International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 10 No. 4, 2024
https://theaspd.com/index.php

Climate Change In The Guir-Ziz-Gheris Hydraulic Basin: Statistical Study On Temperature.

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***Abstract**: Climate change is altering the Earth's thermal balance and has many consequences for humans and the environment. In Indeed, modern agriculture is optimized to handle the subject of temperature change. This study aims to forecast temperature variations within the Guir-Ziz-Gheris basin located in the Errachidia region. Temperature data for the 1983 to 2015 years have been collected at different meteorological stations in Errachidia province. To investigate the similarities between different years and the correlations among various months, Principal Component Analysis (PCA) was utilized. Preliminary results demonstrate that PCA is useful for classifying years and identifying correlations. To forecast the mean annual temperature (MAT), Partial Least Squares (PLS) regression was employed. This method confirmed the year-to-year similarities (from 1983 to 2015) and the month-to-month correlations previously established by PCA.*
***Keywords**: temperature, classification, prediction, Principal Component Analysis (PCA), Partial Least Squares (PLS), Guir Ziz Rheris basin, altitude.*

INTRODUCTION:

The earth's climate has always varied, and has done so since the formation of the planet, so this is not a new event. Many phenomena participate in these changes.
some processes increase the temperature and others decrease it. Several phenomena act in parallel, sometimes in opposition, and it is the accumulation of all these phenomena that will impose a temperature at a given moment in the history of the Earth. Over the past few decades, climate change has influenced natural and human systems across the globe. These effects are linked to observed shifts in climate, independent of their origins, demonstrating the susceptibility of both ecosystems and human societies to evolving climate patterns [1].
Temperature is a key factor in aquatic ecosystems, significantly affecting the presence and standard, and ecosystems distribution [2]. The significant impact of temperature on hydrous organisms has sparked a revitalized focus on understanding the thermal dynamics of flowing waters. While various studies have shown that latitude can influence the relationship between temperature and mortality, there is limited understanding of the extent to which latitude modifies this temperature-mortality connection [3]. Sea surface temperature is a fundamental climate variable, according to the Global Climate Observing System, and it is vital in regulating climate patterns and their fluctuations [4].
Additionally, over seasonal timescales, changes in the amplitude or phase of seasonal patterns can significantly influence the interannual variability in mean temperatures [5]. Latitude affects temperature because it influences the amount of insolation a location receives. Since insolation varies with latitude, so does temperature [6]. The atmosphere is indirectly warmed by terrestrial radiation, which means that locations near sea level typically experience higher temperatures compared to those at higher elevations. Generally, temperature decreases with increasing altitude, and this rate of temperature decrease with height is known as the normal lapse rate [7]. The primary factor influencing temperature is a location's proximity to the sea. The sea heats up and cools down more slowly than land, which causes coastal areas to experience smaller

temperature fluctuations compared to inland regions, where temperatures can change more rapidly [8]. Locations near the sea are influenced by moderating sea and land breezes, which help regulate temperature and reduce temperature extremes [9]. The movement of air masses also influences temperature in a manner similar to land and sea breezes [10].
Locations affected by warm air masses experience higher temperatures, while those influenced by cold air masses experience lower temperatures [11]. Similarly, coastal areas influenced by warm ocean currents tend to have higher temperatures compared to those where cold currents prevail [12]. The understanding, detection, and analysis of anthropogenic climate change, which has been progressing since the Industrial Revolution, depend significantly on the long-term observation records available [13]. Regression is a widely used technique for prediction in fields such as climate forecasting and various other domains [14].
Weather prediction is a captivating field with a crucial role in meteorology. It involves estimating future atmospheric conditions based on various weather variables, such as rainfall, thunderstorms, cloud cover, temperature, pressure, and wind direction [15].

Material and methods

Geographical Context of the Study

The Guir-Ziz-Rhéris-Maider watershed lies in the southeastern region of the country. It is geographically enclosed by Algeria on its eastern and southern flanks, the High Atlas Mountains to the north, and the Anti-Atlas range to the southwest [16].
This region covers approximately 59,000 km2, making up over 8% of Morocco's total land area. It includes the Hydrological basins of the Guir, Ziz, Rheris, and Maïder rivers from east to west (see Figure 1).

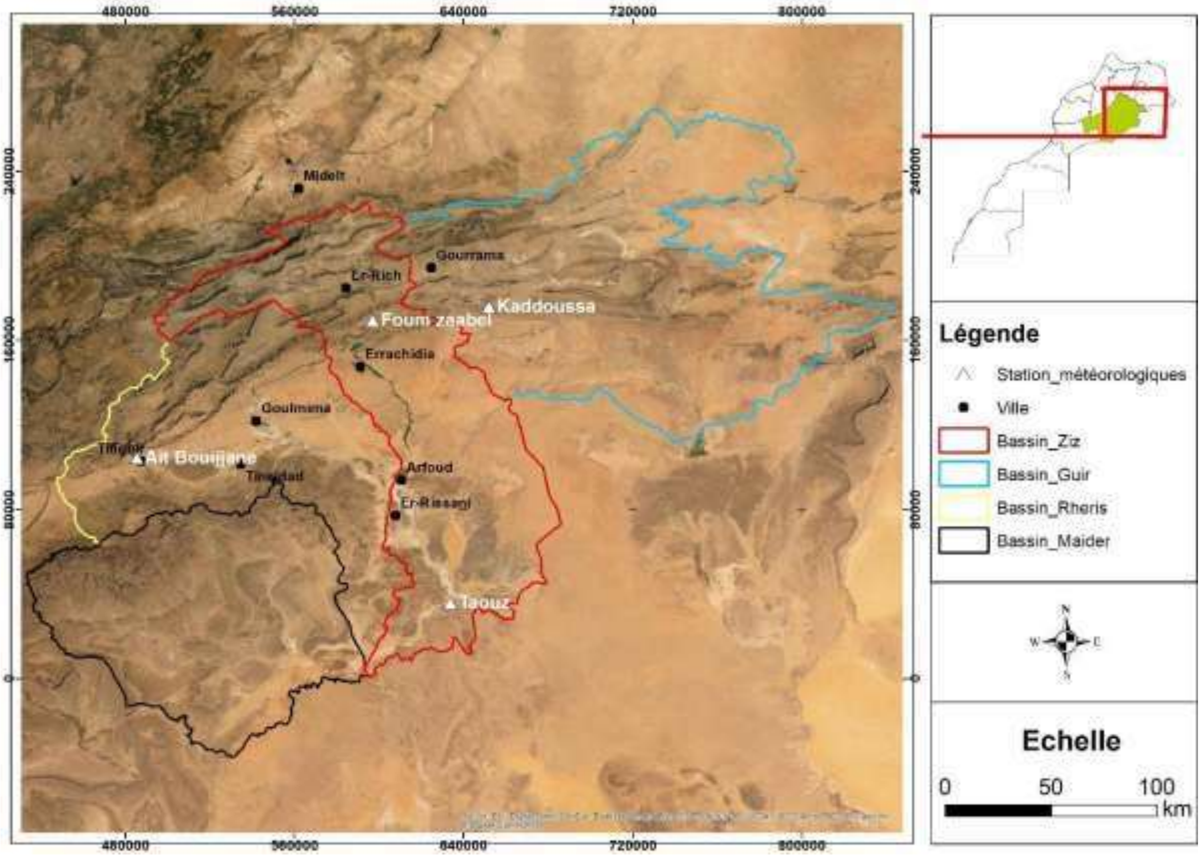

Figure 1: A spatial representation of the Guir-Ziz-Gheris basin was generated using ArcGIS software.

Data collection

Data spanning thirty-one years, from 1983 to 2015, have been preserved by the Guir-Ziz-Gheris Water Basin Agency. The Collection sites include Three catchment areas per basin, with one station per basin, except

International Journal of Environmental Sciences
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for the Ziz basin, which has two sampling stations. Consequently, the data selected had to meet two crucial criteria: a long temporal coverage and high quality, with minimal missing data [17].

Instrumentation

Chemometric analysis, including Partial Least Squares (PLS) of the rainfall data of 30 years (1985 to 2015), was carried out using UNSCRAMBLER 10.2 CAMO software.

Principal Component Analysis (PCA) and Partial Least Squares (PLS) regression are widely adopted statistical methods in climate research for forecasting temperature trends. PCA serves to simplify complex climate datasets by transforming correlated variables into a smaller set of uncorrelated components, making it easier to detect underlying temporal patterns and inter-variable relationships. On the other hand, PLS regression creates predictive models by relating input variables—such as past temperature records—to target variables, even when the data exhibit multicollinearity or high dimensionality. When used together, these techniques offer a comprehensive approach for identifying thermal dynamics and improving the accuracy of temperature predictions across both spatial and temporal scales.

RESULTS AND DISCUSSIONS

Principal component analysis of 12-month variables and 130 area-years as individuals

The outcomes of the analysis are illustrated on the PC1–PC2 plot, representing the two leading principal components obtained through PCA (refer to Figure 2).

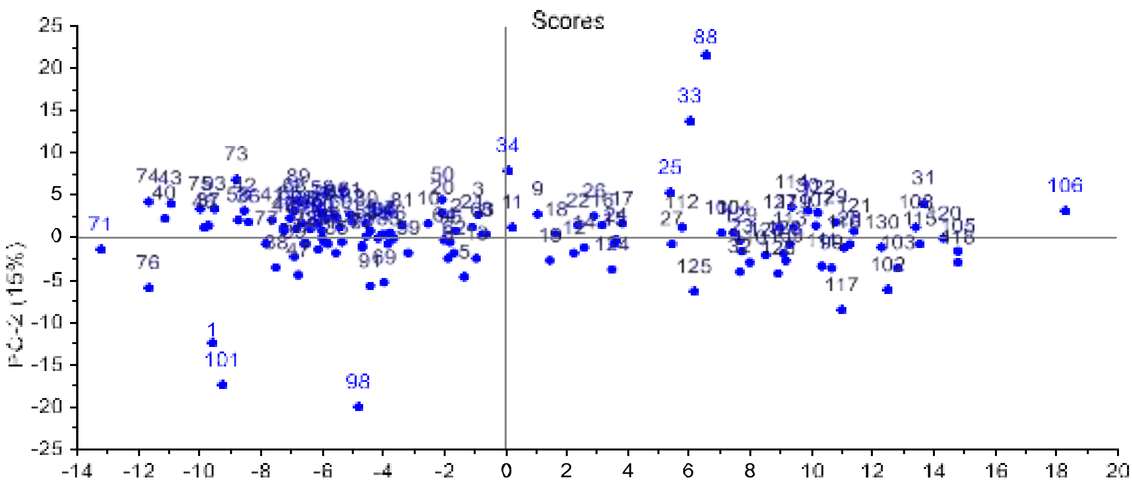

Figure 2: Factor Map (PC1 and PC2) for 12 Months Based on the drawing underneath:

1. The principal components 1 and 2 explain 62% of the variability in the original information in the initial table.
2. The data is classified into two distinct groups.

To enhance the retention of information derived straight from the source temperature data across 12 months, we mapped the 274 areas into a 12-month vector space. The projection outcomes are displayed in a three-dimensional format (Figure 3).

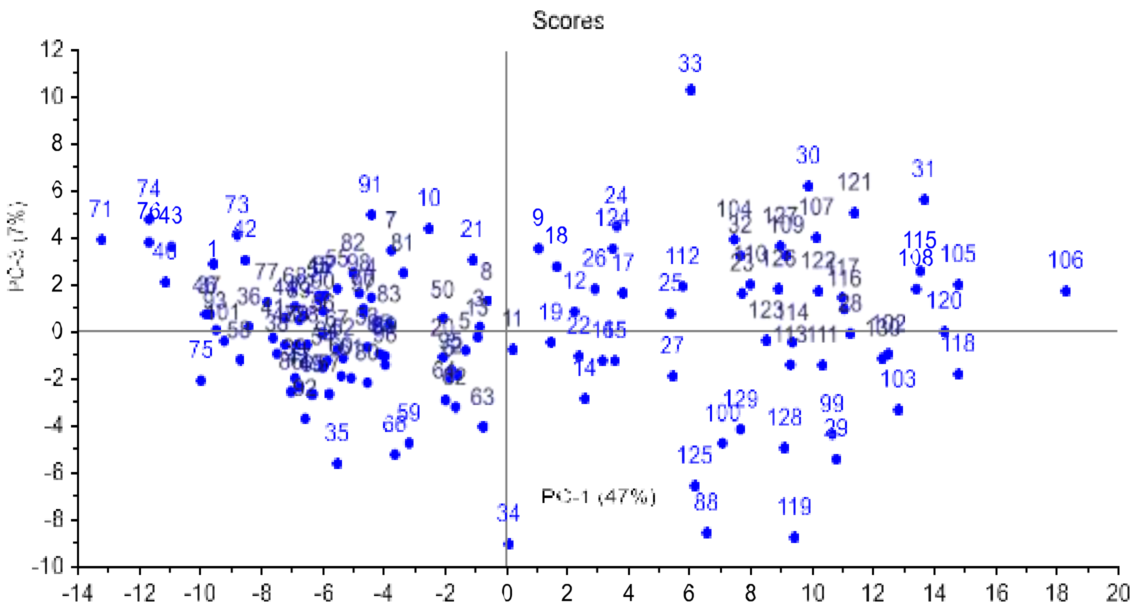

Figure 3: 2D (PC1 et PC3) PCA Factor Map for 12 months

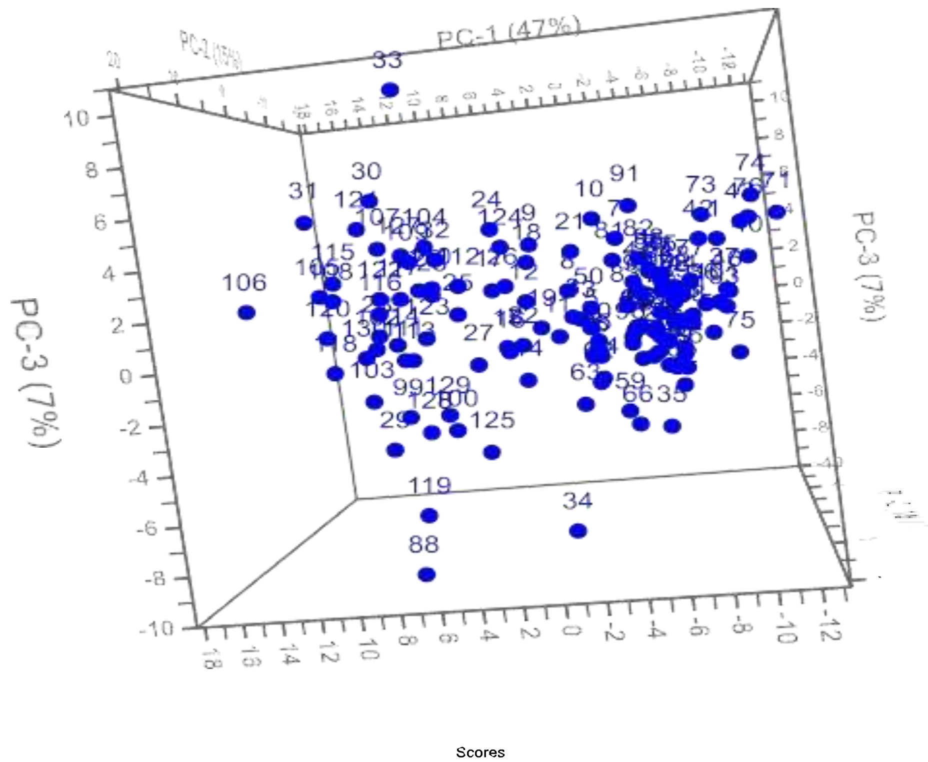

Figure 4: 3D PCA Factor Map for 12 months

The first three principal components account for a total of 69% of the variance in the straight from the source, showing a 7% improvement over the two-dimensional analysis. The three- dimensional (3D) factorial map supports the findings of the two-dimensional (2D) factorial map, confirming the presence of two distinct classes.

To examine the relationships between monthly temperature data across the 12 zone-specific years, the months were projected into a vector space structured by those years. The results are displayed as correlation circles on the PC1–PC2 plane (see Figure 5).

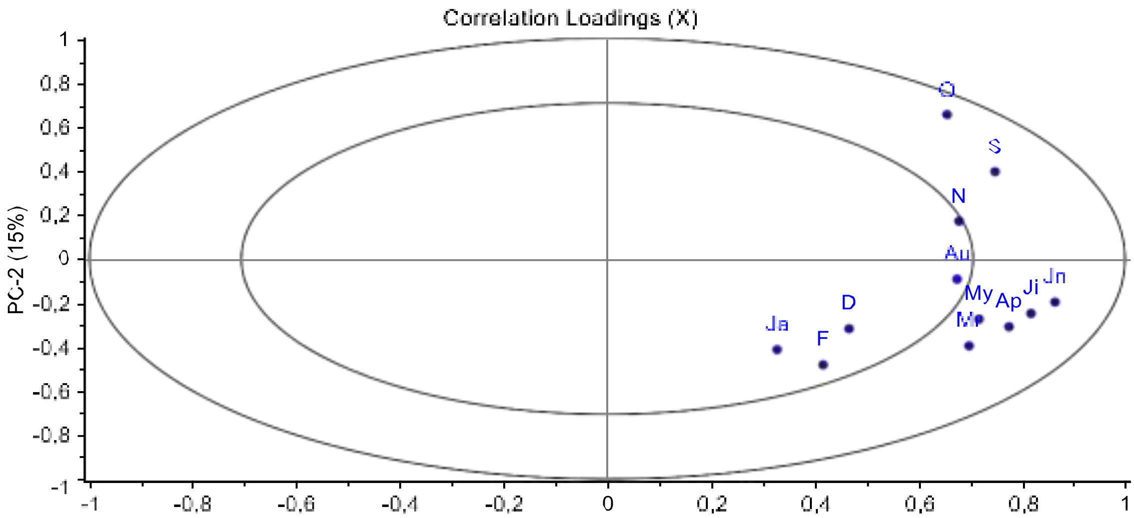

Figure 5: Correlation circles representing data for all twelve months of the year

It can be seen that nearly half of the months (five out of twelve) lie inside the first circle, suggesting that the correlations among these months are relatively weak, with relevance below 50%. Conversely, the other seven months fall between the first and second circles, indicating moderate correlations, with relevance values ranging between 50% and 75%.

Specifically, there is a generally strong positive correlation among the five months within the first circle. For example, February and December show a notable positive correlation. Similarly, there is a moderate positive correlation between January and November.

Among the seven months between the first and second circles, there is also a generally strong positive correlation. For instance, May and March exhibit a significant positive correlation.

Analyse of principal component of 31-years as variables and 12 areas- maxminmoy as individuals.

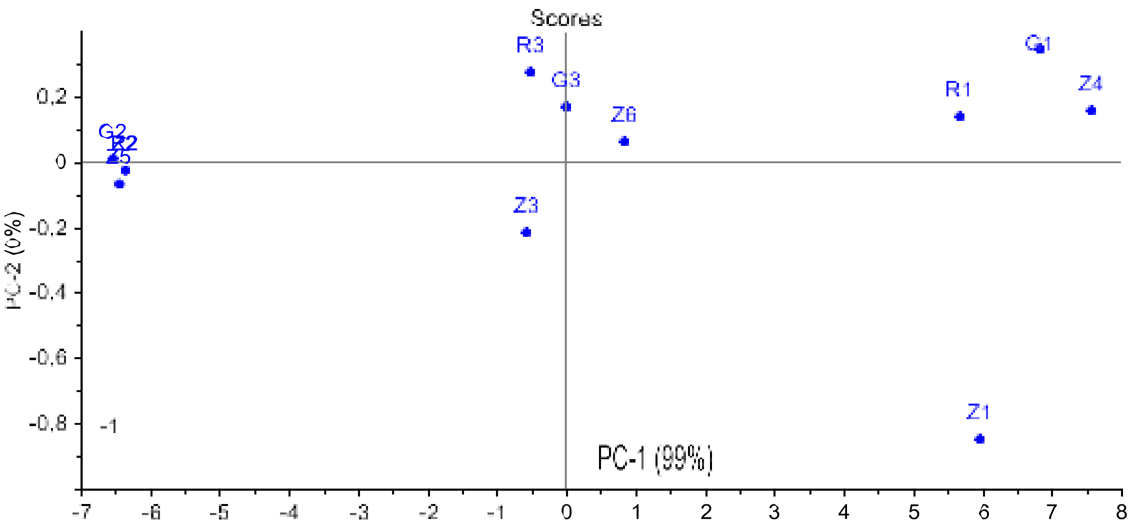

Figure 6: Two-dimensional PCA factor map illustrating data across 31 years and 12 regions

As shown in this figure:
1. The first two principal components (PC1 and PC2) capture 99% of the total variance in the data.
2. The areas are categorized into three distinct classes:
a. Class 1: Includes G1, R1, and Z4.
b. Class 2: Includes R3, G3, Z6, and Z3.
c. Class 3: Includes G2, Z5, R2, and Z2.

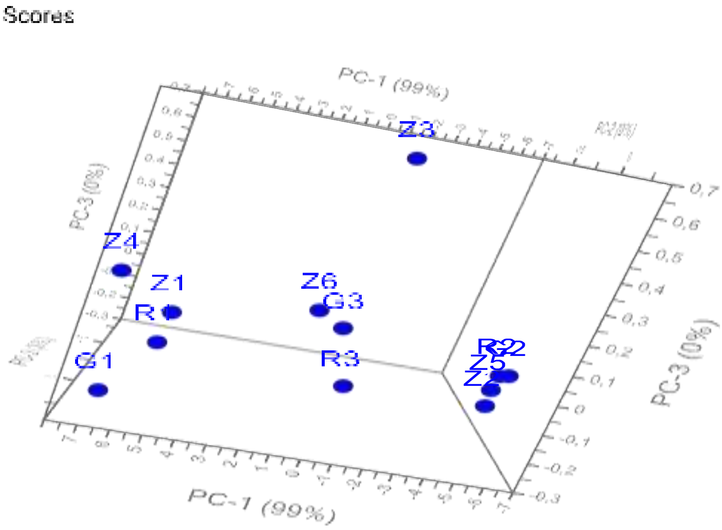

Figure 7: 3D PCA Factor Map 12 areas

The first three principal components account for 99% of the variance in the base data. The Tri- dimensional (3D) factorial map corroborates the findings from the two-dimensional (2D) factorial map, identifying three distinct classes of areas-maxminmoy:
- Class 1: Includes G1, R1, Z1, and Z4.
- Class 2: Includes R3, G3, and Z6.
- Class 3: Includes G2, Z5, R2, and Z2.

Additionally, the mean-maximum zone Z3 is notably different from all other zones.

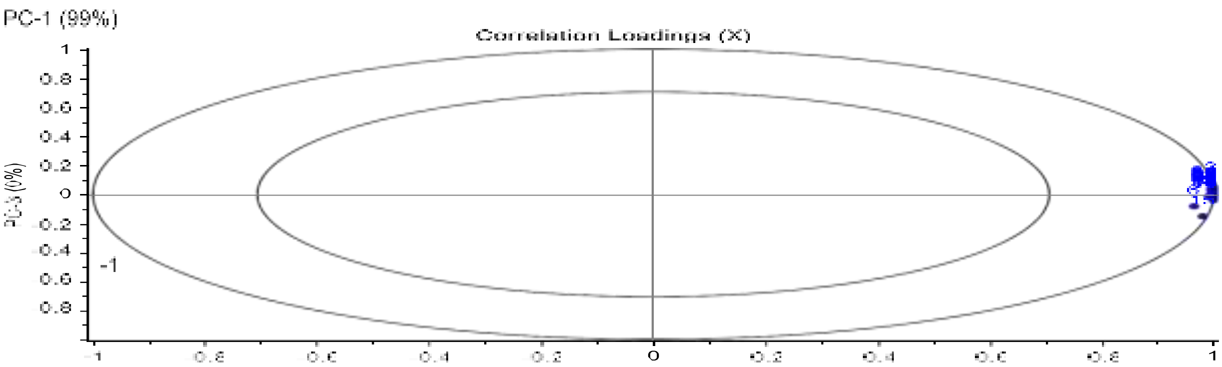

Figure 8: Correlation circles for temperature years

We note that all points for the 31 years are situated between the first and second circles, suggesting that correlations between any two years are relatively significant, ranging from 50% to 75%. There is no significant variation in temperature parameters (maximum, minimum, and average) across the 31 years studied.

Overall, a strong positive correlation is observed throughout the entire 31-year period, with some years showing particularly high positive correlations. Notably, the years 2004, 2006, and 2007 demonstrate especially strong positive relationships

PLS Forecast of Mean Annual Temperature (MAT)

In accordance with the figure, with the exception of individual 15, there are two distinct classes:

- Class 1: Consists of individuals 13, 97, and 98, representing the years 2013, 1997, and 1998, respectively.
- Class 2: Includes all other individuals.

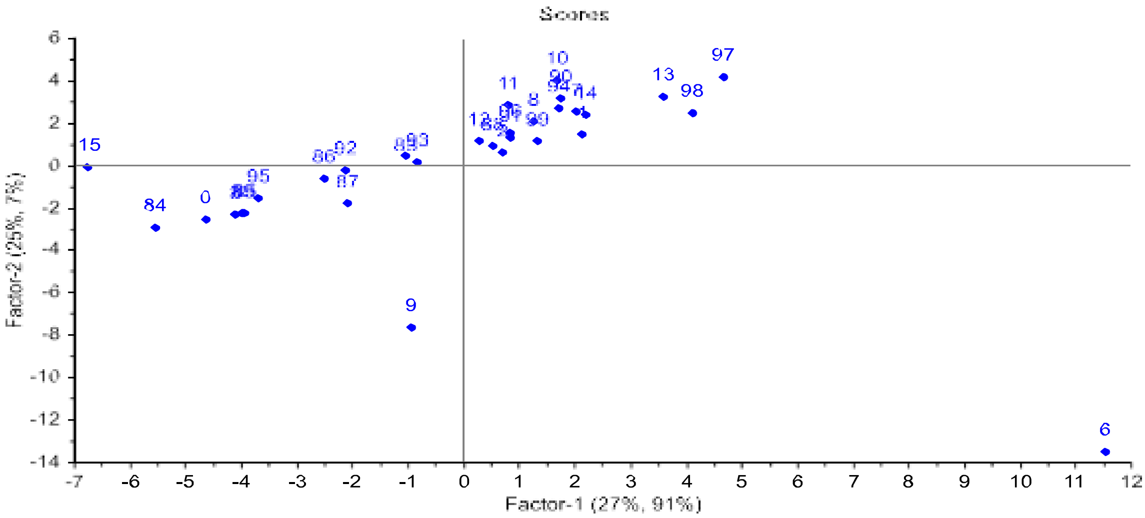

Figure 9: Score plot of individuals

As illustrated in the following figure, the inclusion of a third latent variable (Factor 3) accounts for nearly all the information in the original raw data table. This indicates a significant overall dependency among the natural variables studied.

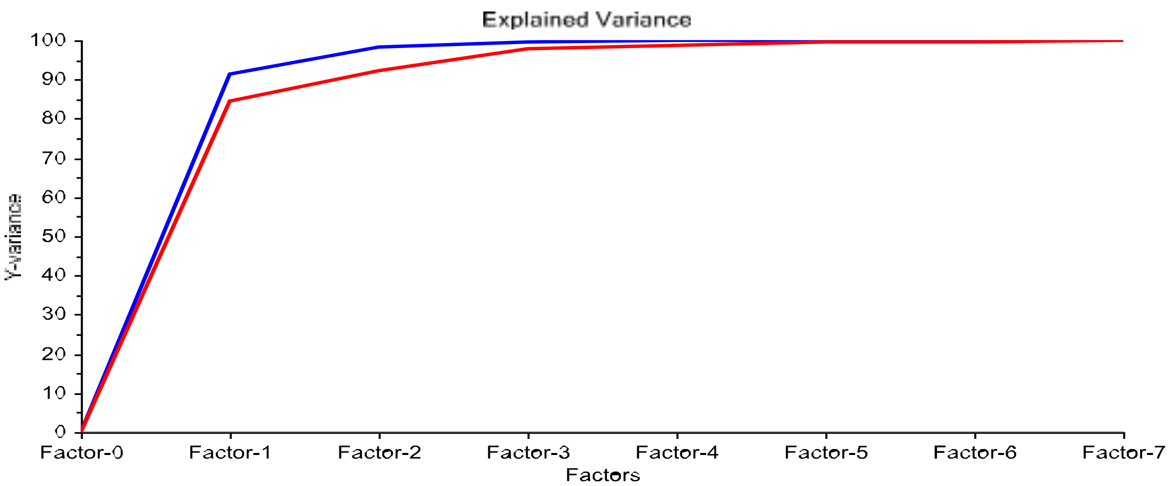

Figure 10: Explained variance using latent constructs: A single latent factor, referred to as Factor 3, was utilized.

The predictive model, calibrated through the Partial Least Squares (PLS) approach, demonstrated high robustness, as evidenced by its strong statistical performance. The coefficient of determination was nearly perfect (R2 = 0.995), while the Root Mean Square Error of Calibration (RMSEC) remained minimal (0.061). Additionally, there was a strong concordance between predicted and observed TAM values, as shown by a regression slope very close to one (Slope = 0.995).

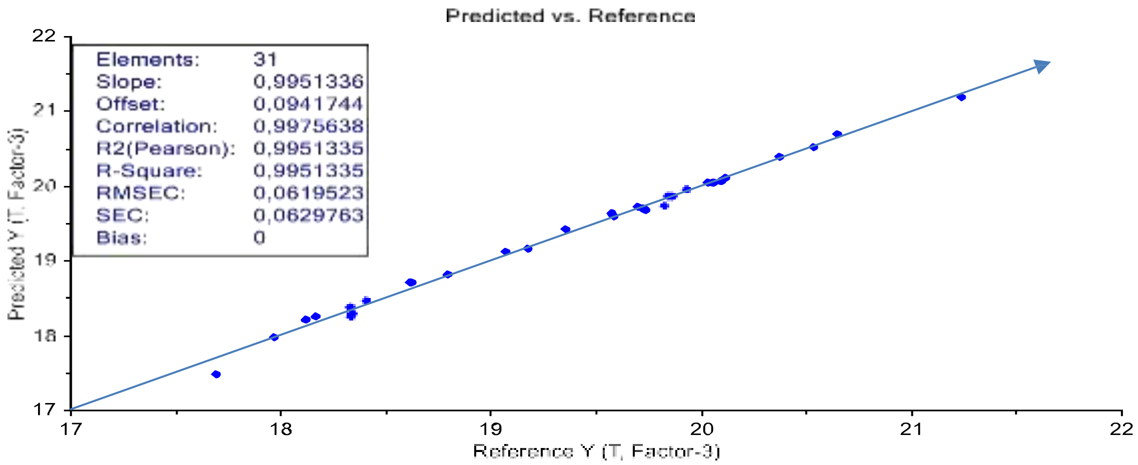

Figure 11: Calibration plot comparing predicted Mean Annual Temperature (MAT) against baseline MAT based on the third principal component

The Partial Least Squares (PLS) model exhibited strong predictive reliability during cross-validation, as demonstrated by key performance metrics:

- A high determination coefficient (R2 = 0.973) and a notably low Root Mean Square Error of Cross-Validation (RMSECV = 0.156).
- Furthermore, the alignment between predicted and observed TAM values remained consistent with calibration findings. The regression slope between these values was close to 1, indicating a strong level of agreement (Slope = 0.905).

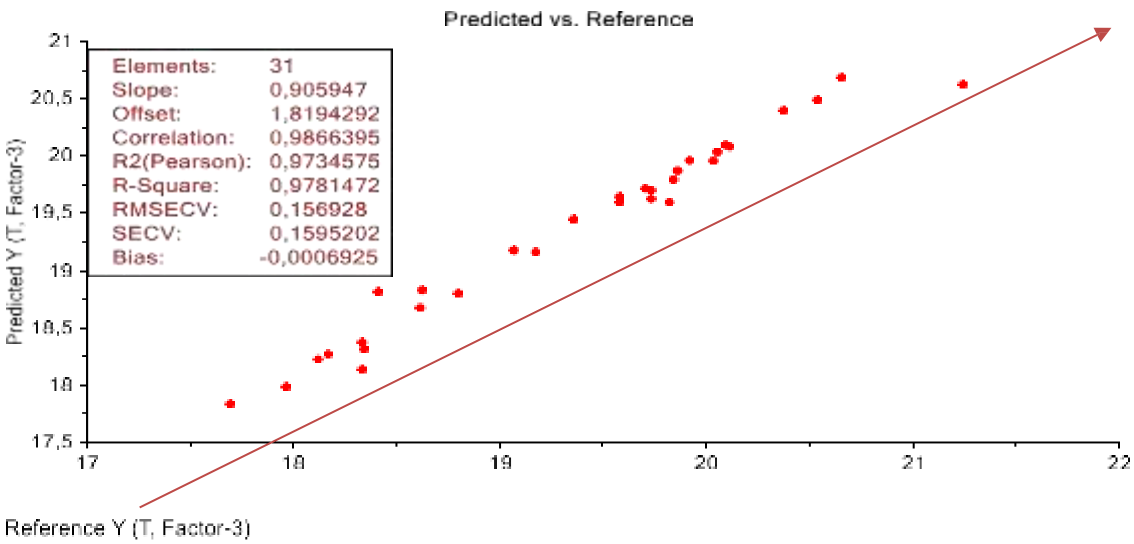

Figure 12: Using the third principal axis for cross-validation: Predicted Mean Annual Temperatures were evaluated against baseline values.

The use of four latent variables, as illustrated in the following figure, considerably improves the model's stability and performance, with all key statistical indicators reaching optimal values. During the cross-validation process, the model achieved a high coefficient of determination (R2 = 0.986) and a low Root Mean Square Error of Cross-Validation (RMSECV = 0.119). Consistent with the calibration stage, a strong agreement was observed between predicted and reference TAM values, as indicated by a regression slope of 0.928.

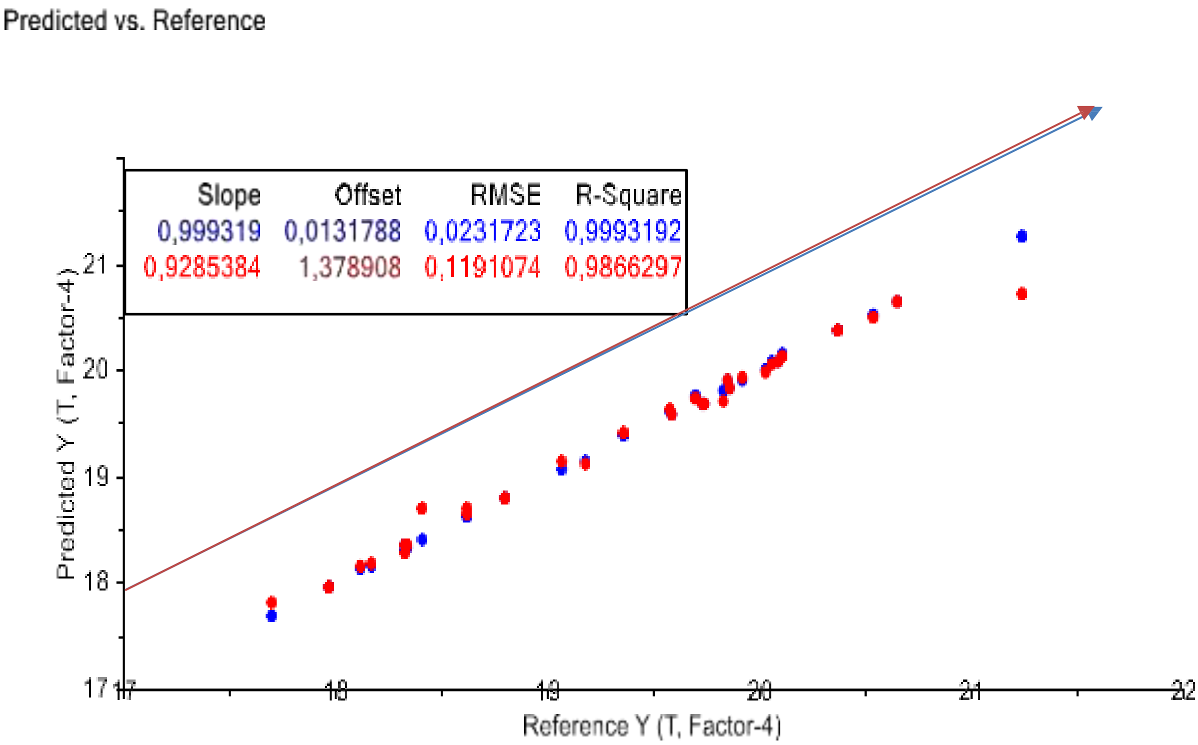

Figure 13: Comparison of predicted versus baseline MAT values using the first four principal components, illustrating calibration and cross-validation performance.

CONCLUSION:

This investigation successfully outlined the key aspects of climatic variability in the Guir-Ziz- Gheris basin. The Partial Least Squares (PLS) prediction model for the Mean Annual Temperature (MAT) demonstrated robustness and provided several benefits:

- This approach facilitates rapid evaluation of interannual similarities and temperature-related correlations across the various geographical areas of the Guir-Ziz-Rhéris basin.
- Efficient Prediction: It offers fast and accurate predictions for all the years studied, with minimal error.
- The model showed acceptable performance, as evidenced by statistical metrics such as the coefficient of determination (R2) and the Root Mean Square Error of Calibration (RMSEC), which confirm the strength and reliability of the PLS method.

Overall, the PLS method proved to be a fast and robust tool for predicting MAT across the years studied (1983–2015). Additional results are being finalized to enhance understanding of MAT prediction for the years in question. In order to improve the relevance and applicability of temperature forecasting using PCA and PLS approaches, it is recommended to integrate these tools into regional climate management systems. Public authorities should consider supporting the creation of dynamic platforms capable of analyzing updated climate data through these methods, to better anticipate thermal fluctuations. Such predictive outputs could inform strategic decisions in sectors sensitive to temperature changes, particularly agriculture, water management, and urban planning. Strengthening cooperation between researchers and decision-makers would facilitate the practical use of model outputs in shaping climate adaptation strategies. Moreover, future investigations could expand these models by including variables related to socio-economic conditions and land use, thereby increasing the predictive accuracy and policy relevance of the results.

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