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# Climatic Variations in Central Italy

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**Abstract:** The province of Macerata, Italy, is a topographically complex region which has been little studied in terms of its temperature and precipitation climatology. Temperature data from 81 weather stations and precipitation data from 55 rain gauges were obtained, and, following quality control procedures, were investigated on the basis of 3 standard periods: 1931-1960, 1961-1990 and 1991-2014. Spatial and temporal variations in precipitation and temperature were analysed on the basis of six topographic variable (altitude, distance from the sea, latitude, distance from the closest river, aspect, and distance from the crest line). Of these, the relationship with altitude showed the strongest correlation. Use of GIS software allowed investigation of the most accurate way to present interpolations of these data and assessment of the differences between the 3 investigated periods. The results of the analyses permit a thorough evaluation of climate change spatially over the last 60 years. Generally, the amount of precipitation is diminished while the temperature is increased across the whole study area, but with significant variations within it. Temperature increased by 2 to 3°C in the central part of the study area, while near the coast and in the mountains the change is between about 0 and 1°C, with small decreases focused in the Appennine and foothill belt (-1 to 0°C). For precipitation, the decrease is fairly uniform across the study area (between about 0-200 mm), but with some isolated areas of strong increase (200-300 mm) and only few parts of territory in which there is an increase of 0-200 mm, mainly in the southern part of the coast, to the south-west and inland immediately behind the coast. The monthly temperature trend is characterized by a constant growth, while for precipitation there is a strong decrease in the amount measured in January, February and October (between 25 and 35 mm on average).

**Keywords:** climate change; gis; geostatistic; raster math

## 1. Introduction

Macerata is the largest of the provinces in the Marche Region of Italy, with an area of about 2800 km$^2$ (**Figure 1**). Macerata is bordered by the province of Perugia(Umbria Region) to the west, by the Adriatic Sea, an arm of the Mediterranean Sea, to the east, and by three other provinces in the same Region, Ancona to the north, Fermo to the south and Ascoli Piceno to the southwest.

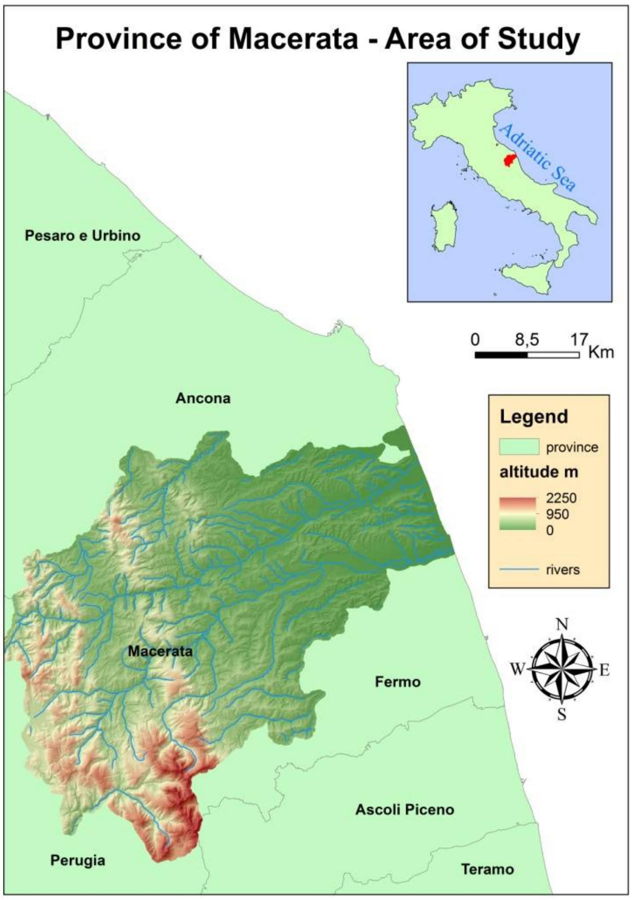


**Figure 1** - Geography of the study area.

This part of Central Italy is a transition point between coastal areas with a Mediterranean climate, an inland Temperate climate and then to the west the Highland climates of the mountains (Cs, Cf and H respectively in the Köppen-Geiger classification [1]). In some years there is a dominance of one climate type over the other, even if this difference is only shown strongly in the coastal zone. The aim of the present study was to create a new way to analyze temperature and precipitation, through GIS software, in order to have a spatial analysis of climate variability across this topographically complex region. In the literature there are several climate reports for Italy, but not for the Marche Region. Indeed, there is only one published work, by the Experimental Geophysical Observatory of Macerata [2] which can be considered a climate report. In this, an arbitrary time interval from 1950 to 2000 is considered, which is not in line with the WMO (World Meteorological Organization) approach [3]. There are two different studies for the Marche Region focusing on climate change aspects. One considers the variations through projections until 2100 using climate modeling [4] and the other investigates the extreme indexes [5], to assess whether there are any trends in the observed data. Finally there is another study for a larger area in Central Italy that analyses climatic variations in relation to land, sea, social reaction and adaptation [6], but this does not consider the Marche Region. Consequently, there is a lack of any detailed studies analyzing and mapping temperature and precipitation patterns in Macerata province which can highlight climate change.

## 2. Materials and Methods

Temperature and precipitation data were collected from 5 institutions: the former National Hydrographic Service (SIMN), Multiple-Risk Functional Center of the Civil Protection, Italian Air Force, Service Agency for the Agrifood Sector of the Marche Region (ASSAM), Functional Center of Umbria. Temperature data from 81 weather stations and precipitation data from 55 rain gauges were

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obtained. For further analyses these were divided on the basis of 3 standard periods: 1931-1960, 1961-1990 and 1991-2014. The data were validated with 5 quality controls on the basis of the WMO prescriptions [7] and through the procedures developed by Gentilucci et al. in 2018 [8]: logical and gross error check, internal consistency check, tolerance test, temporal consistency, and spatial consistency. For logical and gross error checking, temperatures outside the range (-40°C; +50°C) were removed [9]and precipitation measurements greater than 2000 mm were also excluded [8]. The internal consistency check verified the consistency of the data: for example, whether a maximum value was higher than a minimum one, for temperature, and if there were negative values for precipitation. Temporal consistency was useful to investigate errors between temporally contiguous values, for example if there is too much difference between one day and the next, by setting a limit of 3 times the standard deviation added (upper limit) or subtracted (lower limit) to the mean [10]. In the case of temporal consistency, the deletion of data is not immediate, but was subject to the spatial consistency. The spatial consistency was performed taking into consideration the neighbouring weather stations, grouped on the basis of their similarity [8]. After validation, climate data were homogenized through the creation of a reference time series for each candidate weather station. There are no reference weather stations of demonstrated reliability near the study area, so to assess the suitability of the data it is necessary to reconstruct some reference time series to compare the weather stations under investigation. The creation of the reference time series was performed daily on the basis of 10 neighbouring weather stations, for all investigated periods, with empirical Bayesian kriging (EBK), after a comparison with the inverse distance weighted (IDW) and the ordinary co-kriging based on altitude, which is the most correlated independent variable [11]. An interpolation was then prepared for each day by EBK and the climate value taken in the exact coordinates of the weather station under investigation. The creation of the reference time series for each weather station is indispensable for the analysis of breakpoints, which are points where there is a sudden difference (an error) between the reading before and after the current one in the climatic values time series of the same weather station. The breakpoints were analyzed through the SNHT (Standard Normal Homogenity Test) [12], and the penalized t-test [13] was used to avoid an excess of false breakpoints near the extremes of the time series. Finally, again using the SNHT method, the time series was homogenized, multiplying it with the ratio between the mean before and after shifting, produced by the breakpoint. The aim was to homogenize the time series of the weather station with the most reliable part of it, which is mainly represented by the latest climate values (if there are no systematic errors detected in the most recent data of the time series). A GIS database was then prepared by editing a detailed Digital Elevation Model (DEM) with a cell size 5x5 m, obtained using CTR (Regional Technical Map, Regione Marche, 2000), topographical map and LIDAR reliefs [14]. The relationship of climatic variables with topographical parameters was assessed and the elevation has been found to be the most correlated factor [15]. Thus, the DEM was essential for data interpolation, in order to improve the results through the use of the geostatistical technique of ordinary co-kriging, chosen after a cross-validation assessment between kriging (ordinary and simple), empirical Bayesian kriging and Co-kriging (ordinary and simple). Co-kriging was the method that minimized the error (in terms of Mean Error, RMSE, Mean Standardized error, RMSSE, Mean standard error) more than all others, it was prepared with altitude as independent variable and precipitation or temperature as the dependent one. The interpolation maps obtained were compared between different periods (1931-1960, 1961-1990, 1991-2014) through GIS with the mathematics between rasters, in order to assess spatial climatic variations.

## 3. Results

This section may be divided by subheadings. It should provide a concise and precise description of the experimental results, their interpretation as well as the experimental conclusions that can be drawn.

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### *3.1. Data quality control*

The first important result achieved was to have reliable data after the accurate quality controls and homogeneity tests have been carried out. The validation process removed 0.02 % of the data for temperature and 1.67 % of the data for precipitation. Instead, the homogenization, performed with the SNHT and the Penalized T-test, after a long process of reference time series construction, involved only the data of 4 weather stations. The EBK [16] was compared with IDW and ordinary co-Kriging and was found that it improves the performance of IDW of about 5% (in terms of root mean square error) on the same dataset, while it is quicker and easier, even if less accurate than ordinary co-kriging (Table 1).

**Table 1**- Comparison between 3 interpolation methods (Inverse Distance Weighting (IDW), empirical Bayesian kriging (EBK) and Ordinary Co-Kriging).

| Statistical quality parameters | IDW | EBK | Co-Kriging |
|---|---|---|---|
| Regression function | 0.6x + 6.8 | 0.7x + 5.7 | 0.9x + 1.2 |
| Mean | 0.0119 | 0.0311 | 0.0566 |
| Root-mean-square | 1.6870 | 1.6429 | 1.2465 |
| Mean standardized | | -0.0002 | 0.0237 |
| Root-mean-square-standardized | | 0.9514 | 0.9890 |
| Mean standard error | | 1.7366 | 1.5278 |

The reference time series obtained with EBK was related with the candidate time series, in order to investigate if this series (candidate) needs homogenization. The result of subsequent homogenization leads to 2 weather stations homogenized for temperature and 2 rain gauges for precipitation. In particular, the case of Civitanova Marche, a city on the Adriatic coast, is particularly evident with a growing mean, after the breakpoint, of about 300 mm (**Figure 2**) which is homogenized by the tests [12,13] (**Figure 3**).

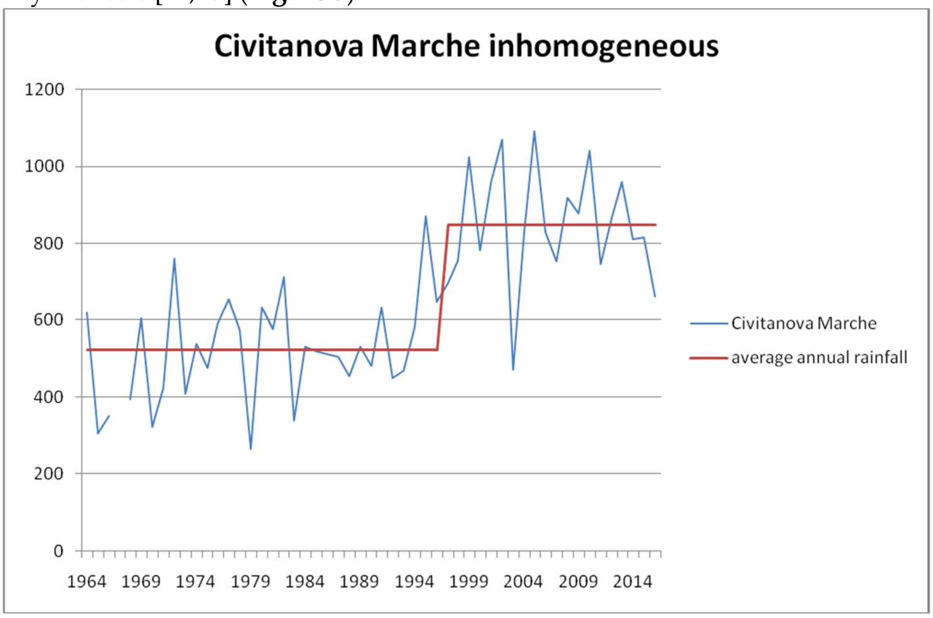


**Figure 2** - Civitanova Marche rain gauge inhomogeneous.

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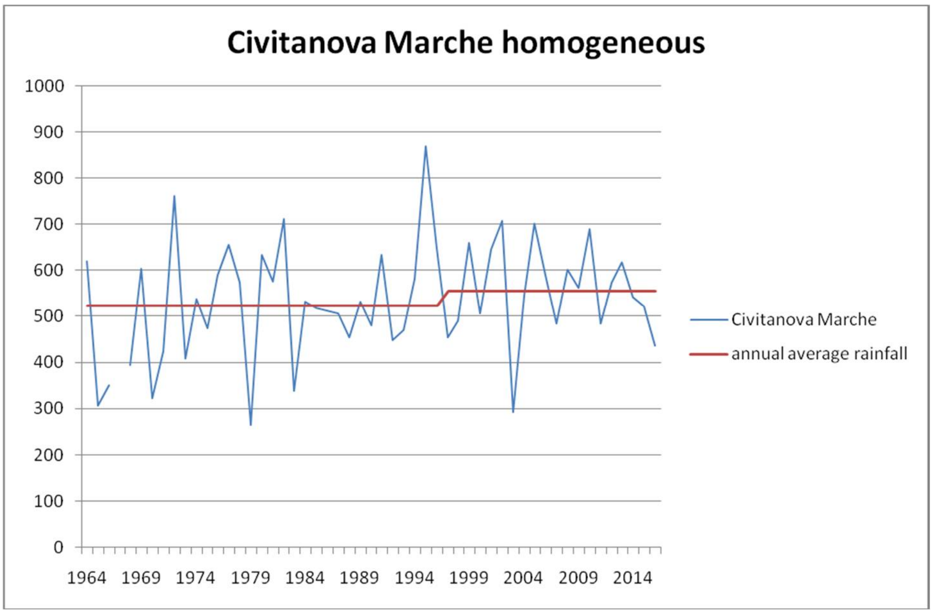


**Figure 3** - Civitanova Marche rain gauge homogeneous.

*3.2. Assessment of correlation between topographical and climatic variables*

The adjusted data were used for the creation of detailed interpolation maps, passing through an assessment of the influence of topographic co-variables on precipitation and temperature in this area for all investigated periods (1931-1960/1961-1990/1991-2014). Six different topographic variables were considered [11]: altitude, distance from the sea, latitude, distance from the closest river, aspect, and distance from the crest line. The variables were assessed using the adjusted coefficient of determination ($R^2$) [11], with an assessment of the goodness of correlation represented by the calculation of the standard error of the mean and the F-test. These 3 parameters can explain the relation between the topographic variables and temperature or precipitation; in fact the $R^2$ adjusted ($R^2_{adj}$) shows the amount of variation explained by the estimated regression line (**Figure 4**) [17]:

$$R^2_{adj} = 1 - (1 - R^2)\frac{n-1}{n-k-1} \quad (1)$$

$n$ = sample size
$k$ = number of explanatory variables (independent), in this case 6

$$R = \frac{\sum(x-\bar{x})(y-\bar{y})}{\sqrt{\sum(x-\bar{x})^2 \sum(y-\bar{y})^2}} \quad (2)$$

$\bar{x}$ and $\bar{y}$ = mean values of dependent and independent variables
$x$ and $y$ = values of dependent and independent variables

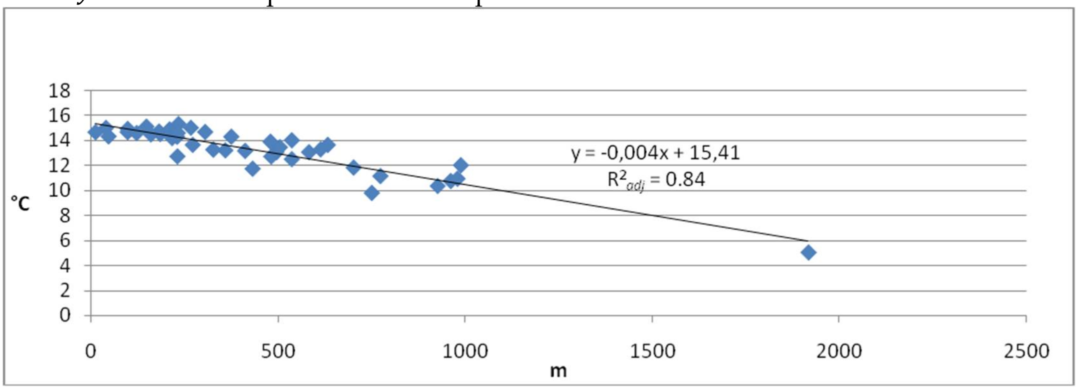


**Figure 4** - Ratio between elevation and temperature annual mean in the period 1991-2014.

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The standard error of the mean allows calculation of the dispersion of sample means around the population, and also in this case the altitude shows the better value compared to the other topographic variables both for temperature (**Table 2**) and precipitation (**Table 3**). Finally, the F-test was performed to estimate if there can be a significant difference (based on 5% of rejection probability) between the sample means of precipitation or temperature and those of the geographic variables. When the variances of the two populations are equal, the variable cannot be used as independent to obtain a correlation factor with the dependent one, because both of them would be estimators of an unknown quantity $\sigma^2$. The variance is an index of variability and it's expressed by the formula:

$$\sigma_x^2 = \frac{\sum_i (x_i - \bar{x})^2}{n} \tag{2}$$

whilst the F-test is obtained from the ratio between major and minor sampling variances.

$$F = \frac{(s_{max}^2)}{(s_{min}^2)} \tag{3}$$

As demonstrated in Gentilucci et al., 2018 [11] for precipitation (**Table 3**), even for temperatures the most correlated variable for the whole period (1931-2014) is the altitude (**Table 2**).

**Table 2** - Comparison between topographic variables and mean annual temperature 1931-2014.

| Regr. stats for T | Alt.-yrs T 1931-2014 | Dist. sea-yrs T 1931-2014 | Lat.-yrs T 1931-2014 | Dist. river-yrs T 1931-2014 | Aspect-yrs T1931-2014 | Dist. cre.-yrs T 1931-2014 |
|---|---|---|---|---|---|---|
| $R^2$adj. | 0.84 | 0.46 | 0.44 | 0.06 | -0.01 | -0.02 |
| Std error | 0.76 | 1.40 | 1.43 | 1.86 | 1.92 | 1.93 |
| Sign. F | 8.31 E-18 | 4.29 E-07 | 9.03 E-07 | 0.07 | 0.49 | 0.84 |

**Table 3** - Comparison between topographic variables and mean annual precipitation 1931-2014.

| Regr.stats for P | Alt.-yrs P1931-2014 | Dist. sea-yrs P 1931-2014 | Lat.-yrs P 1931-2014 | Dist.river-yrs P 1931-2014 | Aspect-yrs P 1931-2014 | Dist. cre.-yrs P 1931-2014 |
|---|---|---|---|---|---|---|
| $R^2$adj. | 0.70 | 0.69 | 0,26 | 0.07 | -0.02 | -0.02 |
| Std error | 102.32 | 103.50 | 159.80 | 178.40 | 187.33 | 187.39 |
| Sign. F | 6.92E-13 | 1.14E-12 | 2.24E-4 | 0.04 | 0.75 | 0.79 |

Thus, Tables 2 and 3 highlight the goodness of the correlation between altitude and temperature or precipitation, in order to have a reliable independent variable for interpolation by cokriging methods.

*3.3. Interpolation and climate change analysis*

Interpolation was performed by analysing three different types of cokriging, in order to identify the most suitable for the available data:

- Ordinary co-kriging, [18] a particular case of the universal cokriging, in which the residuals mean is assumed constant and unknown.

$$Z_{OCK}(u) = \sum_{\alpha_1=1}^{n_1(u)} \lambda_{\alpha_1}^{OCK}(u) Z_1(u_{\alpha_1}) + \sum_{\alpha_2=1}^{n_2(u)} \lambda_{\alpha_2}^{OCK}(u) Z_1(u_{\alpha_2}) \tag{4}$$

$\lambda_{\alpha_1}^{OCK}(u)$ *and* $\lambda_{\alpha_2}^{OCK}(u)$= weights of the data assigned to $Z_1(u_{\alpha_1})$ *and* $Z_1(u_{\alpha_2})$ and varies between 0 and 100%.

$Z_1(u_{\alpha_1})$ *and* $Z_1(u_{\alpha_2})$ = regionalized data at a given location,primary and secondary data.

- **Simple co-kriging**, [18] is used when the mean is stationary and the residuals mean is considered a global constant and known in the whole study area, this method can be good only if there are a large number of sample points.

$$Z_{SCK}(u) - \mu_1 = \sum_{\alpha_1=1}^{n_1(u)} \lambda_{\alpha_1}^{SCK}(u)[Z_1(u_{\alpha_1}) - m_1] + \sum_{\alpha_2=1}^{n_2(u)} \lambda_{\alpha_2}^{SCK}(u)[Z_1(u_{\alpha_2}) + m_2] \tag{5}$$

$m_1$ *e* $m_2$ = mean of the primary and secondary data

- **Universal Co-Kriging**, [19] a generalization of the ordinary cokriging, is used when the mean isn't stationary, i.e. if there is a trend, and the residual isn't correlated to the trend (stationarity of the residuals).

$$Z_{UCK}(u) = \varepsilon_1 + \varepsilon_2 + \sum_{\alpha_1=1}^{n_1(u)} \lambda_{\alpha_1}^{UCK}(u) Z_1(u_{\alpha_1}) + \sum_{\alpha_2=1}^{n_2(u)} \lambda_{\alpha_2}^{UCK}(u) Z_1(u_{\alpha_2}) \quad (6)$$

$\varepsilon_1$ *and* $\varepsilon_2$ = mean of the residuals in the primary and secondary variable.

Ordinary cokriging has been chosen by an iterative process through many tests of cross-validation performed within the ArcGis extension, Geostatistical Analyst. In the interpolations the independent variable was elevation, whereas the dependent variable was temperature or precipitation [20]. All interpolations were verified through 4 statistical indicators [21], which allowed selection of the correct parameters for the semivariogram setting:

1. Root Mean Square Error (RMSE) - the standard deviation between observed and predicted values: this parameter allows an assessment of the prediction errors for different weather stations. However, RMSE isn't an absolute parameter, since it's impossible to compare different variables with the RMSE; anyhow it can be anuseful to compare within the same data set. The value of RMSE should be the smallest possible and similar to the ASE (mean standard error): in this way when it is predicting a value in a point without observation points, it has only the ASE to assess the uncertainty of the prediction.

$$\sqrt{\frac{\sum_{i=1}^{n}[\hat{Z}(s_i)-z(s_i)]^2}{n}} \quad (7)$$

$\hat{Z}(s_i)$ = measured value at position $s_i$;
$z(s_i)$ = predicted value at position $s_i$;
$n$= number of weather stations;
$\hat{\sigma}$=standard deviation of the population.

2. Mean Standard Error (ASE) - this statistical tool is known from the mean and it is used to estimate the standard deviation of a sampling distribution. The ASE is an estimator of the bias of the RMSE (i.e. the standard deviation of the estimation error). A value close to zero and similar to RMSE represents a very low error in the estimation of the variability of the sampling distribution.

$$\sqrt{\frac{\sum_{i=1}^{n}\hat{\sigma}^2(s_i)}{n}} \quad (8)$$

3. Mean Standardized Error (MSE) - It's similar to the mean error and calculates the difference between measured and predicted values; however MSE values aren't related to single variables, but it can be used to compare different variables. The standardization procedure leads a variable with mean x and variance $\sigma^2$, to another with mean zero and variance equal to 1, in order to allow comparison between different variables. The mean standardized error is represented by the ratio between the mean absolute error and the standard deviation of the estimation error.

$$\frac{\sum_{i=1}^{n}[\hat{Z}(s_i)-z(s_i)]/\hat{\sigma}(s_i)}{n} \quad (9)$$

4. Root Mean Square Standardized Error (RMSSE) - allows assessment of the goodness of prediction models. It is desirable to have a value close to 1. If the value of RMSSE is lower than 1 the variability is overestimated, otherwise it is underestimated. This is a dimensionless statistical tool, independent from the considered variable; it is the most significant instrument to evaluate the interpolative model with other variables.

$$\sqrt{\frac{\sum_{i=1}^{n}[\hat{Z}(s_i)-z(s_i)/\hat{\sigma}(s_i)]^2}{n}} \quad (10)$$

The results of this cross-validation were represented by a table (for example Table 4) for each investigated period (1931-1960/1961-1990/1991-2014), in which it is possible to assess the goodness of

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interpolations for temperatures (maximum, mean, minimum) [22] and precipitation, on a monthly and annual basis.

**Table 4** - Period 1961-1990, statistical indicators for interpolations of maximum, mean and minimum temperatures

| P. 1961-1990 | RMSE | MSE | RMSSE | ASE | P. 1961-1990 | RMSE | MSE | RMSSE | ASE |
|---|---|---|---|---|---|---|---|---|---|
| Annual mean | 1,89 | -0,15 | 1,14 | 2,05 | Av. January | 1,36 | -0,13 | 1,01 | 1,62 |
| Av. February | 1,71 | -0,14 | 1,13 | 1,89 | Av. March | 1,91 | -0,17 | 1,16 | 2,01 |
| Av. April | 2,19 | -0,16 | 1,17 | 2,25 | Av. May | 2,39 | -0,16 | 1,21 | 2,58 |
| Av. June | 2,21 | -0,17 | 1,16 | 2,31 | Av. July | 2,17 | -0,17 | 1,16 | 2,31 |
| Av. August | 2,00 | -0,17 | 1,17 | 2,03 | Av. September | 2,38 | -0,14 | 1,13 | 2,62 |
| Av. October | 1,83 | -0,15 | 1,08 | 1,95 | Av. November | 1,55 | -0,13 | 1,04 | 1,71 |
| Av. December | 1,54 | -0,11 | 1,02 | 1,91 | | | | | |
| Max ann. mean | 3,05 | -0,18 | 1,14 | 3,04 | Max January | 2,15 | -0,17 | 1,09 | 2,22 |
| Max February | 2,70 | -0,19 | 1,12 | 2,70 | Max March | 3,05 | -0,20 | 1,23 | 2,95 |
| Max April | 3,23 | -0,18 | 1,17 | 3,16 | Max May | 3,54 | -0,18 | 1,23 | 3,54 |
| Max June | 3,44 | -0,20 | 1,22 | 3,30 | Max July | 3,56 | -0,20 | 1,20 | 3,43 |
| Max August | 3,51 | -0,19 | 1,18 | 3,31 | Max September | 3,77 | -0,17 | 1,17 | 3,75 |
| Max October | 2,97 | -0,19 | 1,12 | 2,83 | Max November | 2,42 | -0,17 | 1,09 | 2,38 |
| Max December | 2,35 | -0,16 | 1,04 | 2,57 | | | | | |
| Min ann. mean | 1,30 | -0,04 | 1,08 | 1,44 | Min January | 0,88 | -0,05 | 0,87 | 1,18 |
| Min February | 0,97 | -0,03 | 0,93 | 1,33 | Min March | 1,15 | -0,07 | 0,99 | 1,32 |
| Min April | 1,40 | -0,06 | 1,15 | 1,53 | Min May | 1,68 | -0,07 | 1,09 | 1,87 |
| Min June | 1,60 | -0,05 | 1,14 | 1,61 | Min July | 1,86 | -0,05 | 1,18 | 1,69 |
| Min August | 1,66 | 0,11 | 1,20 | 1,46 | Min September | 1,67 | -0,03 | 1,14 | 1,79 |
| Min October | 1,36 | -0,01 | 1,17 | 1,41 | Min November | 1,20 | -0,01 | 1,12 | 1,28 |
| Min December | 1,03 | -0,05 | 0,97 | 1,31 | | | | | |

The table (**Table 3**) highlights the quality of interpolation, with the statistical indicators always close to the optimum value of the 4 statistical indicators. In fact, the value of the root mean square error standardized is about 1 in all interpolations and the mean standardized error is close to 0. In this way 65 maps were created, in order to observe the distribution of temperature maximum, mean, minimum and of precipitation, in the area of study. The varied climate condition of Macerata Province is shown in (**a**)

(**b**)

**Figure 5**: there is a decrease of temperature and an increase of precipitation going from east (Adriatic Coast) to west (Appennine Mountains).

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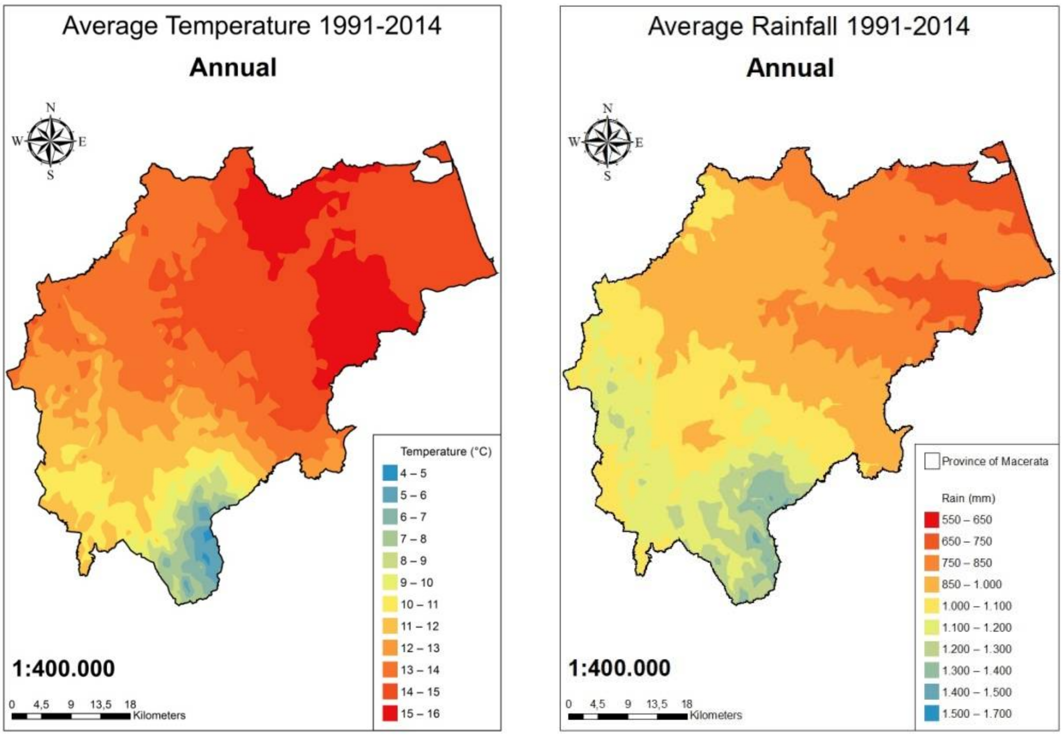


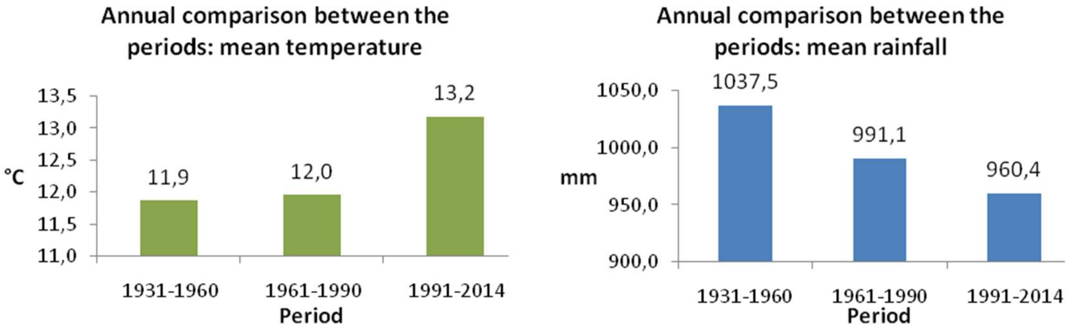

(**a**) (**b**)

**Figure 5** - Mean annual temperature (a) and mean annual precipitation (b) in the period 1991-2014 for Macerata province.

The interpolation maps were averaged with the raster math tool, in order to compare different periods of the same parameter. A positive trend from the past to the present is evident for temperature, and a negative one for precipitation ( (**a**)

(**b**)

**Figure 6**).




(**a**) (**b**)

**Figure 6** - Interpolation annual mean of the 3 periods (1931-1960/1961-1990/1991-2014) for temperature (a) and precipitation (b).

Finally, the most important part of this research is represented by the comparison between the interpolation maps of 1931-1960 and those of 1991-2014, to assess climate change in the last 60 years. These variation maps (**Figure 7**) were obtained through the raster math tool, by subtracting to the values of 1991-2014 from those of 1931-1960.

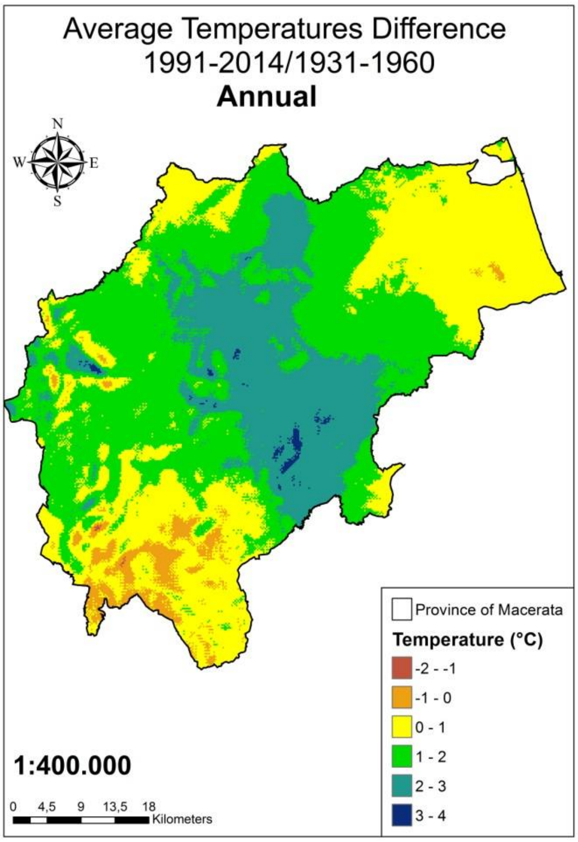



**Figure 7**- Variations of mean annual temperature between 1991-2014 and 1931-1960.

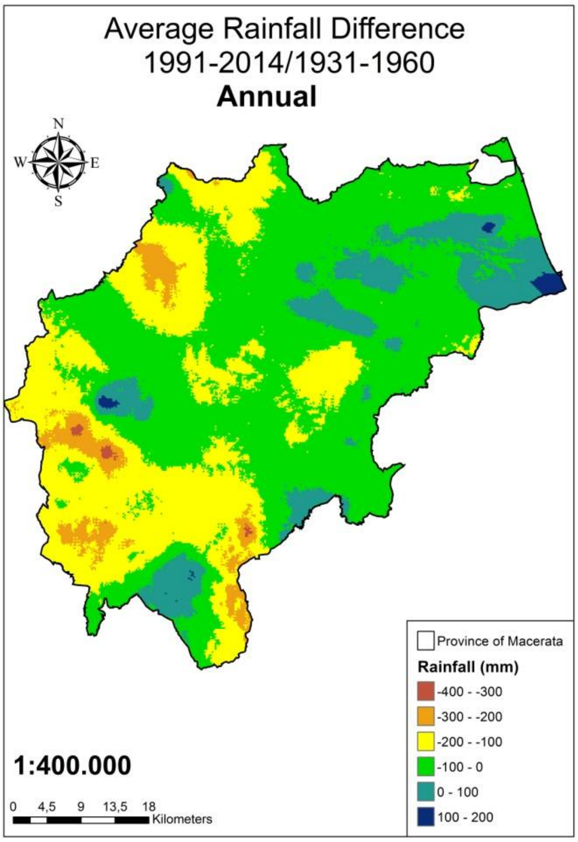


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**Figure 8** - Variations of mean annual rainfall between 1991-2014 and 1931-1960.

The variation map of mean temperature (**Figure 7**) shows a strong increase in the hilly zone, the central part of the study area, while there is a slight decrease of temperature in the mountainous region (west). For mean annual rainfall, the variation map (**Figure 8**) highlights a decrease in precipitation over the whole province overall, but with small localized parts in which there is an increase.

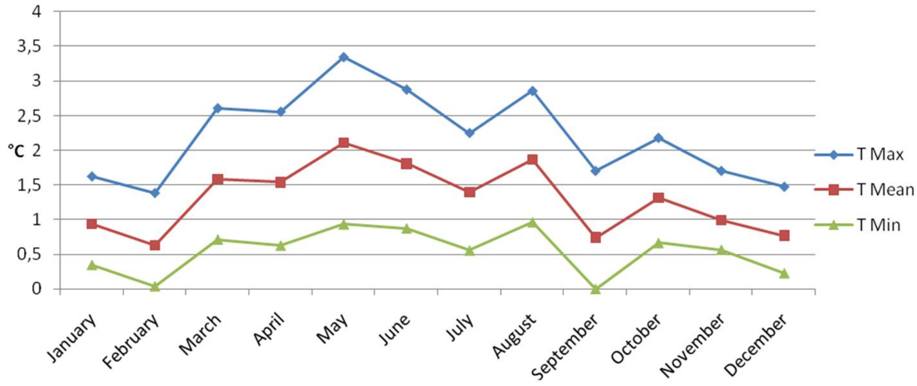


**Figure 9** - Monthly temperature variations (maximum, mean and minimum) between the periods 1991-2014 and 1931-1960.

The graphs (Figure 9) records the differences on average in the whole territory between the periods 1991-2014 and 1931-1960; it highlights, for each parameter, a bell-shaped trend strongly increasing in spring and summer months, with a drop during winter and autumn. In February and September, minimum temperatures are in a counter trend because there is no trend a strong temperature increase in these two months.

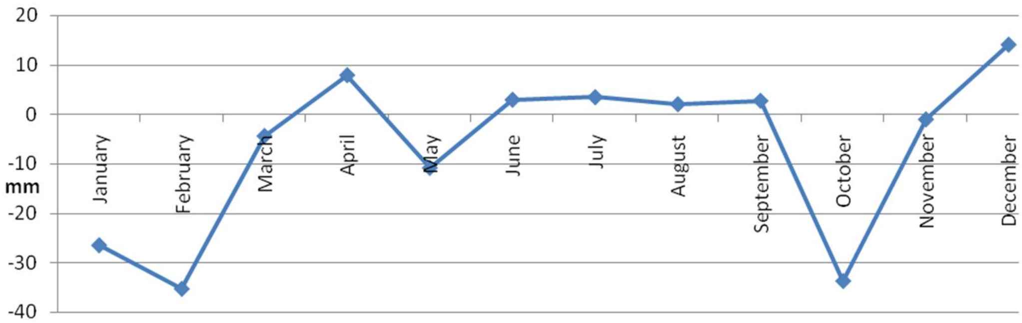


**Figure 10** - Trend of monthly variations in precipitation between the periods 1991-2014 and 1931-1960 for precipitations.

Precipitation has a reverse trend compared with temperatures (**Figure 10**) in that there is an absence or even an augmentation of precipitation in spring and summer, while the decreasing peak is focused on January, February and October, with significant amount between 25 mm and 35 mm. December is an exception, because it shows the highest augmentation of rainfall (about 15 mm).

## 4. Discussion

This analysis has achieved some important goals for understanding and mapping the climate of Macerata Province, Italy. Firstly, it has described the conditions of temperature and precipitation of Macerata province in 3 different standard periods 1931-1960, 1961-1990, 1991-2014. The GIS software allowed creation of maps, in order to comprehend the spatial distribution of temperature and precipitation. Furthermore, a strong relationship with altitude has been identified. In fact,there is a differentiation that follows the altitudinal trend quite well, from the coast with high temperature, even if the highest temperatures are located in the hilly belt behind the coast, to the lowest temperatures in the Appennine Mountains (west). For precipitation, the smallest amount occurs on the southern part of the coast, while the highest quantity is in the Appennine Mountains to the south-west.

The second and most important result is represented by the study of climate change, with GIS software in order to assess the variations through algebraic operations between rasters. The differences between the period 1991-2014 and 1931-1960 were investigated in order to assess the climatic change in the last 60 years. Generally, the amount of precipitation from 1931-1960 to 1991-2014 is diminished while the temperature is increased. However, spatially the situation is more complex. In fact there is a central part of the study area in which temperature increased strongly by 2 to 3°C, while near the coast and in the mountains the change is about 0-1°C, with small decreases focused in the Appennine and foothill belt (-1 to 0°C). For precipitation, the decrease is fairly uniform across the study area (between about 0-200 mm), but with some isolated areas of strong increase (200-300 mm) and only few parts of territory in which there is an increase of 0-200 mm, mainly in the southern part of the coast, to the south-west and inland immediately behind the coast. The monthly temperature trend is characterized by a constant growth, while for precipitation there is a strong decrease in the amount measured in January, February and October (between 25 and 35 mm on average). This analysis, unlike previous studies, allows consideration of thespatial climate change, which is moderately strong and unequivocal, but with some important counter-trends. In future it would be interesting to investigate the variations between the different areas within the province. Furthermore, to improve analysis, it would be desirable to install more reliable weather stations, especially in the Appennine area (as this is under sampled).

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