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Modeling and forecasting MODIS-based Fire Potential Index on a pixel basis using time series models

Margarita Huesca[a], Javier Litago[b,*], Silvia Merino-de-Miguel[c], Victor Cicuendez-López-Ocaña[a], Alicia Palacios-Orueta[a]

[a] Departamento de Silvopascicultura, ETSIM, Universidad Politécnica de Madrid, Spain
[b] Departamento de Estadística, ETSIA, Universidad Politécnica de Madrid, Spain
[c] Departamento de Topografía, EUITF, Universidad Politécnica de Madrid, Spain

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ABSTRACT

The aim of this research was to model and forecast MODIS-based Fire Potential Index (FPI), implemented with Normalized Difference Water Index (NDWI), as a proxy of forest fire risk, in Navarre (Spain) on a pixel basis using time series models with a forecasting horizon of one year.

We forecast FPI_{NDWI} for 2009 based on time series from 2001 to 2008. In the modeling process, the Box and Jenkins methodology was applied in two consecutive stages. First, several generic models based on average FPI_{NDWI} time series from different "fuel type-ecoregion" combinations were developed. In a second stage, the generic models were implemented at the pixel level for the entire study region. The usefulness of the proposed autoregressive (AR) model, using the original data and introducing significant seasonal AR parameters, was demonstrated.

Results show that 93.18% of the estimated models (EMs) are highly accurate and present good forecasting ability, precisely reproducing the original FPI_{NDWI} dynamics. Best results were found in the Mediterranean areas dominated by grasslands; slightly lower accuracies were found in the temperate and alpine regions, and especially in the transition areas between them and the Mediterranean region.

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1. Introduction

The need for understanding and monitoring long-term vegetation dynamics over large areas is widely accepted by the scientific community. In order to carry out these studies, long time series of spatially continuous and frequent data are essential, as well as efficient tools and advanced techniques for analyzing this information. In this sense, the use of satellite data time series can be considered a sound alternative since satellite observations are objective, comparable, and spatially comprehensive at global to local scales. Remote sensing data are a source of frequently collected information that makes it possible to obtain updated data and to extract patterns to model vegetation response to either meteorological dynamics or extreme events (e.g. forest fires). Up to now, sensors such as the advanced very high resolution radiometer (AVHRR), VEGETATION or the moderate resolution imaging spectroradiometer (MODIS) have provided data with a high temporal frequency at a moderate spatial resolution that can be used to monitor ecosystem dynamics at several scales. In the near future, new sensors will be developed, increasing the amount of high temporal and spatial resolution information. For instance, it is expected that the Sentinel missions will provide Europe with an autonomous and operational framework for earth observation (Berger et al., 2012), which will ensure long time series of remote sensing data at different scales and resolutions.

Statistical time series analysis (TSA) in its frequency and temporal domains (Box et al., 1994), offers a set of tools and methodologies to understand, model and forecast a variable based on the quantitative identification of temporal patterns, which are therefore based on the history of the variable itself. These techniques have been used widely in economics (Granger and Newbold, 1977), and less frequently in some other disciplines such as hydrology (Modarres, 2007; Gemitzi and Stefanopoulos, 2011) agriculture (Mariño et al., 1993), or forestry (Telesca et al., 2005).

Abbreviations: ACF, autocorrelation function; Adj-R^2, adjusted coefficient of determination; AR, autoregressive; ARIMA, autoregressive integrated moving average; B&J, Box and Jenkins; EMR, estimated model from representative series (significant lags + estimated coefficients); EM, estimated model (significant lags + estimated coefficients); GM, generic model (significant lags); L–B Q, Ljung–Box Q; MODIS, moderate resolution imaging spectroradiometer; PACF, partial autocorrelation functions; SARIMA, multiplicative seasonal autoregressive integrated moving average; TSA, statistical time series analysis; U, Theil inequality coefficient U; U^B, bias proportion; U^C, covariance proportion; U^V, variance proportion.

* Corresponding author at: Departamento de Estadística, ETSIA, Universidad Politécnica de Madrid, Ciudad Universitaria, 28040 Madrid, Spain.
Tel.: +34 913365840.
E-mail address: javier.litago@upm.es (J. Litago).

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Conversely, TSA has hardly been applied to remote sensing data. The application of TSA techniques to spatially continuous time series, such as those in remote sensing data, opens a new perspective in terms of environmental variable monitoring. This is because it can be applied to large areas, taking into account the history of each pixel and the spatial coherence of the scene. However, to implement TSA methodologies at the pixel level is a major challenge due to the complexity of some models and the large amount of data.

In the remote sensing domain, TSA has been applied mainly to specific representative pixels or average series from a selected group of pixels. For example, Liang (2001) discriminated 13 cover types based on 12 years of AVHRR-NDVI and brightness temperature average time series. Beck et al. (2011) studied productivity changes in an Alaskan boreal forest based on 88 time series from GIMMS-NDVI (NOAA) and tree rings. Horion et al. (2013) assessed the relationship between 12 average SPOT-VEGETATION-NDVI time series and meteorological data. Huesca et al. (2009) assessed fire seasonality in different ecoregions by means of autoregressive (AR) models applied to Fire Potential Index (FPI) (Burgan et al., 1998) using NDVI or NDWI as remote sensing data. García et al. (2010) analyzed the relationship between representative AVHRR-NDVI time series and rainfall data in order to evaluate the influence of precipitation disturbances on different types of ecosystems.

The application of TSA to remote sensing images in a spatially explicit manner (i.e. at the pixel level) has been applied mainly to evaluate temporal trends in large areas (Verbesselt et al., 2010a; Fensholt et al., 2012; Bunn and Scott, 2006). It has also been used to detect seasonal changes usually associated with phenological dynamics (Fensholt et al., 2012; Verbesselt et al., 2010b). In addition, TSA has been used to analyze the temporal relationship between different environmental variables by means of cross-correlation analysis (Peng et al., 2010).

Generally, the most typical TSA applications are associated with variable modeling and forecasting (Harvey and Andrew, 1981). The first applications to modeling were based on time series decomposition, a technique in which a series is considered as the sum of three components: tendency, seasonality and randomness (Harvey and Andrew, 1981). In the seventies, Box and Jenkins (1970) introduced the autoregressive integrated moving average (ARIMA) models, an approach in which a time series is modeled as a stationary stochastic process. In the remote sensing domain, some authors have applied ARIMA models (Piwowar and Ledrew, 2002); however, due to the highly significant seasonal component usually associated with remote sensing time series, it is more common to use multiplicative seasonal autoregressive integrated moving average (SARIMA) models instead (Xiao et al., 2011; Fernández-Manso et al., 2011; Jiang et al., 2010).

The Box–Jenkins methodology is typically applied in five standard stages (identification, estimation, validation, forecasting, and evaluation). The identification stage involves a 'labor-intensive' design, which makes it difficult to apply it to a large number of pixels (i.e. time series) from spatially continuous remote sensing data. Several approaches have been used to deal with this issue. Xiao et al. (2011) forecasted Leaf Area Index (LAI) using the same estimated SARIMA model (i.e. same structure and coefficients) for all pixels of the MODIS image. They obtained low-accuracy results, possibly due to the lack of model specificity at the pixel level. Han et al. (2010) applied a generic AR (1) model at the pixel level to forecast the Vegetation Temperature Condition Index (VTCI); in this case, the model coefficients were specific for each time series, which resulted in a highly accurate forecast. Jiang et al. (2010) also found accurate predictions using the same approach with one generic SARIMA model to predict MODIS LAI time series. Fernández-Manso et al. (2011) improved forecast accuracy by applying two different generic SARIMA models to predict conifer forest NDVI-AVHRR time series with a forecast horizon of 10 days.

TSA has a direct and relevant application within the scope of forest fire assessment. According to Pausas (2004), current climate trends in the Iberian Peninsula indicate an increase in annual and summer temperatures, and a slight decrease in summer rainfall, which will amplify the risk of forest fires (IPCC, 2007). Under this scenario, the approach of statistical time series modeling and forecasting with RS data would contribute to a better understanding of the fire risk dynamics and the development of effective early warning methods.

The FPI (Burgan et al., 1998; Sebastián-López et al., 2002; Schneider, 2008) is a dynamic forest fire risk index that is highly specific for fuel type, weather conditions and vegetation status, resulting in values with high spatial variability. This requires the development of pixel-specific models to account for specific environmental characteristics. In addition, forest fire risk estimation models should be able to predict fire risk with a short and medium-term forecast horizon to obtain this information early enough to define fire-prevention plans.

The objective of the present study is to model and forecast MODIS-based FPI_{NDWI}, as a proxy of forest fire risk, using pixel-specific autoregressive models based on a large number of generic models and with a forecast horizon of one year.

2. Study area

Navarre, which is located in the northern Iberian Peninsula (Fig. 1), occupies an area of 10,420 km^2 and is located on the edge of the temperate, alpine, and Mediterranean ecoregions. The presence of significant climate gradients results in distinct vegetation types and highly variable fire regimes.

The temperate ecoregion is characterized by a warm, temperate maritime climate that is strongly influenced by the Cantabrian Sea, with frequent rain, fog and drizzle. This region is dominated by deciduous broad-leaved forests, mainly *Quercus robur* L., *Quercus petraea* (Matts.) Liebl. and *Fagus sylvatica* L. Fire regimes are characterized by their high frequency and relatively small burned area (Vélez, 2000). The northern part of the alpine ecoregion is characterized by a moist continental climate and is mainly occupied by coniferous and broad-leaved forests. On the other hand, there is a clear influence of the Mediterranean climate in southern part, resulting in a drier continental climate that is dominated by more xerophitic species. Fire regimes are characterized by low frequency and marked seasonal and annual variability resulting in an irregular pattern (Vélez, 2000). Finally, the Mediterranean ecoregion is dominated by a Mediterranean climate, with the Western area clearly influenced by the temperate climate and the Eastern area by the continental characteristics. Forests in this region are characterized by Mediterranean sclerophyllous species such as *Quercus ilex* L. and *Quercus coccifera* L., among others. Fire regimes are intermediate in frequency and may affect medium to large areas. In terms of forest fire patterns there is a clear difference between temperate and Mediterranean regions. Forest fires in the temperate region follows a bi-modal pattern with relative maxima in spring and late summer-fall while forest fires in the Mediterranean region follows a unimodal pattern with an absolute maximum in summer (Vélez, 2000). Fig. 1 shows monthly distribution of forest fires occurrence during the period 2001–2010, for the Spanish temperate and Mediterranean ecoregions (http://www.magrama.es/).

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