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Environmental susceptibility model for predicting forest fire occurrence in the Western Ghats of India

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Abstract. Forest fires are a recurrent management problem in the Western Ghats of India. Although most fires occur during the dry season, information on the spatial distribution of fires is needed to improve fire prevention. We used the MODIS Hotspots database and Maxent algorithm to provide a quantitative understanding of the environmental controls regulating the spatial distribution of forest fires over the period 2003–07 in the entire Western Ghats and in two nested subregions with contrasting characteristics. We used hierarchical partitioning to assess the independent contributions of climate, topography and vegetation to the goodness-of-fit of models and to build the most parsimonious fire susceptibility model in each study area. Results show that although areas predicted as highly prone to forest fires were mainly localised on the eastern slopes of the Ghats, spatial predictions and model accuracies differed significantly between study areas. We suggest accordingly a two-step approach to identify: first, large fire-prone areas by paying special attention to the climatic conditions of the monsoon season before the fire season, which determine the fuels moisture content during the fire season; second, the most vulnerable sites within the fire-prone areas using local models mainly based on the type of vegetation.

Additional keywords: environmental controls, fire susceptibility model, Maxent, MODIS, nested study areas.

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Introduction

Wildland fires are a major environmental issue in many tropical biomes across the world (Goldammer 1990). Although fires can play an ecologically significant role in biogeochemical cycles and ecosystem functioning (e.g. co-evolution of savanna and grasslands and fire), they often lead to the destruction of forest vegetation with huge negative effects on atmospheric chemistry (atmospheric pollution, carbon emission), ecology (biodiversity loss, landscape instability) and forestry (reduction in wood production) (Chuvieco 2003). In recent decades, the proliferation of agricultural systems due to population growth and economic necessity has fragmented most forests throughout the tropics (Mueller-Dombois and Goldammer 1990; Myers *et al.* 2000). As a consequence, fires now continually erode forest edges and have become a major factor of ecological disturbance in tropical regions (e.g. Cochrane and Laurance 2002).

Forest fires also represent a recurrent management problem in the Western Ghats (WG) of India, a mountain range that extends along the western coast of peninsular India, and which is classified, along with the island of Sri Lanka, as one of the 34 global biodiversity hotspots (Myers *et al.* 2000). The region harbours one of the last few remnants of non-equatorial tropical rainforest around the globe, with a high number of endemic species (Pascal 1988; Das *et al.* 2006). It is also critical for regulating regional hydrology, climate and carbon storage (e.g. Krishnaswamy *et al.* 2009; Bonell *et al.* 2010). Forest fires are recurrent disturbances in the WG, where the mean fire-return interval shortened from 10 to 3 years between the 1910s and 1990s (Kodandapani *et al.* 2004). Although most fires occur during the dry season (January–April), information on their spatial distribution and environmental determinants is still lacking (Kodandapani *et al.* 2008).

Fire susceptibility models aim at predicting, from a set of localised observations, a fire risk level as a function of external explanatory variables (Chuvieco 2003). This is a very similar problem to predicting the potential geographical distribution of biological species from the observation of species occurrences in particular conditions of habitat, following the ecological niche concept (Scott *et al.* 2002). Fire is similarly strongly regulated by the 'fire environment triangle', i.e. topography, fuels and weather (Pyne *et al.* 1996; Parisien and Moritz 2009), which can be assessed from the conditions in which fires have already been observed. Unlike species distribution models, however, fire susceptibility models can be developed from remotely sensed fire occurrence data (Giglio *et al.* 2003).

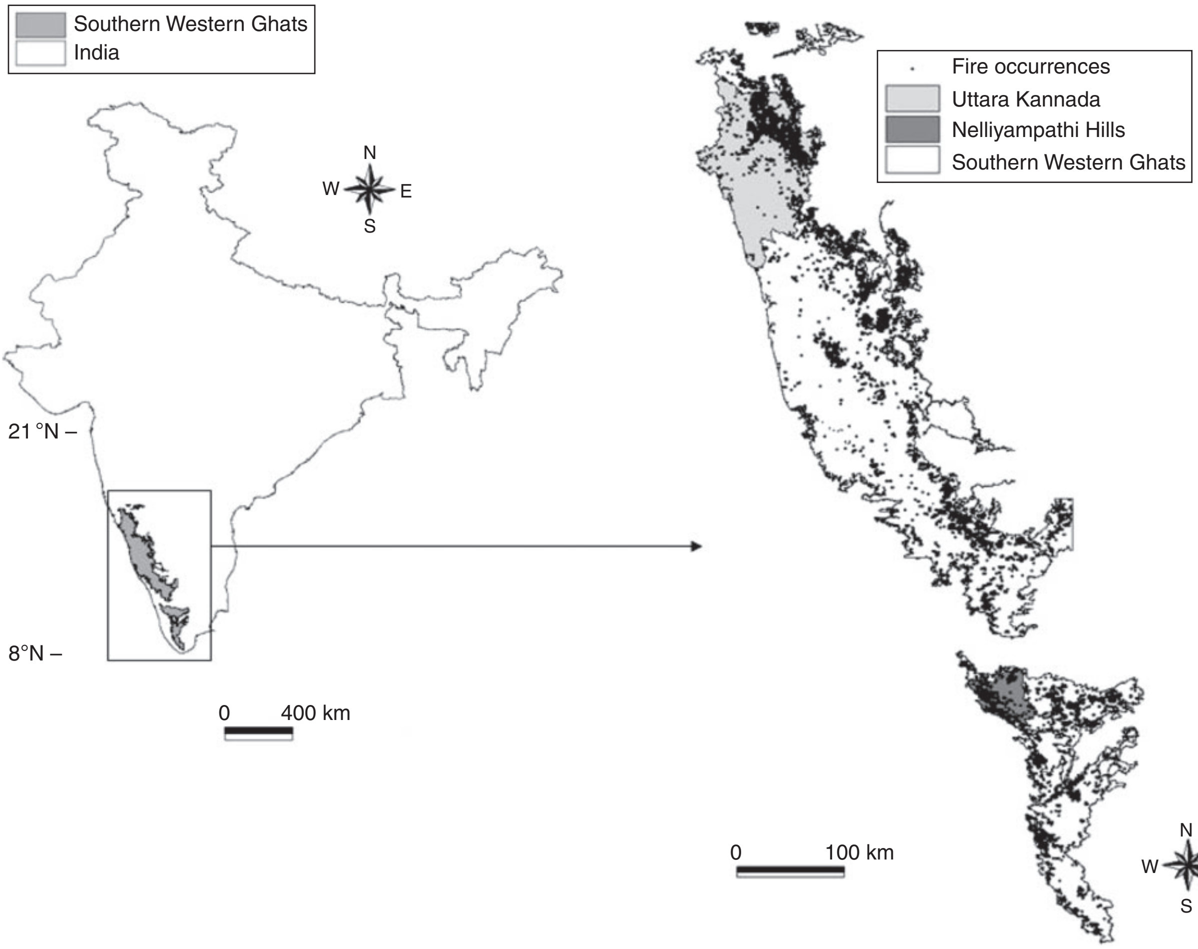

Fig. 1. Location of the study areas in the southern Western Ghats of India with a map of fire occurrences detected by MODIS for the period 2003–07.

Among the various methods of habitat distribution modelling, Maxent (Phillips *et al.* 2006) has proved to perform well in comparison with other methods (Elith *et al.* 2006; Hernandez *et al.* 2006). It is moreover particularly suited for dealing with presence-only data, which means that verified absence is not required to fit the model. The principle of Maxent is to estimate the probability distribution of maximum entropy, which is, under a set of constraints (the environmental conditions), the most spread out or closest to uniform (Phillips *et al.* 2006; Deblauwe *et al.* 2008). The model expresses from a set of environmental raster layers a per-pixel probability of fire occurrence, which results in a map of relative fire susceptibility that can be used, together with knowledge of the environmental causal factors, as a critical tool for forest management.

In this paper, we assess the predictive power of fire susceptibility models built from MODIS Hotspots data and different sources and combinations of environmental predictors representing the fire environment triangle. Our objective is first to provide a quantitative understanding of the environmental factors regulating the potential distribution of forest fires in the Western Ghats of India. From the analysis of parsimonious but nevertheless efficient Maxent fire susceptibility models, we then provide some practical insights for fire management in the region.

Material and methods

Study areas

The Western Ghats of India cover an area of 160 000 km^2 that stretches for 1600 km along the west coast of southern peninsular India, 40 km on average from the shore line, from the Tapti river (21°N) to Kanyakumari, the southernmost tip of the Indian peninsula (8°N) (Fig. 1). This relief barrier, which forms an almost continuous escarpment of $\sim$1000 m in spite of the presence of a few passes and high-elevation peaks, orographically exacerbates summer monsoon rains and is responsible for steep bioclimatic gradients that have long been recognised as major ecological determinants of the WG forest vegetation (e.g. Champion 1936; Pascal 1986). In the coastal plain, annual rainfall is >2000 mm, commonly reaching more than 5000 mm near the crest of the Ghats. Beyond the crest, annual rainfall rapidly diminishes, reaching values below 1000–1500 mm at 10–50 km towards the interior region. Temperature, in particular mean coldest month temperature, also decreases with increasing altitude in this mountainous region. Correlating with the sharp decrease in rainfall beyond the crest of the Ghats, the length of the dry season rapidly increases in a west–east direction. However, the northward monsoon front displacement from the south to the Himalayas, and its retreat in the reverse, creates a differential seasonal pattern with latitude, which does not correlate with mean annual rainfall. Consequently, dry season length also increases from south to north (see Gunnell 1997 or Pascal 1982, 1988 for more details about the climate of the region). Approximately 4000 species of flowering plants including 1600 endemic species (40%) have been reported for the WG region (Manokaran *et al.* 1997), which is now included within a world biodiversity hotspot.

In this paper, we only considered the southern part of the WG, i.e. a study area of 73 784 km^2 between 74 and 78°E and 8 and 16°N (see Fig. 1). Land-cover types range from wet evergreen to dry deciduous forest habitats in various stages of degradation, to mountain forests and grasslands, alternating with zones converted into agroforests, monoculture plantations and to agriculture (see Table S1 in the Supplementary material, see http://www.publish.csiro.au/?act=view_file&file_id=WF10109#_AC.pdf). We also selected two contrasting subregions within the southern WG, namely the Uttara Kannada (UK; 10 284 km^2) district of Karnataka state to the north and the Nelliyampathi Hills (NH; 1861 km^2) in the Palakkad district of Kerala state (see Fig. 1). UK is an area running from the seashore to the crest of the Ghats, and therefore exhibiting important variation in annual rainfall and thus a high diversity of vegetation types, from wet evergreen primary forests to dry deciduous forests. NH is an area dominated by wet evergreen forests, which was recently studied within the framework of a pilot landscape approach to forest management (Ramesh and Gurrukkal 2007). Details about the southern WG and the two subregions are provided in the Supplementary material (Table S1).

Fire occurrence data

Data on fire occurrences were obtained from MODIS (Moderate-Resolution Imaging Spectroradiometer), which is the first satellite to provide thermal sensors specifically designed for fire monitoring (Giglio *et al.* 2003). In this paper, we used the MODIS Hotspots database collection 4 (http://maps.geog.umd.edu/firms/, accessed 14 December 2011), which daily recorded flaming and smouldering fire hotspots from $\sim$1000 m^2 in size for the period 2003–07. The MODIS system is considered as the most accurate and reliable in terms of detection accuracy and completeness (Langner and Siegert 2009), but as with any satellite system, the information gathered depends on the technical properties of the sensors, so that fire occurrences can be subject to false detections. Elaborate algorithms have thus been developed to improve fire detection accuracy (Kaufman and Justice 1998; Roy *et al.* 2008) and each fire occurrence is provided with a detection confidence level. However, as our study area is entirely covered by vegetation and any place is thus likely to burn, we considered that missing any occurrence was less desirable than having false occurrences. Following Langner and Siegert (2009), we therefore retained all hotspots detected, although 2007 has some missing data from mid-August. A total of 7438 fire occurrences were recorded in the southern WG over the period 2003–07, including 1392 and 288 occurrences in the UK and NH areas.

Environmental predictors

We considered different sets and sources of environmental predictors of fire occurrences, which are summarised in Table 1.

Vegetation layer

Three different sources of vegetation data were tested. The first one is derived from a set of 1 : 250 000-scale forest maps of south India published by the French Institute of Pondicherry (FIP) (Pascal *et al.* 1997*a*, 1997*b*, 1997*c*; Ramesh *et al.* 1997, 2002). These maps classify the natural vegetation of the WG based on its physiognomy, phenology and floristic composition and according to bioclimatic and disturbance factors with reference to the concepts of climatic climax and dynamics of succession (Pascal 1986). More than 150 different vegetation classes were initially defined for the WG region. We simplified those classes into broader categories taking into account dryness of vegetation and dominant presence of deciduous species, grasses and weeds, which could act as fuel loads for fires. The FIP simplified 1-km resolution vegetation map (*FIP* map; Renard *et al.* 2010) encompasses 13 different classes, of which 10 are represented in UK and 9 in NH (see Table S1).

We also used as another source of vegetation data the MODIS 1-km Land Cover Type 1 (*LCT*; Friedl *et al.* 2010), which identifies 17 classes defined by the International Geosphere Biosphere Program: 11 natural vegetation classes, three developed and mosaic land classes, and three non-vegetated land classes. As this *LCT* is available yearly, we chose the 2004 version, which is the year that had the highest number of fire occurrences in the southern WG during the study period (2673 records).

Finally, we used as a third source of vegetation data the Normalised Difference Vegetation Index (*NDVI*), which is the most commonly used index to assess live fuel moisture content (Chuvieco 2003). We used the MODIS 1-km resolution *NDVI* of March 2004 too. Unlike the two other sources of vegetation data that are categorical, *NDVI* is a continuous variable. More details about MODIS *LCT* and *NDVI* data for the southern WG can be found on the NASA website (https://lpdaac.usgs.gov, accessed 14 December 2011), and in Renard *et al.* (2010) for the WG extract.

Topographical and climatic variables

The *Elevation* layer was resampled at 1-km resolution from SRTM (NASA Shuttle Radar Topography Mission) 90-m Digital Elevation Data, version 4 (Jarvis *et al.* 2008) using the nearest-neighbour method available in *ArcView GIS 3.2a* (ESRI Inc., Redlands, CA). *Aspect* (in degrees) and *Slope* (as a percentage) were then derived using standard methods (Renard *et al.* 2009).

Three different sources of climatic data were used. We first derived, from the bioclimatic maps (Pascal 1982) that were prepared by the French Institute of Pondicherry in the framework of its vegetation mapping program, three layers of climatic normals (annual rainfall, temperature and dry season length) obtained from 3000 rain gauges and 50 temperature stations

Table 1. Definition of environmental predictors used in Maxent models of fire occurrence for the southern Western Ghats, India
Sources (all last accessed 15 December 2011): 1, http://hal.archives-ouvertes.fr/hal-00481614; 2, https://lpdaac.usgs.gov/; 3, http://hal.archives-ouvertes.fr/hal-00411120; 4, www.worldclim.org/; 5, present study (see Material and methods). FIP, French Institute of Pondicherry; MODIS, Moderate Resolution Imaging Spectroradiometer; NDVI, Normalised Difference Vegetation Index; SRTM, Shuttle Radar Topography Mission

Code (number of variables in the dataset)	Variable	Source
Vegetation		
FIP	FIP simplified vegetation map	1
LCT	MODIS 1-km MCD12Q1 Land Cover Type 1, v. 4, 2004	1, 2
NDVI	MODIS 1-km MYD13A3 NDVI, v. 5, March 2004	1, 2
Topography data interpolated at 0.01 decimal degrees (DD) from SRTM 90-m Digital Elevation Model		3
Elevation	Elevation (m)	
Aspect	Aspect derived from elevation grid (°)	
Slope	Slope angle derived from elevation grid (%)	
T	*Elevation* + *Aspect* + *Slope*	
Climatic normals (1950–80) interpolated at 0.01 DD from FIP bioclimatic maps		3
Rainfall	Seven rainfall classes	
Temperature	Five temperature classes	
Dry season	Dry season length (months)	
p_{RTD}	*Rainfall* + *Temperature* + *Dry season*	
Climate normals (1950–2000) from WorldClim database (1-km^2 resolution interpolations)		4
p	Average monthly precipitation (12 monthly values, mm)	
t	Average monthly maximum temperature (12 monthly values, °C × 10)	
W24	$p + t$ (i.e. 24 variables)	
b	19 bioclimatic variables	
b1	Annual mean temperature (°C × 10)	
b12	Annual mean precipitation (mm)	
DI	Annual dryness index computed as *b1*/*b12*	
W3	*b1* + *b12* + *DI*	
W20	*b* + *DI*	
Yearly climate data (2002–07) interpolated at 0.01 DD from Indian Meteorological Department (IMD)		5
Rf	Total yearly rainfall (mm)	
Tp	Mean yearly temperature (°C)	
Ds	Mean yearly number of dry months	
n	$Rf(n) + Tp(n) + Ds(n)$ (same year as the fire occurrences)	
$(n-1)$	$Rf(n-1) + Tp(n-1) + Ds(n-1)$ (year preceding the fire occurrences)	
TW	Mean yearly temperature of the warmest quarter (Mar–May) (°C)	
TC	Mean yearly temperature of the coldest quarter (Jun–Aug) (°C)	
PW	Yearly precipitation of the wettest quarter (Jun–Aug) (mm)	
PD	Yearly precipitation of the driest quarter (Jan–Mar) (mm)	
DF	Yearly dryness index of the fire season (Feb–Apr) (°C mm^{-1})	
S	$DF(n) + PD(n) + PW(n-1) + TC(n-1) + TW(n)$ (*DF*, *PD* and *TW* from same year, *PW* and *TC* from the year preceding the fire occurrences)	
Climatic normals (2002–07) derived from yearly climate data interpolated at 0.01 DD from IMD		
Rfmean	Mean annual rainfall derived from *Rf* (mm)	
Tmean	Mean annual temperature derived from *Tp* (°C)	
Dsmean	Mean number of dry months per year derived from *Ds*	
M	*Rfmean* + *Tmean* + *Dsmean*	
Anthropogenic factor		5
Dist_to_roads	Classes of 1-km distance to the closest road	

over the period 1950–80. These maps, which present interpolated surfaces combining rainfall and temperature classes over which dry season length is superimposed, were digitised with 1-km sampling. This dataset is referred to as Pascal's bioclimatic dataset (p_{RTD}) hereafter (see Table 1).

Second, we extracted from the Worldclim version 1.4 database (Hijmans *et al.* 2005) another set of climatic normals (average monthly precipitation and temperature) interpolated at 1-km resolution over the period 1950–2000 (see Table 1), as well as a set of 19 bioclimatic variables, which are biologically meaningful variables derived from monthly temperature and rainfall values. Definition of these bioclimatic variables is provided on the Worldclim website (see also Table S2). As none of these referred to dryness, we also added a dryness index (*DI*), defined as the ratio between annual mean temperature and annual precipitation (Brown and Lugo 1982).

Finally, we interpolated yearly climatic data corresponding to the study period and obtained from the Indian Meteorological Department (IMD) for 30 stations throughout the southern WG. Annual rainfall, mean temperature and dry season length (as defined in Pascal 1982) were computed for each station and each year from 2002 to 2007. We also built, for each year, seasonal variables, i.e. mean temperature of warmest and coldest quarters and precipitation of wettest and driest quarters, as well as a *DI* for the fire season (February–April). We also derived climatic normals from these data, by averaging the annual values over the period 2003–07 (see Table 1). We computed all spatial interpolations with the minimum curvature method using *Surfer 8* software (Scientific Software Corp., Sandy, UT) at a 1-km resolution.

Anthropogenic variables

In most cases, forest fires have an anthropogenic origin, whether voluntary or involuntary (Chuvieco 2003). As the WG are the biodiversity hotspot with the highest human density, it is highly vulnerable to anthropogenic disturbances (Kodandapani *et al.* 2008). Including such a factor in a fire susceptibility model is therefore of primary importance (Chou 1990; Vega-Garcia *et al.* 1993; Chuvieco 2003). In particular, the two latter papers demonstrated that the presence of roads increases human pressure on wildland and is therefore a possible cause of ignition by accident and negligence. Therefore with GIS we created 10 buffer zones from 1 to 10-km width from the road network, and used these layers as an anthropogenic fire risk variable.

Maxent modelling of fire occurrences

We fitted Maxent models to our data using 70% of the fire occurrences (training points). We then assessed the predictive power of models by cross-validations using the 30% remaining occurrences (test points) not used to fit the model (Guisan and Zimmerman 2000; Deblauwe *et al.* 2008) and a set of 10 000 random locations representing background (or pseudo-absence) points (Phillips *et al.* 2006). In our case, a high value of Maxent function at a particular location indicates that it is fire-prone. We used default values of the regularisation parameters for all models (more details can be found in Phillips 2005; Phillips *et al.* 2006; Phillips and Dudik 2008).

Model performance was evaluated by the ROC (Receiver Operating Characteristic) analysis commonly used for evaluating species distribution models (Fielding and Bell 1997). The method is based on the probability for positive (test points) and negative (pseudo-absence points) instances to be correctly predicted by the model. It provides an AUC (Area Under Curve) value as a general measure of model performance, which we used to compare the efficiency of various sets of environmental variables to predict fire occurrence. Note that in the case of pseudo-absences, AUC values of 0.5 (random predictions) and 1 (perfect predictions) are no longer valid references because they are dependent on the area of distribution (Jimenez-Valverde 2011). AUC values are therefore comparable among different models in a given study area, but not between study areas. Maxent was thus run with different data sources considering vegetation, topographical or climatic sets of predictors independently. Full models combining the three types of variables from different sources were then fitted for the entire region of the southern WG and for the UK and NH subregions, using all fire occurrences from 2003 to 2007 (integrated models), as well as annual data (annual models; the number of occurrences considered in each case is provided in Table S3). All models were run 50 times to allow statistical analysis on AUC distributions, each time with a different random selection of training and testing fire occurrences. We then performed ANOVA and Mann–Whitney multiple comparison tests to assess potential significant differences between models performances.

Variables selection

We analysed the environmental variables' relative contributions to the most suited models based on Maxent jack-knife tests (Elith *et al.* 2006). This method indicates which variables matter most when each variable is used in isolation or is excluded in turn from the predictive model. However, a major drawback of the method is that it doesn't account for multicollinearity relations between predictors (Elith *et al.* 2006). Therefore, we also used hierarchical partitioning (HP; Chevan and Sutherland 1991), which segregates explanatory power of k variables into independent effects and effects caused jointly with other variables among all possible 2^k models (Mac Nally 2000). We performed HP using the package *hier.part 1.0–3* of R statistical software (R Development Core Team 2010). Finally, based on both Maxent jack-knifes and independent contributions obtained with the HP method, we selected the most significant predictors for each study area in order to build parsimonious predictive models of fire occurrence.

Results

Comparison of multiple data sources

In each study area, we compared the independent predictive power of the different data sources from mean test AUC values obtained over 50 Maxent runs (simply referred to as AUC in the following text). This showed (Table 2) that, when used alone for predicting all fire occurrences from 2003 to 2007 (integrated models), the *FIP* vegetation cover map and MODIS *NDVI* layer exhibited significantly higher AUC ($P \leq 0.01$) than MODIS *LCT*, the *FIP* map performing significantly better than *NDVI* for WG and UK. We therefore considered that the *FIP* vegetation cover map was the best source of vegetation data to be included in a prediction model of fire occurrences in the Western Ghats of India.

Among the three sources of climatic normals, those derived from IMD (*M*) and Worldclim (*W3* subset, see Table 1) databases performed significantly better ($P \leq 0.01$) than those derived from Pascal's bioclimatic map (p_{RTD}). *M* performed significantly better than *W3* in WG and NH, underlying the importance of time concordance between fire and climatic records.

Finally, the best sources of climatic data appeared to be *W20* and *W24*, which exhibited the best predictive power in all study areas, with AUC values between 0.82 and 0.92. Note that these data sources involved a large number of predictors (20 and 24) and included seasonal climatic variables instead of annual means as for the climatic normals (see Table 1). This indicates that seasonal climatic variations are probably important determinants of fire occurrence in the Western Ghats of India.

We therefore retained *W3* as a good, freely available source of climatic normals for predicting all fire occurrences from 2003

Table 2. Predictive performance of different data sources on all MODIS fire occurrences from 2003 to 2007 (integrated models) over the southern Western Ghats (WG) of India and in two nested subregions in Uttara Kannada (UK) and Nelliyampathi Hills (NP)

Similar letters indicate non-significant statistical differences ($P > 0.01$) between mean test AUC (Area Under Curve) over 50 Maxent runs (s.d. = standard deviation) based on ANOVA and Mann–Whitney tests (both adjusted for multiple comparisons). Codes for the variables are given in Table 1

Data sources	WG		UK		NP	
	AUC	s.d.	AUC	s.d.	AUC	s.d.
FIP	0.702	0.004	0.820	0.009	0.673^{a}	0.02
LCT	0.603	0.005	0.653	0.009	0.585	0.021
NDVI	0.674	0.005	0.789^{a}	0.007	0.690	0.022
T	0.786^{a}	0.003	0.786^{a}	0.011	0.674^{a}	0.022
p_{RTD}	0.784^{a}	0.005	0.834	0.008	0.729^{b}	0.014
M	0.891	0.003	0.875	0.005	0.803	0.017
W3	0.878	0.003	0.889	0.007	0.731^{b}	0.02
W20	0.915	0.002	0.909	0.005	0.828^{c}	0.016
W24	0.912	0.002	0.914	0.004	0.829^{c}	0.019

to 2007 (integrated models), and decided to investigate independently the relationship between fire occurrence and annual climatic variations (annual models). We also note from Table 2 that topography appeared to have an effect on fire occurrences not significantly different from those of climatic normals (WG) or vegetation (UK and NP).

Variables contributions to integrated models

We then investigated the contributions of variables to the complete integrated models combining, for each study area, a vegetation layer (*FIP* map), climatic normals ($W3$ = annual mean temperature ($b1$) + annual mean precipitation ($b12$) + dryness index ($DI = b1/b12$)), topography ($T = Elevation + Aspect + Slope$) and an anthropogenic factor, which is the distance to road network (*Dist_to_roads*). Fig. 2 shows that importance of variables contributions varied widely among the three study areas. Jack-knife tests showed, however, that in the three cases, rainfall (*b12*) and vegetation (*FIP* map) were the variables with highest training gains when used in isolation, along with *DI* in UK. The other variables with significant training gains were *DI* in WG and NH, and *Elevation*, temperature (*b1*) and *Dist_to_roads* in NH.

Independent and joint variables contributions as computed with the HP method, however, revealed complex multicollinearity relationships between the explanatory variables, which made the response curve of each single variable difficult to interpret. For instance, the *FIP* vegetation layer showed a very small independent contribution at the scale of WG, which means that it had a high degree of overlap with the other variables. Similarly, *Aspect*, *Slope* and *Dist_to_roads* exhibited very small independent contributions in all three study areas, though the latter showed a significant training gain in NH, and a surprising and maybe spurious negative independent contribution in WG, which would indicate a slight suppressor effect on fire occurrence (Chevan and Sutherland 1991).

Parsimonious fire susceptibility models

Based on the above analyses, we then selected the most significant variables in order to obtain more parsimonious but nevertheless efficient fire susceptibility models for each study area (Fig. 3). At the scale of the entire WG (Fig. 3*a*), the retained parsimonious model performed significantly better ($P \leq 0.01$) than the full model with an AUC of 0.880 (s.d. = 0.002 over 50 runs). It is in fact the model that showed the best performance among the 256 possible combinations of variables. It involved rainfall (*b12*; with independent contribution $I = 9.3\%$), dryness index (*DI*; $I = 7.2\%$), temperature (*b1*; $I = 5.6\%$), *Elevation* ($I = 4.5\%$) and *Slope* ($I = 4.2\%$).

In the UK (Fig. 3*b*) and NH (Fig. 3*c*) study areas, the best parsimonious models didn't differ significantly from the respective full models. In UK (AUC = 0.877; s.d. = 0.006), the parsimonious model involved, in decreasing order of importance, dryness index (*DI*; with independent contribution $I = 5.7\%$), rainfall (*b12*; $I = 5.7\%$), temperature (*b1*; $I = 4.4\%$), vegetation (*FIP* map; $I = 4.2\%$) and *Elevation* ($I = 4.1\%$). In NH (AUC = 0.731; s.d. = 0.020), it involved rainfall (*b12*; with independent contribution $I = 6.9\%$), vegetation (*FIP* map; $I = 5.5\%$), dryness index (*DI*; $I = 5.1\%$), *Elevation* ($I = 4.3\%$), temperature (*b1*; $I = 4.2\%$) and *Dist_to_roads* ($I = 1.5\%$), which we retained for its substantial training gain when used alone as shown by the jack-knife tests. It has to be noted that the vegetation layer was here the second most important variable in terms of independent contribution, whereas it was only the fourth in UK.

The parsimonious models are represented as maps of relative susceptibility to fire occurrences in Fig. 4. At the regional scale (i.e. southern Western Ghats), areas with high relative susceptibility to fire occurrence correspond mainly to the eastern slopes of the Ghats, which support dry to moist deciduous forest habitats (Fig. 4*a*). However, the local extracts of this map corresponding to UK and NH areas (Fig. 4*b*, *c*) largely overestimated the surfaces of high susceptibility when compared with the maps obtained from the specific UK and NH parsimonious models (Fig. 4*f*, *g*).

Annual models

Performances of annual models are given in Table 3, which shows that AUCs were very low, thus predictions inefficient, in

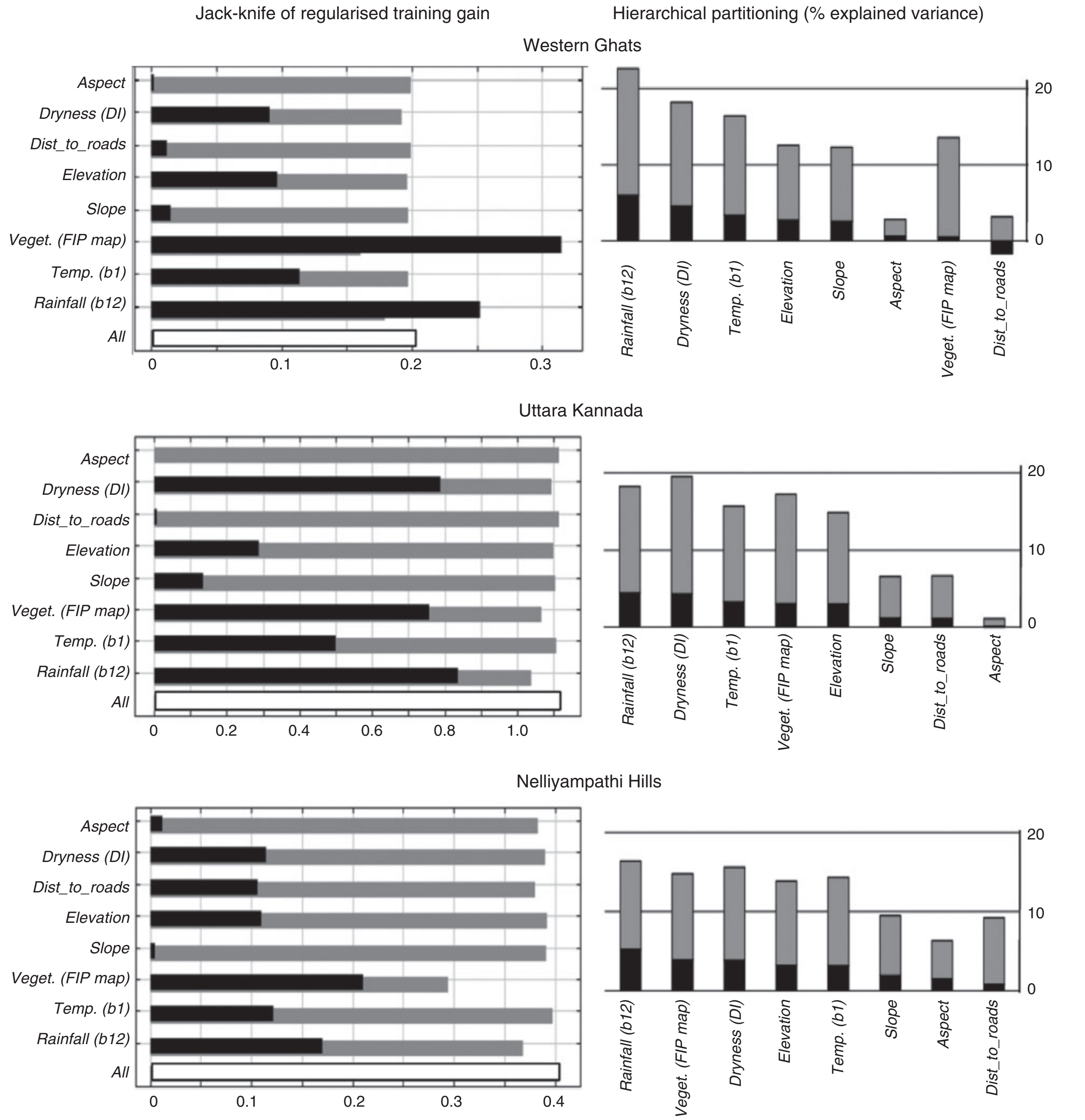

Fig. 2. Variables contributions to prediction models of all fire occurrences from 2003 to 2007 (integrated models) over the southern Western Ghats of India (WG) and in two nested subregions in Uttara Kannada (UK) and Nelliyampathi Hills (NH). Jack-knifes of regularised training gains (right) when variables are used alone (black), are not used (grey) or are all used together (white bar). Hierarchical partitioning of variables importance (left) into independent (black) and joint (grey) contributions. Codes for the variables are as given in Table 1.

NH in 2003 and 2006 because of the extremely small number of fire occurrences recorded these years (4 and 6). The seasonal model *S*, which involves bioclimatic variables centred on the driest quarter (or dry season) of the year *n* and on the wettest quarter (or monsoon season) of the preceding year ($n-1$), generally performed significantly better ($P \leq 0.01$) than models centred on the current (n) or prior calendar year ($n-1$). We therefore used these seasonal climatic variables to study variables importance in the models.

The annual models showed a quite consistent pattern of variables contributions across years, with climatic seasonal variables exhibiting a high, independent contribution at all scales (Fig. 5), particularly precipitation of the wettest quarter before the fire season ($PW(n-1)$) and dryness index of the fire

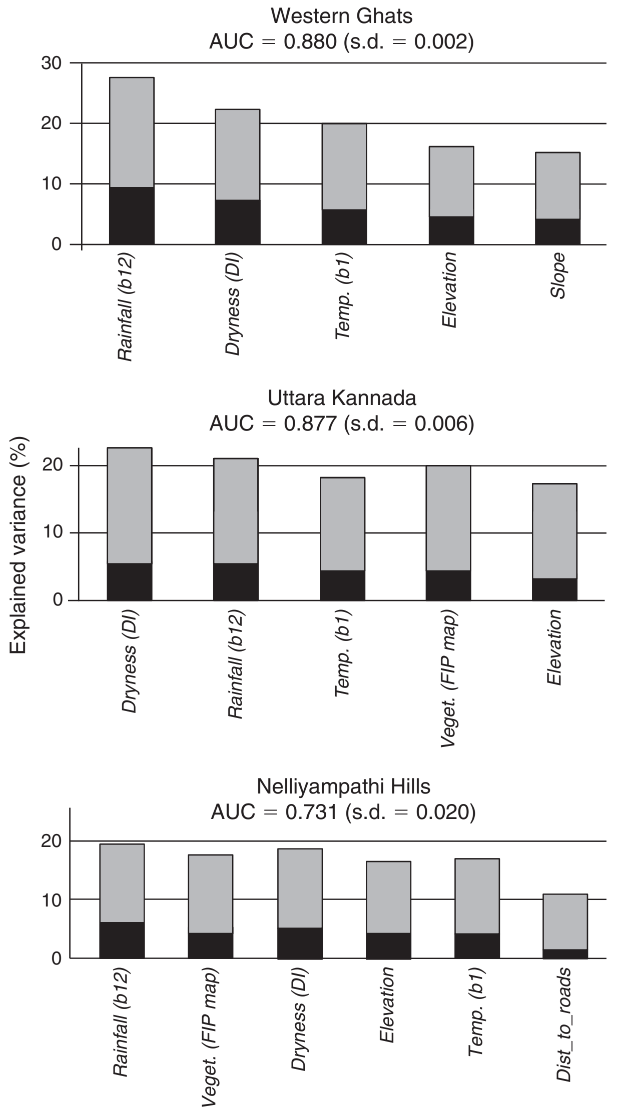

Fig. 3. Proportion of explained variability accounted for by the different variables in the best parsimonious models of prediction of fire occurrences from 2003 to 2007 over the southern Western Ghats of India (WG) and in two nested subregions, in Uttara Kannada (UK) and Nelliyampathi Hills (NH). Independent (black) and joint (grey) contributions of each variable are obtained by hierarchical partitioning of goodness-of-fit statistics (i.e. Maxent's AUC). Mean AUC (Area Under the Curve) and their standard deviations (s.d.) are given from 50 Maxent runs of each model. Codes for the variables are given in Table 1.

season (*DF*(*n*)). *Aspect* and *Dist_to_roads* did not contribute significantly in any study area. At the scale of the entire WG, the other seasonal variables as well as *Elevation* and *Slope* also contributed significantly to the model, whereas vegetation (*FIP* map) had a very small independent contribution as in the integrated models. In the two nested areas, and particularly in UK, vegetation contributed significantly, whereas the other seasonal variables (*PD*(*n*), *TC*(*n* – 1) and *TW*(*n*)) contributed less than at the scale of the WG.

Discussion

Environmental determinants of forest fires in the Western Ghats

We have demonstrated that a combination of variables representing the fire environment triangle through vegetation, climate and topography can lead to reasonable predictions of the spatial distribution of fire occurrence in the Western Ghats of India. However, the large spatial variability of fire occurrence attributed to the joint effects of more than one environmental variable revealed complex multicollinear relations between these variables. Correlations were substantial because vegetation largely reflects both climatic and topographic conditions in the Western Ghats of India (e.g. Pascal 1988; Ramesh *et al.* 2010). Thanks to the HP method, we also demonstrated that variables contributions varied with respect to the specific characteristics of the studied areas. At the regional scale of the southern WG, climatic variables contributed most to the predictive power of the models, whereas the independent contribution of vegetation did not. The reason is that information contained in the vegetation layer is already expressed by the climatic variables. This is especially true at such a large spatial scale, where the main forest types (dry *v.* moist) directly depend on the total amount of annual rainfall. In the two nested subregions of smaller extent (i.e. UK and NH), climatic conditions are more homogeneous, whereas differences still exist in vegetation and topography, which influence fire occurrences. Hence, climatic variables and especially precipitation are more appropriate to discriminate fire-prone areas at a regional scale, whereas vegetation becomes one of the most important explanatory factors at the local scale.

Consequently, a parsimonious fire susceptibility model was built for the entire WG region without a vegetation layer, which could appear surprising at first sight as fuels (i.e. vegetation) are basically required for a fire to happen. However, this result is in accordance with Parisien and Moritz (2009), who also found advantages in not taking vegetation into account. Nevertheless, although vegetation can be omitted for large-extent (e.g. 100 000 km^2) fire prediction models, it still needs to be explicitly included in local models where differences between climatic conditions are negligible or not discriminant for identifying fire-prone areas.

For the entire WG and for the two nested subregions, parsimonious models reached the same or better predictive power than full models. This allowed us to work with efficient fire susceptibility models based on a reduced number of variables without a substantial loss of classification accuracy. Furthermore and in contrast to the full models, all the variables included in the parsimonious models presented a significant (i.e. $>$4%) independent contribution to model performance and can thus be considered as ecologically meaningful for identifying fire-prone areas. The only variable excepted is the *Dist_to_roads* network, only kept in NH. Although its independent contribution was weak in the full model, we decided to keep it in the parsimonious model because its influence was clearly visible on the fire susceptibility map of Fig. 4*f*, where fire occurrences and roads are almost exclusively located in the south-western part of the area. However, HP results did not highlight the efficiency or importance of such human-related

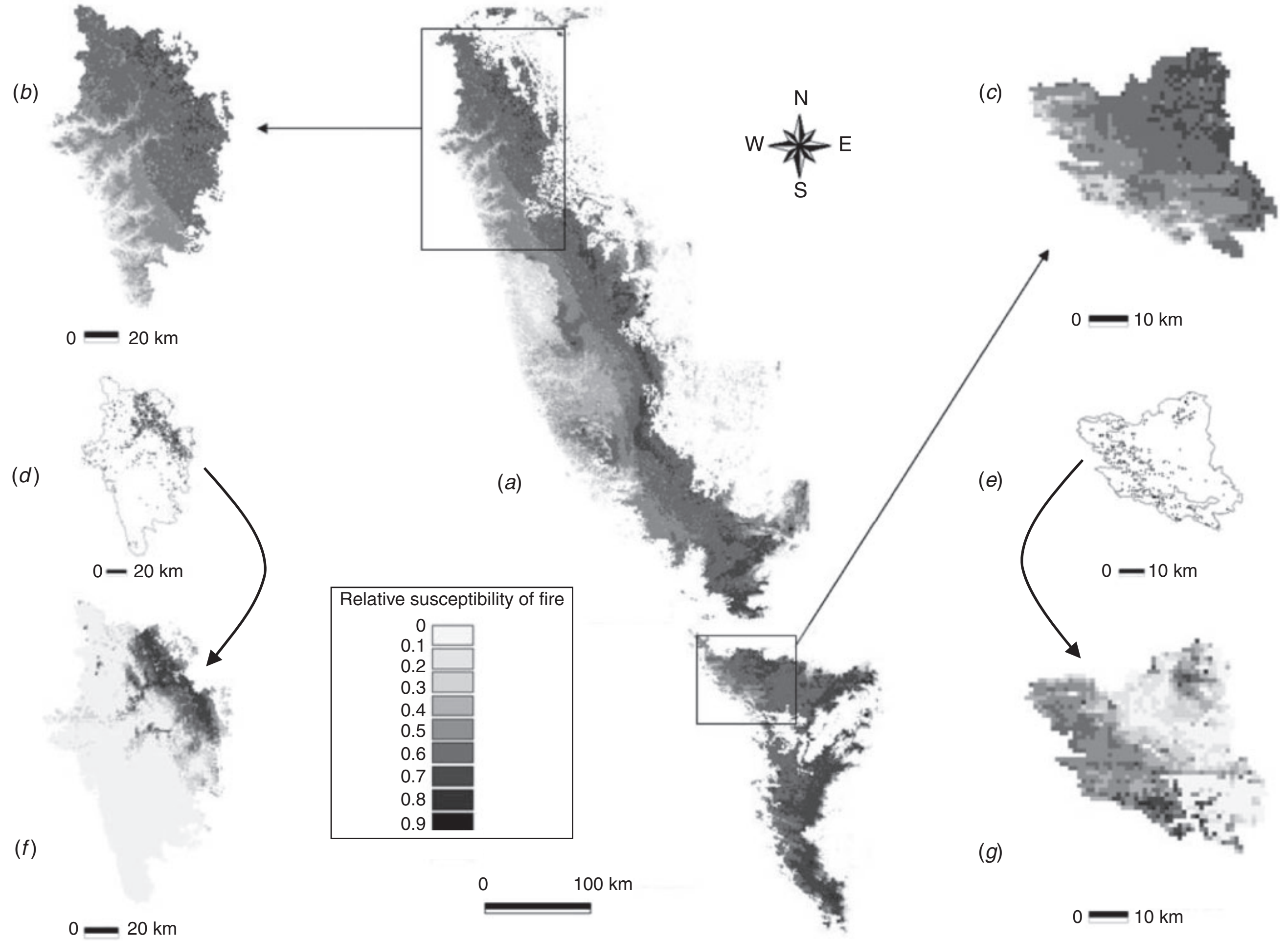

Fig. 4. Relative susceptibility to fire maps built from parsimonious models based on MODIS Hotspots data of fire occurrences from 2003 to 2007 for the southern Western Ghats (WH) and for two nested subregions in Uttara Kannada (UK) and Nelliyampathi Hills (NH). WG susceptibility map (*a*), UK (*b*) and NH (*c*) areas extracted from the WG susceptibility map; fire occurrences in UK (*d*) and NH (*e*); specific UK (*f*) and NH (*g*) fire susceptibility maps.

Table 3. Predictive performance of the annual models (mean test AUC (Area Under Curve) values over 50 Maxent runs and associated standard deviations) of prediction of fire occurrences (MODIS Hotspots data) over the southern Western Ghats (WG) of India and in two nested subregions in Uttara Kannada (UK) and Nelliyampathi Hills (NP)

Similar letters indicate non-significant statistical differences ($P > 0.01$) based on ANOVA and Mann–Whitney tests (both adjusted for multiple comparisons). Codes for the variables are given in Table 1

	Model	2003		2004		2005		2006		2007	
		AUC	s.d.	AUC	s.d.	AUC	s.d.	AUC	s.d.	AUC	s.d.
WG	n	0.921^{a}	0.007	0.901	0.004	0.896^{a}	0.005	0.893	0.005	0.884	0.005
	$(n-1)$	0.922^{a}	0.005	0.904	0.003	0.896^{a}	0.006	0.878	0.006	0.897	0.004
	S	0.921^{a}	0.007	0.924	0.002	0.907	0.005	0.908	0.005	0.887	0.004
UK	n	0.868	0.018	0.892	0.009	0.882^{a}	0.01	0.821^{a}	0.024	0.898^{a}	0.023
	$(n-1)$	0.857	0.017	0.875	0.011	0.881^{a}	0.012	0.825^{a}	0.016	0.868	0.021
	S	0.916	0.014	0.908	0.009	0.907	0.01	0.88	0.018	0.893^{a}	0.021
NH	n	$0.309^{a,b}$	0.171	0.753	0.023	$0.818^{a,b}$	0.053	0.545^{a}	0.171	0.742^{a}	0.042
	$(n-1)$	0.378^{a}	0.136	0.782	0.027	0.804^{a}	0.049	0.580^{a}	0.231	0.715	0.043
	S	0.289^{b}	0.163	0.816	0.022	0.838^{b}	0.047	0.385	0.143	0.764^{a}	0.045

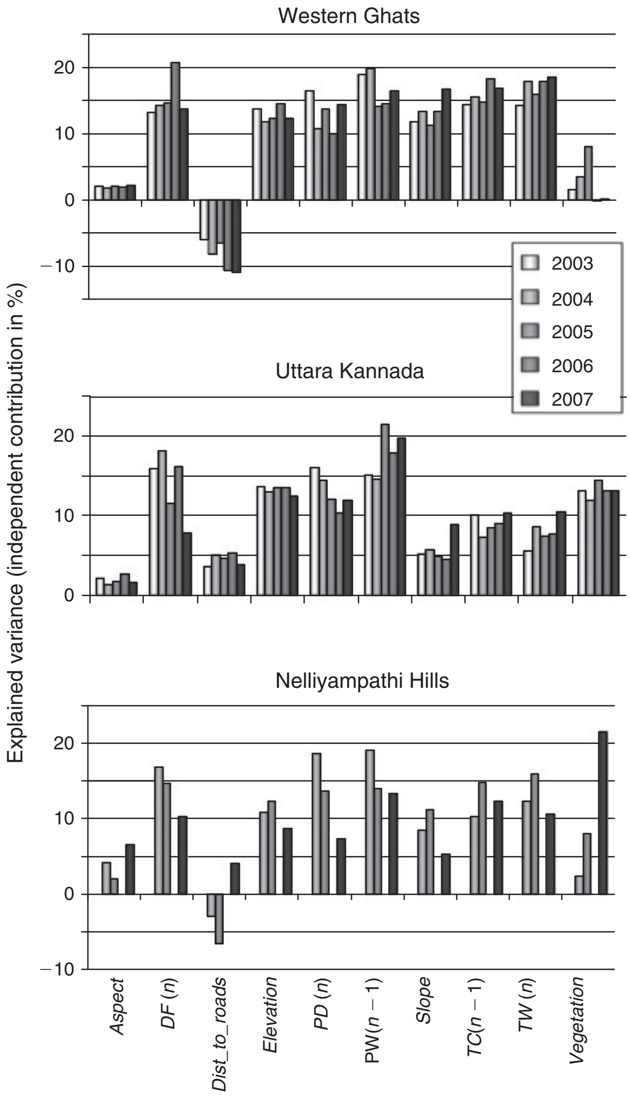

Fig. 5. Proportion of explained variability accounted for by the different variables in annual models of predictions of fire occurrences for 2003 to 2007 in the Western Ghats of India and in the two nested subregions in Uttara Kannada (UK) and Nelliyampathi Hills (NH). 2003 and 2006 are not represented for NH because of a very small number of fire occurrences recorded these years. Independent contributions of each variable are obtained by hierarchical partitioning of goodness-of-fit statistics (i.e. Maxent's AUC (Area Under Curve)). Codes for the variables are given in Table 1.

variables in our fire susceptibility models. In fact, roads can help provide access for fire-causing agents but they also provide access to fire detection and suppression activities.

Importance of interannual climatic variations

The three sources of climatic normals represented slightly different information, which might have their own sources of errors. Besides, despite the small number of climatic stations used for interpolating climatic normals derived from the IMD dataset (M), the good performance of the corresponding models underlines the importance of temporal concordance between observed fire occurrences and measured climatic variables. Indeed, IMD climatic layers were interpolated with climatic data related to the same period as the fire occurrences (2003–07), whereas Pascal bioclimatic layers (p_{RTD}) were interpolated with data related to the 1950–80 period and Worldclim climatic layers (*W3*) with data related to the 1950–2000 period.

But a more interesting pattern detected in our analyses is the good performance of models based on seasonal data and the preponderant contributions of variables related to the monsoon period that precedes the fire season. Temperature of the coldest quarter (corresponding to the wettest quarter) of the year before the fire season contributed consistently more than temperature of the actual fire season. This result, which can appear surprising at first, probably comes from the correlation between temperature and precipitation, as the fuel moisture content during the fire season mostly depends on rainfall conditions of the previous year. Hence efficient predictive models of fire occurrence could be based on available climatic data of the monsoon season before the fire season.

The importance of dealing with variables that express intra-annual (i.e. seasonal) climatic variations is also well illustrated by the good performance of models *W24* and *W20* compared with other partial climatic models. Without any consideration about the quality of the different climatic datasets or the different methods used for data interpolation, the good performance displayed by these models can certainly be explained by the number of seasonal (*W20*) and monthly (*W24*) variables involved, whereas the other models were only based on mean annual variables (climatic normals). Unfortunately, we were not able to assess the independent contributions of variables in these models because the *hier.part* package for R cannot run with more than nine independent variables in its current version (Olea *et al.* 2010). Further analyses are therefore needed to design more efficient parsimonious fire susceptibility models taking into account both inter- and intra-annual climatic variations.

Practical insights for fire management in the WG

The most interesting outputs of Maxent algorithm are certainly the fire susceptibility maps, showing where a fire is most likely to happen within the study area. Such maps extend the fire-prone areas to zones that might have not yet witnessed fire but that present required climatic and vegetation conditions for a fire to occur. The current prevention method applied by Forest Departments in WG consists of creating fire-breaks before the dry season in places where fire occurrences have been reported or observed on remote sensing images (Murthy *et al.* 2006). The proposed fire susceptibility maps could therefore help the departments to build an appropriate network of fire-breaks with effective communication and mobility to reach potentially fire-prone areas.

However, comparing the fire susceptibility maps obtained with Maxent models run at different spatial extents revealed non-intuitive insights for forest fire management and forest conservation in the WG. UK and NH susceptibility maps extracted from the WG model appeared to be more fire-prone than those obtained from the specific local models. This comes from the fact that, owing to its poor independent contribution, vegetation was not included in the parsimonious model performed at the WG level. Hence, the local extracts mainly reflected the large-scale climatic conditions, ignoring the type of local vegetation that provides the necessary fuel for the fire. As a consequence, the model at the WG level predicted vast highly suitable areas that we assume to be somewhat unrealistic with respect to local variations in vegetation structure and cover. Conversely, the local parsimonious models specifically built for each subregion did integrate the *FIP* vegetation layer, which precisely documents the vegetation types and degradation levels. They consequently show more limited areas of high susceptibility in places where fires actually occurred in the past, and exhibit differences between UK and NH more related to the particular vegetation features of these two subregions.

The fire susceptibility maps built at different spatial scales can be used to gain practical insights for the management and prevention of forest fires in the Western Ghats. For instance, effort that has to be directed to fire prevention could be adapted according to a two-steps analysis. At the scale of the entire WG, regional fire-prone areas can be identified with respect to normal climatic conditions that determine climax vegetation types. At the regional level, attention should also be paid to interannual climatic variation, in particular the climatic data of the prior monsoon season (year $(n-1)$), which determine fuel moisture content, and could provide a good fire alert model. In a second step, local models incorporating precise vegetation data as a proxy to fire-fuel content could be run to accurately determine the most endangered areas, depending also on the density of the road network or other anthropogenic factors that we did not incorporate in the present study.

Conclusions

In this paper, we worked with the concept of the ecological niche, classically used for species distribution modelling, for identifying and characterising the spatial distribution of forest fires in different nested areas of the Western Ghats of India. We demonstrated that local extracts of regional models largely overestimated the surfaces predicted as highly susceptible to forest fires. We also demonstrated that the importance of environmental controls of forest fires occurrence depends considerably on the study area. At large spatial scales such as the southern Western Ghats, we highlighted the importance of the climatic conditions of the monsoon before the fire season in accurately predicting the fire-prone areas during the following dry season. We also showed that vegetation data were not essential at this scale owing to its interactions with climatic and topographic conditions. However, in the two small nested study areas where climatic conditions are more homogeneous, we demonstrated that vegetation becomes a crucial factor for predicting the spatial distribution of fire occurrence. We finally identified key combinations of ecologically meaningful variables for each study area. These results led to the construction of efficient and parsimonious (based on a few variables) predictive models of fire occurrence with different spatial ranges. These models could be useful for forest managers to improve their forest fires prevention actions and focus their efforts on endangered sites predicted as highly suitable for forest fires.

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Supplementary material

Environmental susceptibility model for predicting forest fire occurrence in the Western Ghats of India

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Table S1. Geographic, bioclimatic and vegetation features of the three areas studied in the southern Western Ghats of India.

Mean annual rainfall and temperature ranges are from the Wordclim database (Hijmans *et al*. 2005). Vegetation cover types are extracted from the simplified *FIP* vegetation map (Renard *et al*. 2010)

Variable	Southern Western Ghats	Uttara Kannada	Nelliyampathi Hills
Area (km^2)	73 784	10 284	1861
Latitudinal range (°N)	8–16	13.5–15.3	10–10.3
Elevation range (m)	0–2594	0–1006	25–1537
Mean annual number of fire occurrences (2003–07)	1487.6	278.4	57.6
Mean annual precipitation range (mm)	383–7150	734–5105	1416–3741
Mean annual temperature range (°C)	12.2–29.2	22.5–27.6	18.9–27.8
Vegetation types (% total cover):			
• Primary and degraded deciduous forest	15.3	1.7	3.0
• Non-forest and agricultural	14.9	18.9	1.5
• Degraded formation in the potential area of wet evergreen zone	14.1	8.4	0
• Wet evergreen primary forest	10.9	4.1	31.4
• Secondary moist deciduous forest	9.8	17.4	23.8
• Wet evergreen secondary or disturbed forest	8.1	29.2	8.4
• Commercial plantation	6.8	0	2.7
• Forest plantation	6.2	4.2	18.5
• Tree savanna to grassland in dry zone	4.6	1.4	0
• Primary moist deciduous forest and degradation	4.5	12.4	2.3
• Tree savanna to grassland in wet zone + mountain grassland	2.4	2.3	8.3
• Mountain forest and degraded stages	1.4	0	0
• Dry evergreen forest and degradation	0.8	0	0

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Table S2. Definition of the 19 bioclimatic variables of the Wordclim database, as given at http://www.worldclim.org/bioclim

Code	Variable
BIO1	Annual mean temperature
BIO2	Mean diurnal range (mean of monthly (maximum temperature – minimum temperature))
BIO3	Isothermality (BIO2/BIO7) (×100)
BIO4	Temperature seasonality (standard deviation × 100)
BIO5	Maximum temperature of warmest month
BIO6	Minimum temperature of coldest month
BIO7	Temperature annual range (BIO5 – BIO6)
BIO8	Mean temperature of wettest quarter
BIO9	Mean temperature of driest quarter
BIO10	Mean temperature of warmest quarter
BIO11	Mean temperature of coldest quarter
BIO12	Annual precipitation
BIO13	Precipitation of wettest month
BIO14	Precipitation of driest month
BIO15	Precipitation seasonality (coefficient of variation)
BIO16	Precipitation of wettest quarter
BIO17	Precipitation of driest quarter
BIO18	Precipitation of warmest quarter
BIO19	Precipitation of coldest quarter

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Table S3. Number of fire occurrences used for training (70%) and testing (30%) the annual and integrated (2003–07) models

	Western Ghats			Uttara Kannada			Nelliyampathi Hills		
	Training	Testing	Total	Training	Testing	Total	Training	Testing	Total
2003	460	197	657	162	69	231	3	1	4
2004	1871	802	2673	307	131	438	126	54	180
2005	1035	444	1479	286	123	409	33	14	47
2006	804	345	1149	131	56	187	4	2	5
2007	1036	444	1480	89	38	127	36	16	52
2003–07	5207	2231	7438	974	418	1392	202	86	288