EVALUATION OF A MULTIPLE LINEAR REGRESSION MODEL AND SARIMA MODEL IN FORECASTING ^{7}BE AIR CONCENTRATIONS

1. Introduction

^{7}Be is widely used as an atmospheric radiotracer due to its relatively short life ($T_{1/2} = 53.3$ days) and ease of measurement by γ-spectrometry, which provides important information on atmospheric air mass motions. A better understanding of its distribution would facilitate refinement and validation of global atmospheric circulation models (Dueñas et al. 2015). ^{7}Be forecasting can thus be adopted as a target value in analyzing fluctuations or deviations that could imply important atmospheric changes.

It is generally accepted that the ^{7}Be production rate depends on a number of atmospheric factors. Several studies have pointed out that the intensity of galactic cosmic rays in the Earth's orbit is affected by solar activity and the geomagnetic field, which is under constant cosmic ray bombardment from space (O'Brien, 1979; Vogt et al., 1990; Hötzl et al., 1991; Ioannidou&Papastefanou, 1994). In particular, an increase in solar activity and the geomagnetic field reduce the galactic cosmic ray flux, which is followed by reduced ^{7}Be production.

In addition to the above-mentioned sources of variability, ^{7}Be concentrations in the lower layers of the atmosphere present temporal variations caused by solar radiation and meteorological parameters that can affect regional weather patterns (temperature, relative humidity, precipitations, wind speed and wind direction) (Feely et al., 1989; Baeza et al., 1996).

Many research studies have analyzed the relation between ^{7}Be air concentrations and the meteorological and atmospheric variables using a simple correlation analysis (e.g. Dueñas et al., 1999; Ioannidou et al., 2006; Piñero-García & Ferro-García, 2013; Ceballos et al., 2016; Neroda et al.; 2016). Furthermore, some of these studies have applied Multiple Linear Regression (MLR) analysis to develop an explanatory and predictive model for ^{7}Be air concentrations using the atmospheric and meteorological variables as predictors (Table 1).

Location	Period	Significant variables used in MLR	R^2	Source
Málaga, Spain	1992-1995	- Maximum Temperature - Rainfall - Relative Humidity - Hours of sunshine	27%	Dueñas et al. (1999)
Thessaloniki, Greece	1987-2001	- Temperature - Relative Humidity - Sunspot Number	38.5%	Ioannidou et al. (2006)
Granada, Spain	1993-2001	- Temperature - Rainfall - Sunspot Number	71%	Azahra et al. (2004)
Málaga, Spain	1997-2007	- Solar energetic proton - Aerosol optical depth	34%	Dueñas et al. (2015)
Granada, Spain	1996-2010	- Temperature - Relative Humidity - Sunspot Number	52%	Piñero-García & Ferro-García (2013)
Granada, Spain	2005-2009	- Temperature - Relative Humidity - Rainfall	72.16%	Piñero-García et al. (2012)
Plymouth, UK	2009-2010	- Rainfall	94%	Taylor et al. (2016)
Granada, Spain	2011-2014	- Solar Irradiance - Total suspended particles	66.9%	Essaid et al. (2015)
Vladivostok, Russia	2013-2014	- Altitude - Precipitation - Temperature - Aerosol concentration - Trajectories in the pacific (North-East)	55%	Neroda et al. (2016)

Table 1. ^{7}Be predictive models for different time periods at different locations.

Each study uses several predictors to explain ^{7}Be air concentration in different time periods at different locations. The explicative power of the model, measured by the R square coefficient, is, in general, less than 50%. The studies that get the highest R^2, use a historical data range of less than five years, which may not be enough information to forecast the ^{7}Be air concentration for the following year. In addition to explanatory power, it is very important to compute accuracy measurements with data that have not been used to develop the model. This procedure is not applied in the above MLR models and is important in measuring the validity and forecasting power of the model, which is one of the aims of the present study.

Several authors recommend the use of time series modelling techniques instead of multiple linear regression when monitoring correlated process data (Alwan & Roberts 1988; Harris & Ross 1991; Wardell et al. 1994). Classical regression is often insufficient for explaining all the interesting dynamics of a time series. For instance, the estimated autocorrelation function (ACF) of the residuals of the regression model could reveal additional structure in the data that the regression did not capture. Instead, the introduction of Box-Jenkins models could deal with the limitations of classical regression in time series (Shumway & Stoffer, 2006).

A recent study applied a decomposition of the ^{7}Be time series into a trend-cycle, a seasonal and an irregular component in order to separate the inter- and intra-annual patterns of ^{7}Be variability (Bas et al, 2016). The results of this study showed the suitability of applying time series analysis to correlated data in order to separate the different sources of variability of ^{7}Be concentrations and to develop a forecasting model.

The aim of this study is to propose two models to explain and forecast ^{7}Be air concentrations: i) a Seasonal Autoregressive Integrated Moving Average (SARIMA) model and ii) a Multiple Linear Regression (MLR) model using meteorological and atmospheric variables. Both the time series and multiple linear regression models are evaluated by comparison with real ^{7}Be air concentrations for the city of Valencia in 2007-2014 and with out-of-sample tests for the 12 months of the year 2015, using the Root Mean Square Error (RMSE) and the Adapted Mean Absolute Percentage Error (AMAPE) as forecasting accuracy measures. Finally, the results of the accuracy measurements of both models are compared.

2. Material and methods

2.1. Study area and sampling

Airborne particulate samples were collected weekly on the campus of the Universitat Politècnica de Valencia from January 2007 to December 2015. Valencia is situated on the east coast of Spain (15m above sea level) in the western Mediterranean Basin (39°28′50″ N, 0°21′59″ W) and has a relatively dry subtropical Mediterranean climate with very mild winters and long hot summers. The sampling point was located approximately 2 km away from the coastline.

Aerosol samples were collected using Eberlyne G21DX and Saic AVS28A air samplers placed approximately 1 m above ground level. The aerosol particles were retained on a cellulose filter of 4.2×10^{-2} m effective diameter and 0.8 µm pore size. The filters were changed weekly and the average volume ranged from 300 to 400 m^3 per week. Each filter was put inside a plastic box and kept in a desiccator until it was measured.

2.2. ^{7}Be activity measurements

A monthly composite sample containing 4-5 filters was measured by γ-spectrometry to determine specific ^{7}Be activities using an HPGe detector (ORTEC Industries, USA) n-type with relative efficiency of 18% for 60Co gamma-ray. A certificated standard containing radionuclides with energies ranging from 59 to 1836.1 keV was used for preparing the calibrated filters, which were placed inside their plastic boxes on the top of the detector. The counting time was 60000s and the γ-line 477.7 KeV was used to calculate the activity. ORTEC Gamma-Vision software was used for acquisition and analysis. Concentration activities were corrected for the radioactive decay to the mid-collection period. The mean measured uncertainties (K=2) were around 10 %.

2.3. Statistical analysis

SARIMA MODEL

The SARIMA model building process is designed to take advantage of the association in the sequentially lagged relationships that usually exists in data collected periodically. A time series $\{z_t, t = 1, \ldots, N\}$ is generated by a SARIMA$(p, d, q)(P, D, Q)_s$ model if:

$$\phi_p(B)\Phi_P(B^s)(1 - B)^d(1 - B^s)^D z_t = \theta_q(B)\Theta_Q(B^s)a_t$$

where N is the number of observations; p, d, q, P, D, Q are integers; B is the lag operator (e.g. $w_t = z_t - z_{t-s} = (1 - B^s)z_t$); s is the seasonal period length; d is the number of regular differences ($d \leq 2$); D is the number of seasonal differences, and a_t is the estimated residual at time t, which is a usual Gaussian white noise process (WN).

$\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$, is the regular autoregressive operator (AR) of order p,

$\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$, is the regular moving average operator (MA) of order q,

$\Phi_P(B^s) = 1 - \Phi_1 B^s - \Phi_2 B^{s2} - \cdots - \Phi_P B^{sP}$, is the seasonal autoregressive operator (SAR) of order P,

$\Theta_Q(B^s) = 1 - \Theta_1 B^s - \Theta_2 B^{s2} - \cdots - \Theta_Q B^{sQ}$, is the seasonal moving average operator (SMA) of order Q.

As reported by Box & Jenkins (1976) and Shumway &Stoffer (2006), the SARIMA model consists of three main steps:

Identification and estimation step

First, the periodogram technique was applied to identify the periodic cycle in the time series (Schuster, 1898). The periodogram plot should have clear peaks at points corresponding to the 'hidden periods' of the cyclic model.

The time series should then be differenced in order to be stationary in mean and variance (identifying d and D parameters). The differencing technique can also be used to remove trends, which are usually detected by inspecting the plot of the ^{7}Be data over the period considered. However, they are also characterized by the autocorrelation function.

After differencing the time series, a tentative autoregressive moving average (ARMA) process is carried out based on the estimated autocorrelation function (ACF) and the estimated partial autocorrelation function (PACF). The shape of the ACF and PACF of the real time series is compared with the shape of the theoretical model to identify possible different p, q, P and Q parameters of the SARIMA model (Peña, 2010; Shumway & Stoffer, 2006). Having specified tentative models in the identification step, the parameters of the candidate models are estimated by a maximum likelihood function (Shine & Lee, 2000).

After trying several combinations for parameters p, q, P and Q, the best model was selected, considering the minimum MAPE, AMAPE and RMSE (defined in the section on the Forecasting Step) for the forecasting data of the sample and out-of-sample as accuracy measures of predictive power.

The selection of the most parsimonious model is also based on Akaike's Information Criterion (AIC), which rewards models for good fit and penalize them for complexity. The model with the minimum AIC is chosen as the parsimonious model. The AIC coefficient is defined as follows:

$$AIC = 2\ln(RMSE) + \frac{2(p+q)}{n}$$

where p and q are the number of parameters of AR and MA estimates, RMSE is the Root Mean Square Error (defined in the section on the Forecasting Step) and n is the sample size of the data used to fit the model.

Validation step

In this step, several statistics were used to check the suitability of the identified models. An essential part of the procedure is to examine the residuals of the SARIMA model, which, if the model is satisfactory, should be considered as White Noise (WN). We examine some simple tools for checking the hypothesis that the residuals are WN and the model is valid. If the fit model passes the following tests, it can be used to make a forecast.

- *t-ratio test* to evaluate the significance of the parameters estimated in each model. The parameters are considered significant with a 95% of confidence level if p-values<0.05.
- *Kolmogorov-Smirnov test* applying Lilliefors correction of the residual series to check that the noise process is Gaussian. The residual series is Gaussian if p-values>0.05.
- *Q* Ljung-Box statistic* to check the condition that the residuals can be considered as a WN. The statistic proposed is:

$$Q^* = n(n+2)\sum_{K=1}^{m}(n-k)^{-1}\, r_k(a)$$

where $r_k(a)$ is the sample autocorrelation f order k of the residual, n is the length of residual series and m is the number of lags considered, $Q^* \approx \mathcal{X}^2_{m-n}$, $n = p + q + P + Q$. The model is considered valid if $P(\mathcal{X}^2(m-n) > Q^*) > 0.05$. In this study, the Q* Ljung-Box statistic is calculated for a large m in each model, as suggested by Peña (2010).

Forecasting step

To assess the forecasting performance of different models the data set is divided into two samples for training and testing. This procedure is known as an out-of-sample technique, which means that the training data used in model fitting are different to the test sample (out-of-sample) used to evaluate the established model.

Several measurement statistics can be used to examine the forecast accuracy of different models. Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) are the criteria most frequently used to evaluate the performance of the forecasting models. One of the disadvantages of the MAPE criteria is the adverse effect of small actual values, in which case MAPE criteria will contribute large terms to the

MAPE coefficient, even if the difference between the actual and forecast values is small. It is therefore better to use an adapted MAPE (AMAPE), as defined in various studies (Tsay, 2005; Wu & Shahidehpour, 2010):

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(\hat{z}_t - z_t)^2}{n}}$$

$$MAPE = \left(\frac{1}{N}\sum_{t=1}^{n}\left(\frac{|\hat{z}_t - z_t|}{z_t}\right)\right)100\%$$

$$AMAPE = \frac{1}{n}\sum_{t=1}^{n}\left(\frac{|\hat{z}_t - z_t|}{\frac{1}{n}\sum_{t=1}^{n} z_t}\right) * 100\%$$

where t represents the time and n is the sample size for forecasts; $\hat{z}_t$ is the forecast at t from any mentioned model and z_t is the actual value at t. The RMSE statistic depends on the scale of the variables and measures the absolute errors. The MAPE and AMAPE statistics measure the relative errors. The smaller the RMSE, MAPE and AMAPE the better the accuracy of the model.

MULTIPLE LINEAR REGRESSION

Multiple linear regression analysis is a multivariate statistical technique used to examine the relationship between a single dependent variable and a set of independent variables. The main objectives of MLR are explanation and prediction. Explanation examines the regression coefficients, their magnitude, sign and statistical inference, for each independent variable. Prediction involves the extent to which the independent variables can predict the dependent variable (Hair et al., 2010). MLR forecasting models are expressed in the following format:

$$Y_t = X_t\beta + \varepsilon_t$$

where Y_t is the predicted value at time t, $X_t = (1, x_{1t}, x_{2t}, \dots, x_{kt})$ is a vector of k explanatory variables at time t, $\beta = (\beta_0, \beta_1, \dots, \beta_k)^T$ is the vector of coefficients, and ε_t is a random error term at time t, $t = 1, \dots, N$. The errors terms should be independent and have a Gaussian distribution.

The assumptions of the MLR model (independent errors and Gaussian error term distribution) could be analyzed by obtaining the Kolmogorov-Smirnov test and the Q* Ljung-Box statistic, as in the time series.

The explanatory power of the MLR is commonly measured by the R square coefficient defined as follows:

$$R^2 = \left(\frac{\sigma^2_{\hat{Y}_t,Y_t}}{\sigma^2_{\hat{Y}_t}\sigma^2_{Y_t}}\right)100\%$$

where $\sigma^2_{\hat{Y}_t,Y_t}$ is the covariance of the forecast and actual values; $\sigma^2_{\hat{Y}_t}$ and $\sigma^2_{Y_t}$ the variance of the forecast and actual values respective.

The forecasting power could be measured using the same accuracy measurements as in the time series.

3. Results in forecasting ^{7}Be air concentrations

The first step in developing any forecasting model is to plot the data. In view of the results obtained in a recent study (Bas et al., 2017), the best ^{7}Be concentration forecasting results are based on a time window of at least eight years of data. This result supports the training sample of eight years of historical data (2007-2014) and the out-of-sample test for one year (2015) selected in this study. Figure 1 shows the evolution of ^{7}Be air concentrations during the entire period 2007-2015. ^{7}Be activity concentrations ranged from 2.28 to 8.11 mBq/m^3 with an arithmetic mean of 4.62 ± 1.19 mBq/m^3 during the period studied.

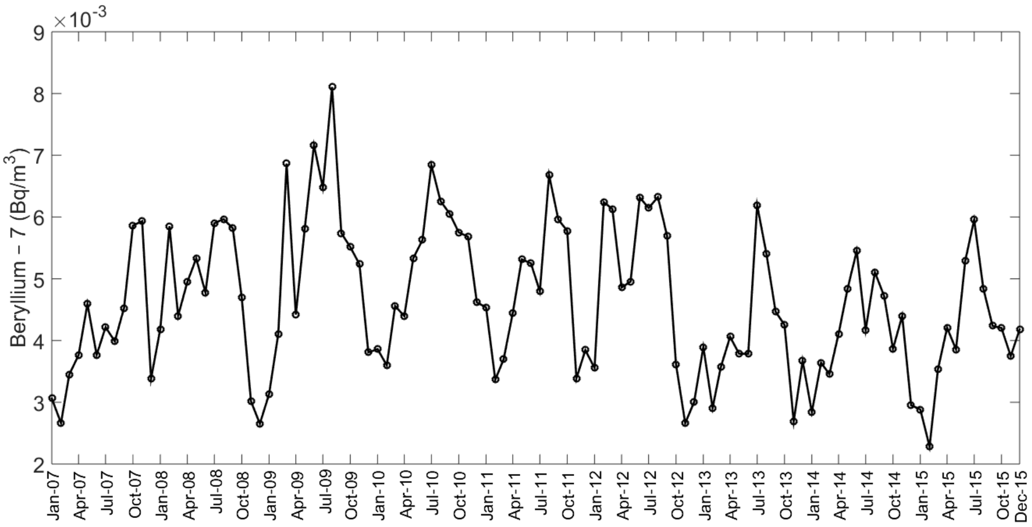

Fig 1. Temporal evolution of ^{7}Be air concentration over the period 2007-2015.

3.1. SARIMA model

The evolution of ^{7}Be air concentrations suggests that there exists a seasonal pattern with a sinusoidal trend. The result of the periodogram technique identified a relevant peak corresponding to a period of 12 months (annual periodicity, $s = 12$).

For the identification step, a simple ACF (Figure2) that is positive and very slowly decaying in lag 1 and in the seasonal lag 12 suggests a regular and seasonal difference ($d = D = 1$). The SARIMA$(p, 1, q)(P, 1, Q)_{12}$ model is therefore useful for representing ^{7}Be air concentrations with a trend. The differenced ^{7}Be time series is stationary.

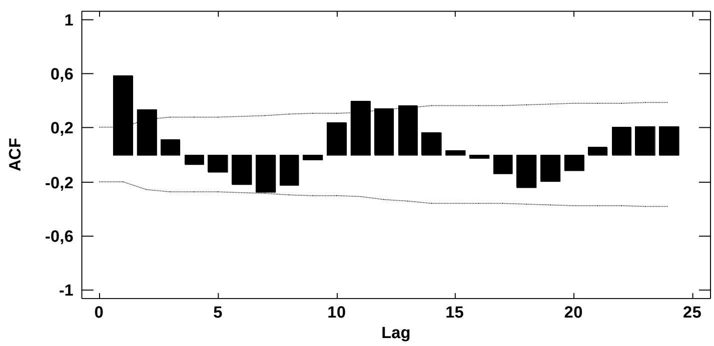

Fig.2. The sample ACF of the ^{7}Be time series

After differencing the time series, a tentative autoregressive moving average process is carried out based on the estimated autocorrelation function (ACF) and the estimated partial autocorrelation function (PACF). Figure 3 shows that the autocorrelations at lag 1, 12 and 24 are significant in the PACF of the residuals.

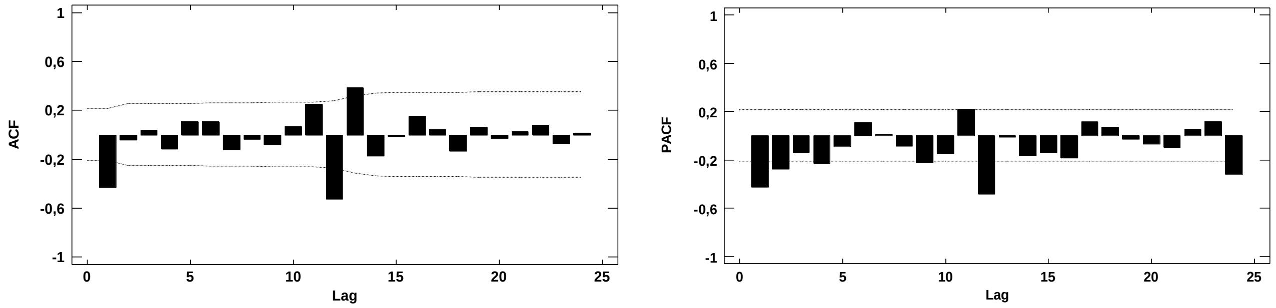

Fig. 3. The sample ACF and PACF of the residuals after applying a regular and seasonal difference.

Table 2 reports the results of tentative SARIMA models considering the ACF and PACF of the residuals (Figure 3) after applying a regular and a seasonal difference ($d = D = 1$). The following accuracy measurements were used to select the best and most parsimonious model: RMSE, MAPE, AMAPE and AIC.

	Training sample (2007-2014)				**Out-of-sample (2015)**		
	RMSE	**MAPE**	**AMAPE**	**AIC**	**RMSE**	**MAPE**	**AMAPE**
$\mathbf{SARIMA(0,1,1)(2,1,2)_{12}}$	0.000722	13.00%	11.89%	-14.36	0.00147	29.19%	27.18%
$\mathbf{SARIMA(0,1,2)(2,1,2)_{12}}$	0.000723	13.08%	11.98%	-14.37	0.00147	29.59%	27.13%
$\mathbf{SARIMA(0,1,1)(1,1,3)_{12}}$	0.000678	11.93%	10.74%	-14.49	0.00078	17.75%	17.20%
$\mathbf{SARIMA(0,1,2)(1,1,3)_{12}}$	0.000672	11.76%	10.70%	-14.49	0.00078	18.05%	17.40%

Table 2. Models selection criterion

Table 2 show that the AIC criterion is similar in the different models proposed. However, considering that the RMSE, MAPE and AMAPE coefficients should be minimum, the SARIMA(0,1,1)(1,1,3) and SARIMA(0,1,2)(1,1,3) models are the best options, considering the analysis in both samples (training and out-of-samples). Of the two, we propose the SARIMA(0,1,1)(1,1,3) model as it is simpler than the other and the RMSE, MAPE and AMAPE coefficients in the training sample and in out-of-sample are similar in both models.

Having specified the best model in the identification step, the parameters are estimated by a maximum likelihood function and the estimated model can be written as follows:

$$(1+0.814B^{12})(1-B)(1-B^{12})z_t = (1-0.665B)(1-0.555B^{12}-0.932B^{24}+0.687B^{36})a_t$$

where $a_t \approx WN(0, \sigma = 8.07\mathrm{E}-04)$. WN=White Noise.

The parameters estimated in the model are significant (p-values<0.05) (Table 3). The residuals obtained from fitting a SARIMA$(0,1,1)x(1,1,3)_{12}$ model to ^{7}Be concentration data for a time window of eight years (2007-2014) are normally distributed (K-S test, $p-value > 0.05$) with mean zero and standard deviation $\sigma = 8.07\mathrm{E}-04$. Moreover, significant autocorrelation is not found in the residuals (Q* test, $p-value > 0.05$), therefore the residuals can be considered as WN and the SARIMA$(0,1,1)x(1,1,3)_{12}$ can be considered a suitable forecasting model.

	t-ratio test (p-value)	**K-S Lilliefors (p-value)**	**Q^* Ljung-Box (p-value)**
$\boldsymbol{\theta_1}$	8.0431 (<0.000001)	D = 0.079983	χ^2 = 47.809
$\boldsymbol{\Phi_1}$	-9.4919 (<0.000001)	(p-v: 0.2119)	(p-v: 0.2837)
$\boldsymbol{\Theta_1}$	8.08721 (<0.000001)		m=48
$\boldsymbol{\Theta_2}$	19.5035 (<0.000001)		
$\boldsymbol{\Theta_3}$	-13.7005 (<0.000001)		

Table 3. Validation of the proposed SARIMA model.

The predictive model obtained, after developing the above expression, is:

$$\hat{z_t} = z_{t-1} + 0.186z_{t-12} - 0.186z_{t-13} + 0.814z_{t-14} - 0.814z_{t-25} - 0.665a_{t-1} - 0.555a_{t-12} + 0.369a_{t-13} - 0.932a_{t-24} + 0.619a_{t-25} + 0.687a_{t-36} - 0.456a_{t-37} + a_t$$

Figure 4 shows the comparison between measured and forecast values using a SARIMA$(0,1,1)x(1,1,3)_{12}$in the 2007-2014 training sample and in the out-of-sample data in 2015. The time series proposed explains 70.88% of the variability of the actual data.

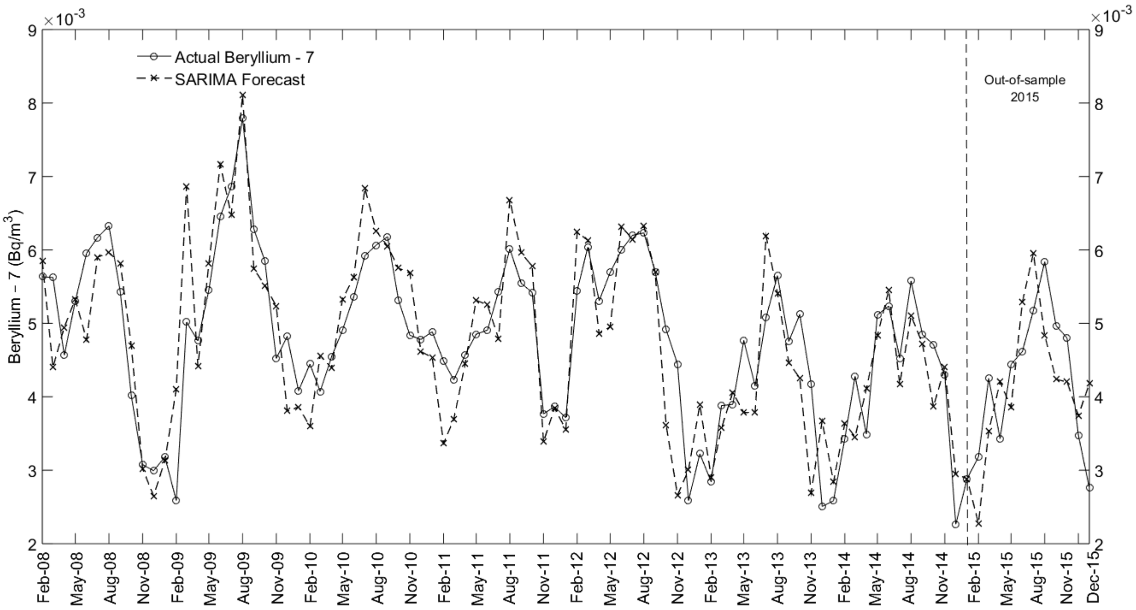

Fig. 4. Comparison between measured and forecast (SARIMA) power

3.2. MULTIPLE LINEAR REGRESSION analysis model

A multiple linear regression model is developed to explain and forecast ^{7}Be air concentrations. The atmospheric parameters studied in the present work are: sunspot number (SSN), temperature (T) (in tenths of °C), precipitation (PP) (in tenths of a millimetre), relative humidity (RH) (in %) and wind speed (WS) (in km/h). The meteorological factors were collected by the Universitat Politècnica de Valencia's weather station, which was also the sampling point for ^{7}Be activity. The sunspot number parameter (SSN) was collected daily during the period 2007-2015 by the World Data Center SILSO, Royal Observatory of Belgium, in Brussels (SILSO, 2015).

We selected these variables after taking into account the atmospheric parameters that mainly affect Valencia weather, with a relatively dry subtropical Mediterranean climate, very mild winters and long hot summers, and considering the variables adopted in a previous study (Bas et al, 2016) and the variables most frequently considered to study ^{7}Be activity in the literature.

A logarithmic transformation of the ^{7}Be variable is applied to better identify a Gaussian distribution in the data. In this study we considered the mean monthly values of temperature, relative humidity, wind speed, and sunspot number. The precipitation factor was considered as the number of rainy days per month due to the particular rainfall regime in Valencia, with few days of torrential rainfall and many dry days. Solar activity was considered as measured by the sunspot number parameter.

The R^2 obtained for the regression given below is significant at the 95% confidence level, however this model explains only 48.76% of the ^{7}Be variability. The predictive model obtained is:

$$LN(\,^7Be) = -5.3631 + 0.0025 * \mathrm{T} - 0.0602 * \mathrm{WS} - 0.0112 * \mathrm{PP} - 0.0018 * \mathrm{SSN}$$

Parameter	*Estimation*	*St. Error*	*t-statistic*	*p-value*
β_0	-5.3631	0.1449	-37.0094	<0.00001
T	0.0025	0.0004	6.3614	<0.00001
WS	-0.0602	0.0176	-3.4199	0.0009
PP	-0.0112	0.0049	-2.2957	0.0240
SSN	-0.0018	0.0004	-4.1275	0.0001

Table 4. Estimated parameters and its significance in the MLR model.

The significant variables that affect ^{7}Be air concentration are: temperature, wind speed, precipitation and sunspot number (Table 4). However, the relative humidity variable is positively correlated with temperature $(r = 0.67, p - value < 0.00001)$, so that both variables explain the same behaviour of ^{7}Be activity and the multiple regression technique selected the variable most highly correlated with ^{7}Be. Note that all the variables have an inverse influence on ^{7}Be activity, except temperature, which has a positive effect.

The Kolmogorov-Smirnov test was applied to check the normality of the residuals, obtaining D = 0.056379 with a p-value of 0.604. The residuals can therefore be considered Gaussian. Finally, the Ljung-Box test was also applied to check the randomness of the residuals. In this case, the p-value obtained for any lag (m) considered is less than 0.05, which means that the residuals are not random and this result reveals additional structure in the data that the regression could not capture.

Figure 5 shows the comparison between measured and forecast values using an MLR in the training sample 2007-2014 and in the forecasting data in 2015.

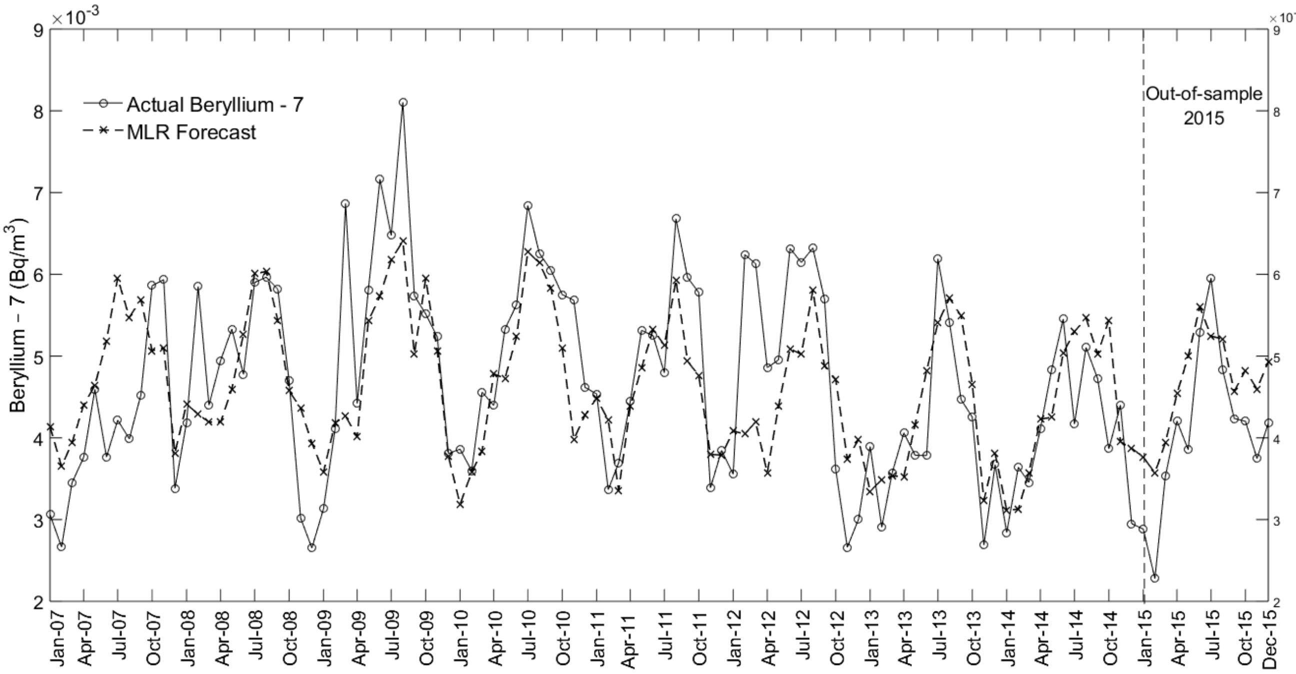

Fig. 5. Comparison between measured and forecast (MLR) power

3.3. Comparison of the forecasting performance of the SARIMA and MLR models

Table 5 shows the explanatory and forecasting power of the SARIMA and MLR models. For the former power we used the R^2 coefficient.The accuracy measures used to analyze the validity of the model are the RMSE and AMAPE coefficients, considering the following sample sizes for the out-of-sample forecasts: $n = 1$, $n = 3$, $n = 6$, $n = 9$, and $n = 12$ months. As can be seen in Table 5, the RMSE value for $n = 1$ is very different to that of $n > 1$, suggesting that predictions for 1-month periods are uncertain. The selection model criterions are therefore based on forecasts for at least three months.

Model	**Explanator y power**	**Forecasting power Out-of-sample Year=2015 RMSE and AMAPE**				
	R^2	$n = 1$	$n = 3$	$n = 6$	$n = 9$	$n = 12$
MLR	48.76%	0.00088	0,00093 29,68%	0,00083 19,81%	0.00073 15.59%	0,00074 16,27%
SARIMA$(0,1,1)(1,1,3)_{12}$	70.88%	1E-07	0.00067 18.70%	0.00068 16.61%	0.00073 16.66%	0.00078 17.20%

Table 5. Comparison of explicative and forecasting power between SARIMA and MLR

In the MLR model the atmospheric variables explain 48.76% of the variability of the ^{7}Be air concentration, whereas the SARIMA model explains 70.88%. The predictive model cannot explain more variability in ^{7}Be activity due to the joint effect of the parameters considered, which masks the intra and inter annual components of the time series. This result agrees with observations made in previous studies (Piñero-García & Ferro-García, 2013, Dueñas et al., 2015, Bas et al., 2016).

Considering the forecasting power in the out-of-sample year, the RMSE and AMAPE accuracy measures are very similar for $n = 9$ and $n = 12$ in both models, although slightly lower in the MLR model. However, these coefficients are much lower for $n = 3$ and $n = 6$ in the SARIMA than in the MLR model. Furthermore, the RMSE and AMAPE coefficients are more constant in the SARIMA than in the MLR model. This is an important property that a predictive model should have in order to control the errors associated with different predictions.

4. Conclusions

^{7}Be forecasting models can be adopted as a target value in analyzing fluctuations or deviations that could imply important atmospheric changes. In this study an explicative and forecasting model of ^{7}Be air concentrations is proposed, using two different statistical techniques: the SARIMA time series and the MLR model. In both models, the historical data used to develop the model was for the period 2007-2014. The data for the 12 months of the year 2015 was used to measure the validity of the models.

Considering the forecasting power measured by the RMSE, MAPE and AMAPE accuracy coefficients, and the simplicity of the model measured by the AIC coefficient, a SARIMA$(0,1,1)x(1,1,3)_{12}$time series is proposed. The analysis of the residuals in the validation step reveals that the model is suitable for forecasting.

The MLR model was developed considering the meteorological variables that mainly affect the climatology of Valencia. The significant variables obtained to predict ^{7}Be activity are: sunspot number, temperature, precipitation and wind speed, which explain only 48.76% of ^{7}Be variability. The predictive model cannot explain a higher degree of variability of ^{7}Be activity due to the joint effect of the variables considered, which may mask the intra and inter annual components of the time series. In addition, the analysis of the residuals in the validation step reveals additional structure in the data that the regression did not capture. MLR also has the disadvantage of requiring forecast meteorological parameters to predict ^{7}Be air concentrations.

The comparison between SARIMA and MLR reveals the greater explanatory power of the SARIMA model (70.88%), while its accuracy measurements are consistently lower for both short terms (3-6 months) and long terms (9-12 months) in the out-of-sample period. The MLR model performs well in the long term, but its errors are less consistent in short terms. The proposed SARIMA model can therefore be considered a good forecaster of ^{7}Be air concentrations. However, the MLR model provides information on significant meteorological variables that affect these concentrations, which could be useful in identifying meteorological or atmospheric changes that could cause deviations in ^{7}Be concentrations.

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