Proceedings of ERAD (2004): 444–449 © Copernicus GmbH 2004

ERAD 2004

Nowcasting of precipitation by using radar and NWP model data

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Abstract. Three models (REG, REGC and NN) for nowcasting of 1-h and 2-h accumulation of precipitation are developed and compared on data from the warm season. The models use predictors derived from radar data and NWP model outputs to forecast mean area precipitation in squares $10\times10\,\text{km}^2$. REG is a linear regression model. REGC consists of several linear regression models and which is applied depends on a simple decision tree. NN is a 3-layer neural network of the perceptron type. The accuracy of the forecast depends on the daytime, however all models yield significantly better results than the forecast based on a simple advection. The results for morning and night (01–12 and 22–24 UTC) are quite satisfactory. Large errors in forecasting afternoon precipitation show that the models are not able to satisfactorily describe the development of convective storms. The performance of REG and REGC is similar, however for larger precipitation amounts and especially for 2-h accumulation REGC shows slightly better results. NN yields the best forecasts for morning and night, and for 2-h accumulations. For afternoon 1-h accumulation NN results are not satisfactory.

1 Introduction

For some hydrological applications, especially flash flood warning and urban drainage management, the 0–6 h forecasting (nowcasting) of heavy precipitation is required. At present most of nowcasting methods is based on an extrapolation of radar echo. The methods based only on a simple extrapolation technique (e.g. Dixon, Weiner, 1993; Johnson et al., 1993; Mecklenburg et al., 2000) loose rapidly their accuracy with the lead time. As they do not consider storm initiation, growth and dissipation the simple extrapolation is usually applicable up to 30–60 min. Radar data including extrapolated radar echo together with other data from satellite, lightning and numerical models were used as predictors in a statistical model by Kitzmiller (1996). The statistical regression model was developed at real data by application of the technique, which is very similar to the model output statistics (MOS; Glahn, Lowry, 1972). To better simulate diurnal variation of precipitation processes different models were developed for different daytimes.

Another approach to nowcasting of heavy precipitation is represented by NIMROD (Golding, 1998), which utilises both radar echo extrapolation and numerical model precipitation forecasts. For shorter time periods the primary weight is given to extrapolation of the existing precipitating field, which is derived from satellite and radar data. With increasing forecast time the weight shifts to the numerical model and becomes almost totally dependent on the model for the 6 h forecast.

Different approach is presented by an automated nowcasting system of convective precipitation GANDOLF (Pierce et al., 2000) that attempts to model storm development. It contains a precipitation model, which incorporates a conceptual model of the life cycle of shower clouds. Using satellite and radar data and a variety of forecast products from a numerical weather prediction (NWP) model, convective cells are identified and their development is forecast.

In this paper nowcasting technique similar to that used by Kitzmiller (1996) is applied to the forecast of mean 1-hr and 2-hr precipitation in squares 10 by $10\,\text{km}^2$. The forecast region includes the territory of the Czech Republic and is well covered by the Czech radar network. The main differences between the proposed method and Kitzmiller's approach are the forecast quantities and the models describing the relationship between the input data and forecast precipitation. Three different models are developed and compared. The model evaluation is mainly focussed on the forecast of large precipitation.

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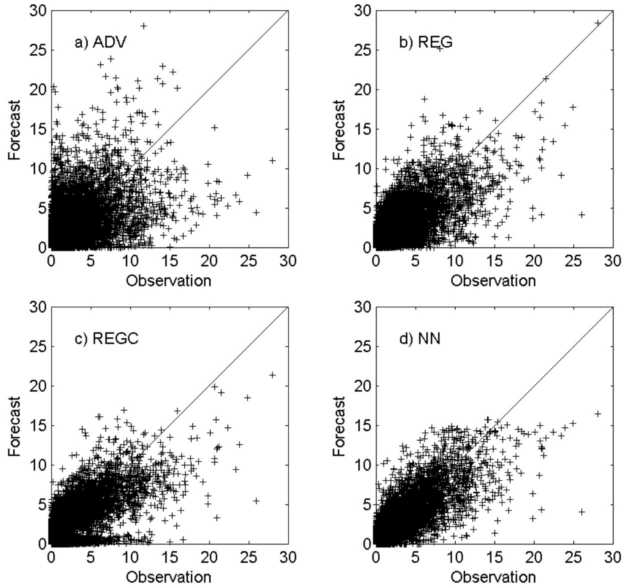

Fig. 1. Scatterplots of the observed and forecast values of 1-h precipitation for the daytimes 01, 02 and 03 UTC. The plots a)–d) correspond to the ADV, REG, REGC and NN models. The solid line is the perfect fit.

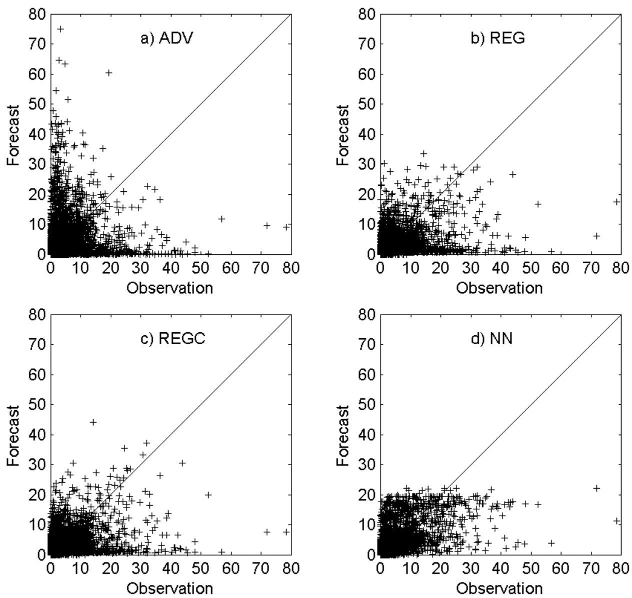

Fig. 2. The same as Fig. 1 for the daytimes 19, 20, and 21 UTC.

2 Forecast region and data used

The nowcasting technique used two sources of data: measured radar reflectivity and prognostic data from a NWP model. Precipitation amounts were derived from radar measurements only. Small number of rain gauges and their highly irregular distribution in the area did not allow us to apply an adjustment of radar derived precipitation to rain gauge measurements.

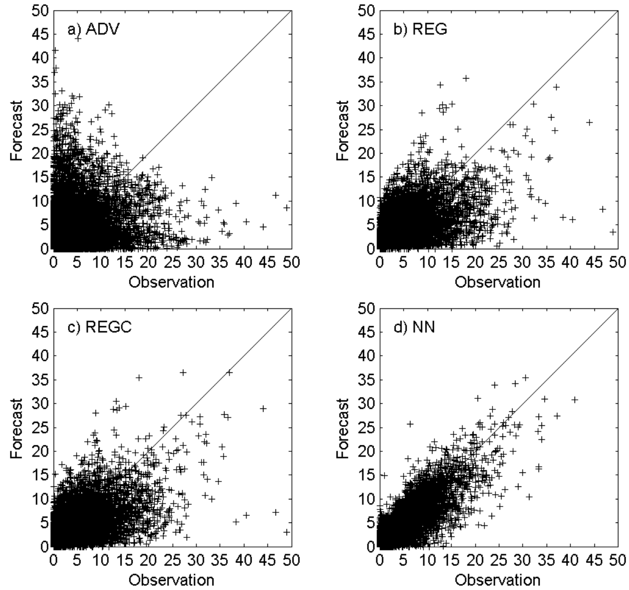

Fig. 3. The same as Fig. 1 for the daytimes 01, 02 and 03 UTC and 2-h precipitation.

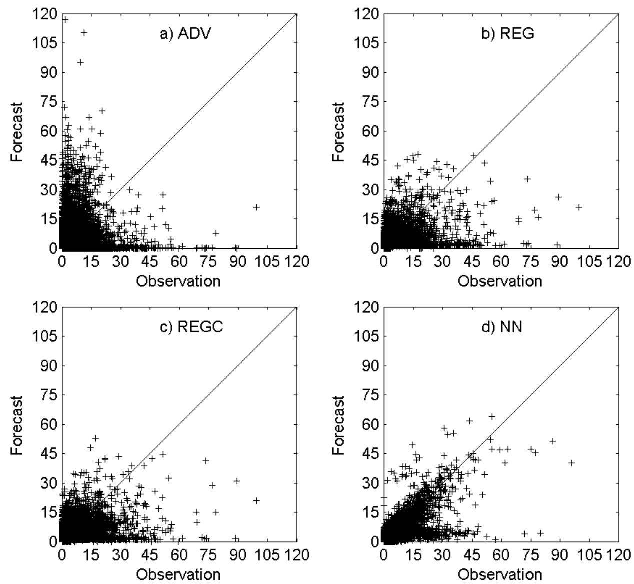

Fig. 4. The same as Fig. 3 for the daytimes 19, 20 and 21 UTC.

The data used for development and verification of the nowcasting procedures were selected from the terms with significant hourly precipitation from the warm season 2002. We also included preceding and following hourly terms into the data sets to study the development and dissipation of precipitation. Basic statistics of 1-h and 2-h accumulated precipitation are shown in Table 1.

Table 1. Mean value [mm] of observed 1-h and 2-h precipitation and the number of cases when a given threshold is exceeded [%] in dependence on the daytime.

UTC	Mean 1-hr	≥ 0.5 mm	≥ 5 mm	Mean 2-hr	≥ 1 mm	≥ 10 mm
1–3	1.15	39.0	5.9	2.23	41.8	4.9
4–6	1.45	47.0	8.0	2.87	47.8	7.9
7–9	0.95	39.4	3.5	2.06	44.2	3.2
10–12	0.88	31.0	4.1	1.72	33.5	3.6
13–15	1.22	34.9	6.4	2.37	38.8	5.9
16–18	1.30	37.4	6.5	2.57	41.4	6.7
19–21	1.62	43.2	9.2	3.24	46.6	9.6
22–24	1.10	41.7	5.4	2.33	45.8	5.0

The Czech radar network consists of two weather radars Brdy and Skalky, which measure in C band and the interval of radar scans is 10 min. Precipitation amounts are calculated by integration in time of rain intensities, which are derived from the maximum column radar reflectivity by using the Marshal-Palmer relationship (Havránek, Kráčmar, 1996). Precipitation amounts are calculated for each radar separately in 256×256 pixels, where each pixel represents an area of 2×2 km^2. The pixel values are smoothed by using the median from 3×3 nearby pixels. This modification improves radar precipitation when compared with the gauge measurements (Kráčmar et al., 1998). Maximum of two radar estimates is applied in the overlapping pixels to obtain precipitation estimate in the forecast region. Using the aforementioned algorithm 20 min precipitation amounts were calculated and used as basic precipitation data. The forecast region was divided into squares consisting of 5 by 5 radar pixels (10×10 km^2). For these squares the mean pixel values of 1-h and 2-h precipitation amounts (predictands) are forecast.

Prognostic outputs from the NWP model ALADIN/LACE, which is operated by the Czech Hydrometeorological Institute (CHMI) are used. ALADIN/LACE NWP model is a hydrostatic limited area model with the horizontal resolution of 12 km. The model integration starts every 12 h and prognostic fields are recorded every 6 h.

3 Predictors

The list of the predictors is given in Table 2. The NWP model outputs were interpolated in space and in time to get predictor values for individual squares and forecast times. For a given square, precipitation predictors were obtained from the same place but previous times and from areas obtained by a backward advection in time. Prognostic wind fields at the level 700 hPa were used to advect precipitation fields with the time step 20 min.

4 Forecast models

The forecast models were developed by using the approach very similar to MOS. The model parameters were calculated on a developmental data set and then applied to an independent data set. As precipitation is significantly influenced by diurnal course, 8 sets of the model parameters were derived for the forecast belonging to 1–3 UTC, 4–6 UTC etc. The data consisted of 24 000 values of predictands and they were divided into 3 subsets with the same size. Two of them were used as the calibration (historical) data to develop the models and the remaining subset served for verification. By choosing different combinations of the data subsets the independent forecast was produced for all data.

Three models were developed and tested: linear regression model (REG), classified regression model (REGC) and neural network (NN). The classified regression consisted of several linear regression models and which one was applied depended on a simple decision tree. The intention of this approach was to develop separate models for different data. It increases the number of parameters, which can better describe large variability of precipitation data. The division was based on one or two values of predictors and "if then" construction. The selection of threshold values resulted from several tests.

4.1 Linear regression model

The multiple linear regression model (e.g. Wilks, 1995) was in the form of

$$y = a_0 + a_1x_1 + a_2x_2 + ... + a_Nx_N, \quad (1)$$

where a_1,..., a$_N$ are model parameters, y is the predictand value and x_j, j=1,..,N, are predictor values. The predictors were selected by the stepwise screening algorithm with the maximum p-value for a predictor to be added 0.05, and minimum p-value for a predictor to be removed 0.1 (Wilks, 1995). The maximum number of predictors was restricted to 7 as the tests shown that additional predictors did not improve the forecast. The REG outputs significantly underestimate heavy precipitation because they are rare in the data set. This is the

Table 2. The list of predictors divided into radar and NWP predictors. Advection means that the quantity was advected by the NWP model wind field at 700 hPa. For the forecast issued at time T, precipitation amounts were accumulated from the intervals <T-2h, T-1h>, <T-1h, T> and also immediate intensity of precipitation at T was used. The NWP model predictors corresponded to T.

Radar predictors:
Precipitation amount
Precipitation amount
Precipitation amount (advection)
Precipitation amount (advection)
NWP model predictors:
Temperature, relative humidity, vertical wind speed and geopotential at 925, 850, 700, 500 hPa
Surface relative humidity, temperature, wind speed, total precipitation, convective precipitation
Mean column temperature, relative humidity and vertical velocity (925–500 hPa)
Vertically integrated specific humidity from 925 to 500 hPa
K index, wind shear 700–500 hPa, 850–500 hPa and 925–500 hPa

reason for a posterior correction of REG outputs p_i. They are corrected according to the formula

$$p_{cor,i} = \alpha p_i + \beta \quad , i = 1, .., n_c \tag{2}$$

where α minimizes the function

$$F(\alpha) = \sum_{i;y_i,p_i>M} (y_i - \alpha p_i)^2 \tag{3}$$

and the sum is over all data i, where whether y_i or p_i are greater than a given value M. After determining α, β is calculated by the following iterative process (k=1,..,k_{max}):

$$\beta^{(0)} = \frac{1}{n_c} \sum_{i=1}^{n_c} (y_i - \alpha p_i) \quad , \tag{4}$$

$$p_{cor,i}^{(k)} = \max\left(\alpha p_i + \beta^{(k)}, 0\right), i = 1, .., n_c \tag{5}$$

$$\beta^{(k+1)} = \beta^{(k)} + \frac{1}{n_c} \sum_{i=1}^{n_c} (y_i - p_{cor,i}^{(k)}). \tag{6}$$

The steps (5) and (6) are repeated several times (k_{max}=5 iterations are used in this study) and β is assigned to the last $\beta^{(kmax)}$. For M>0 the value of α is greater than 1, which results in the overestimation of the forecast. The iterative application of (4–6) reduces this overestimation. Values 0, 1, … 15 of M were tested in (3).

4.2 Neural network model

We used the multilayer feedforward neural network model (NN) with 3 layers (Demuth and Beale, 2000). The input layer used all predictors from Table 2 and the predictand value was the output. The inner layer contained 5 neurons. The number of the neurons was subjectively selected based on several test calculations. The inner neurons used the log-sigmoid function while the output neuron used the linear transfer function. NN was trained with the backpropagation algorithm and mean square error was the performance function.

5 Results

The accuracy of the forecast was evaluated by root-mean-square-error (RMSE), bias (BIAS) and correlation coefficient (CC):

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - p_i)^2}, \tag{7}$$

$$BIAS = \sum_{i=1}^{n} p_i \Big/ \sum_{i=1}^{n} y_i, \tag{8}$$

$$CC = \sum_{i=1}^{n} \left(y_i - \frac{1}{n}\sum_{j=1}^{n} y_j\right)\left(p_i - \frac{1}{n}\sum_{j=1}^{n} p_j\right) \Big/ \sqrt{\sum_{i=1}^{n} \left(y_i - \frac{1}{n}\sum_{j=1}^{n} y_j\right)^2 \sum_{i=1}^{n} \left(p_i - \frac{1}{n}\sum_{j=1}^{n} p_j\right)^2}, \tag{9}$$

where p_i, y_i were forecast and observed values of predictands. As the forecast was focussed on large precipitation, RMSE and CC were calculated in dependence on observed precipitation amounts, i.e. only those pairs of p_i and y_i were used in (7) and (9) where y_i exceeded a given threshold. The applied crossvalidation technique can cause that BIAS significantly differs for individual verification subsets, however, the total BIAS in the whole data set is close to 1. Therefore BIAS was separately calculated at each verification subset and averaged. The model results were compared with a reference method which was the forecast obtained by advection by NWP wind at 700 hPa (ADV).

The quality of the forecast essentially depended on the daytime. The forecast values were apparently less scattered around the perfect fit for the terms 01–03, 04–06, 07–09, 10–12 and 22–24 UTC than for the remaining terms. It is illustrated by Figs. 1–4 for 01–03 UTC and 19–21 UTC. The comparison of Fig. 1a and Fig. 3a with Fig. 2a and

Table 3. RMSE of ADV, REG, REGC and NN models for 1-hr precipitation in dependence on the daytime [UTC]. Only observed values ≥5 mm are considered.

Model/UTC	1–3	4–6	7–9	10–12	13–15	16–18	19–21	22–24
ADV	5.23	5.15	5.31	7.44	10.35	11.15	9.23	5.55
REG	4.20	4.44	5.17	6.38	8.44	9.82	7.67	4.32
REGC	3.99	4.32	4.95	6.35	8.25	9.81	7.47	4.17
NN	3.52	3.52	3.91	5.59	7.94	7.90	6.03	3.70

Table 4. The same as Table 3 for 2-h accumulation of precipitation and observed data ≥10 mm.

Model/UTC	1–3	4–6	7–9	10–12	13–15	16–18	19–21	22–24
ADV	11.39	10.31	10.80	13.51	17.81	19.15	16.79	12.47
REG	9.25	8.49	9.75	12.02	15.59	16.33	15.05	9.54
REGC	8.99	8.11	8.72	11.18	14.67	15.63	13.72	9.08
NN	7.17	6.62	6.65	9.62	13.01	14.20	11.28	7.55

Fig. 4a confirms that development and dissipation of convective cells, which is not captured by ADV, is important for afternoon precipitation (13–21 UTC). The models REG, REGC and NN yield better forecast than ADJ mainly because they correct false heavy precipitation forecasts. The performance criterion (mean square error) causes that NN does not forecast more than 23 mm for 18–21 UTC and 1-h precipitation (Fig. 2d). Similar or even worse results would have been obtained by REG and REGC if the correction (3–7) had not been applied.

All REG, REGC and NN models yield apparently lower RMSE and higher CC than ADJ for all ranges of thresholds. Examples of RMSE for precipitation (thresholds 5 and 10 mm for 1-h and 2-h precipitation, respectively) are shown in Tables 3 and 4 and CC in Tables 5 and 6. Although the performance of REG and REGC is similar, for larger precipitation amounts, and especially for 2-h accumulation, REGC shows better results. The decision tree in REGC used NWP model values of relative humidity at the surface or at the level 850 hPa. The essentially best values of RMSE and CC yields NN, however, as mentioned above, the forecast of 1-h accumulation for 18–21 UTC is not satisfactory. BIAS significantly differed for individual verification subsets, especially in case of the REG model. In general, as Table 7 shows for 1-h precipitation, there are no significant differences between the models. The general tendency to overestimate precipitation forecast can be caused by the selected data, on the other hand the fact that negative forecast values are set to zero also contributes to the overestimation.

Table 5. CC of model forecast with observed 1-hr precipitation in dependence on the daytime [UTC]. Only observed values ≥0.5 mm are considered.

Model/UTC	1–3	4–6	7–9	10–12	13–15	16–18	19–21	22–24
ADV	0.50	0.53	0.51	0.45	0.24	0.18	0.38	0.55
REG	0.67	0.66	0.52	0.59	0.51	0.43	0.50	0.64
REGC	0.66	0.68	0.59	0.59	0.54	0.42	0.56	0.60
NN	0.77	0.78	0.74	0.69	0.61	0.61	0.71	0.75

Table 6. The same as Table 5 for the 2-h precipitation and 1 mm threshold.

Model/UTC	1–3	4–6	7–9	10–12	13–15	16–18	19–21	22–24
ADV	0.20	0.39	0.33	0.36	0.10	0.08	0.20	0.40
REG	0.53	0.61	0.44	0.51	0.33	0.33	0.36	0.61
REGC	0.55	0.64	0.54	0.56	0.39	0.38	0.46	0.66
NN	0.71	0.75	0.72	0.67	0.51	0.46	0.62	0.74

Table 7. BIAS of the model forecast for 1-hr precipitation in dependence on the daytime [UTC].

Model/UTC	1–3	4–6	7–9	10–12	13–15	16–18	19–21	22–24
ADV	1.02	1.00	0.99	1.04	1.02	1.06	1.05	1.02
REG	1.02	1.00	0.99	1.04	1.02	1.06	1.06	1.02
REGC	1.02	1.00	0.99	1.04	1.03	1.06	1.08	0.96
NN	1.04	1.02	1.02	1.04	1.05	1.03	1.04	1.05

6 Conclusion

The REG, REGC and NN models yield essentially better forecast for 1-h and 2-h precipitation than simple advection. The results for morning and night (01–12 UTC and 22–24 UTC) are quite satisfactory. For this daytime the best results are obtained by NN model. For afternoon hours the quality of the forecast is significantly worse. Both regression models as well as neural network models are not able to satisfactorily describe the development and dissipation of storms. The results confirm that neural network could be an appropriate tool for description of complicated and essentially nonlinear relationships between predictors and predictands.

Acknowledgements. The work was supported by the grants S3042101 GA ASCR and 205/04/0114 GA CR. The data were kindly provided by the Czech Hydrometeorological Institute.

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