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Prediction of the pluviometry in the Guir-Ziz-Rheris hydraulic basin

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Abstract: Predicting pluviometry plays a very important role in the field of agricultural innovation, especially in conditions of water stress as in the case of the Guir-Ziz-Rheris hydraulic basin (GZRHB). For this, we carried out analyzes (Analysis Component Principal: ACP and Partial Least Square: PLS) of rainfall data in the Guir-Ziz-Rheris area, on the basis of 30 years (1984-2015). Climatological locations were found to be classified into the following 2 classes. The first class composed of 2 subclasses: The 1st subclass contains, in particular, locations from the Guir and Rheris geographic zones while the 2nd subclass includes, in particular, locations from the Rheris and Ziz geographic zones. The second class is composed of the remaining locations. In fact, we have discussed this classification according to the altitude. In addition, the PLS regression has shown some correlations between 30 years of rainfall data (1984-2015). We observe that there is a more or less strong positive correlation between the 30 years. The PLS has allowed us to predict rainfall in the studied 30 years. Such a prediction can be extrapolated for the next 3 decades (2022-2053) in order to have rich and useful information for the benefit of innovation in agriculture when establishing climate scenarios.

Keywords: *Pluviometry; Classification; Prediction; PCA; PLS; Altitude; Guir Ziz Rheris basin*

1. Introduction

Precipitation is one of the variables commonly used to study climate variability. It is the result of the interaction of various physical phenomena and is characterized by its spatial and temporal variation. Thus, the analysis of rainfall data is essential for the prediction of meteorological information and also for the planning and management of water resource systems (Dastorani *et al.* 2016; Krishna et al. 2013; Li et al. 2017; Radhakrishnan and Dinesh 2006). Water chemistry is an essential complement to the study of water, the nature of the surrounding area, the supply and circulation areas, etc (Kouassi 2012). Because of their immediate and lasting repercussions on the natural environment and on humans, issues of climate change and variability have for some time been placed at the center of the preoccupations of scientists and policy makers around the world (Kouassi 2010).

Climate variability is accentuated by variations in the atmospheric circulation and local interactions between land and atmosphere (Xavier *et al.* 2022). predictability of monthly amounts based on auto-

regression algorithms (Lana et al. 2021), relation-ships between monthly amounts and atmospheric circulation indexes (Lana et al. 2017) and characteristics of rainfall intensities at the metropolitan area causing floods (Rodríguez-Solà et al. 2017; Lana et al. 2020). Other climate variables have received little interest from hydrologists, as have studies on the impacts of climate change. Important changes are occurring in pluviometry and have the potential to cause hydrological and climatic risks (Lira et al. 2022). In the literature, many definitions of drought have been offered, but the more precise definition of drought is the concept of a water deficit over a limited period of time (Maliva and Missimer 2012). The assessment of the impacts of climate change on water resources is an essential step in any process of setting up adaptation strategies for this sector (Driouech 2010). Global climate change is expected to have serious implications on the earth's environment; the impacts may be especially severe for water resources (Hailegeorgis and Burn 2009). Although not specifically designed to reproduce extremes of temperature and precipitation, general circulation models are increasingly being used to assess the climate change risk associated with such extreme events (Fowler *et al.* 2010).
The investigation and analysis of precipitation is so essential for prediction of metrological information (Radhakrishnan and Dinesh 2006) accurate prediction of precipitation is vital to better management of water resources, especially in arid environment (Feng *et al.* 2015). Rainfall is the most important part of the hydrology cycle (Venkata Ramana *et al.* 2013). The objective is to predict pluviometry for the next three decades.

2. Study area and method

2.1. Presentation of the study area

The Guir-Ziz-Rheris hydraulic basin is located in the south-east of the country, delimited by the Algerian border to the east and south, by the High Atlas massifs to the north and those of the Anti-Atlas to the south-west (Agence du bassin hydraulique du Guir-Ziz-Rheris d'Errachidia 2019). This action zone covers an area of approximately 59,000 km², or more than 8% of Moroccan territory. It includes, from east to west, the watersheds of Guir, Ziz, Rheris and Maïder (**Figure 1**).

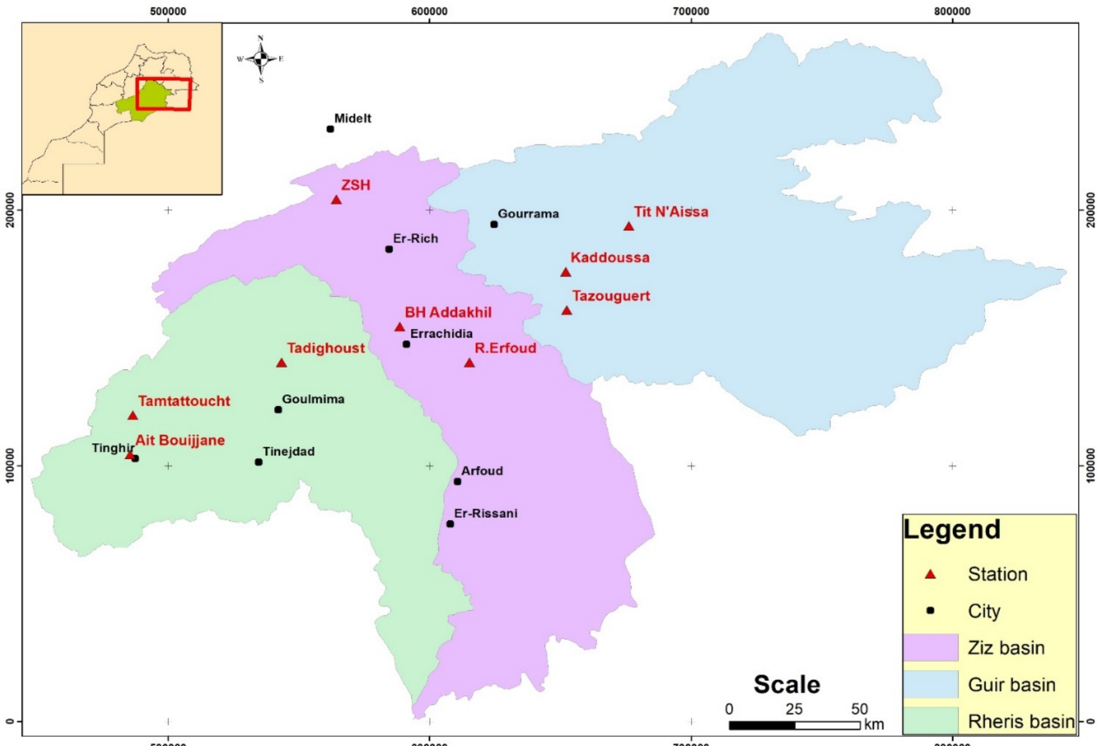

Figure 1. Geographic map of the Guir-Ziz-Gheris basin by ArcGIS.

2.2. Data collection

Thirty years of data archived by the Guir-Ziz-Rheris hydraulic basin agency for the period from 1984 to 2015.The sampling points concerned three watersheds in each basin three stations except the basin of Gheris two sampling stations; one station has been eliminated because it does not compose the total rainfall of the years dedicated to the analysis. This is why the data used had to respect two important criteria: the length of the chronicles on the one hand (covering the longest period of time possible), and the quality of the data on the other hand (the least amount of missing data possible) (Bambara 2019).

2.3. Instrumentation

In the present study Chemometric analysis, including the PLS analysis of the rainfall data for the thirty years from 1985 to 2015, has been performed using UNSCRAMBLER 10.2.

3. Results and discussions

3.1. Statistical analysis: PCA on 30-years variables and 24 areas individuals.

In order to be able to compare the 24 areas between them on the basis of the 30 years (1984-2015) of raw rainfall data, we projected them onto the vector space of the 30 years. In this paper the following abbreviations ‘‘max’’ and ‘‘min’’ (maximum- and minimum rainfall) are used. The results of this projection are presented graphically on the PC1-PC2 plane of the first two main components of the PCA (**Figure 2**).

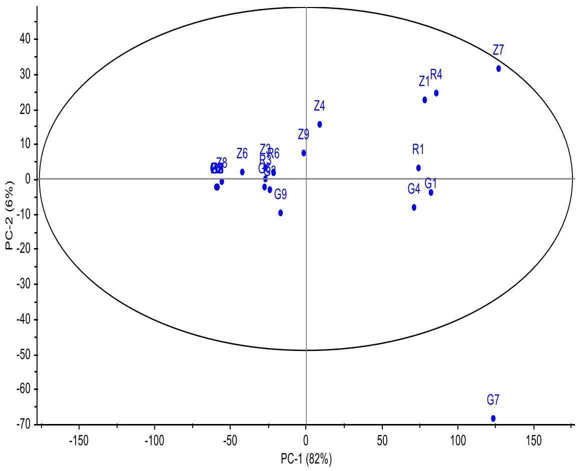

Figure 2. 2D PCA Factor Map for 30 years and 24 areas

According to **figure 2**:

1-Already 88% of the information in the raw data table is provided by the first two main components (PC1 and PC2).

2- The areas-maximum are classified in 2 or 3 classes such as:

A class made up of 2 sub-classes: The 1st sub-class contains notably: G1(Kaddoussa-max), G4(Tazouguert-max), R1(Ait boujane-max) while the 2nd sub-class contains notably: R4(Tadighoust-max), Z1(B.H.Dakhil-max), Z7(Z.Sidihamza-max).

A class that consists of the other areas-max.min.mean.

3- The areas-max.min.mean of index 1 (notably G1, R1 and Z1) resemble globally, in terms of the 30 years data, the areas-max.min.mean of index 4 (notably G4 and R4). from another point of view, it can be observed that altitude does not influence the distribution of the mean-max zones; for example, zones R1 and G1 (or G4) belonging to the same class despite the fact that they have different altitudes (see **Table 1**). Moreover, zones with similar altitudes, and geographically close to each other, are similar in the same class (G1 and G4).

4- The areas-max.min.mean of index 6 notably R6 (tadighoust-mean) and Z6(R.Erfoud-mean) which have similar altitudes globally resemble, in terms of the raw data of the 30 years, the max-min-moy zones of indices 3, 6 and 8 which have different altitudes.

5- According to the raw rainfall data for the 30 years, the areas-max.min.mean of indexes 1 and 4 (max), on the one hand, do not resemble the areas-max.min.mean of indexes 3, 6 and 9 (mean), on the other hand.

Table 1. Altitude of different stations

Station	Index	X	Y	Elevation (Z) in m (altitude)
Kaddoussa	G1,2 et 3	652150	175970	1108
Tazouguert	G4,5 et 6	652595	161045	1043
Tit N'Aissa	G7,8 et 9	676310	193940	1149
Ait Bouijjane	R1,2 et 3	485600	104450	1310
Tadighoust	R4,5 et 6	543500	140600	1036
BH Addakhil	Z1,2 et 3	588700	154500	1059
R.Erfoud	Z4,5 et 6	615400	140600	1009
Z.Sidi Hamza	Z7,8 et 9	564400	204390	1636

In order to retain as much information as possible from the raw rainfall data for the 30 years, we projected the 24 areas-max.min.mean onto the vector space of these years. The results of this projection are presented graphically in 3 dimensions (**Figure 3**).

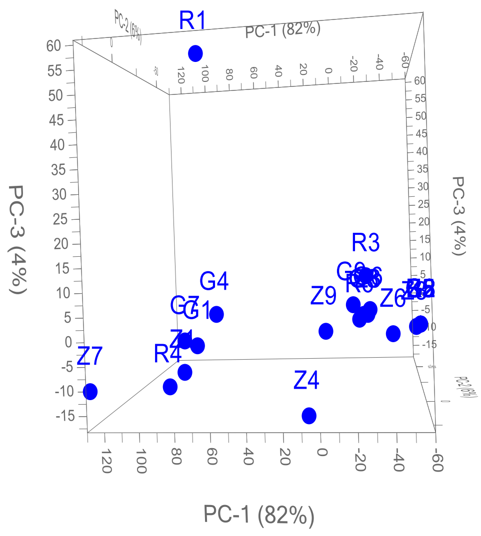

Figure 3. 3D PCA Factor Map 24 areas

The first 3 principals components provided us with a total of 92% of the information from the raw data. The 3-dimensional (3D) factorial map confirms the results found in the 2-dimensional (2D) factual map. Thus, we are dealing with 2 classes of areas-maxminmoy:

A 1st class which contains in particular: G1, G4, G7, R4, Z1 and Z7; these individuals correspond to maximum rainfall. For this purpose, this class can be divided into two sub-classes; the first one contains Z7, which has a high altitude and is characterized by a sub-Saharian climate, and the second one contains the remaining zones, which have average altitudes with a Saharian climate.

A 2nd class which contains R3, Z6, Z9 and others; these indices correspond to and minimum rainfall, and is subdivided into two subclasses; the first contains R3 and Z9, which have high altitudes and a sub-Saharan climate, and the second contains the remaining areas with medium altitudes and a Saharian climate. It can be noted that the mean-maximum zone R1 was found to be different from all the others. It can be concluded that this classification is manifested by the altitude and the nature of the climate of each zone. To this end, the Saharan regions where the increase in dry surfaces cause an increase in air temperatures by heat transfer. This results in an affection of the hydrological cycle in general and the formation of rain clouds in particular, hence the low annual rainfall heights. Consequently, hydrologic cycles are being transformed rapidly (Chang et al., 2015), with negative consequences also on the spatio-temporal availability of water resources (Molina and Zazo 2018). On the other hand, in sub-Saharan regions where forest areas are very extensive and sensitive to surface conditions, and where atmospheric humidity has a marked continental origin. Forest cover, which naturally absorbs carbon dioxide from the atmosphere, will contribute to reducing the atmospheric content of this greenhouse gas (Sultan et al. 2001). In addition to rainfall, the main source of plant water supply, potential evapotranspiration (ETP) and relative air humidity (RH) are climatic parameters with significant agro ecological impacts on plant development (Faurie et al. 2011). Finally, this possible rainfall patterns–CO_2 correlation is expected to be complemented by taking advantage of warming land's surface data, probably much more depending on GHGs (greenhouse gasses) increments than some patterns of the pluviometric regimes (Xavier et al. 2022). Being interested in being able to determine the correlations between the 30 years of rainfall data based on the 24 areas-max.min.mean, we have projected these years into the vector space of these mean-minimum zones. The results obtained are presented, in terms of correlation circles, in the PC1-PC2 plane (**Figure 4**).

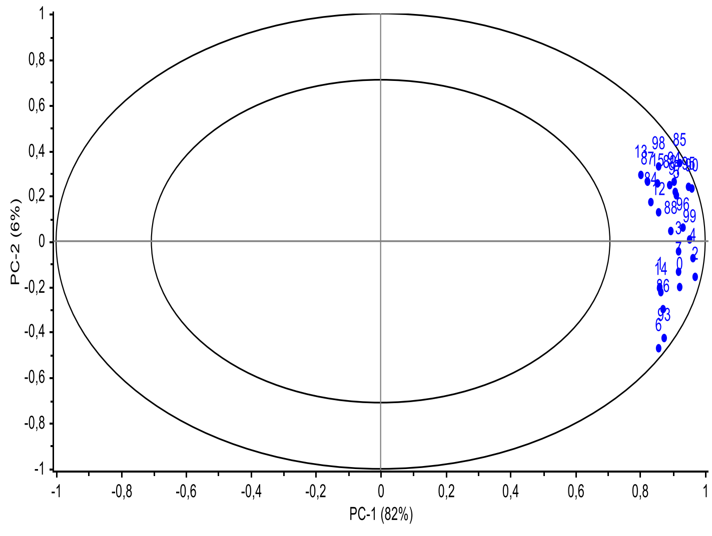

Figure 4. Correlation circles for rainfall years

We notice that since all the points of the 30 years are between the 1st and 2nd circle any information on the correlation between 2 years is relatively relevant with a relevance between 50 and 75%. In terms of rainfall parameters (maximum, minimum and mean) of the geographical areas studied there is no great difference between the 30 years. In fact, we observe that there is a more or less strong positive correlation between all 30 years. Very strong positive correlations can be noticed between years. We cite the 2 following examples knowing that there are others:

- 1st example: Years: 2002, 2003, 2004, 2007.
- 2nd example: Years: 2013, 1985, 1987, 1998.

3.2. PCA: 12-month variables and Individuals 274 areas year

In order to be able to compare the 274 areas years with each other based on the 12 months of raw rainfall data, we projected them onto the 12-months vector space. The results of this projection are presented graphically on the PC1-PC2 plane of the first two main components of the PCA (**Figure 5**).

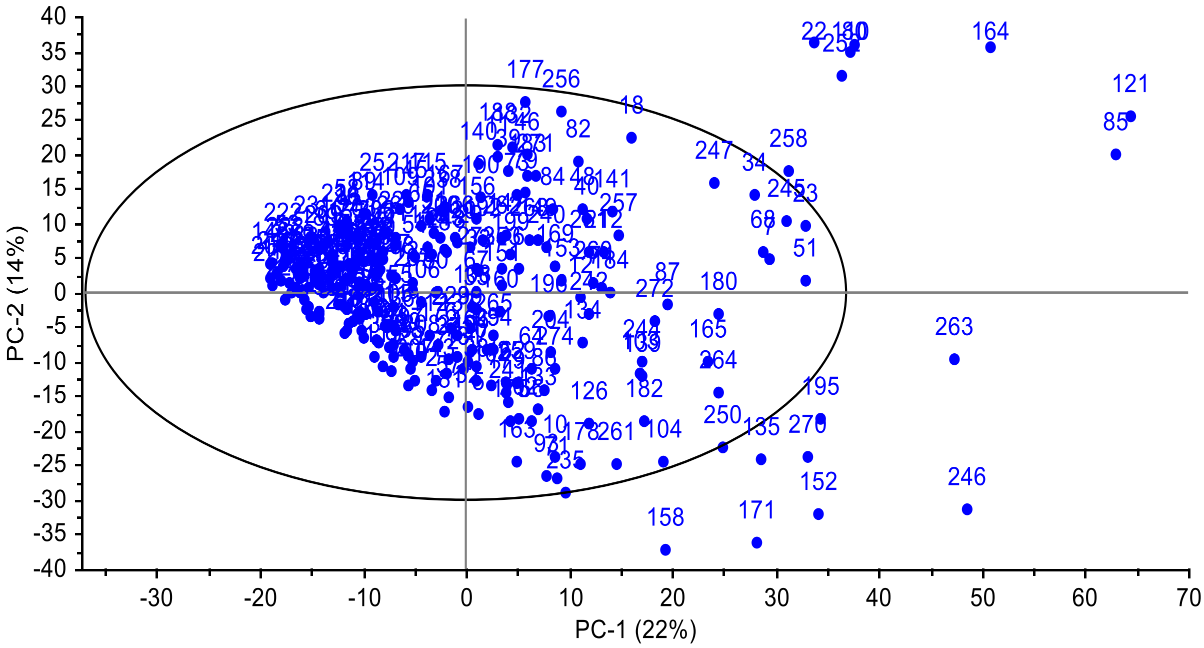

Figure 5. 2D PCA Factor Map for 12 months

According to the figure above:

1- The first two main components (PC1 and PC2) provide 36% of the information existing in the raw data table.

2- There is only one class that is net.

In order to keep as much information as possible from the raw rainfall data for the 12 months, we projected the 274 areas years onto the vector space of these months. The results of this projection are presented graphically in 3 dimensions (**Figure 6**).

The first 3 main components gave us a total of 49% of the information from the raw data with a 13% improvement compared to 2D. The 3-dimensional (3D) factorial map confirms the results found in the 2-dimensional (2D) factual map. Thus, it is a single class.

Since we are interested in determining the correlations between the 12 months of rainfall data based on the 274 zone years, we projected these months into the vector space of these zone years. The results obtained are presented, in terms of correlation circles, in the PC1-PC2 plane (**Figure 7**).

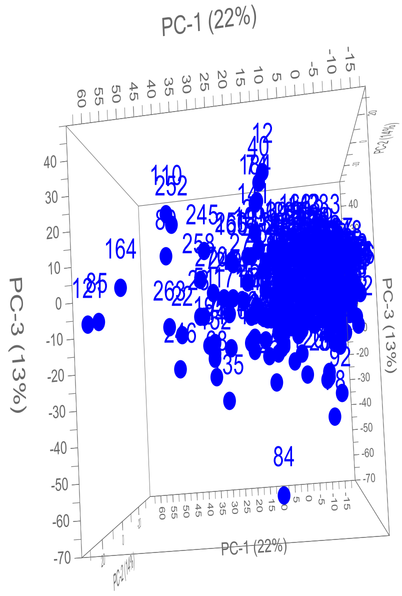

Figure 6. 3D PCA Factor Map for 12 months

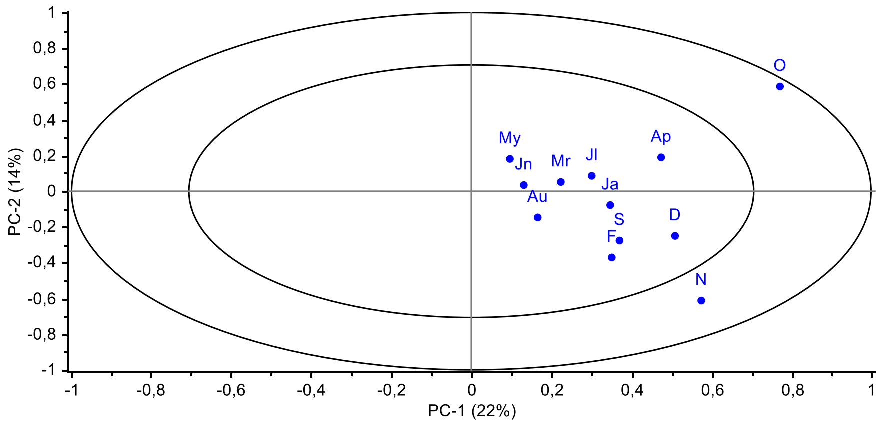

Figure 7. Correlation circles for the 12 months of the year

We notice that the majority of the months are inside the 1st circle, so any information on the correlation between 2 months of this group is irrelevant with a relevance of less than 50%, except for the 2 months (November and October) which are between the 1st and 2nd circle, any information on the correlation between these 2 months is relatively relevant with a relevance between 50 and 75%.

In fact, we observe that there is a more or less strong positive correlation between every 10 months within the 1st circle.

- Example: the months of February and September.

A mean positive correlation between the 2 months October and November.

3.3. PLS Prediction of Mean Annual Pluviometry (MAP)

According to the **figure 8**, apart from individual 15, 2 classes are observed:

- 1st class: 7, 90 and 96 (the years 2007, 1990 and 1996 respectively).
- 2nd class: all other individuals.

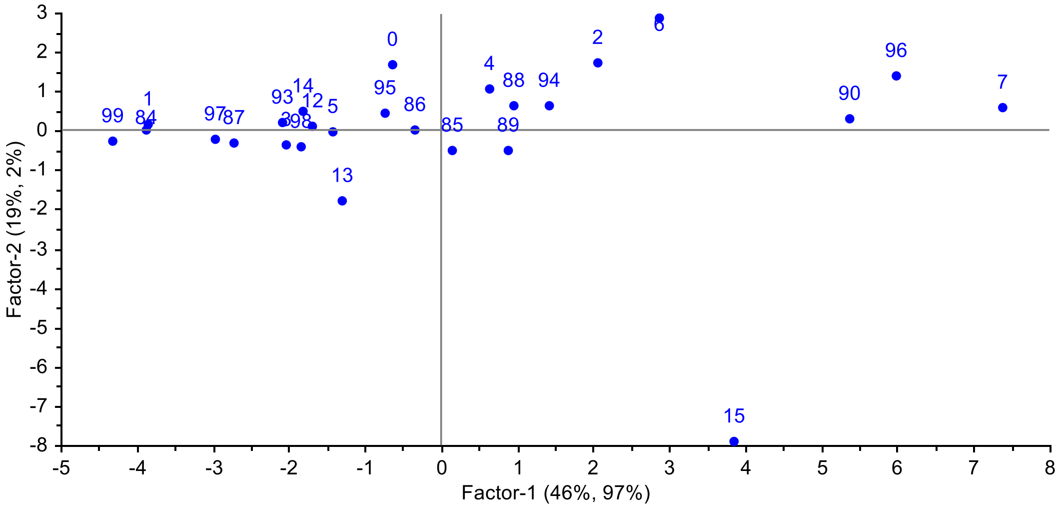

Figure 8. Factor map of individuals (Score plot)

Moving on to the graph of variables (**Figure 9**), apart from the variable R2, two classes are observed:
- 1st class: Z2, Z4, Z5, Z6, Z8, R5, G2, G5 and G8.
- 2nd class: all other variables: The rainfall in the case of these variables is closer to the average annual rainfall (point M) than in the case of the first class.

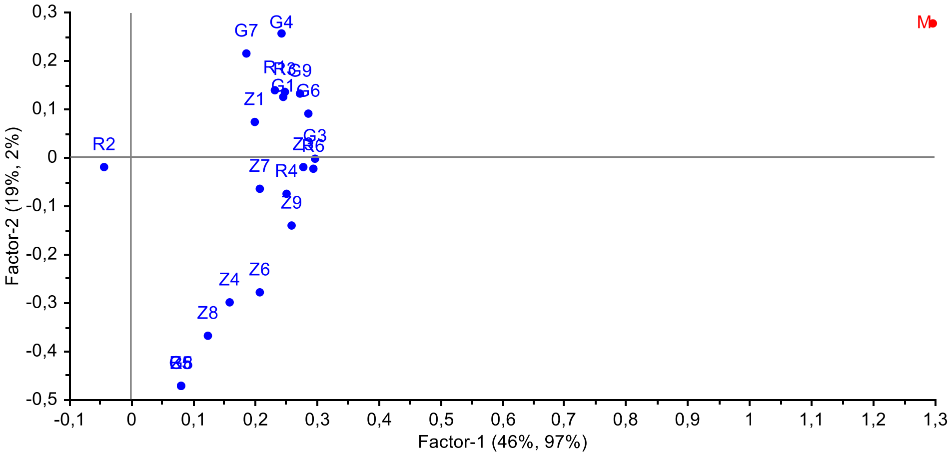

Figure 9. Loading Variables Graph

We have noticed that, as shown in the **figure 10**, a single latent variable (factor 1) is sufficient to explain almost all of the information in the initial table of raw data. That is, there is an overall dependency between the natural variables studied.

The **figure 11** approve that the calibration of the prediction model by PLS is good since the statistical parameters are satisfactory:
- Coefficient of determination close to 1 (R^2=0.97)
- Low error (RMSEC=0.687)

Moreover, the **figure 12** confirm that the predicted PAM coincides relatively well with the reference PAM since the slope of their two corresponding lines is close to 1 (Slope=0.97).

The cross-validation of the prediction model by PLS also remains good since the statistical parameters remain satisfactory:

- Coefficient of determination close to 1 (R^2=0.97)
- Low error (RMSECV=0.725)

As in the case of calibration, the predicted PAM still coincides relatively well with the reference PAM since the slope of their two corresponding straight lines remains close to 1 (Slope=0.91).

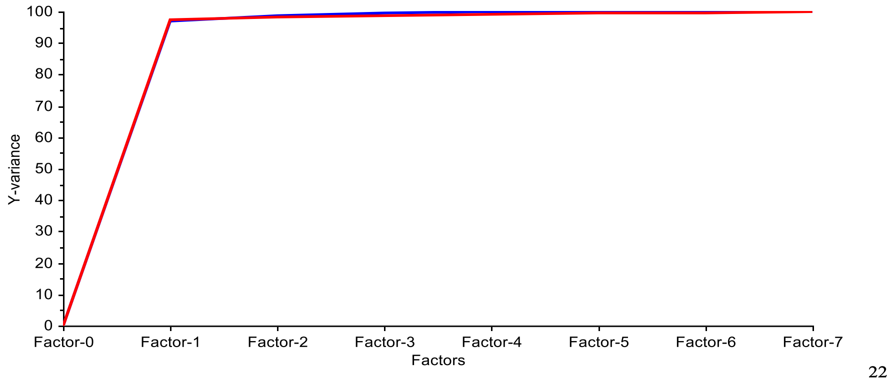

Figure 10. Explained variance according to the number of latent variables using a single latent variable (Factor)

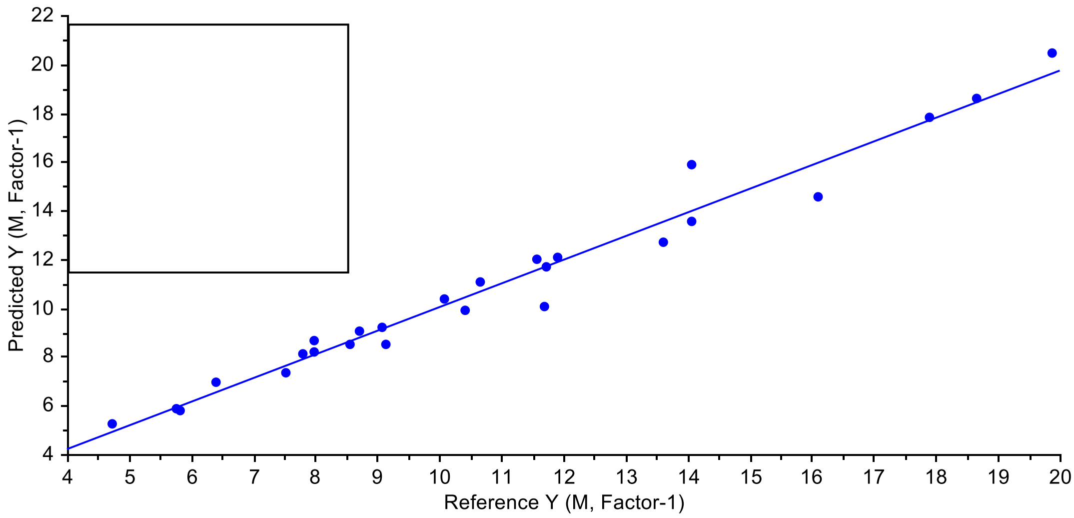

Figure 11. Calibration: Predicted Mean Annual Rainfall (MAP) versus baseline MAP using the first major component

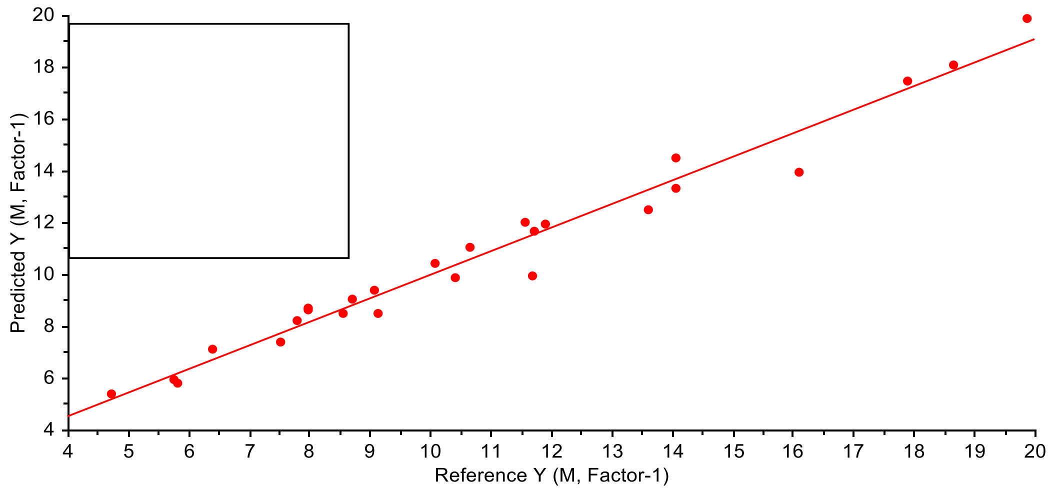

Figure 12. Cross-validation: Predicted Mean Annual Rainfall (MAP) as a function of baseline MAPs using the first major component

By using the 7 latent variables (**Figure 13**) we observe that the model becomes very robust since all the statistical parameters become perfect. In fact, in cross-validation we have:
- Coefficient of determination close to 1 (R^2=0.998)
- Low error (RMSECV=0.198)

As in the case of calibration, the predicted PAM still coincides relatively well with the reference PAM since the slope of their two corresponding straight lines remains close to 1 (Slope=0.990).

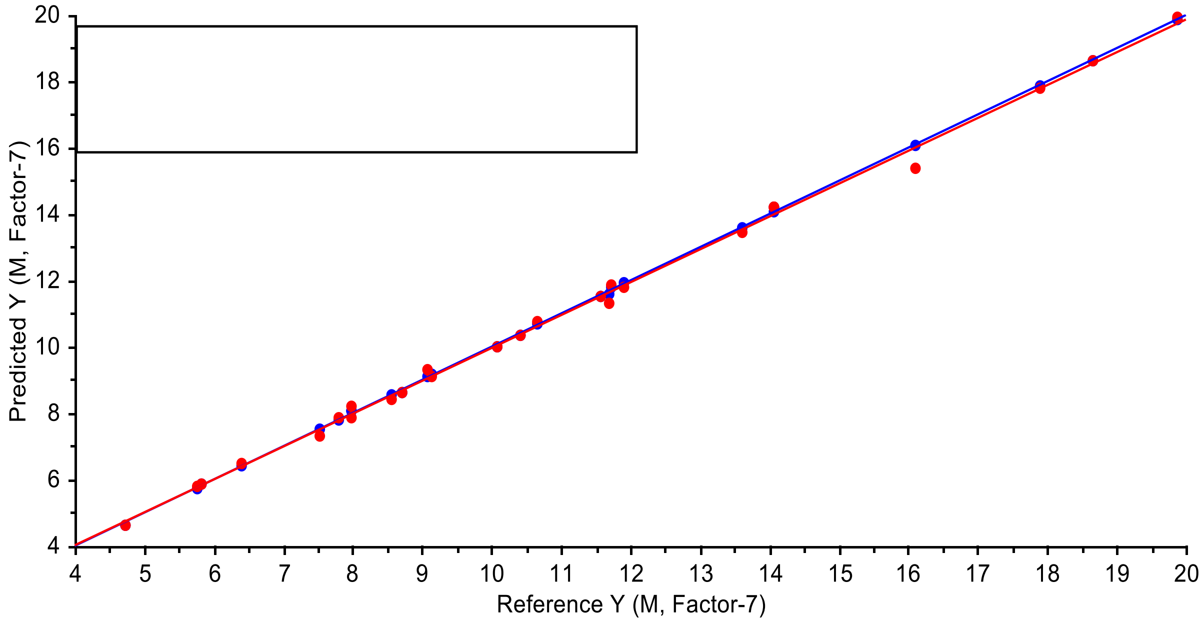

Figure 13. Predicted mean annual rainfall (MAP) as a function of baseline MAPs using the 7 main components. Calibration and cross-validation

Conclusion

Climate change is a current issue that challenges researchers. In Indeed, modern agriculture is optimized to low rainfall. This study characterized the main manifestations of climate variability in the ZIZ, RHERIS and GUIR geographical areas in Morocco.

The obtained results draw attention to the complexity of the relationship between climate change and the environment in arid and semi-arid environments.

In conclusion, the prediction model of the MAP by PLS proved to be robust. It allows to predict the similarities between years and the correlations between the geographical areas of the Guir-Ziz-Rheris basin in terms of rainfall and to offer a prediction on all the studied years in a fast way and with less error.

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Compliance with Ethical Standards: This article does not contain any studies involving human or animal subjects.

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