



ISSN: 2230-9926

Available online at <http://www.journalijdr.com>

IJDR

International Journal of Development Research
Vol. 08, Issue, 02, pp.19097-19101, February, 2018



ORIGINAL RESEARCH ARTICLE

OPEN ACCESS

MODELING OF TEMPERATURE AND SUNSHINE FOR A TUNISIAN CITY

^{1,*}Chaima Baazaoui and ²Yacin Jerbi

¹Department of Economics, University of Economics and Management, 3018 Sfax, Tunisia

²Department of Computer Engineering and Applied Mathematics, National School of Engineers, 3038Sfax, Tunisia

ARTICLE INFO

Article History:

Received 10th November, 2017
Received in revised form
07th December, 2017
Accepted 23rd January, 2018
Published online 28th February, 2018

Key Words:

Average daily temperature, Daily sunshine,
ARMA, ARCH / GARCH,
JEL classification: Q54, C22, C32.

ABSTRACT

By 2030, Tunisia expects a warmer and more variable climate. This climate change will lead to increased pressure on natural resources. This requires the effective integration of the environmental dimension into management and governance. This article addresses the climate change estimate needed for climate risk management. The purpose of this estimate is to determine, using the Box-Jenkins methodology and the ARCH / GARCH models, the future behavior of the average daily temperature and daily sunshine for a Tunisian city over the period 01-01- 2004 to 31-12-2014. The modeling of the temperature and the sunshine is mainly for the evaluation of the energy produced by photovoltaic panels of customers installed in the governorate of Sfax.

Copyright © 2018, Chaima Baazaoui and Yacin Jerbi. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Citation: Chaima Baazaoui and Yacin Jerbi, 2018. "Modeling of temperature and sunshine for a Tunisian city", *International Journal of Development Research*, 8, (02), 19097-19101.

INTRODUCTION

In recent decades, a number of indicators and studies show that the climate is warming around the world. The Fourth assessment report of the intergovernmental panel on climate change in 2007 confirms this fact. The warming of the climate system is unequivocal. Indeed, in the 20th century, the global average temperature of the atmosphere and the ocean rose by 0.6 ° C and the average sea level rose between 10 and 20 centimeters. Climate change is likely to have a significant impact on the prospects for economic growth. Currently, several studies show the dependence of different sectors of the weather (energy, agriculture, tourism, construction) (Dorfleitner and Wimmer, 2010; Amelung and Moreno, 2012; Dawson and Scott, 2013; Day *et al.* 2013). Climate change has a direct impact on the company's production, inventory management, supply lines, sales, etc. It is important to note that the global market provides some security for its operations as meteorological data is determined by independent bodies.

***Corresponding author: Chaima Baazaoui**

Department of Economics, University of Economics and Management, 3018 Sfax, Tunisia.

To be covered against climate risks, economic agents have traditionally used insurance (Aerts and Botzen, 2011). Unfortunately, few traditional insurance mechanisms manage this risk. To circumvent these difficulties, weather derivatives have emerged as new hedging products (Sturm and Oh, 2010). Climate derivatives are based on meteorological data, such as temperature, sunshine, precipitation level (rain or snow), wind speed, and other "usual" weather phenomena. But the temperature that is the most used underlying (Dischel, 2002; Geman, 1999; Mraoua and Bari, 2007). These products reflect the shape of traditional financial derivatives such as swaps, futures, options and bonds. In Africa, the climate derivatives market is not yet developed, except for some attempts in South Africa (Stoppa and Hess, 2003; Ncube, 2010). This article will deal with the modeling of the average daily temperature and the daily sunshine for the city of Sfax. First, we examine the models that have been suggested so far to account for the dynamics of these variables. After a brief description of the characteristics of a climatic, seasonal and cyclic behavior of the variance, we perform the stationarization of the raw series in a second time. Applying later the Box-Jenkins method, we model the dynamics of seasonally adjusted and trend-corrected chronics through the ARMA and GARCH models.

MATERIALS AND METHODS

The theory shows that climate change affects the size of the economy (Tol, 2014). First, when temperatures rise, it has negative effects on economic growth - but only in poor countries. In rich countries, however, changes in temperature did not have a noticeable effect on growth (Burke *et al.* 2015). The use of time series allows for the seasonality and trend of the estimated weather variable. Cao and Wei (2004), Campbell and Diebold (2005) have shown that autoregressive models with orders greater than 1 better reflect the structure of temperature. Moreover, Carmona (1999) has shown that a generalization of previous models with ARMA type models does not bring much added value compared to AR type models. Richards *et al.* (2004) used an ARCH process while Cao and Wei (2004) advocated a rather circular characteristic to enter the seasonal behavior of volatility. For their part, Campbell and Diebold (2005) supported a model combining the GARCH effect and the sum of the sinusoids.

Box-Jenkins methodology

This methodology can determine the best model that reproduces the behavior of a time series according to a three-step procedure: identification, estimation and validation, which must be repeated until the result is considered satisfactory.

Identification

The first step is to identify the three parameters p , d and q of the ARIMA model (p , d , q). This identification involves first checking stationarity of the series since the basic processes, whether autoregressive or moving averages, are essentially stationary because of the constraints on their parameters. In the presence of trend and seasonality, it is necessary to transform the series to obtain a stationary series. The most common transformation is the differentiation of the series, an operation where each value in the series is replaced by the difference between that value and the one preceding it. Logarithmic transformation or square root can be used in heteroscedasticity, where the variance of the series is not constant and depends on the values taken, for example with high volatility for high values and low volatility for low values. The next step is to specify the p order of the autoregressive process using the graph of the partial autocorrelation function and q that of the moving average using the graph of the simple autocorrelation function. In addition to the correlation coefficients, the correlograms display the 95% confidence intervals, which make it possible to determine which are the statistically significant coefficients to be taken into account.

Estimation

The second step consists of estimating the coefficients of the model previously identified by the maximum likelihood method. The execution of the procedure gives us several models. The choice of a single model that represents the data generating process is based on a set of control and diagnostic criteria.

Validation

The third step is to analyze the residues which must not have any deterministic configuration: their characteristics must correspond to those of a white noise.

We must apply tests of null hypothesis of homoscedasticity (ARCH tests, Lagrange Multiplier) and null hypothesis of autocorrelation (Box-Pierce tests, Ljung-Box). To check if the residue process is Gaussian white noise, the most common test is Jarque-Bera. If, after the application of these different diagnostic tests, several models are validated, the validation step must continue with a comparison of the qualities of these models. The criteria for choosing the model to remember can be standard or information.

Methodology and data

We are interested in modeling the average daily temperature and sunshine of the city of Sfax. To test the stationarity of the series, we will implement in this part of the KPSS test. We will first apply the Box-Jenkins method to determine the orders p and q of the seasonally adjusted and trend-adjusted chronicles. However, this model is inadequate because it does not account for the non-stationary variance. This is why, secondly, we estimate volatility by applying ARCH / GARCH modeling. The study behaves on the series of the average daily temperature in Celsius and the daily sunshine in Joules of Sfax which are collected from the National Institute of Meteorology. The data cover the period 01-01-2004 to 31-12-2014 and each include a total of 4018 observations.

RESULTS AND DISCUSSION

Descriptive study

The figure will allow us to illustrate the shape of the series of the average daily temperature and the daily sunshine of the city of Sfax. We can detect a strong cyclical movement whose amplitude does not increase over time. In general, the trend is represented by a line. Given Figure a, our series shows a sinusoidal movement that justifies seasonality. The non-stationarity of the temperature series and sunshine can also be confirmed by the KPSS test. This test shows that consistency and trend are significant at the 5% level. The test statistic is less than the critical value of this threshold. Thus, we can conclude that our different series present a non-deterministic stationarity. In most cases, a first differentiation makes the series stationary. But if the trend is still present, we go to the second differentiation that is necessary and sufficient. We find the evolution of stationary chronicles in Figure b. The chronicles $dtemp_{sfax}$ and $dsun_{sfax}$ seem that they no longer include trend nor seasonality. The series are stationary. However, they do not appear perfectly linear, we can distinguish a slight oscillation in the dispersion of the values which augurs a periodic modeling for the volatility. From this point of view, these chronicles are stationary on average but not stationary in variance.

Estimation of the model

The application of this methodology is the result of three main steps such as the identification of the p and q orders of ARMA (p , q), the estimation and validation of the model. The simple correlogram allows us to identify the model MA (q) while the partial correlogram allows us to conclude on the order p of the model AR (p). The first three simple autocorrelations of the $dtemp_{sfax}$ series and both for $dsun_{sfax}$ are significantly different from zero. However, the first six partial autocorrelations of the two series are significantly different from zero. We chose $q = 3$ and $p = 6$ for the temperature; $q = 2$ and $p = 6$ for sunshine.

Table 1. ARMA Selection Criteria

	dtempsfax			dsunsfax		
	AIC	SC	LL	AIC	SC	LL
AR(1)	4.076	4.080	-8241.945	5.040	5.043	-10118.59
AR(2)	4.065	4.070	-8157.347	4.940	4.954	-9914.796
AR(3)	4.043	4.049	-8110.848	4.910	4.916	-9850.938
AR(4)	4.028	4.036	-8077.926	4.881	4.889	-9788.740
AR(5)	4.011	4.021	-8040.828			
MA(1)	4.049	4.052	-8192.326	4.854	4.857	-9748.945
MA(2)	4.014	4.019	-8058.995	4.815	4.799	-9627.726
MA(3)	4.003	4.009	-8036.430			
ARMA(1.1)	4.797	4.803	-8032.717	4.805	4.805	-9626.221
ARMA(1.2)	4.002	4.009	-8032.707	4.804	4.803	-9624.272
ARMA(2.1)	4.102	4.019	-8033.679	4.795	4.802	-9623.105
ARMA(2.2)	4.241	4.247	-8033.558	4.797	4.812	-9624.214
ARMA(1.3)	4.003	4.010	-8032.927			

Table 2. ARCH-GARCH Selection Criteria

	dtempsfax			dsunsfax		
	AIC	SC	LL	AIC	SC	LL
ARCH(1)	3.975	3.988	-7970.238	4.781	4.790	-9591.377
ARCH(2)	3.963	3.978	-7945.864	4.773	4.784	-9575.108
ARCH(3)	3.959	3.975	-7936.187			
GARCH(1.1)	3.953	3.964	-7930.344	4.748	4.760	-9525.413
GARCH(1.2)	3.948	3.961	-7920.380	4.745	4.758	-9518.457

Table 3. Estimation of ARMA-GARCH for the average daily temperature and sunshine of the city of Sfax

	dtempsfax		dsunsfax	
	ARMA(1.2)-GARCH(1.2)		ARMA(2.1)-GARCH(1.2)	
	Estimation	t-student	Estimation	t-student
θ_0	0.001	2.104	0.013	2.189
θ_1	0.361	7.268	0.280	13.913
θ_2	-0.634	-12.421	-0.021	-2.124
θ_3	-0.128	-4.474	-0.909	-99.236
α_0	0.097	4.398	0.163	5.576
α_1	0.127	7.238	0.122	6.999
α_2	0.088	4.826	0.067	3.659
β	0.631	79.362	0.623	95.006
LL	-7920.380		-9518.457	
AIC	3.948		4.745	
SC	3.961		4.758	

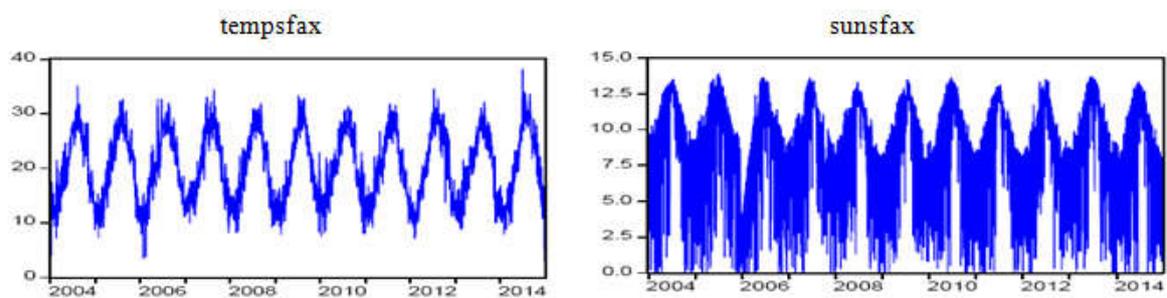


Figure 1. Average daily temperature and daily sunshine (01/01/2004-31/12/2014)

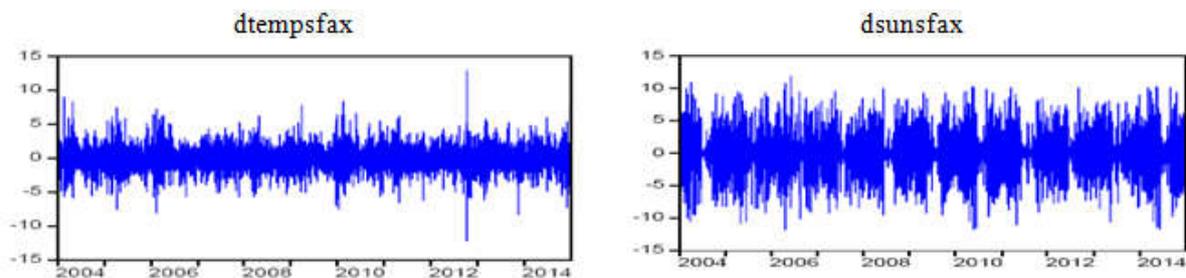


Figure 2. Daily average temperature and daily sunshine seasonally adjusted and adjusted for trend (01/01/ 2004)

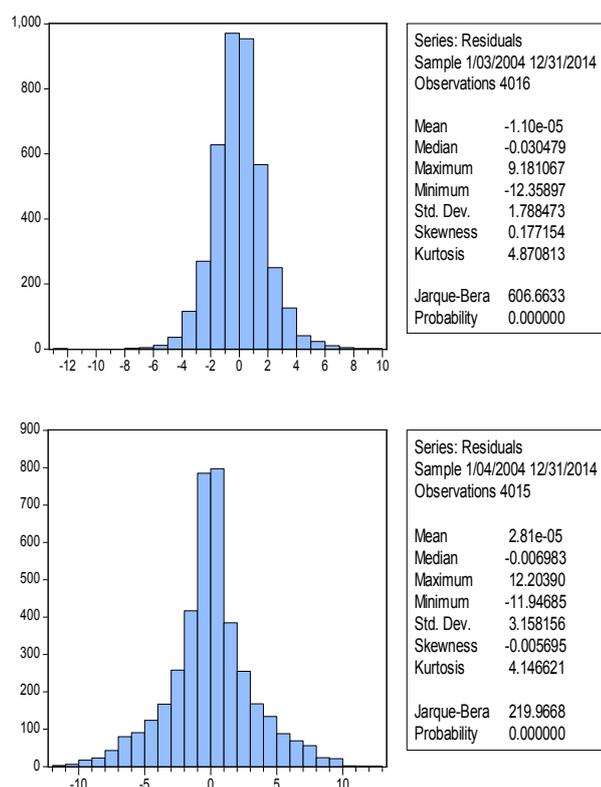


Figure 3. Histograms of the series of residues resulting from the estimation of the ARMA process for the average daily temperature and sunshine of the city of Sfax (01/01 / 2004-31 / 12/2014)

The preserved models are those that have more coefficients with t-student is greater than $|1,96|$; AR (1), AR (2), AR (3), AR (4), AR (5), MA (1), MA (2), MA (3) and their combinations ARMA (1,1), ARMA (1,2), ARMA (2,1), ARMA (2,2) and ARMA (1,3). Table 1 presents the calculated values of the AIC, SC and LL criteria for each series. We noticed that ARMA (1,2) and ARMA (2,1) represent the dynamics of temperature and sunshine for the city of Sfax.

Residue analysis

We examine the non-normality of residues through Figure c which illustrates the histograms of the residue series. The value of the flattening coefficient "kurtosis" is much greater than 3. Moreover, the asymmetry coefficient "Skewness" is non-zero. This leads us to conclude that the distribution of the residues of these series does not follow a normal distribution. The Jarque-Bera test confirms this result. The critical probability associated with this test is zero, which forces us to reject the null hypothesis of residual normality at the 5% threshold. Analysis of the residue histograms indicates that the tailings are not white noise. Thus, they exhibit the characteristics of heteroscedasticity. The order of the GARCH (p, q) is obtained from the analysis of the correlations of the square residuals of the ARMA model already validated for each series of the study. In doing so, for simple autocorrelations, the first three in the dtmpsfax series and the first two in the dsunsfax series are significantly different from zero. On the other hand, the first partial autocorrelation is significantly different from zero for both series. We have the ARCH (1), ARCH (2) ARCH (3), GARCH (1,1) and GARCH (1,2) process estimation.

To choose the most appropriate model, we report the values of the criteria in Table 2. GARCH (1,2) represents the conditional variance of temperature and sunshine of the city of Sfax. The estimation results of the combination of the ARMA and GARCH models appeared in Table 3. Reading this table, we observed, first of all, that the coefficients of the equation of the mean ($\theta_0, \theta_1, \theta_2, \theta_3$) are significantly different from zero. Secondly, the coefficients of the variance equation ($\alpha_0, \alpha_1, \alpha_2, \beta$) are significantly different from zero and they verify the constraints, which ensure the positivity of the variance. For these reasons, the ARMA (1.2) -GARCH (1.2), ARMA (2.1) -GARCH (1.2) models have described well the dynamics of the daily average temperature and daily sunshine series of the city of Sfax for the period from 1 January 2004 to 31 December 2014.

Conclusion

The climate derivatives market is still in its infancy and still in development. Similarly, literature is evolving. However, a general model that is accepted does not exist yet. In addition, practitioners and risk management companies jealously keep their climate market data private and do not publish their models. Tunisia is endowed with a still significant wealth in terms of solar energy and its energy, economic and social benefits on our country. Indeed, Tunisia has a sunshine rate exceeding 3000 hours per year which allows it to develop new promising and potential niches such as photovoltaics. The results of the estimations made should serve as a basic tool to develop and calibrate a model of the energy produced by a photovoltaic generator for the customers installed in the governorate of Sfax.

REFERENCES

- Aerts, J.C., and Botzen, W.J. 2011. Climate change impacts on pricing longterm flood insurance: a comprehensive study for the Netherlands. *In Global Environmental Change*. 21, pp.1045-1060
- Amelung, B., and Moreno, A. 2012. Costing the impact of climate change on tourism in Europe: results of the PESETA project. *In Climatic Change*. 112, pp.83-100
- Burke, M., Hsiang, S., and Miguel, E. (2015) Global Non-linear Effect of Temperature on Economic Production. *In Nature*. 527, pp.235-39
- Campbell, S.D., and Diebold, F.X. 2005. Weather forecasting for deather derivatives. *In Journal of the American Statistical Association*. 100, pp.6-16
- Cao, M., and Wei, J. 2004. Weather derivatives valuation and market price of weather risk, *In Journal of Future Markets*. 24, pp.1065-1089
- Day, J. N., Sydnor Chin, S. and Cherkauer, K. 2013. Weather, climate, and tourism performance: a quantitative analysis. *In Tourism Management Perspectives*. 5, pp.51-56
- Dawson, J., and Scott, D. 2013. Managing for climate change in the alpine ski sector. *In Tourism Management*. 35, pp. 244-254
- Dischel, R.S. 2002. Climate Risk and the weather derivatives : Financial risk management with weather hedges", Vol.I, Risk Books Publication, London.
- Dorfleitner, G., and Wimmer, M. 2010. The pricing of temperature futures at the Chicago Mercantile Exchange. *In Journal of Banking & Finance*. 34, pp.1360-1370

- Geman, H. 1999. Insurance and weather derivatives: from exotic options to exotic underlyings, Vol.I, Risk Books Publication, London.
- Mraoua, M., and Bari, D. 2007. Temperature stochastic modeling and weather derivatives pricing : empirical study with Moroccan data. In *Afrika Statistika*. 2, pp.22–43
- Ncube, M. 2010. Risques climatiques, dynamique de la température et assurance en Afrique, du Sud. In *Note d'information sur le marché*. 1, pp.1–8
- Carmona, R. 1999. Calibrating degree day options. 3rd seminar on stochastic analysis, random field and applications. Lausanne Polytechnic school, Ascona, Switzerland. September 23.
- Richards, T. J., Manfredi, M. R., and Sanders. D. R. 2004. Pricing weather derivatives. In *American Journal of Agricultural Economics*. 4, pp.1005–1017
- Stoppa, A., and U. Hess 2003. Design and use of weather derivatives in agricultural policies: The case of rainfall index insurance in Morocco, International Conference on Agricultural Policy Reform and the WTO: Where are we Heading ?.
- Sturm, T., and Oh, E. 2010. Natural disasters as the end of the insurance industry? scalar competitive strategies, alternative risk transfers, and the economic crisis. In *Geoforum*. 41, pp.154–163
- Tol, R. 2014. Correction and Update: The Economic Effects of Climate Change. In *Journal of Economic Perspectives*. 28, pp.221–26
