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ANALYSIS OF CEREAL PRODUCTION IN ALGERIA

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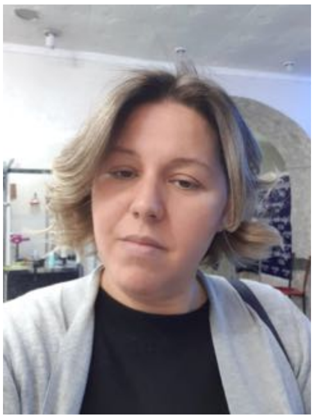

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ABSTRACT

Analysis of cereal production allows one to make decisions about the importance of certain products and the water resources. Improving cereal production is crucial in developing the standard of living in Algeria. Actually, it should be part of any future strategy for the country. Most of the arable land in Algeria is in a Mediterranean climate, where droughts are common and rainfall is distributed unevenly throughout the year. Research on the impact of climate variability and irrigation on cereal production is necessary due to the effects on the uneven performance of crops in Algeria. The study considered here is based on statistical methods to model the production of durum wheat, bread wheat, barley and oats. The first method used is principal component analysis. It was applied to classify the data in order to determine the relative importance of the various regions for the evaluation of cereal production. The results exhibit an increasing trend in the cereal production on the period from 2009 to 2012. The 2012 cereal harvest in Algeria proved to be the second highest ever recorded, after that of 2009, despite an unusual period of snow in February. It appears that durum wheat production was explained jointly by precipitation and irrigation. However, the variations in the production of the common wheat, oat and barley can only be explained by precipitation. Agriculture currently depends mainly on precipitation rather than irrigation. Modern irrigation systems could increase production. Therefore, if agricultural production is to be improved, important agricultural irrigation methods are needed to mitigate the impact of climate variability in each agricultural area, mainly in the southern regions of the country.

Key words: cereal, irrigation, rainfall, regression, production, wheat, oat, barley

INTRODUCTION

Agro-climatic constraints, combined with the recent effects of climate change, are weighing in on the development of Algerian agriculture. Research on the impact of climate change showed declining rainfall levels. The weather projections suggest that Algeria will have a sharp increase in aridity, which makes it more vulnerable to water stress and desertification. Agro-climatic in Algeria models predict that climate change will modify the water cycle, contributing to a degradation of agricultural land, a decline in agricultural production and yields, and a loss of biodiversity [1]. Most of Algeria's land is arid desert (the Sahara) and semi-arid, with low and unreliable rainfall, and few crops can be grown there. The Atlas Mountain ranges in the north separate the Sahara and high desert from the Mediterranean coast, and most crops are grown on lands in the foothills and along the coast. Therefore, most arable land, only 3.5% of the total surface of Algeria, is under a Mediterranean climate, where droughts are common, rainfall is uneven, and unreliable throughout the year. Algerian agriculture depends mostly upon rainfall rather than irrigation, and irrigation projects are often of limited scope. Algeria's agriculture evolved after independence. The country experienced multiple changes in order to modernize and decrease its high dependency on food imports. Nowadays, Algeria's agriculture industry continues to expand modern irrigation and size of cultivable land. Despite Algeria's geographical size, less than 4% of its total land area is cultivable.

The theme developed in this work has been treated by previous authors. A brief overview is given in the following. Knowing the water level of the Akosombo dam is heavily related to the hydro-electric power. According to Bessaoud [2], the principal component regression was applied to the input variables in the goal of reducing the large number to a few main components in order to explain the variations in the original data set. Locally generated agricultural land management models can be more effective in achieving sustainable agricultural production. The study due to Nuwategeka *et al.* [3] uses locally generated local knowledge to model the suitability for growing maize, rice and beans.

Two spatial models were paired using software applications to obtain land suitability comparisons. Maize is the most widely grown staple food crop in the sub-Saharan Africa. The research by Ogendo *et al.* [4] evaluates the influence of organic fertilizers based on manure on the growth, nutrient absorption and yield of maize, in two separate agro-ecological zones. Climate fluctuations are expected to have an adverse impact on agriculture in the poorest regions of the world, particularly those of developing countries such as Nigeria. In the paper [5], the authors used descriptive statistics (tables) and co-integration analysis to examine the considered data. Sellam *et al.* [6] analyzes the environmental parameters such as area under cultivation, annual rainfall, and food price index that influences the yield of the crop and establishes a relation between these parameters.

The aim of this work is to determine the impact of various factors on cereal production in Algeria. The data used are cereal production, irrigation (areas irrigated) and rainfall. The study conduction is to evaluate the effects of irrigation and rainfall on the cereal

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production. The data were subjected to principal component analysis and, regression modeling. The results showed that the crop yield depended heavily on rainfall and very little on irrigation.

The forthcoming Section 2 is devoted to the presentation of the methods used, namely principal component analysis and linear regression method. In Section 3, main results are stated. Conclusion is proposed in Section 4.

METHODS

Regression methods continue to be an area of active research. Regression analysis is the method of using observations (data records) to quantify the relationship between a target variable (a field in the record set), also referred to as a dependent variable and a set of independent variables, and also referred to as a covariate. In linear regression, the relationships are modeled using linear predictor functions whose unknown model parameters are estimated from the data. Most commonly, the conditional mean of the response given the values of the explanatory variables (or predictors) is assumed to be an affine function of those values. Linear regression models are often fitted using the least squares approach. Ordinary least squares find the value of parameters that minimizes the sum of squared errors; these coefficient estimates are the best possible estimates. In fact, the Gauss-Markov theorem states that OLS produces estimates that are better than estimates from all other linear model estimation methods when the OLS assumptions hold true. The coefficients computed are the ones that best fits the data. The analysis done using linear regression is based on the identification of factors that depend on cereal production. The coefficients computed are the ones that fit best for the data used [6]. The contributions related to the regression model are extensive. The main reference used here is Coursol's book [7], Diday [8], Rawling *et al.* [9], and Saporta [10]. Regression analysis is widely used for prediction, error reduction and forecasting. It can be used to infer causal relationships between the independent and dependent variables.

The study begins with the use of a descriptive statistical method, namely: the principal component analysis. Principal Component Analysis is a dimensionality-reduction method that is often used to reduce the dimensionality of large data sets, by transforming a large set of variables into a smaller one that still contains most of the information in the large set. Because smaller data sets are easier to explore, visualize and make analyzing data much easier, the idea of the principal component analysis is to reduce the number of variables. The principal components are linear combinations of the original variables weighted by their contribution to explaining the variance in a particular orthogonal dimension. The information maximum is in the first component, then maximum remaining information in the second and so on [10].

Sometimes variables are highly correlated in such a way that they contain redundant information. This allows the reduction of variables. Thus it is more interesting to have an input with correlated variables. Principal components represent the directions of the data that explain a maximum amount of variance, that is, the lines that capture most of the information in the data. Finding the directions of the data that contain the greatest

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variance is achieved by decomposing the sample correlation matrix into eigenvalues. The eigenvalues are ordered in decreasing order; this allows finding the main components in order of significance. Since there are as many principal components as there are variables in the data, the principal components are constructed in such a way that the first principal component represents the greatest possible variance in the data set. The second principal component is calculated in the same way; provided that it does not correlate with the first principal component and that it represents the next greatest variance. The principal component analysis shrinks the data by geometrically projecting it onto smaller dimensions called Principal Components (PCs), with the goal of finding the best data summary using a limited number of PCs. The relationship between variance and information is that, the larger the variance carried by a line, the greater the dispersion of data points along it and the greater the dispersion along a line, the more information it contains. To simplify it all, the principal components are new axes that provide the best angle to see and evaluate the data, so that the differences between the observations are more visible. These principal component analysis methods exist in other books, including that of Anderson [11], Escofier *et al.* [12], Jolliffe [13], Lebart *et al.* [14] and Dillon W and M Goldstein [15].

RESULTS AND DISCUSSION

Principal component analysis

Principal component analysis (PCA) allows to summarize and to visualize the information in a data set containing individuals (observations) described by multiple correlated quantitative variables. The principal component analysis assumes that the directions with the largest variances are the most important. Principal components represent the directions of the data that explain a maximal amount of variance, that is to say, the lines that capture most information of the data. Computing the eigenvectors and ordering them by their eigenvalues in descending order, allow finding the principal components in order of significance. The dataset contains the harvest of 4 types of cereals for 48 wilayas.

The correlation between a variable and a principal component (PC) is used as the coordinates of the variable on the principal component. The representation of variables differs from that of observations: observations are represented by their projections, but variables are represented by their correlations. The dimension with the most explained variance is called F1 and plotted on the horizontal axes; the second-most explanatory dimension is called F2 and placed on the vertical axis. Inside this 2-dimensional circle the original 4 variables are projected in red onto this 2-dimensional factor space. If 2 red lines are pointing in the same direction then they are highly correlated, if they are orthogonal (this means at a 90 degree angle) they are unrelated and if they are pointing in opposite directions they are negatively correlated.

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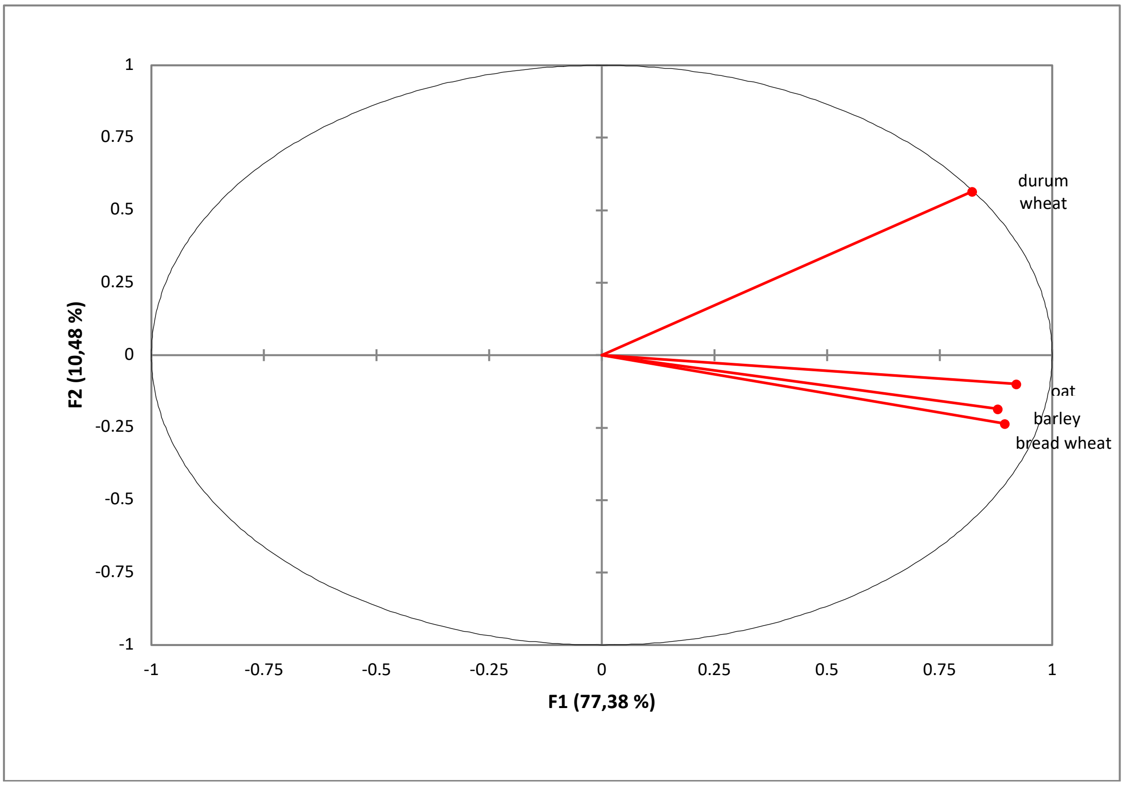

Figure 1: correlation circle

The correlation circle shows the correlations between the components and the initial variables. To interpret each component, we must compute the correlations between the original data and each principal component. The distance between variables and the origin measures the quality of the variables. Variables that are away from the origin are well represented. The group of three very tightly knit variable markers for 3 variables "productions" barley, bread wheat and oat, suggests a group of highly correlated variables. In dataset, the variable durum wheat is pointing up and to the right, and then the rest of the variables are bunched up together pointing down and to the right. Since all the variables are pointing to the right, they are at correlating on this first principal component F1, it represents all cereal productions. The more interesting might be the second principal component F2, since that is where we see a clear division between the durum wheat on the one hand and all the other cereal productions on the other hand.

Interpretation of the principal components is based on finding which variables are most strongly correlated with each component. The PCs can then be interpreted based on which variables they are most correlated in either a positive or negative direction. The very high proportion of variability explained by the two-dimensional principal subspace provides solid grounds for conclusions. The first two PCs account for 77.378% and 10.478%, respectively, of the total variation in the dataset, so the two-dimensional scatter-plot of the 48 wilayas given by figure 1 is a very good approximation to the original scatter-plot in four-dimensional space. It is, by definition, the best variance-preserving two-dimensional plot of the data, representing over 88% of total variation. Percentage of total variation is an obvious measure of how good two-

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dimensional representation is. There is, therefore, some distortion in the two-dimensional representation.

All of the loadings in the first PC have the same sign, so it is a weighted average of all variables, representing "overall size". In Figure 2, large productions are on the right and small productions on the left. The first principal component increases with increasing productions. The second PC has negative loadings for three variables and positive loading for the durum wheat variable, representing an aspect of the "shape" of production. This second component is a contrast of durum wheat (0.873) against bread wheat (-0.417), oats (-0.201) and barley (-0.175). Wilayas near the top of figure 2 have smaller productions of durum wheat, relative to their others productions, than those towards the bottom. The relatively compact cluster of points in the bottom half of figure 2 is thought to correspond to small productions. Such PCA plots are often used to find potential clusters. Based on Figure 2, it is clear that the wilayas of Sétif, Tiaret and Sidi-Bel-Abbès form a distinct cluster on the right. These wilayas are characterized by large productions. Projecting the marker for "Tiaret" onto the positive direction of all variable markers suggests that wilaya Tiaret (on the right of the plot) has a large cereal production. Inspection of the data matrix confirms that it is the largest production on two of the four variables, and close to largest for the durum wheat. South wilayas (on the right) have small productions. Individuals whose markers are close to the origin have values close to the mean for all variables, like Saida and Constantine. Compact cluster structure in Figure 2 in the left of the plot, is formed by the wilayas which produces little or no cereal.

Conclusion: it is essentially the wilayas of the east and center produce more durum wheat than the other cereals; while in the west it is bread wheat but also barley and oats grown there. It should also be noted that southern wilayas have low yields in different types of cereals (practically nonexistent).

The latest component explains only 0.005 of the variability in the data. This component may not be important enough to include. The third component is correlated with barley. This component could be viewed as a measure of the barley production. The third and fourth principal component explain very small percentages of the total variation, so it would be surprising if it found that they were very informative and separated the groups or revealed apparent patterns. Thus, PC3−PC4 can be ignored, which contribute little (12%) to explaining the variance, and express the data in two dimensions instead of four.

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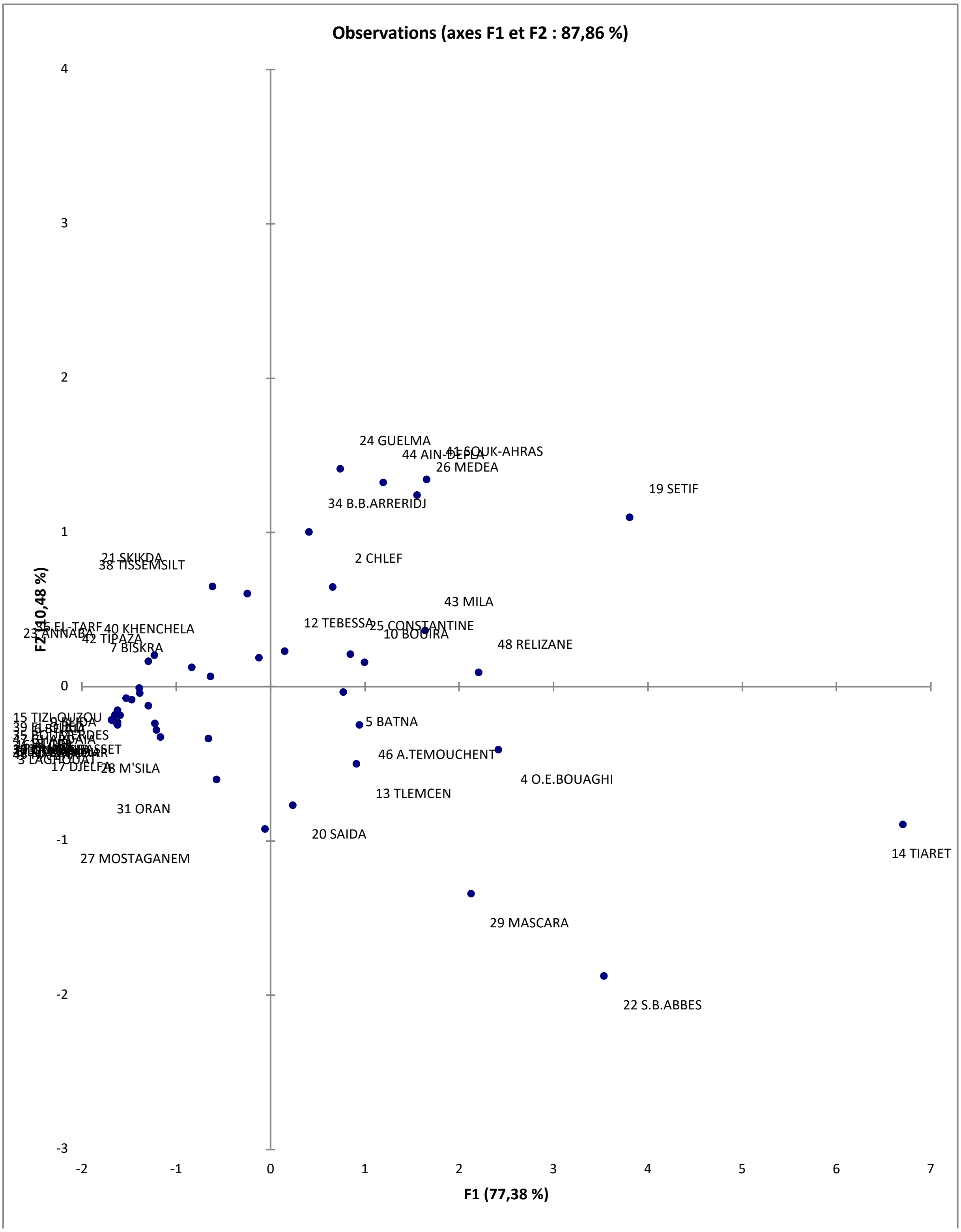

Figure 2: Graphical representation of data points on the two first components

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Second analysis
It may be interesting in describing and analyzing how years differ in the cereal productions. The following analysis concerns the principal component analysis carried out on the data table contains years and types of cereals. The table is of dimension (13 × 4), the productions are in quintals. The principal component analysis was done on the correlation matrix, even though it could be argued that, since all measurements are made in the same units, the covariance matrix might be more appropriate. The correlation matrix was preferred because the covariance matrix gives greater weight to larger, and hence more variable, measurements, such as durum wheat production. The first eigenvalue is equal to 3.550 and the PC1 provides 88.579% of the initial information. This means that if we represent the data on this axis, then we will have 88.579% of the total variability which will be preserved. Using the first two PCs, we obtain 95.403% of the total inertia of the initial data table. Consequently, the projection on the first two axes offers a quality of faithful representation of the initial data.

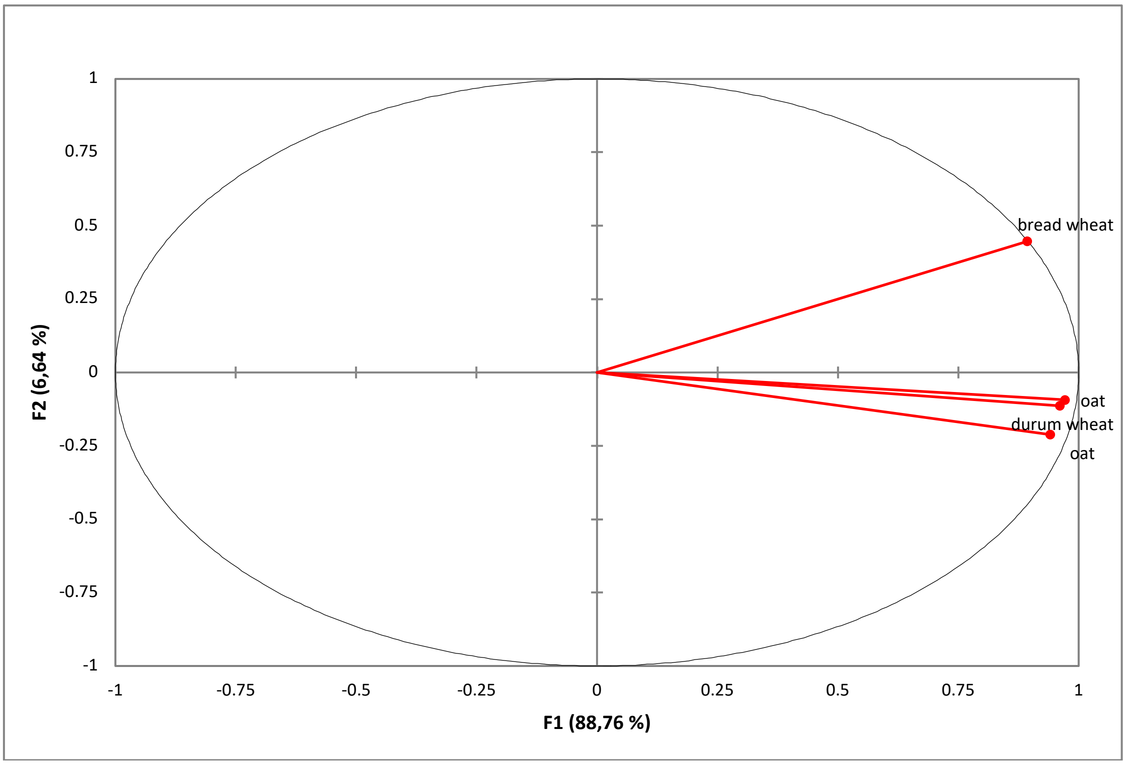

Figure 3: Correlation circle

The principal component analysis constructs low dimensional plots of a set of data from information about similarities or dissimilarities between observations. In any case, a description of the sample, rather than inference about the underlying population, is often what is required, and the PCs describe the major directions of variation within a sample, regardless of the sample size.

The first PC has positive coefficients for all variables and simply reflects overall "size" of the individuals.

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A graph of these data with respect to the first two PCs has been given in Figure 4, and it was noted that the first PC succeeds in separating years with high productions from years with low productions. The second PC accounts for slightly less than 20% of the total variation. This second PC contrasts some of the productions with others, and can often be interpreted as defining certain aspects of "shape". The second PC can be interpreted as a contrast between 'bread wheat' and the others productions.

Overall, the first two PCs account for a substantial proportion of total variation, 86.5%. Because there are relatively strong correlations among the 4 variables, the effective dimensionality of the 4 variables is around 1 or 2, a substantial reduction then occurs.

Interpreting observations consists of examining their coordinates and especially their resulting graphical representation referred to as first principal plane (Figure 4). The aim is to see how the observations are scattered, which observations are similar and which observations differ from the others. The use of the results of the analysis of the variables allows the interpretation of the observations. For example, the first component is strongly correlated with the original variables, this means that years with large positive coordinates on axis 1 (2009, 2012) are characterized by the fact that productions have values much larger than average (the origin of the axes represents the center of gravity of the data cloud). And vice versa years with negative coordinates on axis 1(2000, 2008) are characterized by the fact that productions have values much lower than average.

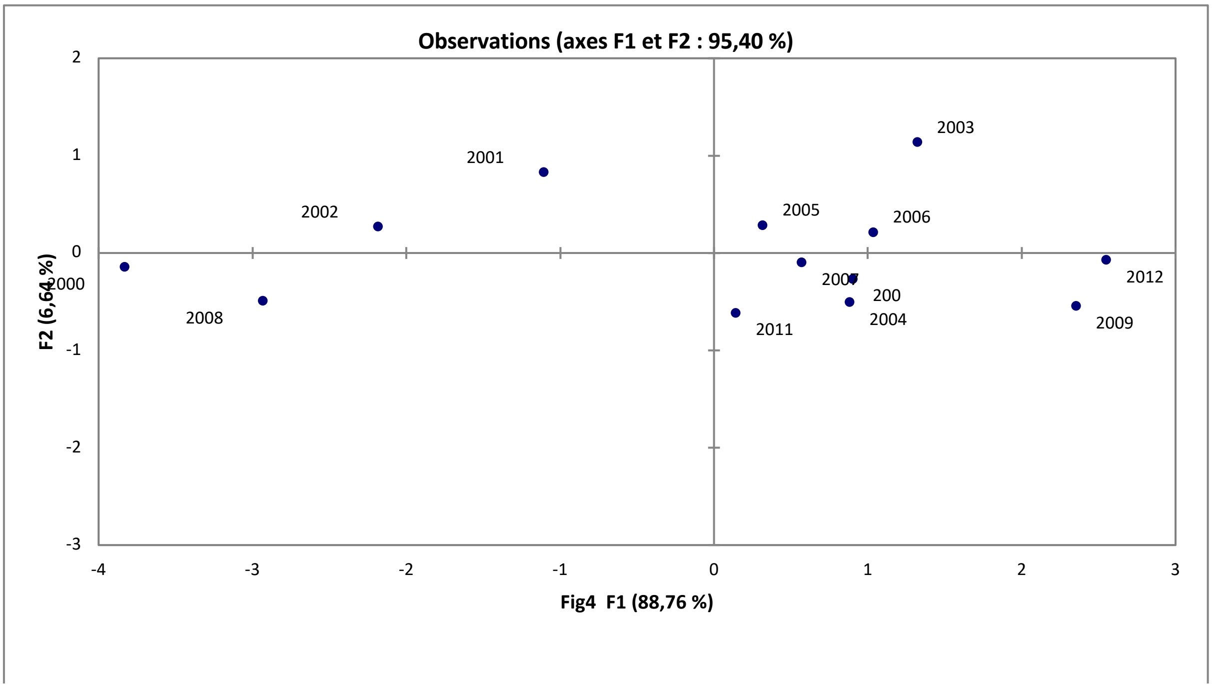

Figure 4: Graphical representation of data points on the two components

If a good representation of the data exists in a small number of dimensions then the principal component analysis will find it, since the first two PCs give the 'best-fitting' 2-dimensional subspace. An examination of the evolution of cereal production reveals

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three clusters. The first group contains the years when there was high cereal production (2009, 2012), the second consists of years with low production (2000, 2008, 2002 and 2001) and the third includes the years when production was average (the remainder).

The coverage rate of national production remained constant over the whole period from 2000 to 2012; with the exception of a few exceptional campaigns such as 2008, a particularly dry year and 2009, the year in which production was the best of all time. Production in this year reached 61.2 million quintals. Thus, we see that the country has managed to "maintain" the same level since 2000, with limited variations. This is an important achievement, in the sense that the performance in terms of production volume does not record such large and abrupt variations from one year to the next; apart from the two years mentioned.

The principal component analysis differs from linear regression in that the principal component analysis minimizes the perpendicular distance between a data point and the principal component, whereas linear regression minimizes the distance between the response variable and its predicted value.

Regressions Analysis

Regression model is widely used for prediction, error reduction and forecasting. It can be used to infer causal relationships between the independent and dependent variable. Regression analysis is a way of mathematically sorting out which of those independent variables does indeed have an impact on dependent variable.

Linear regression models are often fitted using the least squares approach. Ordinary least squares find the value of parameters that minimizes the sum of squared errors. These coefficient estimates to be the best possible estimates. In fact, the Gauss-Markov theorem states that OLS produces estimates that are better than estimates from all other linear model estimation methods when the OLS assumptions hold true. The coefficients computed are the ones that best fits the data. First, a regression analysis of durum wheat production vs. irrigation is performed. High quality durum wheat is grown in areas with a relatively dry climate, with warm days and cool nights during the growing season. The highlands (Hauts Plateaux) are the main cereal zones of Algeria. Durum wheat produced in moist conditions tends to have lower vitreous grain content, making it less suitable for making pasta. The crop considered for analysis is durum wheat because it is the most common crop cultivated in many areas of Algeria. The production of durum wheat$y_i$and irrigation x_i were measured over a period of 13 years. For linear regression, the model is as follows:

$$\mathrm{y_i} = b + ax_i + e_i$$

The random variablee_i is the error term in the model. In this context, error does not mean mistake but is a statistical term representing random fluctuations, measurement errors for example. Using the observed values x and y, parameters can be estimated and inferences such as hypothesis tests will be made. Also, the estimated model can be used to predict the value of y, for a particular value of x, in which case a measure of predictive precision may also be of interest. The correlation coefficient between production and irrigation is

$$r = 0.66408$$

The existence of a linear relationship between these two variables is, therefore, proven. The estimates of the two parameters provide us the equation regression (see Table 6)

$$y = 162.71x + 5.6215 \times 10^5$$

This means that increasing irrigation by one unit increases durum production by 162.71. It can be said that there is a significant linear relationship between durum wheat production and irrigation.

It is important to check if the model fits well with the data. Indeed, one of the objectives is to be able to predict the value of y, knowing a value of the variable x. However, if the fit is wrong, there is no hope of getting a good prediction. The Figure 5 presents the residuals which are the differences between the observed value of the dependent variable and the predicted value.

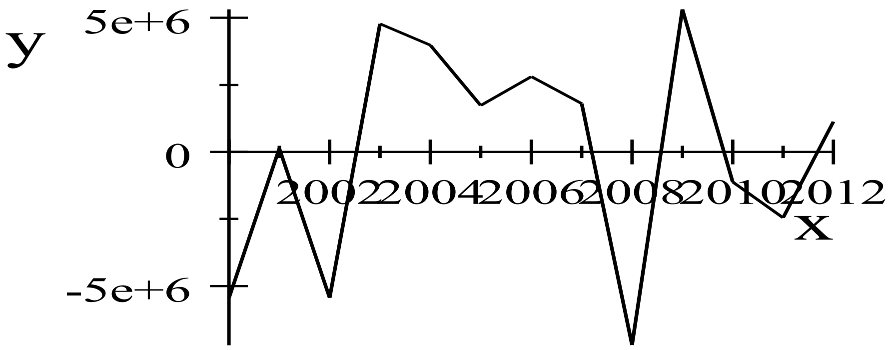

Figure 5: Residues

The biggest difference is during 2008; in other words, the production of durum wheat produced during 2008 is much lower than the expected production in view of the irrigation carried out. The opposite occurred during the year 2009. Production exceeded "forecasts" that could be made in relation to production of durum wheat.

The second regression concern production of durum wheat vs. rainfall
The model is as follows:

$$y_i = b + ax_i + e_i$$

The random variable e_i is the error term in the model.
The correlation coefficient between production and precipitation is r = 0.85809. This is favorable to the existence of a linear relationship between these two variables. Since there is a relationship between these two variables, then it is possible to build a model that predicts cereal production based on rainfall. The results are given in Table 7. We deduce the model

$y = 35401x - 1593170$ (*)

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Again, from table 7, the p-value: 0.0001748, being very low, the hypothesis $H_0: a = 0$ is rejected**.** Therefore, the existence of a significant linear relationship between durum wheat production and rainfall is accepted. The results of R^2clearly indicate that the crop's yield is highly dependent on the rainfall. Similarly, it is found that durum wheat yield plays a good role as a response variable for the explanatory variable rainfall. Glancing at (*), it is noticeable that probably the production is higher when it rains a lot. If x=0 then y=-1593170.

The other regressions are summarized below:

- Irrigation does not affect the production of bread wheat.
- Rainfall affects the production of bread wheat.
- Irrigation does not affect barley production.
- Rainfall affects the barley production.
- Irrigation does not affect oat production.
- Rainfall affects oat production.

Unequivocally, the null hypothesis can be rejected; the slope of the line is not null in the case of rainfall. On the other hand, the null hypothesis that the slope is zero is accepted almost systematically in the case of irrigation. This can be interpreted as follows: Irrigation does not affect the production of cereals other than the production of durum wheat; there is only rainfall that influences all productions.
Conclusion: Algerian agriculture relies mainly on rainfall rather than irrigation.

The last regression is production vs. irrigation and rainfall
Simple linear regression is useful, but it is oftentimes desirable to see how several variables can be used to predict a dependent variable. The response y is often influenced by more than one predictor variable. For example, the yield of a crop may depend on the amount of rainfall and irrigation. The model in this case, is written as

$$y_i = b_0 + b_1 x_{1i} + b_2 x_{2i} + e_i$$

Where$x_1$denote the variable "rainfall" and$x_2$the variable "irrigation". The parameters estimators were calculated; the results are given in Table 8. Thus, the model is:

$$y_i = -7.2160 \times 10^6 + 29136\mathrm{x}_{1\mathrm{i}} + 93.9\mathrm{x}_{2\mathrm{i}}$$

The conclusion is that the coefficient of the first variable is significantly different from 0 (p-value 0.00028 ***). In other words, the rainfall variable influences durum wheat production. Idem, the variable “irrigation” influences the production of durum wheat (Table 8).

Yield prediction is one of the most critical issues faced in the agricultural sector. Uncertainties in the weather conditions lead irregularities in the production of the crops. Regression analysis is used to establish the relationship crop yield among these two factors and to identify their influence.

CONCLUSION

Over the next few decades, a central goal in agricultural decision-making will be to decrease the risk associated with a changing climate. The previous studies have used statistics models to represent cereal yield responses to climate. The results exhibits that statistical models contains substantial information on the importance of climate and management variables for yield variability. The methods developed in this study links observations with the analysis of probabilistic properties of cereal productions, thus responding to the critical need for knowledge on yield responses to rainfall and irrigation. In general, the yield of wheat in Algeria has exhibited an increasing trend and small variability over the period 2003 to 2012. Major limitations of our results arise from the aggregation of some data variables. The limitations in the application of the approach are a consequence of the availability of data. The regression showed that rainfall has a strong influence on cereal production, unlike irrigation. This latest gives significant results for durum wheat but not for other types of cereals, despite the intensive irrigation introduced in some wilaya as Biskra. This wilaya is the most irrigated but cereal production is very low. Except the wilaya of Biskra is more known for its production of dates and therefore it is probably "the most irrigated wilaya" for this type of production. Conversely the wilaya of Sidi Bel Abbès is ranked among the first 3 wilayas that produce the most grain, but in terms of irrigation, it is among the last.

Using a principal components analysis, it was possible to determine a classification; the wilayas forme 3 groups according to their productions. Barley production is found to be much higher in the highlands than in other regions better known for the production of durum wheat in the center of the country and common wheat and oats in the west of the country. It is also noted that production differs from one type of grain to another. Farmers tend to prefer to invest in durum wheat and bread wheat because they have a better return on investment by exploiting them rather than growing oats.

The second principal component analysis enabled us to detect the years when production was weakest, such as the year 2008, which experienced a severe drought. This gave a classification of years in relation to grain yields. There are two groups of years, namely the first years (2000-2002 and 2008) where the cereal yield is low and the more recent years (2003-2012) with a higher yield.

In the end, it seems that for better cereal production, it would be necessary to review the irrigation policy, since the latter is only present on about 2 to 4% of the planted area. This could bring a plus to the yield of the cereal crop; since we can consider that the productions recorded to date are mainly due to rainfall. An additional and controlled water supply will significantly and positively affect production. The conclusion is that irrigation can play a central role in improving food security, because of the semi-arid and arid climate that characterizes a predominant part of the territory of Algeria.

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Table 1: Eigen analysis of the Correlation Matrix

	F1	F2	F3	F4
Eigenvalue	3.095	0.419	0.292	0.194
Proportion	0 .77378	0.10478	0.07292	0.04852
Cumulative	0.77378	0.87855	0.95148	100

Table 2: Correlation between variables and factors

	F1	F2	F3	F4
Durum wheat	0.465	0.869	-0.131	-0.108
Bread wheat	0.505	-0.417	-0.546	-0.523
Barley	0.504	-0.175	0.815	-0.225
Oats	0.524	-0.201	-0.142	0.809

Table 3: Eigen analysis of the Correlation Matrix

	F1	F2	F3	F4
Eigen value	3.550	0.266	0.125	0.059
Variability (%)	88.759	6.644	3.121	1.475
% cumulative	88.759	95.403	98.525	100

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Table 4: Correlation between variables and factors

	F1	F2	F3	F4
Durum wheat	0.961	-0.114	-0.207	-0.143
Bread wheat	0.893	0.447	0.052	-0.015
Oat	0.940	-0.212	0.264	-0.038
Barley	0.972	-0.093	-0.098	0.192

Table 5: Data Table

	Durum wheat production	Rainfall	Irrigation
2000	4863340	211.324	59910
2001	12388650	509.6775	71890
2002	9509670	289.322	88430
2003	18022930	666.9	77940
2004	20017000	524.184	95126
2005	15687090	418.028	82303
2006	17728000	539.514	88250
2007	15289985	574.676	79430
2008	8138115	342.53	90846
2009	20010378	574.116	86846
2010	18089739	511.876	114615
2011	19274740	569.352	130110
2012	24071180	590.416	137567

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Table 6: Parameter estimation

Residual standard error: 4273000 on 11 degrees of freedom

Multiple R-squared: 0.441, Adjusted R-squared: 0.3902

F-statistic: 8.678 on 1 and 11 DF, p-value: 0.01331

Coefficients	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	5.619e+05	5.248e+06	0.107	0.9167
x	1.627e+02	5.524e+01	2.946	0.0133 *

Table 7: Parameter estimation

Residual standard error: 2935000 on 11 degrees of freedom

Multiple R-squared: 0.7363, Adjusted R-squared: 0.7123

F-statistic: 30.71 on 1 and 11 DF, p-value: 0.0001748

Coefficients	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	-1593170	3211206	-0.496	0.629568
x	35401	6388	5.542	0.000175 ***

Table 8: Parameter estimation

Residual standard error: 2249000 on 10 degrees of freedom

Multiple R-squared: 0.8593, Adjusted R-squared: 0.8311

F-statistic: 30.53 on 2 and 10 DF, p-value: 5.519e-05

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-7.204e+06	3.107e+06	-2.318	0.04290 *
x_1	2.910e+04	5.338e+03	5.452	0.00028 ***
x_2	9.371e+01	3.170e+01	2.956	0.01438 *

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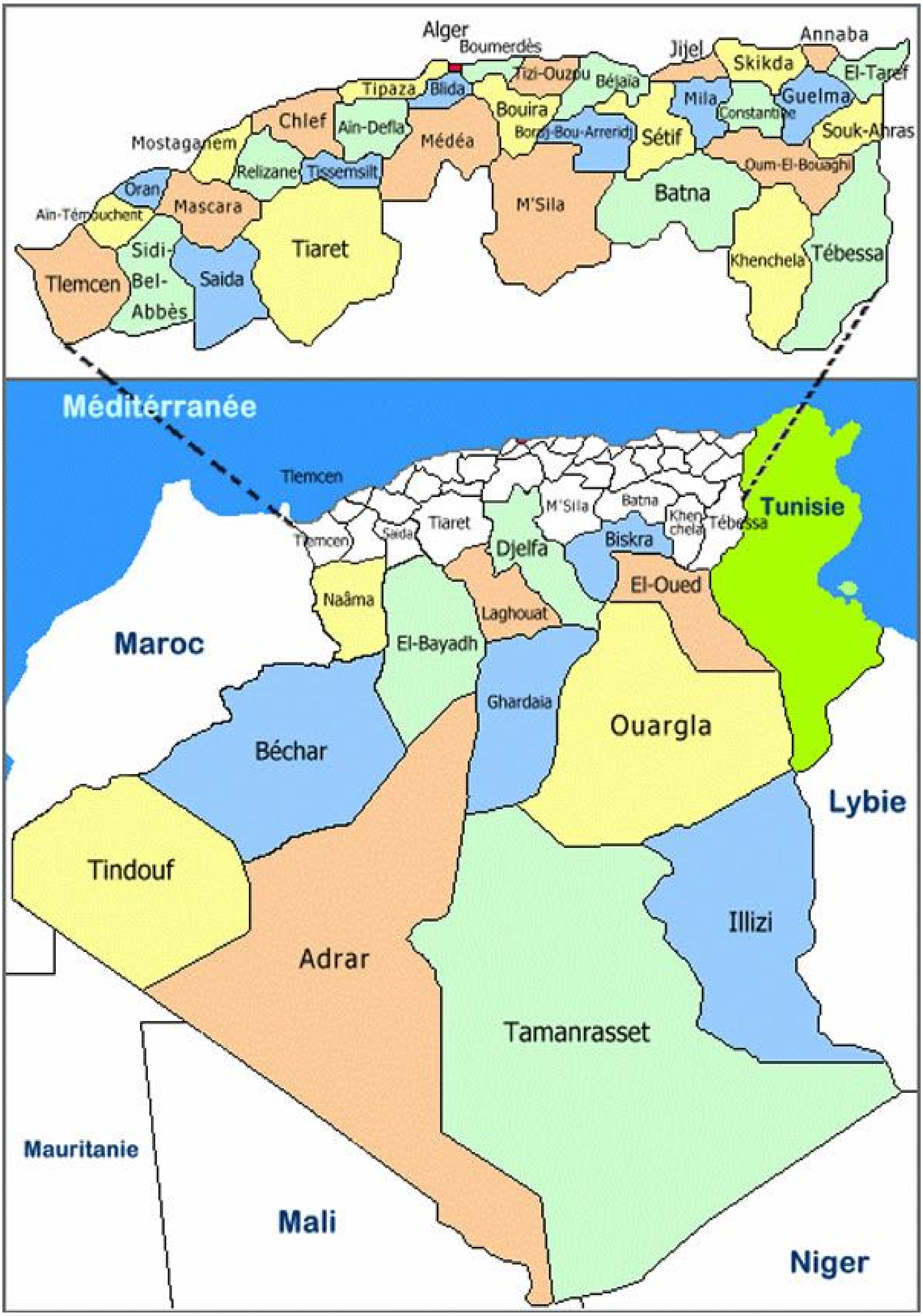

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