Environmental Earth Sciences (2020) 79:11
https://doi.org/10.1007/s12665-019-8769-z

ORIGINAL ARTICLE

Accounting for elevation and distance to the nearest coastline in geostatistical mapping of average annual precipitation

G. Buttafuoco[1] · F. Lucà[1]

Received: 25 April 2019 / Accepted: 2 December 2019 / Published online: 10 December 2019
© Springer-Verlag GmbH Germany, part of Springer Nature 2019

Abstract
Spatial distribution of precipitation in mountainous areas suggests strong control of surface orography on precipitation processes. Generally, quantifying orographic control of precipitation and identifying homogeneous areas are difficult because of the complex combination of factors, which could influence the precipitation process. The objective of this study was to account for morphometric attributes (elevations and distances to the nearest coastline) in geostatistical mapping of average annual precipitation in southern Italy. The study area was the Calabria Region, which has a spatially variable Mediterranean climate because of its high orographic variability. In this study, annual precipitation data collected by the former Italian Hydrographic Service for the 1916–2006 period were used. Elevations and distances to the nearest coastline were derived from a digital elevation model with 250 m × 250 m cell size in a geographic information system environment and used to delineate areas with homogeneous morphological features [landscape units (LU)]. The effectiveness of LU was assessed estimating the expected value of the average annual precipitation with polygon kriging and comparing their differences with the Mann–Whitney–Wilcoxon test. The average annual precipitation map showed that mountains areas receive more precipitation than low elevation areas and, in the Tyrrhenian side, it was also evident the orographic influence of Coastal chain on precipitation with high precipitation values. Results can help in understanding the differences among LU and the influence of surface orography on spatial patterns of annual precipitation in mountainous regions.

Keywords Precipitation · Orography · Landscape unit · Spatial variability · Polygon kriging

Introduction

Precipitation is a process highly variable in space and time (Bárdossy and Li 2008), which often is measured at fixed and sparse point locations (rain gauges), even though the quantity of greatest interest is a mean value over specified areas such as an hydrological catchment or a grid cell of various climatic, hydrologic and ecological models (Grimes and Pardo-Igúzquiza 2010; Hengl et al. 2013). Different methods have been developed for characterising and modelling precipitation (Goovaerts 2000; Szentimrey et al. 2010; Lloyd 2010; Grimes and Pardo-Igúzquiza 2010). Most of such methods give similar results in areas with low relief, even distribution of rain gauges and abundant data. Unfortunately, such conditions are rarely met, and when data are sparse, especially in mountainous areas, the implicit or explicit underlying assumptions about the variation among measured points may differ significantly even at relatively reduced scales (Collins and Bolstad 1996; Diodato 2005). In these cases, the choice of an interpolation approach is a key issue because it needs taking into account how orography influences precipitation. Particularly, caution is required in using information from precipitation atlases relying only on statistical relationships because they may not be generally applicable (Roe 2005). Methods producing smooth surfaces include various approaches, which may combine regression analysis and distance-based weighted averages (Hartkamp et al. 1999; Brunsdon et al. 2001; Kumari et al. 2017; Lucà et al. 2018). The key difference among such approaches is the criteria used to determine the weights of point data in relation to distance. These criteria can include simple distance relations as in the inverse distance weighting methods (Gotway et al. 1996), minimization of

✉ G. Buttafuoco
gabriele.buttafuoco@cnr.it

1 National Research Council of Italy, Institute for Agricultural and Forest Systems in the Mediterranean, 87036 Rende, CS, Italy

المنارة للاستشارات
www.manaraa.com

variance as in the different types of kriging algorithms (Chilès and Delfiner 2012), minimization of curvature and enforcement of smoothness criteria as in splining (Dubrule 1984; Hutchinson 1995).

Geostatistics is a suitable solution for describing and quantifying the spatial variability of precipitation because it is often measured at fixed point locations and varies more or less continuously in the geographical space (Matheron 1971; Grimes and Pardo-Igúzquiza 2010). Geostatistics also provides a measure of reliability of the estimated precipitation and takes into account the support size (area of measurement unit), because precipitation is recorded by rain gauge punctually, whereas its estimation is provided for larger extent (Dowd and Pardo-Igúzquiza 2012; Lucà et al. 2018).

Topographic attributes may improve the estimation of precipitation if used as auxiliary variables in multivariate geostatistics or they may allow to understand factors controlling the distribution of precipitation. Such factors, as known, can be ascribed to converging–ascending air flow, air temperature, winds, distance to the coast, and mountain ranges (Hayward and Clarke 1996; Strangeways 2007; Makarieva et al. 2009).

In areas as Calabria region (southern Italy), with variable morphology, high mountains and plain areas or valleys, the precipitation–elevation relationship is well documented. Particularly, using geostatistical methods, it has been showed, worldwide, how elevation strongly controls the variability of precipitation at fine scale of monthly, annual, or interannual precipitations (Chua and Bras 1982; Hevesi et al. 1992; Martínez-cob 1995; Pardo-Igúzquiza 1998; Goovaerts 2000; Deraisme et al. 2001; Gómez-Hernández et al. 2001; Diodato 2005; Lloyd 2005; Mirás-Avalos et al. 2007; Feki et al. 2012; Bárdossy and Pegram 2013; Ding et al. 2014; Zeng et al. 2016; Yao et al. 2016).

However, in mountainous regions, it may not be possible to capture the relationship between precipitation and topographic attributes because it depends on spatial scale. Moreover, beyond a specific spatial scale, there is not a simple relationship when topography and precipitation are smoothed (Haiden and Pistotnik 2009).

In addition, the relationship precipitation–elevation depends on the temporal aggregation (i.e., the sum of precipitation in a considered interval time) (Bárdossy and Pegram 2013). Particularly, the influence of elevation on precipitation has been demonstrated important at monthly to annual scales (Hevesi et al. 1992; Martínez-cob 1995; Pardo-Igúzquiza 1998; Goovaerts 2000; Deraisme et al. 2001; Gómez-Hernández et al. 2001; Diodato 2005; Lloyd 2005; Bárdossy and Pegram 2013) and that such a relation increases with the time of aggregation (Bárdossy and Pegram 2013).

Precipitation depends also on distance from the sea (Hayward and Clarke 1996; Agnew and Palutikof 2000) which could be used to account for maritime/landmass influences.

Finally, the relationships precipitation–topographic attributes are spatially complex and understanding their nature and spatial pattern is not easy and simple. Topographic attributes have been used as environmental covariates to produce more accurate maps with different geostatistical methods (Chua and Bras 1982; Hevesi et al. 1992; Martínez-cob 1995; Pardo-Igúzquiza 1998; Prudhomme and Reed 1999; Goovaerts 2000; Gómez-Hernández et al. 2001; Diodato 2005; Lloyd 2005; Mirás-Avalos et al. 2007; Feki et al. 2012; Bárdossy and Pegram 2013; Kumari et al. 2017).

However, topographic attributes and precipitation data are associated with different support sizes, which can be considered pointwise (very small surface unit) for precipitation compared to the support size of the topographic attributes (large surface unit). Generally, different types of data are reported in a way as to not reflect the original support sizes with significant effect on geostatistical analysis. To combine such different spatial data, it is necessary defining methods to take into account the underlying uncertainties and change of support (Gotway and Young 2002).

An alternative approach of using topographic attributes as covariates to explore the complex nature of such a relation, which does not require taking into account the change of support, might be to incorporate the influence of topography on precipitation patterns delineating areas with homogeneous morphological features. Such areas could be called landscape units (LU) and delineated using morphometric attributes easily derivable from a digital elevation model (DEM) in a geographic information system (GIS) environment as elevation above sea level and distance to the nearest coastline.

Estimating the mean value of precipitation over the different landscape units (having irregular shapes) using data values from *n* rain gauges with arbitrary location can be solved by polygon kriging (Buttafuoco et al. 2017). It can be used to estimate the expected value and standard deviation of precipitation for each landscape unit by taking spatial correlation into account. Moreover, the effectiveness of landscape units' delineation based on elevation and distance to the nearest coastline has been evaluated by polygon kriging.

Studying the relationships between precipitation and topographic attributes is a central part of the interaction between the land surface and the atmosphere and it is important for natural ecosystems, water resources management, and for its connections to other physical components of the Earth system (Roe 2005). The study would contribute to understanding how topographic attributes influence annual precipitation in a Mediterranean environment.

The objective of this paper was to account for morphometric attributes, such as elevation and distance to the

المنارة للاستشارات
www.manaraa.com

nearest coastline, in geostatistical mapping of average annual precipitation in a region of southern Italy (Calabria). To accomplish this objective: (1) it was proposed an approach for delineating contiguous landscape units based on elevation and distance to the nearest coastline and (2) the landscape units were validated by comparing statistically the expected values of precipitation estimated by polygon kriging for each landscape unit.

Materials and methods

Study area and precipitation data

The Calabria Region (Italy) has an area of 15,080 km^2 and it is one of the most mountainous Italian regions (Fig. 1), even though it does not have many high summits. The elevation has an average value of 597 m above sea level (a.s.l.) and a maximum of 2266 m a.s.l. (Fig. 1b). Calabria Region has an elevation greater than 500 m a.s.l. for 42% of the land, between 50 and 500 m a.s.l. for 49%, and for only 9%, its elevation is lower than 50 m a.s.l. The study area has high climatic contrasts because of its geographic position and mountainous nature.

The climate is Mediterranean and highly spatially variable with precipitation less frequent in summer. Coastal zones are characterised by mild winters (average air temperature: about 10 °C) and hot summers (average air temperature: about 23 °C) with little precipitation (average precipitation: about 23 mm). The climate in the Ionian side of the study area (Fig. 1) is influenced by currents coming from Africa with high temperatures and short and heavy precipitation, while western air currents influence the Tyrrhenian side (Fig. 1) determining lower temperatures and orographic influence on precipitation. In the inland zones, winters are colder than in the coastal zones, whereas summers are fresher with some precipitation (Federico et al. 2000; Caloiero et al. 2015; Buttafuoco et al. 2015).

A long-term database (1916–2006) of the annual precipitation collected by the former Italian Hydrographic Service has been used. After data homogenization, 129 precipitation gauges (Fig. 1b) have been selected. More details on precipitation data are reported in Buttafuoco et al. (2015).

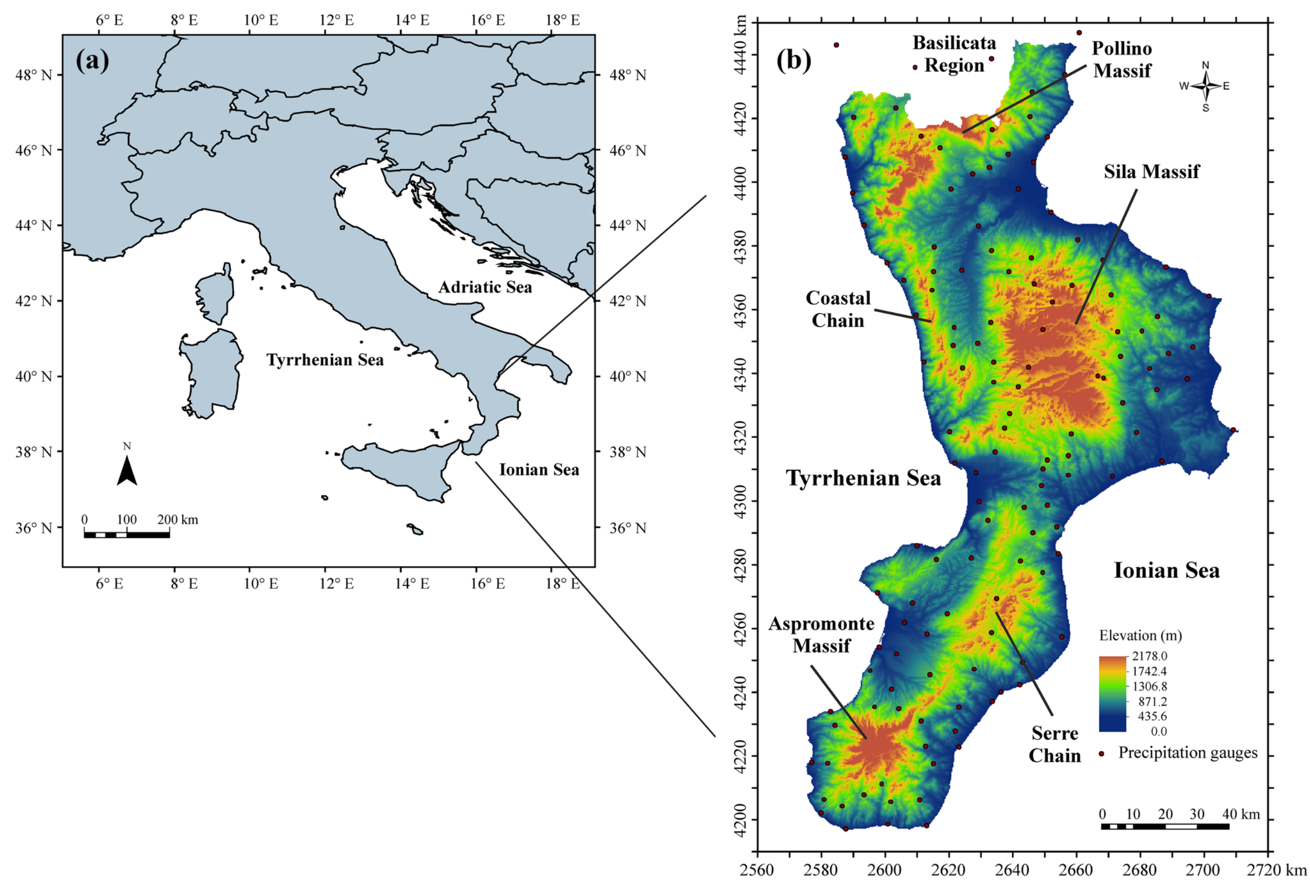

Fig. 1 Location (**a**) and digital elevation model (**b**) of the study area. Precipitation gauge locations are also reported (filled points) (**b**)

المنارة للاستشارات
www.manaraa.com

Landscape units

The study area was split in subareas (landscape units) with homogeneous morphological features. The delineation of such landscape units was based on elevation above sea level and the distance to the nearest coastline derived from a digital elevation model (DEM) with 250 m × 250 m cell size in a GIS environment. As starting point, to combine elevation and distance to the nearest coastline in classes and to optimize the number of landscape units, both morphological features were divided into three classes:

- Elevation (E):
  1. $0\ \mathrm{m} < E \le 500\ \mathrm{m}$
  2. $500\ \mathrm{m} < E \le 1000\ \mathrm{m}$
  3. $E > 1000\ \mathrm{m}$
- Distance (D) to the nearest coastline:
  1. $0\ \mathrm{km} < D \le 5\ \mathrm{km}$
  2. $5\ \mathrm{km} < D \le 10\ \mathrm{km}$
  3. $D > 10\ \mathrm{km}$

By definition, the landscape units may not be contiguous and consequently, the same landscape unit can be found at different locations.

Geostatistical approach

The average annual precipitation data were modelled as an intrinsic stationary process using the methods of geostatistics (Matheron 1971) in which each average annual precipitation value $z(\mathbf{x}_\alpha)$ at different location $\mathbf{x}_\alpha$($\mathbf{x}$ denotes the coordinates in two dimensions and $\alpha = 1, \ldots, N$ are the sampling points) is interpreted as a particular realization of a random variable $Z(\mathbf{x}_\alpha)$. The set of such random variables $Z(\mathbf{x}_1)$, $Z(\mathbf{x}_2)$, …, constitutes a random function (Journel and Huijbregts 1978; Goovaerts 1997; Webster and Oliver 2007; Chilès and Delfiner 2012). The set of actual values of Z (precipitation data) including the realization of the random function is known as a regionalized variable $z(\mathbf{x}_\alpha)$. However, a random function has not a mathematical description as a deterministic one (i.e., an equation), but it may have a correlation (structure) in space with values at different places related to one another in a statistical sense (Webster and Oliver 2007). Such a structure in space is estimated by the experimental variogram $\gamma(\mathbf{h})$ from sample data. The variogram is a measure of variability and is a function of the distance (h) and direction of data pair values $[z(\mathbf{x}_\alpha), z(\mathbf{x}_\alpha + \mathbf{h})]$ (Chilès and Delfiner 2012). A theoretical function, called variogram model, is fitted to the experimental variogram and allows the analytical estimate of the variogram for any distance h. Sill, range, and nugget summarize the main features of the modelled variogram (Goovaerts 1997). The range is the distance over which pairs of precipitation values are spatially correlated, while the sill is the variogram value corresponding to the range (Webster and Oliver 2007). The nugget effect is a discontinuity at variogram origin, which characterises the very short-scale variability within the shortest sampling interval and the errors of measurement (Goovaerts 1997). Alternative modelled variograms were compared by cross-validation, which consists in removing temporarily in turn each sample value and estimate it using the modelled variogram and its neighbouring data. The goodness of fit was assessed by the mean error (ME) and the mean squared deviation ratio (MSDR). A mean error (ME) close to 0 proves the unbiasedness of estimate, whereas a model is accurate if MSDR is close to 1 (Webster and Oliver 2007).

Even though the geostatistical approach does not require the data follow a normal distribution, variogram modelling is sensitive to strong departures from normality because a few exceptionally large values may contribute to many very large squared differences. A data transformation is suggested when skewness is greater than 0.5 (Webster and Oliver 2007) and Gaussian anamorphosis is a suitable procedure to transform skew data into a Gaussian-shaped variable with zero mean and unit variance (Wackernagel 2003; Chilès and Delfiner 2012).

The fitted variogram was used with Polygon kriging (Buttafuoco et al. 2017) and all data to estimate an average value of precipitation and its associated variance of estimation over each of the irregular-shaped landscape units. Polygon kriging is used when the estimation has to be made over polygon of irregular shape and different size and it is an almost straightforward extension of block kriging (Webster and Oliver 2007). Polygon kriging requires that each polygon is firstly discretized in a number of regular cells i, then the average covariance function relative to each polygon ν, is calculated as a weighted discrete summation of the point covariance function:

$$K_{\alpha\upsilon} = \frac{1}{\sum_{i=1}^{N_c} w_i} \sum_{i=1}^{N_c} w_i K_{\alpha c_i}, \tag{1}$$

where each w_i relates to the proportion of the intersection area between the cell i, centred in the point c_i and the polygon ν, N_c is the number of the cells i within the polygon ν, α is a data point, $K_{\alpha c_i}$ is the covariance function calculated at each point c_i and $K_{\alpha\upsilon}$ is the average point-area covariance relative to the polygon ν.

Finally, the differences in precipitations among different landscape units were statistically compared using the Mann–Whitney–Wilcoxon test (Kanji 2006). It is a nonparametric test to compare the means of two populations when

المنارة للاستشارات
www.manaraa.com

the two distributions have the same shape and spread. The test is based on independent random samples and does not require the normal distribution. However, the test has an important limitation in spatial analysis because of the spatial dependence of the precipitation values.

All geostatistical analyses were performed using the software package ISATIS, release 2018.2 (Bleines et al. 2018).

Results and discussion

Combining the different classes of elevation and distance to the coastline, the study area was split into 107 polygons, which were classified in 8 types of landscape units (Fig. 2 and Table 1). The polygons belonging to the landscape units 3 and 4 (Fig. 2) are mostly contiguous, whereas the other landscape units include polygons at different degrees of continuity (Fig. 2).

The landscape unit 3 includes coastal areas between 0 and 5 km from the coastline and an elevation between 0 and 500 m a.s.l. (Fig. 2), whereas landscape unit 4 differs from unit 3 only for the distance to the coastline (5–10 km from) and includes hilly areas. The different degree of continuity of the other landscape units reflects the orography of the study area (Fig. 2).

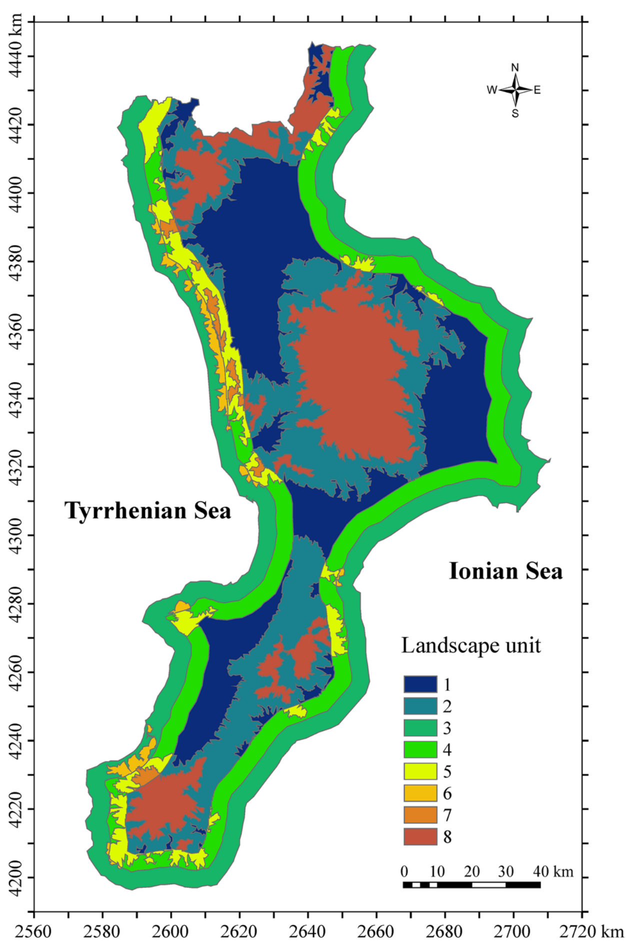

Fig. 2 Landscape units obtained combining the different classes of elevation and distance to the coastline

Table 1 Results of combination of the classes of elevation and distances to the nearest coastland

Landscape unit	Number of polygons	Elevation (E, m)	Distance (D, km)
1	26	$0<E\leq 500$	$D>10$
2	8	$500<E\leq 1000$	$D>10$
3	1	$0<E\leq 500$	$0<D\leq 5$
4	16	$0<E\leq 500$	$5<D\leq 10$
5	14	$500<E\leq 1000$	$5<D\leq 10$
6	9	$500<E\leq 1000$	$0<D\leq 5$
8	6	$E>1000$	$5<D\leq 10$
9	27	$E>1000$	$D>10$

The distribution of average annual precipitation is slightly positive skewed (Fig. 3a) because mean (1062.6 mm) and median (1015.4 mm) do not coincide, and median is closer to lower quartile (785 mm). In addition, the upper whisker (maximum precipitation value = 2143 mm) is longer than the lower whisker (minimum precipitation value = 502.7 mm). The skewness coefficient is 0.70 and, for the subsequent analysis, precipitation data were transformed into a Gaussian-shaped variable using the above-mentioned Gaussian anamorphosis.

A map of the 2D variograms (not shown) of precipitation data was computed to explore the precipitation data for modelling and interpreting spatial dependence in all

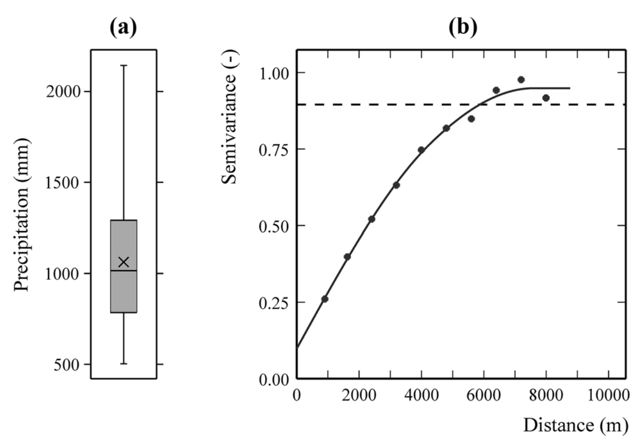

Fig. 3 Box plot of the annual precipitation data (**a**) and variogram of the Gaussian precipitation data (**b**). The filled points are the experimental semivariance values, whereas the solid line is the model of variogram. The dashed line is the experimental variance

www.manaraa.com

the directions of the space and to identify possible anisotropic behaviours of precipitation. A bounded isotropic nested variogram model was fitted to the experimental variogram, because no relevant difference as a function of direction (anisotropy) was detected (Fig. 3b). The variogram combines three basic structures including a nugget effect and two spherical models (Webster and Oliver 2007) with ranges 42,210 m and 76,072 m. The results of cross-validation were quite satisfactory because the mean of the estimation error was close to zero (0.0116) and the variance of the mean squared deviation ratio was close to 1 (0.96). The presence of differences in spatial pattern of variation could be interpreted as changes in local weather situation and in the large-scale organization of storms and climate patterns. The shorter range of spatial variation (42,210 m) could be related to the orographic effect (Fig. 1b), whereas the longer range of variation (76,072 m) could be related to large-scale factors of variation as global atmospheric circulation. Such a hypothesis about the longer range of variation might be confirmed by the proportion of precipitation and wet day variance for all seasons explained by the Western European Zonal Circulation Index and by the Mediterranean Circulation Index (Brunetti et al. 2002).

The fitted variogram and the Gaussian annual precipitation data were used with polygon kriging to estimate the expected value (average) of annual precipitation and its associated variance of estimation over each landscape unit. The Gaussian estimates were back-transformed to the raw values of the variables through the anamorphosis functions previously calculated. The spatial distribution of average annual precipitation over Calabria Region (Fig. 4) shows that generally mountains areas receive more precipitation than low elevation areas. In the Tyrrhenian side, it is also evident the orographic influence of Coastal chain on precipitation with high precipitation values (Fig. 4).

The values of expected precipitation for each landscape unit (LU) are summarized in Fig. 5. Such values were compared with the Mann–Whitney–Wilcoxon test and the results are reported in Table 2. Two expected precipitations are statistically different when the calculated values of the test (Table 2) are smaller than the one tabulated. In the study case, the tabulated value is 0.05: the expected precipitation value of landscape unit (LU) 4 is statistically different from the ones of LU1 and LU2. The expected precipitation values of LU5 and LU6 are different from the one of LU2, whereas both the expected values of LU7 and LU8 are different from the ones of LU4 and LU6.

Though the Mann–Whitney–Wilcoxon test has some limitations because of the spatial dependence of precipitation, its results can help to understand the differences among the landscape units and the influence of surface orography on patterns of annual precipitation.

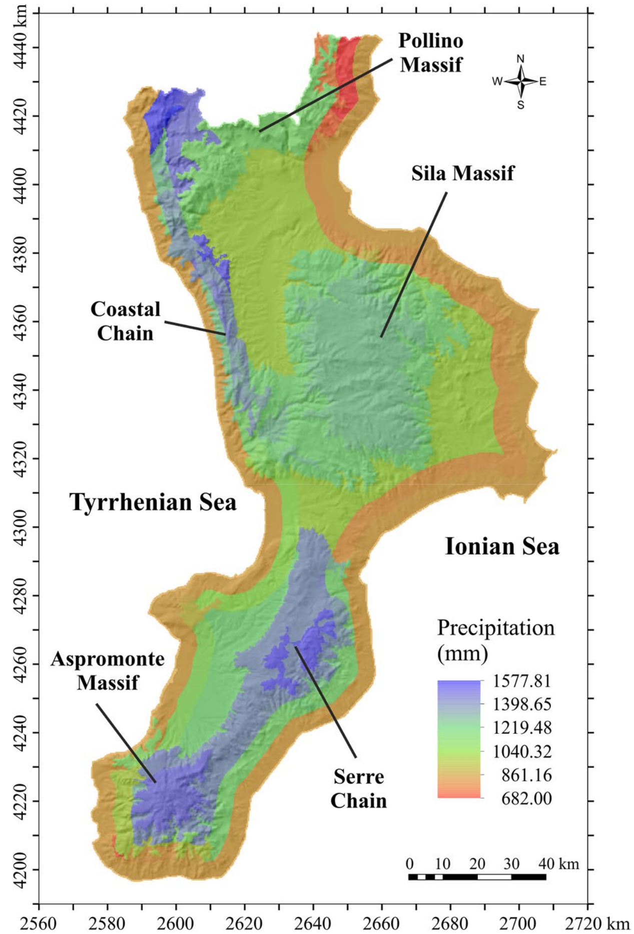

Fig. 4 Polygon kriging map of the expected values of annual precipitation

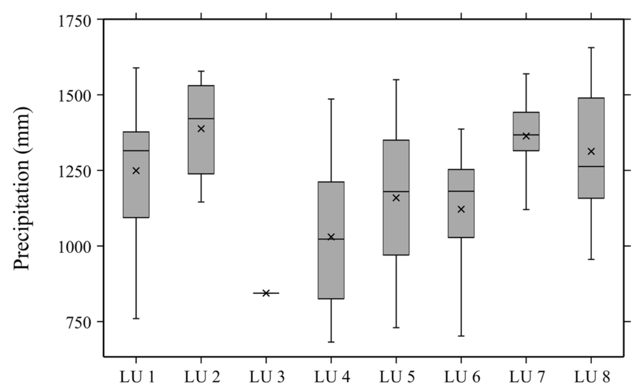

Fig. 5 Box plots summarizing the polygon kriging annual precipitations for each landscape unit (LU)

Since it is well known that it may not be possible or, however, easy to capture the relationship between precipitation and topographic attributes because it depends on spatial scale and the temporal aggregation (Bárdossy

المنارة للاستشارات
www.manaraa.com

Table 2 Results of the Mann–Whitney–Wilcoxon test

Landscape unit	1	2	3	4	5	6	7	8
1	–	0.113	0.158	0.012	0.202	0.141	0.267	0.423
2		–	0.121	0.003	0.029	0.021	0.699	0.366
3			–	0.683	0.165	0.223	0.134	0.095
4				–	0.124	0.336	0.018	0.001
5					–	0.705	0.058	0.074
6						–	0.034	0.039
7							–	0.544
8								–

and Pegram 2013), the results suggest the need for further analyses at different spatial scales and temporal aggregations to draw meaningful conclusions.

Conclusions

The combination of the different classes of elevation and distance to the coastline has allowed to split the study area into 107 polygons, which have been classified into 8 types of landscape units. With the exception of landscape units 3 and 4, the other ones have included polygons at different degrees of continuity.

The spatial variation of the average annual precipitation has been described and modelled by a bounded isotropic nested variogram model, which has combined three basic structures including a nugget effect and two spherical models at short and long range. The presence of differences in spatial pattern of variation has been interpreted as changes in local weather situations and in the large-scale organization of storms and climate patterns.

The map of the expected annual precipitation obtained using polygon kriging has shown that, generally, mountains areas receive more precipitation than low elevation areas. In the Tyrrhenian side, it was also evident the orographic influence of Coastal chain on precipitation with high precipitation values.

The Mann–Whitney–Wilcoxon test has allowed to compare the expected precipitation values of the different landscape units. The expected values were not always statistically different, but such results might be due to the spatial dependence of precipitation. However, the results can contribute in understanding the control of surface orography on patterns of annual precipitation and their differences in mountainous regions.

Understanding natural processes is often an iterative approach and then analysing the relationship between landscape features and precipitation data at different spatial scales and temporal aggregations could contribute to draw meaningful conclusions. The results could provide a stepping stone to further study and investigations.

Acknowledgements The authors thank the reviewers of this paper for providing constructive comments, which have contributed to the improvement of the published version.

References

Agnew MD, Palutikof JP (2000) GIS-based construction of baseline climatologies for the Mediterranean using terrain variables. Clim Res 14:115–127. https://doi.org/10.3354/cr014115

Bárdossy A, Li J (2008) Geostatistical interpolation using copulas. Water Resour Res. https://doi.org/10.1029/2007WR006115

Bárdossy A, Pegram G (2013) Interpolation of precipitation under topographic influence at different time scales. Water Resour Res 49:4545–4565. https://doi.org/10.1002/wrcr.20307

Bleines C, Deraisme J, Geffroy F et al (2018) Isatis technical references. Geovariances, Avon Cedex

Brunetti M, Maugeri M, Nanni T (2002) Atmospheric circulation and precipitation in Italy for the last 50 years. Int J Climatol 22:1455–1471. https://doi.org/10.1002/joc.805

Brunsdon C, McClatchey J, Unwin DJ (2001) Spatial variations in the average rainfall-altitude relationship in Great Britain: an approach using geographically weighted regression. Int J Climatol 21:455–466. https://doi.org/10.1002/joc.614

Buttafuoco G, Caloiero T, Coscarelli R (2015) Analyses of drought events in Calabria (Southern Italy) using standardized precipitation index. Water Resour Manag 29:557–573. https://doi.org/10.1007/s11269-014-0842-5

Buttafuoco G, Castrignanò A, Cucci G et al (2017) Geostatistical modelling of within-field soil and yield variability for management zones delineation: a case study in a durum wheat field. Precis Agric 18:37–58. https://doi.org/10.1007/s11119-016-9462-9

Caloiero T, Buttafuoco G, Coscarelli R, Ferrari E (2015) Spatial and temporal characterization of climate at regional scale using homogeneous monthly precipitation and air temperature data: an application in Calabria (southern Italy). Hydrol Res 46:629–646. https://doi.org/10.2166/nh.2014.022

Chilès J-P, Delfiner P (2012) Geostatistics: modeling spatial uncertainty, 2nd edn. Wiley, Hoboken

Chua SH, Bras RL (1982) Optimal estimators of mean areal precipitation in regions of orographic influence. J Hydrol 57:23–48. https://doi.org/10.1016/0022-1694(82)90101-9

Collins FC, Bolstad PV (1996) A comparison of spatial interpolation techniques in temperature estimation. In: Proceedings of the third

المنارة للاستشارات
www.manaraa.com

international conference/workshop on integrating GIS and environmental modeling. National Center for Geographic Information Analysis (NCGIA), Santa Barbara, New Mexico, pp 122–134
Deraisme J, Humbert J, Drogue G, Freslon N (2001) Geostatistical interpolation of rainfall in mountainous areas. In: Monestiez P, Allard D, Froidevaux R (eds) geoENV III—Geostatistics for environmental applications. Springer, Dordrecht, pp 57–66
Ding B, Yang K, Qin J et al (2014) The dependence of precipitation types on surface elevation and meteorological conditions and its parameterization. J Hydrol 513:154–163. https://doi.org/10.1016/j.jhydrol.2014.03.038
Diodato N (2005) The influence of topographic co-variables on the spatial variability of precipitation over small regions of complex terrain. Int J Climatol 25:351–363. https://doi.org/10.1002/joc.1131
Dowd PA, Pardo-Igúzquiza E (2012) Geostatistical analysis of rainfall in the West African Sahel. In: Gómez-Hernández JJ (ed) Proceedings of geoENV2012. Editorial Universitat Politècnica de València, Valencia, pp 95–108
Dubrule O (1984) Comparing splines and kriging. Comput Geosci 10:327–338. https://doi.org/10.1016/0098-3004(84)90030-X
Federico S, Dalu GA, Bellecci C, Colacino M (2000) Mesoscale energetics and flows induced by sea-land and mountain-valley contrasts. Ann Geophys 18:235–246. https://doi.org/10.1007/s00585-000-0235-3
Feki H, Slimani M, Cudennec C (2012) Incorporating elevation in rainfall interpolation in Tunisia using geostatistical methods. Hydrol Sci J 57:1294–1314. https://doi.org/10.1080/02626667.2012.710334
Gómez-Hernández JJ, Cassiraga EF, Guardiola-Albert C, Rodríguez JÁ (2001) Incorporating information from a digital elevation model for improving the areal estimation of rainfall. In: Monestiez P, Allard D, Froidevaux R (eds) geoENV III—Geostatistics for environmental applications. Springer, Dordrecht, pp 67–78
Goovaerts P (1997) Geostatistics for natural resources evaluation. Oxford University Press, New York
Goovaerts P (2000) Geostatistical approaches for incorporating elevation into the spatial interpolation of rainfall. J Hydrol 228:113–129. https://doi.org/10.1016/S0022-1694(00)00144-X
Gotway CA, Young LJ (2002) Combining incompatible spatial data. J Am Stat Assoc 97:632–648. https://doi.org/10.1198/016214502760047140
Gotway CA, Ferguson RB, Hergert GW, Peterson TA (1996) Comparison of kriging and inverse-distance methods for mapping soil parameters. Soil Sci Soc Am J 60:1237–1247. https://doi.org/10.2136/sssaj1996.03615995006000040040x
Grimes DIF, Pardo-Igúzquiza E (2010) Geostatistical analysis of rainfall. Geogr Anal 42:136–160. https://doi.org/10.1111/j.1538-4632.2010.00787.x
Haiden T, Pistotnik G (2009) Intensity-dependent parameterization of elevation effects in precipitation analysis. Adv Geosci 20:33–38. https://doi.org/10.5194/adgeo-20-33-2009
Hartkamp AD, De Beurs K, Stein A, White JW (1999) Interpolation techniques for climate variables interpolation. CIMMYT, Mexico
Hayward D, Clarke RT (1996) Relationship between rainfall, altitude and distance from the sea in the Freetown Peninsula, Sierra Leone. Hydrol Sci J 41:377–384. https://doi.org/10.1080/02626669609491509
Hengl T, Aghakouchak A, Percěc Tadić M (2013) Methods and data sources for spatial prediction of rainfall. In: Testik FY, Gebremichael M (eds) Rainfall: state of the science. American Geophysical Union, Washington, pp 189–214
Hevesi JA, Istok JD, Flint AL (1992) Precipitation estimation in mountainous terrain using multivariate geostatistics. Part I: structural analysis. J Appl Meteorol 31:661–676. https://doi.org/10.1175/1520-0450(1992)031%3c0661:PEIMTU%3e2.0.CO;2
Hutchinson MF (1995) Interpolating mean rainfall using thin plate smoothing splines. Int J Geogr Inf Syst 9:385–403. https://doi.org/10.1080/02693799508902045
Journel AG, Huijbregts CJ (1978) Mining geostatistics. Academic Press, London
Kanji GK (2006) 100 Statistical tests, 3rd edn. SAGE, Thousand Oaks
Kumari M, Singh CK, Basistha A et al (2017) Non-stationary modelling framework for rainfall interpolation in complex terrain. Int J Climatol 37:4171–4185. https://doi.org/10.1002/joc.5057
Lloyd CD (2005) Assessing the effect of integrating elevation data into the estimation of monthly precipitation in Great Britain. J Hydrol 308:128–150. https://doi.org/10.1016/j.jhydrol.2004.10.026
Lloyd CD (2010) Nonstationary models for exploring and mapping monthly precipitation in the United kingdom. Int J Climatol 30:390–405. https://doi.org/10.1002/joc.1892
Lucà F, Buttafuoco G, Terranova O (2018) 2.03-GIS and Soil A2-Huang, Bo BT-Comprehensive geographic information systems. Elsevier, Oxford, pp 37–50
Makarieva AM, Gorshkov VG, Li BL (2009) Precipitation on land versus distance from the ocean: evidence for a forest pump of atmospheric moisture. Ecol Complex 6:302–307. https://doi.org/10.1016/j.ecocom.2008.11.004
Martínez-cob A (1995) Estimation of mean annual precipitation as affected by elevation using multivariate geostatistics. Water Resour Manag 9:139–159. https://doi.org/10.1007/BF00872465
Matheron G (1971) The theory of regionalized variables and its applications. Ecole Nationale Superieure des Mines de Paris, Fontainebleau
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. Adv Geosci 10:51–57. https://doi.org/10.5194/adgeo-10-51-2007
Pardo-Igúzquiza E (1998) Comparison of geostatistical methods for estimating the areal average climatological rainfall mean using data on precipitation and topography. Int J Climatol 18:1031–1047. https://doi.org/10.1002/(SICI)1097-0088(199807)18:9%3c1031:AID-JOC303%3e3.0.CO;2-U
Prudhomme C, Reed DW (1999) Mapping extreme rainfall in a mountainous region using geostatistical techniques: a case study in Scotland. Int J Climatol 19:1337–1356. https://doi.org/10.1002/(SICI)1097-0088(199910)19:12%3c1337:AID-JOC421%3e3.0.CO;2-G
Roe GH (2005) Orographic precipitation. Ann Rev Earth Planet Sci 33:645–671. https://doi.org/10.1146/annurev.earth.33.092203.122541
Strangeways I (2007) Precipitation: theory, measurement and distribution. Cambridge University Press, New York
Szentimrey T, Bihari Z, Szalai S (2010) Comparison of geostatistical and meteorological interpolation methods (What is What?). Spatial Interpolation for Climate Data: The Use of GIS in Climatology and Meteorology. ISTE, London, pp 45–56
Wackernagel H (2003) Multivariate geostatistics: an introduction with applications. Springer, New York
Webster R, Oliver MA (2007) Geostatistics for environmental scientists. Wiley, Chichester
Yao J, Yang Q, Mao W et al (2016) Precipitation trend-Elevation relationship in arid regions of the China. Glob Planet Change 143:1–9. https://doi.org/10.1016/j.gloplacha.2016.05.007
Zeng W, Yu Z, Wu S, Qin J (2016) Changes in annual, seasonal and monthly precipitation events and their link with elevation in Sichuan province, China. Int J Climatol 36:2303–2322. https://doi.org/10.1002/joc.4496

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

المنارة للاستشارات
www.manaraa.com

Reproduced with permission of copyright owner. Further reproduction prohibited without permission.

www.manaraa.com