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STOCHASTIC MODELLING OF MONTHLY SUN BRIGHT IN COFFEE GROWING AREAS

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Resumen

Se ajustaron modelos ARIMA a series mensuales de brillo solar obtenidas en 32 estaciones meteorológicas de la Federación Nacional de Cafeteros de Colombia. La estructura de los modelos ajustados fue $ARIMA(0,1,1) * (0,1,1)_{12}$ de promedios móviles con componente estacional de 12 meses. Los parámetros estimados fueron suficientes para describir el comportamiento de la serie. Los pronósticos obtenidos fueron muy cercanos de los valores observados, actualizados mensualmente. Esta característica permite reajustar el modelo cuando haya cambios en el patrón de la serie y planificar actividades relacionadas con la absorción de la energía solar. El mayor error de pronóstico fue de 23 %, considerado como aceptable.

Palabras Clave: *Modelo estocástico, ARIMA, Series Temporales, Brillo solar.*

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Abstract

Autorregressive integrated moving average models ARIMA, were adjusted to series of monthly sun bright for 32 meteorological stations of The National Federation of Coffee Growers of Colombia. The structure of the adjusted models was $ARIMA(0,1,1)*(0,1,1)_{12}$ this is a moving average with a seasonality component each 12 month, the estimated parameters were sufficient to describe the behavior of the series, they were statistically different from zero and non correlated. The estimated forecasts were found very approximated to observed values, they are actualized monthly, this characteristic allow to readjust the model when the pattern series change and to plan activities related with absorption of solar energy. The greatest forecast error was 23% and it is considered acceptable.

Key words: *stochastic model, ARIMA, time series, sun bright.*

1 Introduction

Solar radiation that reaches crop surfaces is affected by atmospheric components through energy diffusion and absorption processes. That is why energy observed at the earth's surface is lower than the one initially enters into the atmosphere, which is named solar constant (1.367 w/m^2).

Radiant energy at the earth's surface can be measured by means of sun bright using the following linear function:

$$A = a + b * \frac{Z}{N} + e_i$$

Where:

A: Is the atmospheric transmission showed by the relationship between daily global radiation observed at each of the sites and daily extraterrestrial global radiation.

Z: Is the number of daily sun bright hours.

N: Is the number of sun bright hours in the top of the atmosphere; a and b are the parameters to be estimated.

At the present the National Federation of Coffee Growers does not possess all the equipment needed to measure radiation in it's various meteorological stations; it is mainly because of the cost of getting information. Hence, the above expression (A)can be used for calculating the observed daily global radiation, having mean daily sun bright in the surface which was estimated in the top of the atmosphere. The calculation of radiation using sun bright lets determinate energy quantity that reaches the crop and that is absorbed by it; or else the one used for generating heat and electric energy for another applications.

Modeling sun bright as a mechanism for stimulating and forecasting dry matter accumulation and coffee yield represents a primary element for the production model's functioning.

Models for time series are applied for describing variables whose observations are generally made at equally spaced intervals of time; this makes they depend on each other. Theory and methods for time series have had a strong development in the three last decades of this century. Its application has spread to the different branches of science.

Three basic stages are required for building models for time series: model identification, estimation of the parameters or fitting the identified model; then its diagnostic and evaluation. Last stage involves calculation and evaluation of the forecast. It allows one to decide whether to go back to the identification stage or not, according to the fitting level that the model presents.

Study and development of models for climate variables through forecasts let plan and program strategies for pest management and control, soil conservation methods, proper irrigation and drainage management, proper time for farm practices as well to make forecast for crops, growing, yield and post harvest management.

So far there is not much work leading to the building of stochastic models for climate variables in which coffee growers and researchers can be based on when they want to make crop forecasts.

Modelling climate variables is very useful for the different fields in whichresearch on coffee is carried out and even for people who growth it. That is the reason why this paper pretends to show that using Box and Jenkins methodology (2)it is possible to build ARIMA models which describe sun bright behavior and let make forecast.

Based on ARIMA models theory and methods, models for time series will be built and applied and then make short-term forecast for monthly sun bright at 32 meteorological stations owing to the National Federation of Coffee Growers.

In 1954, Trojer (16) assured that the statistical survey of the different macroclime developments could permit the classification of the climate of a given area in dynamic way. He considered thaat the dynamic method for tropical zone meteorology is of great importance. In 1959 Trojer (17) argued that dynamic climatology lets meteorology be proved in topics of the studued processes in another areas. Those provide technical basis for climate analysis and forecast. Also he mentioned the meteorological basisi - among other ones - for dynamic processes: atmospheric, pressure, temperature, air humidity, cloudiness and radiation.

In 1960 Trojer (18)manifested that time forecast had not been applied in tropical areas mainly because of inappropriate methods. he stated that seasonal distribution for both dry and rainy seasons essentially depends of three factors:

1. The displacement of intertropical circulation system is synchronized to sun position movement and therefore the radiation quantity that reaches earth's surface, which is in terms of number of sunspots an influence on global solar radiation.
2. The seasonal variation of sun position and inclination angle of sun's rays in relation to the receiving surface.
3. And last, atmospheric turbidity.

Using stochastic model of Markov chains, probability and continuity of wet periods in coffee areas were studied by Jaramillo (7). He stated that the most common way for showing climatic data is by means of simple statistics as totals or arithmetic means. These hardly ever represent appropriately those phenomena to be explained.

Montgomery and Johnson (11) considered that Box and Jenkins models are probably the most accurate ones for forecasting phenomena occurring in time series. The authors stated that in practice, methods for exponential smoothing to time series are often used. Although results are reasonably good, there are forecast techniques exploring the reliance among observations yielding better results; most of those forecast techniques are based on recent advances in time series analysis consolidated and developed by Box and Jenkins (2).

Kuehl et. al. (18) argued that correlation techniques are important tools for researching relationships between crop growth and enviromental exogenous variables. However, when they are applied to time series, the presence of autocorrelations of each series affects the estimations of correlations. They proposed -as a solution to this problem- to use the cross correlation in order to relate residuals of series modeled through Box and Jenkins methodology and using ARIMA models. They concluded that modeling time series is a good technique for identification of relationships among agronomic variables which are measured during the time.

Persaud and Chang (14) used expectral analysis for estimating the relationship that exists between deterministic components of temperature series and solar radiation. They concluded that an annual cycle with 2π frequency/365 radians/day and a semiannual cycle with 4π frequency/365 radians/day contributed the most to explain series variation. After those components were removed, Box and Jenkins's transference function theory was used for relating both temperature and radiation remainders. Above references evidence that seasonal components, i.e., periodical behavior of climate variables, constitutes a basic characteristic for climate variables and its period is a year. This seasonal component is not treated in a deterministic way since it is not and exactly constant cycle.

Time series have been used for madelling climate variables in areas not awing to the tropics. Pérez, Gallego and Castillo (13) worked on mean annual temperature series from 6 Spanish cities. The purpose of this work was modelling every studied series and making short-term forecast. ARIMA models were fitted using Box and Jenkins' methodology. Following results were found: autoregressive of order 2 was fitted for Badajoz; autoregressive AR(1) of order 1 for Barcelona and integrated moving average ARIMA(0,1,1) of order 1 for Madrid, La Coruña, San Fernando and Valencia. Forecast errors were low, therefore fitted models were considered fairly acceptable.

A bivariate model for daily sequences of solar radiation and air temperature was developed by Book and Finney (3). An autoregressive model was first used to produce a monthly time series. A disaggregation process was then employed to produce daily series. Under forecast error judgement, fitted models were considered very good since they found little differences when historical obserced series were compared to data resulting from the models. This made authors consider the models suitable for simulating solar energy systems for short -and long- term performance.

An analysisi of the stationary and sequential properties of monthly global horizontal solar radiation is presented by Gordon and Reddy (6) for 13 locations of widely varying climatic conditions. They considered that information obtained by means of the above analysis is essential as input to analytic models for solar energy systems and for generating daily radiation sequences that can serve as input to numerical simulations which model solar system.

Univariate autoregressive stationary models of differents orders for anomalies of specific humidity of 1000 and 850 mbar levels were built by Borisova (1). He stated that fitted models success lay in getting fairly accurate forecast from the point of view of statistics.

Nash, Wirenga and Gutjahr (12) employed time series theories and techniques to examine relationships between soil water content and rainfall, and to compare the relationship of the overall average (the entire transect)soil moisture content with that of individual transect segments. The study of correlograms and estimated cross-correlograms showed relationship between soil moisture and rain through the time.

Using Box and Jenking' methods, Loveday and Craggs (9) carried out univariate models for three different air temperatures influencing the performance of a solar-assisted heat pump system. They concluded that this approach can be used for developing models for time series which describe climate thermal bahavior. Solar radiation mus be considered in development of stochastic models for describing such performance of heating system. Also, they (10)used multivariate models for time series to illustrate the time-dependent relationships between air temperature -at outward ambient, at entry to, and at exit from. They concluded that these models are the menas for readjust heating system which were built to optimize energy savings.

In Colombia -for the Savanna of Bogotá- monthly atmospheric electrical discharges series were studied and modelled by Castaño (4) as well as its relation to monthly rainfall series (number of days with precipitation), monthly vapor pressure average and number of monthly sun bright hours. he employed ARIMA models for describing each of the above-mentioned series. he used transfer functions to make their relationships. He inferred that according to statistical test used for measuring model fitting goodness, every studied series was adequately fitted to $ARIMA(0,1,1)x(0,1,1)_{12}$ model, i.e., seasonal moving average series with 12-month periods and moving average in the regular part. Also, he concluded that this method is quite useful for this kind of modelling, however, as well as mathematic theory knowledge, much skill is needed to develop and understand the intended models.

2 Materials and Methods

First, reviewed methodology for building ARIMA models is presented. Then, locations are described.

2.1 Statistical methodology

In general, the models to be developed have the following form:

$$\Phi_p(B^s)\Phi_p(B)\nabla^d\nabla^D Z_t^a = \mu + \theta q(B)\Theta_Q(B^s)a_t$$

Where Z_t is the observed sun bright in the month t. $\Phi_p(B^s) = (1 - \Phi_1 B^s - ... - \Phi_p B^{Ps})$ is the autoregressive operator of order P from seasonal structure, polynomial in B^s of degree P.$\Phi_p(B) = (1 - \Phi_1 B - ... - \Phi_p B^p)$ is the autoregressive operator of order p from the regular structure, polynomial in B of degree p. $\theta q(B) = (1 - \theta_1 B - ... - \theta_p B^q)$ is the mean-moving operator of order q from the regular structure, polynomial in B of the degree q. $\Theta Q(B^s) = (1 - \Theta_1 B^s - ... - \Theta_Q B^{qs})$ is the mean-moving operator of order Q from seasonal structure, polynomial in B^s of degree Q. ∇^d and ∇^D are regular and seasonal difference operator. μ is the mean of the series. λ means that the serie is transformed, a_t is the aleatory error in the month t. This model is named $ARIMA(P, D, Q)_s x(p, d, q)$.

In a explicit way, a moving average stationary model -differentiated in the regular part $d = 1$ and in the seasonal part of order 12, $D = 1$ having parameters $\theta\Theta$ and Θ for regular part and seasonal part, respectively- can be described in the following way:

$$Z_t = Z_{t-1} + Z_{t-12} - Z_{t-13} + a_t - \theta a_{t-1} - \Theta a_{t-12} + \theta\Theta a_{t-13}$$

Box and Jenkins' methodology (2) have been used to model data.

Forecast error is indicated in percentages and obtained as a coefficient produced by the difference -in absolute value- of the observed value from the calculated value, divided by the observed value. It is the main goodness indicator for the fitted model. A forecast error of $\leq 25\%$ was considered acceptable for the present study.

2.2 Meteorological Stations to be Modelled

Sun bright for 32 meteorological stations listed in table 1, will be modelled using the available information and applying Box and Jenkins () time series theory and methods. Information concerns with meteorological observations from the stations owing to the National Federation of Coffe Growers of Colombia. Depuration and checking of daily data were carried out by the Agroclimatology Section at CENICAFE which constantly keeps the climate data bank up dated. The extent of the series to be modelled ranges from 10 and 43 years of sun bright data recorded every day.

Table1. Geographic information about methodological stations in the study

STATION	ALTITUDE	LATITUDE	LONGITUDE	BRIGHT[1]
El Cedral	2120	4° 42’	75° 32’	925.9
Luis Bustamante	1610	3° 55’	74° 34’	1003.1
Jorge Villamil	1500	2° 20’	75° 31’	1186.6
Heraclio Uribe	1540	4° 17’	75° 55’	1262.5
El Sena	1550	4° 34’	75° 39’	1277.1
Mesitas de Sta Inés	1250	4° 43’	74° 28’	1396.2
La Bella	1450	4° 30’	75° 40’	1402.3
Aguas Blancas	920	6° 50’	73° 29’	1419.2
Blonay	1235	7° 34’	72° 37’	1420.7
Agronomía	2150	5° 03’	75° 29’	1431.8
Tibacuy	1550	4° 22’	74° 26’	1546.1
La Trinidad	1430	4° 54’	75° 03’	1554.0
Santa Helena	1450	5° 19’	75° 00’	1607.6
Maracay	1450	4° 36’	75° 46’	1628.1
Limón	990	3°40’	75° 35’	1658.5
Manuel Mallarino	1380	4° 13’	76° 19’	1659.1
La Montaña	1260	3° 33’	74° 54’	1692.4
Montelibano	1340	5° 28’	74° 22’	1708.9
Rafael Escobar	1320	5° 28’	75° 39’	1727.5
Julio Fernández	1360	3°48’	76° 32’	1736.4
Ospina Pérez	1700	1° 15’	77° 29’	1737.2
Arturo Gómez	1320	4°40’	75° 47’	1772.4
La Joya	1250	4° 46’	75° 47’	1780.0
Manuel Mejía	1700	2° 25’	76° 45’	1782.4
Naranjal	1400	4° 59’	75° 39’	1798.1
Miguel Valencia	1570	5° 36’	75° 51’	1802.8
Paraguaicito	1250	4° 23’	75° 44’	1829.8
Cenicafé	1310	5° 00’	75° 36’	1887.8
Santagueda	1010	5° 05’	75° 40’	2007.8
Granja Luker	1020	5°05’	75° 41’	2065.3
El Rosario	1600	5° 58’	75° 43’	2076.2
Pueblo Bello	1000	10° 25’	73°34’	2386.3

3 Results and Discussion

Sun brigth original series for the 32 studied stations did not show stationarity. Having a difference at the regular part of the series and one at the seasonal part, this characteristic was achieved. By means of estimations of simple and partial autocorrelation functions from series distinguished at the regular and seasonal (12 month period) parts, seasonal moving average model was identified. This model was consistent for sun bright series a the modelled meteorological stations. It is characterized for presenting first order dependence in the errors. Seasonal structure for identified model is due to the annual cycle's effect of extraterrestrial sun bright on the climatic perfomance.

When the model was identified, parameters were estimated. Then, the fitted model and forecast goodness were evaluated. Parameter estimations were significantly different to zero. They did not show correlation and were enough to describe monthly sun birght perfomance. The residuals estimated by the difference between observed values and forecasted ones, were distinguished for adjusting to a completely aleatory series or white noise. This assures that there are not more components which must be included in the model.

In multiplicative way, the fitted model is the following:

$$(1-B)(1-B^{12}Z^{\lambda}t = (1-\theta B)(1-\Theta B^{12})a_t$$

Where B is delaying operator ($B^r Z_t = Z_{t-r}$); Z_t is sun bright λ is a transformation value, θ is regular parameter, Θ is the seasonal parameter and a_t are aleatory errors. In an explicit was, the model is

$$Z_t = Z_{t-1} + Z_{t-12} - Z_{t-13} + a_t - \theta a_{t-1} - \Theta a_{t-12} + \theta\Theta a_{t-13}$$

The preceding equation shows that sun bright in month t depends on: sun bright observed the preceding month corrected by the same month aleatory error and considered by the estimation of regular part parameter, and sun bright observed a year before and affected by the aleatory error, considered by the estimation of seasonal-part parameter and on sun bright observed 13 months before and modified by interaction between estimations of regular and seasonal parameters and aleatory error of the corresponding month.

Forecast fuction is derived from the fitted equation; the last allows forecast sun bright for subsequent months to the last observed. Forecast standard error increases as time passes. Therefore, forecast after the first and second months are best accuate. Table 2 shows the estimated parameters, its standard errors and the forecast error, considering just the next month forecast. Once the corresponding month is observed, forecast for the next month are made. Thus, a forecast for the next month is always made. However, Forecast fuction is:

$$Z_{t+1} = Z_t + Z_{t-11} - Z_{t-12} - \theta a_t - \Theta a_{t-11} + \theta\Theta a_{t-12}$$

Where Z_{t+1} is the forecasted value for the month following the last one observed in the series. a_t, a_{t-11} and a_{t-12} are calculated taking the difference between the observed value and the forecasted value for the registered periods. Forecast errors listed in table 2, show that maximum error is in the neighborhood of 23%. It is acceptable from the meteorological point of view.

According to Castaño's findings (4) and results showed in table 2, it can be stated that monthly sun bright series between 1° 15' and 10° 25' latitudes and 72° 39' and 77° 29' longitudes perform as an ARIMA(0,1,1)(0,1,1)$_{12}$ model. The main characteristic from the above model is the dependence of a given month on the immediately preceding year determining the seasonal part and on an interaction of the two components.

Forecast fuction derived from the fitted model lets no only calculate further values but it indicates the model goodness. So, if there are changes in the performance pattern for monthly sun bright, these will be reflected in the differences between the forecasted value and the observed value. Thus, the model is permanently evaluated and can be intervened in order to meteorological station's information is necessary for this model to behave well and currently.

Sun bright study and modelling, as well as its relation to radiation, constitute one of many components involved in mathematic modellation for crop growth and yield. Radiation forecast for various farm practices in different environmental conditions is essential for simulation and forecasting of results development, production and validation. From sun bright study and stochastic modelling, it can be concluded that found expressions for describing its behavior just represent its behavior in the analyzed stations and by forecast functions, a very accurate radiation can be forecasted. In addition, it is a component of primary importance on building mathematic models for crops. It can be used for another applications when radiation intervenes.

A negative correlation was found between the estimation of the egular part parameter from the model and the overall annual sun bright average. It means that the more sun bright hours in a year, the fewer it is the value for parameter estimation. Correlation between sun brigth and altitude was negative; when altitude increase, fewer number of sun bright hours occurs.

Those relations can not be generalized. The studied characteristic depends not only on the altitude. There are another elements wich make it change, e.g., valley-mountain circulation system, climatic equator, hydrographic slop, etc.

Direct relation between number of sun bright hours and radiation lets conclude that in stations with the most sun bright, there is most available energy to be received by solar collectors or plants.

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Table 2. Estimated Parameters and forecast errors

STATION	θ	E.STD	Θ	E.STD	Error^2
El Cedral	0.7224	0.04461	0.9194	0.06787	21.02
Luis Bustamante	0.7038	0.04718	0.8117	0.05376	20.27
Jorge Villamil	0.6961	0.04809	0.8711	0.05608	8.93
Heraclio Uribe	0.6362	0.05011	0.8569	0.05414	18.44
El Sena	0.6094	0.05256	0.8064	0.05293	20.06
Mesitas de Sta Inés	0.6501	0.05250	0.7331	0.05293	21.73
La Bella	0.6199	0.05071	0.8953	0.05912	18.08
Aguas Blancas	0.6083	0.05978	0.8385	0.06455	14.55
Blonay	0.5955	0.05171	0.8883	0.05974	21.75
Agronomía	0.7190	0.04845	0.6923	0.05819	22.75
Tibacuy	0.7014	0.04654	0.8001	0.05100	14.38
La Trinidad	0.8274	0.04091	0.9111	0.09047	19.34
Santa Helena	0.8476	0.04743	0.8547	0.10075	18.97
Maracay	0.7550	0.05817	0.8959	0.17672	16.41
Limón	0.7277	0.04478	0.9555	0.12159	14.13
Manuel Mallarino	0.6555	0.04912	0.8920	0.06053	14.57
La Montaña	0.6253	0.05273	0.8352	0.05391	16.37
Montelibano	0.6118	0.05226	0.8673	0.05415	16.31
Rafael Escobar	0.4998	0.05611	0.9559	.12213	20.56
Julio Fernández	0.7456	0.04335	0.9418	0.09045	12.04
Ospina Pérez	0.7484	0.04324	0.8778	0.05720	14.12
Arturo Gómez	0.6598	0.04908	0.8156	0.05720	13.60
La Joya	0.5048	0.07937	0.7366	0.09557	12.30
Manuel Mejía	0.5557	0.05459	0.8696	0.05380	13.43
Naranjal	0.6159	0.03815	0.9103	0.03136	11.88
Miguel Valencia	0.5947	0.05396	0.7878	0.05354	14.21
Paraguaicito	0.6387	0.04448	0.7776	0.04266	14.37
Cenicafé	0.7502	0.02889	0.9573	0.02994	11.31
Santagueda	0.7290	0.04637	0.7723	0.05522	11.92
Granja Luker	0.6687	0.05885	0.7766	0.07007	11.42
El Rosario	0.5826	0.05399	0.8344	0.05372	14.70
Pueblo Bello	0.2526	0.06080	0.9690	0.15062	8.05