAN verification scores for all data together without dependence on lead time or threshold. Bold values indicate better scores.

Score	ALADIN	MEAN	Range	Perfect score
Correlation (COR)	0.0396	**0.0774**	[−1, 1]	1
Root mean squared error (RMSE)	7.3250	**6.6944**	[0, +∞]	0
Mean absolute error (MAE)	5.0287	**4.5540**	[0, +∞]	0
Bias (BIAS)	**0.7611**	0.7011	[0, +∞]	1
Brier score (BS)	0.3878	**0.3630**	[0, 1]	0
Ranked probability score (RPS)	0.2440	**0.2439**	[0, 1]	0
Equitable threat score (ETS)	0.1354	**0.1614**	[−1/3, 1]	1
Threat score (TS)	0.3915	**0.3997**	[0, 1]	1
Probability of detection (POD)	**0.4955**	0.4858	[0, 1]	1
False alarm ratio (far)	0.3489	**0.3071**	[0, 1]	0
Probability of false detection (POFD)	0.2579	**0.2091**	[0, 1]	0
Proportion correct (PC)	0.6206	**0.6406**	[0, 1]	1
Heidke skill score (HSS)	0.2385	**0.2779**	[−1, 1]	1
Odds ratio (OR)	2.8266	**3.5734**	[0, +∞]	+∞
Odds ratio skill score (ORSS)	0.4773	**0.5627**	[−1, 1]	1
Pierce skill score (PSS)	0.2376	**0.2767**	[−1, 1]	1

step). Figure 2 shows error metrics (ME, MAE and RMSE) and correlation (COR). With the exception of ME, the accuracy does not decrease substantially with increasing time ahead. ALADIN is evaluated as best only for ME. That is in contrast with MAE, where absolute error values are used. It is therefore likely that ALADIN's positive and negative errors compensate one another. ME for all models indicates negative bias (underforecast). MEAN is the best ensemble-based result. Poorer results, albeit still better than those of ALADIN (except for ME), are achieved by MEDIAN and CF.

4.2. Binary Events. As seen in Figure 3, methods for binary events yield less substantial differences between the forecasts compared to the error metrics of continuous variables. POD is the proportion of occurrences that were correctly forecasted [26] and the perfect score is 1. Figure 3 shows a better performance of MEAN in the near lead time but a sizeable drop in the score from the time 48 h ahead, whereas ALADIN's success rate from this time increases. TS also concerns correctly predicted events, as is reflected in the similar increase of score difference between MEAN and ALADIN from 48 h ahead. A different perspective is provided by FAR and POFD, which emphasize mainly the false alarms, and the perfect score is 0 in both cases. FAR evaluates ALADIN best in all time steps. On the other hand, POFD evaluates ALADIN significantly more poorly while MEAN is around the average values, and only in this case does MEDIAN have the best score. The reason for these differences in results is that FAR calculation takes hits into account but POFD takes correct rejections into account.

Figure 4 shows the threshold-dependent POD, TS, FAR, and BS curves. This verification method evaluates insignificant divergence in the forecasts accuracy and the skill levels of all models are similar. Except for BS, all scores have a declining trend of success in dependence on increasing thresholds. In addition, BS (in contrast to other scores) does not consider only binary values. The ensemble probabilistic forecast is expressed as one probability value (in the range from 0 to 1), while observation is a binary value, i.e., 0 or 1 [30]. For this reason, the ensemble is represented by a single grey line in the BS graph.

Figure 5 compares the ensemble forecast skill with respect to the reference forecast (here ALADIN, MEAN, MEDIAN, and CF are considered as reference forecasts). The perfect score is 1 (with 0 indicating no skill) in both RPSS and BSS. This means that the higher the value, the less successful is the deterministic model vis-à-vis the probabilistic ensemble forecast. RPSS increases with increasing forecast lead time and differs only slightly for different reference forecasts. According to BSS, MEAN is the best deterministic forecast, though still poorer than the probabilistic ensemble forecast. The ensemble shows the greatest skill improvement relative to ALADIN in the middle part of the forecast lead time.

4.3. Rank Histogram. A rank histogram constitutes a verification method providing information about ensemble spread and dispersion characteristics. This method is not suitable for comparing deterministic forecasts, and therefore, only the ALADIN-LAEF ensemble was assessed. In order to obtain the dispersion characteristics for different rainfall amounts, the rainfall was divided into classes with 6 h rainfall amounts of less than 1, 2.5, 5, and 10 mm and greater than 10 mm. Figure 6 shows a U-shaped histogram characterizing too small ensemble spread. Furthermore, due to decomposition, it is obvious that the ensemble overestimates smaller rainfalls and underestimates larger rainfalls.

4.4. Hydrological Regions. For more detailed evaluation, all hydrological regions were verified individually. The success of predictions in each region was determined by application of five verification methods (COR, MAE, RMSE, TS, and POD). Based on the results, the regions were ranked from best to worst for each method separately. The rank values (five for each region) were then summed and divided into

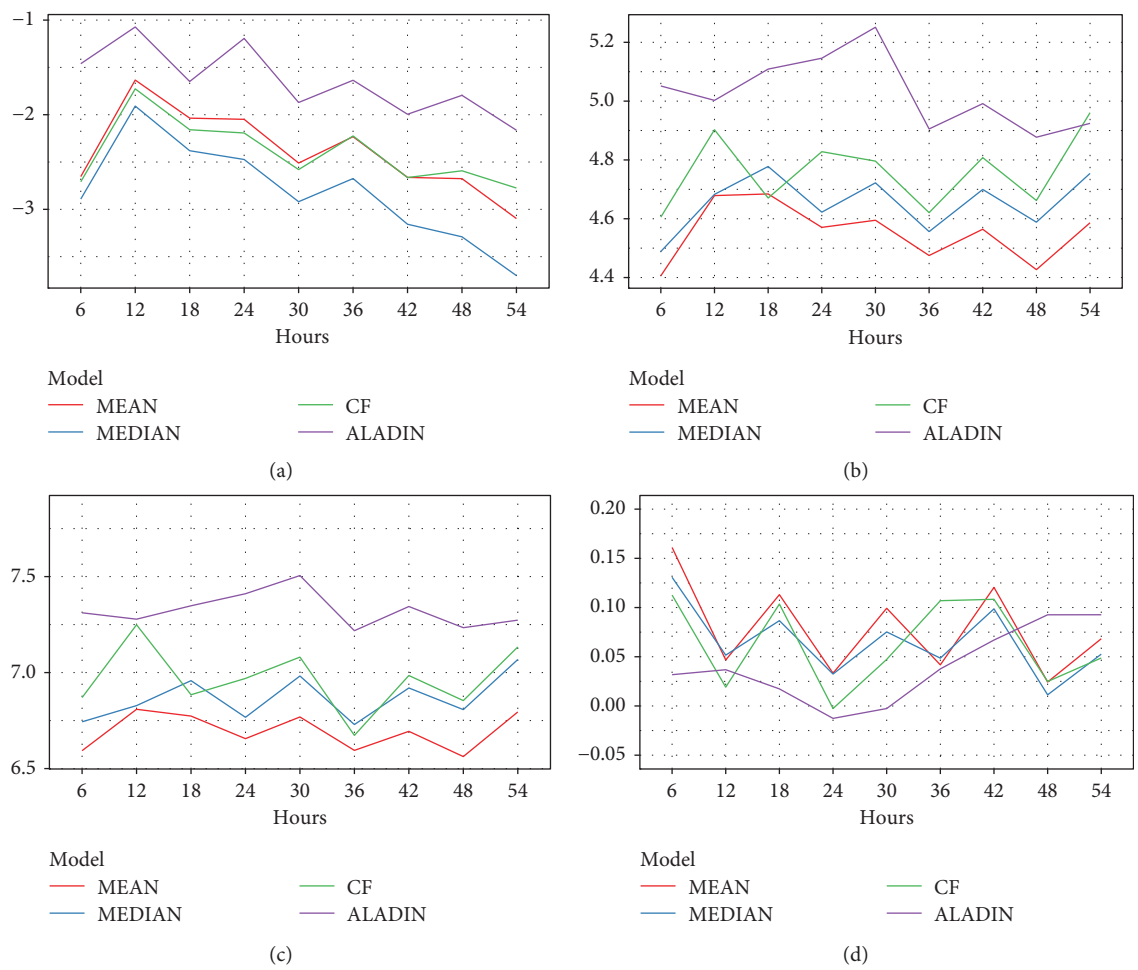

Figure 2: Comparison of ALADIN (purple), MEAN (red), MEDIAN (blue), and CF (green) for ME (a), MAE (b), RMSE (c), and COR (d) as a function of lead time. Grey lines represent 16 ensemble members.

five groups representing forecasting skill, where 1 means the best and 5 the worst results, as seen in Figure 7. Forecasts of ALADIN and ensemble MEAN were assessed in dependence on thresholds (1, 2.5, 5, and 10 mm) and, for additional comparison purposes, by the average of these results. Figure 7 shows that some problematic regions are situated in the northwestern part of the Czech Republic. Border and mountain areas provide surprisingly better results in most cases, especially in the western and eastern parts of the country.

4.5. Synoptic Weather Types. The ALADIN and MEAN forecasts during the five most frequently occurring weather types were verified by COR, MAE, RMSE, POD, TS, and BS. As can be seen in Figure 8, predictions during the Ec weather type achieved the highest rate of success. In contrast, the forecast accuracy is lowest during the Swc2 weather type. Differences between ALADIN and MEAN forecast in Figure 8 confirm the conclusions drawn from Figures 2 and 3.

4.6. Flood Event on 3 June 2013. At the end of May, the territory of the Czech Republic was affected by several waves of heavy rainfall causing strong soil saturation. The strongest precipitation wave came on 1 June, however. This was due to a trough of low pressure moving from the east over the Czech territory (synoptic weather type "C") [33]. An area of high pressure over Northern Europe and a ridge of high pressure over Western Europe prevented the trough of low pressure from advancing further west. This resulted in retrograde movement of waved frontal systems over Central Europe and total precipitation sporadically exceeding 100 mm day^{-1} [34]. Figures 9(a) and 9(c) display the measured (OBS) and predicted rainfall amounts aggregated from 1 June 00 UTC in areas "k" and "i". These two areas are both in the southeastern part of the South Bohemia Region. The areas were selected due to availability of data from the ensemble hydrological forecast and also because they were in the main precipitation belt. Figures 9(b) and 9(d) show the measured flows (OBS) and hydrological forecasts from the same date as the precipitation forecast created on the basis of data from the ALADIN-LAEF ensemble and from the deterministic ALADIN-CZ forecast for the Pilař and Lásenice measuring profiles. The Pilař profile is located on the River Lužnice in region "i" with a watershed area of 935.23 km^2. The Lásenice profile is on the River Nežárka in region "k"

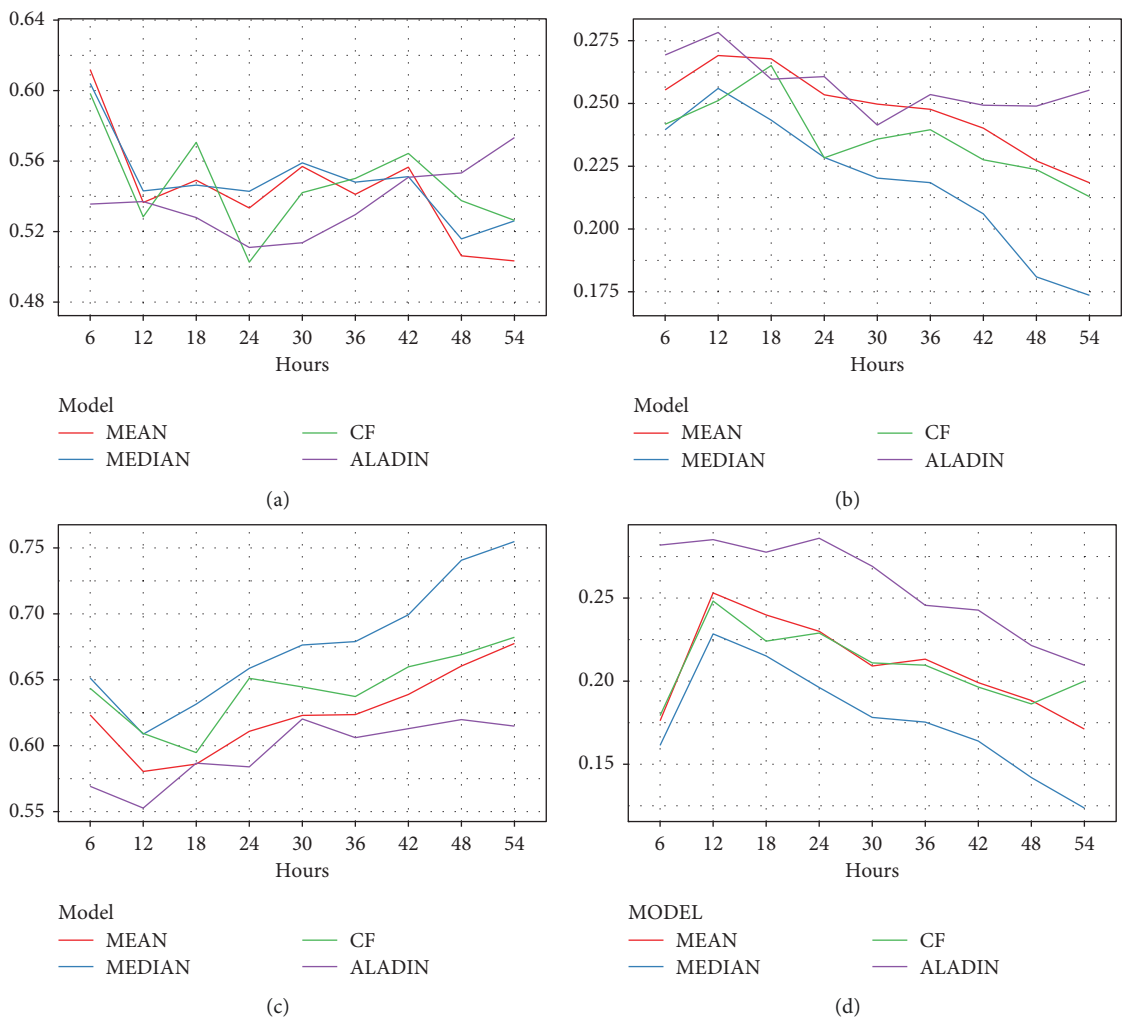

Figure 3: Comparison of ALADIN (purple), MEAN (red), MEDIAN (blue), and CF (green) for POD (a), TS (b), FAR (c), and POFD (d) as a function of lead time. Grey lines represent 16 ensemble members.

with a watershed area of 684.66 km^2. For more information, see Table 2.

Total precipitation estimates generally were being underestimated in all areas, which also affected flow predictions. In the case of regions "i" and "k", as well as in other areas, the rains started earlier than expected. Nevertheless, the hydrological models successfully estimated the onset of the flood wave. As time passed, the effect of the underestimation of precipitation became apparent and predicted flows started to be lower than measured values. The models produced greater inaccuracies in the case of the Lásenice measuring profile, where culmination flow was reached at an earlier time than that was in the Pilař profile. Even though the ensemble average was worse than the deterministic forecast, its distribution of predicted flows affected the measured culmination values. This extreme precipitation outflow event corresponds with the results of verification in this study, where use of the mean precipitation ensemble model suitably complements the simultaneous deterministic forecast. It also indicates the suitability of applying an ensemble forecast in operational hydrology in order more accurately to describe the uncertainty of hydrological forecasting.

5. Summary and Conclusions

In this paper, two different models providing precipitation forecasts are verified and compared. The first of these is the ALADIN-CZ regional deterministic model. Precipitation predictions of this model are used operationally for hydrological forecasting at CHMI. The second of these is ALADIN-LAEF. This model provides an ensemble precipitation forecast and, even though the data is available, it is considered not to be beneficial for hydrological forecasting. This study was undertaken to assess potential benefits of using ALADIN-LAEF precipitation forecasts for hydrological modelling, especially in cases of significant rainfall events. The results from this paper will be used in developing effective postprocessing methods for hydrological prognostication.

Various verification methods were applied in evaluating the two models. For comparison with the deterministic

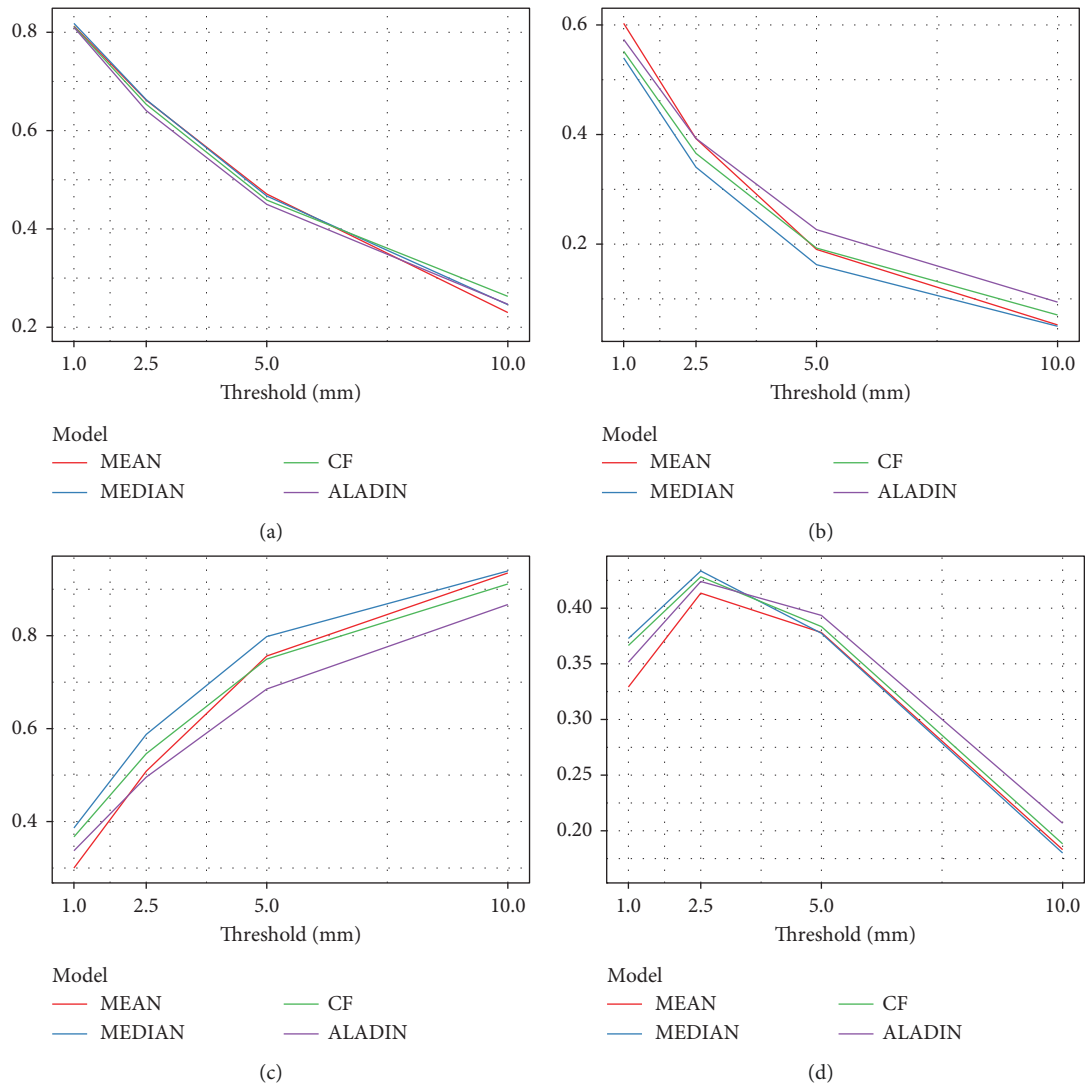

Figure 4: Comparison of ALADIN (purple), MEAN (red), MEDIAN (blue), and CF (green) for POD (a), TS (b), FAR (c), and BS (d) as a function of thresholds. Grey lines represent 16 ensemble members. In case of BS, the ensemble is represented by single grey line.

ALADIN-CZ (ALADIN), the ALADIN-LAEF ensemble (consisting of 16 members) was in most cases represented by simple mean (MEAN), median (MEDIAN), and control forecast (CF). According to ME, both models tend to underestimate precipitation. In the case of the ensemble forecast, the rank histogram shows increasing underestimation with increasing rainfall. It is necessary to point out, however, that verified rainfall events were determined using observations, not model predictions. ME is also the only score that clearly evaluates ALADIN as best. This could be caused by error compensation. The results are different in the case of MAE, where absolute values are used. MAE, RMSE, and COR evaluate MEAN as the best. Verification scores for binary and discrete values provide less-clear results. MEAN performed more poorly compared to ALADIN as measured by FAR, which means that ALADIN deals better with false alarms. On the other hand, MEAN performed better according to POFD, indicating poorer performance of ALADIN in correct rejections. POD and TS indicate no significant divergence between ALADIN and MEAN. It is noteworthy that ALADIN predictions improved at the end of the lead time. It is generally assumed that due to the higher resolution of the deterministic model compared to the ensemble, the deterministic model is more valuable in the first few hours of prediction. Effect of data aggregation into hydrological regions, with an area significantly larger than the models' resolution, leads to the results that even in the early hours, ALADIN-CZ does not yield higher success rate.

In addition to the deterministic approaches, probabilistic forecasts were also assessed by RPSS and BSS. Figure 5 shows the positive skill of the ensemble forecast relative to ALADIN, MEAN, MEDIAN, and CF, which were used as reference forecasts. This method also allowed for comparison of the reference forecasts themselves. Especially in the case of

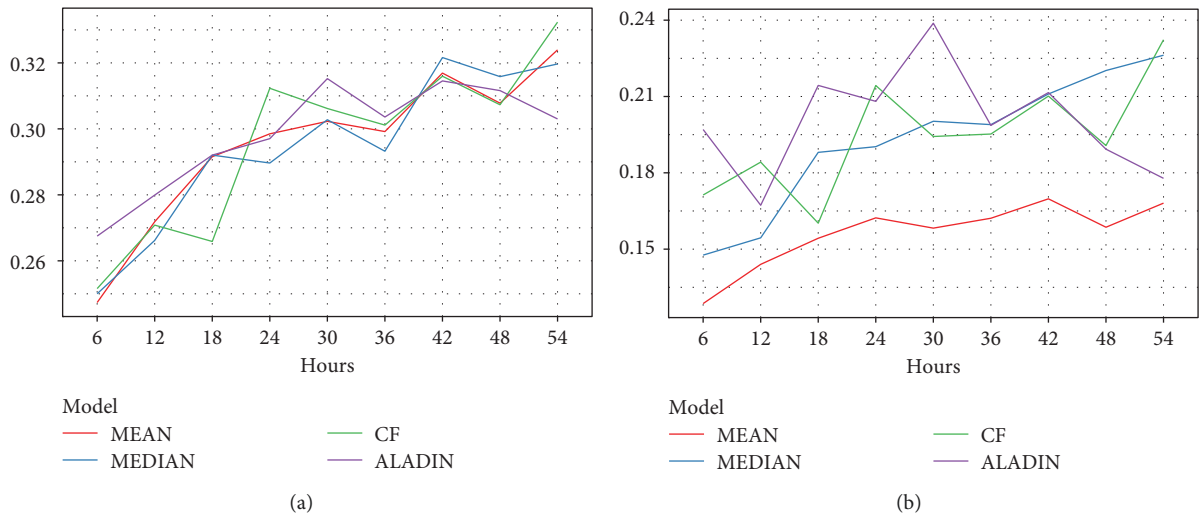

Figure 5: Ensemble skill scores using ALADIN (purple), MEAN (red), MEDIAN (blue), and CF (green) as reference forecasts. RPSS (a) and BSS (b) show positive ensemble skill as a function of lead time.

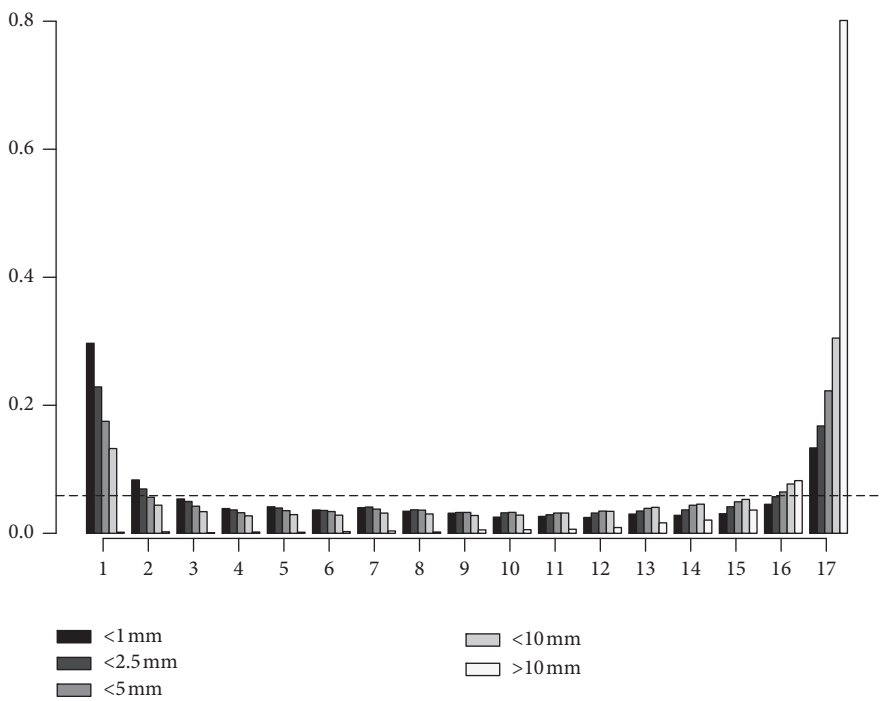

Figure 6: Rank histogram for ensemble forecast (ALADIN-LAEF). Bins decomposition is based on 6 h rainfalls <1 mm (black bars), <2.5 mm, <5 mm, <10 mm, and >10 mm (white bars).

BSS, it is obvious that the performance of MEAN is better in comparison with ALADIN, meaning that the ensemble forecast has lower positive skill relative to MEAN than to ALADIN.

The influence of weather type on forecast skill was assessed. It is clear from Figure 8 that in the cases of ALADIN and MEAN, the weather types were evaluated similarly. There were greater differences between the individual situations, and especially as measured by RMSE, than between models. The poorest skill was achieved during SWc2 situations, which are characterized by frontal systems frequently passing from the Atlantic Ocean.

Finally, five verification metrics were used to rank ALADIN and MEAN forecast accuracy in individual hydrological regions. The regions with the poorest forecast accuracy were similar for both models. The same is true for regions where the prediction was most successful. Unfortunately, the poorest-rated regions are among those most

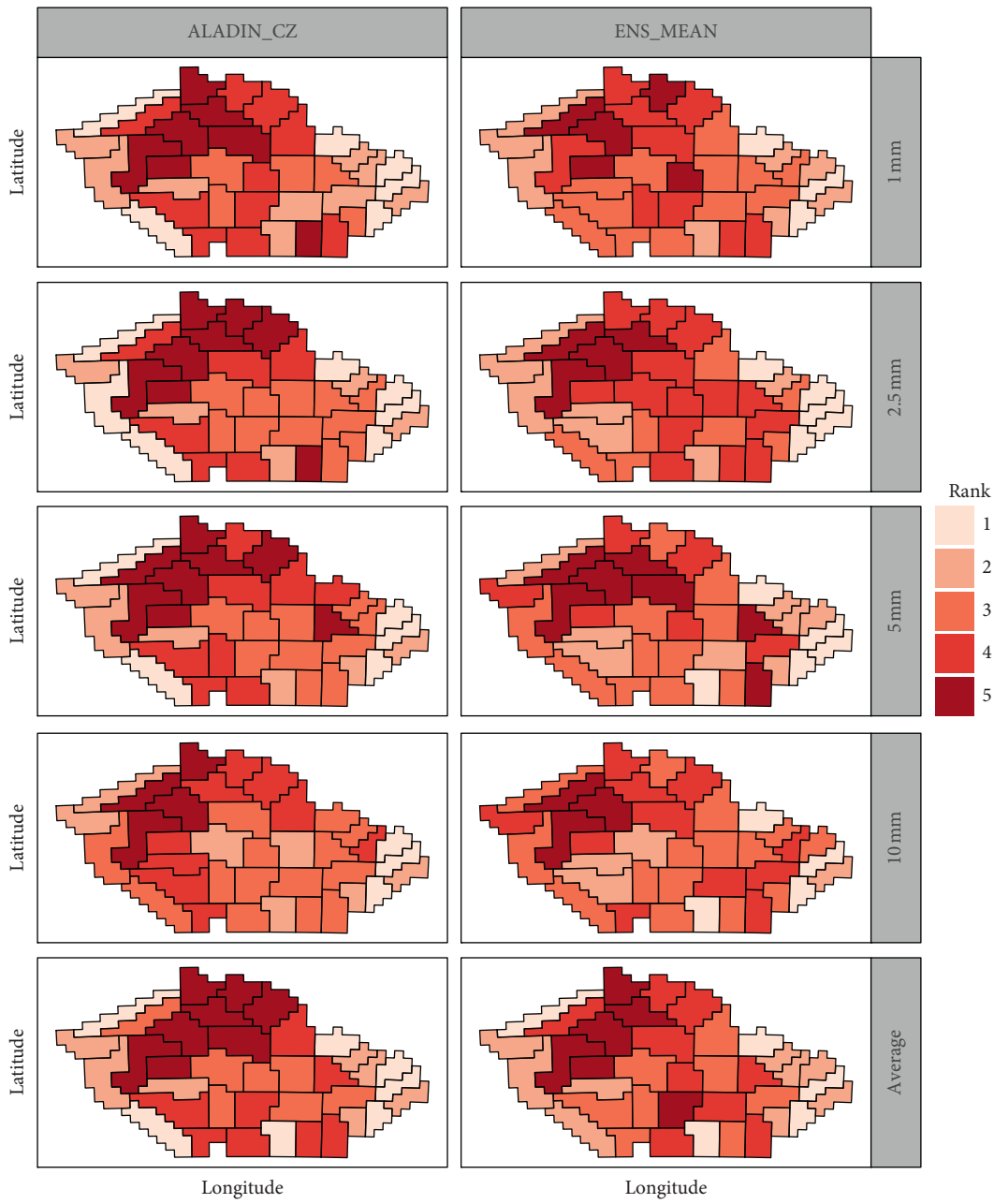

Figure 7: Ranking of forecast accuracy in dependence on threshold in the individual hydrological regions. Regions are ranked from 1 to 5, where 1 means the best forecast (light red) and 5 means the poorest forecast (dark red). Results are shown for ALADIN and MEAN. The last row presents average rank of 1, 2.5, 5, and 10 mm thresholds.

often hit by floods in the last 60 years. However, the success rate of predictions in the individual areas corresponds to the results of the evaluation of synoptic weather types. Predictions during the weather situation Ec and NEc reach the highest accuracy. This situation brings in most cases significant rainfall to the east part of Czech Republic, where the success rate of the forecast compared to the rest of the territory is higher. On the other hand, the worst-rated weather situation C brings the most rainfall to the area between the southwestern and northern parts of the Czech Republic, where the poorest-rated regions are situated.

Finally, the influence of weather type on forecast skill was assessed. It is clear from Figure 8 that in the cases of ALADIN and MEAN, the weather types were evaluated similarly. There were greater differences between the individual situations, and especially as measured by RMSE, than between models. The poorest skill was achieved during SWc2 situations, which are characterized by frontal systems frequently passing from the Atlantic Ocean.

Whether the deterministic ALADIN-CZ is or is not more skilful than the simple ensemble mean is not so clear. Although for most verification scores and metrics, MEAN

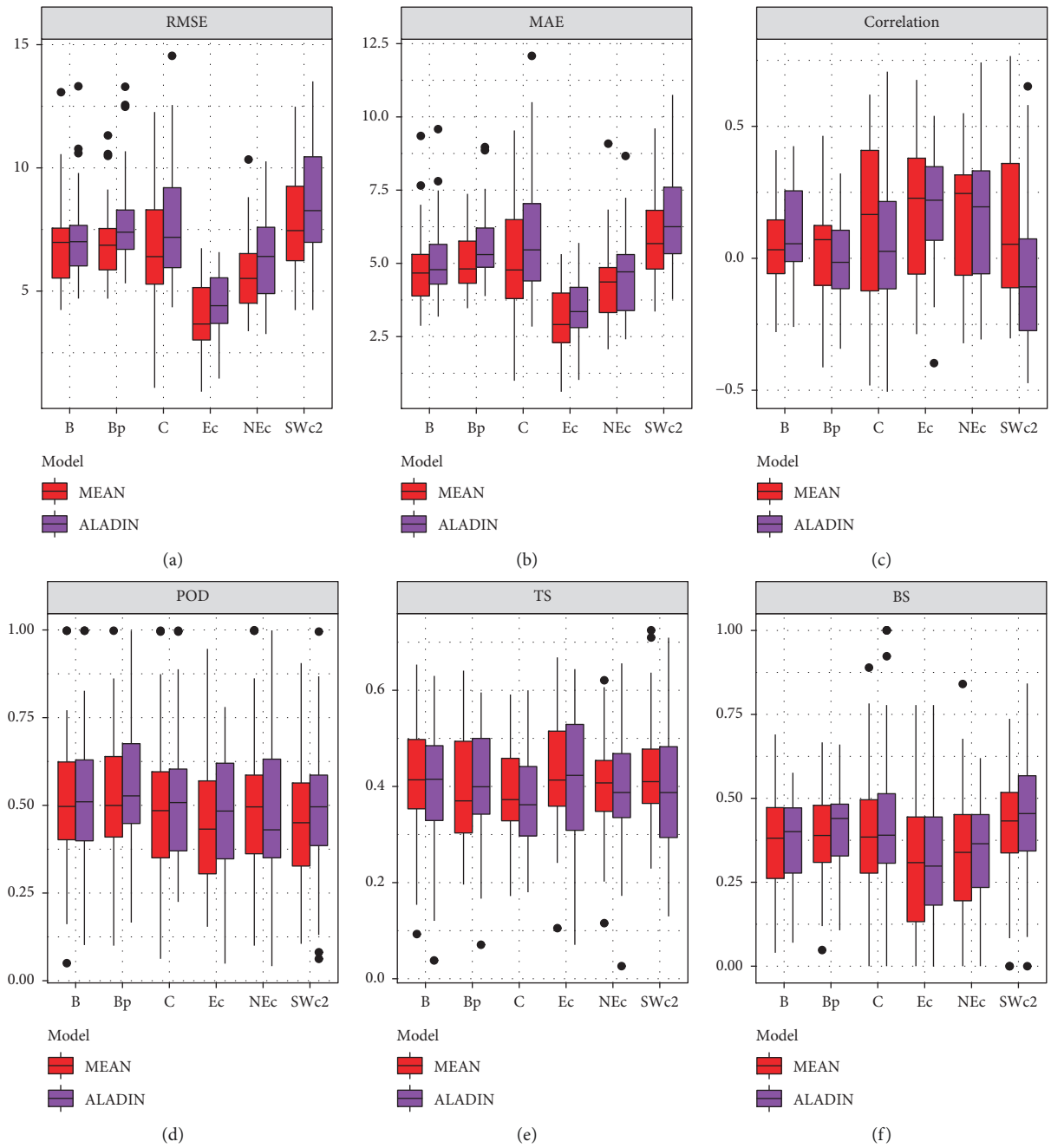

Figure 8: Boxplots of RMSE (a), MAE (b), COR (c), POD (d), TS (e), and BS (f) dependence on weather types. ALADIN results are plotted with purple boxes, MEAN with red boxes.

was assessed as more skilful (Table 2), and the differences were often not substantial. RMSE and MAE were examples of exceptions in which ALADIN reached a markedly greater error rate, but its applicability from the perspective of use in hydrological forecasting was verified. From the results reported above, it can be seen that ALADIN-LAEF could at least be used as an additional data source for hydrological forecasting, especially in the form of a probabilistic forecast. ALADIN-LAEF is at least an equally valuable source in comparison to deterministic ALADIN-CZ, and it should be considered as a relevant source of information for hydrological prediction. In general, ensemble systems are commonly used to determine the degree of uncertainty of predictions. However, it is clear from the results that the mean of the ensemble is also beneficial, and therefore, it would be appropriate to include it in the form of deterministic prediction alongside the current ALADIN-CZ prediction. A suitable form for combining high-resolution deterministic forecasting and an ensemble prediction system has been described by Rodwell [4] and termed the combined prediction system. This method produces probabilistic forecasts while including a deterministic model as an

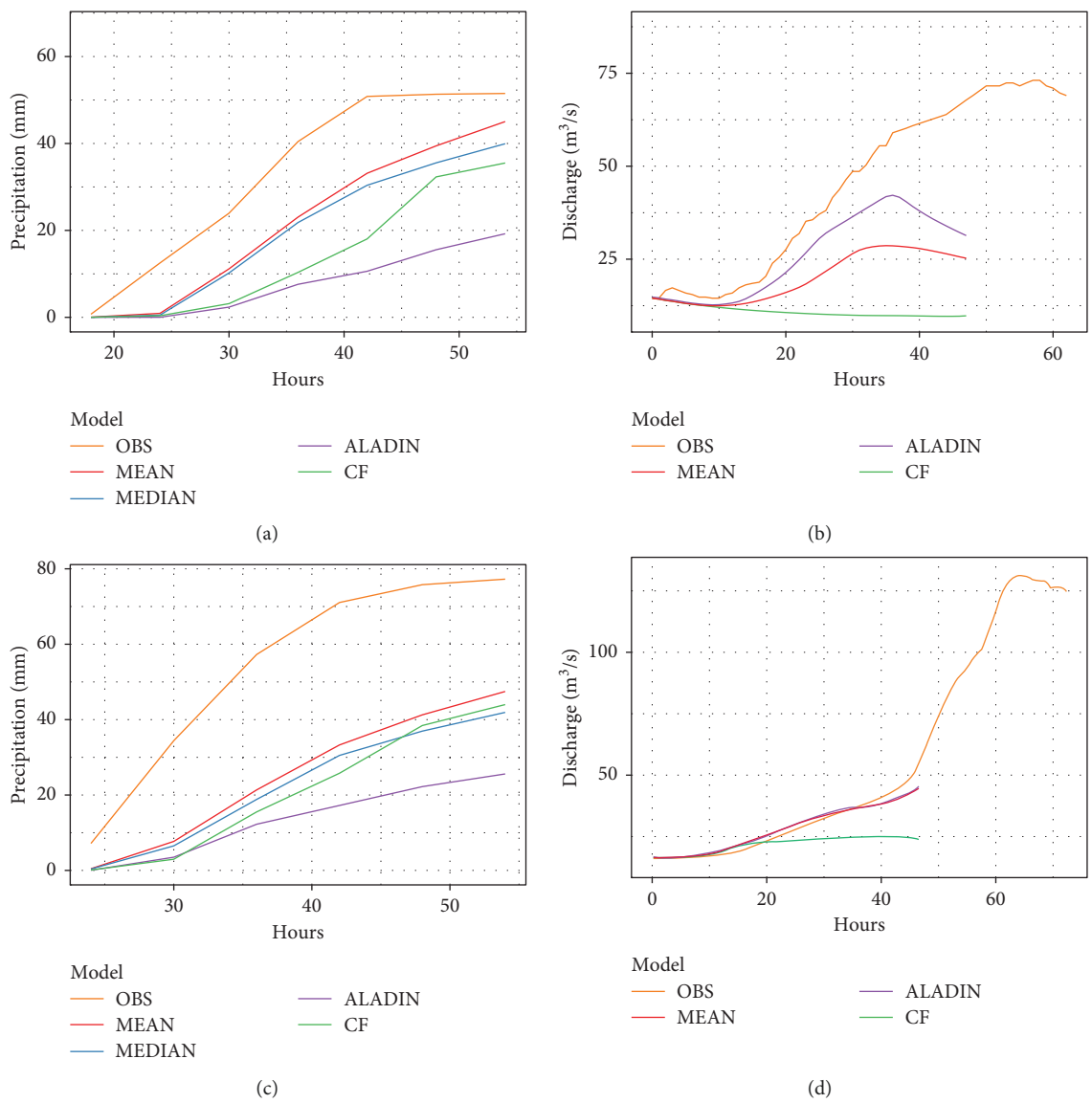

Figure 9: Comparison of ALADIN (purple), MEAN (red), MEDIAN (blue), CF (green), and measured data-OBS (orange). Lines with measured flows are extended to the culmination time. (a) region k, (b) Lásenice, (c) region i, and (d) Pilař.

Table 2: Hydrological characteristics for regions "k" and "i" during the flood event on 3 June 2013.

Region	Observed rainfall (mm)	ALADIN-CZ (mm)	ALADIN-LAEF MEAN (mm)	ALADIN-LAEF maximum (mm)	Gauging station/river	Gauging station basin area (km^2)	Maximum outflow ($m{\cdot}s^{-1}$)
K	51.5	19.2	45.0	62.4	Lásenice/Nežárka	684.7	73.1
I	77.3	25.6	47.4	66.7	Pilař/Lužnice	935.2	133.0

ensemble member with weight determined by the count of equivalent ensemble members.

Appendix

Synoptic Weather Types

B: Trough of Low Pressure over Central Europe. The characteristic feature of this situation is a primary cyclone over Western Scandinavia. From this cyclone a trough extends as far as the Mediterranean Sea. This trough is in the area between anticyclones over the Atlantic and Eastern Europe. A dissipating frontal zone moves over the Bay of Biscay and brings cold air to the Western Mediterranean. This movement causes an inflow of warm air from the southeast over the north of Italy. At the boundary of these two different air masses, there forms a new frontal zone, which moves to the northeast. Precipitation occurs most often over Western Slovakia and the eastern part of the Czech Republic.

BP: Trough Moving over Central Europe. The Bp type differs from B by the primary cyclone position. In the Bp type, there is a cyclone over Iceland and an anticyclone situated further south over the Atlantic Ocean. The trough moves from west to east over central Europe, and the frontal boundary is located within its axis. Frontal systems move from south to north by this boundary. The trough moves quickly, and this situation is of short duration.

C: Cyclone over Central Europe. The main feature of this situation is a stationary primary cyclone over Western Europe, which at the end of the period moves slowly eastward. A high-pressure area is over northeastern Europe and over the Atlantic Ocean. The frontal disturbances in the warm air pass from the south around the primary cyclone. The fact that the centre of the primary cyclone is positioned over Western Europe causes the greatest occurrence of precipitation over the Czech Republic during this situation.

Ec: Eastern Cyclonic Situation. This weather type is characterized by a stationary primary cyclone with its centre over the Tyrrhenian Sea (to the west of Italy). At higher levels around the cyclone, warm air flows from the southeast over Central Europe. A high-pressure area is over Scandinavia and causes cold air to flow southwest to Central Europe. Over Hungary, where these two air masses meet, convection currents develop and form frontal disturbances. These fronts shift to Western Europe.

NEc: Northeastern Cyclonic Situation. The NEc situation is typified by an area of high pressure over Great Britain or a ridge of high pressure from southwest Europe, over Great Britain, and up to Scandinavia. At lower levels, cold air flows to Central Europe. At the same time, warm air flows to Central Europe at higher levels around the cyclone over the Balkans. This air brings persistent rainfall. In some situations, there may be colder air at lower levels and not too warm air at higher levels. The frontal waves can then shift from the Azores over the Mediterranean Sea, where fronts may intensify and shift around the Balkan cyclone to Poland and then to the Czech Republic.

SWc2: Southwestern Cyclonic Situation 2. The main feature of this situation is a frontal zone oriented from southwest to northeast over northwestern Europe. A warm anticyclone or only a ridge of high pressure is situated over the Mediterranean Sea. A cyclone to the south of Iceland causes cold air to flow from Greenland to the middle part of the Atlantic Ocean, where this cold air meets up with warm air from the southwest. This frontal zone produces frontal waves, and cyclones continue to move in a direction over the British Isles, Finland, and the North Sea. Frontal systems frequently pass over Central Europe. An area over the Czech Republic is alternately in a cold and a warm sector. The situation ends with a cold front passing through Central Europe and with wind in a northwesterly direction.

The forecasts and observed data used to support the findings of this study were supplied by Czech Hydrometeorological Institute under license and so cannot be made freely available. Requests for access to these data should be made to chmi@chmi.cz.

Data Availability

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Disclosure

The abstract of this paper was presented in EMS Annual Meeting Abstracts, 2017.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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References

[1] J. Daňhelka, "Operativní hydrologie: hydrologické modely a nejistota předpovědi," *Sborník prací Českého Hydrometeorologického Ústavu*, vol. 51, p. 104, 2007.

[2] Aqualogic, *ESP Teorie a Referenční Příručka*, Aqualogic, Prague, 2011.

[3] A. Musy, B. Hingray, and C. Picouet, "Data required for hydrological analysis and modeling," in *Hydrology: A Science for Engineers*, CRC Press, Boca Raton, FL, USA, 2014.

[4] M. Rodwell, "Comparing and combining deterministic and ensemble forecasts: how to predict rainfall occurrence better," *ECMWF Newsletter*, vol. 106, pp. 17–23, 2006.

[5] H. I. Cloke and F. Pappenberger, "Ensemble flood forecasting: a review," *Journal of Hydrology*, vol. 375, no. 3-4, pp. 613–626, 2009.

[6] L. Alfieri, F. Pappenberger, F. Wetterhall, T. Haiden, and D. Richardson, "Evaluation of ensemble streamflow predictions in Europe," *Journal of Hydrology*, vol. 517, pp. 912–922, 2014.

[7] J. D. Brown, L. Wu, M. He, S. Regonda, H. Lee, and D. Seo, "Verification of temperature, precipitation, and streamflow forecasts from the NOAA/NWS Hydrologic Ensemble Forecast Service(HEFS): 1. Experimental design and forcing verification," *Journal of Hydrology*, vol. 519, pp. 2869–2889, 2014.

[8] J. C. Schaake, T. M. Hamill, R. Buizza, and M. Clark, "HEPEX: the hydrological ensemble prediction experiment," *Bulletin of the American Meteorological Society*, vol. 88, no. 10, pp. 1541–1547, 2007.

[9] T. Palmer, R. Buizza, R. Hagedorn et al., "Ensemble prediction: a pedagogical perspective," in *ECMWF Newsletter*, pp. 10–17, 2006.

[10] J. Mašek and T. Vlasák, *Calibration of ALADIN/LAEF Precipitation Ensembles*, RC LACE predictability, 2011.

[11] Y. Wang, M. Bellus, J.-F. Geleyn, X. Ma, W. Tian, and F. Weidle, "A new method for generating initial condition perturbation in a regional ensemble prediction system: blending," *Monthly Weather Review*, vol. 142, no. 5, pp. 2043–2059, 2014.

[12] A. Bučánek, P. Benáček, and A. Trojáková, *Operational Implementation of BlendVar Scheme at CHMI*, RC LACE, 2015.

[13] P. Novak, "The Czech Hydrometeorological Institute's severe storm nowcasting system," *Atmospheric Research*, vol. 83, no. 2–4, pp. 450–457, 2005.

[14] Y. Wang, M. Bellus, C. Wittmann et al., "Central European limited-area ensemble forecasting system: ALADIN-LAEF," *Quarterly Journal of the Royal Meteorological Society*, vol. 137, no. 655, pp. 483–502, 2011.

[15] Y. Wang and A. Kann, "ALADIN Limited Area Ensemble Forecasting (LAEF)," in *ALADIN Newsletter*, pp. 1–7, Meteo-France, Toulouse, France, 2006.

[16] T. Schellander-Gorgas, Y. Wang, F. Meier, F. Weidle, C. Wittmann, and A. Kann, "On the forecast skill of a convection-permitting ensemble," *Geoscientific Model Development*, vol. 10, no. 1, pp. 35–56, 2017.

[17] D. Rezacova, B. Szintai, B. Jakubiak et al., "A radar-based verification of precipitation forecast for local convective storms," in *Parameterization of Atmospheric Convection: Current Issues and New Theories*, pp. 173–214, Imperial College Press, London, UK, 2015.

[18] P. Novak and H. Kyznarova, "MERGE2-modernizovany system kvantitativnich odhadu srazek provozovany v Ceskem hydrometeorologickem ustavu," *Meteorologicke Zpravy*, vol. 69, pp. 137–144, 2016.

[19] M. Salek, "Operational application of the precipitation estimate by radar and raingauges using local bias correction and regression kriging," in *Proceedings of the Sixth European Conference on Radar in Meteorology and Hydrology (ERAD 2010)*, National Meteorological Administration of Romania, Sibiu, Romania, 2010.

[20] M. Salek, L. Brezkova, and P. Novak, "The use of radar in hydrological modeling in the Czech Republic—case studies of flash floods," *Natural Hazards Earth System Sciences*, vol. 6, no. 2, pp. 229–236, 2006.

[21] Hydrometeorological Institute Prague, *Katalog Povětrnostních Situací Pro Území ČSSR*, Hydrometeorologický ústav Praha, SNTL, Prague, Czech Republic, 1968.

[22] M. Hanel and P. Maca, "Spatial variability and interdependence of rain event characteristics in the Czech Republic," *Hydrological Processes*, vol. 28, no. 6, 2013.

[23] V. Svoboda, M. Hanel, P. Máca, and J. Kyselý, "Characteristics of rainfall events in regional climate model simulations for the Czech Republic," *Hydrology and Earth System Sciences*, vol. 21, no. 2, pp. 963–980, 2017.

[24] W. H. Wischmeier and D. D. Smith, *Predicting Rainfall Erosion Losses–A Guide to Conservation Planning*, Agriculture Handbook, 1978.

[25] A. Bakhshaii and R. Stull, "Deterministic ensemble forecasts using gene-expression programming," *Weather and Forecasting*, vol. 24, no. 5, pp. 1431–1451, 2009.

[26] J. H. Hogan and I. B. Mason, "Deterministic forecasts of binary events," in *Forecast Verification: A Practitioner's Guide in Atmospheric Science*, I. T. Jolliffe and D. B. Stephenson, Eds., John Wiley & Sons, Hoboken, NJ, USA, 2nd edition, 2011.

[27] I. T. Jolliffe and D. B. Stephenson, *Forecast Verification: A Practitioner's Guide in Atmospheric Science*, John Wiley & Sons, Hoboken, NJ, USA, 2012.

[28] D. S. Wilks, *Statistical Methods in the Atmospheric Sciences*, Elsevier, Oxford, UK, 3rd edition edition, 2011.

[29] World Meteorological Organization, *Recommendations for the Verification and Intercomparison of QPFS and PQPFS from Operational NWP Models*, World Meteorological Organization, Geneva, Switzerland, World Weather Research Programme, 2008.

[30] A. P. Weigel, "Ensemble forecast," in *Forecast Verification: A Practitioner's Guide in Atmospheric Science*, I. T. Jolliffe and D. B. Stephenson, Eds., John Wiley & Sons, Hoboken, NJ, USA, 2nd edition, 2012.

[31] T. M. Hamill, "Interpretation of rank histogram for verifying ensemble forecast," *Monthly Weather Review*, vol. 129, no. 3, pp. 550–560, 2001.

[32] O. Talagrand, R. Vautard, and B. Strauss, "Evaluation of probabilistic prediction systems," in *Proceedings of the ECMWF Workshop on Predictability*, ECMWF, Reading, UK, October 1997.

[33] Czech Hydrometeorological Institute Prague, *Povodně v České Republice v Červnu 2013*, Český hydrometeorologický ústav Praha, Prague, Czech Republic, Czech Hydrometeorological Institute, 2014.

[34] C. M. Grams, H. Binder, S. Pfahl, N. Piaget, and H. Wernli, "Atmospheric processes triggering the central European floods in June 2013," *Natural Hazards and Earth System Sciences*, vol. 14, no. 7, pp. 1691–1702, 2014.