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Application of a multivariate statistical index on series of weather measurements at local scale

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ABSTRACT

In this study an innovative statistical procedure based on multivariate techniques is applied. It is able to identify and to interpret the correlation structure among different meteo-climatic descriptors measured in different sampling sites. The test case of Agri valley (Southern Italy), is presented, analyzing daily data of temperature, relative humidity and precipitation measured in seven monitoring sites, from 2000 to 2013. The Principal Component Analysis technique is recursively applied for each year and for each station, for calculating the synthetic Normalized Principal Component Index. This index allows to characterize quantitatively the information content of descriptors and/or of sites and to compare the behavior of the different variables in the correlation structure. The results show that temperature and relative humidity have high weights in the correlation structure, while the precipitation represents a singular variable. Moreover sampling sites may be classified according to their degree of stability in the correlation structure. A low degree of stability may be correlated with the occurrence of climate changes at the microscale.

1. Introduction

Climate is the primarily responsible of diversification in natural environments. In recent years, many studies put in evidence like climate changes influence water resources, ecosystem and human health. Rapid human-induced climate change are increasing vulnerability in ecosystems. Changes in temperatures, variations in snow events, frequency and intensity of other hydro-meteorological extreme events have been recently observed [1–7 and references therein]. Nowadays monitoring networks are rapidly evolving in complex systems: multi-objective approaches [8,9], modeling of data as prognostic rather than diagnostic tool [10], the spread of wireless sensors and low-cost technologies [11,12], are profoundly changing the traditional concept of monitoring network.

In this study we focus on data collected by weather monitoring stations; they are equipped with multiple sensors to monitor meteorological parameters such as temperature, relative humidity, dew point, atmospheric pressure, wind direction and wind speed [13]. These measurements may be also useful for a more adequate formulation, with a more robust parameterization, of actual evapotranspiration that is crucial for the development and the improvement of hydrological, meteorological and climatologic models [14–16].

The effects of climate change, well known at a global scale, are not negligible even at a local scale. The Mediterranean basin is particularly exposed to climate changes; it is very reactive to variations in meteorological parameters and it is considered to be a global hot-spot in terms of climate variability and land transformation processes [17–19]. Furthermore in this region, the significant changes in the precipitations and the uncontrolled exploitation of water resources, due to the growing demand in the civil, agricultural and industrial sectors, are causing numerous phenomena of drought and desertification, especially in areas characterized by arid or semiarid climate [20–23]. In particular, several studies have shown that the Italian climate is becoming drier and warmer: the maximum temperature has increased, especially in the regions of Southern Italy, and it is possible to observe a higher frequency of events with heavy rainfall and long periods of drought [24–27].

In this context, effective procedures for observing, measuring, collecting and analyzing hydro-meteorological parameters are required. In this study an application of an innovative statistical procedure, based on multivariate techniques, able to identify the correlation structure among different variables and its spatial and temporal changes, is presented. A synthetic multivariate index (Normal Principal Component Index) is calculated for assigning standardized weights to each descriptor in the correlation structure [28,29]. In this way, it is possible to identify the role of each variable in the investigated period by means an

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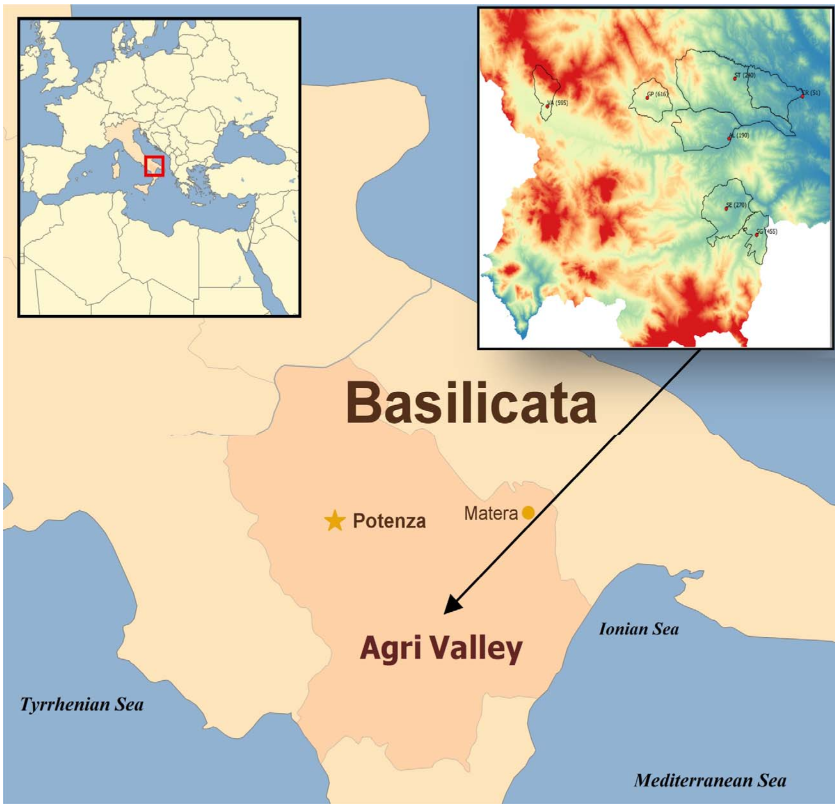

Fig. 1. Study area and monitoring sites.

Table 1
Available data.

Monitoring site	Aliano AL	Craco CR	Guardia Perticara GP	S. Giorgio Lucano SG	Senise SE	Stigliano ST	Villa D'Agri VA	Hn_{sy}
2000					x	x	x	3
2001	x	x	x	x	x	x	x	7
2002	x	x	x	x		x		5
2003	x	x		x		x		4
2004	x	x	x			x	x	5
2005		x		x		x	x	4
2006	x	x	x	x		x	x	6
2007	x	x	x	x	x	x	x	7
2008	x	x	x	x	x			5
2009	x	x			x		x	4
2010	x	x	x	x	x	x	x	7
2011		x	x	x	x	x	x	6
2012		x	x	x	x	x	x	6
2013		x	x		x	x		4
Hn_{ys}	9	13	10	10	9	12	10	$H = 73$

Hn_{sy} = number of annual series available per year; Hn_{ys} = number of annual series available per site; H = number of annual series available.

only quantitative index. Moreover it is possible to characterize the spatial-temporal evolution of the multi-dimensional correlation structure as well as the occurrence of isolated events. In many studies, the analysis of change weather variables is based on characterization of trends [19,30–32], but it needs continuous data, with no gaps in the data series collected. Often data collection is discontinuous. The multivariate data analysis procedure, applied in this paper, allows to analyze the data avoiding this difficulty. The data can be discontinuous, and in this way it is possible to select large parts of raw data so as to maintain unchanged the information content of the data.

Particularly, in this study, measurements of temperature, relative humidity and precipitations, collected from 2000 to 2013 in seven monitoring sites of Agri valley (Basilicata region, Southern Italy) are analyzed and discussed.

2. Materials and methods

2.1. Study area

This study concerns the area of Agri valley (Fig. 1), located in Basilicata region (Southern Italy). Basilicata is an inner mountainous region in which two main zones can be distinguished: the western one, formed by the Appennino Lucano and the eastern one, a hilly area sloping to the coastal plain on the Ionian Sea.

The Agri valley has a cool temperate Mediterranean climate, but there is a strong gradient from the coastline (Lower Agri valley) to the inner mountains (Upper Agri valley). The average yearly temperature ranges from 12 °C to 15 °C, rainfalls are frequent during winter, the average yearly precipitation ranges from less than 600 mm near the coast to more than 1200 mm in the Upper Agri valley; the prevailing

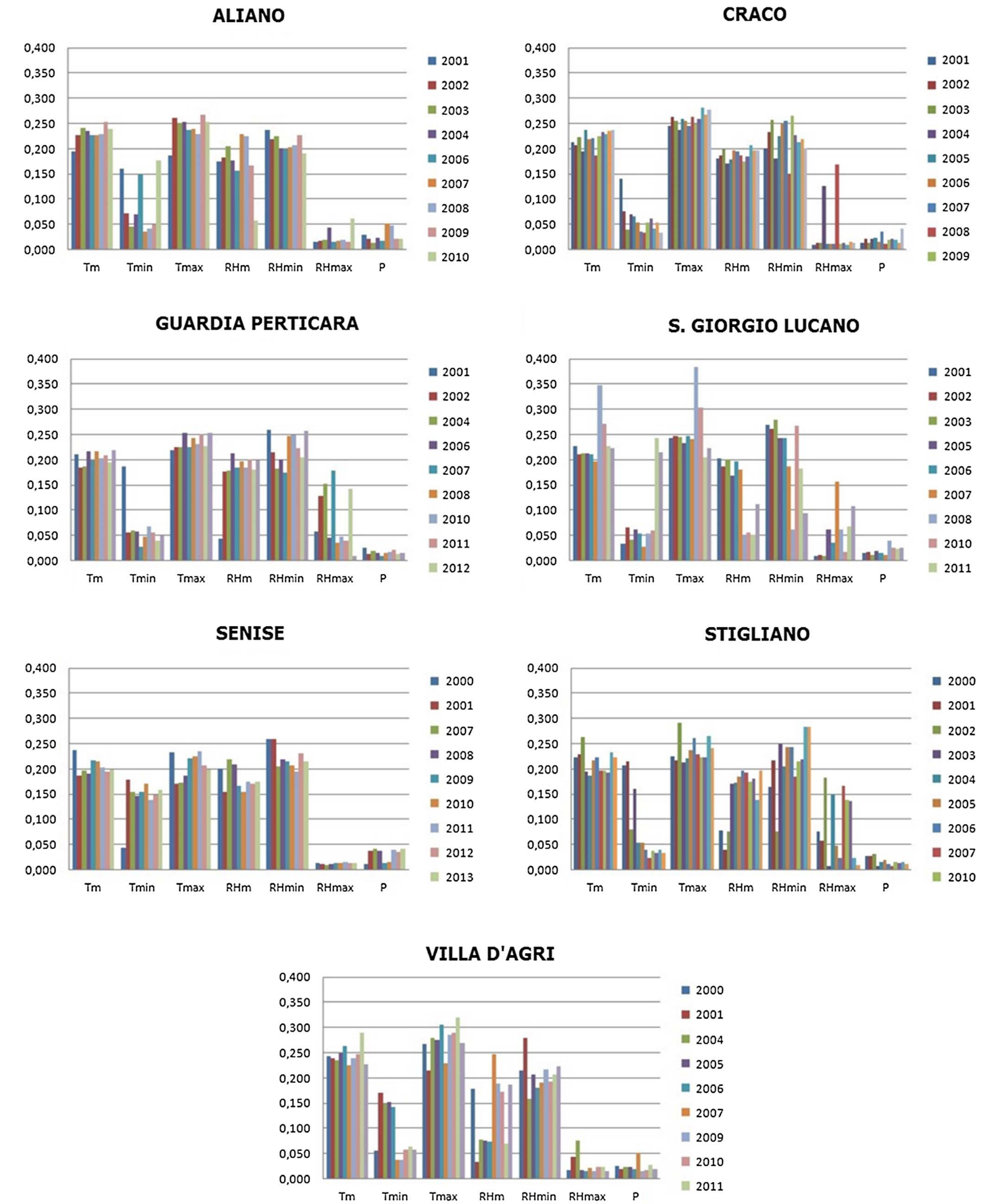

Fig. 2. *NPCI* values.

wind direction is West-Southwest. The main land use is agriculture (arable lands, vineyards and vegetable cultivations) but there are also many forests surrounding the area. The geology is quite uniform; the area is characterized by sand and silt soils [33,34]. In the recent years, this area has suffered a strong anthropogenic pressure due to intensive oil exploration and extraction. The Agri valley houses the largest

Table 2
Values of *NPCI*-range r and the corresponding mean values, r_m with standard deviations sd, expressed in percentage (top part); characteristics of the area surrounding monitoring sites (bottom part).

	SE	CR	AL	GP	VA	ST	SG
T_m	0.050	0.051	0.058	0.035	0.065	0.077	0.151
T_{min}	0.135	0.108	0.141	0.159	0.133	0.191	0.216
T_{max}	0.065	0.044	0.080	0.034	0.104	0.080	0.180
RH_m	0.066	0.036	0.171	0.170	0.213	0.158	0.151
RH_{min}	0.066	0.115	0.046	0.083	0.121	0.208	0.218
RH_{max}	0.005	0.160	0.046	0.171	0.060	0.175	0.147
P	0.029	0.031	0.039	0.017	0.037	0.023	0.029
r_m (%)	6	8	8	10	10	13	16
sd (%)	4	5	5	7	6	7	6
q (m a.s.l.)	270	51	190	616	595	240	455
HY	x	x	x				x
AT	x	x			x		
WA				x	x	x	x

r_m = average of r-values in percentage; sd = standard deviation in percentage; q = quote; HY = presence/absence of streams or dams; AT = presence/absence of urban or industrial activities; WA = presence/absence of wooded or agricultural zones.

European on-shore reservoir and the largest crude oil/gas pre-treatment plant within an anthropized zone.

2.2. Data

Meteorological data used in this study are daily temperature, humidity and precipitation collected from 2000 to 2013 by regional agency for development and innovation in agriculture (Italian acronym – ALSIA). All the ALSIA monitoring sites are equipped with instruments for continuous and automatic measurement of agro-meteorological parameters. Particularly for this study, seven monitoring stations are selected, the map is shown in Fig. 1. The examined variables are: average air daily temperature (T_m in °C), minimum air daily temperature (T_{min} in °C) maximum air daily temperature (T_{max} in °C), average daily relative humidity (RH_m in%), minimum daily relative humidity (RH_{min} in%), maximum daily relative humidity (RH_{max} in%) and daily precipitations (P in mm).

At first the anomalous measurements are deleted on raw data. In fact outliers are understood as values accidentally registered, which do not represent a true process behavior, but might significantly influence results about the data; in this context Chauvenet criterion is applied for the outliers removal [35].

In the investigated period (fourteen years), taking into account all the seven sites, there are many data missing. In the literature, it is possible to find many ways to fill in the missing data [36–38], the method chosen must be much more precise and reliable as much as the percentage of missing data is high. It is likely to introduce a significant bias. In our operational procedure, we do not have the constraint that the data must be consecutive. In this way can select large sub-matrices with a low percentage of missing data. Particularly we take into account only annual series in which the percentage of data missing, for all the measured variables, is lower than 5% and in which there are no more than three consecutive days of missing. For the few remaining data missing even a simple criterion for filling is effective, we use the mean value of nearest neighbors. In table 1, for each monitoring station and for each year, available data selected with this criterion are shown.

2.3. Multivariate data analysis procedure

In this study, all available data (table 1) are organized in H bi-dimensional annual matrices (H = 73) at daily scale: M^h = [365 sampling days x N descriptors] (with $h=1,\dots,H$ and N = 7: T_m, T_{min}, T_{max}, RH_m, RH_{min}, RH_{max} and P). For each matrix M^h, Principal Components Analysis (PCA) is applied to descriptors association matrix, in order to highlight the correlation structure implicitly contained in the data set. For each PCA run, the *NPCI*-values are calculated.

Normal Principal Component Index (*NPCI*) estimates a standardized weight for each descriptor in a correlation structure. It allows to assess quantitatively the role of each descriptor in the different years and, at the same time, the role of the different descriptors in each year [28,29]. Principal Component Index (*PCI*) for the n-th descriptor and for h-th annual matrix is defined as:

$$PCI_n^h = \frac{1}{P^h}\left[1-\left(\frac{R_n^h-1}{Q^h}\right)\right]\frac{w_{n,\max}^h p_n^{*h}}{wq_n^h} \tag{1}$$

in which Q^h is the number of the considered eigenvalues, P^h is the corresponding percentage of explained variance, $wq_n^h = \sum_{q=1}^{Q} w_{q,n}^h < 100\%$ is the cumulative percentage weight of the n-th descriptor in the Q^h principal components; $w_{n\max}^h = \max(w_{n,1}^h,\dots,w_{n,Q}^h)$ is the maximum percentage weight; R_n^h is the rank of the principal component in which $(w_{n,q}^h)_{q=1}^{Q}$ show the maximum value and p_n^{*h} is the percentage of explained variance by this component. The corresponding normalized value is $NPCI_n^h = PCI_n^h / \sum_n PCI_n^h$ with $\sum_n NPCI_n^h = 1$.

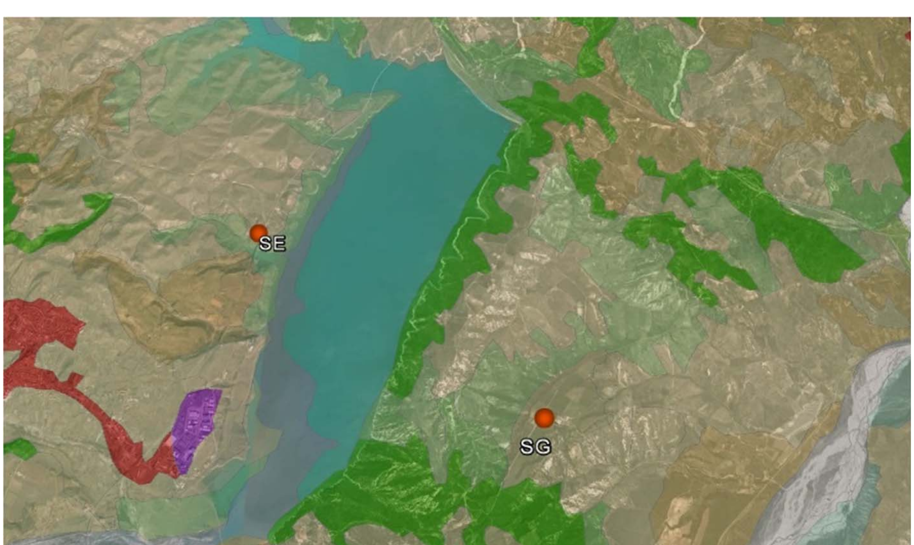

Fig. 3. Senise (**SE**) and S. Giorgio Lucano (**SG**) sites near Monte Cotugno reservoir.

3. Results and discussions

In Fig. 2, *NPCI* values, calculated for all the 73 available matrices, are shown. Higher values of *NPCI* ($NPCI > 1/N$) indicate the descriptors with a dominant role in the correlation structure, whereas lower values ($NPCI < 1/N$) highlight the descriptors with a minor informative content. Moreover, for each *n*-th variable and for each sampling site, the *NPCI*-range, $r_n = (\max\{NPCI_n^1 ... NPCI_n^H\} - \min\{NPCI_n^1 ... NPCI_n^H\})$ is calculated, in order to assess the temporal changes of the correlation structure. The *r*-values are shown in table 2; moreover, for each site, the mean value r_m and standard deviation *sd* (expressed in percentage) is calculated. Higher values of range suggest a temporal variation of the correlation structure, and consequently, changes in the relationships among the meteorological descriptors. The values of this parameter may be considered as proxy indicators of climate changes at the local scale, putting in evidence sites and descriptors more sensitive to changes. At first, we note that the variable *P* (precipitations) weighs less than other variables in the correlation structure (for all the sites and for all the years, *NPCI* values are lower than 0.05, Fig. 2). Moreover, this variable shows small *r*-values in all the examines sites, suggesting that *P* has an unchanged role in the correlation structure on the entire investigated period. This result emphasizes that there is low correlation between the behavior of precipitations and the trends of other meteorological variables. Furthermore, it indicates that precipitation represents a variable with little redundancy. On the contrary, in many sites, *NPCI* calculated for T_{min} shows a larger variability in the investigated period (Fig. 2); also larger *r*-values are observed (Table 2). These results suggest, for this variable, a more significant role in the correlation structure and in its temporal evolution. The role of precipitation and minimum temperature in the correlation structure, put in evidence by NPCI analysis, agrees with the behavior of these variables in other studies focused on their spatial and temporal patterns [39–42].

In Table 2, for each site, the average of *r*-values expressed in percentage (r_m) is shown. This makes it possible to establish a ranking among the sampling sites, in terms of r-values and so to identify homogeneous sub-groups of sites. Particularly two sub-groups may be highlighted: ***Group 1* = *(SE, CR, AL)*** that includes monitoring sites in which a stable correlation structure is observed ($r_m < 10\%$) and ***Group 2* = *(GP, VA, ST, SG)*** including monitoring sites in which $r_m \geq 10\%$. Comparing this classification with some characteristics of sites summarized in the lower part of Table 2, it is possible to note that the sites of ***Group 1*** are all located at low altitude, near streams or dams and/or in anthropogenic areas. On the contrary the sites in ***Group 2*** are at high altitude and are located in wooded or agricultural areas. For all the examined sites, we may note that the standard deviation of r_m is about 6%. This parameter represents a distance among the weights of the different variables in correlation structure. The observed values, similar for all the sites, confirm that the variations observed in mean values are indicative of the different influences of external factors in the correlation structure.

It is interesting to compare the behavior of meteorological descriptors in S.Giorgio Lucano (**SG)** and in Senise (**SE**). In **SE** site all the variables (except T_{min}) show little changes in correlation structure, on the contrary, in **SG** site they are observed significant changes in all the examined variables. Both these two sites are located near Monte Cotugno reservoir; the **SE** is at 280 *m a.s.l.*, in an industrial area next to lake, instead the **SG** is located at 456 *m a.s.l.* in an wooded area (Fig. 3). These different characteristics of the two sites determine different values of NPCI, suggesting that the microclimatic effects of artificial basins may be also influenced by other factors as the altitude or the presence of green areas. In other studies, carried out with different data analysis methods and in areas with different climatic characteristics, at small scales similar behaviors are highlighted [42–44].

4. Conclusions

In this study an innovative designed experimental approach for analysis of multivariate data is applied; it maximizes the information content of data and ensures highest quality database. The aim is to analyze series of weather measurements collected in a limited area of Southern Italy, in order to evaluate possible emerging local climate changes.

The multivariate procedure allows to assign a standardized weight to each descriptor in the correlation structure. The analysis defines a hierarchical order or among descriptors or among sampling sites, in order to individuate, for each, the role played in the correlation structure. So the Normalized Principal Component Index allows to examine and characterize spatial and temporal changes of of the descriptors on small scale and over short periods, namely in all those cases where the data available are few to effectively apply the classical techniques of trend analysis. In the examined test case, regarding the role of descriptors, results put in evidence that the precipitation represents an isolated variable in the correlation structure. This variable has a specific informative content. On the contrary, among temperatures (minimum, maximum and average daily values) and relative humidity (minimum, maximum and average daily values), in which the redundancy is elevated, the procedure puts in evidence the specific role of minimum temperature, and of relative humidity (minimum and maximum), suggesting a possible reduction of measured parameters. Furthermore these observations may to be combined with data collected on different spatial-temporal scales (for example the increasing of temperature in the Mediterranean basin with changes in the extreme values, or the decreasing of precipitations with higher frequency of intense events and longer dry period) in order to obtain a deeper characterization of microclimatic conditions in small areas and, so, in order to better plan actions on a local scale.

Regarding the sampling sites, there are sites in which a stable correlation structure is observed, and others in which significant changes are revealed. The analysis of the characteristics of the areas surrounding the monitoring stations, suggests that the proximity to green areas and water basins might have a potential effect on microclimate variables, and also in their correlation structure.

In conclusions, the results confirm that the data analysis procedure is able to highlight significant statistical spatial-temporal changes in limited datasets. In other studies, similar behaviors were highlighted; this suggests that the method represents a general approach which can be applied in different contexts and that other test cases have to be proposed and discussed.

Furthermore, the results may be used for optimizing the hydrometeorological monitoring in the study area; in particularly the procedure can be used effectively for the weather forecast modeling management, for the management of hydro-meteorological data sets.

Further applications of this statistical procedure may be tested in studies for the water balance determination, for bioclimatic indexes development, for the evaluation of environmental impact and hydrogeological risk assessment.

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