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## The De Martonne aridity index in Calabria (Southern Italy)

Gaetano Pellicone , Tommaso Caloiero and Ilaria Guagliardi

National Research Council of Italy, Institute for Agriculture and Forest Systems in the Mediterranean (CNR-ISAFOM), Rende (CS), Italy

### ABSTRACT

In this paper, the annual rainfall and temperature values, measured in the period 1951–2016 in a region of southern Italy (Calabria), have been spatially interpolated using deterministic and geostatistical techniques in an R environment. In particular, Inverse Distance Weighting (IDW), Ordinary Kriging (OK), Kriging with External Drift (KED) and Ordinary Cokriging (COK) were compared to evaluate the best suitability method in reproducing the actual surface. Then, the spatial variation of aridity in Calabria has been evaluated using the De Martonne aridity index (IDM), which is based on rainfall and temperature data. As a result, geostatistical methods incontrovertibly show a better estimate than the IDW. Specifically, the KED was identified as the best predictor method for both rainfall and temperature data. Moreover, the spatial distribution of the IDM evidenced that the majority of the study area can be classified as humid, with semi-arid conditions mainly identified in the coastal areas.

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spatial interpolation; IDW;  
kriging

## 1. Introduction

Aridity can be considered one of the major risks for most areas of the world (Şarlak & Mahmood Agha, 2018). The assessment and monitoring of such a phenomenon is particularly important in those regions where agriculture is one of the largest sectors of the tradable economy. Climatic indices are reliable tools to classify climate and investigate the aridity or humidity in any region (Araghi, Martinez, Adamowski, & Olesen, 2018). Different indices have been proposed for different parts of the world. In particular, the indices proposed by Lang (1920), De Martonne (1926), UNESCO (1979) and UNEP (1992) have been employed by many researchers to display spatial variation in many regions (e.g. Paltineanu, Tanasescu, Chitu, & Mihailescu, 2007 and Haider & Adnan, 2014). Unfortunately, the frequent discontinuity in the spatial distribution of monitoring networks, which is a well-known problem not only on the Italian territory, makes it difficult to estimate the aridity in uncovered geographic areas (Mirás-Avalos, Paz-González, Vidal-Vázquez, & Sande-Fouz, 2007).

The analysis of spatial variability of meteorological variables is essential to infer estimates of point values from a dataset that is recorded at a limited number of stations (Abteu, Obeysekera, & Shih, 1993). This is important especially because improved methods of interpolation will enhance the ability to quantify the effects of climate on both natural and managed ecosystems, such as forests, wetlands and agroecosystems (Buttafuoco, Caloiero, Guagliardi, & Ricca,

2016; 2018; Price, McKenney, Nalder, Hutchinson, & Kesteven, 2000). Several methods have been developed to interpolate meteorological data, and the choice of the most suitable interpolator may vary depending on the regions (Buttafuoco, Guagliardi, Tarvainen, & Jarva, 2017; Ly, Charles, & Degré, 2011; Xu, Zou, Zhang, & Linderman, 2015) and according to many key factors influencing the climate, such as elevation, large-scale circulation, morphological features and natural vegetation. Within this context, the comparison between deterministic (Agnew & Palutikof, 2000; Hutchinson & Gessler, 1994; Legates & Willmott, 1990; Vicente-Serrano, Saz-Sánchez, & Cuadrat, 2003) and geostatistical (Goovaerts, 1997, 1999; Isaaks & Srivastava, 1989; Journel & Huijbregts, 1978) techniques is widely adopted providing a tool to support the choice of the most suitable interpolation method. A large amount of literature has focused on the comparison between different interpolation models used in the latest decades worldwide, such as in Australia (Hutchinson, 1995), Norfolk Island (Dirks, Hay, Stow, & Harris, 1998), Canada (Price et al., 2000), Spain (Moral, 2010), Sri Lanka (Plouffe, Robertson, & Chandrapala, 2015), China (Xu et al., 2015), Brazil (Borges, Franke, da Anunciação, Weiss, & Bernhofer, 2016) and Italy (Pellicone, Caloiero, Modica, & Guagliardi, 2018). Following these studies, a clear picture emerges: geostatistical techniques better estimate the meteorological data distribution than deterministic techniques. Nevertheless, other authors affirm that the estimates depend on the sampling density (e.g.

Dirks et al., 1998). Therefore, there is no common agreement in the scientific community.

The Calabria region (southern Italy) is one of the centremost regions within the Mediterranean basin, where climate changes dynamics are directly caused by the influence of the central Europe and the North Africa climates, and is one of the Italian regions most affected by drought (Caloiero, Sirangelo, Coscarelli, & Ferrari, 2016) and prone to desertification phenomena (Coscarelli, Caloiero, Minervino, & Sorriso-Valvo, 2016). Several studies evidenced changes in the rainfall (e.g. Caloiero et al., 2016) and temperature (e.g. Caloiero, Coscarelli, Ferrari, & Sirangelo, 2017) temporal patterns. Besides, the rainfall and temperature spatial distributions have been studied in the past years (e.g. Buttafuoco, Caloiero, & Coscarelli, 2010a, 2011; Longobardi, Buttafuoco, Caloiero, & Coscarelli, 2016), although no comparison of the different techniques has been carried out.

This paper aims to compare several interpolation techniques (both deterministic and geostatistical methods) for the spatial analysis of annual rainfall and temperature data, to detect the best interpolation method that better represents the spatial distribution. It also aims to identify the areas of the region, which are more prone to aridity. The results of this study can assist agricultural policy makers to manage agriculture, one of the largest sectors of the regional tradable economy of Calabria.

## 2. Study area and data

The Calabria region has a length of about 250 km, a width ranging from 31 to 111 km, and covers an area of about 15,000 km<sup>2</sup> (see Main Map). The Calabrian territory is almost hilly (on average 500 m a.s.l. with an extension of about 40% of the whole region), while the highest mountain exceeds 2,200 m a.s.l. (Ricca & Guagliardi, 2015). The Calabrian climate is generally Mediterranean but the rather complex orographic characteristics of this territory, combined with the simultaneous exposure to the Tyrrhenian Sea (which implies more continental climate in the coast compared to the Ionian side) and to the Ionian Sea (which implies high temperatures and short and abundant rainfall due to frequent African warm air currents) makes the climate of this territory very changeable and complex (Guagliardi et al., 2013, 2016, 2018).

In order to perform a spatial analysis of the rainfall and temperature data in the Calabria region, in this work, several annual series have been selected. In particular, the analysis focused on 224 rainfall and 55 temperature annual series with more than 50 years of observation, spanning over the period 1951-2016 (see Main Map).

## 3. De Martonne aridity index

An aridity index is defined as the numerical indicator of the degree of climate dryness at a given location

and classifies the type of climate in relation to water availability. The higher the aridity indices of a region, the greater the water resources variability (Tabari, Hosseinzadeh Talaei, Mousavi Nadoushani, Willems, & Marchetto, 2014). In this study, the De Martonne aridity index (De Martonne, 1926) was calculated for Calabria based on temperature and rainfall data for the period 1951-2016. Although it is one of the oldest aridity/humidity indices, because of its efficiency and relevance in relation to the arid/humid climate classification, it is still worldwide used with good results in order to identify dry/humid conditions of different regions (Coscarelli, Gaudio, & Caloiero, 2004).

The index may be as presented in Equation (1):

$$I_{DM} = \frac{P}{T_a + 10} \quad (1)$$

where  $P$  is the annual amount of rainfall (in millimetres) and  $T_a$  is the mean annual air temperature (in degrees Celsius).

According to the De Martonne aridity index, the types of climate are shown in Table 1. For example, in Greece, Baltas (2008) detected  $I_{DM}$  values ranging from Semi-Arid to Very-Humid climates.

## 4. Spatial interpolation methods

In the present paper, following Pellicone et al. (2018), four methods were applied to interpolate the mean annual rainfall and temperature data in the Calabria region: the inverse distance weighting (IDW), the ordinary kriging (OK), the kriging with external drift (KED) and the co-kriging (COK). The IDW is a deterministic method, which estimates the climatic values at an unsampled point as the distance-weighted average of the climatic values at sampling points. On the other hand, OK, KED and COK are geostatistical approaches. The OK is the most common kriging algorithm, which estimates a value of the random variable at a point of a region, using data in the neighbourhood of the estimation location. The KED method allows analysis to predict the variable of interest (primary variable) considering auxiliary information (supplementary variables in no stationary conditions) especially in wide uncovered station point areas. For example, Wagner et al. (2012) considered four covariates: elevation, distance from the main orographic barrier in main wind direction, X-coordinate and a

**Table 1.** De Martonne Aridity index values.

Type	Value
Semi-arid	$15 \leq I \leq 24$
Moderately-arid ( <i>Mediterranean</i> )	$24 \leq I \leq 30$
Slightly-arid	$30 \leq I \leq 35$
Moderately-humid	$35 \leq I \leq 40$
Humid	$40 \leq I \leq 50$
Very-humid	$50 \leq I \leq 60$
Excessively-humid	$60 \leq I \leq 187$

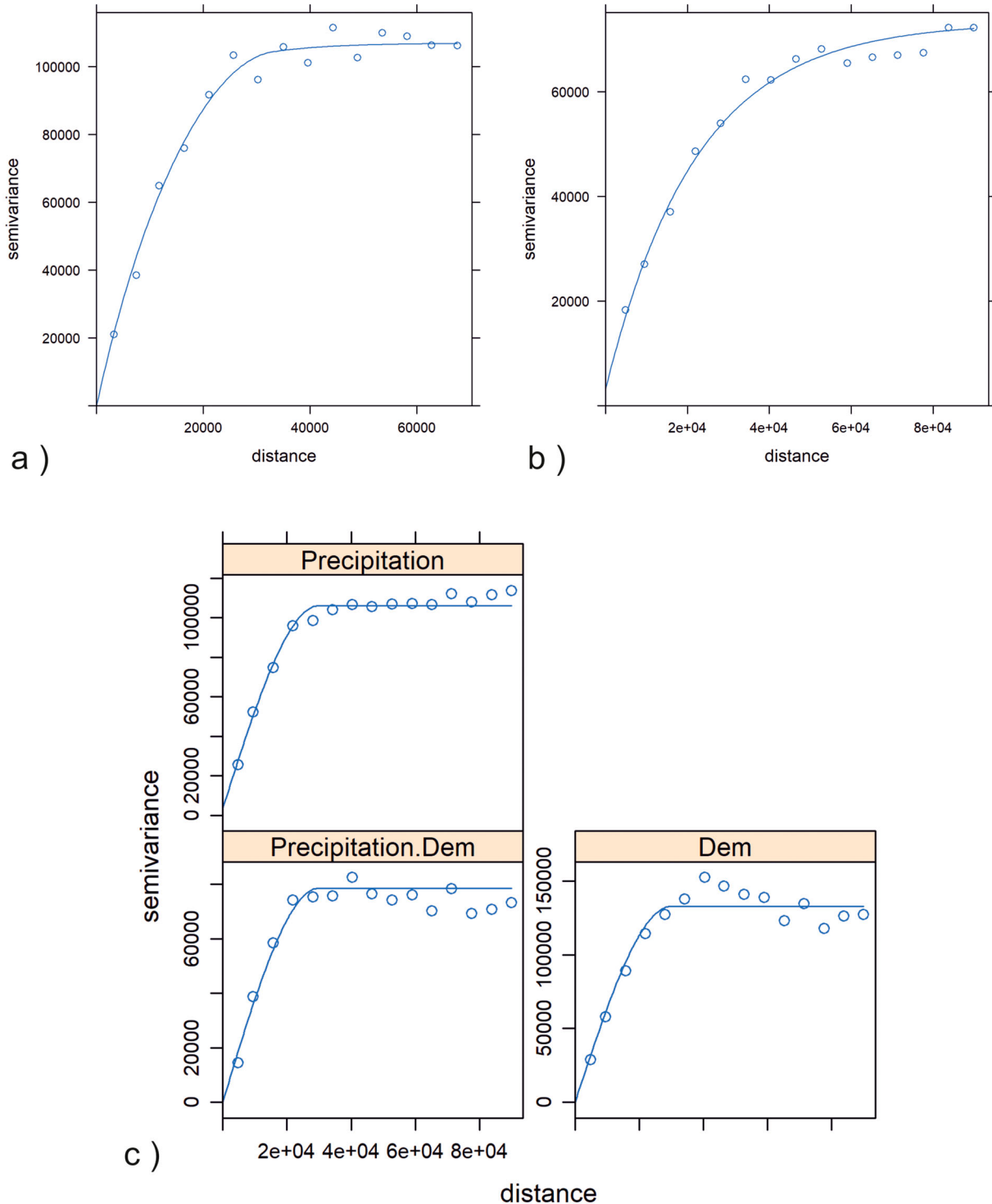
**Table 2.** Descriptive statistics of the annual rainfall (mm) and temperature data (°C).

Variables	Mean	Median	Max	Min	CV	SK	SD
Rainfall	1107.6	1070.4	2081.8	502.7	0.30	0.53	332.98
Temperature	16.17	17.1	19.3	8.5	16.96	-1.29	2.74

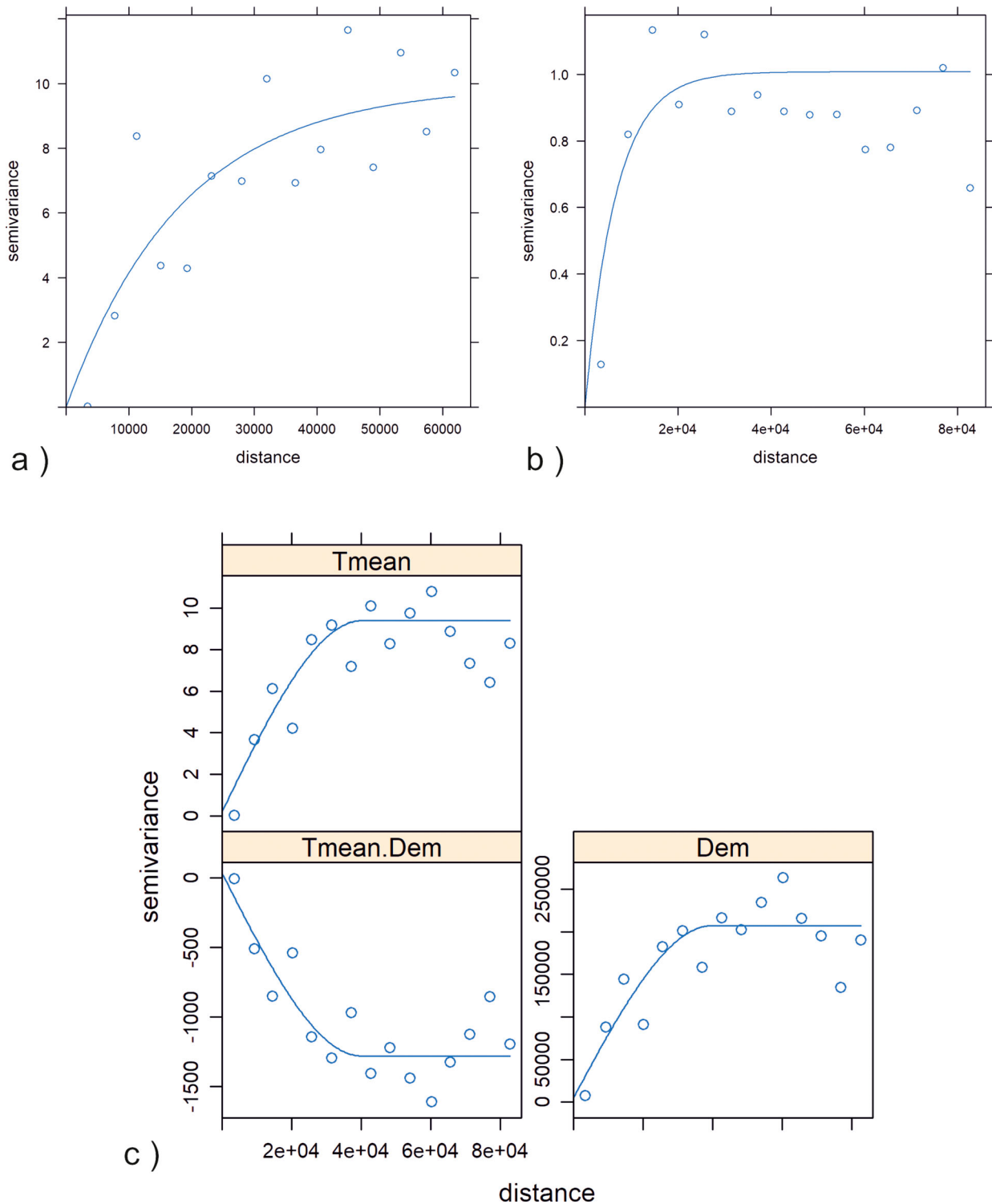
Note: CV: coefficient of variation; SK: skewness index; SD: standard deviation.

pattern of mean annual rainfall derived from satellite data acquired by the Tropical Rainfall Measuring Mission (TRMM). For this study, the elevation and distance to coastline were both utilized as predictors of primary variable. The COK is another variant of the

basic kriging algorithm that utilizes regionalized variables (one or more) to predict the target variable at unsampled locations by a cross-covariance function. For a detailed description of the presented geostatistical methods, interested readers should refer to textbooks



**Figure 1.** Annual rainfall semi-variograms for (a) OK, (b) KED, and (c) cross-variograms for COK.



**Figure 2.** Annual temperature semi-variograms for (a) OK, (b) KED, and (c) cross-variograms for COK.

such as Wackernagel (2003), Webster and Oliver (2007) and Chilès and Delfiner (2012), among others.

The various interpolation methods were implemented in R statistical computing environment using the gstat package (Pebesma & Graeler, 2016). Before the interpolation, a log transformation was applied on rainfall and temperature data. Moreover, for the geostatistical methods, a variographic analysis, which consists of the analysis of the experimental variogram calculated from the data and the variogram model fitted to the data, was carried out.

The goodness of the adopted methods, and consequently their possible utilization, was evaluated by means of a cross-validation technique. This method estimates the model prediction by excluding one observed point at a time (leave-one-out method) and predicting the response values for all the objects excluded from the model. Thus, the experimental error is found by comparing step-by-step the estimated value with the measured one (Buttafuoco, Tallarico, Falcone, & Guagliardi, 2010b). In particular, the mean absolute error (MAE), and the root mean square

**Table 3.** Details of the variogram models used.

Variable	Model	Range (m)	Sill	Nugget
Rainfall	Circular	14,673.10	0.991	0.02
Temperature	Matern	22,155.93	70,046.328	4203.00

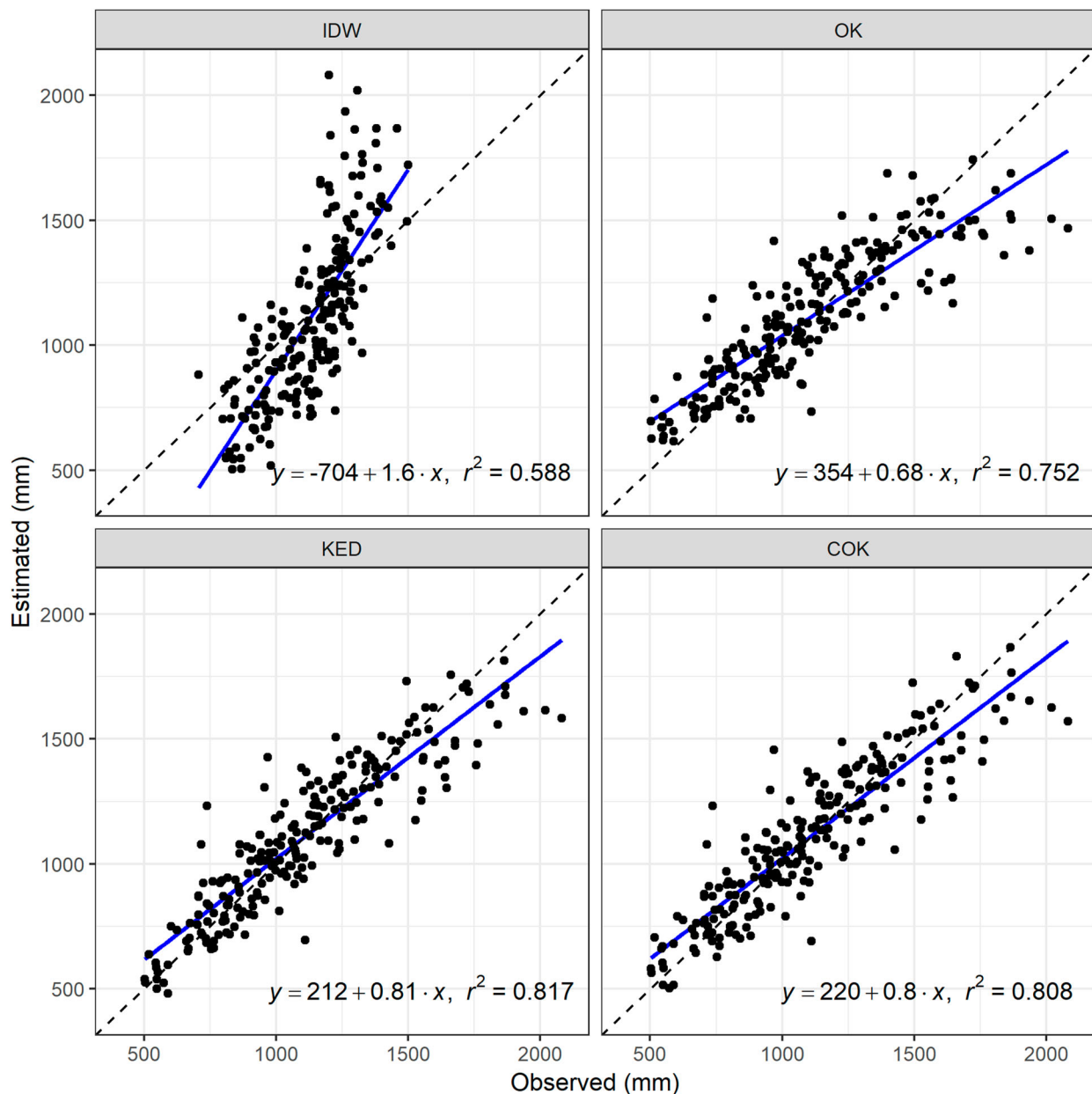
error (RMSE), were evaluated to appreciate the accuracy of the various interpolation methods.

## 5. Results and discussion

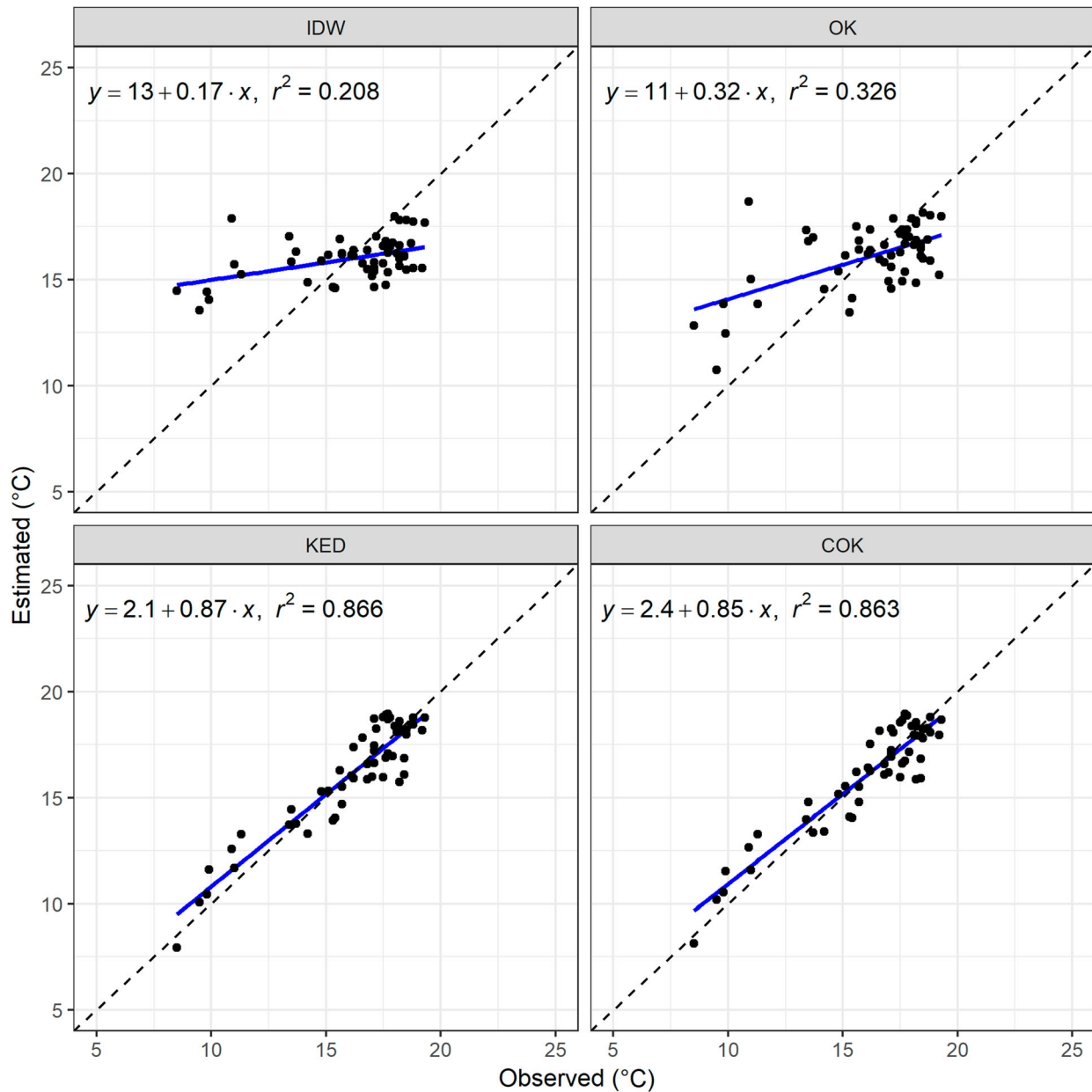
The descriptive statistics of the annual data for the rainfall and temperature series are presented in Table 2. In particular, the skewness coefficients (SK) evidenced a clear asymmetry of the probability distribution making a classical log-transformation of all the annual series data necessary in order to allow for the use of normally distributed variables. Due to the

number of measured data, an omnidirectional semi-variogram was used for the spatial dependence analysis and, therefore, the spatial variability has been considered identical in every direction (Figures 1 and 2). The details of the variogram model used are shown in Table 3. The scatter plots of predicted versus measured values are shown in Figures 3 and 4. The results of the comparison methods (MAE and RMSE) are shown in Table 4.

As expected, from the MAE and RMSE results, the IDW interpolator can be classified as the worst approach for the spatial analysis of the rainfall and temperature information. These findings are confirmed by the results of past studies (Goovaerts, 2000; Lloyd, 2005) which showed a lower accuracy of the IDW than geostatistical approaches in the estimation of monthly and annual rainfall although there are no important differences in computational time among



**Figure 3.** Scatterplots between observed and estimated annual rainfall for the selected interpolation methods.



**Figure 4.** Scatterplots between observed and estimated annual temperature for the selected interpolation methods.

the various methods. The OK gives better results than IDW, although the validation results indicated that the method was not the best approach for interpolating annual data. In the KED computation, elevation evaluated from a digital elevation model (DEM) and distance to coastline were used as the secondary information. In particular, the elevation values have been extracted from a DEM with a cell resolution of

20 m given by the Basin Authority of the Calabria region. Comparing validation results among adopted methods, the KED’s MAE and RMSE values show the best results, confirming that KED is the best interpolator approach for both annual rainfall and temperature data in the Calabria region. Finally, as well as for KED interpolation, elevation was incorporated as secondary variable in the COK. Validation results

**Table 4.** RMSE, MAE and BIAS for the selected interpolation methods.

Variable	Error	IDW	OK	KED			COK		
				DC	EL	DC + EL	DC	EL	DC + EL
Rainfall	RMSE	235.8	168.1	164.8	146.5	142.1	172.4	146.2	144.8
	MAE	186.0	124.2	119.7	108.1	105.1	126.8	108.8	105.7
	BIAS	2	0.5	0.2	0.1	0.1	0.3	0.2	0.2
Temperature	RMSE	2.438	2.233	1.8	0.99	0.97	2.08	1.06	1.03
	MAE	1.926	1.716	1.3	0.78	0.7	1.46	0.86	0.82
	BIAS	-1	-0.5	0.1	0.035	0.03	0.13	0.042	0.05

Note: DC: distance to coastline; EL: elevation; DC + EL: distance to coastline and elevation.

confirm that the COK method can be considered a good approach for interpolating rainfall and temperature annual data. These results confirm the ones obtained in Germany (Berndt & Haberlandt, 2018; Verworn & Haberlandt, 2011), in the Lesser Antilles (Cantet, 2017) and in the high-altitude catchments of the Indus basin (Dahri et al., 2016) which detected that the KED performs significantly better than other methods for various climate variables. On the other hand, different results were obtained in Nigeria, where partial thin-plate splines was identified as the optimal method for spatial interpolation of monthly total precipitation and minimum and maximum temperatures (Arowolo, Bhowmik, Qi, & Deng, 2017) and in Turkey, where surprisingly IDW was identified as the best modelling of precipitation and temperature (Hadi & Tombul, 2018).

Given the rainfall and temperature annual maps, obtained with the KED method with a spatial resolution of 250 m, a final map with the spatial distribution of the  $I_{DM}$  has been processed using Esri ArcGIS 9.3.1 through some map algebra operations which, in a Geographic Information System (GIS), allows two or more raster layers of similar dimensions to produce a new raster layer using algebraic operations such as addition, subtraction, etc. As a result, the spatial distribution of the  $I_{DM}$  reveals, as expected, that the majority of the study area can be classified mainly as humid, due to the Mediterranean moist air mass influence. In fact, about 79.5% of the regional area falls within one of the arid classes and, in particular, 13.2% of the regional area shows *slightly humid* conditions, 11.6% *moderately humid*, 16.6% *humid*, 12.7% *very humid* and 25.2% *excessively humid* conditions. Conversely, about 20.5% of the region presents arid condition falling within the Semi-arid (7.5%) and the Moderately arid (13.0%) classes. Finally, the spatial distribution of the  $I_{DM}$  is strictly related to the orography, with the most humid conditions observed near the main mountains of the region, and the semi-arid conditions mainly identified in the coastal areas (see Main Map).

## 6. Conclusions

Due to their importance for the cropping pattern, productivity, flooding and drought hazards, erosion and sedimentation, rainfall and temperature can be considered two of the most significant climatic parameters. For these reasons, knowledge of the spatial distribution of rainfall and temperature is paramount. This study allowed to assess the aridity prone areas in a southern Italian region (Calabria) by using the  $I_{DM}$  and a geostatistical approach. In this paper, four annual rainfall and temperature maps for the Calabria region, obtained by four different interpolators, have been analysed. In particular, a comparison among several interpolator methods, both deterministic (IDW) and

geostatistical (OK, KED and COK), has been performed and evaluated by their cross-validation results in order to test their accuracy and peculiar properties in a specific context. As a result, among the geostatistical approaches, the KED with elevation and distance to coastline as secondary variables was detected as the best method for interpolating annual rainfall and temperature distribution in Calabria. In addition, the spatial distribution of  $I_{DM}$  has been mapped. As a result, humid areas were identified in the highest mountains whereas arid areas in the lowest and coastal areas showing a strong relation between  $I_{DM}$  values and orography.

## Software

In order to organize the average annual data Microsoft Excel was used. The several interpolation methods were implemented in the R statistical computing environment using the gstat package. All the spatial procedures were performed using Esri ArcGIS 9.3.1.

## Disclosure statement

No potential conflict of interest was reported by the authors.

## ORCID

Gaetano Pellicone  <http://orcid.org/0000-0002-6802-5269>  
Tommaso Caloiero  <http://orcid.org/0000-0002-0393-4592>  
Ilaria Guagliardi  <http://orcid.org/0000-0001-5360-7197>

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