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Research article

Analysis and prediction of climate forecasts in Northern Morocco: application of multilevel linear mixed effects models using R software

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ABSTRACT

For many years, the application of mixed-effects modeling has received much attention for predicting scenarios in the fields of theoretical and applied sciences. In this study, a “new” Multilevel Linear Mixed-Effects (LME) model is proposed to analyze and predict multiply-nested and hierarchical data. Temperature and rainfall observation were carried out successively between 1979-2014 and 1984–2018; and the data input was organized on monthly basis for each year. Besides, a daily observation was made for “Dar Chaoui” zone of Northern Morocco. However, we chose in the first time a simple linear regression model, but the estimation has been just for fixed effects and ignoring the random effect. On the other hand, in multilevel linear mixed effects models, once the model has been formulated, methods are needed to estimate the model parameters. In this section, we first deal with the joint estimation of the fixed effects (β), random effects (ui) and then with estimation of the variance parameters (γ, ρ and σ_2). The study revealed that the predicted values are very close to the real value. Besides, this model is capable of modelling the error, fixed and random parts of the sample. Moreover, in this range, the results showed that there is three standard deviations measures for fixed and random effects, also the variance measure, which demonstrate us a great prediction. In conclusion, this model gives a decisive precision of results that can be exploited in studies for forecast of water balance and/or soil erosion. These results can also be used to inhibit the risk of erosion with possible arrangements for the environment and human security.

1. Introduction

Climate change is a natural component of the earth's cycle. In fact, it is well known today as the biggest challenge on the planet (Seif-Ennasr et al., 2016). The Industrial Revolution that the world has known in the last decades has greatly amplified the scale of climate change (Pachauri et al., 2014). This anthropogenic cause returns to influence and threaten living beings on the planet, including humans by causing upheavals such as: extreme weather events (droughts, storms), arise in average temperature, rising sea levels, threaten the sustainability of the soils that may lead to desertification (Simonneaux et al., 2015) and others. However, Morocco is one of many countries who are not immune to the negative repercussions of climate change (Schilling et al., 2012). Morocco is very vulnerable to the harmful effects of climate change; In addition, water and the environment which are under high demographic pressure, industrial effects and agricultural extension, are particularly threatened (El Jaouhari et al., 2018). Several studies have shown that this country will be the site of a major climate change in the future (Driouech et al., 2010; Simonneaux et al., 2015; Tramblay et al., 2012). Future simulated climatic conditions show a decrease in average precipitation, an increase in average temperature and a change in the geographic distribution of the runoff (Zittis et al., 2019). This leads to a serious situation especially since the country is based on agriculture as the capital source of the economy. Crop yields, growth rates, photosynthesis, transpiration rates, and soil moisture availability, would be likely affected by the predicted climate change scenarios, due to changes in water use and agricultural inputs (Chisanga et al., 2017). Therefore, agricultural incentives must be adopted to cushion the effects of droughts and increase resilience to

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climate change. Thus, future forecasts of climate change on a local and regional scale are manifested as the first essential step before any intervention. Mathematical models seem the best approach to study these predictions of future climate scenarios and for monitoring the risks of climate change. It is the most flexible tool to understand, at what rate, climate data changes over time. For many years, mixed-effects modelling has received much attention on the theoretical level as well as on the practical one (El Halimi, 2009). The scopes of it applications are indeed very varied and include hydrology, meteorology, and biology, etc (Harrison et al., 2018). The complication of Multilevel Linear Mixed-Effects (LME) models means that classical diagnostics are rendered less effective. This is due to a disruption of asymptotic results, confines issues, and visible patterns in residual plots that are introduced by the model fitting process (Servo et al., 2016). Both, fixed and random effects in linear mixed-effects models occur linearly in the model function. They develop linear models by integrating random effects, which can be considered as an additional error to consider the correlation between the observations within the same sample group (Pinheiro and Bates, 2000). Model monitoring is a fundamental step in statistical modelling in order to maintain necessary assumptions that guarantee valid inference (Loy et al., 2017). This process involves both the search for contradictions of model assumptions, and an appraisal of how well the model captures the characteristics of the data. Such examination can be carried out using test statistics and p-values to gauge the strength of evidence, while such methods indicate only the degree to which there is a problem with the model. The objective of this work consists of predicting the future temperature and precipitation in Northern Morocco in order (i) to demonstrate the efficiency of Multilevel Linear Mixed Effects Models for a precise evaluation of the future climate prediction, and (ii) to determine the dry and wet periods for the coming years to provide a decision support system for stakeholders concerned with soil degradation, water resources management and the impact of climate change to control and avoid the most vulnerable phenomena such as flood, erosion, desertification ... etc.

2. Materials and methods

2.1. Study site description

The study site, 9th April watershed, is located in North of Morocco with coverage of 240 km^2 (Figure 1). It is a Mediterranean basin characterized by a sub-humid climate (Aboumaria, 2009), with a wet season relatively high annual precipitation (in the vicinity of 850 mm) and mean temperature close to 10 °C, and dry seasons with mean temperature around 20 °C and precipitation tends towards 370mm. The driest months are July and August, and the highest values are recorded particularly in the months of December and January.

According to a series of records precipitation (i.e., 1984–2018) and temperature (i.e., 1979–2014) by the Hydraulic Basin Agency of Loukkos (ABHL) at the Dar Chaoui weather station known by the Lambert coordinates as X = 471 km et Y = 547.45 km (Figure 1), the average annual rainfall is 725 mm and the annual temperature is relatively high (18 °C) (ABHL, 2019). This would be more due to very mild winters (the minimum recorded and in January with 11 °C), than to the summers that ultimately are not very hot (the maximum recorded is in July and August with 25 °C) (Briak et al., 2016(a)).

On the other hand, the region is characterized by a predominance of dry, hot and violent winds coming from the eastern zone (Chergui) and which dominate especially during the summer season. The humid winds coming from the West sector (Gharbi) are mainly in winter, and would be in relation to the Azores high (Aboumaria, 2009).

The topography of this area is diverse with an altitudinal variation ranging from 47m to the outlet up to 1031 m at the highest point, while the average slope is 45 m/km. The basin contains a dam near the locality Dar Chaoui with a storage capacity equal to 300Mm^3. This dam named 9th April 1947, is intended for the supply of drinking water to the Atlantic area located between Asilah and Tangier. The irrigation of agricultural areas located downstream of the dam. From a geological and pedological point of view, the basin shows the predominance of marl and clay formations of the Tangier unit (Suter, 1980), with generally poorly developed soils and complex soils.

2.2. Data input

The data illustrated in Figures 2 and 3 were obtained from *Dar Chaoui* weather station, Morocco for the purpose of evaluating the magnitude of the expected climate changes, and the level of impact, which were brought at regional and local scales in Northern of Morocco. For this, the parameters studied were the temperature (T) (daily, monthly and annual) and rainfall (Y) (daily, monthly and annual) as a function of time over the northern regions of Morocco. These figures show a sinusoidal variation in the series observed, with a maximum daily temperature value of around 33 °C and a minimum value of 3 °C. While the maximum of daily precipitation up to 110 mm.

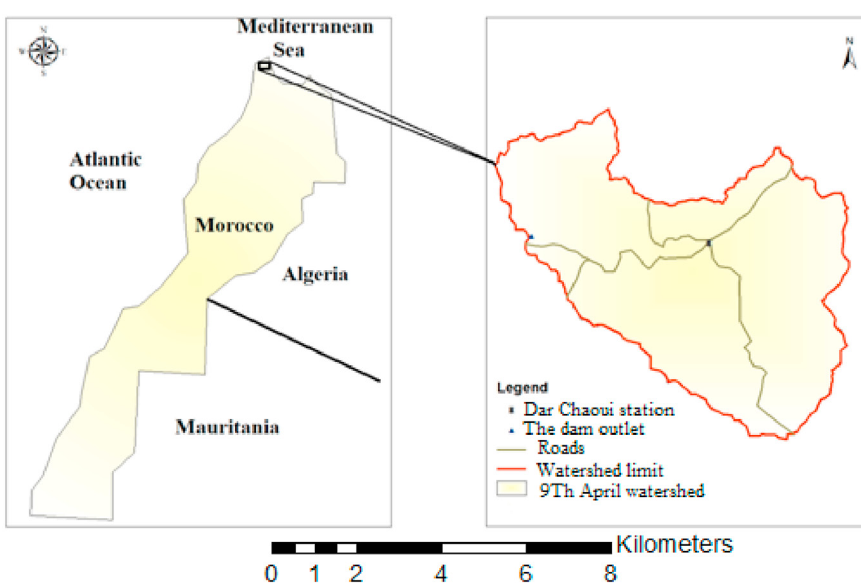


Figure 1. Location map of 9th April Watershed, Northern Morocco.

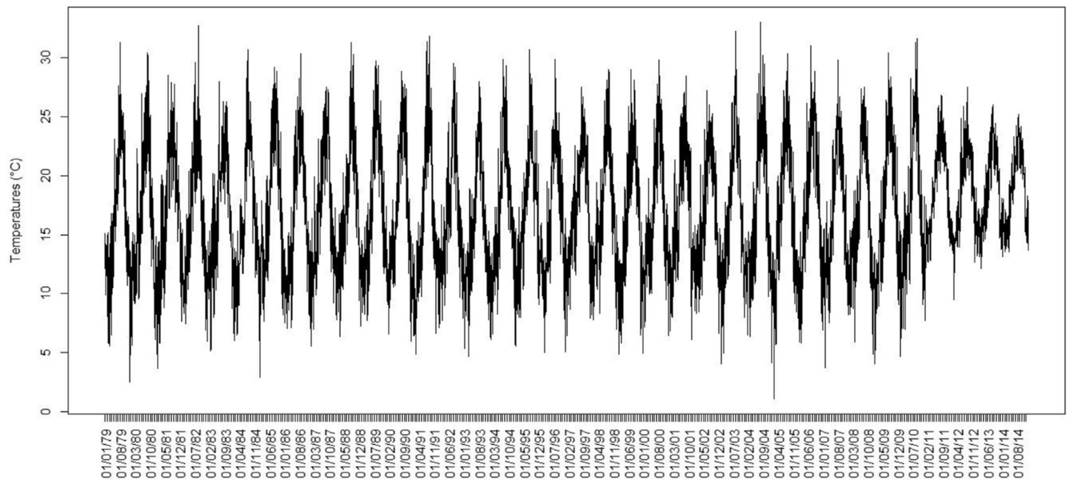


Figure 2. The evolution of the temperature over the time horizon 1979–2014.

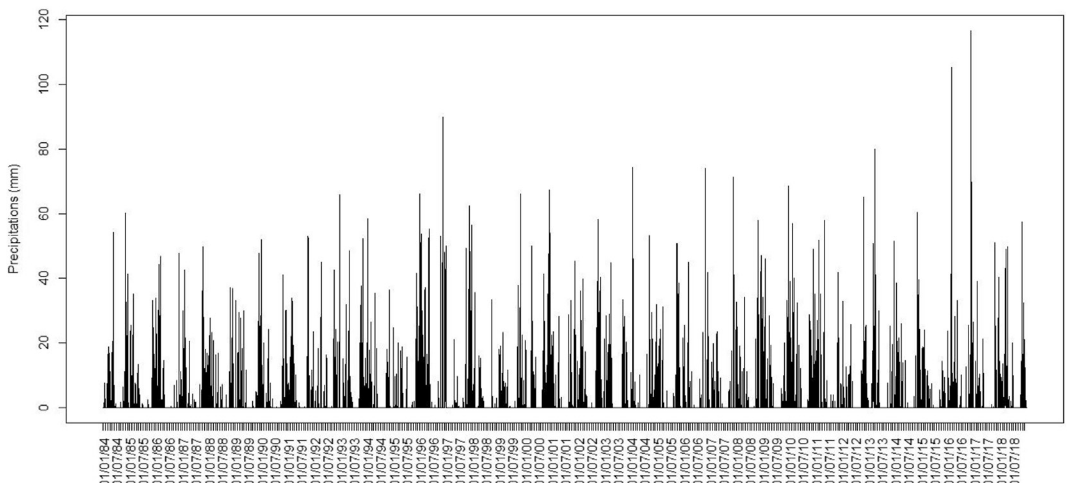


Figure 3. The evolution of precipitation over the time horizon 1984–2018.

2.3. Statistical method

2.3.1. Theoretical modelling

The study of natural phenomena such as those occurring in an environment (for example, climate change) generally involves repeated observations on each of the individuals of the same population, ordered in time and/or space. Two sources of variability appeared on the repeated datasets: the variability between the observations measured on the same individual and the variability between the individuals themselves. The mixed model is a statistical tool allowing highlighting a relationship between the observed response and explanatory covariates, taking into account these two types of variations. Practical examples of model construction using mixed effect models can be found in (El Halimi, 2009; Pinheiro and Bates, 2000; Vock et al., 2012).

The general writing of the mixed model which will be adopted in this study was introduced by (Laird and Ware, 1982) and subsequently taken up by several authors such as (Littell et al., 1998).

$$y_i = X_i\beta + Z_iU_i + \varepsilon_i \tag{1}$$

where for each individual *i*, $E\ (yi \mid Ui) = X_i\beta + Z_iU_i$ is the conditional mean of yi given *Ui*, *Zi* is a matrix $ni \times q$ of incidence of random effects *Ui*. We assume that $Ui \sim N\ (0, D)$ where 0 is the vector of dimension $q \times 1$, *D* is the covariance variance matrix of *u*. We suppose that *u* and $\boldsymbol{\varepsilon}$ are independent. We still have the variance of y conditionally to *u* is $Var(yi|Ui) = Var(\varepsilon i) = Ri$.

The components of the variance, the parameters of the fixed effects and the realizations of the random effects, are the different parameters of the mixed linear model, its implementation involves the estimation of these different parameters (Wang et al., 2019). The maximum likelihood method and the restricted maximum likelihood method are the mixed model estimation methods (El Halimi, 2009; Pinheiro and Bates, 2000). The hypotheses of the Maximum Likelihood method are relatively strong, but it is known that they lead to estimators with optimal asymptotic properties. This constitutes the essential justification for the systematic use of the method. The estimation of the variance parameters by the maximum likelihood (ML) method leads to biased estimators. The estimation (ML) of the variance parameters doesn't take into account the loss of the degrees of freedom induced by the estimation of the fixed effects. The limited maximum likelihood (REML) is a method derived from the maximum likelihood, allowing considering this degree of loss of freedom caused by the estimation of the fixed parameters.

The formulation (1) for the simple level LME models presented above can be extended to several levels of random effects. In case two nested random effect levels, the mixed model will be rewritten in the following individual form (Pinheiro and Bates, 2000):

$$yij = Xij\ \beta + Z(i)j\ Ui + ZijUij + \varepsilon_{ij} \tag{2}$$

The 1st level random effects, *Ui*, are assumed to be independent of different individuals *i*, 2nd level random effects, *Uij* are supposed to be independent for different *i* or *j* and independent of 1st level random effects, and the errors ε_{ij} are presumed to be independent for different i or j and independent of the random effects.

2.4. Applications to climatological data

2.4.1. Ambient temperature and precipitation modelling

Considering the cyclical shape of the temperature and the daily precipitation as a function of time for each month in each year (Figures 2 and 3), it seems logical to apply, for example, an ordinary regression model to all the observed values of temperature and the predictive variable time (without taking into account neither the months nor the years). In addition to the biases that this procedure can generate (Uzoh and Oliver, 2008; Woodhouse et al., 1996), the analysis is ineffective since the individual effects (months) for each year is not included (Austin, 2017; Paterson and Goldstein, 1991). Indeed, for the case of ambient temperature a simple linear model can be proposed (compared to the parameters) which stipulates that there is a linear dependence with time, without taking into account the hierarchical structure of data (Figure 4).

The result will come out using the following equation:

$$T_j = \beta 0 + \beta 1 \times \cos\left(wX_j - \varphi T\right) + \varepsilon_j \tag{3}$$

With: $w = 0.2$, $\varphi T = 20$, *Tj*, the *Xj* are fixed, $\beta 0$, $\beta 1$ represent the fixed effects and ε_j represents the random error. The parameters $\beta 0$, $\beta 1$ and σ_ε are estimated using the least square method.

The results of the above equation show that the estimate of the slope (β1) is equal to -0.07 (0.06) with a p-value equal to 0.1729. This means that for every 1 increase in the daily rate (days), there is a (very small) temperature decrease of 0.07 in the value of the slope.

Graphically, every month has the same behavior over time; this translates to one of the limits of the fixed effects model which supposes independence between the observations of temperatures *Tj*. To take into account the dependence and the hierarchical structure of data, we add to the fixed effect model (4) a random effect, the model thus obtained is called mixed effect model at two levels: The first level represents months (level 1) and the second level represents years (level 2), each of these levels bringing a particular dimension to the analysis.

Formally, this can be written in the form:

$$T_{ijk} = \beta_0 + \beta_1 * \cos\left(wX_{ijk} - \varphi T\right) + U_{0i} + U_{0ij} + \varepsilon_{ij} \tag{4}$$

The index *i* designates the level 1 observations, *j* those of level 2, *Tijk* is then the k*th* observation of the temperature/precipitation variable for the month *(i)* in the year *(j)*, **β0** represents the “standard” or average temperature/precipitation of a month at the start time (Zero Time). The term *U0i* constitutes the random effect specifying the month *i* associated with the intercept **β0** and representing the variations in the temperatures/precipitation of the months with respect to the start time. The term *U0ij* constitutes the random effect specifying the year *j* including the month *i* associated with the intercept **β0**. **β1** also represents the average temperature/precipitation increase per unit of time.

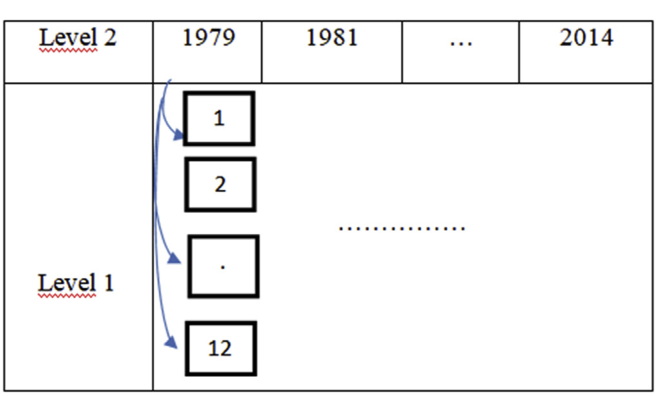


Figure 4. Example of structured data from two levels: months (Level 1) grouped into Years (Level 2).

2.4.2. Skewness and kurtosis

- Skewness

It is a statistical tool that measures the degree of asymmetry of the distribution, either the moment of order 3, it is given by the following equation:

$$S = \frac{1}{N} * \sum_{i=1}^{N} 1 \left(\frac{Xt - \overline{X}}{\widehat{\delta}}\right)^3 \tag{5}$$

with:

N: Number of observations.
Xt: The observation at time (t).
$\overline{X}$: Average observations.
$\widehat{\delta}$: The standard deviation estimator.

Three cases are to be considered:
S > 0: The distribution is skewed to the right.
S = 0: The distribution is described as normal and symmetrical.
S < 0: The distribution is skewed to the left.

- Kurtosis

This is a coefficient that measures the degree of flattening of the distribution, either the moment of order 4, it is given by the following equation:

$$K = \frac{1}{N} * \sum_{i=1}^{N} 1 \left(\frac{Xt - \overline{X}}{\widehat{\delta}}\right)^4 \tag{6}$$

Three cases are to be considered:
K > 3: The distribution is said sharp and therefore leptokurtotic.
S = 3: The distribution is qualified as normal.
S < 3: The distribution is said overwritten and therefore playkurtotic.

2.5. R software programming code

All statistical calculations were carried out using the statistical software "R" version 3.6.2 (R Development Core Team, 2019). Mixed linear models have been adjusted using the library "nlme" (Pinheiro and Bates, 2000). The computer programming code describing the different R procedures which were used to make this analysis, as well as the manipulations made in the basic files are presented in the results.

3. Results

3.1. Adjustment of the model (3)

The adjustment of the first model (3) gives the following results (Table 1):

The most important value to verify is the “p-value”. For the validation of the model, p-value must be less than 0.05: p-value <0.05.

We observe that the parameter (β1) doesn't respect this condition (Table 1).

In addition, the values are poorly adjusted (Figure 5), which indicates that the model is inapplicable to these kinds of sample: this is likely to distort the results obtained.

Table 1. Summary table of model (3) adjustment.

Parameters	Estimation		
	Value	Std.Error	p-Value
β0	17.1449	0.0447	**0.0000**
β1	0.0863	0.0633	**0.1729**
σΣ	Residual standard error: 5.13431		

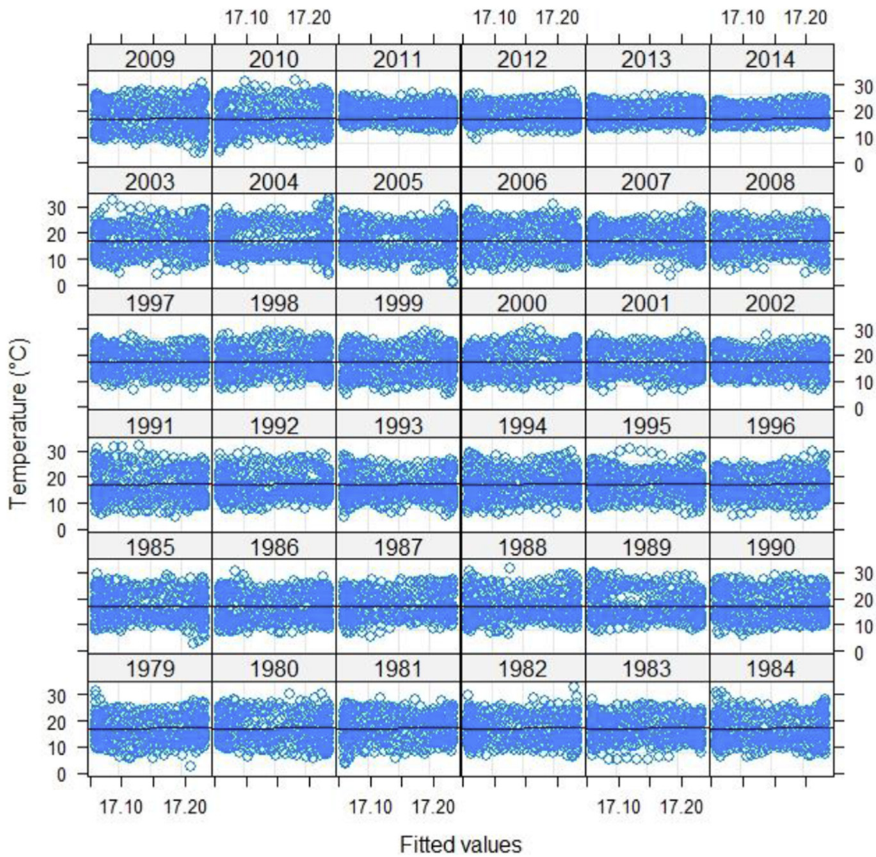


Figure 5. The temperature according to the adjusted values.

3.2. Adjustment of the model (4)

The adjustment of the second model (4) gives the following results (Tables 2 and 3):

According to the results of the summary tables (Tables 2 and 3), p-value is less than 0.05 for the two parameters, the fixed effect of Temperature and precipitation. The values obtained for the parameters of the random effect and the error are therefore consistent.

Thereby, to confirm the validation of the model, we just have to check the fit of the adjusted values and errors:

For temperatures and precipitation, the points are well adjusted by contribution to normality; there are only some extremes in the years 2000 and 2010 in terms of the precipitation that we can neglect (Figures 6 and 7). Thus, the measurement errors are also aligned in terms of the average.

Therefore, the multi-level linear mixed effect model is adequate for the sample that we want to process.

3.3. Comparison between the two models

To confront the reliability of the two models, the following parameters must be compared and analyzed (Figure 8):

Table 2. Summary table of model (4) adjustment temperature case.

fixed Effect	Estimation		
	Value	Std.Error	p-Value
β0	17.117	1.330	**0.000**
β1	0.082	0.027	**0.003**
Random Effect	Value		
σb0(i)	4.604		
σb0(i)j	1.331		
σΣ	2.265		

Table 3. Summary table of model (4) adjustment precipitation case.

fixed Effect	Estimation		
	Value	Std.Error	p-Value
β0	1.9910	0.4087	**0.0000**
β1	-0.2333	0.0799	**0.0035**
Random Effect	Value		
σb0(i)	1.3683		
σb0(i)j	1.8179		
σΣ	6.3873		

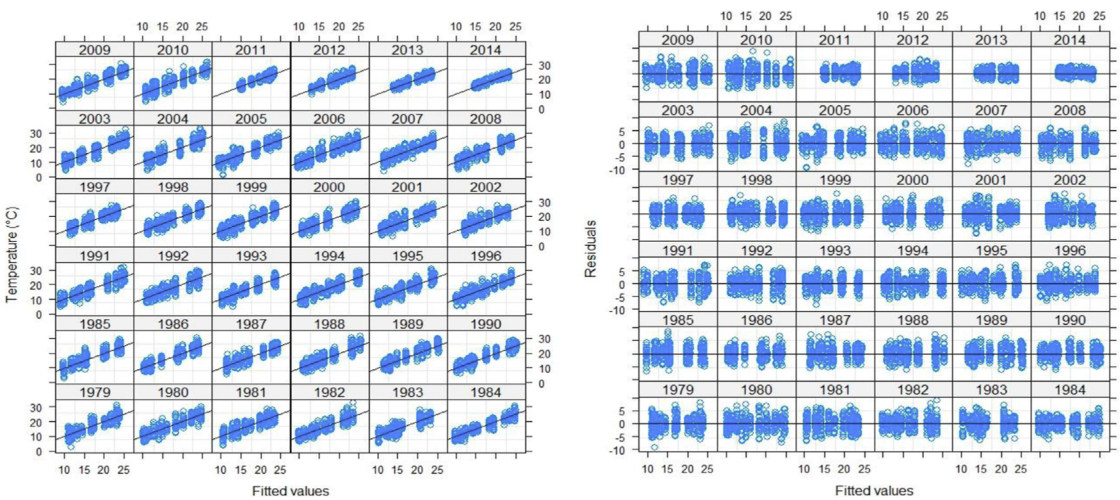


Figure 6. Temperatures and errors in terms of the adjusted values.

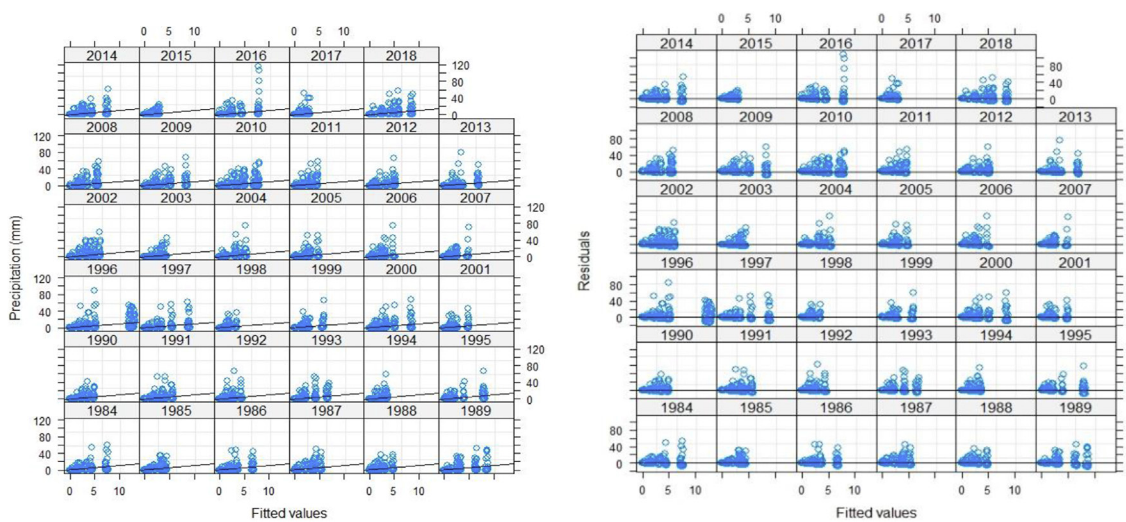


Figure 7. Precipitation and errors in terms of the adjusted values.

- **AIC:** Akaike information criterion.
- **BIC:** Bayesian information criterion.
- **LogLik:** Log-Likelihood.

The best model should contain small "AIC", small "BIC" and large "logLik". The result shows that model 2 has values of AIC and BIC lower than model 1 as well as the value of logLik is higher with regard to model 2 (Figure 8). According to previous statistics, model 2 is therefore better than model 1.

- **KIC:** Kashyap information criterion.

The Kashyap Information Criterion (KIC) can be considered as a General Information Criterion (GIC) whose equation can solve two information criteria Akaike (AIC) and Bayesian (BIC), and this according to the following equation:

$$GICk = -2\ LLk + an\ mk + bk \tag{7}$$

where GIC denotes Generalized Information Criterion, and.

Lk = maximized likelihood for Model k;
LLk = ln Lk;
mk = number of independent parameters in the k-th model,

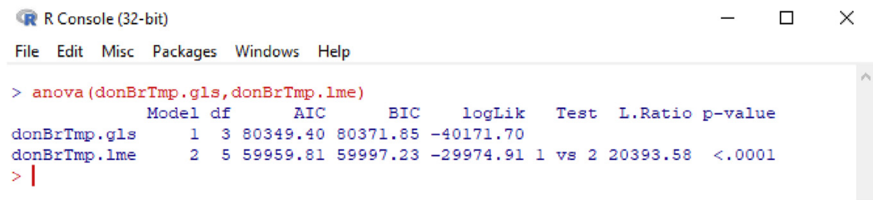


Figure 8. Comparison between the linear regression model and the multi-level linear mixed effect model.

an = 2; for all n; bk = 0; for Akaike's criterion AIC;
an = ln n; bk = 0; for Schwarz's criterion BIC,

From the analysis obtained by R software (Figure 9), we observe that the second model contains a KIC value lower than the first model, this suggests that the second model is more efficient that the first one.

3.4. Seasonal temperature and precipitation forecasting

After having carried out the modelling of the climatic scenarios, from the data obtained at the Dar Chaoui station, the forecast of seasonal temperatures and precipitation by 2050 can be approved. The result obtained is shown in Tables 4, 5, 6, and 7.

The average seasonal temperatures are quite high in the winter and spring periods with values 12 °C and 15 °C respectively (Tables 4 and 5), while the temperatures in the summer and fall seasons varied between 23 °C and 19 °C respectively (Tables 6 and 7).

The average seasonal precipitation is very low, even in the winter and fall seasons with an average value of 3mm (Tables 4, 5, 6, and 7).

In addition to calculate the mean and standard deviation of precipitation and temperature, the analysis of descriptive statistics consists of evaluating the Skewness - an indicator of asymmetry - and the Kurtosis which has a coefficient of flattening.

3.5. Skewness and kurtosis results

The precipitation series is characterized by an asymmetry coefficient (S) greater than 0 in all seasons, therefore an asymmetry to the right.

On the other hand, temperatures are characterized by a coefficient of asymmetry (S) greater than 0 in the winter and spring seasons, a fact which gives asymmetry to the right. While the coefficient of asymmetry, in the summer season, remains less than 0, leaving the asymmetry to the left (Tables 4, 5, 6, and 7).

The flattening coefficient (K) of precipitation is less than 3 during the fall season: the distribution of the series is accordingly platykurtic, while the other seasons are characterized by a flattening coefficient greater than 3: the distribution is said sharp, therefore leptokurtotic.

Regarding temperatures, the flattening coefficient (K) is less than 3 in the four seasons. This distribution is said overwritten, therefore playkurtotic (Tables 4, 5, 6, and 7).

3.6. Daily temperature and precipitation forecasting

The graphs below (Figure 10 (a) and Figure 10 (b)) show the variety of daily temperatures and precipitation carried out by the multi-level model. The forecast precipitation is experiencing a very significant decrease, especially in winter; also the minimum temperatures increase.

The average daily temperature for 30 years is between 18 and 22 °C and varies steadily with increasing towards the maximum value of 27 °C and the minimum value of 9 °C (Figure 10 (a)), along with a maximum daily value of precipitation about 13mm (Figure 10 (b)).

4. Discussion

Climate change is currently considered a major concern for humanity (D'Oria et al., 2017). Indeed, Future climate projections carried out by Multilevel (LME) models for the Mediterranean region of Tangier, in the north of Morocco, have shown significant results up to 2050. In the first step, it had to be chosen between the classical simple regression model and the multilevel mixed-effect model. This step is based on several comparison criteria such as (AIC), (BIC) and (KIC). Subsequently, the analysis of these three criteria shows that these values, in mixed models,

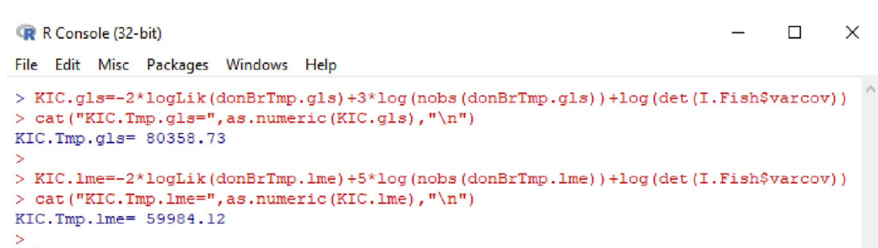


Figure 9. Comparison between models using Kashyap Information Criterion (KIC).

Table 4. Winter season results.

	Months	December	January	February
Temperature	Mean	12.47	11.39	11.97
	Sd	1.44	1.65	1.53
	Skewness	1.04	1.40	0.12
	Kurtosis	0.87	1.23	-0.55
Precipitation	Mean	3.36	3.04	2.92
	Sd	3.58	2.83	2.49
	Skewness	1.76	2.51	1.41
	Kurtosis	3.38	8.84	1.64

Table 5. Spring season results.

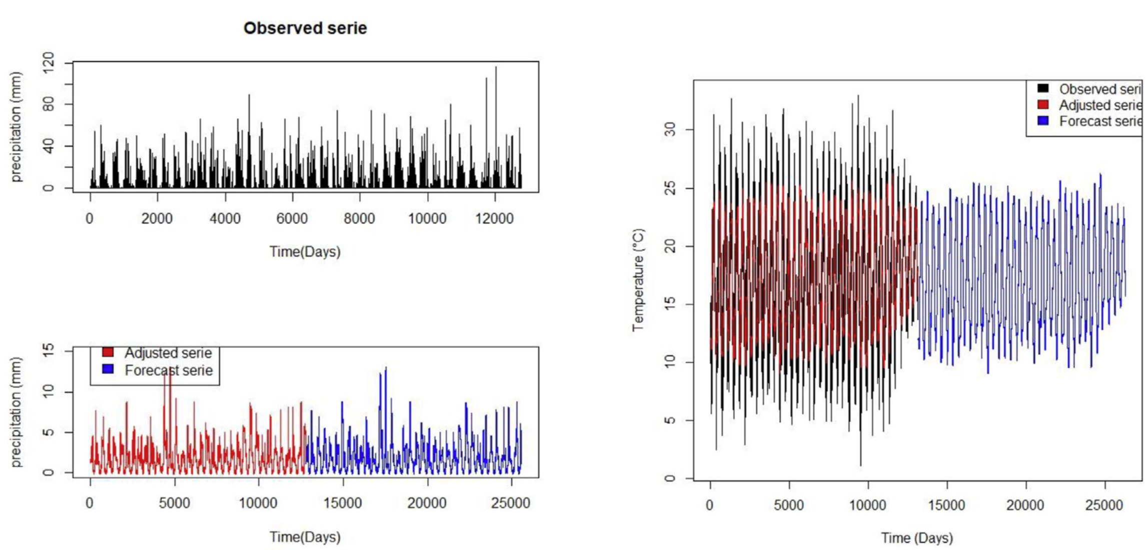
	Months	March	April	May
Temperature	Mean	13.51	14.68	17.17
	Sd	1.28	1.37	1.40
	Skewness	0.11	0.30	-0.02
	Kurtosis	-0.87	-0.34	-0.64
Precipitation	Mean	2.40	2.35	1.03
	Sd	2.32	1.39	1.50
	Skewness	1.88	0.67	2.32
	Kurtosis	4.09	-0.34	5.24

Table 6. Summer season results.

	Months	June	July	August
Temperature	Mean	20.75	23.44	24.06
	Sd	1.14	1.15	1.02
	Skewness	-0.43	-0.30	0.03
	Kurtosis	0.51	-0.70	-0.34
Precipitation	Mean	0.15	0.04	0.16
	Sd	0.34	0.12	0.34
	Skewness	3.44	3.50	2.28
	Kurtosis	13.14	12.57	4.77

Table 7. Autumn season results.

	Months	September	October	November
Temperature	Mean	22.11	18.84	14.97
	Sd	1.28	1.67	1.56
	Skewness	-0.49	0.02	0.66
	Kurtosis	0.00	-1.20	-0.47
Precipitation	Mean	1.24	2.91	4.24
	Sd	1.67	2.34	3.23
	Skewness	2.10	0.61	0.57
	Kurtosis	4.89	-0.95	-0.80



(a): Daily precipitation curve (2019-2050) **(b): Daily temperature curve (2015-2050)**

Figure 10. (a): Daily precipitation curve (2019–2050) (b): Daily temperature curve (2015–2050).

are inferior to conventional models. Thus, it can be said that the mixed model is the most effective. As far as model fitting is concerned, the classical model has obtained a P-value greater than 0.05 in the parameter β1; and that's going to skew the results. On the other hand, in the mixed model, the parameters β1 and β0 have a P-value of less than 0.05. In addition, the random parameters that are absent in the first model are well modelled.

Seasonal average temperatures will increase significantly in the winter and fall seasons. As well as a slight increase for the spring and summer seasons. On the flip side, average seasonal rainfall will decrease in all seasons, and this will be followed by periods of drought. For that, water resources and agriculture will be directly affected. The average daily temperature will reach a maximum value of 27 °C in the future. In addition, the maximum value of the average daily rainfall that will be recorded is 13mm.

This study confirms the results of other studies conducted on climate change in the Moroccan context (Seif-Ennasr et al., 2016; Hirich et al., 2016; Ouhamdouch and Bahir, 2017; Brouziyne et al., 2018), and in the Mediterranean region (Ozturk et al., 2015; Tellería et al., 2016; D'Oria et al., 2017; Zittis et al., 2019). In other the regions in Morocco that have different climate type such as Chtouka Aït Baha region in the South of Morocco, the temperature increases of 3 °C for 2030–2049 and precipitation shows a reduction of 10%–30% for 2030–2049 (Seif-Ennasr et al., 2016). Concerning Souss region, also in the South of Morocco, the temperature will increase by 3 °C and the precipitation will significantly decrease by 63% (Hirich et al., 2016). On the other hand, in Essaouira region (Northwest of Morocco), the results showed a downward trend along with an upward trend of annual rainfall. But the annual mean temperature was found to increase by 0.72 °C (Ouhamdouch and Bahir, 2017). About the region of Fez-Meknes region (Northeast of Morocco), the area will definitely experience rainfall drop and mean temperature increase (Brouziyne et al., 2018).

Otherwise, respecting to the Mediterranean region, the temperature will be increased from 3.5 °C to 6.5 °C in Turkey, Morocco, Algeria, Southeast Europe, Central Europe and Iberian Peninsula. While precipitation will definitely decrease from 0.9mm to 1.2mm in the northern part of the Mediterranean region like in south Balkans, France, Italy, Caucasia and Switzerland (Ozturk et al., 2015). As in other countries, the temperature will also increase in southern Spain, while precipitation will decrease relatively (Tellería et al., 2016). Consequently, climate change could favor synergistic interactions within species, ecological and evolutionary processes and many other phenomena like water loss due to drought (Tellería et al., 2016). About Italy, the study that was done in northern Tuscany showed that the mean annual rainfall will be decreased, whilst temperature will know growing by 1.9 °C (D'Oria et al., 2017). Concerning Middle East part of the Mediterranean, the future summer warming will be increased from 4.5 °C to 7 °C (Zittis et al., 2019). Finally, the significance of this study will be very useful from several viewpoints. We will use these results in the same region by integrating them into an agro-hydrological modelling system in order to estimate and predict the impact of climate scenarios on water balance, sediment yield and agricultural practices … etc. Moreover, we will apply the same approach for the same objective of a previous research that was carried out in the Northern Morocco watersheds (Briak et al., 2016(b); Briak et al., 2019; Ouallali et al., 2020).

5. Conclusion

The linear mixed multi-level model is a statistical model in which we consider, at the same time, factors with fixed effects - which will intervene at the level of the average of the model -and factors with random effects, whichever will intervene in the variance of the model. The model applied is able to estimate the fixed part and the random part at the same time; that allows the samples to be modeled more precisely, so that the results are satisfactory. Adjusting the model gives consistent results for temperature and precipitation, with very low standard deviation values in the fixed and random parts. Also the "p-values" are strictly less than 0.05. On the other hand, precipitation, temperatures and errors are well aligned with the adjusted values: this confirms, therefore, that the model is adequate. Precipitation and temperature forecasts by 2050 in Dar Chaoui region (Northern of Morocco) showed the results to be feared. Precipitation has decreased significantly, and the temperature has increased markedly during these years. This indicates the possibility of dry periods. The results of this study will subsequently help to better conduct studies on the forecast of water balance, soil erosion and other natural risk sand, above all, predict the impact of climate change on human life.

Declarations

Author contribution statement

M. Beroho: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

H. Briak: Conceived and designed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

R. El Halimi, K. Aboumaria: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Wrote the paper.

A. Ouallali, I. Boulahfa: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data.

R. Mrabet, F. Kebede: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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The authors declare no conflict of interest.

Additional information

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