DOI: 10.15201/hungeobull.70.1.3 Hungarian Geographical Bulletin **70** 2021 (1) 35–48.

Precipitation interpolation using digital terrain model and multivariate regression in hilly and low mountainous areas of Hungary

Tamás SCHNECK[1,2], Tamás TELBISZ[1] and István ZSUFFA[2,3]

Abstract

The relationship between precipitation and elevation is a well-known topic in the field of geography and meteorology. Radar-based precipitation data are often used in hydrologic models, however, they have several inaccuracies, and elevation can be one of the additional parameters that may help to improve them. Thus, our aim in this article is to find a quantitative relationship between precipitation and elevation in order to correct precipitation data input into hydrologic models. It is generally accepted that precipitation increases with elevation, however, the real situation is much more complicated, and besides elevation, the precipitation is dependent on several other topographic factors (e.g., slope, aspect) and many other climatic parameters, and it is not easy to establish statistically reliable correlations between precipitation and elevation. In this paper, we examine precipitation-elevation correlations by using multiple regression analysis based on monthly climatic data. Further on, we present a method, in which these regression equations are combined with kriging or inverse distance weighting (IDW) interpolation to calculate precipitation fields, which take into account topographic elevations based on digital terrain models. Thereafter, the results of the different interpolation methods are statistically compared. Our study areas are in the hilly or low mountainous regions of Hungary (Bakony, Mecsek, Börzsöny, Cserhát, Mátra and Bükk montains) with a total of 52 meteorological stations. Our analysis proved that there is a linear relationship between the monthly sum of precipitation and elevation. For the North Hungarian Mountains, the correlation coefficients were statistically significant for the whole study period with values between 0.3 and 0.5. Multivariate regression analysis pointed out that there are remarkable differences among seasons and even months. The best correlation coefficients are typical of late spring-early summer and October, while the weakest linear relationships are valid for the winter period and August. The vertical gradient of precipitation is between one and four millimetres per 100 metres for each month. The statistical comparison of the precipitation interpolation had the following results: for most months, co-kriging was the best method, and the combined method using topography-derived regression parameters lead to only slightly better results than the standard kriging or IDW.

Keywords: precipitation, elevation, DTM, kriging, IDW, co-kriging, multivariate regression

Received March 2020, accepted February 2021.

Introduction

The relationship between precipitation and elevation is a well-known topic in the field of geography and meteorology (Henry, A.J. 1919; Duckstein, L. *et al.* 1973; Basist, A. *et al.* 1994; Weisse, A.K. and Bois, P. 2001; Sasaki, H. and Kurihara, K. 2008; Haiden, T. and Pistotnik, G. 2009). Climatological precipitation maps of diversified terrains can be prepared using the connections among measured precipitation data at hydrometeorological stations. Nowadays, precipitation data can be accessed in high spatial and tem-

[1] Department of Physical Geography, Eötvös Loránd University, H-1117 Budapest, Pázmány Péter sétány 1/c. Hungary. Corresponding author's e-mail: tomi.schneck@gmail.com
[2] VITUKI Hungary Ltd., H-1173 Budapest, Mendei u. 3. Hungary.
[3] Department of Water and Environmental Policy, National University of Public Service, H-6500 Baja, Bajcsy-Zsilinszky u. 12–14. Hungary.

poral resolution due to radar measurements. However, these radar-derived precipitation data require correction. The use of digital terrain data can be an essential step in this data correction process (Crochet, P. 2009). Precipitation is an important input data in hydrological models, thus, the main reason for studying the relationship between precipitation and topography is to make hydrological models more accurate.

We often simplify the relationship of precipitation and elevation by stating that the amount of precipitation increases with elevation. However, this relationship is an oversimplification, because elevation, rise, exposure and orientation are equally important in defining this relation (Spreen, W.C. 1947).

Already a century ago, Henry, A.J. (1919) presented a statistical analysis of several sites with high amount of precipitation (e.g., Hawaii, India, Indonesia), in which he concluded that the increase of precipitation correlates mostly with slope steepness. Spreen, W.C. (1947) correlated the mean annual precipitation with elevation and other parameters, and it turned out that elevation itself determines only 30 per cent of precipitation variance. However, when he used multivariate regression including aspect, terrain, and the line of drift of the mountains, it turned out that these parameters together determine 85 per cent of precipitation variance. According to Duckstein, L. *et al.* (1973), it is important to examine whether the increasing precipitation in mountainous areas comes from the growing number of rainfall events or from the increasing amount of precipitation in each rainfall event. According to their observations, the amount of precipitation moderately increases with elevation during each rainfall event, and the seasonal amount of precipitation also increases linearly with elevation.

Basist, A. *et al.* (1994) stated that the best determining factors are combined topographic factors, while elevation itself does not correlate well with precipitation according to their regression analysis. Because of the cooling of air temperature, the maximum humidity decreases with higher elevation, therefore there is a theoretical 'elevation of maximum precipitation' (Alpert, P. 1986), thus, precipitation can increase only up to this elevation. However, due to the rarity of upland stations, it is hard to determine this 'elevation of maximum precipitation', but in the region of Alps it is estimated to be at 3,500 m a.s.l. (Schwarb, M. 2000), therefore a linear correlation between precipitation and elevation can be used only below this elevation, while above this elevation, the precipitation-elevation relationship can be modelled only by higher order polynomials. Sasaki, H. and Kurihara, K. (2008) examined this relationship for the months of June and July in Central Japan. In this case, they used raster-based precipitation data instead of station data to find a connection with elevation. Their results demonstrated that there is a statistically significant relationship between precipitation and elevation, but the correlation is low ($r = 0.3$-0.4). According to Smith, C.D. (2008), there is a strong linear relationship between the monthly sum of precipitation and elevation in the cold periods of the year in the Canadian Rocky Mountains, but in summer, this relation is much weaker. Cambi, C. *et al.* (2010) examined the central part of the Apennines in Italy from a hydrogeological perspective, but they also used station data of precipitation and temperature. Their research came to a conclusion that there are relationships between elevation and precipitation, and also between elevation and temperature, but the correlation is weaker ($R^2 = 0.88$) in the case of precipitation than in the case of temperature ($R^2 = 0.93$).

Several authors studied the horizontal trends in the spatial distribution of precipitation, which are often reflected in ecosystems as well. Ha, K.J. *et al.* (2007) investigated directional features of rainfall distribution over the Korean Peninsula, and they found that apparent band-type rainfall tends to be dominant with a SW–NE tilted pattern in July and August. Millett, B. *et al.* (2009) pointed out that the Prairie Pothole region has a strong NE–SW precipitation trend. Lauenroth, W.K. *et al.* (1999) emphasized that W–E gradient in precipitation and the N–S gradient in temperature result in corresponding gradients in plant community types of the Prairie. Ruiz Sinoga, J.D. *et al.* (2011) mentioned that precipitation is very irregular but generally decreases in a W–E gradient in southern Spain. Cortesi, N. *et al.* (2012) described that the annual precipitation concentration index shows a NW to SE gradient for Europe. Goodwell, A.E. (2020) presented the dominant directions of precipitation influence in the USA using longterm precipitation data and information theory. Although directional trends are often incorporated into interpolation methods, they can also be more directly examined by regression analysis.

The correction of precipitation data via digital elevation models is also a well-known field of research. Daly, C. *et al.* (1997) developed the method of PRISM where the precipitation field was corrected by an effective height grid which was a smoothed large-scale representation of the topography of the USA. In this case, the 'effective height' was calculated for each pixel as the difference between the real and the smoothed terrain. This model used several parameters to estimate the amount of precipitation, for instance, slope exposure, wind speed and wind direction data. Goodale, C.L. *et al.* (1998) developed a method for Ireland, in which precipitation data were mapped and corrected using digital terrain models (DTMs), polynomial regression and quadratic trend surfaces. The application of the quadratic trend surfaces allowed them to estimate the change in precipitation and in temperature in a regional scale, while the actual elevation allowed them to estimate the difference between the elevation and the trend surface. Weisse, A.K. and Bois, P. (2001) developed the method named AURELHY, which concentrated on rainfall events. In this model, the precipitation variables are connected to local topography using 'kriging' regression residuals and multivariate linear regression.

Szentimrey, T. and Bihari, Z. (2007) worked out a compound interpolation method for the Hungarian climatological studies called MISH. This method uses multiplicative interpolation formula for the lognormally distributed precipitation along with homogenization (called MASH), local statistical parameters and other background information (e.g., satellite, radar and predicted data) for the interpolation. Haiden, T. and Pistotnik, G. (2009) used station pairs across the Alpine region with a horizontal distance of about 4 km and a vertical distance of 1 km with 12-h precipitation observation intervals alongside with correction factors like precipitation intensity, wind speed and wet-bulb temperature (i.e. the temperature read by a thermometer covered in water-soaked cloth). This method can be used for making high-resolution precipitation maps in a mountainous area with a temporal resolution of 1 day or lower. Mair, A. and Fares, A. (2010) compared interpolation methods for Hawaii using 3 years of data measured by 21 meteorological stations. They came to the conclusion that the method named 'ordinary kriging' was the best interpolator. Ly, S. *et al.* (2011) also compared geostatistical interpolation methods for Belgium. They tested the following methods: 'Thiessen polygons', 'inverse distance weighting' and various types of 'kriging'. Elevation was used as an additional factor during the interpolation, and they had the conclusion that the best methods were the 'inverse distance weighting' and two types of 'kriging'. Noori, M.J. *et al.* (2014) used precipitation data measured at 21 meteorological stations in Duhok, North Iran for comparing the 'inverse distance weighting' method with its improved versions. They found that 'inverse distance weighting' can be used for interpolating precipitation data – with certain settings – because the correlation coefficient between the measured and predicted precipitation exceeded the value of 0.74 in most cases.

In Hungary, it is stated that the yearly sum of precipitation increases with 35 millimetres every 100 metres of elevation, but this gradient shows a decrease from southwest to northeast (Bartholy, J. and Pongrácz, R. 2013, OMSZ). In the case of Mátra Mountains Roncz, B. (1982) examined the precipitation-elevation relationship, and he used precipitation data from 64 stations. The research led to a conclusion that the relationship between elevation and precipitation can be described as a stochastic linear connection with a higher value of correlation coefficient in the period of spring and October, and a lower value in the period of winter and August.

The aim of our research is to study the relationship between precipitation and elevation in Hungary, thus, we examine areas where the topographic differences are relatively high (in a Hungarian context), namely Bakony, Mecsek, Börzsöny, Cserhát, Mátra and Bükk mountains. We use monthly sums of station-measured precipitation data because according to our hypothesis, there are significant differences in correlation among months. As for daily and rainfall event data, they have a higher random component, thus, statistical relationships are less recognizable. We apply simple and multivariate regression analysis to examine the relationship between precipitation and elevation and location coordinates. In the following, we also present how the results of the regression analysis and the DTM can be used in a combined interpolation process to derive topographically corrected precipitation rasters. Finally, we compare these methods to other interpolation methods, such as kriging, inverse distance weighting (IDW) and co-kriging. While kriging and IDW do not use explicit topographic information, in co-kriging, the DTM is added as a secondary variable. The results of these interpolations are compared using independent station data.

Data and study area

The data used for our work is provided by the Hungarian Meteorological Service (Országos Meteorológiai Szolgálat, OMSZ), the Hungarian General Directorate of Water Management (Országos Vízügyi Főigazgatóság, OVF) the Central Danubian Valley Water Management Directorate (Közép-Duna-völgyi Vízügyi Igazgatóság, KDVVIZIG) and the North Hungarian Water Management Directorate (Észak-magyarországi Vízügyi Igazgatóság, ÉMVIZIG). We used data from 52 stations found at six hilly and low mountainous study areas, of which 10 were located in Bakony, 8 in Mecsek, 8 in Börzsöny, 3 in Cserhát, 12 in Mátra and 10 in Bükk mountains *(Figure 1).* The combined North Hungarian Mountains study area extent is

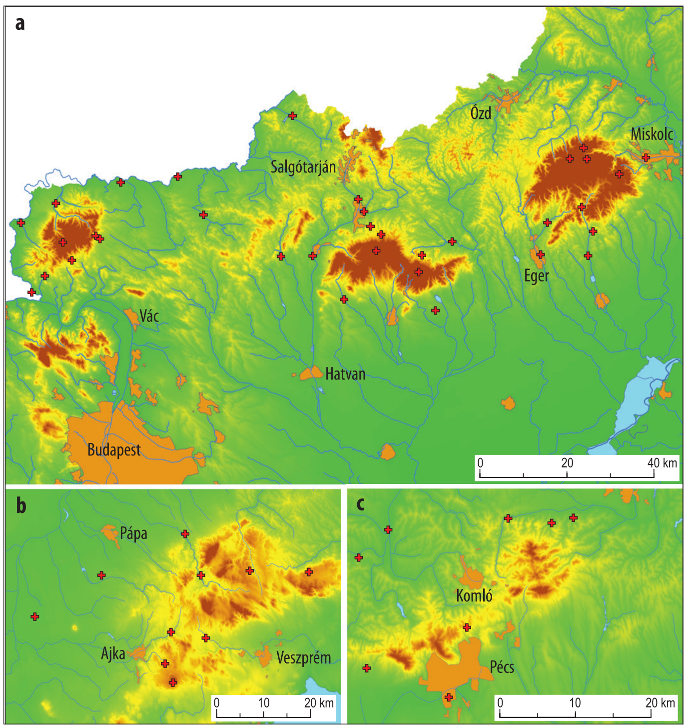

Fig. 1. Location of the applied meteorological stations (red crosses) in the North Hungarian Mountains (a), in the Bakony Mountains (b), and in the Mecsek Mountains (c)

marked with a red boundary in *Figure 1* (a), whereas the other study areas are shown in *Figure 1* (b) and (c). Precipitation data were available in monthly, daily and hourly time steps between 2011 and 2015. However, due to the high randomness of daily (and even more hourly) data, we used monthly sums of precipitation for each station in the present analysis. The mean station density of the study area is 1.5 station/100 km^2.

Methodology

Simple and multivariate regression analysis

The first step of our research was to perform a simple regression analysis on the monthly sums of precipitation. We investigated the relationship of precipitation and elevation for each month and each area. As we mentioned in the Introduction, several authors pointed out that there may be a directional trend in precipitation like the decrease of precipitation in a continental scale from the oceans to the inner parts of continents. Thus, we were also curious to know if directional changes can be recognized in precipitation patterns or not on the scale of Hungarian mountains. For this reason, easting and northing were also added as further independent parameters, therefore multivariate regression models were used.

In the case of simple regression, the relationship between precipitation and elevation is characterized by the following equation:

$$P = a_1 z + a_0,$$

where P is the amount of precipitation measured at the station, z is the elevation above sea level, while a_1 and a_0 are the coefficients of the regression equation.

Thereafter, we added northing and/or easting coordinates alongside elevation to see if North–South, East–West or other directional trend exists in precipitation. According to the Hungarian National Grid system (HD72 / EOV), x denotes northing and y denotes easting. However, as in most GIS systems, x is easting and y is northing, we used this latter notation. We tried several combinations. The combination of northing and elevation, the combination of easting and elevation and finally, the use of all three parameters. In these cases, the equations can be written as below:

$$P = a_2 z + a_1 x + a_0, \quad (2)$$

$$P = a_2 z + a_1 y + a_0, \quad (3)$$

$$P = a_3 z + a_2 y + a_1 x + a_0, \quad (4)$$

where a_3, a_2, a_1 and a_0 are the coefficients of the equations.

Combination of deterministic and stochastic methods in the interpolation of precipitation

The steps following the regression analysis are illustrated in *Figure 2.* In the first step, the predicted precipitation is calculated for each meteorological station based on the coordinates of the station and the regression equations mentioned above. Thereafter, either kriging or IDW interpolation is used for the

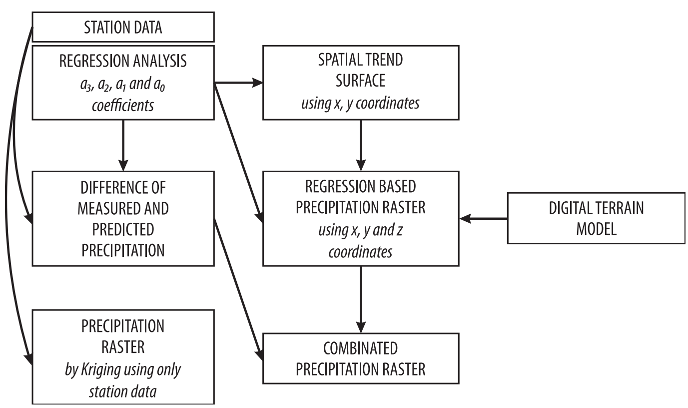

Fig. 2. Flow chart demonstrating the steps of the combined method

difference of the observed and predicted data. This is the stochastic element of the method.

In the next step, we calculate a linear trend surface by using regression equation (4) and the coefficients a_2, a_1 and a_0. Thereafter, with the inclusion of coefficient a_3, we create a precipitation field taking into account elevation based on a digital terrain model, SRTM (van Zyl, J.J. 2001; Rabus, B. *et al.* 2003) in our case. The error of SRTM elevation data is generally below 10 m, though random outliers may occur (Rodriguez, E. *et al.* 2006), thus, it causes little error with respect to several 100 metres of elevation differences within the study area. Its usability for Hungary in geomorphological studies was also thoroughly tested by Józsa, E. and Fábián, Sz.Á. (2016). The SRTM is the deterministic element of the method. Finally, the combined precipitation raster is calculated by adding the interpolated difference map to the regression-based precipitation raster.

The final map can be compared to the rasters created by kriging or IDW, which do not take elevation directly into account. Naturally, station precipitation data inherently include the effect of elevation. In the present study, we applied kriging using a linear variogram model and no anisotropy. The IDW was used with a power of 2 and without smoothing. All rasters had 1 km resolution.

The combined method is basically similar to the methods 'kriging with radar-based error correction' in Goudenhoofdt, E. and Delobbe, L. (2009) and 'conditional merging' in Sinclair, S. and Pegram, G. (2005). However, in the present case, the objective was not to elaborate a radar-based precipitation correction method but to perform a combined interpolation for meteorological station data taking elevation into account.

In addition, for comparison purpose, co-kriging method was also used alongside with kriging and IDW. During the co-kriging process, the measured precipitation values were used as a primary dataset, while the SRTM DTM as a secondary dataset. This interpolation method was also used among others by Azimi-Zonooz, A. *et al.* (1989) and Velasco-Forero, C.A. *et al*. (2009).

Results

Results of the simple and the multivariate regression analysis

All forms of regression equations mentioned in the methodology were studied for each study areas. The test demonstrated that if we use more variables in the model, then the value of the correlation coefficient (also the value of R^2) increases *(Figure 3).* It is also found that the relationship has monthly variations, therefore we suggest the use of monthly coefficients in the elevation-based correction of precipitation data, although even the coefficients for the same month in different years are varied to some extent.

The correlations based on the data of Mecsek and Bakony mountains are only significant if all variables are used, and even in these cases only few months are characterized by statistically significant correlations. In case of the merged North Hungarian Mountains, the use of only z as an independent variable can result significant correlation during the spring period, while using more variables results significant correlations for each month. The correlations were the strongest in the period of late spring-early summer and October, while the weakest correlations can be observed for August (see *Figure 3*). Thereafter, we calculated the precipitation values for the North Hungarian Mountains using the best-fit multiple regression model for each month. We compared the observed and calculated values in *Figure 4.* The point scatters are in agreement with the fact that determination coefficients are relatively low but significant.

The coefficient of elevation in the regression equation can be interpreted as the vertical precipitation gradient. Thus, based on the regression results, we got that the vertical precipitation gradients are between 0.010 and 0.035 both in simple and multivariate regressions with a peak in spring. This implies that in the North Hungarian Mountains monthly precipitation increases by 1.0–3.5 mm as elevation gets 100 m higher. However, the elevation coefficients of Mecsek and Bakony

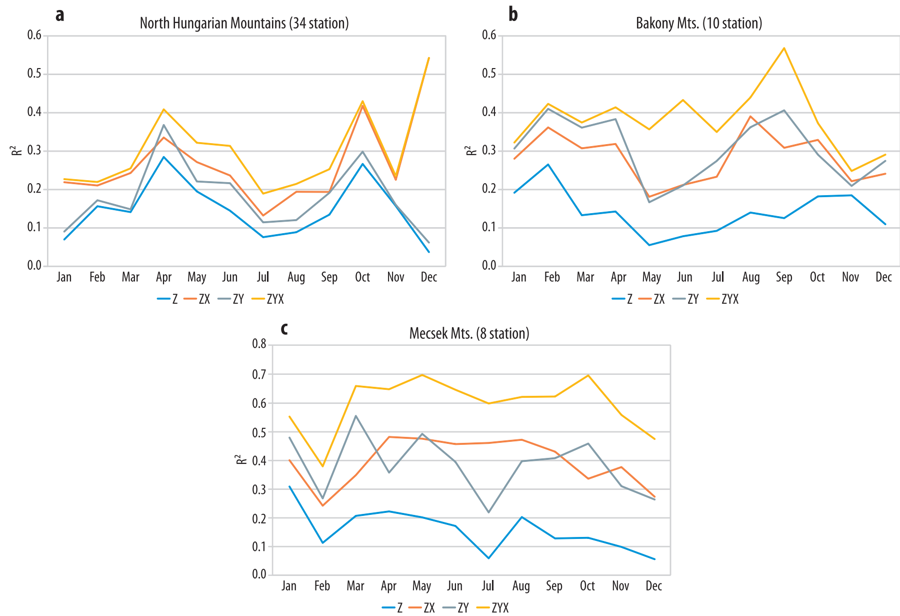

Fig. 3. Values of R^2 for each month according to each variable-combination in the regression equations. Variable-combinations: Z = elevation; ZX= elevation and easting; ZY = elevation and northing; ZYX = elevation, easting and northing. The values of R^2 are shown numerically where they are significant (at a = 0.05).

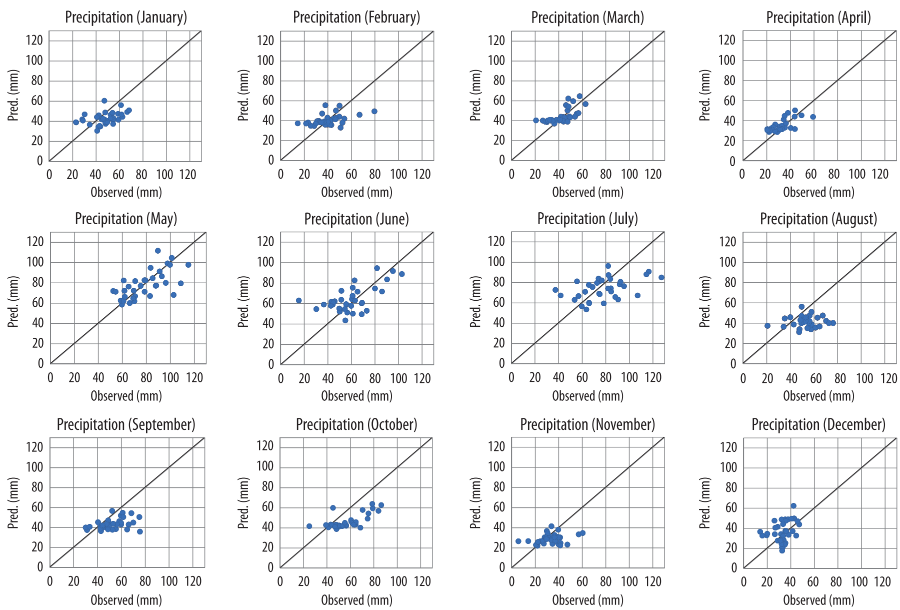

Fig. 4. Observed vs predicted (Pred) precipitation for each month using all independent variables for the North Hungarian Mountains (34 stations)

mountains are between -0.06 and +0.04 that indicates the lack of a clear relationship between precipitation and elevation. This might be due to the low topographical emergence of these mountains or the low density of station precipitation data.

As it can be seen in *Figure 5*, not only the strength but also the gradient of the precipitation-elevation relationship varies by month. In order to demonstrate the precipitation gradient by elevation, we hypothesized two fictional stations at the geometric centre of the study area, one at the lowest and one at the highest elevation of the given area. This way, the *x* and *y* coordinates do not influence the calculated precipitation values. The less steep the orange line in the diagrams of *Figure 5*, the higher the precipitation gradient by elevation is. Based on these diagrams, it is stated that the elevation influences precipitation more intensely in May, June, March and October, while the precipitation gradient is much smaller in the August, November, September and winter months.

Results of the combined interpolation method

The process is presented based on the example of the North Hungarian Mountains for the month of October *(Figure 6)*. The process was run using 34 stations. October was chosen because this is one of the months with the highest correlation coefficients.

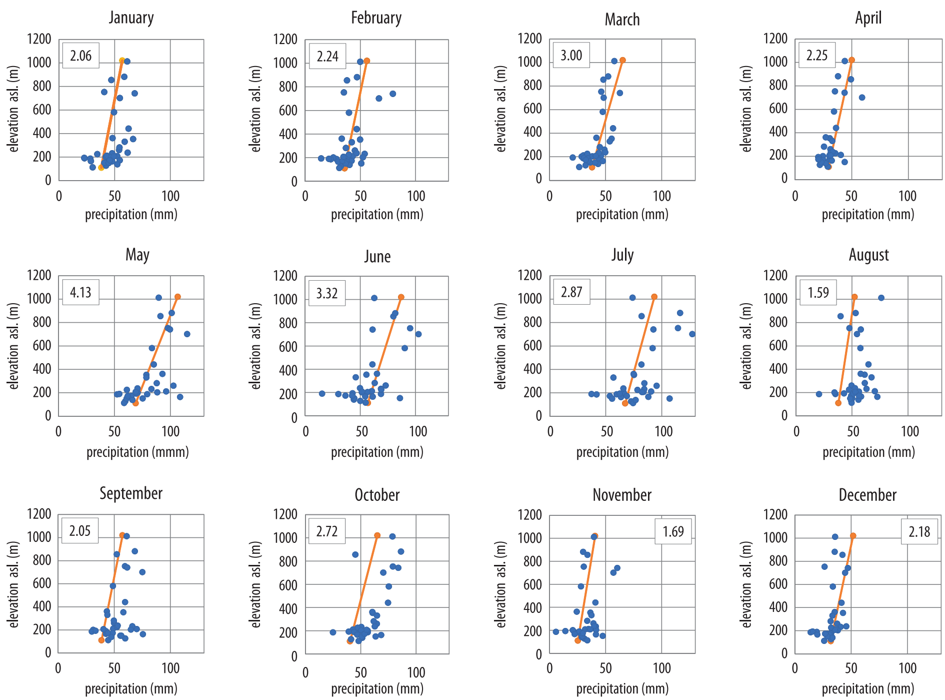

Fig. 5. Relationship between precipitation and elevation by month, in the North Hungarian Mountains study area. Measured precipitation values are marked with blue dots. Orange lines connect the values calculated for the highest and lowest elevation in the centre of the study area. The steepness of the line demonstrates how much the elevation influences the amount of precipitation. The more horizontal the line, the more influential the elevation is. The numbers in the boxes show the precipitation increment in mm by 100 metres of elevation difference. Although elevation is the independent variable, it is plotted on the Y- axis because it is vertical.

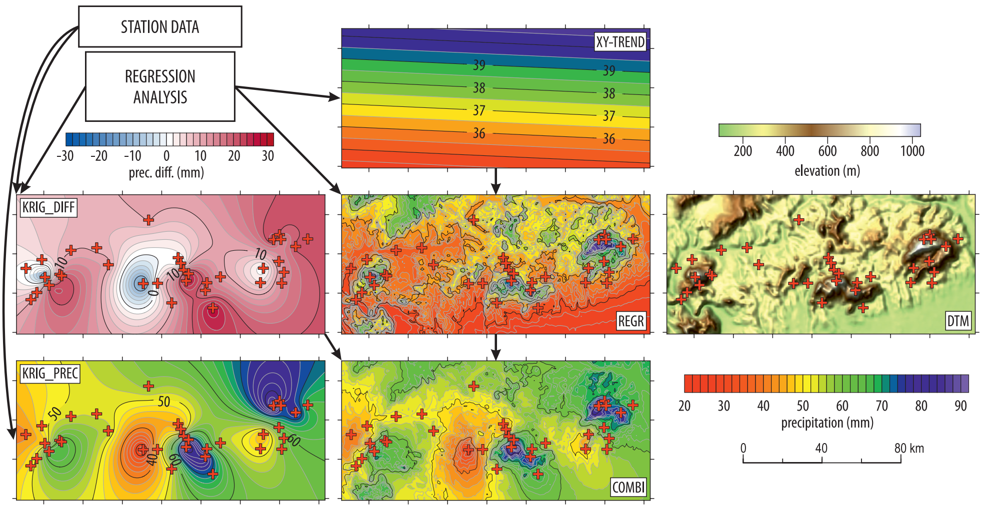

Fig. 6. Synthesized results of the combined method using data from October using kriging interpolation and applying the SRTM DTM of the North Hungarian Mountains. For further explanation see the text and *Figure 2.*

After performing the regression analysis, we calculated the difference map from the differences of the observed and predicted station data by using kriging interpolation (linear model, no anisotropy) first, and IDW (power 2, no smoothing) in the second turn (raster names are KRIG_DIFF, IDW_DIFF). Then a trend map (XY-TREND) was created using the regression coefficients of easting and northing. The trend surface shows us that the average precipitation increases in the direction of north-northeast. Thereafter, a regression-based map (REGR) was calculated using the SRTM digital elevation model (DTM) and the coefficient of *z*. At last, we added the difference map (KRIG_DIFF, IDW_DIFF) to the REGR map that resulted the combined map (CKRI, CIDW).

Comparison of the interpolation results

The comparison of the combined maps (CKRI, CIDW) and the maps resulted by kriging and IDW interpolations using the observed station data (KRIG_PREC, IDW_PREC) demonstrates that the combined process leads to rasters, which follow more closely the small topographic differences (see *Figure 6* bottom-left and bottom-centre image). Nevertheless, besides visual comparison, we carried out a statistical comparison of the results.

Precipitation data from 10 stations provided by the ÉMVIZIG were used for validation *(Figure 7).* These measurements are independent of the previous datasets. Most of these stations are found in different settlements than the original stations, while some of them are in the same settlement, but at another location. The validation time interval was the same as the original, i.e. the period of 2011–2015. As *Figure 8* presents, the measured and predicted precipitation values strongly correlate for the combined kriging (CKRI) method, because the values of R^2 are above 0.9 for each month.

Thereafter, we used five different statistical parameters to compare the interpolation results *(Table 1).* All parameters were calculated using the differences between the interpolation results and the observed values at the validation stations. The average shows if there is a systematic distortion between the

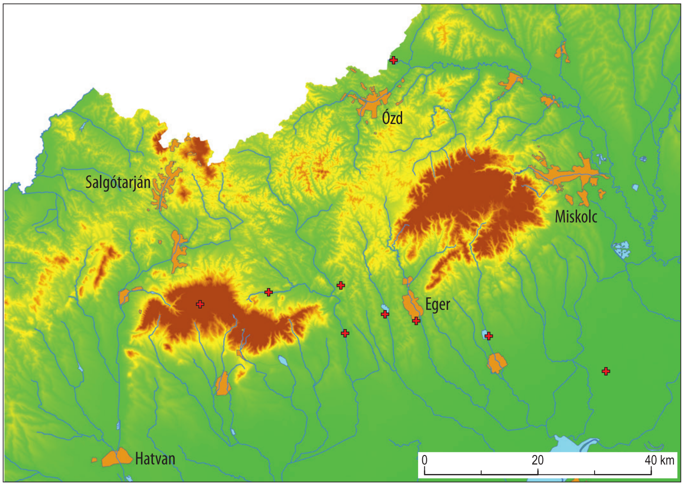

Fig. 7. Location of the meteorological stations (red crosses) used for comparison in the North Hungarian Mountains

observed and interpolated values. The minimum and maximum values present the largest negative or positive errors, finally, the standard deviation and the mean absolute error provide a general measure of how much the interpolated and observed values deviate from each other. For better visual comparison, the mean absolute error statistics are also shown in the diagram of *Figure 9*.

As we can see in *Table 1* and *Figure 9*, where the five interpolation methods are compared, the precipitation

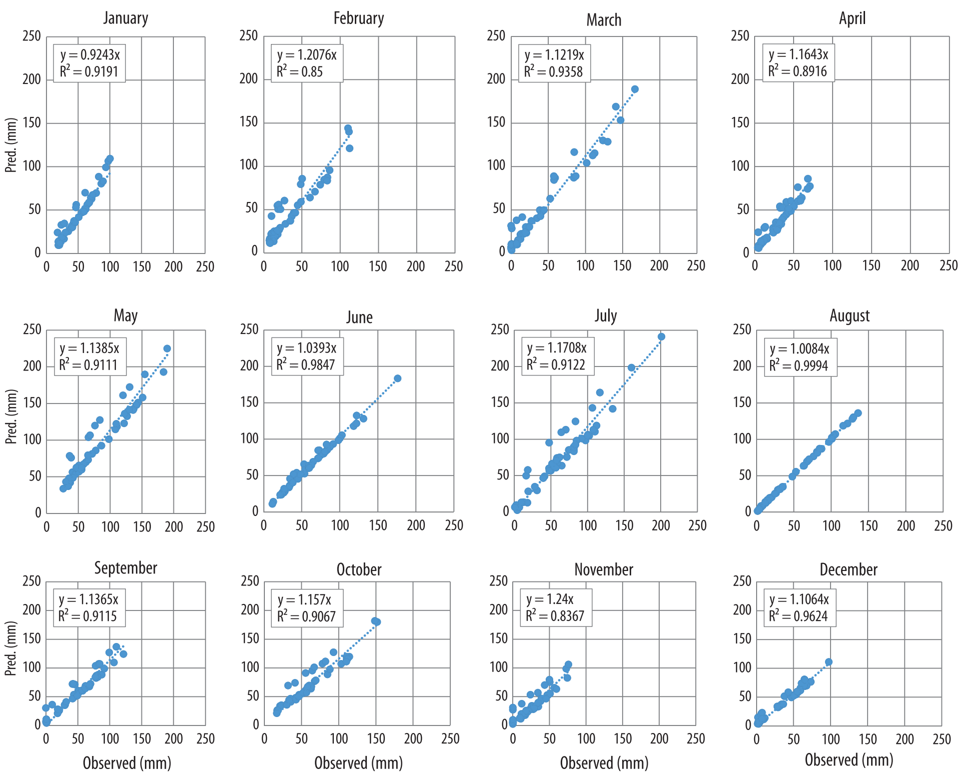

Fig. 8. Results of the validation using the combined kriging (CKRI) method. The observed data are from ÉMVIZIG, while the predicted value (Pred) is the result of our model.

Table 1. Statistics of the differences between the interpolated and observed monthly precipitation, mm*

Month	Average					Standard Deviation				
	CKRI	KRI	IDW	CIDW	COKR	CKRI	KRI	IDW	CIDW	COKR
January	12.06	12.82	14.91	12.17	-3.38	25.56	25.47	26.17	26.21	5.64
February	1.46	2.21	3.63	0.91	-1.95	7.94	8.08	6.76	7.00	5.64
March	0.64	1.27	3.46	0.78	-2.88	9.89	10.63	9.79	9.41	4.97
April	-0.76	-0.15	0.23	-2.04	-3.76	9.38	9.89	8.42	8.48	5.51
May	-4.31	-3.61	-0.73	-3.64	-5.77	20.30	19.75	16.31	17.19	10.62
June	-2.0	-1.51	-0.95	-5.16	-10.59	17.87	18.01	15.98	17.22	15.04
July	1.58	4.54	7.95	0.94	-6.68	19.83	20.73	19.54	17.30	19.43
August	-0.31	0.34	3.72	1.38	-0.62	12.60	12.74	13.52	13.46	9.46
September	1.53	2.29	2.34	-0.21	-3.17	10.54	10.58	7.27	7.83	6.08
October	0.33	1.15	2.74	-0.35	-6.72	9.91	11.20	9.61	9.24	8.64
November	2.97	3.49	4.04	2.06	-0.93	5.30	5.65	5.41	5.07	6.30
December	-5.17	-2.98	-1.75	-7.44	-6.42	12.59	9.81	9.43	12.72	22.80

*CKRI = combined kriging, KRI = kriging, IDW = inverse distance weighting, CIDW = combined IDW, COKR = co-kriging.

Table 1. Continued

Month	Minimum					Maximum					Mean Absolute Error				
	CKRI	KRI	IDW	CIDW	COKR	CKRI	KRI	IDW	CIDW	COKR	CKRI	KRI	IDW	CIDW	COKR
January	-54.14	-54.22	-55.97	-55.47	-18.64	74.49	73.87	72.78	75.83	15.13	19.74	20.09	21.06	19.67	5.10
February	-19.89	-19.77	-9.17	-11.72	-23.74	28.50	37.69	33.03	25.48	10.72	5.54	5.32	5.31	5.22	3.77
March	-36.72	-37.07	-26.48	-25.69	-16.60	33.63	30.78	36.24	34.70	9.28	5.82	6.17	6.66	5.87	3.81
April	-42.62	-42.27	-40.67	-43.14	-20.01	20.41	28.86	26.16	18.95	9.24	5.99	6.22	4.99	5.49	4.67
May	-69.89	-72.32	-66.96	-68.04	-33.61	31.90	35.09	33.89	34.19	26.51	14.80	13.49	11.44	12.44	8.91
June	-50.19	-52.26	-41.99	-46.05	-72.52	35.40	39.70	44.40	27.91	13.74	13.61	13.27	11.55	13.90	11.89
July	-35.28	-34.45	-27.14	-38.48	-77.79	64.76	70.70	62.14	33.98	65.59	15.44	16.01	15.94	14.21	12.89
August	-29.89	-29.41	-22.81	-29.89	-21.30	34.24	33.27	41.19	39.92	44.77	9.34	9.57	9.82	9.49	5.93
September	-26.57	-24.37	-14.77	-19.21	-23.77	33.70	34.17	19.24	16.42	18.91	6.98	7.18	5.82	6.08	4.78
October	-18.57	-20.23	-21.17	-20.41	-35.46	28.74	38.34	37.05	31.88	14.35	7.37	7.97	6.54	6.23	8.25
November	-9.95	-7.70	-6.47	-16.01	-27.18	16.28	18.83	17.03	14.93	15.40	4.47	4.67	5.08	3.89	4.11
December	-49.85	-33.30	-31.43	-46.25	-60.16	30.08	28.70	31.29	28.90	59.12	9.71	7.32	6.37	10.99	14.82

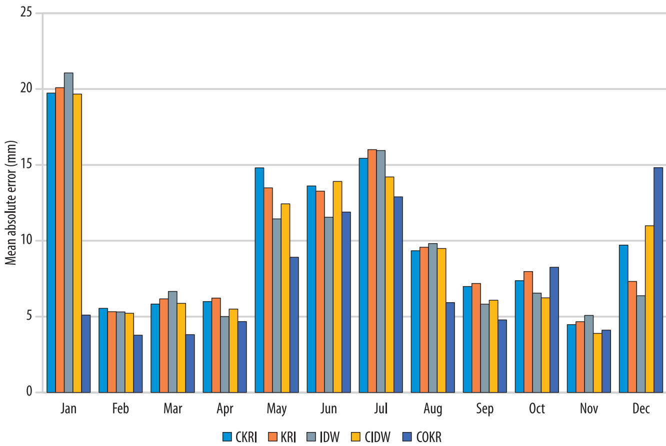

Fig. 9. Comparison of mean absolute error values for each month. CKRI = combined kriging; KRI = kriging; IDW = inverse distance weighting; CIDW = combined IDW; COKR = co-kriging

values of the combined interpolation methods perform slightly better than their original counterparts, but not for all months, and the differences are small. In addition, in slightly more cases, CIDW has less mean absolute error than CKRI. However, we experience that co-kriging provides the best estimates in most cases. Nonetheless, there are certain cases, when co-kriging results worse precipitation predictions than the other methods, namely in the months October, November (partly) and December. Further on, we found that all interpolators worked with relatively little error for February, March, April as well as for September, October and November.

Discussion and conclusions

Based on the above results, it can be stated that there is a linear relationship between the monthly sum of precipitation and elevation. The correlation coefficient of this relationship increases, if more observing meteorological stations and more spatial variables are taken into consideration. The values of the correlation coefficients were statistically significant for the whole study period only in case of the North Hungarian Mountains, where the correlation coefficient values varied from 0.3 to 0.5 for each month. These results are similar to the conclusions presented in the study of Sasaki, H. and Kurihara, K. (2008).

According to the results of our multivariate regression analysis, there are remarkable differences among seasons and also among months. The best correlation coefficients were observed in the period of late spring-early summer and October, while the weakest linear relationships were typical for the winter period and August. Roncz, B. (1982) also came to a similar conclusion that the values of correlation coefficients are higher in the period of spring and October. The orographic effect on precipitation is also stronger in these months in the North Hungarian Mountains. Our results demonstrate that one to four millimetres of precipitation increase can be noticed by every 100 metres of elevation increase for each month. This is again similar to the values of Roncz, B. (1982) referring to the Mátra Mountains. If the annual average of precipitation gradient by elevation is the question, then we get ca. 30-35 mm/100 metres of elevation change that is in agreement with the results of (Bartholy, J. and Pongrácz, R. (2013) and OMSZ (35 mm/100 m).

As *Figure 6* suggests, the advantage of the combined method over the simple interpolation of station data is the precipitation map, which follows more finely the topographic relief. However, differently to Goodale, C.L. *et al.* (1998) we came to the conclusion that in a regional scale the combined use of DTM and polynomial regression has only a neglectable advantage over the simple interpolations like kriging or IDW. On the other hand, co-kriging resulted significantly more precise precipitation predictions for most months, but not for all cases.

The reasons why there are only minor differences between the combined with topography and the standard interpolation methods are unclear at this stage. A more sophisticated distribution of base stations versus validation stations may help to answer this question in future research. Moreover, larger datasets may also contribute to improve interpolation methods and determine vertical gradients with higher precision. Anyway, if vertical precipitation coefficients are determined for a given region, then the combined with topography methods (and co-kriging as well) can help to calculate reliable precipitation rasters even if mountain station data is not available.

***Acknowledgements*:** The research was funded by the National Research, Development and Innovation Office of Hungary (NKFIH) K124497 project. The authors thank G. Varga for his help in data acquisition.

REFERENCES

Alpert, P. 1986. Mesoscale indexing of the distribution of orographic precipitation over high mountains. *Journal of Climate and Applied Meteorology* 25. (4): 532–545.

Azimi-Zonooz, A., Krajewski, W.F., Bowles, D.S. and Seo, D.J. 1989. Spatial rainfall estimation by linear and non-linear co-kriging of radar-rainfall and raingage data. *Stochastic Hydrology and Hydraulics* 3. (1): 51–67.

Bartholy, J. and Pongrácz, R. (ed.) 2013. *Alkalmazott és városklimatológia* (Applied and urban climatology). Budapest, ELTE.

Basist, A., Bell, G.D. and Meentemeyer, V. 1994. Statistical relationships between topography and precipitation patterns. *Journal of Climate* 7. (9): 1305–1315.

Cambi, C., Valigi, D. and Di Matteo, L. 2010. Hydrogeological study of data-scarce limestone massifs: the case of Gualdo Tadino and Monte Cucco structures (Central Apennines, Italy). *Bollettino di Geofisica Teorica ed Applicata* 51. (4): 345–360.

Cortesi, N., González-Hidalgo, J.C., Brunetti, M. and Martin-Vide, J. 2012. Daily precipitation concentration across Europe 1971–2010. *Natural Hazards and Earth System Sciences* 12. (9): 2799–2810.

Crochet, P. 2009. Enhancing radar estimates of precipitation over complex terrain using information derived from an orographic precipitation model. *Journal of Hydrology* 377. (3–4): 417–433.

Daly, C., Taylor, G.H. and Gibson, W.P. 1997. The PRISM approach to mapping precipitation and temperature. In *Proceedings 10th AMS Conference on Applied Climatology*. American Meteorological Society, 20–23 October 1979. Reno, Nevada. Available at https://prism.oregonstate.edu/documents/pubs/1997appclim_PRISMapproach_daly.pdf

Duckstein, L., Fogel, M.M. and Thames, J.L. 1973. Elevation effects on rainfall: A stochastic model. *Journal of Hydrology* 18. (1): 21–35.

Goodale, C.L., Aber, J.D. and Ollinger, S.V. 1998. Mapping monthly precipitation, temperature, and solar radiation for Ireland with polynomial regression and a digital elevation model. *Climate Research* 10. (1): 35–49.

Goodwell, A.E. 2020. "It's raining bits": Patterns in directional precipitation persistence across the United States. *Journal of Hydrometeorology* 21. (12): 2907–2921.

Goudenhoofdt, E. and Delobbe, L. 2009. Evaluation of radar-gauge merging methods for quantitative precipitation estimates. *Hydrology and Earth System Sciences* 13. (2): 195–203.

Ha, K.J., Jeon, E.H. and Oh, H.M. 2007. Spatial and temporal characteristics of precipitation using an extensive network of ground gauge in the Korean Peninsula. *Atmospheric Research* 86. (3–4): 330–339.

Haiden, T. and Pistotnik, G. 2009. Intensity-dependent parameterization of elevation effects in precipitation analysis. *Advances in Geosciences* 20. 33–38.

Henry, A.J. 1919. Increase of Precipitation with Altitude. *Monthly Weather Review* 47. 33–41.

Józsa, E. and Fábián, Sz.Á. 2016. *Az SRTM-1 felszínmodell korrigálása Magyarországra* (Correction of terrain model SRTM-1 for Hungary). Természetföldrajzi Közlemények a Pécsi Tudományegyetem Földrajzi Intézetéből, Pécs, University of Pécs, 1–22. Doi 10.17799/2016.1.13.

Lauenroth, W.K., Burke, I.C. and Gutmann, M.P. 1999. The structure and function of ecosystems in the central North American grassland region. *Great Plains Research* 9. 223–259.

Ly, S., Charles, C. and Degre, A. 2011. Geostatistical interpolation of daily rainfall at catchment scale: the use of several variogram models in the Ourthe and Ambleve catchments, Belgium. *Hydrology and Earth System Sciences* 15. (7): 2259–2274.

Mair, A. and Fares, A. 2010. Comparison of rainfall interpolation methods in a mountainous region of a tropical island. *Journal of Hydrologic Engineering* 16. (4): 371–383.

Millett, B., Johnson, W.C. and Guntenspergen, G. 2009. Climate trends of the North American prairie pothole region 1906–2000. *Climatic Change* 93. (1): 243–267.

Noori, M.J., Hassan, H.H. and Mustafa, Y.T. 2014. Spatial estimation of rainfall distribution and its classification in Duhok governorate using GIS. *Journal of Water Resource and Protection* 6. (2): 75–75.

Rabus, B., Eineder, M., Roth, A. and Bamler, R. 2003. The shuttle radar topography mission – A new class of digital elevation models acquired by spaceborne radar. *ISPRS Journal of Photogrammetry and Remote Sensing* 57. (4): 241–262.

Rodriguez, E., Morris, C.S. and Belz, J.E. 2006. A global assessment of the SRTM performance. *Photogrammetric Engineering & Remote Sensing* 72. (3): 249–260.

Roncz, B. 1982. A csapadék magassági rendszere a Mátra hegységben (The altitude system of rainfall in the Mátra mountain range). *Acta Academiae Paedagogicae Agriensis.* Nova series, Tom. 16. 455–466.

Ruiz Sinoga, J.D., Garcia Marin, R., Martinez Murillo, J.F. and Gabarron Galeote, M.A. 2011. Precipitation dynamics in southern Spain: trends and cycles. *International Journal of Climatology* 31. (15): 2281–2289.

Sasaki, H. and Kurihara, K. 2008. Relationship between precipitation and elevation in the present climate reproduced by the non-hydrostatic regional climate model. *Scientific Online Letters on the Atmosphere* 4. 109–112.

Schwarb, M. 2000. *The Alpine precipitation climate: Evaluation of a high-resolution analysis scheme using comprehensive rain-gauge data*. Doctoral dissertation, Zurich, ETH.

Sinclair, S. and Pegram, G. 2005. Combining radar and rain gauge rainfall estimates using conditional merging. *Atmospheric Science Letters* 6. (1): 19–22.

Smith, C.D. 2008. The relationship between monthly precipitation and elevation in the Alberta foothills during the foothills orographic precipitation experiment. In *Cold Region Atmospheric and Hydrologic Studies. The Mackenzie GEWEX Experience.* Ed.: Woo, M., Berlin–Heidelberg, Springer, 167–185.

Spreen, W.C. 1947. A determination of the effect of topography upon precipitation. *Eos, Transactions American Geophysical Union* 28. (2): 285–290.

Szentimrey, T. and Bihari, Z. 2007. *Mathematical background of spatial interpolation, meteorological interpolation based on surface homogenized data bases (MISH).* COST Action 719. Budapest, COST Office, 17–27.

van Zyl, J.J. 2001. The shuttle radar topography mission (SRTM): A breakthrough in remote sensing of topography. *Acta Astronautica* 48. 559–565.

Velasco-Forero, C.A., Sempere-Torres, D., Cassiraga, E.F. and Gómez-Hernández, J.J. 2009. A non-parametric automatic blending methodology to estimate rainfall fields from rain gauge and radar data. *Advances in Water Resources* 32. (7): 986–1002.

Weisse, A.K. and Bois, P. 2001. Topographic effects on statistical characteristics of heavy rainfall and mapping in the French Alps. *Journal of Applied Meteorology* 40. (4): 720–740.