Simulation and modeling the temperature: Growing season length under various climate change scenarios

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Abstract

This article is interested in modeling of the minimal daily temperature, the maximum daily temperature and the mean daily temperature for two areas of West North of Tunisia (Elkef and Seliana). The study aims to forecast the climatic indices.

The methodology of Box and Jenkins lead us to choose the process ARMA (2, 2)-GARCH (1, 1) to represent the dynamics of the TElkef and TSeliana series.

The increasing of temperature in the two districts causes the GSL to decrease. Seliana and Elkef districts show a decline of GSL during the period 1999 to 2007. The 9 year average GSL was 165 days in Seliana district and 258 days in Elkef district.

We find that high temperatures correspond to a decrease in growing season length. Future increases in temperatures between 1.5 and 3.5° C may reduce the yield of durum wheat in the tow districts. The choice of good varieties of wheat and delaying the date of plantation to December will be the best solution to ameliorate the yield

Keywords*:* simulation, modeling of the temperature, climate change impact, growing season length, Tunisia.

1. Introduction:

Cao and Wei (1998) **[6] [7]** detected the following characteristics of the mean daily temperature: cyclic behavior, seasonal variation in the variance, property of return to the average, auto regression character and a raising tendency due to the warming of planet. Certain authors like Caballero, Jewson and Brix (2002) **[3]**, Moréno (2003) **[14] [15] [16]**, Brody, Syroka and Zervos (2001) **[2]** specify the presence of a long memory in the mean daily temperature. Caballero, Jewson and Brix (2002) **[3]** propose to employ a process ARFIMA (Auto regressive Fractionally Integrated Moving Average) to model this climatic variable in discrete time while Moréno (2003) **[14] [15] [16]** recommends a process ARFIMA-FIGARCH. Brody, Syroka and Zervos (2001) **[2]** adopt the continuous process based on the partial Brownian movement.

This article is interested in modeling of the minimal daily temperature, the maximum daily temperature and the mean daily temperature for two areas of West North of Tunisia (Elkef and Seliana). The study aims to forecast the climatic indices.

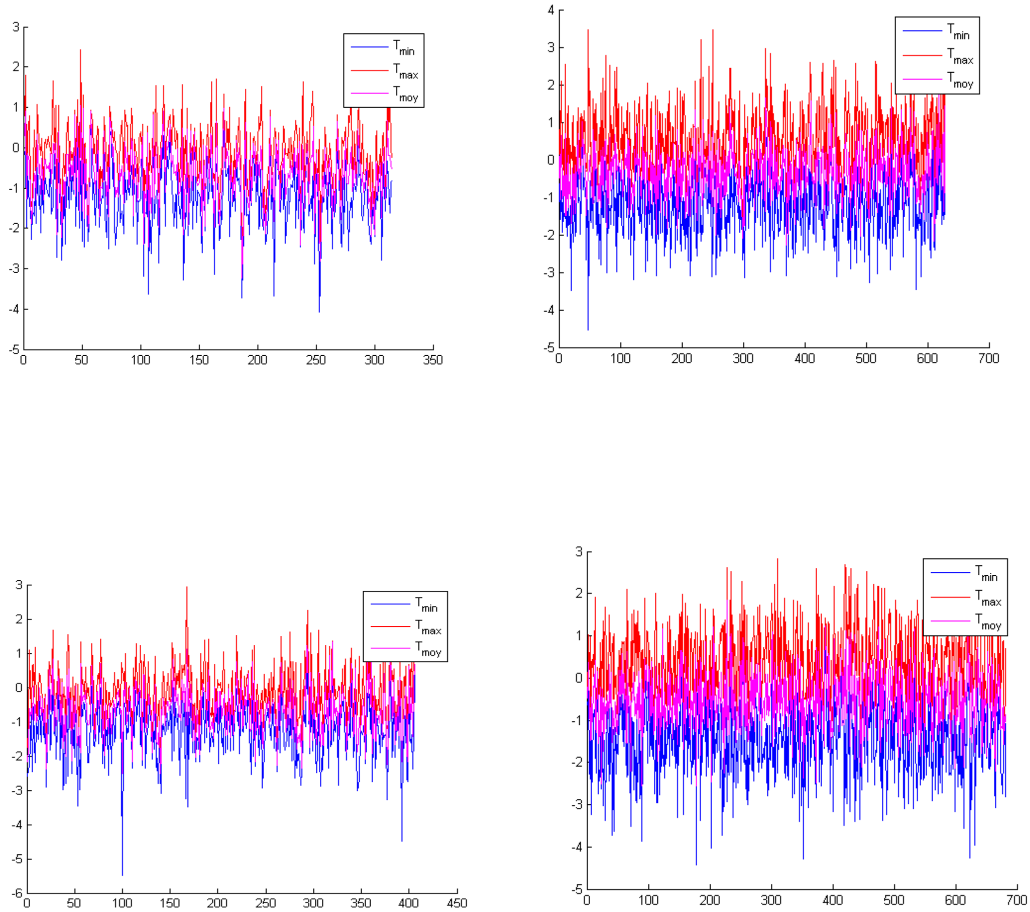
The temperature is a basic component in the studies of the climate change; to determine the future impact of the variations of this variable on the cereal yields it is necessary to simulate the adequate model of the temperature. The agricultural sector is subjected like all the economic sectors to many risks, but it has the effect of being particularly exposed with the climatic risks. We carry out the simulation of the models of temperature in the section 2. We integrate in the section 3 the modeling of the temperature to forecast the climatic parameters. We measure the GSL, the index of growing degree days in section 4. In sections 5 and 6 we give results and conclusions.

2. Simulation of the temperature:

2.1. Principle of simulation:

The simulation programs generated the random trajectories of processes followed by the daily minimal temperature day, the maximum daily temperature and the mean daily temperature according to an ARMA model. The processes have the same number of observations but are characterized by different polynomials. The values of the maximum temperatures are selected so that they are higher than those of the minimal temperatures. The results of simulation are represented in the figure 1.

Figure 1: simulation results



3. Modeling of the temperature:

3.1 Review of the literature:

The goal of the analysis of the time series of the temperature is not to connect variables between them, but to be interested in climatic dynamics in order to forecast the future. Cao and Wei (1998) **[6] [7]** and Roustant (2002) **[20] [21]** adopted an ARIMA process (Autoregressive Integrated Moving Average) to represent the oscillatory movement of the mean daily temperature. The specification of Campbell and Diebold (2004) **[4] [5]** is a generalization of the model of Roustant (2002) **[20] [21]**; this specification is qualified by volatility GARCH (Generalized ARCH) periodic. Caballero, Jewson and Brix (2002) **[3]** announced the presence of a phenomenon of persistence after the application of a whole of tests of long memory. They call upon an ARFIMA structure (Auto regressive Fractionally

Integrated Moving Average). We are interested in this section in the decomposition of the daily mean temperature.

3.2 Decomposition of the mean daily temperature:

The analysis of the two figures below which illustrate the dynamics of the daily mean temperature of the areas Elkef and Siliana shows the presence of a cyclic movement (sinusoidal) whose amplitude does not increase during time. Moreover, certain characteristics of the temperature are obvious: the temperature is a seasonal phenomenon; the temperature presents a correlation over several days. The temperature is stationary at first approximation. Thus we can break up the time series according to the following additive model:

$$T_t = m_t + s_t + \varepsilon_t$$

With m_t : represent the tendency;

s_t : represent the oscillations;

ε_t : represent the random fluctuations.

Where m_t comprises a tendency ($m_t = at + b$ with t is the variable time indicates).

Presentation of the data:

Each series of temperatures corresponds to one period being spread out from 1/1/1999 to 12/31/2007, for a daily frequency; a total of 3285 values. By “daily temperature” we understand the mean daily temperature i.e. the mean of the minimal and maximum temperature observed in the course of the day. Each series comes from a weather station of an area of Tunisia, and was provided by the National institute of Meteorology.

Notations:

We consider that the temperatures observed are achievements of variables controls by laws of probability. The temperature at the date t will be represented by a random variable x_t. We consider the daily mean temperature of Elkef and that of Siliana over the period active from 1/1/1999 to 12/31/2007. These two series, noted TElkef and TSILIANA are represented respectively on the figure 2 and 3.

Figure 2: The daily mean temperature of ELKEF (01/01/1999 - 31/12/2007)

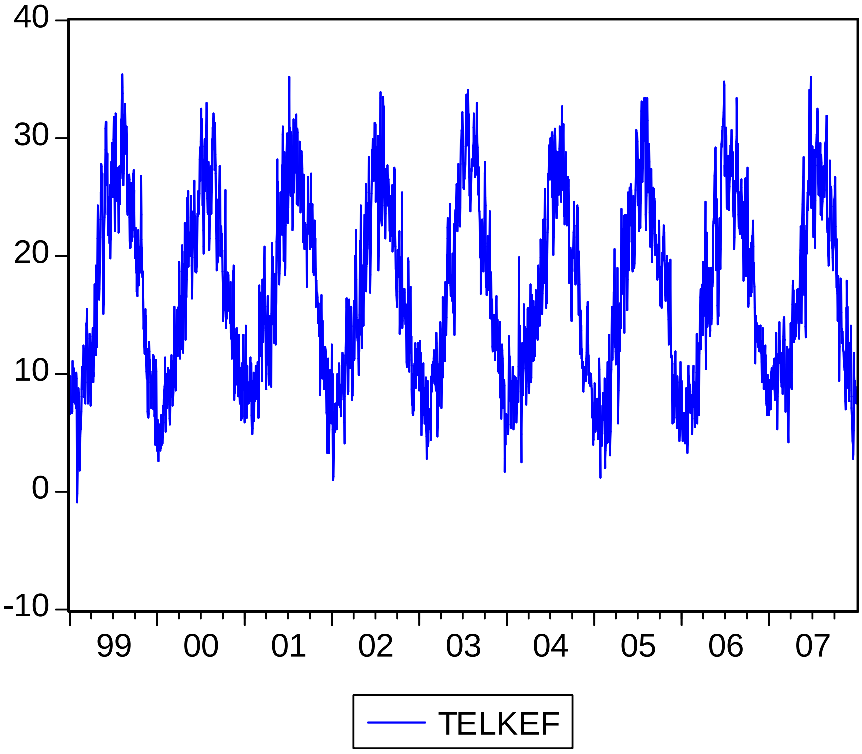
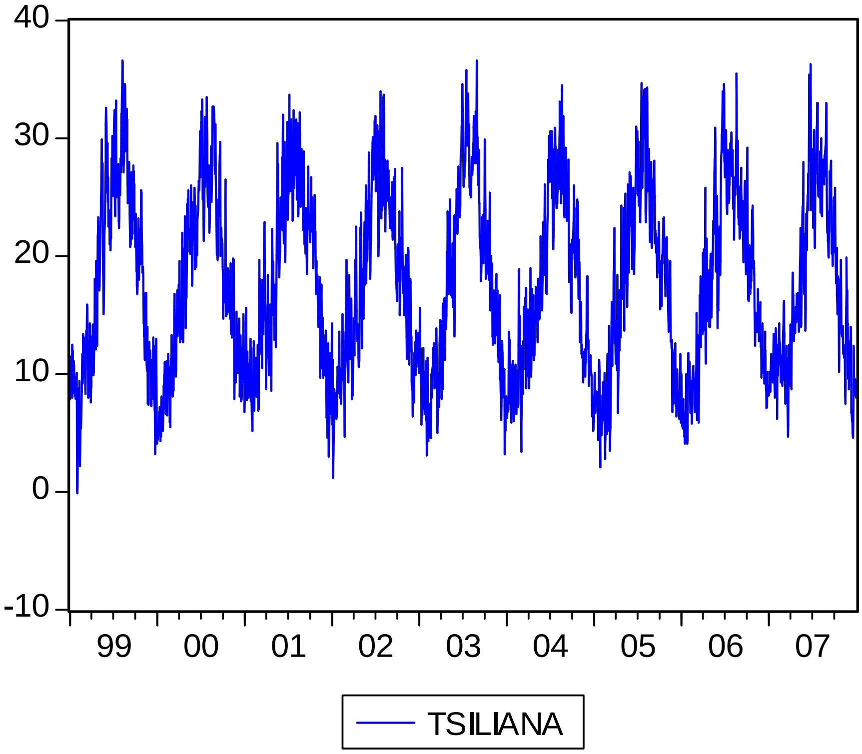


Figure 3: The daily mean temperature of SILIANA (01/01/1999 - 31/12/2007)



3.2.1 Study of stationarity:

There exist several tests of unit root such as Fuller (1976) **[11]**, Dickey and Fuller (1979, 1981) **[8]**, Philips and Perron (1988) **[19]**, Perron (1989) **[17]**, Zivot and Andrews (1992) **[23]**,Perron and Vogelsang (1992) **[18]**, Schmidt and Philips (1992) **[22]**, Elliott, Rothenberg and Stock (1996) **[9]**, Kwiatkowski, Philips, Schmidt and Shin (1992) **[12]**.

We use for our study the test KPSS of Kwiatkowski and others (1992) **[12]** thanks to his specificity to test the null assumption of absence of root unit against the alternative assumption of presence of a unit root. The results are represented in the table 1 and table 2. The analysis of the statistics shows that the series of temperatures of Elkef expresses a stationnarity since its value (0.023066) is lower than the critical point to 5% (0.463000).The same result is found for TSILIANA series (0.022287< 0.463).

Table 1: coefficients regression of the model with constant of kPSS test for TELKEF series

Null Hypothesis: TELKEF is stationary
Exogenous: Constant
Bandwidth: 53 (Fixed using Bartlett kernel)

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.023066
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	60.78202
HAC corrected variance (Bartlett kernel)	2609.288

KPSS Test Equation
Dependent Variable: TELKEF
Method: Least Squares
Date: 06/06/09 Time: 11:03
Sample: 1/01/1999 12/31/2007
Included observations: 3287

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	17.04746	0.136005	125.3447	0.0000

R-squared	-0.000000	Mean dependent var	17.04746
Adjusted R-squared	0.000000	S.D. dependent var	7.797469
S.E. of regression	7.797469	Akaike info criterion	6.945780
Sum squared resid	199790.5	Schwarz criterion	6.947635
Log likelihood	-11414.39	Durbin-Watson stat	0.071918

Table 2: coefficients regression of the model with constant of kPSS test for TSILIANA series

Null Hypothesis: TSILIANA is stationary
Exogenous: Constant
Bandwidth: 53 (Fixed using Bartlett kernel)

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.022287
Asymptotic critical values*:	1% level	0.739000
	5% level	0.463000
	10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	58.65108
HAC corrected variance (Bartlett kernel)	2481.619

KPSS Test Equation
Dependent Variable: TSILIANA
Method: Least Squares
Date: 06/06/09 Time: 11:34
Sample: 1/01/1999 12/31/2007
Included observations: 3287

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	17.63575	0.133599	132.0048	0.0000

R-squared	-0.000000	Mean dependent var	17.63575
Adjusted R-squared	-0.000000	S.D. dependent var	7.659564
S.E. of regression	7.659564	Akaike info criterion	6.910091
Sum squared resid	192786.1	Schwarz criterion	6.911947
Log likelihood	-11355.74	Durbin-Watson stat	0.083267

The series TElkef and TSeliana being stationary, we propose to model them by an ARMA process. For that, we take again the four stages of the methodology of Box and Jenkins **[1].**

3.2.2 Methodology of Box and Jenkins

Stage 1: identification

This first is carried out by studying the autocorrelation and autocorrelation partial functions of the series TElkef and TSeliana. The graph of these functions, deferred on figures 4 and 5, indicate: The first five autocorrelations are significantly different from zero: we deduce q= 5 for the two series and the first eleven partial autocorrelations are significantly the different ones from zero: we deduce p = 11 for TELKEF and TSILIANA series.

So we identify 71 processes for each series : AR (1), AR (2), AR (3), AR (4), AR (5), AR (6), AR (7), AR (8), AR (9), AR (10), AR (11), AM (1), AM (2), AM (3), AM (4), AM (5) and combinations between these various processes.

Figure 4: Autocorrelation and partial autocorrelation of the TElkef series

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.030	0.030	3.0438	0.081
		2	-0.195	-0.196	128.17	0.000
		3	-0.108	-0.098	166.31	0.000
		4	-0.060	-0.097	178.03	0.000
		5	-0.051	-0.095	186.63	0.000
		6	-0.027	-0.074	189.03	0.000
		7	-0.027	-0.080	191.35	0.000
		8	-0.018	-0.069	192.45	0.000
		9	0.010	-0.041	192.79	0.000
		10	0.016	-0.033	193.66	0.000
		11	0.004	-0.033	193.71	0.000
		12	-0.001	-0.027	193.71	0.000
		13	0.005	-0.017	193.80	0.000
		14	-0.017	-0.037	194.74	0.000
		15	-0.002	-0.016	194.75	0.000
		16	0.010	-0.010	195.05	0.000

Figure 5: Autocorrelation and partial autocorrelation of the TSILIANA series

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.061	0.061	12.198	0.000
		2	-0.239	-0.243	199.34	0.000
		3	-0.119	-0.091	245.58	0.000
		4	-0.063	-0.115	258.47	0.000
		5	-0.054	-0.105	268.23	0.000
		6	-0.014	-0.069	268.87	0.000
		7	-0.007	-0.072	269.02	0.000
		8	-0.027	-0.081	271.36	0.000
		9	0.016	-0.030	272.24	0.000
		10	0.004	-0.053	272.30	0.000
		11	-0.005	-0.038	272.39	0.000
		12	0.018	-0.013	273.48	0.000
		13	0.004	-0.027	273.53	0.000
		14	-0.022	-0.036	275.11	0.000
		15	-0.025	-0.042	277.19	0.000
		16	0.023	0.001	278.87	0.000

Stage 2: regression

We carry out the regressions of the 71 processes previously identified AR (1), AR (2), AR (3), AR (4), AR (5), AR (6), AR (7), AR (8), AR (9), AR (10), AR (11), AM (1), AM (2), AM (3), AM (4), AM (5) and the combinations between these various processes.

Taking into consideration regression result, we note that:

- For TELKEF series
- The model AR (1), AR (2), AR (3), AR (4) and AR (5) remain candidates in measurement that the auto regression coefficients of order 1,2,3,4 and 5 are significantly different from zero (T of Student is higher than 1,96).
- The model MA (1), MA (2), MA (3), MA (4) and MA (5) remain also candidates since the coefficient is significantly different from zero.
- Them coefficients auto regression and moving average of the ARMA (1,1), ARMA (1,2), ARMA (1,3), ARMA (1,4) ARMA (2,1) and ARMA (2,2) processes are significantly different from zero.
- For TSILIANA series
- The model AR (1), AR (2), AR (3) and AR (4) remain candidates in measurement that the auto regression coefficients of order 1,2,3 and 4 are significantly different from zero (T of Student is higher than 1,96).
- The model MA (1), MA (2), MA (3), MA (4), MA (5), MA (6) and MA (7) remain also candidates since the coefficient is significantly different from zero.
- Them coefficients auto regression and moving average of the ARMA (1, 1), ARMA (1,2), ARMA (2,1) and ARMA (2,2) processes are significantly different from zero.

Consequently, at the conclusion of the regression stage sixteen models are candidates with the explanation of the dynamics of TKEF series and fifteen models are still candidates with the explanation of the dynamics of TSILIANA series.

Stage 3: validation

In order to decide between the various processes for each series let us compare to them by means of the criteria of models choice. The results are given in tables 3, 4 and 5. All the criteria lead us to choose the process ARMA (2, 2) to represent the dynamics of the TElkef and TSeliana series.

Table 3: Summary of the comparison criteria obtained for the various processes for the two series

Processus	AIC	SIC	Processus	AIC	SIC
AR(1)	4.29	4.30	AR(1)	4.40	4.41
AR(2)	5.05	5.06	AR(2)	4.39	4.40
AR(3)	5.32	5.33	AR(3)	4.34	4.35
AR(4)	5.46	5.47	AR(4)	4.34	4.35
AR(5)	5.54	5.55	MA(1)	5.83	5.84
MA(1)	5.84	5.85	MA(2)	5.25	5.26
MA(2)	6.11	6.12	MA(3)	4.99	5.00
MA(3)	6.22	6.23	MA(4)	4.82	4.83
MA(4)	6.27	6.28	MA(5)	4.72	4.73
MA(5)	6.31	6.32	MA(6)	4.66	4.67
ARMA(1,1)	4.27	4.28	MA(7)	4.60	4.61
ARMA(1,2)	4.23	4.24	ARMA(1,1)	4.39	4.40
ARMA(1,3)	4.21	4.22	ARMA(1,2)	4.37	4.38
ARMA(1,4)	4.20	4.21	ARMA(2,1)	4.37	4.38
ARMA(2,1)	4.26	4.27	ARMA(2,2)	4.30	4.31
ARMA(2,2)	4.19	4.20			

It is very recognized in the literature (Engle, 1982, Borllerslev, 1986) of the modeling time series that the variance of residues of the ARMA models is not constant in time. They are thus the phenomena of heteroscedasticity.

For the aim of testing the existence of this phenomenon, we use the Arch test of Engle 1982. We will test the null assumption of homoscedasticity against the alternative of heteroscidasticity.

Table 4: The estimation of the model ARMA (2, 2) for TELKEF series

Dependent Variable: TELKEF
Method: Least Squares
Date: 06/22/09 Time: 14:23
Sample (adjusted): 1/03/1999 12/31/2007
Included observations: 3287 after adjustments
Convergence achieved after 18 iterations
Backcast: 1/01/1999 1/02/1999

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	17.08315	2.296217	7.439696	0.0000
AR(1)	1.538911	0.033865	45.44256	0.0000
AR(2)	-0.541749	0.033415	-16.21297	0.0000
MA(1)	-0.507388	0.033892	-14.97075	0.0000

MA(2)	-0.303613	0.018761	-16.18289	0.0000

R-squared	0.936059	Mean dependent var	17.05300
Adjusted R-squared	0.935981	S.D. dependent var	7.796538
S.E. of regression	1.972673	Akaike info criterion	4.198177
Sum squared resid	12763.92	Schwarz criterion	4.207457
Log likelihood	-6890.505	F-statistic	12004.39
Durbin-Watson stat	1.990852	Prob(F-statistic)	0.000000

Inverted AR Roots	.99	.55
Inverted MA Roots	.86	-.35

Table 5: The estimation of the model ARMA (2, 2) for TSILIANA series

Dependent Variable: TSILIANA
Method: Least Squares
Date: 06/25/09 Time: 16:00
Sample (adjusted): 1/03/1977 12/29/1985
Included observations: 3287 after adjustments
Convergence achieved after 14 iterations
Backcast: 1/01/1977 1/02/1977

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	17.63712	2.206283	7.994044	0.0000
AR(1)	1.497104	0.034488	43.40881	0.0000
AR(2)	-0.500333	0.034005	-14.71367	0.0000
MA(1)	-0.498156	0.034285	-14.52966	0.0000
MA(2)	-0.305973	0.019252	-15.89293	0.0000

R-squared	0.926305	Mean dependent var	17.64596
Adjusted R-squared	0.926215	S.D. dependent var	7.658237
S.E. of regression	2.080238	Akaike info criterion	4.304364
Sum squared resid	14185.19	Schwarz criterion	4.313649
Log likelihood	-7060.613	F-statistic	10300.64
Durbin-Watson stat	1.995696	Prob(F-statistic)	0.000000

Inverted AR Roots	.99	.50
Inverted MA Roots	.86	-.36

The application of test to the order k =4 provide the calculated statistics of Fischer which is higher than the critical value and a critical probability which is lower than 5%. This result makes it possible to reject the null assumption of homoscidasticity in favor of the heteroscidasticity, a model of the type ARMA (2, 2) - GARCH (1, 1) can be a possible candidate to describe the behavior of the variation in the daily mean temperature for the two areas as shown in tables 6 and 7.

Table 6: The estimation of the model ARMA (2, 2) - GARCH (1,1) for TELKEF series

Dependent Variable: TELKEF
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 06/22/09 Time: 14:30
Sample (adjusted): 1/03/1999 12/31/2007
Included observations: 3287 after adjustments
Convergence achieved after 32 iterations
MA backcast: 1/01/1999 1/02/1999, Variance backcast: ON
GARCH = C(6) + C(7)*RESID(-1)^2 + C(8)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	13.31639	2.339914	5.690973	0.0000
AR(1)	1.538769	0.032993	46.63887	0.0000
AR(2)	-0.541781	0.032544	-16.64775	0.0000
MA(1)	-0.504801	0.033199	-15.20543	0.0000
MA(2)	-0.308314	0.019922	-15.47610	0.0000
	Variance Equation			
C	0.173446	0.043541	3.983527	0.0001
RESID(-1)^2	0.044434	0.007343	6.051536	0.0000
GARCH(-1)	0.911192	0.016361	55.69196	0.0000

R-squared	0.935996	Mean dependent var	17.05300
Adjusted R-squared	0.935859	S.D. dependent var	7.796538
S.E. of regression	1.974557	Akaike info criterion	4.177314
Sum squared resid	12776.61	Schwarz criterion	4.192163
Log likelihood	-6853.239	F-statistic	6846.100
Durbin-Watson stat	1.993910	Prob(F-statistic)	0.000000

Inverted AR Roots	.99	.55
Inverted MA Roots	.86	-.36

Table 7: The estimation of the model ARMA (2, 2) - GARCH (1,1) for TSILIANA series

Dependent Variable: TSILIANA
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 06/25/09 Time: 16:01
Sample (adjusted): 1/03/1977 12/29/1985
Included observations: 3287 after adjustments
Convergence achieved after 36 iterations
MA backcast: 1/01/1977 1/02/1977, Variance backcast: ON
GARCH = C(6) + C(7)*RESID(-1)^2 + C(8)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	14.01282	2.369158	5.914685	0.0000
AR(1)	1.497382	0.034488	43.41781	0.0000
AR(2)	-0.500637	0.034038	-14.70804	0.0000
MA(1)	-0.494957	0.034623	-14.29568	0.0000
MA(2)	-0.311136	0.021035	-14.79159	0.0000
	Variance Equation			
C	0.610260	0.137661	4.433069	0.0000
RESID(-1)^2	0.085173	0.014408	5.911543	0.0000
GARCH(-1)	0.775116	0.041387	18.72847	0.0000

R-squared	0.926239	Mean dependent var	17.64596
Adjusted R-squared	0.926082	S.D. dependent var	7.658237
S.E. of regression	2.082114	Akaike info criterion	4.284950
Sum squared resid	14197.78	Schwarz criterion	4.299806
Log likelihood	-7025.745	F-statistic	5875.058
Durbin-Watson stat	2.000975	Prob(F-statistic)	0.000000
Inverted AR Roots	.99	.50	
Inverted MA Roots	.86	-.36	

The estimation of the model ARMA (2, 2) - GARCH (1, 1) confirm the existence of this phenomenon by the significativity of the coefficients of the equation of the variance

Stage 4: forecast

The last stage of the Box and Jenkins methodology has as an aim the forecast of the two series on the basis of ARMA (2,2) - GARCH (1,1) process. The forecasts of two n series noted FTELKEF and FTSILIANA are represented on figures 6 and 7. Those are located outside the sample of 285 observations. We notice an upward trend of the daily mean temperature.

Figure 6: Forecasting the daily mean temperature of ELKEF, 285 days after (01/01/1999 - 31/12/2007)

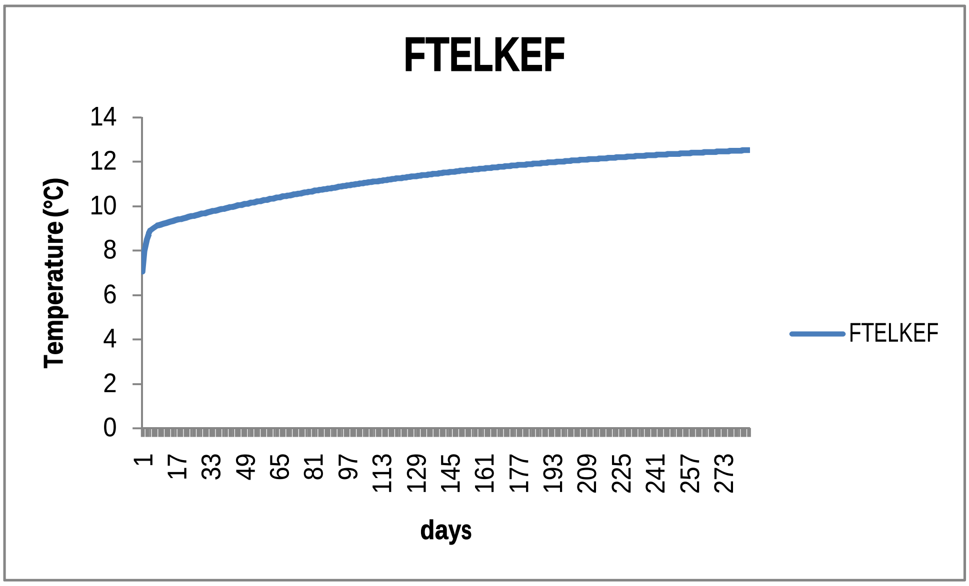
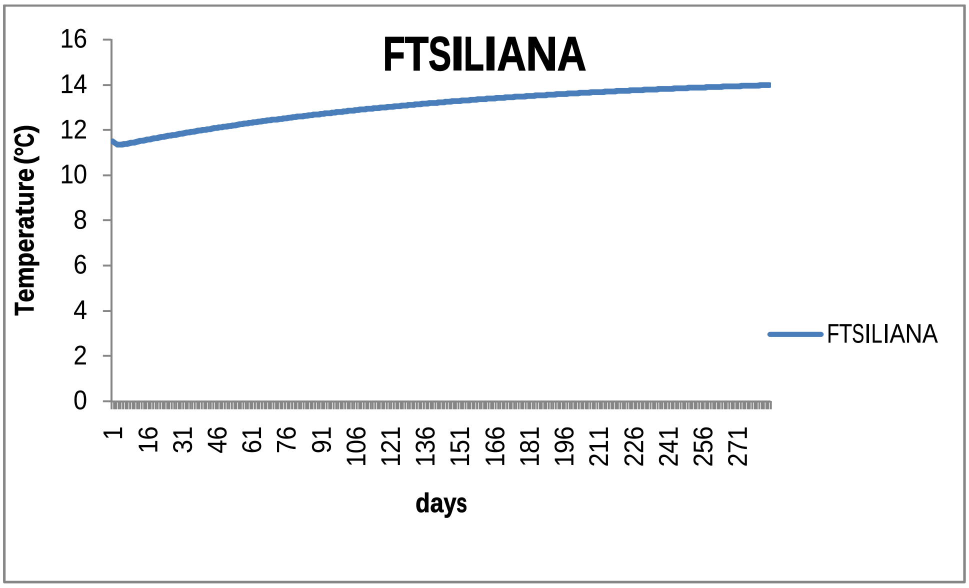


Figure 7: Forecasting the daily mean temperature of SILIANA, 285 days after (01/01/1999 - 31/12/2007)



4. The Basker ville Emin method (BE):

To measure the GSL, the index of growing degree days was computed by (BE) method **[11]**. According to this method, if the minimum daily temperature is greater or equal to the base temperature (for durum wheat the base temperature equal to 5° C), then:

$$GDD_1 = T_{mean} - T_{base}$$

If $T_{mean} \langle T_{base}$ then $GDD_1 = 0$

If $T_{\min} \langle T_{base}$ then $GDD_2 = ((W * \cos(A)) - ((T_{base} - T_{mean})) * (3.14/2 - A))/3.14$

Where $T_{mean} = (T_{\max} + T_{\min})/2$;

$W = (T_{\max} - T_{\min})/2$;

$A = Arc\sin((T_{base} - T_{mean})/W)$;

T_{max} and T_{min} are the maximum and minimum respectively, and T_{base} is the base temperature below which crop growth ceases. Summing GDD_1 and GDD_2 produces the total GDD for the wheat season.

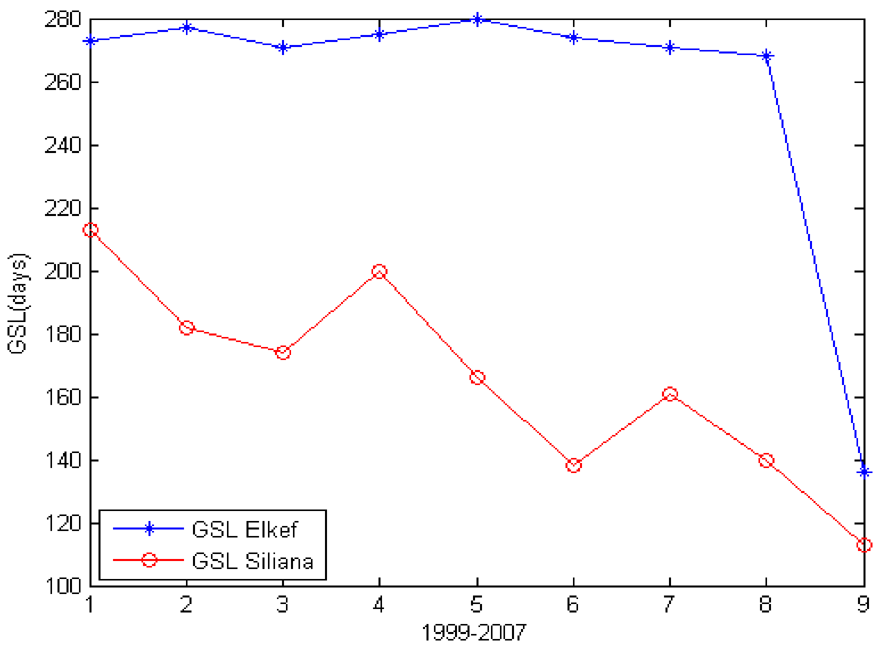
The GSL for wheat was then estimated by measuring the number of days from the date of planting to the date at which the crop would be able to accumulate GDDs of 1800.

5. Results:

5.1. Temperature increasing and growing season length:

The increasing of temperature in the two districts (Figure 1 and 2) causes the GSL to decrease. Seliana and Elkef districts show a decline of GSL during the period 1999 to 2007 (Figure 8). The 9 year average GSL was 165 days in Seliana district and 258 days in Elkef district. Farmers should delay the date of plantation of durum wheat to December to ovoid the negative impact of the increasing of temperature.

Figure 8: The decline of GSL during the period 1999 to 2007 for Seliana and Elkef districts



5.2. Growing season length under various climate change scenarios:

The growing season length for durum wheat is reduced only for ELKEF. If temperature increases by 3°C the growing season length for ELKEF is reduced from 258 to 212 days (18% under the average of GSL) as shown in figure 9, we note that S1is an increase of 1.5°C,S2 an increase of 2°C,S3 an increase of 2.5°C and S4 an increase of 3°C of daily mean temperature . In SILIANA district we find that an increasing of 3°C in temperature for the next 30 years will increase the growing season length from 165 to 197 days as shown in figure 10.The last scenario (an increasing of 3° C) will reduce the growing season length for the ELKEF district. This increasing of temperature may reduce the yield of wheat in the tow districts.

Figure 9: The decline of GSL for Elkef district under various climate change scenarios

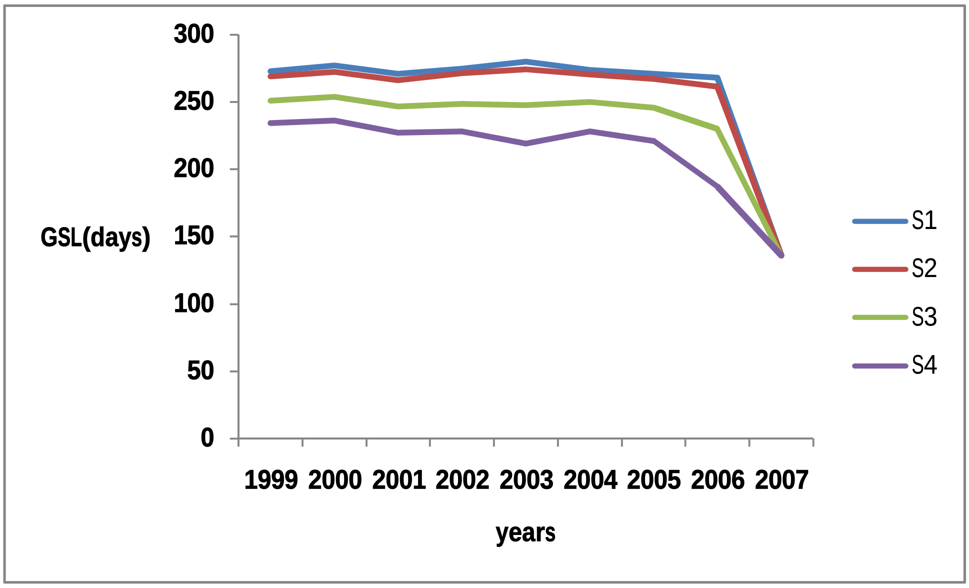
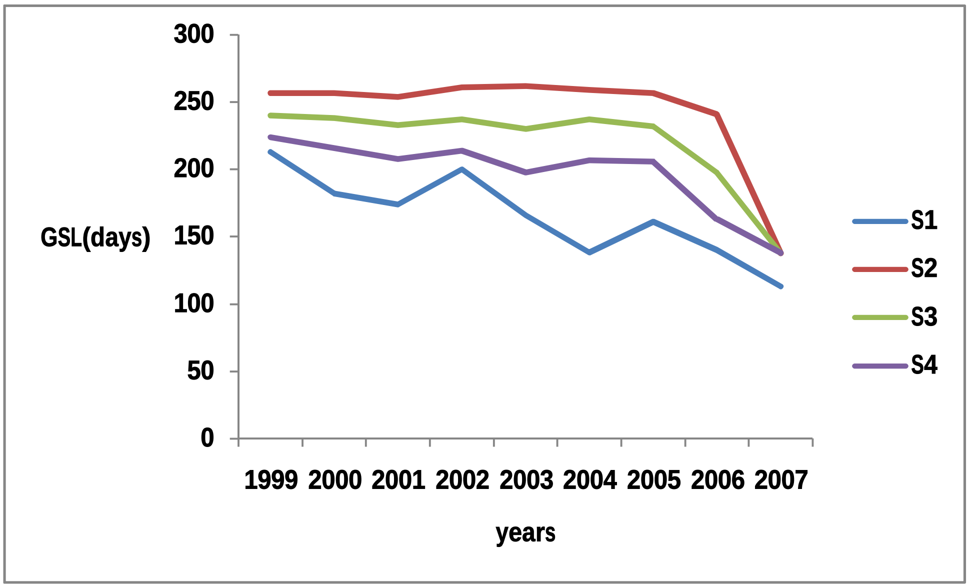


Figure 10: The decline of GSL for SILIANA district under various climate change scenarios



6. Conclusions:

Agriculture has received considerable attention recently with regard to climate change because of the high dependence of agriculture on the climate. Dependence on agriculture especially in developing countries, also mean, that agriculture has an important role to play in debates about adaptation to climate change.

So far we have gained a number of important insights from our research. We have shown that econometric methods are useful in the study of climate change where applied rigorously and consistently. We find that the observed climate change patterns and their impact were diverse both spatially and temporally.

Our empirical results show that historical increases in temperatures in Elkef reduced the growing period (GSL) .The GSL for wheat Elkef may reduce under climate change

We find that high temperatures correspond to a decrease in growing season length. Future increases in temperatures between 1.5 and 3.5° C may reduce the yield of durum wheat in the tow districts. The choice of good varieties of wheat and delaying the date of plantation to December will be the best solution to ameliorate the yield

References

[1] Box G.E.P and Jenkins G.M, 1970. Time Series Analysis: Forecasting and Control, San Francisco, Holden day.

[2] Brody D.C., Syroka J., Zervos M., 2001. Dynamical Pricing of Weather Derivatives, working paper.

[3] Caballero R., Jewson S., Brix A., 2002. Long memory in surface air temperature: detection, modeling, and application to weather derivative valuation, Climate Research, 21, 127-140.

[4] Campbell J.Y., Lo A.W., MacKinlay A.C., 1997. The Econometrics of Financial Markets,(Princeton University Press).

[5] Campbell S., Diebold F.X., 2000. Weather Forecasting for Weather Derivatives,working paper.

[6] Cao M., Wei J., 2001. Stock Market Returns: A Temperature Anomaly, working Paper.

[7] Cao M., Wei J., 2001. Pricing Weather Derivatives: an Equilibrium Approach, working paper.

[8] Dickey D.A and Fuller W.A, 1979. Distribution of the Estimators for Autoregressive Time Series with a Unit Root, journal of the American Statistical Association, 74,427-431.

[9] Elliott G.,Rothenberg T. and Stock J.H.,1996. Efficient Tests For an Autoregressive Unit Root, Econometrica, 64(4), 813-836.

[10] Engle R.F.1982. Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation, Econometrica, 50(4), 987-1007.

[11] Fuller W.A, 1976. Introduction to Statistical Time Series, New York, Willey.

[12] Kwiatkowski D., Phillips P.C.B., Schmidt P. and Shin Y.1992. Testing the Null Hypothesis of Stationarity against the Alternative of a Unit Root. How sure are we that Economic Time Series Have a Unit Root? Journal of Econometrics, 54,159-178.

[13] Moréno M., Rain Risk, 2001. Speedwell Weather Derivatives, www.weatherderivs.com.

[14] Moréno M., 2000. Evaluation des Dérivés Climatiques, Speedwell Weather Derivatives, www.weatherderivs.com.

[15] Moréno M., 2000. Riding the Temp, Weather Derivatives, FOW Special Supplement, December.

[16] Nugent, J., 2000, Calculating growing degree days. Northwest Michigan Horticultural Research station, Traverse City, MI 49684. Available from: http://www.maes.msu.edu/nwmihort/gdd_calc.html

[17] Perron P., 1988. Trends and Random Walks in macroeconomic Time Series: Further Evidence from a new approach, journal of Economic Dynamics and control, and 12,297-332.

[18] Perron P and Vogelsang T.J., 1992. Nonstationarity and Level Shifts with an application to purchasing power parity, journal of Business and Economic Statistics, 301-320.

[19] Phillips P.C.B. and Perron P., 1988. Testing for a Unit Root in a Time Series Regression, Biometrika, 75,335-346.

[20] Roustant O., 2002. Une application de deux modèles économétriques de température à la gestion de risques climatiques (1ère partie), Banque & Marchés, 58, 22-29.

[21] Roustant O., 2002. Une application de deux modèles économétriques de température à la gestion de risques climatiques (2ème partie), Banque & Marchés, 59, 36-44.

[22] Schmidt P. and Phillips P.C.B., 1992. LM Test for a Unit Root in the presence of deterministic trends, Oxford Bulletin of Economic and Statistics, 54,257-287.

[23] Zivot E. and Andrews D.W.K., 1992. Further Evidence on the Great Crash, the Oil price shock and the Unit Root hypothesis, journal of Business and Economic Statistics, 10,251-270.