SEGURIDAD y Medio Ambiente

Year 32 N125 First Quarter 2012

FUNDACIÓN MAPFRE

Pre-empting fire risk

Fire safety

This study develops specific models for estimating and forecasting fire risk based on a combination of time series analysis and remote sensing data. The risk indices used in this procedure are the FPI_{NDWI} and the FPI_{NDVI}, which differ in terms of the vegetation index used in their calculation, NDVI or NDWI. The FPI (Fire Potential Index) pools meteorological data with information from remote sensing images. Time series analysis has unearthed dynamic patterns in fire behaviour during the study period 2000-2009. From the time series for the period 2000-2008, specific forecast models were developed for the two indices by «fuel type-bioclimatic region». The results show a good fit between the original FPI_{NDWI} data and the forecasts for 2009. The study also shows that the FPI_{NDWI}'s risk forecasting accuracy is better than the $FPI_{NDVI's}$, especially for the ecosystems of the north of the study region.

By **M. HUESCA.** Sc. Geo-information Science and doctorate student. ETSI Montes, Ciudad Universitaria s/n, 28040, Madrid, Madrid.mhuescamartinez@alumnos.upm.es.s.

A. PALACIOS ORUETA. Doctor in agronomy and tenure holding professor of the university. ETSI Montes, Ciudad Universitaria s/n, 28040, Madrid. alicia.palacios@upm.es.

J. LITAGO LAVILLA. Doctor in agronomy and tenure holding professor of the university. ETSI Agrónomos Ciudad Universitaria s/n, 28040, Madrid. javier.litago@upm.es..

S. MERINO DE MIGUEL. Doctor in forestry engineering and professor of the university college. EUIT Forestal, Ciudad Universitaria sn, 28040, silvia.merino@upm.es..

J. SAN ROMÁN ORTIZ. Forestry engineer, MSc student ETSI Montes, Ciudad Universitaria s/n, 28040, Madrid. guisandero@hotmail.com. guisandero@hotmail.com..

V. CICUENDEZ LÓPEZ-OCAÑA. Student of forestry engineering and researcher of UPM. ETSI Montes, Ciudad Universitaria s/n, 28040, Madrid. victor.cicuendez.lopezocana@alumnos.upm.es..

J. MAQUEDA BUENO. Student of forestry engineering and researcher of UPM, ETSI Montes, Ciudad Universitaria s/n, 28040, Madrid. jmaqueda@gmail.com..

Fire is considered to be a natural component of many ecosystems. Mediterranean ecosystems in particular have been heavily fire-adapted over time. Human pressure, however, has distorted this natural balance. The ecosystems can no longer cope with the sheer number of fires that break out and the vast area burnt, and are now suffering a grave environmental damage in terms of species make-up and biodiversity.

Fire behaviour is governed by three natural factors: fuel availability, the lie of the land and the weather[1]. For a fire to break out there must be sufficient biomass, the environmental conditions must be suitable and there must also be some source of ignition.

Although sociological factors weigh heavily on fire occurrence[2], fires in Spain, especially the big ones, tend to break out in summer, showing that the prevailing weather does play a key role. At this time of year the accumulated biomass becomes an easily combustible fuel under the right conditions. The fuel's availability and water content therefore also play a key role in fire outbreak. Furthermore, while the sociological and meteorological factors are very difficult to control, the former being hard to predict and the second inevitable, direct action is possible on the fuel by means of a suitable management of silvicultural work[3]. The working hypothesis of this study is therefore that fuel type is a fundamental risk factor; the risk is also modulated by vegetation response to weather fluctuations, a highly variable factor.

Fuels can be described in terms of type, load and state. The fuel type is a static characteristic intrinsic to the fuel itself, whereas load and state are dynamic variables that vary throughout the year. These variations might be daily, seasonal or annual. Daily variations are responses to the changing weather conditions; seasonal variations are governed mainly by the biophysiological cycle of the fuel and cumulative weather effects while annual variations are the system's response to the plant species' growing cycle[3].

Identifying the high fire-risk areas, and also understanding their dynamic over time, is essential for the prevention, control and management of woodland. This identification process also furnishes a useful tool for assessing ecological conditions, since many of Spain's ecosystems are moulded by the effects of wildfires[1] . This type of analysis favours a better understanding of how variables like climate and vegetation exert a dynamic influence on fire behaviour[4], but it is a complex task since these variables all have different variation scales. Hence the need for defining specific forecasting models for each climate-vegetation combination showing different fire behaviour.

The time pattern of wildfires can be analysed by means of the risk indices, used to estimate the likelihood of a fire breaking out. The indices most widely used in Spain depend only on the weather conditions; nonetheless in Spain's geographical conditions it has proven very hard to forecast the number of fires or area burnt in terms solely of the weather. The Fire Potential Index (FPI)[5] is a dynamic fire risk indicator combining information on fuel type, weather information and vegetation state, provided by remote sensing images. The FPI has been successfully tried and tested in very different geographical areas. Several authors[6,7 and 8] have shown the usefulness of this index for describing wildfire behaviour in temperate and Mediterranean regions. Other authors[9] have drawn up an FPI-based statistical model for forecasting the number of large fires, thus demonstrating this index's capacity for estimating and forecasting fire occurrence.

IDENTIFYING HIGH FIRE RISK AREAS AND ALSO UNDERSTANDING THEIR DYNAMIC IS ESSENTIAL FOR FIRE PREVENTION AND THE MANAGEMENT AND CONTROL OF WOODLAND

The space-time coverage of some remote sensing systems makes the information supplied especially suitable as an indicator of the vegetation state within the risk indices. The multispectral images are generally analysed using vegetation indices, which are reflectance ratios at different wavelengths and depend on the specific properties of the vegetation. The most widely used spectral indices are the NDVI (Normalized Difference Vegetation Index)[10], related to photosynthetic activity, and the NDWI (Normalized Vegetation Water Index)[11], more dependent on humidity.

Time series analysis (TSA), in its frequency-domain methods and time-domain methods[12], offers a highly useful forecasting tool in nearly all areas of knowledge in which a magnitude can be measured with a given frequency, ranging from economics to engineering or meteorology. For wildfires it has been used, among other aspects, to study the area burnt per year[13], to monitor fuel humidity and assess fire risk[14], verify the dominant fire cycle[15], or to identify pre- and post-fire vegetation trends[16]. TSA furnishes us with a series of tools for pinpointing the time patterns that determine the past and present dynamic of a given variable. It also offers us a methodology for building up forecasting models based on well-defined statistical models, such as AR (autoregressive), MA (moving average), ARMA (combining the two former) and ARIMA (autoregressive integrated moving average, incorporating an integration term to establish the variable's stationarity). In reality it is not a single model but rather a set of possible models. The estimation procedure is a trial and error process to find the model that best fits the selected variable. These models have been used in various environmental fields such as hydrology[17] and in climate change studies[18], among others. These models may be used to study, analyse and model the behaviour of a variable and also to forecast its future value. Several authors[19] use an ARIMA Model to forecast drought in China.

The objective of this study is to develop specific or local fire-risk forecasting models by means of time series analysis. The fire risk is estimated using the Fire Potential Index proposed by Burgany et al (FPI_{NDVI}) and the modification proposed by Huesca et al[8] (FPI_{NDWI}).

Study Area

The study area is the *Comunidad Foral de Navarra* (Region of Navarre), which occupies an area of 10,420 km^2 and lies on the borderline of the temperate (or Atlantic), Alpine and Mediterranean bioclimatic zones. Within each ecoregion the climate characteristics are sufficiently alike to ensure similar behaviour in terms of soil evolution and climax woodland, and therefore different fire behaviour within each one.

The Atlantic region is characterised by a warm temperate maritime climate, heavily influenced by the Cantabrian sea, with high rainfall, mists and drizzle and mild temperatures. The climax woodland in this region is deciduous. Fires are frequent but typically small in area. They have a bimodal distribution with two peaks, one at the start of spring and the other in summer-autumn.

The Alpine region can be broken down into two zones: the first, higher up, with a cold, humid continental climate and the second, lower down and closer to the borderline with the Mediterranean region. The latter is in fact a transitional area between the cold Mediterranean climate and temperate Mediterranean climate. The predominant woodland in the Alpine region is conifer and beech with a low fire frequency and a marked seasonal and annual variability.

THE WILDFIRE TIME PATTERN CAN BE ANALYSED BY MEANS OF FIRE POTENTIAL INDICES FOR CALCULATING THE LIKELIHOOD OF A FIRE BREAKING OUT

In the Mediterranean region the climate is Mediterranean as a whole but with a clear Atlantic influence in the western part verging into continental towards the east. The typical woodland of this region is sclerophyll Mediterranean, with an intermediate fire frequency likely to affect middling to large areas. The distribution of the fires is unimodal with a single peak in summer.

Materials and methods

- *Remote sensing information*
  The remote sensing information used consists of a set of 454 images captured by the MODIS sensor (MODerate resolution Imaging Spectroradiometer) onboard the TERRA satellite (https://lpdaac.usgs.gov/). The product used is the MOD09A, consisting of surface reflectance images taken in the spectral zone ranging from blue to SWIR channels. The images used have a spatial resolution of 500 metres and are 8-day compounds, making up 46 images per year, i.e., 46 values for each pixel making up the image. The study period ran from February 2000 to December 2009.

  The images were downloaded from NASA's server and were reprojected on the UTM30N projection system WGS-84 datum. The time series were built up from the extracted red (648 nm), near-infrared (858 nm) and SWIR1 (1240 nm) channels. This gives reflectance time series at three wavelengths during a 10-year period and about every 8 days. Finally, the NDVI and NDWI vegetation indices were calculated (equations 1 and 2), to be used for calculating the fire potential index FPI.

$$NDVI = (\rho_{nir} - \rho_r / \rho_{nir} + \rho_r)$$

  (Eq.1)

$$NDWI = (\rho_{nir} - \rho_{swir1} / \rho_{nir} + \rho_{swir1})$$

  (Eq.2)

  where ρ_r, ρ_{nir} and ρ_{swir} represent the reflectance in red, near infrared and SWIR1 channels respectively.

  The series were smoothed as far as possible by identifying and filtering out any outliers, using thresholds defined in terms of the mean and standard deviation of the time series. The outliers were replaced by the mean between the value of the previous date and the next date. If the previous or next date were also outliers, the first non outlying value was used.

- *Meteorological Information*
  The meteorological information was taken from the existing meteorological stations in the *Comunidad Foral de Navarra* and in the bordering provinces. The latter were tapped into to ensure a good quality of information in the borderline areas of the study. The daily readings from the meteorological stations of the *Comunidad Foral de Navarra* for the period 2000-2009 were furnished by the *Departamento de Desarrollo Rural y Medio Ambiente* (Environment and Rural Development Department) of the *Gobierno de Navarra* (Regional Government of Navarre). The meteorological data from the stations of the bordering provinces was obtained from the 17 meteorological stations of the State

Meteorological Agency (*Agencia Estatal de Meteorología: AEMET*). Since 2000 the number of available stations in Navarre has been increasing so the maximum number was used each year in the interests of obtaining the best possible results.

The variables used were maximum temperature and minimum relative humidity each day to work with the most adverse wildfire situation. The daily data was summarised to 8 days to tally with MODIS 8-day data. A calculation was therefore made of the mean value of maximum temperatures (Tmax) and minimum relative humidity (Hrel) of the 8 dates corresponding to a MODIS compound. Tmax and Hrel were the spatially interpolated date-to-date to build up maps of Tmax and Hrel for each date of the study period. The temperature was interpolated using the inverse distance method and minimum relative humidity by means of a multiple linear regression according to equation 3.

$$H_{rel} = 72.1761 - 1.4181xT_{max} + 0.0049xH$$

(Eq.3)

where H is the height (taken from the digital land model of Navarre).

- *Auxiliary Information*
  Other resources used in the study were the Digital Elevation Model (www.ign.es) and the Navarre Fuel Map (www.marm.es). The latter is based on the 13 fuel models established for the NFDRS (National Fire Danger Rating System) and duly adapted to Spanish vegetation. In Navarre all the fuel models are present except for those in which the fire propagation mechanism is logging slash. Each fuel model is associated with an extinction moisture, which is the moisture level at which the fire will no longer spread; this parameter is used in calculating the FPI.

- *Calculation of the Fire Potential Index (FPI)*
  The Fire Potential Index (FPI) is expressed as follows:

$$FPI = 100x(1 - Hcm_{10hr frac})x(1 - CV_{cor})$$

(Eq.4)

where FPI is the Fire Potential Index, which takes maximum values of 100 when the risk is very high and values close to zero or negative when there is no risk. FMC10hr represents the moisture content of the small dead fuel and LR is the live ratio of the combustible fuel charge.

The indices used were the FPI_{NDVI} and FPI_{NDWI}. The FPI was calculated on the basis of the formulation described by Huesca et al[8].

- *Time Series Analysis (TSA)*
  First of all a qualitative study was made of the FPI trend over the period 2000-2009 for four zones with a vegetation type and fuel model representative of the region. A quantitative time series analysis was then carried out[12]. The time series of FPI_{NDVI} and FPI_{NDWI} of each pixel were grouped by their behaviour using descriptive statistics (mean and variance) and autocorrelation function analysis. Zones with a similar trend were thus defined within the study area to build up an idea of the variability over time of the whole study area.

Descriptive statistics give us a preliminary quantitative idea of the global nature of the risk in each zone. The autocorrelation function measures the correlation of the risk value at various time intervals apart. This enables us to assess the risk dynamic and estimate its stability over time, i.e., how repetitive its pattern is.

For each zone with a similar behaviour a specific model was built up following the methodology proposed by Box et al [12], based on the construction of a statistically suitable model that meets the succinct parameterisation principle (maximum structural simplicity and minimum number of parameters). This methodology is three phase: (1) Identification, (2) Estimation and Validation, and (3) Forecasting. In the first stage a study was made of the series' stationarity and seasonality and an identification was also made of the model's autoregressive and moving average terms. The model parameters were then calculated in the second stage and, in the third, a check was made of the statistical validity of the estimates for the series analysed. Forecast assessment enables the error to be estimated, accepting or rejecting the estimated model and then returning to a new identification. In this study a model was initially proposed for each one of the previously defined zones; the next step was to group all the models with a common structure. The models were estimated using the time series 2000-2008, basing the forecast on 2009.

The statistical significance of the models was estimated by the Student's t test and the absence of residual autocorrelation was determined by Ljung–Box Q(k) tests. The model's forecast accuracy was estimated by means of Theil's U test[20].

Results

- *FPI Time Trend*

Figure 1 shows the map of fuel models broken down by the fire propagation element, grass, undergrowth or leaf litter and also the localisation of selected pixels to explain the risk time trend from 2000 to 2009. Zone 1 corresponds to Mediterranean dryfarming land, mainly cereal, in which the propagating element is mainly the grass itself. Zone 2, lying in the Alpine region is occupied by conifer woods dominated by *Pinus silvestris* and firs, with leaf litter being the main fire propagation element. In northwest Navarre (Atlantic region) two zones were selected (3 and 4). Zone 3 is occupied by broadleaved beech woods. This type of wood is closed canopy with no undergrowth so the fire is propagated mainly by leaf litter. The predominant woodland type in zone 4 is broadleaved oak and chestnut. These woods are more open with undergrowth, which thus becomes the main fire propagation element.

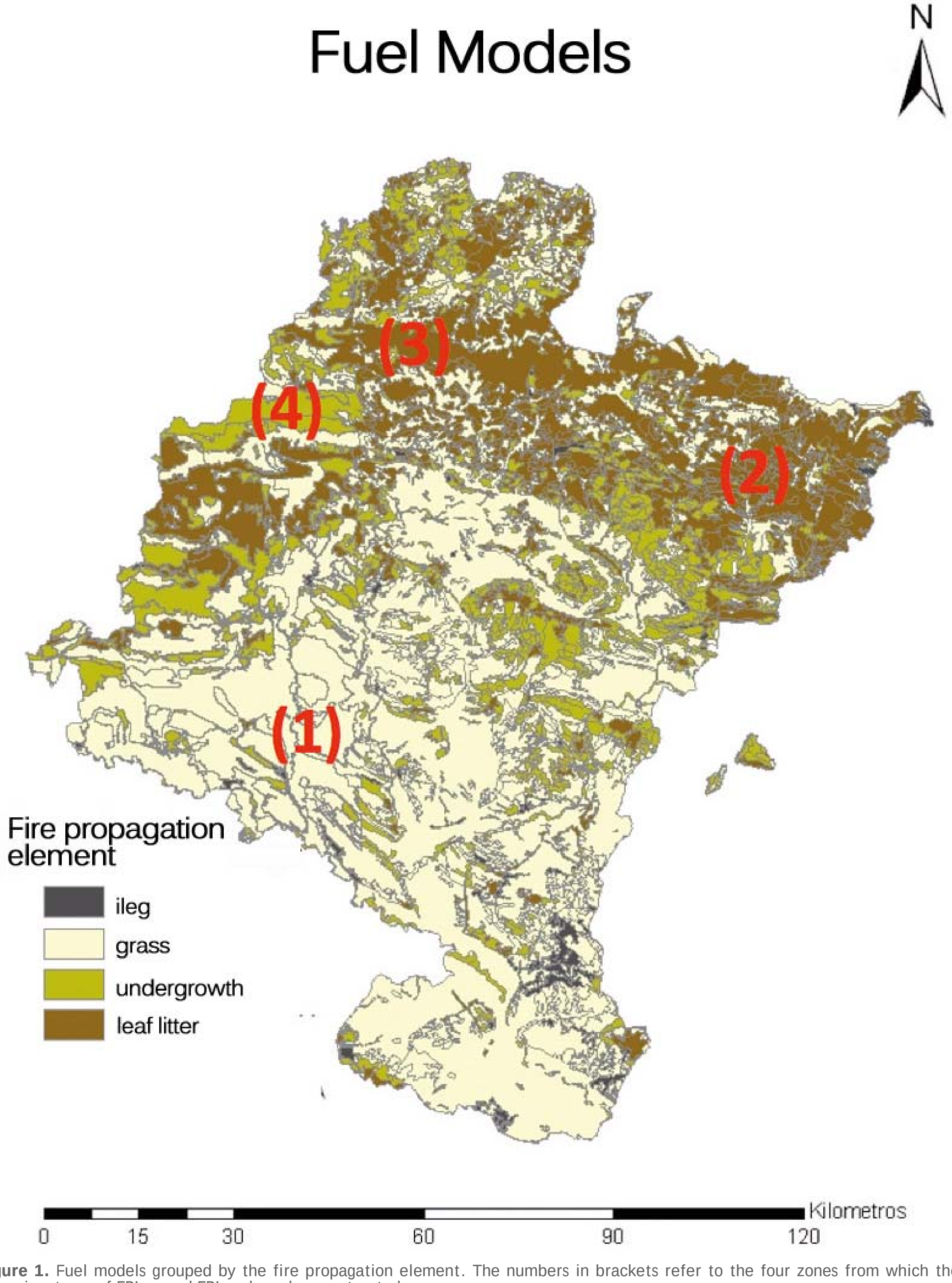


Figure 1. Fuel models grouped by the fire propagation element. The numbers in brackets refer to the four zones from which the time signatures of FPI_{NDVI} and FPI_{NDWI} have been extracted

(1) Mediterranean dryfarming land.
(2) Conifer woods in the Alpine region.
(3) Deciduous broadleaved woodland of the Atlantic region.
(4) Open deciduous broadleaved woodland with undergrowth of the Atlantic region.

Figure 2 shows the trend over time of FPI_{NDVI} and FPI_{NDWI} in the representative zones indicated in figure 1.

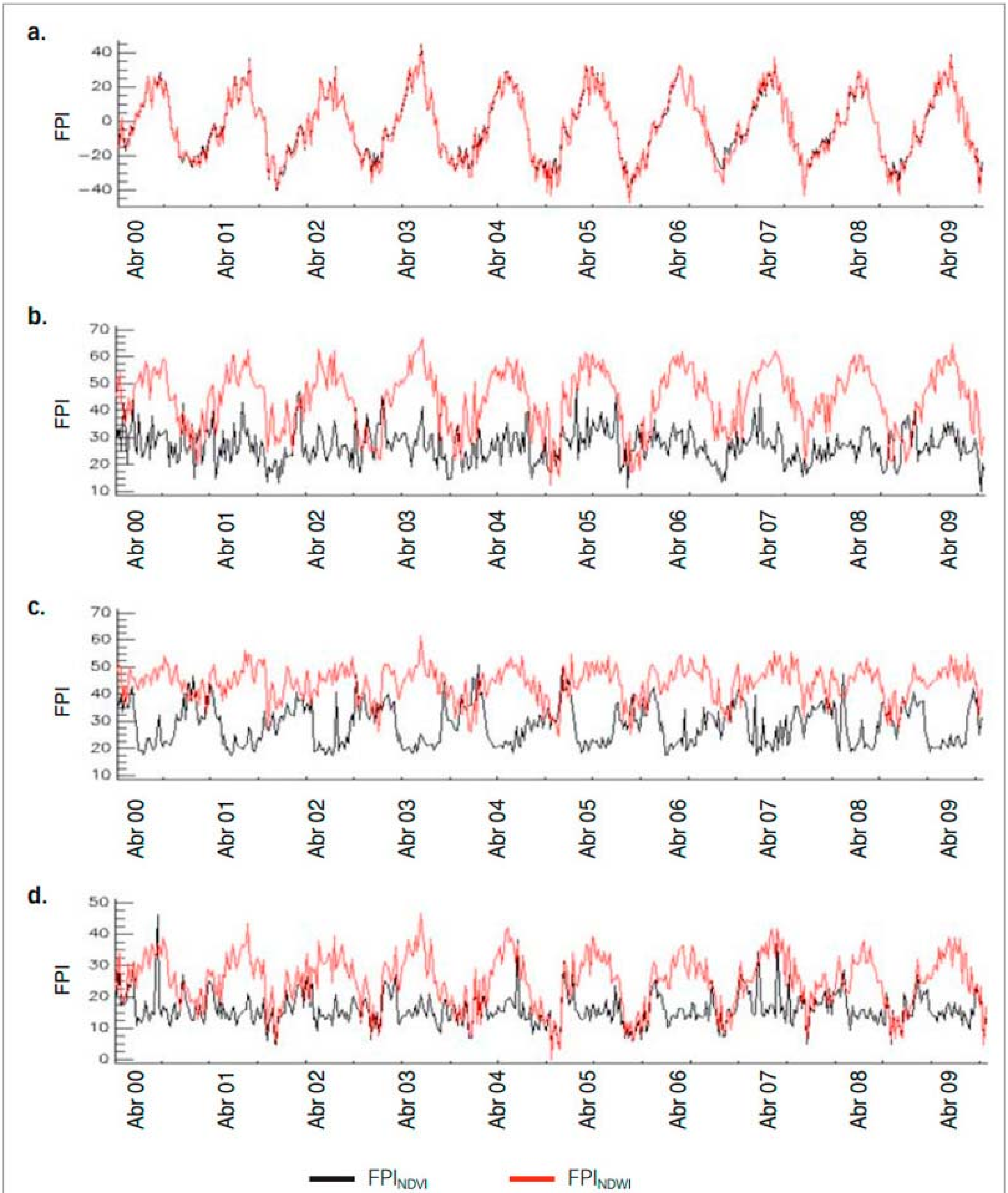
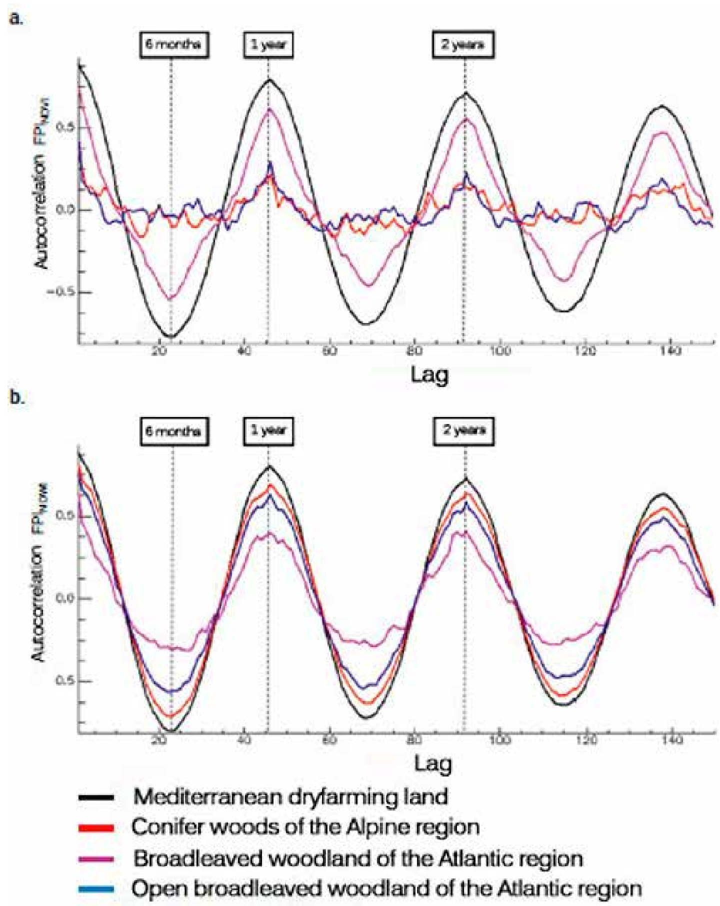


Figure 2. Risk trend calculated from the two indices in the four selected zones from 2000 to 2009. (a) Dryfarming land in the Mediterranean region. (b) Conifer woods in the Alpine region. (c) Broadleaved deciduous woodland of the Atlantic region. (d) Open broadleaved deciduous woodland with undergrowth in the Atlantic region.

THE FIRE POTENTIAL INDEX IS A DYNAMIC FIRE-RISK INDICATOR COMBINING INFORMATION ON FUEL TYPE, METEOROLOGICAL INFORMATION AND INFORMATION ON VEGETATION STATE FROM REMOTE SENSING IMAGES

In the herbaceous crops of the Mediterranean region (figure 2a) both indices show an almost identical risk behaviour. The risk shows a unimodal pattern with unmistakable summer peaks. In the woodland of the northern zone (figures 2b, 2c and 2d) the risk estimated from the FPI_{NDWI} is seen to be considerably higher than that estimated by the FPI_{NDVI} except in the winter, when the risk is lower. In the conifer woods of the Alpine zone (figure 2b) a more obvious annual pattern is shown by the FPI_{NDWI}. The FPI_{NDVI} shows a very irregular pattern. The broadleaved woods (figure 2c) show similar values for FPI_{NDWI} and FPI_{NDVI} during the winter and early spring but a very divergent trend in the summer, the risk rising with the FPI_{NDWI} and falling with the FPI_{NDVI}. In the autumn the values of the two indices come back together. In the open deciduous broadleaved woodland with undergrowth (figure 2d) the behaviour is very similar in winter, spring and autumn. The summer behaviour, however, is divergent in values and trend, FPI_{NDWI} showing higher values than FPI_{NDVI}.

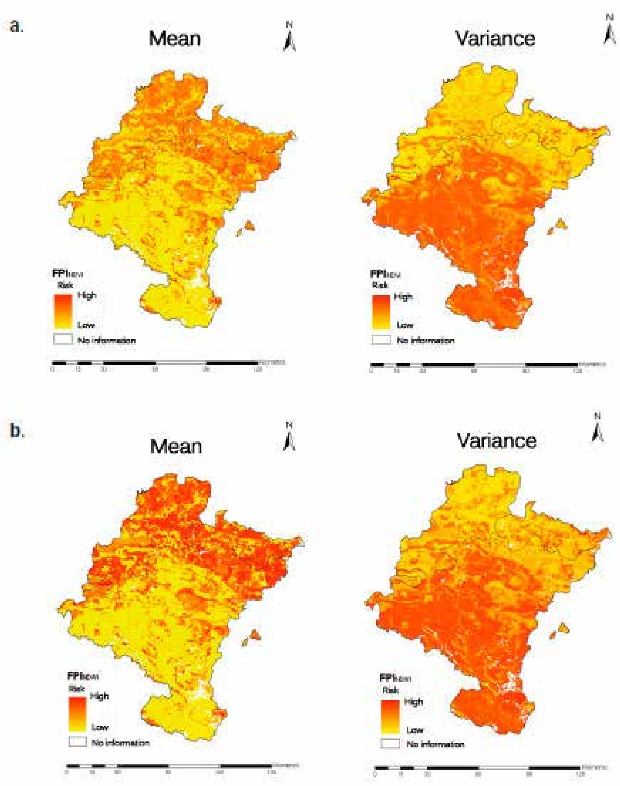
Figures 3a and 3b show the autocorrelation function up to 150 lags (a little over 3 years) calculated for the series of FPI_{NDVI} and FPI_{NDWI} in the selected zones (figure 1). These graphs show that autocorrelation is high in Mediterranean grassland and positive in the two indices in lag 1 (~8 days) and in lag 46 (~1 year) and very negative in lag 23 (~6 months). In the conifers of the Alpine zone the autocorrelation function of FPI_{NDWI} shows similar values to those of grass, while the autocorrelation values of FPI_{NDVI} are very low and irregular at all lags. The broadleaved woods of the Atlantic region with leaflitter propagation show slightly higher autocorrelation values for both indices. The broadleaved woods of the Atlantic region with undergrowth show a similar pattern to conifers in both indices.



Figures 3a y 3b. Autocorrelation up to 150 risk return periods calculated from FPI_{NDVI} (a) and FPI_{NDWI} (b) in the four selected zones from 2000 to 2009.

- *Zoning of the study area*

Figures 4a and 4b show the spatial distribution of the descriptive statistics (mean and variance) for FPI_{NDVI} and FPI_{NDWI} respectively; table 1 shows their mean values per fuel model. The leaflitter- or undergrowth-propagated fuel models show a higher mean and lower variance than grass propagated models.

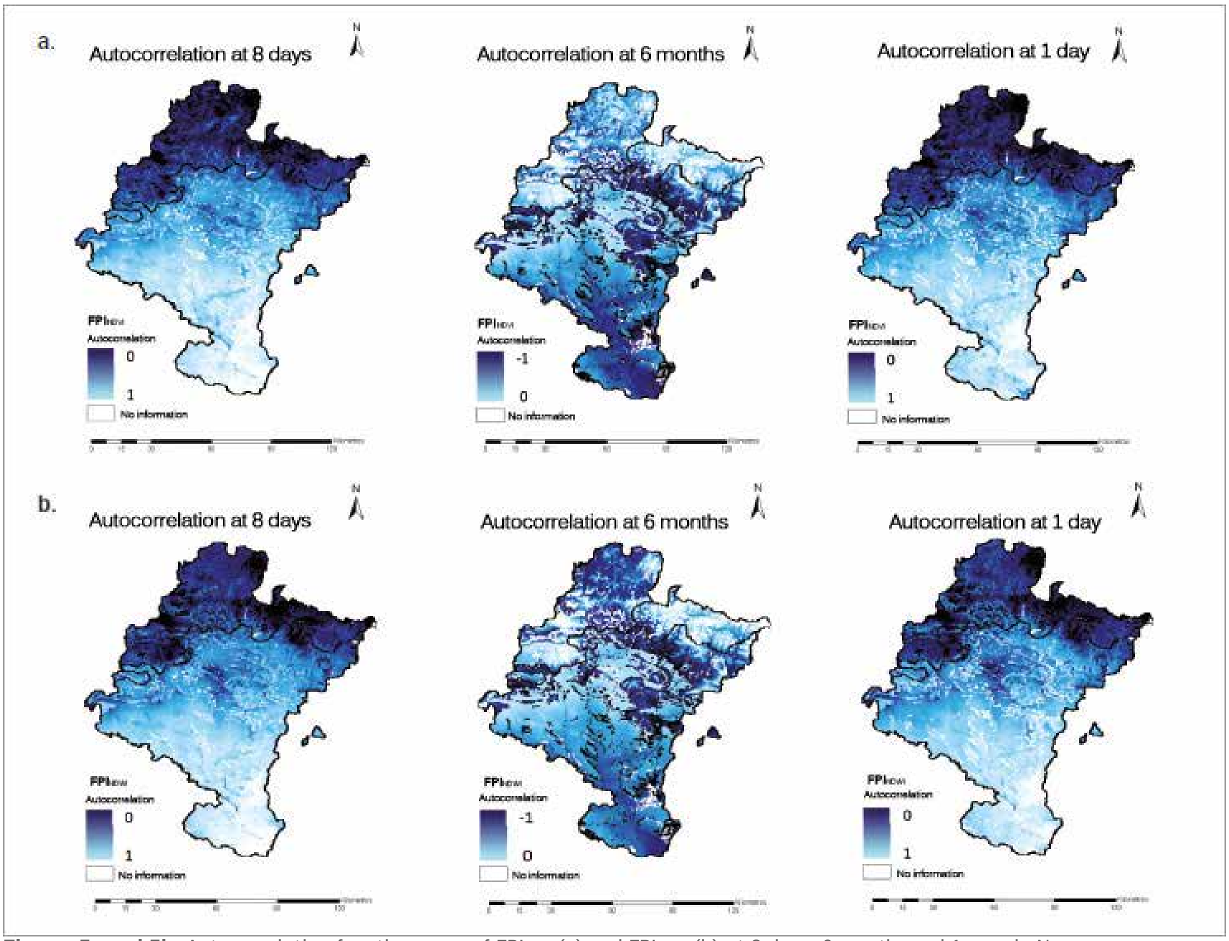


Figures 4a and 4b. Risk variance and mean maps estimated with FPI_{NDVI} (a) and FPI_{NDWI} (b) for the study period.

Table 1. Risk mean and variance estimated with FPINDVI and FPINDWI for each fuel model.

Fuel Model	FPI_{NDVI}		FPI_{NDWI}	
	Mean	Variance	Mean	Variance
1	-1.87	345.54	-2.64	397.86
2	6.59	207.94	7.58	256.42
3	27.04	37.81	38.26	50.03
4	21.78	37.81	28.51	121.22
5	18.14	67.17	25.51	122.55
6	29.30	74.48	38.99	88.76
7	40.78	110.19	56.93	23.94
8	29.48	52.06	44.29	63.37
9	28.79	64.54	39.32	68.57

Figures 5a and 5b shows the spatial distribution of the autocorrelation at 8 days, 6 months and 1 year for FPI_{NDVI} and FPI_{NDWI} respectively. There is a clear north-south gradient especially in the autocorrelations at 8 days and 1 year. The southern zone of Navarre shows higher and more positive values than the northern zone. In all cases the autocorrelation at 6 months is negative; in the north, however, the values are closer to zero.



Figures 5a and 5b. Autocorrelation function maps of FPI_{NDVI} (a) and FPI_{NDWI} (b) at 8 days, 6 months and 1 year in Navarre.

The result of these analyses (table 1 and figures 5a and 5b) show that the zones with similar statistics and autocorrelation functions at 8 days and 1 year correspond mainly to fuel types and bioclimatic zones. We therefore set up previous zoning based on the combination of these two variables and the presence of pure pixels within each class. The result was a 26-class «fuel type-bioclimatic region» zoning.

- *Construction of fire risk forecasting models*

  A model for each class was built up from the zoning obtained in the previous section. This was based on the mean values of the time series corresponding to the pure pixels completely included in each zone.

> *THE SPACE-TIME COVERAGE OF SOME REMOTE SENSING SYSTEMS MAKES THEM ESPECIALLY SUITABLE AS INDICATORS OF THE VEGETATION STATE WITHIN THE RISK INDICES*

The constructed models show a high statistical significance in the estimates of their coefficients, measured by student's t tests and also a high probability of absence of residual autocorrelation calculated from Ljung and Box Q(k) tests. For most of the estimated coefficients an absolute value student's t of over 2 was obtained. Ljung and Box Q(k) test values were low for all models for periods of half a year, one year and two years (23, 46 and 92 lags). The probability of rejecting residual autocorrelation in these models (information loss in explaining the model variable) for any lag is higher than 0.05 (barring 5 cases) and in some cases is higher than 0.8 (80%). This was then the criterion used for assessing the global model fit.

In a second stage the classes of the former phase were grouped in terms of the coincidence in the autoregressive model structure. Tables 2 and 3 show the new groups, their composition, significant lags of the selected autoregressive models and the forecasting accuracy estimated by Theil's U test for FPI_{NDVI} and FPI_{NDWI} respectively.

All the models show a structure with a very short term autoregressive parameter (1, 2 and 3 lags   8, 16 and 24 days) and another long term (45 and 46 lags   c. 1 year). In all cases (except for the Atlantic chaparral-woodland), the model estimates a significant medium-term relationship (21, 22 and 23 lags   c. 6 months) with a negative character and especially low values in the southern zone of Navarre. In the models including grass the system estimates a significant low-value and negative relation at 10 lags (c. 2.5 months).

IN THE MEDITERRANEAN REGION THE TWO INDICES SHOW AN ALMOST IDENTICAL BEHAVIOUR, WHILE IN THE ATLANTIC AND ALPINE REGIONS THE FPI$_{NDWI}$ SEEMS TO GIVE A BETTER REFLECTION OF THE RISK IN SUMMER

Theil's *U* coefficient shows very low values in all models except for grass, although in the latter most of their value is built up in the covariance parameter, showing that the errors are random and proving the suitable forecasting accuracy of the models.

From the selected models the risk forecast has been drawn up for 2009 (46 dates) only of the FPI$_{NDWI}$, since this is the index that shows the best forecasting accuracy. Figure 6 shows the forecasts of FPI$_{NDWI}$ for 2009 together with the calculated value. As can be seen the estimates replicate the actual risk pattern very closely, practically all the forecasts falling within the confidence interval.

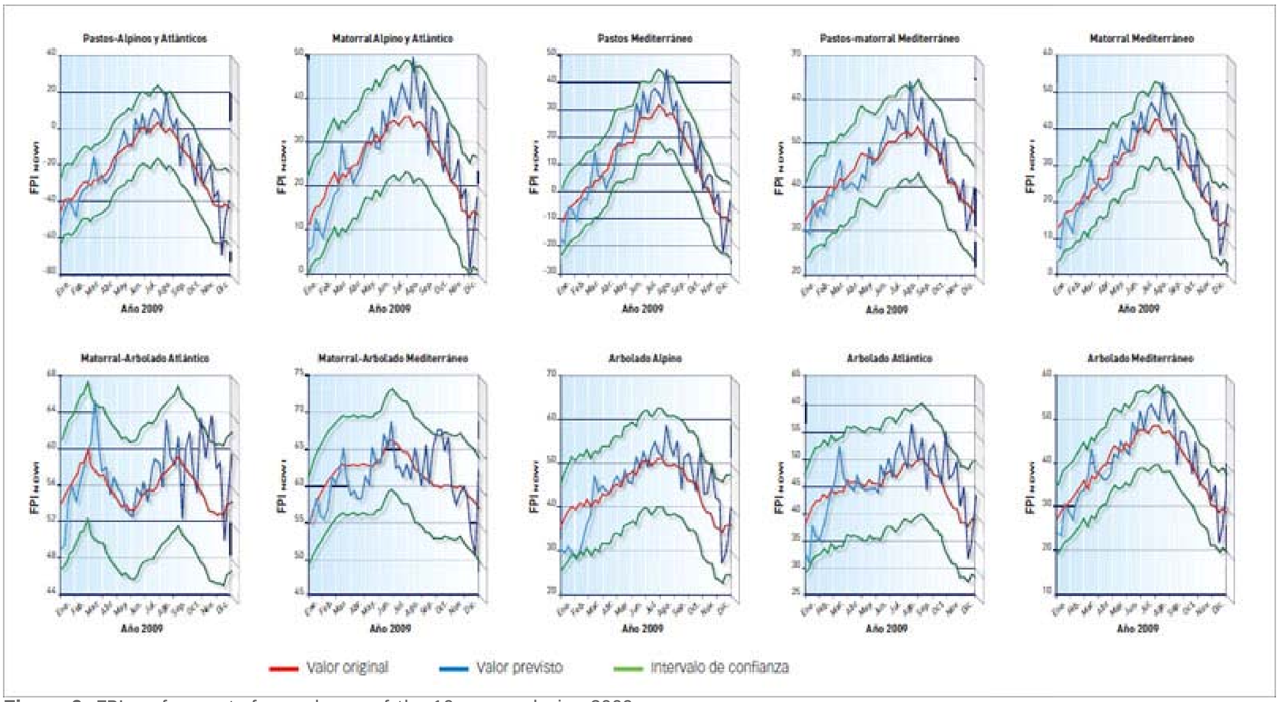


Figure 6. FPI$_{NDWI}$ forecasts for each one of the 10 groups during 2009.

Discussion

FPI Time Trend

The similar behaviour of the two FPIs in herbaceous farmland of the Mediterranean region (figure 2a) is due to the fact that photosynthesis activity in these ecosystems is perfectly synchronised with the vegetation's moisture content. Thus, the pattern shown by the photosynthesis-related NDVI vegetation index and the moisture-related NDWI vegetation index is the same. The autocorrelation function (high and positive –figure 5a and 5b– in both indices in the short term and at one year) confirms a very marked annual cycle that tallies with the pattern of the Mediterranean region[1], for this is the predominant model in the zone.

The higher irregularity shown by the FPI$_{NDVI}$ in conifer woods of the Alpine zone (figure 2b) is borne out by the autocorrelation function, which shows no significant values at any time lag. Moreover, the autocorrelation function of the FPI$_{NDWI}$ shows significant short-, medium- and long-term autocorrelations, confirming the existence of an annual pattern. The difference between the two indices could be put down to the frequent presence of overcast skies in the area, even in summer. This introduces an information-distorting level of noise into the NDVI series, while the effect on the NDWI is less because it is calculated from longer, cloud-penetrating wavelengths.

THIS STUDY INTEGRATES TIME SERIES ANALYSIS INTO THE FIELDS OF REMOTE SENSING AND FIRE RESEARCH. THIS HAS UNEARTHED DYNAMIC RISK

In the broadleaved woods with leaflitter-propagated fires the autocorrelation function for the two indices shows a clear annual pattern with more significant values in the FPI$_{NDVI}$ (figure 2c). The most important difference between the two occurs in summer, when the FPI$_{NDVI}$ shows very low values and the FPI$_{NDWI}$ peaks. This divergence is probably due to the fact that the NDVI is more photosynthesis dependent, responding very directly to phenological changes (very marked in deciduous broadleaved woodland), reflecting itself in the higher absolute autocorrelation values. The summer leaf cover thus produces a very high live-load reading in the FPI_{NDVI}, and hence a very low estimate of the fuel likely to ignite. The more moisture-related NDWI, on the other hand, responds more directly to weather conditions and hence estimates a higher risk in summer, detecting as it does the leaves' water stress as the summer progresses.

Table 2. Selected models, structure and forecasting accuracy estimated by means of Theil's U coefficient for the index FPINDVI

Code Group	Description	Grouped models	Significant lags	Theil's Coefficient			
				U	P.skew	P.Variance	P.covariance
1	Alpine and Atlantic grass	AP1, AP2, AT1 y AT2	1, 3, 10, 22, 46	0,1938	0,0002	0,2433	0,7565
2	Alpine and Atlantic grass type 2	AP3, AT3	1, 2, 10, 22, 46	0,0733	0,0249	0,4658	0,5093
3	Mediterranean grass	M1 y M2	1, 2, 3, 10, 22, 46	0,2102	0,0684	0,2709	0,6607
4	Mediterranean grass-chaparral	M3	1, 2, 3, 6, 7, 11, 21, 46	0,0613	0,1388	0,3219	0,5393
5	Alpine and Atlantic chaparral,	AP4, AP5,AT4, AT5,	1, 2, 10, 23, 46	0,1409	0,0629	0,5778	0,3593
6	Mediterranean chaparral	M4, M5 y M6	1, 2, 3, 10, 21, 46	0,1132	0,1095	0,5388	0,3517
7	Alpine and Atlantic chaparral	AP6, AT6	1, 9, 27, 46	0,0778	0,0624	0,6069	0,3307
8	Atlantic chaparral-woodland	AT7	1, 2, 3, 11, 23, 45, 46	0,0624	0,0029	0,2154	0,7817
9	Mediterranean chaparral-woodland	M7	1, 2, 12, 21, 46	0,0464	0,0297	0,0074	0,9629
10	Alpine and Atlantic woodland	AP8, AP9, AT8 y AT9	1, 9, 23, 45, 46	0,0663	0,0001	0,2632	0,7367
11	Mediterranean woodland	M8 y M9	1, 3, 10, 21, 46	0,0707	0,1335	0,4865	0,3800

Table 3. Selected models, structure and forecasting accuracy estimated by means of Theil's U coefficient for the index FPINDWI.

Code Group	Description	Grouped models	Significant lags	Theil's Coefficient			
				U	P.skew	P.Variance	P.covariance
1	Alpine and Atlantic grass	AP1, AP2, AT1 y AT2	1, 3, 10, 21, 23, 34, 45,	0,1666	0,0246	0,2734	0,7020
2	Alpine and Atlantic chaparral	AP3, AP4, AP5, AP6, AT3, AT4, AT5, AT6	1, 3, 10, 21, 23, 34, 46	0,1065	0,0203	0,4752	0,5045
3	Mediterranean grass	M1 y M2	1, 3, 10, 21, 45, 46	0,1744	0,0699	0,3037	0,6264
4	Mediterranean grass-chaparral	M3	1, 2, 3, 10, 21, 46	0,0472	0,0257	0,3459	0,6284
5	Mediterranean chaparral	M4, M5 y M6	1, 3, 4, 10, 22, 42, 46	0,0833	0,0725	0,2865	0,6410

Code Group	Description	Grouped models	Significant lags	Theil's Coefficient			
				U	P.skew	P.Variance	P.covariance
6	Atlantic chaparral-woodland	AT7	1, 3, 10, 34, 42, 46	0,0327	0,1316	0,2185	0,6499
7	Mediterranean chaparral-woodland	M7	1, 3, 21,23, 46	0,0282	0,0090	0,1675	0,8235
8	Alpine woodland	AP8, AP9	1, 3, 22, 42, 46	0,0629	0,0032	0,3416	0,6551
9	Atlantic woodland	AT8 y AT9	1, 3, 16, 22, 34, 42, 46	0,0500	0,0247	0,3445	0,6308
10	Mediterranean woodland	M8 y M9	1, 3, 10, 21, 23, 46	0,0500	0,0416	0,2990	0,6594

In the open broadleaved deciduous woods with undergrowth (figure 2d) the autocorrelation function shows a clear pattern in the FPI_{NDWI} index, while FPI_{NDVI} shows no significant autocorrelations at any time lag. In this ecosystem the phenological cycle captured by the vegetation indices is the result of the admixture of the evergreen woods with undergrowth and the deciduous trees. This is reflected in a great irregularity throughout the year, especially when using the FPI_{NDVI}, heavily dependent on the phenological cycle. This is clearly shown in the autocorrelation function. Nonetheless, the FPI_{NDVI} series does show a reduction of the risk in spring, when the foliage begins to grow, albeit less marked that the deciduous woods without undergrowth. The same effect is seen in winter when the verdure of the undergrowth brings down the FPI_{NDVI} values as compared with the previous ecosystem because it detects a higher load of live vegetation, undergrowth. Moreover the FPI_{NDWI} follows a similar pattern as in the previous ecosystem, estimating the highest risk values in summer.

THE RISK HAS BEEN MODELLED AND FORECAST FROM A SINGLE TYPE OF MODEL, THE AUTOREGRESSIVE MODEL. THIS SIMPLIFIES THE FORECASTING PROCEDURE, FOR THE RISK DEPENDS ONLY ON ITS OWN HISTORY

The results of the spatial analysis of the basic statistics and the autocorrelations at 8 days, 6 months and one year validate a preliminary zoning based on the bioclimatic zone and fuel model. The fuel models show very different means and variances, indicating different risk levels and variability throughout the year. The autocorrelation function, for its part, shows a different pattern from one bioclimatic region to another, indicating a very different stability of the risk pattern. For example the better autocorrelation at 1 year in the Mediterranean zone is probably due to the fact that the summer drought is very regular and constant, thereby conferring stability on the risk. In the north, on the other hand, cooler and more humid, the water limitation is not an annual constant so the risk pattern varies more from year to year. On the basis of these results we have drawn up a specific preliminary model for each «fuel model-bioclimatic region» combination. In all cases the proposed models are autoregressive, modelling the variable in terms solely of the past. The main differences between them lie in their structure (necessary risk-modelling lags). In a second phase the models sharing the same structure were pooled and forecasts were made only for the FPI_{NDWI} in view of its better forecasting accuracy. The 26 original classes were grouped in 10 for this index. The pure Atlantic and Alpine grassland show a similar behaviour so they have been pooled into one class. The two tree fuel models (8 and 9) were also pooled, while maintaining the distinction between bioclimatic zones. The chaparral with various levels of association with grassland and Atlantic and Alpine woodland has been grouped, except for the Atlantic chaparral-woodland, which had to be modelled separately. In the Mediterranean region chaparral was broken down into three classes according to its association with grassland or trees.

All these models share a common structure with an autoregressive parameter in the very short term and another in the long term. This shows that the risk value depends largely on its value in the recent past and shows a similar behaviour to the previous year on these same dates. The significant negative medium-term relation found (except in the Atlantic chaparral-woodland), can be explained by the bearing of the spring's risk on the autumn's risk. Wet springs generate a lot of biomass and ipso facto a higher risk in late summer and autumn. The significant negative low value at 2.5 months found in the models with grassland among the fuel might be due to the fact that this model captures a dynamic risk relation associated with the short-term vegetative trend of some fuels, such as some grassland ecosystems.

Conclusions

In this study the fire risk has been modelled on the basis of two indices: the FPI_{NDVI} and the FPI_{NDWI}. In the Mediterranean region both indices show an almost identical behaviour whereas in the Atlantic and Alpine regions the FPI_{NDWI} seems to give a more faithful reflection of summer risk, probably because it is more related to moisture than photosynthesis. This index also shows a better forecasting accuracy.

The study shows that the fuel type-bioclimatic region combination engenders classes with a characteristic risk behaviour. It has also been possible to model and forecast the risk with a single model type, the autoregressive. This simplifies the forecasting procedure because the risk depends only on its own history without taking auxiliary variables into account.

This study has integrated time series analysis into remote sensing and fire research. This is a groundbreaking and original approach. In our opinion the results suggest that this methodology has a great potential in fire research and management. These methodologies can also be easily extrapolated to other environmental contexts.

ACKNOWLEDGEMENTS

This work has been funded by a FUNDACIÓN MAPFRE research grant..

BY WAY OF A GLOSSARY

FPI: Fire Potential Index.
FPI_{NDWI}: Fire Potential Index alculado con el índice NDWI.
FPI_{NDVI}: Fire Potential Index calculado con el índice**NDVI.**
NDVI: Normalized Difference Vegetation Index.
NDWI: Normalized Vegetation Water Index.
AST: Análisis estadístico de series temporales
AR: Modelo autorregresivo.
MA: Modelo media-móvil.
ARMA: Modelo autorregresivo y media-móvil.
ARIMA: Modelo autorregresivo y media-móvil con término de integración.
MODIS: MODerate resolution Imaging Spectroradiometer.
ρ_r: Reflectancia en el canal rojo.
ρ_{nir}: Reflectancia en el canal infrarrojo cercano.
ρ_{swir}: Reflectancia en el canal SWIR 1.
T_{max}: Temperatura máxima.
H_{rel}: Humedad relativa mínima.
H: Altitud.
$Hcm_{10hrfrac}$: Humedad del combustible fino y muerto.
Cv_{cor}: Carga de combustible susceptible de arder.

TO FIND OUT MORE

1. Vélez, R. et al. La defensa contra incendios forestales. Fundamentos y experiencias. McGraw-Hill. 2000, 1.3 – 9.43
2. Bartlein, P.J., Hostetler, S.W., Shafer, S.L., Holman, J.O. and Solomon, A.M. Temporal and spatial structure in a daily wildfire-start data set from the western United States (1986-96). International Journal of Wildland Fire, 2008, (17), 8-17.
3. Pyne, S., Andrew, P. and Laven, R.D. Introduction to wildland fire. 2nd .ed. Wiley, New York.1996.
4. Morgan, P., Hardy, Colin C., Swetnam, Thomas W., Rollings, Matthew G. and Long, Donald G. Mapping fire regimes across time and space: Understanding coarse and fine-scale fire patterns. International Journal of Wildland Fire, 2001, (10), 329–342
5. Burgan, R. E., Klaver, Robert W. and Klaver, Jacqueline M. Fuel models and fire potential form satellite and surface observations. International Journal of Wildland Fire. 1998, (8), 159-170.
6. Sebastián-López, A., San Miguel-Ayanz, J. and Burgan, Robert E. Integration of satellite sensor data, fuel type maps and meteorological observations for evaluation of forest fire risk at the pan-European scale International Journal of Remote. Sensing, 2001, (13), 2713–2719.

7. Schneider, P., Roberts, D.A. and Kyriakidis, P.C. A VARI-based relative greenness from MODIS data for computing the Fire Potential Index. Remote Sensing of Environment, 2008, (112), 1151-1167.
8. Huesca, M., Litago, J., Palacios-Orueta, A., Montes, F., Sebastián-López, A., and Escribano, P. Assessment of forest fire regimes using MODIS fire potential: a time series approach. Agricultural and Forest Meteorology, 2009, (149), 1946-1955.
9. Preisler H.K., Burgan R.E., Eidenshink J.C., Klaver J.M., and Klaver R.W. Forecasting distributions of large federal-lands fires utilizing satellite and gridded weather information. International Journal of Wildland Fire, 2009, (18), 508–516.
10. Rouse, J.W., Haas, R.H, Schell, J.A. and Deering, D.W. Monitoring vegetation systems in the Great Plains with ERTS, Third ERTS Symposium, NASA SP-351 I, 1973, 309-317.
11. Gao, B.C. NDWI a normalized difference water index for remote sensing of vegetation liquid water form space. Remote Sensing of Environment 1996, (58), 257 – 266.
12. Box G.E.P., Jenkins G.M. and Reinsel G.C. Time series analysis, Forecasting and control. Prentice-Hall, Englewood Cliffs, New Jersey, 1994.
13. Armstrong, G.W. A stochastic characterisation of the natural disturbance regime of the boreal mixed-wood forest with implications for sustainable forest management. Canadian Journal of Forest Research, 1999, (29), 424-433.
14. Stow, D., Niphadkar, M. and Kaiser, J. MODIS-derived visible atmospherically resistant index for monitoring chaparral moisture content. International Journal of Remote Sensing, 2005, (26), 3867-3873.
15. Carmona-Moreno, C., Belward, A., Malingreau, J., Hartley, A., García-Alegre, M., Antonovskiy, M., Buchshtaber, V. and Pivovarov, V. Characterizing interannual variation in global fire calendar using data from Earth observing satellites. Global Change Biology, 2005, (11), 1537-1555.
16. Telesca, L. and Lasaponara, R. Preand post-fire behavioral trends revealed in satellite NDVI time series. Geophysical Research Letters, 2006, 33.
17. Modarres, R. Streamflow drought time series forecasting. Stochastic Environmental Research and Risk Assessment, 2006, (21) 223-233.
18. Piwowar, J. M. and Ledrew, E. F. ARMA time series modelling of remote sensing imagery: a new approach for climate change studies. International Journal of Remote Sensing, 2002 (23), 5225-5248.
19. Han, Ping, Wang, Peng Xin, Zhang, Shu Yu and Zhu, De Hai. Drought forecasting based on the remote sensing data using ARIMA models. Mathematical and Computer Modelling in Agriculture, 2010, (51), 1398-1403
20. Theil, H. 1971. Principles of Econometrics. John Wiley & Sons, Inc., New York.