

SPATIAL PATTERNS OF VARIABILITY FOR RAIN FIELDS AT DIFFERENT TIMESCALES: AN APPLICATION IN SOUTHERN ITALY

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ABSTRACT

Rainfall is characterized by spatial variability which depends on the timescale used. Experiences in analysing rainfall for different time periods have shown, in fact, that the spatial patterns of variability change within the time scale (from hours through days and months to seasonal and annual scales). Geostatistics offers a variety of methods for modelling spatial variability and mapping rain fields considered as realizations of random functions.

The aim of this study was to analyse and quantify the spatial structure of rain fields at various timescales for climatological and water resources purposes.

In Calabria (Southern Italy), high-quality datasets have been collected since 1916 by the former Italian Hydrographic Service, now “Centro Funzionale” of the Regional Agency for the Environmental Protection (ARPACAL) of the Calabria region. The data used in this study are a set of different timescales precipitation series registered in Calabria in the last years. Spatial structures of rain fields were identified over the range of timescales most often used in climatological and water resources studies varying from daily to monthly, to seasonal, to annual timescale.

Results showed that spatial structure of rainfall measurements change through the months and as the timescale increases from days to months and seasons to annual total.

1 INTRODUCTION

Water resources problems are becoming increasingly more and more interconnected with other development-related issues and also with social, economic, environmental, legal, and political factors at local and national levels and sometimes at regional and even international levels. Rainfall is responsible for the spatial and temporal variability of water resources and any changes in precipitation impact on hydrology and water resources (Novotny & Stefan, 2007). It is thus obvious that climate change, either of a global or regional nature, may lead to changes in the spatial and temporal distribution of rainfall, with significant consequences for water resources and water management practices. For these reasons, the temporal and spatial patterns of precipitation and its impacts on surface water resources have become one of the key issues in the hydrology

and ecology (Delitala et al., 2000; De Luis et al., 2000; Oguntunde et al., 2006; Cannarozzo et al., 2006; McVicar et al., 2007). Several studies have detected rainfall changes both on global (Bradley et al., 1987; Diaz et al., 1989; Hulme et al., 1998) and regional scales (Maheras, 1988; Yu and Neil, 1993) associated with global warming during the last 20 years. The implications of these changes are particularly significant for areas already under stress, such as the Mediterranean Basin (Palutikof, 1996), that suffer from a water shortage due to a combination of a dry climate (or a highly seasonal rainfall regime) and excessive water demand (De Luis et al., 2000). In fact, Mediterranean regions are transitional climate zones where climatic changes have been assumed to have the greatest effects (Lavorel et al., 1998). Precipitation over the Mediterranean basin is extremely variable both on a temporal and spatial scale (Lionello et al., 2006; Norrant and Douguédroit, 2006) because of the basin latitudinal position between two strongly contrasting masses of water (the Atlantic Ocean and the Mediterranean Sea). In addition, various mountains distributed along the coastal areas from east to west impact on precipitation variability.

Rainfall is measured at fixed point locations and it is a quantity ideally suited to geostatistical analysis (Grimes and Pardo-Igúzquiza, 2010) because rainfall varies more or less continuously in geographical space and it can be regarded as a regionalized variable (Matheron, 1971). Geostatistics provides a valuable tool to study spatial structure of rainfall taking into account the spatial autocorrelation in data to create mathematical models of spatial correlation structures.

Usually the rain gauges are located where rainfall measurements are needed but during time the network is subject to change both in location and number of the rain gauges, and for this reason the density of the rain gauges network (defined as the average area served by one rain gauge) can decrease. Consequently, the importance of rainfall for water management, coupled with possible the reduction of rain gauges, makes the geostatistical methods particularly relevant. Accurate geostatistical interpolation of rainfall requires incorporating an accurate description of the variation of spatial continuity into our procedures. The spatial continuity is commonly described using the variogram function which is a measure of average dissimilarity between observations as a function of separation distance and direction.

Analysis of rainfall measurements for different periods of accumulation showed that the pattern of spatial continuity described by variogram changes as the time scale increases from hours through days and months to seasonal and annual totals: as the accumulation time increases, correlation on larger scale becomes more important (Lebel et al., 1987; Bacchi and Kottegoda, 1995; Grimes and Pardo-Igúzquiza, 2010).

The main objective of this study was to analyse and quantify the spatial structure of rain fields at various timescales for climatological and water resources purposes.

2 MATERIALS AND METHODS

2.1 Study area and rainfall data

The Calabria region occupies the southern part of the Italian peninsula (Fig. 1) with a surface of 15,080 km² and a coastline of 738 km on the Ionian and Tyrrhenian seas. In the North, it borders Basilicata region for 80 km. The Calabria region has an oblong shape with a length of 248 km and a width ranging between 31 and 111 km. Although

Calabria does not have many high summits, it is one of the most mountainous regions in Italy (Fig. 1): 42% of the land is mountainous, 49% hilly and only 9% is flat. The maximum elevation is 2,267 m a.s.l., while the average elevation is 597 m a.s.l.

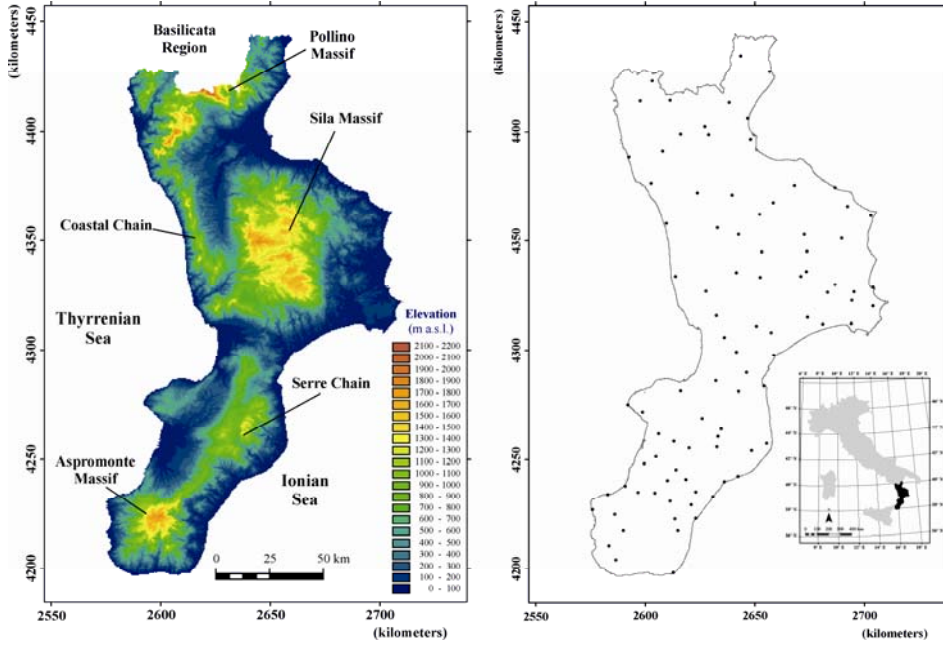


Figure 1. Digital elevation model (left) of the study area and location (right) of the rain gauges station (filled points).

In the Calabria region (Southern Italy), high-quality datasets have been collected since 1916 by the former Italian Hydrographic Service, now “Centro Funzionale” of the Regional Agency for the Environmental Protection (ARPACAL) of the Calabria region. The density of the regional rain gauges network changed during the years and in particular decreased in the last period.

The present analysis was based on precipitation data measured at 90 rain gauges for 2007, one of the recent year with more data (Fig. 1).

In particular rainfall data for 4 single days (February 20th, March 20th, September 25th, October 7th), for all the months (January through December), and the seasons (Winter, Spring, Summer, Autumn) and for the whole year were chosen.

2.2 Geostatistical approach

In Geostatistics each measured value, $z(\mathbf{x}_\alpha)$, at location $\mathbf{x}_\alpha$ ($\mathbf{x}$ is the location coordinates vector and α the sampling points = 1, ..., N) is interpreted as a particular realization, or outcome, of a random variable $Z(\mathbf{x}_\alpha)$. The set of dependent random variables $\{Z(\mathbf{x}_\alpha), \alpha = 1, \dots, n\}$ constitutes a random function $Z(\mathbf{x})$. For a detailed presentation of the theory of random functions, interested readers should refer to textbooks such as Journel and Huijbregts (1978), Isaaks and Srivastava (1989), Goovaerts (1997), Chilès and Delfiner (1999), Webster and Oliver (2007), Wackernagel

(2003), among others.

An important tool in geostatistics is the experimental variogram, which is a quantitative measure of spatial correlation of the regionalized variable $z(\mathbf{x}_\alpha)$. The experimental variogram $\gamma(\mathbf{h})$ is a function of the lag $\mathbf{h}$, a vector in distance and direction, of data pairs values $[z(\mathbf{x}_\alpha), z(\mathbf{x}_\alpha + \mathbf{h})]$; it refers to the expected value of the squared differences; a way of calculating this is reported in Eq(1):

$$\gamma(\mathbf{h}) = \frac{1}{2N(\mathbf{h})} \sum_{\alpha=1}^{N(\mathbf{h})} [z(\mathbf{x}_\alpha) - z(\mathbf{x}_\alpha + \mathbf{h})]^2 \quad (1)$$

where $N(\mathbf{h})$ is the number of data pairs for a given class of distance and direction. A theoretical function, known as the variogram model, is fitted to the experimental variogram to allow one to estimate the variogram analytically for any distance $\mathbf{h}$. The function used to model the experimental variogram must be conditionally negative definite to ensure that the kriging variances are positive (Webster and Oliver, 2007). The aim is to build a model that describes the major spatial features of the attribute under study. The models used can represent bounded or unbounded variation. In the former models the variance has a maximum (known as the sill variance) at a finite lag distance (range) over which pairs of values are spatially correlated. The best fitting function can be chosen by cross-validation, which checks the compatibility between the data and the model. It takes each data point in turn, removing it temporarily from the data set and using its 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 estimate and measurement, which can also be standardized by estimating the standard deviation. The goodness of fit was evaluated by: first the mean error (ME), which proves the unbiasedness of estimate if its value is close to 0:

$$ME = \frac{1}{N} \sum_{\alpha=1}^N [z^*(\mathbf{x}_\alpha) - z(\mathbf{x}_\alpha)] \quad (2)$$

where N is the number of observation points, $z^*(\mathbf{x}_\alpha)$ is the predicted value at location α , and $z(\mathbf{x}_\alpha)$ is the observed value at location α ; the second is the mean squared deviation MSDR, which is the ratio between the squared errors and the kriging variance ($\sigma^2(\mathbf{x}_\alpha)$):

$$MSDR = \frac{1}{N} \sum_{\alpha=1}^N \frac{[z^*(\mathbf{x}_\alpha) - z(\mathbf{x}_\alpha)]^2}{\sigma^2(\mathbf{x}_\alpha)} \quad (3)$$

If the model for the variogram is accurate, the mean squared error should equal the kriging variance and the MSDR value should be 1.

As is well known, the variogram model can be used with the data to predict rainfall values at unsampled locations using a kriging algorithm.

Variogram modelling is sensitive to marked departures from normality, because a few exceptionally large values may contribute to a high number of large squared differences (Webster and Oliver, 2007). In this scope, the rainfall data $\{Z(\mathbf{x}), \mathbf{x} \in R^2\}$ were

transformed into a Gaussian-shaped variable $\{Y(\mathbf{x}), \mathbf{x} \in R^2\}$ with zero mean and unit variance, such that:

$$Z(\mathbf{x}) = \phi[Y(\mathbf{x})] \quad (4)$$

Such a procedure is known as Gaussian anamorphosis (Chilès and Delfiner, 1999; Wackernagel, 2003) and it is a mathematical function which transforms a variable Y with a Gaussian distribution in a new variable with any distribution. To transform the raw variable into a Gaussian one we have to invert this function:

$$Y(\mathbf{x}) = \phi^{-1}[Z(\mathbf{x})] \quad (5)$$

The Gaussian anamorphosis can be achieved using an expansion into Hermite polynomials $H_i(Y)$ (Wackernagel, 2003) restricted to a finite number of terms:

$$\phi(Y) = \sum_{i=0}^n \psi_i H_i(Y) \quad (6)$$

The modelling of the anamorphosis starts with the discrete version of the curve on the true data set; then a model expanded in terms of Hermite polynomials (Eq. (6)) is fitted to the discretized anamorphosis. This model gives the correspondence between each one of the sorted raw data and the corresponding frequency quantile in the standardized Gaussian scale.

3 RESULTS AND DISCUSSION

The basic statistics of the rainfall data are presented in Table I. Comparing values for mean, median and skewness it can be seen that the distributions of the rainfall values range from normal to very positively skewed (Table I). For subsequent analyses the rainfall data were transformed to normality and standardized to zero mean and unit variance using the Gaussian anamorphosis by an expansion of Hermite polynomials restricted to the first 30 terms (Wackernagel, 2003).

3.1 Spatial structure for daily rainfall

Maps of the 2-D variograms (not shown) to a maximum lag distance of 100,000 m were computed for each of the 4 daily rainfall dates and no anisotropy was evident. Figure 2 shows the omnidirectional experimental variogram of Gaussian rainfall data for February 20th. Semivariance values increase with the separation distance and they reach a maximum at about 100,000 m. The experimental variogram was modelled by nested variogram (Fig. 2) that combines three basic structures (Table II) including a nugget effect (c_0), a short range spherical model (Sph) with a range (a) of 32,823 m and a long range spherical model (Sph) with a range (a) of 64,539 m. The nugget effect c_0 implies a discontinuity in $Z(\mathbf{x})$ and is a positive intercept of the variogram. It arises from errors of measurement and spatial variation within the shortest sampling interval (Webster and Oliver, 2007).

Table I. Statistics for the daily, monthly, seasonal and annual rainfall data.

Period	Min (mm)	Max (mm)	Mean (mm)	Median (mm)	St. Dev. (mm)	C.V. (-)	Skewness (-)	Kurtosis (-)
Feb 20 th	3.8	102.2	33.2	27.1	23.12	0.70	1.12	3.66
Mar 20 th	0.0	103.0	16.9	11.9	18.75	1.11	2.15	8.95
Sep 25 th	0.0	100.2	23.8	17.3	19.35	0.81	1.14	4.32
Oct 7 th	0.4	103.0	16.3	11.1	17.22	1.06	2.23	9.50
Jan	2.0	116.0	42.6	42.7	26.46	0.62	0.35	2.55
Feb	14.2	304.0	132.4	126.7	68.68	0.52	0.74	2.93
Mar	23.6	303.4	125.1	113.6	61.55	0.49	0.67	2.99
Apr	24.2	138.8	67.3	63.5	25.49	0.38	0.83	3.45
May	3.2	150.0	58.2	55.9	38.30	0.66	0.47	2.22
Jun	2.8	142.8	31.5	27.6	23.13	0.73	2.47	11.90
Jul	0.0	9.6	0.5	0.0	1.31	2.47	4.49	27.89
Aug	0.0	17.6	2.7	1.4	3.90	1.45	2.31	8.33
Sep	8.8	139.0	54.6	52.1	26.00	0.48	1.07	4.74
Oct	32.6	315.6	126.3	119.1	58.97	0.47	0.54	2.80
Nov	6.4	304.8	120.2	112.3	49.98	0.42	0.96	4.39
Dec	2.8	242.2	114.8	106.3	49.66	0.43	0.41	2.92
Winter	158.6	751.4	357.1	326.0	136.23	0.38	0.79	3.22
Spring	63.4	493.4	250.6	250.7	92.60	0.37	0.43	3.01
Summer	3.0	144.6	34.8	32.1	23.56	0.68	2.14	10.35
Autumn	104.4	517.0	301.1	292.8	94.75	0.31	0.23	2.68
Annual	348.8	1606.0	876.4	858.6	293.46	0.33	0.44	2.84

The spherical model is

$$\gamma(h) = \begin{cases} c \left[\frac{3}{2} \frac{h}{a} - \frac{1}{2} \left(\frac{h}{a} \right)^3 \right] & \text{for } 0 < h \leq a \\ c & \text{for } h > a \end{cases} \quad (7)$$

where a is the range and c the sill.

The experimental variogram of Gaussian rainfall data for March 20th (not shown) was modelled by a nested variogram that combines two basic structures (Table II) including a short range spherical model (Sph) with a range (a) of 24,860 m and a long range spherical model (Sph) with a range (a) of 146,724 m.

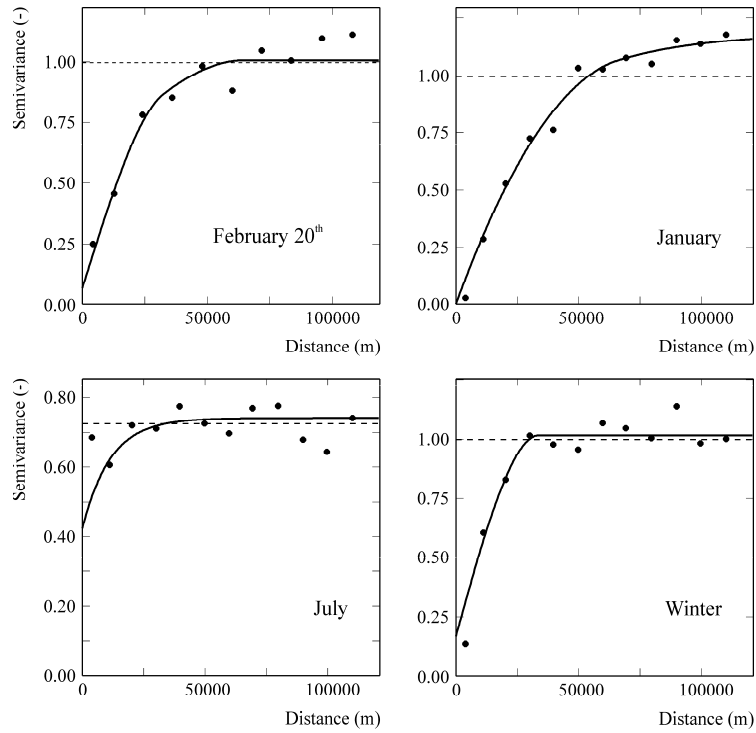


Figure 2. Variograms of the Gaussian variables of daily (Feb 20th), monthly (January and March) and seasonal (winter) rainfall. The experimental values are the filled points and the solid lines are of the model of variograms. The dashed lines are the experimental variances.

Table II. Variogram model parameters for Gaussian daily rainfall data.

Period	Model	Parameters		
		Sill (-)	Range (m)	α (-)
Feb 20 th	Nugget	0.0669	-	-
	Sph.	0.4900	32823	-
	Sph.	0.4494	64539	-
Mar 20 th	Sph.	0.4633	24860	-
	Sph.	0.6445	146724	-
Sep 25 th	Nugget	0.0909	-	-
	Stable	0.9868	57298	1.6
Oct 7 th	Nugget	0.0620	-	-
	Sph.	0.5853	53783	-
	Sph.	0.5395	190141	-

The experimental variogram of Gaussian rainfall data for September 25th (not shown) was modelled by a nested variogram that combines two basic structures (Table II) including a nugget effect and a stable model with a practical range (a) of 57,298 m. The stable model (Webster and Oliver, 2007) is:

$$\gamma(h) = c \left[1 - \exp\left(-\frac{3h}{a}\right)^\alpha \right] \quad (8)$$

where c is the sill, a the practical range and α a gradient parameter. A practical range is usually defined as the distance at which γ equals 95% of the sill variance.

The experimental variogram of Gaussian rainfall data for October 7th (not shown) was modelled by three basic structures (Table II) including a nugget effect (c_0), a short range spherical model (Sph) with a range (a) of 53,783 m and a long range spherical model (Sph) with a range (a) of 190,141 m.

The goodness of fitting was verified by cross validation and the results were quite satisfactory because the statistics used, i.e. mean of the estimation error and variance of the mean squared deviation ratio, were quite close to 0 and 1, respectively.

3.2 Spatial structure for monthly rainfall

Also for the monthly rainfall data, the maps of the 2-D variograms (not shown) were computed and no anisotropy was evident. Table III reports the parameters of the fitted variograms.

Table III. Variogram model parameters for Gaussian monthly rainfall data.

Period	Model	Parameters		Period	Model	Parameters	
		Sill (-)	Range (m)			Sill (-)	Range (m)
Jan	Sph.	0.4809	65647	Jul	Nugget	0.4229	-
	Exp.	0.7055	112091		Exp.	0.3189	34348
Feb	Nugget	0.0459	-	Aug	Nugget	0.1721	-
	Sph.	0.7707	37138		Exp.	0.9719	110567
Mar	Nugget	0.0073	-	Sep	Nugget	0.0682	-
	Sph.	0.5994	30891		Sph.	0.2694	26538
	Sph.	0.2403	66937		Sph.	0.7708	156412
Apr	Nugget	0.0670	-	Oct	Nugget	0.1207	-
	Sph.	0.2436	22634		Sph.	1.0983	120068
	Sph.	0.5285	91508	Nov	Nugget	0.1156	-
May	Exp.	0.6258	41735		Sph.	0.2099	25080
	Sph.	0.1993	82628		Sph.	0.8611	94426
Jun	Sph.	1.1907	73836	Dec	Nugget	0.1949	-
					Sph.	0.8530	25837

The experimental variogram of Gaussian rainfall data for January (Fig. 2) was modelled by a nested variogram that combines two basic structures (Table III) including a short range spherical model (Sph) with a range (a) of 65,647 m and a long range exponential model (Exp) with a practical range (a) of 112,091 m. The exponential model (Webster and Oliver, 2007) is Eq. (8) with $\alpha=1$.

Also the experimental variogram of the Gaussian rainfall data for May was modelled by a nested variogram that combines two basic structures (Table III) including a short range model with a long range model.

The experimental variograms of the Gaussian rainfall data for February, July, August, October and December (not shown) were modelled by nested variograms that combines two basic structures (Table III) including a nugget and a short range or long model.

The experimental variogram of Gaussian rainfall data for June (not shown) was modelled by a spherical model (Sph) with a range (a) of 73,836 m (Table III).

As it was expected, the spatial structure becomes more erratic in the summer months (Fig. 2).

3.3 Spatial structure for seasonal and annual rainfall

The experimental variograms of Gaussian rainfall data for winter (Fig. 2) and spring (not shown) were modelled by a nested variogram that combines two basic structures (Table IV) including a nugget effect and a short range spherical model (Sph).

Table IV. Variogram model parameters for Gaussian seasonal and annual rainfall data.

Period	Model	Parameters	
		Sill (-)	Range (m)
Winter	Nugget	0.1664	-
	Sph.	0.8493	33968
Spring	Nugget	0.1535	-
	Sph.	0.7064	30266
Summer	Sph.	0.4005	33951
	Sph.	0.5995	75000
Autumn	Nugget	0.0325	-
	Sph.	0.3532	24282
	Sph.	0.7573	98253
Annual	Sph.	0.6254	30878
	Sph.	0.2979	133375

The experimental variogram of the Gaussian rainfall data for summer was modelled by a nested variogram that combines two basic structures (Table IV) including a short range model with a long range model.

The experimental variogram of the Gaussian rainfall data for autumn was modelled by a nested variogram that combines three basic structures (Table IV) including a nugget

effect, a short range model and a long range model.

Finally, the experimental variogram of the Gaussian annual rainfall data was modelled by a nested variogram that combines two basic structures (Table IV) including a short range model with a long range model.

4 CONCLUSIONS

The proposed approach allowed to characterize the spatial structure of rainfall measurements at different timescales. Results showed that spatial structure of rainfall measurements change through the months and as the timescale increases from days to months and seasons to annual total. That is explained because the variogram associated with a defined timescale depends on a number of events different from days to months and season to years.

As said before, the reduction of rain gauges makes the geostatistical methods particularly relevant, but, at the same time, the number of available rain gauges (90 in 2007) increases the parameters uncertainty of variograms.

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