Application of several spatial interpolation techniques to monthly rainfall data in the Calabria region (southern Italy)

A comparison among spatial interpolation techniques for monthly rainfall data in the Calabria region (southern Italy)

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ABSTRACT: The spatial distribution of precipitation is an issue of particular importance for water-related researches such as hydrological modelling and watershed management. The use of different interpolation methods in the same area may cause large differences and deviations from the real spatial distribution of rainfall, which depend on the type of model chosen, its mode of geographical management and the resolution used. In this study, different algorithms of spatial interpolation of rainfall in a region of southern Italy (Calabria) were applied and the results of geostatistical and deterministic approaches were compared in order to choose the best method for reproducing the actual surface. In particular, inverse distance weighting (IDW), ordinary kriging (OK), kriging with external drift (KED), ordinary cokriging (COK) and Empirical Bayesian kriging (EBK) were applied to produce the monthly rainfall maps of Calabria. Cross-validation and visual analysis of the precipitation maps were performed to analyse the results of the different methods. Results clearly indicate that geostatistical methods outperform inverse

distance. Moreover, among these methods, the kriging with an external drift showed the smallest error of prediction.

Keywords: monthly rainfall; spatial interpolation; IDW; kriging; Calabria.

1. Introduction

Rainfall is an irregular phenomenon showing large spatial variability. The spatial availability of precipitation data is problematic, because the information is recorded at permanent but very disperse weather stations (Vicente-Serrano *et al*., 2003) which only collect point estimates (Miràs-Avalos *et al*., 2007). Therefore, in order to obtain spatial interpolation from point measurement to continuous surfaces, it is necessary to estimate rainfall at unrecorded locations from values at surrounding sites (Goovaerts, 2000). In fact, the spatial distribution of rainfall is essential in several scientific and engineering fields, such as hydrological modelling, disaster prediction, and watershed management (Buttafuoco *et al*., 2016a; Frazier *et al*., 2016; Ly *et al*., 2011). For example, rainfall maps at different timescale can be used as input to crop growth simulation models or hydrological models for flood forecasting (Delbari *et al*., 2013).

Many uncertain factors, such as latitude, longitude, altitude, slope, aspect, and large-scale circulation, could affect the spatial distribution of precipitation; therefore, it is necessary to conduct a detailed study to improve the accuracy of such analyses (Chen *et al*., 2017). In the past years, several methods have been proposed for the interpolation of rainfall data and many papers have been dedicated to the comparison between the different models in various areas. In fact, the application of the appropriate interpolation method may vary in different regions (Buttafuoco *et al*., 2016b; Ly *et al*., 2011; Xu *et al*., 2015). Within this aim, one of the most common approach is the comparison between deterministic (inverse distance weighting, IDW - Legates and Willmott, 1990; splines - Hutchinson and Gessler, 1994; empirical multiple regressions - Agnew and Palutikof, 2000; Vicente-Serrano *et al*., 2003) and geostatistical techniques (Goovaerts, 1997; Isaaks and Srivastava, 1989). Analysing the findings of these comparisons, several authors (Goovaerts, 2000; Moral, 2010; Phillips *et al*., 1992; Tabios and Salas, 1985; Tsintikidis *et al*., 2002; Xu *et al*., 2015) have shown that geostatistics, which are based on the theory of regionalized variables (Goovaerts, 1997, 1999; Journel and Huijbregts, 1978), provide a better rainfall estimation than deterministic techniques. However, other authors have concluded that results depend on the sampling density (e.g., Dirks *et al*., 1998). Accordingly, no consensus exists in the literature about which is the best method for interpolating monthly rainfall.

As to what concern the Calabria region, in the past years several studies have been conducted on the spatial interpolation of monthly (Caloiero *et al*., 2014) and annual rainfall (Buttafuoco *et al*., 2011; Longobardi *et al*., 2016), but without a comparison of the different methods. The aim of this paper was to compare several methods for interpolating spatial patterns of monthly rainfall in the Calabria region (southern Italy). Within this purview, the paper represents an innovation in comparative studies of interpolation methods including, among others, the use of auxiliary variables such as elevation and geographical coordinates to integrate into multivariate geostatistics and the application of Empirical Bayesian kriging (EBK) for spatial interpolation of monthly rainfall.

2. Study area and data

Located at the toe of the Italian peninsula, Calabria has a surface of 15,080 km^2; on average its altitude is 597 m a.s.l. and its tallest relief is 2,266 m a.s.l.. Calabria does not present many high peaks, yet it is one of the most mountainous areas in the country, as mountains (over 500 m a.s.l.) occupy 42% of the regional area, while hills between 50 and 500 m a.s.l. cover 49% of the territory and only 9% of the region is under 50 m a.s.l. (Figure 1). Calabria has an oblong shape, with a length of 248 km and a width ranging between 31 and 111 km, and it has a coastline of 738 km on the Ionian and Tyrrhenian seas (Ricca and Guagliardi, 2015). To the north, it borders the Basilicata region for 80 km. It is a region characterised by a typical Mediterranean climate, presenting sharp contrasts due to its position within the Mediterranean sea and its orography (Coscarelli and Caloiero, 2012; Guagliardi *et al*., 2015; 2016a; 2016b). Specifically, warm air currents coming from Africa and high temperatures affect the Ionian side, leading to short and heavy rainfall. The Tyrrhenian side, instead, is affected by western air current, which causes temperatures to be milder and higher precipitation amount on the mountains than on the Ionian side. Cold and snowy winters and fresh summers with some precipitation are typical of the inner areas of the region (Caloiero *et al*., 2014).

The database used in this study was the one presented in Brunetti *et al*. (2012). The original precipitation series registered in the Calabria region from 1916, and stored by the Multi-Risk Functional Centre of the Regional Agency for Environment Protection, were checked to eliminate inhomogeneities from the data series and lack of data. As a result, the analysis focused on 129 rainfall series (Figure 1) for the period 1916÷2006.

3. Methodology

Deterministic (IDW) and geostatistical algorithms (ordinary kriging, OK; kriging with an external drift, KED; ordinary cokriging, COK and Empirical Bayesian kriging, EBK) were used to compare interpolated monthly rainfall and the spatial distribution of precipitation in Calabria region. Each method was evaluated in order to choose the best one for reproducing the actual surface.

While IDW, OK, KED and COK were implemented in R statistical computing environment using the gstat package (Pebesma *et al*., 2016), the ArcGIS 10.5 geostatistical analyst was used to implement EBK (Krivoruchko 2011; 2012).

3.1 The inverse distance weighting (IDW)

The most known deterministic method, the IDW, is based on the assumption that the rainfall value at unsampled point is a distance-weighted average of the rainfall values at sampling point. Hence, those measured values closest to the prediction location will have more influence on the predicted value than those farther away. Thus, IDW assumes that each measured point has a local influence that diminishes with distance. The weight can be computed by:

$$\hat{v}_i = \frac{\sum_{i=1}^{n} \frac{1}{d^{p}{}_{i}} v_i}{\sum_{i=1}^{n} \frac{1}{d^{p}{}_{i}}} \qquad (1)$$

where $\hat{v}_i$ is the value to be estimate, v_i is the known value, $d^{p}{}_{i} \ldots, d^{p}{}_{n}$ are distances from *n* data points to the power of *p* of the point estimated.

The lower the exponent, the more uniformly all neighbours are incorporated into the calculation (regardless of their distance), and therefore, the “smoother” the estimated surface. The higher the exponent, the more accentuated and “unsettled” is the surface because only the weight of the nearest neighbours is integrated in the interpolation.

Using a power value of 2 for monthly time steps, would appear to minimize the interpolation errors. Furthermore, this power is usually set to 2, following Goovaert (2000) and Lloyd (2005) and hence inverse square distances are used in the estimation. Consequently, a power value of 2 was adopted for IDW in this study.

3.2 Geostatistical methods

Geostatistical interpolation methods assume that the spatial variation of a continuous climatic variable is too irregular to be modelled by a mathematical function and its spatial variation could be better predicted by a probabilistic surface (Vicente-Serrano *et al.*, 2003). This continuous variable is called a regionalized variable, which consist of a drift component and a random but spatially correlated component. A detailed presentation of geostatistical theories can be found in Cressie (1991), Goovaerts (1997), Chilés and Delfiner (1999), and Webster and Oliver (2007).

One of the most widely used geostatistical interpolation method is kriging, which takes advantage of the spatially dependent correlation of environmental variables, assigning more weight to stations nearby (Webster and Oliver, 2007). The weighting is chosen so that the calculation is not biased and variance is minimum. Kriging also provides an uncertainty estimate. The first step in kriging computation is the semi-variogram modelling which represents the core tool to characterize the spatial dependence in the property of interest. A theoretical model is fitted to the experimental semi-variogram, which is a function of the lag of data pair values.

The coefficient of the theoretical model are used to determine the weight through equation systems of the different types of implemented kriging algorithms: OK, KED, COK, EBK.

3.2.1 Ordinary Kriging (OK)

Ordinary kriging is the most widely used kriging method. It aims to estimate a value of the random variable $Z_{(x)}$ at a point of a region x_0 for which a variogram is known, using data in the neighbourhood $Z(x_\alpha)$ of the estimation location.

(Webster and Oliver 2007):

$$Z^{*}_{OK}(x_0) = \sum_{\alpha=1}^{n(x_0)} \lambda_\alpha^{OK} z(x_\alpha) \tag{2}$$

where λ_α are the ordinary kriging weights and $n(x_0)$ is the number of data closest to the location x_0 to be estimated. The weights are obtained such that the estimation is unbiased and the variance is minimized.

3.2.2 Kriging with an External Drift (KED)

In geostatistics, COK is an extension of the basic kriging algorithm which allows one or more supplementary variables, which are spatially correlated (or assumed to be correlated) with the primary variable of interest, to be included in the estimation process. The secondary information can be incorporated using kriging with external drift, which became the value of the covariable. The external drift method allows the prediction of a variable Z, known only at small set of points of the study area, through another variable s, exhaustively known in the same area. The two quantities are assumed to be linearly related. This study dealt with the trend model of the elevation and geographic coordinates as the secondary variables. Indeed, the rainfall data have a global elevation-controlled trend in the south-western – north-east direction.

Let z(x) be the external deterministic variable. The model for the random function can be written as:

$$Y(x) = a + b.z(x) + Y_R(x) \tag{3}$$

where $Y_R(x)$ is a residual stationary random field, z(x) is known everywhere and a and b are coefficients to be estimated if $Y_R(x)$ is needed. Kriging of Y at a location x_0 where it is unknown is a linear combination of the data:

$$Y^*(x_0) = \sum_{i=1}^{n} \lambda_i (x_i) \tag{4}$$

where the $Y(x_i)$'s are the values at the n measured sites and the λ_i's solve the following kriging system:

$$\begin{cases} \sum_{j=1}^{n} \lambda_j C(x_i - x_j) - \mu_1 - \mu_2 z(x_i) = C(x_i - x_0) \quad for i = 1,\ldots,n \\ \sum_{i=1}^{n} \lambda_i = 1 \\ \sum_{j=1}^{n} \lambda_i z(x_i) = z(x_0) \end{cases} \tag{5}$$

compared to the ordinary kriging system, the covariance function C refers to the residual random function $Y_R(x)$ and the last constraint is added so that the linear predictor $Y^*(x_0)$ filters the effect of the external drift. μ_1 and μ_2 are two Lagrange parameters.

3.2.3 Ordinary Cokriging (COK)

COK is another approach which allows samples of an auxiliary variable (also called the covariable), besides the target value of interest, to be used when predicting the target value at unsampled locations. The co-variable may be measured at the same points as the target (co-located samples), at other points, or both. Co-kriging requires that both target and co-variable have a spatial structure that can be modelled, and in addition a spatially-dependent covariance. COK uses a multivariate spatial model and a related secondary 2D or 3D attribute to guide the interpolation of a primary attribute known only at well locations. The mean is specified explicitly and assumed to be a global constant.

3.2.4 Empirical Bayesian Kriging (EBK)

In the Bayesian approach, parameters are treated as random variables, summarizing their uncertainty. Geostatistical interpolation carried out using EBK is a method that automates the most difficult aspects of building a valid kriging model. Other kriging methods require a manually adjustment of parameters to receive accurate results, but EBK automatically calculates these parameters through a process of subsetting and simulations which is implemented by estimating several semivariogram models. EBK using an intrinsic random function as the kriging model but differs from other kriging methods by accounting for the error introduced by estimating the underlying semivariogram. Other kriging methods calculate the semivariogram from known data locations and use this single semivariogram to make predictions at unknown locations; this process implicitly assumes that the estimated semivariogram is the true semivariogram for the interpolation region. By not taking the uncertainty of semivariogram estimation into account, other kriging methods underestimate the standard errors of prediction. The result is a robust non-stationary algorithm for spatial interpolating climatic corrections. This algorithm extends local trends when data coverage is good and allows for bending to a priori background mean when data coverage is poor (Knotters *et al*., 2010; Krivoruchko, 2011; 2012; Krivoruchko and Butler, 2013).

To implement EBK procedure, the following steps are need (Krivoruchko, 2011; 2012):

1. Input data are used to estimate a semivariogram model;
2. Basing on the semivariogram of step 1, a new value at each of the input data locations is simulated.
3. Simulated data of step 2 are used to estimate a new semivariogram model. A weight for this semivariogram is then calculated using Bayes' rule, which shows how likely the observed data can be generated from the semivariogram.

Steps 2 and 3 are repeated a specified number of times. During this process, the predictions and prediction standard errors are produced at the unsampled locations using these weights. This process finally creates a spectrum of semivariograms (150 in our case), and each of these is an estimate of the true semivariogram for the subset.

3.3 Cross validation

Cross-validation technique was adopted for evaluating and comparing the performance of different interpolation methods. It checks the compatibility between the input data and the model. It takes each data point in turn, removing it temporarily from the data set and using neighbouring information to predict the value of the variable at its location. The estimate is compared with the measured value by calculating the experimental error, i.e. the difference between estimatation and measurement, which can also be standardized by estimating the standard deviation (Buttafuoco *et al*., 2010). The mean absolute error (MAE), and the root mean square error (RMSE) were calculated to evaluate the accuracy of interpolation methods.

MAE and RMSE are calculated as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|e_i| \qquad (6)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}e_i^2} \qquad (7)$$

where $|e_i| = |y_i - \hat{y}_i|$, actual = y_i and predicted = $\hat{y}_i$

The most accurate algorithm has an RMSE value closest to zero. Although all geostatistical methods provide an estimate of the error variance, this value has not retained as a performance criterion because it is not adequate to delimit the reliability of kriging estimate (Goovaert, 2000).

The MAE and the RMSE has been used as a criteria of comparison in many studies related to spatial interpolation of rainfall (Dirks *et al*., 1998), comparison of interpolation methods for mapping climatic and bioclimatic variables at regional scale (Attore *et al*., 2007), and spatial distribution of rainfall (Basistha *et al*., 2009).

A scatterplot of measured versus predicted values provided additional evidence on how well an estimation method has performed. The best possible estimates would match the measured values and therefore the slope of the scatterplot should be close to 1.

4. Results and Discussion

First, the descriptive statistics of the monthly precipitation data for the 129 rainfall series were evaluated and then results of the deterministic (IDW) and geostatistical algorithms (OK, KED, COK and EBK) were compared.

Results of the statistical analysis (Table 1) showed that mean monthly rainfall in Calabria varied from 16.79±7.01 mm in July to 160.9±51.03 mm in December. The maximum monthly value has been detected in January (287.2 mm) while the minimum value has been identified in July (2.32 mm). Coefficients of variation (CV, defined as the ratio of the standard deviation to the mean) of monthly rainfall values, ranging between 22.91% and 41.76%, showed a low spatial heterogeneity of the rainfall in Calabria region. Finally, an appreciable difference between monthly mean and median values and the high values of the coefficients of skewness (SK) were observed, thus evidencing a non-normal distribution of the monthly data. This is an important issue in the spatial analysis of the data, in fact, although normality is not a prerequisite for kriging, it is a desirable property and kriging will only generate the best absolute estimate if the random function fits a normal distribution (Moral, 2010). For this reason, a priori logarithmic transformation for all monthly data was performed after which normality was apparent. Considering the limited number of measured data, the spatial dependence analysis was carried out with the omnidirectional semi-variograms. Therefore, the spatial variability was assumed identical in all directions. In particular, three nested models (Gaussian, spherical and circular) were fitted to each month sample semi-variogram alternatively. These three semi-variogram models were also adopted to avoid negative interpolated rainfall. A linear combination of two models provided the best fit for all cases.

The cross-validation results for all months and for the five methods are shown in Table

2. An example of scatter plots of predicted versus measured values for June is shown in Figure 2. Moreover, a graphical comparison of the mean absolute error and the root mean square error for error measurement in each methods is provided in Figure 3.

4.1 The Inverse Distance Weighting (IDW)

As expected, the maps obtained by IDW interpolation showed a distribution with a punctual areas corresponding to high or low rainfall input data values (Figure 4). This is because the IDW generally produces spikes around the sample points (Lloyd, 2005). The coefficient of determination (R^2, R square) of measured versus predicted monthly rainfall range between 0.37 and 0.62 (Figure 2 and Table 2). Moreover, the MAE and RMSE results indicated that the IDW method was the worse approach for interpolating rainfall in any analysed month.

4.2 Ordinary Kriging (OK)

The maps obtained by OK appear more smoothed than the IDW ones in reproducing measured maximum and minimum rainfall values (Figure 5). Moreover, the R square coefficients of measured versus predicted monthly rainfall for OK show better results than IDW. Anyway, the MAE and RMSE results for OK indicated that the method was not the best approach for interpolating rainfall in any analysed month. The main finding of OK outcomes was that the method tended to underestimate rainfall mean values.

4.3 Kriging with an External Drift (KED)

Elevation, extracted from a 5 m x 5 m digital elevation model (DEM), and geographic coordinates were used as the secondary information to improve the interpolation accuracy for monthly rainfall in KED approach. This is a cheaper and widely available data, which can be used to incorporate into multivariate geostatistics of rainfall in the areas where the modern equipment are not available. Figure 6 shows the rainfall maps for all the months, obtained by using the KED technique. The KED method resulted the best interpolator approach for each monthly rainfall data in Calabria, since its MAE and RMSE results show the lowest values among all adopted methods (Table 3). In fact, the KED R square coefficients of measured versus predicted monthly rainfall range from 0.67 to about 0.84 (Figure 2 and Table 2).

4.4 Ordinary Cokriging (COK)

Similarly to the KED, also in the COK elevation was incorporated as secondary variable. Its main purpose is to add information not represented in the primary variable, thereby increasing precision. Indeed, maps of rainfall distribution obtained by COK interpolation are quite similar to those obtained by OK in the driest months (Figure 7). In fact, the benefit of multivariate techniques can become marginal if the correlation between rainfall and elevation is too small (Goovaert, 2000) such in this case study. The R square coefficients of measured versus predicted monthly rainfall range between 0.63 and 0.81 (Figure 2 and Table 2), and the MAE and the RMSE results indicated that the COK method can be considered a good approach for interpolating rainfall data (Table 3).

4.5 Bayesian kriging (EBK)

EBK is both a straightforward and robust method of data interpolation that automates the most difficult aspects of building a valid kriging model eliminating the manual parameter adjusting. The R square coefficients of measured versus predicted monthly rainfall for

EBK approach range between 0.54 and 0.82 (Figure 2 and Table 2). Figure 8 shows the spatial variation of rainfall distribution computed using EBK. These maps are quite similar to those obtained by using COK interpolation.

4.6 Methods comparison

Results from the application of different algorithms provided some insights in terms of strengths and weaknesses, and in terms of the applicability of the deterministic and geostatistical methods to monthly rainfall.

Table 3 and Figure 3 show, for each month, the best interpolation methods as results of the MAE and RMSE values. For both MAE and RMSE, the KED and the COK approaches showed the best values in all months and, specifically, KED can be identified as the best method for interpolating rainfall distribution in Calabria region. The results of the cross-validation provide clear evidence of the usefulness of kriging in the spatial interpolation of rainfall data (Table 3). In fact, because of the cross-validation, geostatistical interpolators clearly outperform the IDW technique, thus confirming past findings by other researchers (Goovaerts, 2000; Lloyd, 2005) which evidenced that IDW was found to be less accurate than geostatistical approaches for estimating monthly and annual rainfall. The visual comparison among all maps obtained by different deterministic and geostatistical interpolation algorithms is also compelling. Obviously, the maps produced using IDW are substantially different than other methods since IDW not consider the pattern of spatial dependence of rainfall data but only the distance between estimated and observed locations. Conversely, the OK, KED, EBK and COK interpolators produced spatial distribution which seem to be more consistent with natural precipitation. In particular, maps of rainfall distribution obtained by OK, EBK and COK are quite similar while, as evidenced in previous studies (Goovaerts, 2000; Kyriakidis *et al*., 2001; Moges *et al*., 2007), by using the KED, which take into account elevation and geographical coordinates, significant better results in spatial distribution can be obtained. The different behaviour of the COK with respect to the KED can be explained following Goovaerts (1997) which states that the contribution of the auxiliary data to the COK predictions depends not only on the correlation between primary and secondary variables, but also on their patterns of spatial continuity. Probably, as evidenced by Kyriakidis *et al*. (2001), if the additional information in KED and COK were, for example, monthly wind speed or humidity that are monthly time series of covariates, instead of a variable fixed in time, such in this case (topography and geographical coordinates), the cross-validation results might be even better.

5. Conclusions

Rainfall is one of the most important climatic parameter influencing the cropping pattern, productivity, flooding and drought hazards, erosion and sedimentation. The knowledge of the spatial distributions of rainfall in the Calabria region is essential for water resource management. In fact, cropping system of this region is decided by several soil and climatic parameters that determine overall agro-ecological setting for nourishment and appropriateness of a crop or set of crops for cultivation.

In this paper, in order to generate different monthly precipitation maps, the spatial distribution of rainfall in Calabria has been investigated through deterministic and geostatistical methodology. In particular, DIW, OK, KED, COK and EBK were applied and the prediction performance of each method was evaluated through cross-validation and visual examination of the precipitation maps produced. Results of the cross correlation confirm the better accuracy of geostatistical methods than deterministic ones and, in particular, that the KED can be identified as the best method for interpolating rainfall distribution in Calabria for all the months. The visual comparison among all maps obtained by the application of the KED and the COK interpolators produced the best rainfall spatial distribution, thus evidencing that taking into account elevation and geographical coordinates as secondary variables could get significant better results in spatial distribution. Moreover, EBK confirms good performance in terms of time-computation and obtained results compared to its ease of implementation.

Future developments of this study could include in the spatial analysis new variables, such as wind speed or humidity, which could improve the results of the rainfall distribution.

References

Agnew MD, Palutikof JP. 2000. GIS-based construction of baseline climatologies for the Mediterranean using terrain variables. *Climate Research* **14**: 115-127, doi: 10.3354/cr014115.

Attorre F, Alfo M, De Sanctis M, Francescsconi F, Bruno F. 2007. Comparison of interpolation method for mapping climatic and bioclimatic variables at regional scale. *International Journal of Climatology* **27**: 1825-1843, doi: 10.1002/joc.1495.

Basistha A, Arya DS, Goel NK. 2009. Analysis of historical changes in rainfall in the Indian Himalayas. *International Journal of Climatology* **29**: 555-572, doi: 10.1002/joc.1706.

Brunetti M, Caloiero T, Coscarelli R, Gullà G, Nanni T, Simolo C. 2012. Precipitation variability and change in the Calabria region (Italy) from a high resolution daily dataset. *International Journal of Climatology* **32**: 57-73, doi: 10.1002/joc.2233.

Buttafuoco G, Tallarico A, Falcone G, Guagliardi I. 2010. A geostatistical approach for mapping and uncertainty assessment of geogenic radon gas in soil in an area of southern Italy. *Environmental Earth Sciences* **61**: 491-505, doi: 10.1007/s12665-009-0360-6.

Buttafuoco G, Caloiero T, Coscarelli R. 2011. Spatial and temporal patterns of the mean annual precipitation at decadal time scale in southern Italy (Calabria region). *Theoretical and Applied Climatology* **105**: 431-444, doi: 10.1007/s00704-011-0398-8.

Buttafuoco G, Caloiero T, Guagliardi I, Ricca N. 2016a. Drought assessment using the reconnaissance drought index (RDI) in a southern Italy region. In *Proceedings of the 6th IMEKO TC19 Symposium on Environmental Instrumentation and Measurements*, Reggio Calabria, 52-55.

Buttafuoco G, Tarvainen T, Jarva J, Guagliardi I. 2016b. Spatial variability and trigger values of arsenic in the surface urban soils of the cities of Tampere and Lahti, Finland. *Environmental Earth Sciences*, doi: 10.1007/s12665-016-5707-1.

Caloiero T. 2014. Analysis of daily rainfall concentration in New Zealand. *Natural Hazards* **72**: 389-404, doi: 10.1007/s11069-013-1015-1.

Chen T, Ren L, Yuan F, Yang X, Jiang S, Tang T, Liu Y, Zhao C, Zhang L. 2017. Comparison of spatial interpolation schemes for rainfall data and application in hydrological modelling. *Water* **9**: 342, doi:10.3390/w9050342.

Chiles J, Delfiner P. 1999. *Geostatistics: Modeling Spatial Uncertainty*. John Wiley & Sons: New York.

Coscarelli R, Caloiero T. 2012. Analysis of daily and monthly rainfall concentration in southern Italy (Calabria region). *Journal of Hydrology* **416-417**: 145-156, doi: 10.1016/j.jhydrol.2011.11.047.

Cressie NA. 1991. Geostatistical analysis of spatial data. In *Spatial Statistics and Digital Image Analysis*. National Academy Press: Washington, D.C. pp. 87-108.

Delbari M, Afrasiab P, Jahani S. 2013. Spatial interpolation of monthly and annual rainfall in northeast of Iran. *Meteorology and Atmospheric Physics* **122**: 103-113, doi: 10.1007/s00703-013-0273-5.

Dirks KN, Hay JE, Stow CD, Harris D. 1998. High-resolution studies of rainfall on Norfolk Island, Part II: interpolation of rainfall data. *Journal of Hydrology* 208: 187-193, doi: 10.1016/S0022-1694(98)00155-3.

Frazier AG, Giambelluca TW, Diaz HF, Needham HL. 2016. Comparison of geostatistical approaches to spatially interpolate month-year rainfall for the Hawaiian Islands. *International Journal of Climatology* **36**: 1459-1470, doi: 10.1002/joc.4437.

Goovaerts P. 1997. *Geostatistics for Natural Resources Evaluation*. Oxford University Press: New York.

Goovaerts P. 1999. Using elevation to aid the geostatistical mapping of rainfall erosivity. *Catena* **34**: 227-242, doi: 10.1016/S0341-8162(98)00116-7.

Goovaerts P. 2000. Geostatistical approaches for incorporating elevation into the spatial interpolation of rainfall. *Journal of Hydrology* **228**: 113-129, doi: 10.1016/S0022-1694(00)00144-X.

Guagliardi I, Rovella N, Apollaro C, Bloise A, De Rosa R, Scarciglia F, Buttafuoco G. 2016a. Effects of source rocks, soil features and climate on natural gamma radioactivity in the Crati valley (Calabria, Southern Italy). *Chemosphere* **150**: 97-108, doi: 10.1016/j.chemosphere.2016.02.011.

Guagliardi I, Rovella N, Apollaro C, Bloise A, De Rosa R, Scarciglia F, Buttafuoco G. 2016b. Modelling seasonal variations of natural radioactivity in soils: a case study in southern Italy. *Journal of Earth System Science* **8**: 1569-1578, doi: 10.1007/s12040-016-0758-y.

Guagliardi I, Cicchella D, De Rosa R, Buttafuoco G. 2015. Assessment of lead pollution in topsoils of a southern Italy area: analysis of urban and peri-urban environment. *Journal of Environmental Science* **33**: 179-187, doi: 10.1016/j.jes.2014.12.025.

Hutchinson MF, Gessler PE. 1994. Splines – more than just a smooth interpolator. *Geoderma* **62**: 45-67, doi: 10.1016/0016-7061(94)90027-2.

Isaaks EH, Srivastava RM. 1989. *An Introduction to Applied Geostatistics*. Oxford University Press: Oxford.

Journel AG, Huijbregts CJ. 1978. *Mining geostatistics*. Academic Press: San Diego.

Knotters M, Heuvelink GBM, Hoogland T, Walvoort DJJ. 2010. *A Disposition of Interpolation Techniques*. Wageningen University and Research Centre, Statutory Research Tasks Unit for Nature and the Environment: Wageningen.

Krivoruchko K. 2011. Spatial Statistical Data Analysis for GIS Users. Redlands, CA: Esri Press, 928 pp

Krivoruchko K. 2012. *Empirical Bayesian Kriging*. ArcUser Fall 2012, pp. 6–10. Also available online at http://www.esri.com/news/ arcuser/1012/empirical-byesian-kriging.htm

Krivoruchko K, Butler K. 2013. *Unequal Probability-Based Spatial Mapping*. Esri: Redlands.

Kyriakidis PC, Kim J, Miller NL. 2001. Geostatistical mapping of precipitation from rain gauge data using atmospheric and terrain characteristics. *Journal of Applied Meteorology* **40**: 1855-1877, doi: 10.1175/1520-0450(2001)040<1855:GMOPFR>2.0.CO;2.

Legates DR, Willmott CJ. 1990. Mean seasonal and spatial variability in global surface air temperature. *Theoretical and Applied Climatology* **41**: 11-21, doi: 10.1007/BF00866198.

Lloyd CD. 2005. Assessing the effect of integrating elevation data into the estimation of monthly precipitation in Great Britain. *Journal of Hydrology* 308**:** 128-150, doi: 10.1016/j.jhydrol.2004.10.026.

Longobardi A, Buttafuoco G, Caloiero T, Coscarelli R. 2016. Spatial and temporal distribution of precipitation in a Mediterranean area (southern Italy). *Environmental Earth Sciences* **75**: 189, doi: 10.1007/s12665-015-5045-8.

Ly S, Charles C, Degré 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**: 2259-2274, doi: 10.5194/hess-15-2259-2011.

Mirás-Avalos JM, Paz-González A, Vidal-Vázquez E, Sande-Fouz P. 2007. Mapping monthly rainfall data in Galicia (NW Spain) using inverse distances and geostatistical methods. *Advances in Geosciences* **10**: 51-57, doi: 10.5194/adgeo-10-51-2007.

Moges SA, Alemaw BF, Chaoka TR, Kachroo RK. 2007. Rainfall interpolation using a remote sensing CCD data in a tropical basin – a GIS and geostatistical application. *Physics and Chemistry of the Earth* **32**: 976-983, doi: 10.1016/j.pce.2007.07.002.

Moral FJ. 2010. Comparison of different geostatistical approaches to map climate variables: application to precipitation. *International Journal of Climatology* **30**: 620-631, doi: 10.1002/joc.1913.

Pebesma E, Graeler B. 2016. Package “gstat.” CRAN Reference Manual. Retrieved from https://cran.r-project.org/web/packages/gstat/index.html.

Phillips DL, Dolph J, Marks D. 1992. A comparison of geostatistical procedures for spatial analysis of precipitation in mountainous terrain. *Agricultural and Forest Meteorology* **58**: 119-141, doi: 10.1016/0168-1923(92)90114-J.

Ricca N, Guagliardi I. 2015. Multi-temporal dynamics of land use patterns in a Site of Community Importance in southern Italy. *Applied Ecology and Environmental Research* **13**: 677-691, doi: 10.15666/aeer/1303_677691.

Tabios GQ, Salas JD. 1985. A comparative analysis of techniques for spatial interpolation of precipitation. *Water Resources Bulletin* **21**: 365-380, doi: 10.1111/j.1752-1688.1985.tb00147.x.

Tsintikidis D, Georgakakos KP, Sperfslage JA, Smith DE, Carpenter TM. 2002. Precipitation uncertainty, raingauge network design within Folsom Lake watershed. *Journal of Hydrologic Engineering* **7**: 175-184, doi: 10.1061/(ASCE)1084-0699(2002)7:2(175).

Vicente-Serrano, SM, Saz-Sánchez MA, Cuadrat JM. 2003. Comparative analysis of interpolation methods in the middle Ebro Valley (Spain): application to annual precipitation and temperature. *Climate Research* **24**: 161-180, doi: 10.3354/cr024161.

Webster R, Oliver MA. 2007. *Geostatistics for Environmental Scientists*, 2nd ed. John Wiley & Sons, Ltd: West Sussex.

Xu W, Zou Y, Zhang G, Linderman M. 2015. A comparison among spatial interpolation techniques for daily rainfall data in Sichuan Province, China. *International Journal of Climatology* 35: 2898-2907, doi: 10.1002/joc.4180.

Figures Captions

Figure 1. Location of the selected 129 rain gauge on a DEM of Calabria.

Figure 2. Scatterplots between observed and estimated monthly precipitation in June for a) IDW, b) OK, c) KED, d) COK, e) EBK.

Figure 3. Mean absolute error (a) and root mean square error (b) for the interpolation methods.

Figure 4. Mean monthly precipitation interpolated using IDW method.

Figure 5. Mean monthly precipitation interpolated using OK method.

Figure 6. Mean monthly precipitation interpolated using KED method.

Figure 7. Mean monthly precipitation interpolated using COK method.

Figure 8. Mean monthly precipitation interpolated using EBK method.

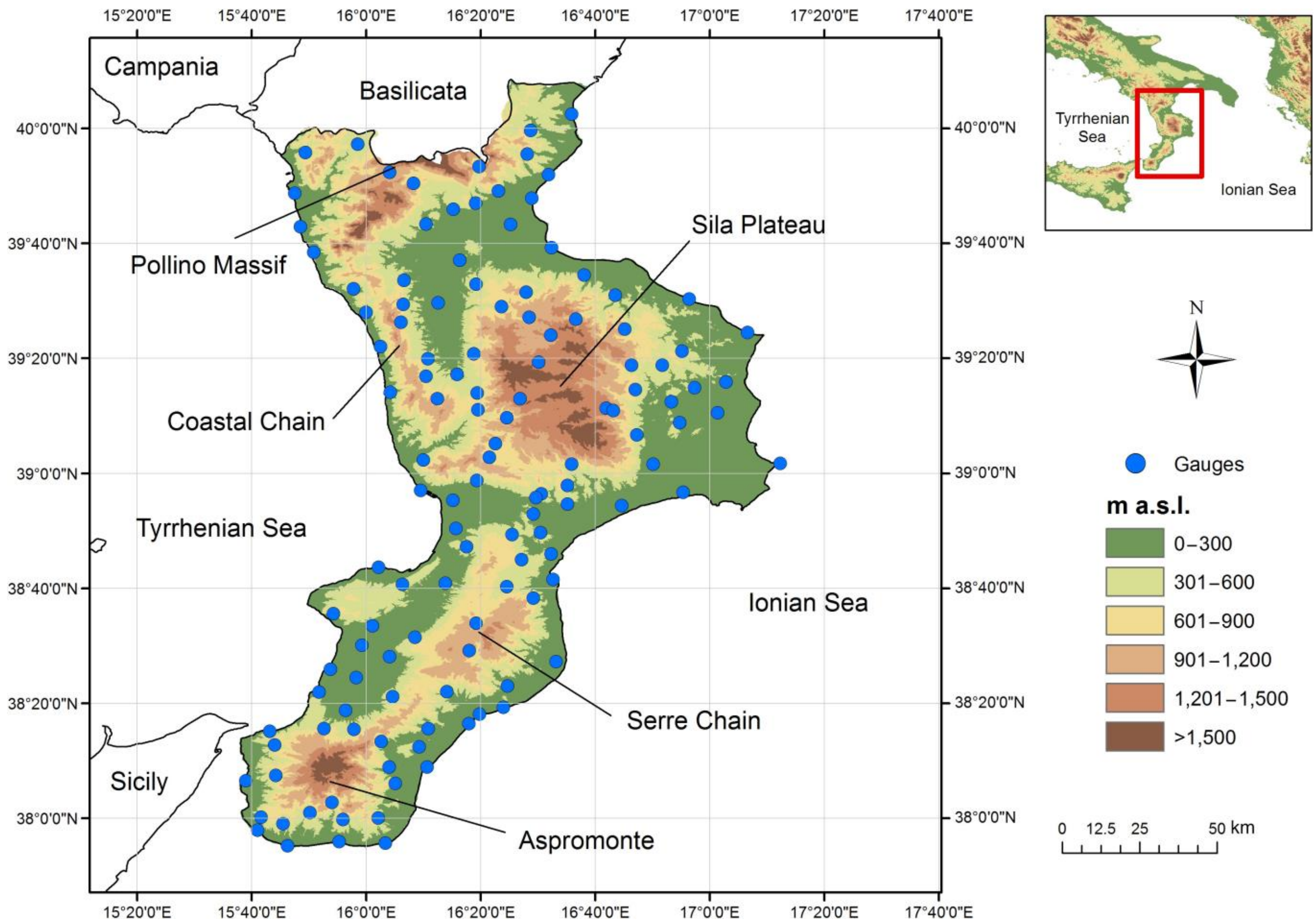


FIGURE 1 Location of the selected 129 rain gauge on a DEM of Calabria [Colour figure can be viewed at wileyonlinelibrary.com]

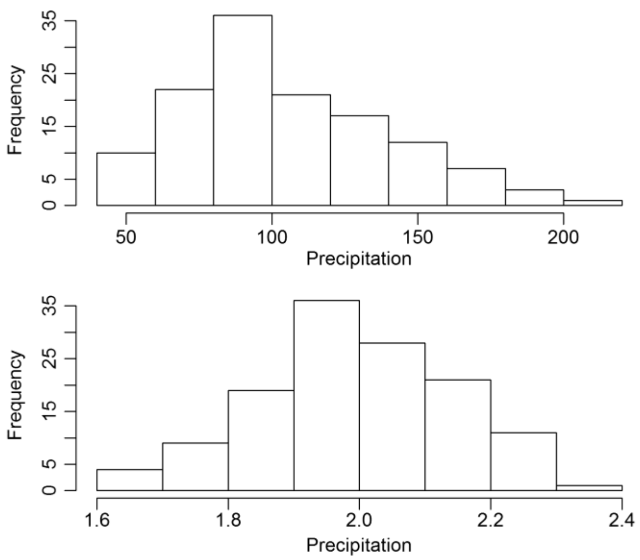


FIGURE 2 Examples of histograms ante and post-transformation for March

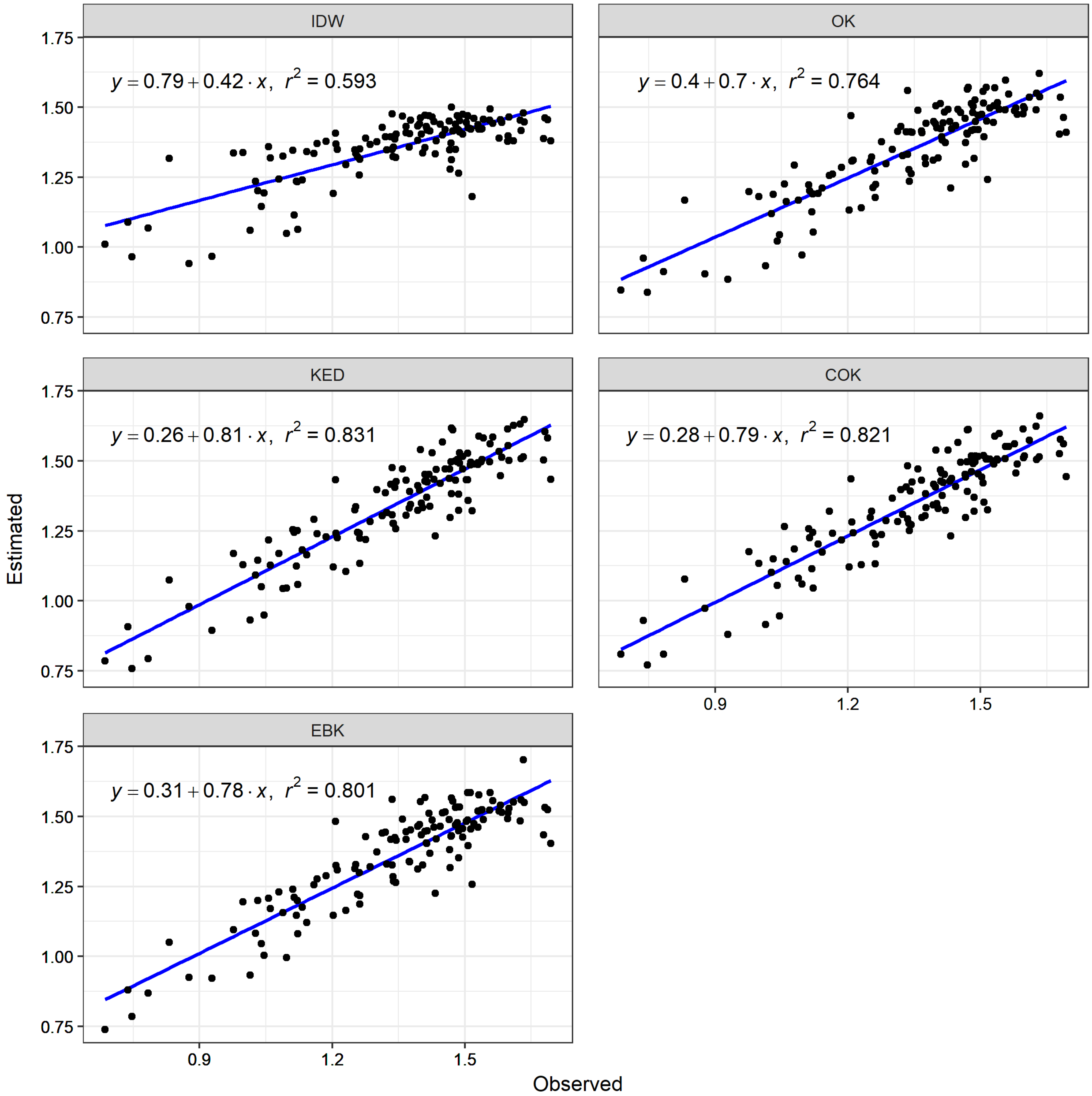


FIGURE 3 Scatterplots between observed and estimated monthly precipitation in June for the selected interpolation methods [Colour figure can be viewed at wileyonlinelibrary.com]

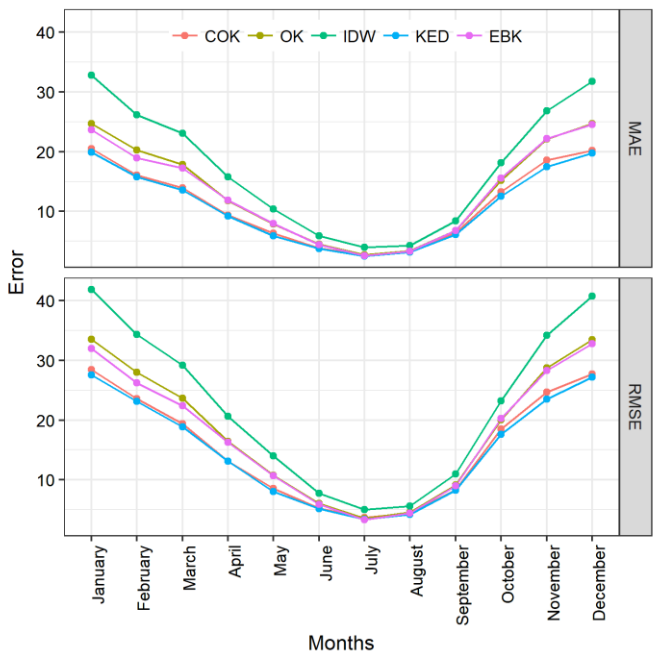


FIGURE 4 MAE and RMSE for the selected interpolation methods [Colour figure can be viewed at wileyonlinelibrary.com]

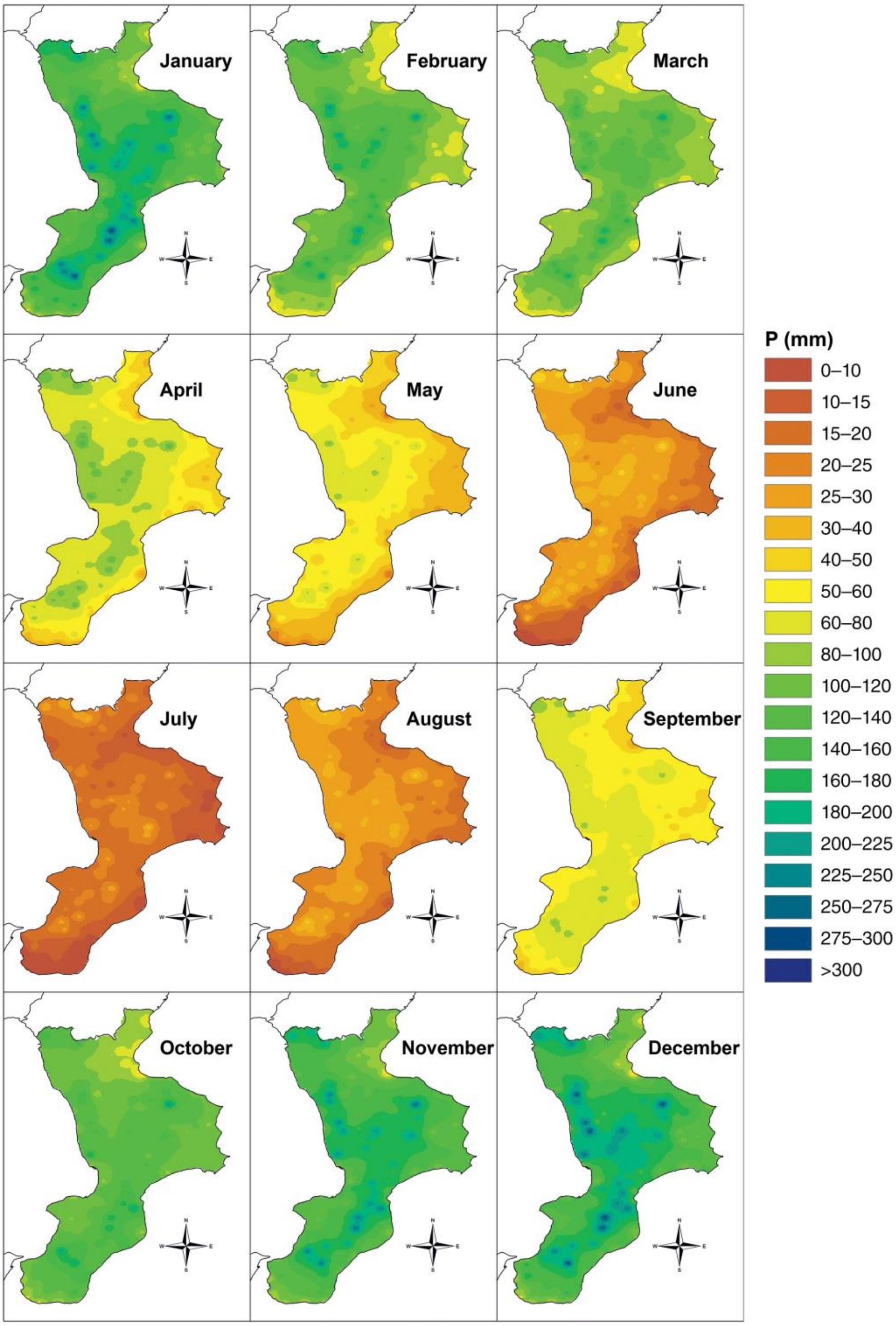
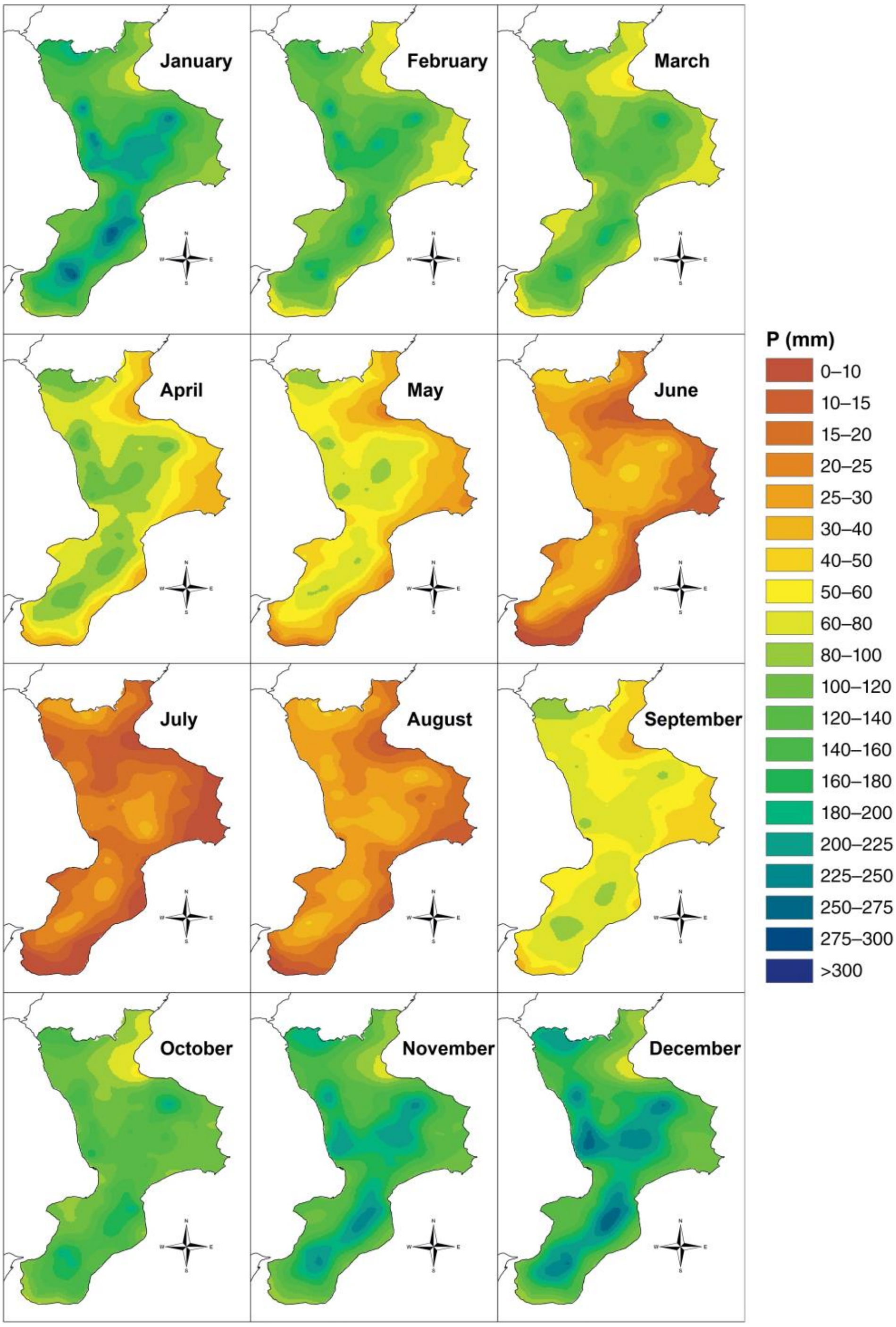


FIGURE 5 Mean monthly precipitation interpolated using IDW method [Colour figure can be viewed at wileyonlinelibrary.com]

FIGURE 6 Mean monthly precipitation interpolated using OK method [Colour figure can be viewed at wileyonlinelibrary.com]



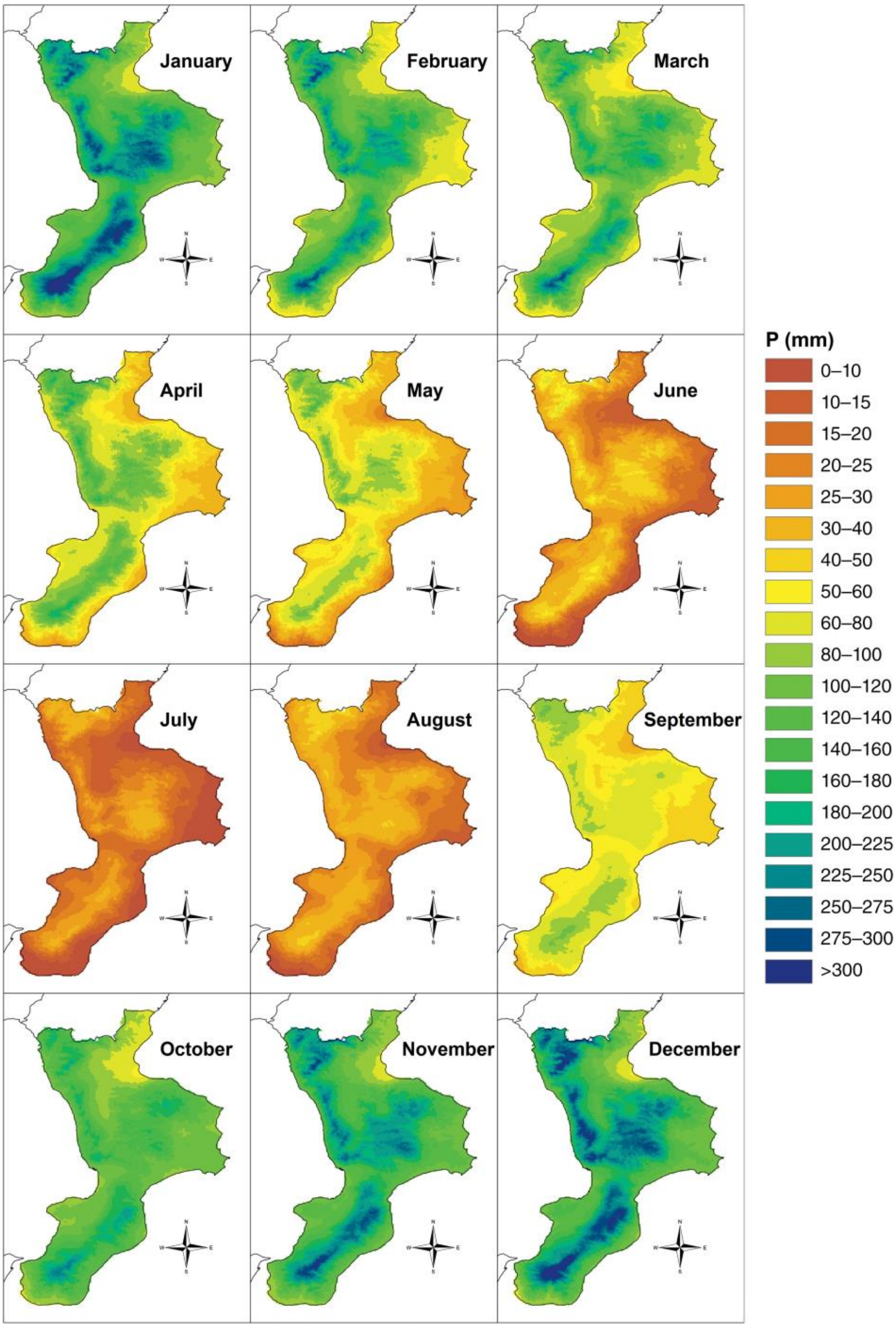
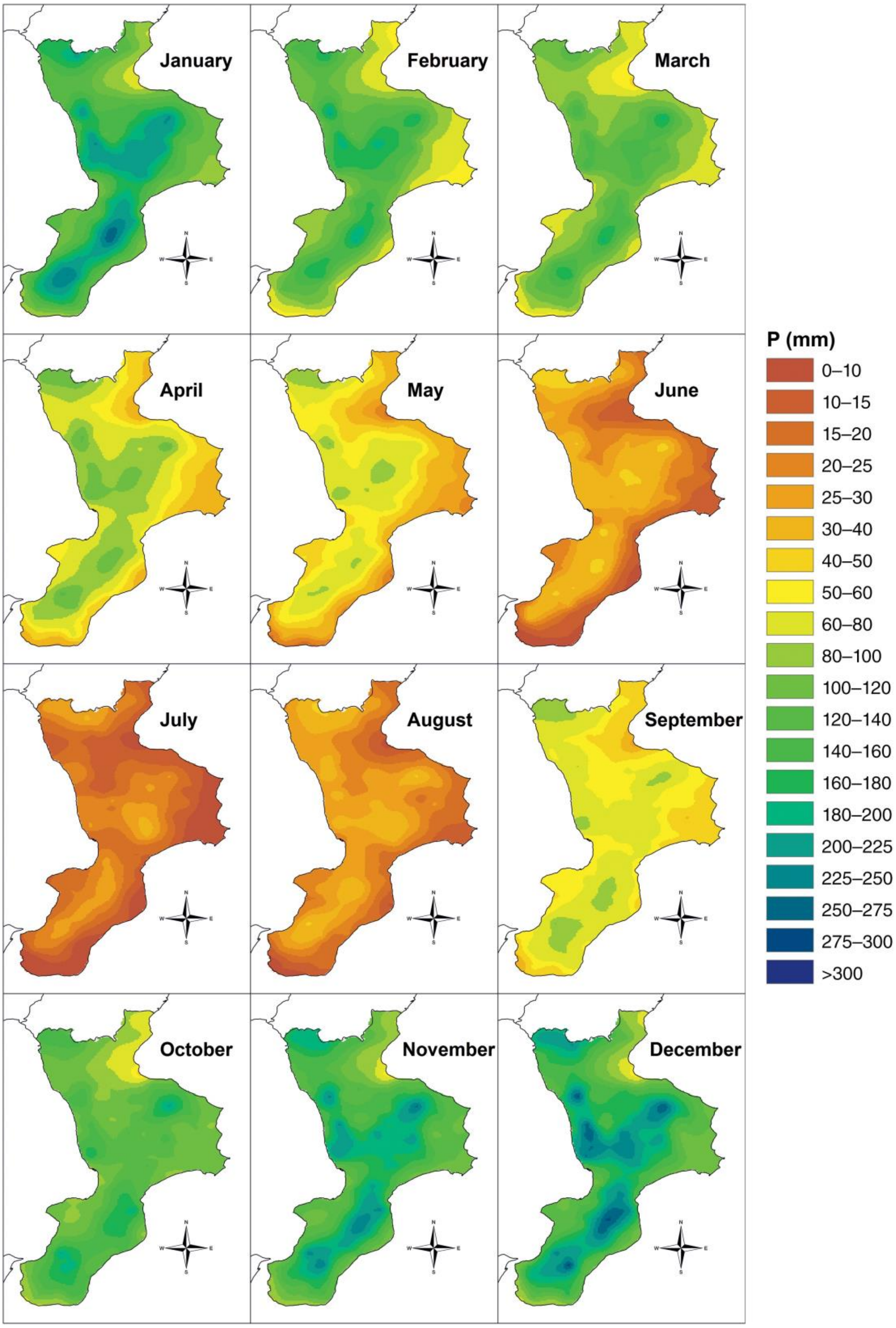


FIGURE 7 Mean monthly precipitation interpolated using KED method [Colour figure can be viewed at wileyonlinelibrary.com]

FIGURE 8 Mean monthly precipitation interpolated using COK method [Colour figure can be viewed at wileyonlinelibrary.com]



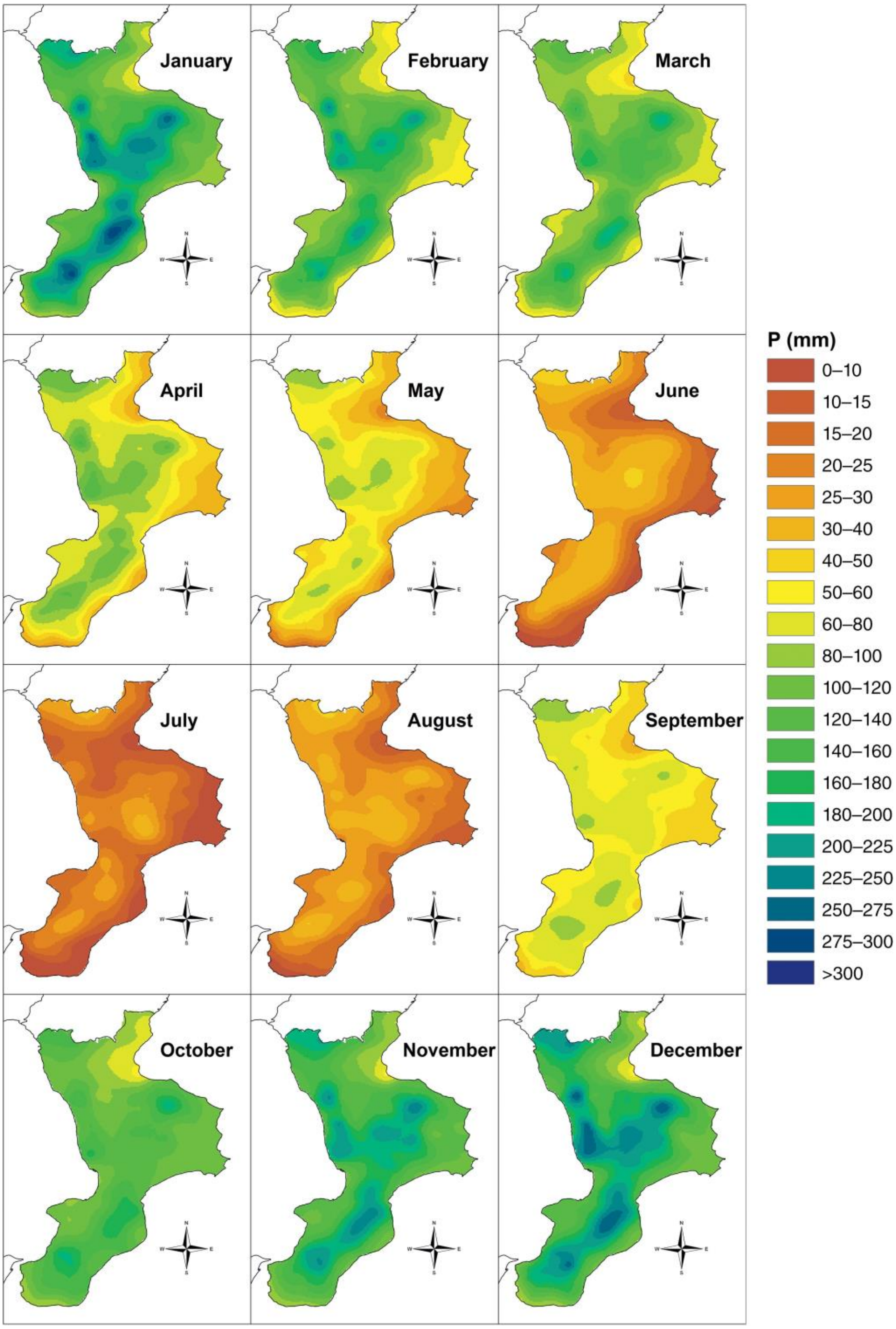


FIGURE 9 Mean monthly precipitation interpolated using EBK method [Colour figure can be viewed at wileyonlinelibrary.com]