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Wildfire hazard mapping: exploring site conditions in eastern US wildland–urban interfaces

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Abstract. Wildfires are a serious threat for land managers and property owners, and over the last few decades this threat has expanded as a result of increased rural development. Most wildfires in the north-eastern US occur in the wildland–urban interface, those regions of intermingling urban and non-developed vegetated lands, where access to firefighting resources can be limited. We created monthly wildfire ignition probability maps from environmental predictors and wildfires occurring between 2000 and 2009 for the states of New Jersey, Ohio and Pennsylvania. Predictor variables included a drought index, long-term soil moisture, percentage forest and wildland–urban interface classifications. Probability maps generated from modelled (Maxent) extrapolations were used to create monthly hazard maps to aid agencies and managers with resource allocation and likelihood projections of wildfires across the region. Our results suggest that monthly hazard assessments provide a better indication of potential wildfires than does a single mean annual probability. Our monthly predictions retain information related to long-term seasonal variability associated with environmental variables and the recorded wildfires providing spatial and temporal information for resource allocation.

Additional keywords: Maxent, New Jersey, Ohio, Pennsylvania, predictive modelling, resource planning.

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Introduction

Eastern US wildfires tend to result more from anthropogenic causes in places where human populations have fragmented the forest landscape (Malamud *et al.* 2005). These locations, where human-built structures occur within vegetated lands, are referred to as the wildland–urban interface (WUI) (Radeloff *et al.* 2005). Areas where houses and properties intermingle with wildland vegetation are referred to as intermix WUI, whereas developed areas that abut wildland vegetation are characterised as WUI communities (Radeloff *et al.* 2005). The north-eastern US is characterised by high proportions of WUI lands and as a result of the frequent human–vegetation contact, the majority of wildfires in this region are human-caused fires (set on purpose or accidentally) which is similar to the situation in the Upper Midwest (Cardille and Ventura 2001). Fires within the WUI are thus an important issue that must be dealt with by agencies and land managers (Cohen 2000); because as the WUI increases from vegetated to interface, so does the potential threat of property-damaging wildfires.

The Northeast Wildfire Risk Assessment conducted by the USDA Forest Service suggests that New Jersey would provide a good case study for the effects of WUI and wildfire occurrences related to risk assessment because of the state's extensive fire history datasets (US Forest Service Northeastern Area State and Private Forestry 2010). The assessment also suggested that use of an Integrated Moisture Index (IMI) might aid in mapping wildfire risk because IMI 'has been shown to be statistically related to many ecological processes' (US Forest Service Northeastern Area State and Private Forestry 2010). These recommendations emphasise the need for research to help identify areas at particular risk for wildfires in the north-eastern US, especially given the projections of increasing fire under changing climate (Dale *et al.* 2001).

Many studies have identified conditions associated with wildfires that are useful in developing risk and hazard models. These conditions vary by location, especially west *v.* east in the US. Lein and Stump (2009) used a fuel model, solar radiation, topographic wetness, population density and distance to roads to model wildfire risk in gentle topography in southern Ohio. Parisien and Moritz (2009) mapped wildfire suitable conditions using climate, solar radiation, humidity, elevation, classified vegetation and fuel loads for the US and California. Keane *et al.* (2010) used climate, humidity, wind speed and dead and live fuel moisture to simulate fires in the northern Rocky Mountains. Syphard *et al.* (2007) used fire records (occurrence and area burnt), WUI, road networks and vegetation to explore human influence on fires in California. These conditions can be modelled utilising geographic information systems (GIS) technology and statistical methods to develop potential risk or hazard maps. Risk maps typically associate the potential effect on a valued resource in conjunction with hazards, where hazard maps identify the potential occurrence of an event (Thompson *et al.* 2011).

Other studies focussed on the western US or at the national scale have used simulated fires to determine the burn probability of a landscape and assign risk to resources (Calkin *et al.* 2010; Thompson *et al.* 2011). An advantage of fire simulation models is that they do not require historical fire records to assess risk like empirical models do (Bar Massada *et al.* 2009); however, they are often parameterised with current knowledge of processes that are often complex and difficult to represent in many models. Thus, Bar Massada *et al.* (2009) recommends the use of empirically developed ignition models for risk or hazard mapping of fires when sufficient data are available.

Our group developed IMI for Ohio and based on the recommendations contained in the North-east Wildfire Risk Assessment decided to expand IMI to New Jersey and Pennsylvania in order to model wildfire ignition probabilities based on the methodology presented by Bar Massada *et al.* (2012). In doing so, we developed monthly probabilistic hazard maps for a 12-month period from four environmental variables and the spatial distribution of reported wildfires between 2000 and 2009 to investigate whether monthly or annualised models performed better. The hazard models were then evaluated using 2010 fire records not included in the model. Public land (federal- and state-owned) and the New Jersey Pine Barrens region were analysed for potential wildfire hazards as a means to evaluate the models. We define wildfire hazard as it relates to our model output as the relative probability of a location having conditions favourable for a wildfire ignition. We recognise that fire plays an important ecological role by maintaining vegetation and soil conditions. However, wildfires that threaten human lives and property are an important issue for wildland firefighters among many other managers and the public, and hazard mapping can help with resource allocation and planning.

Methods

Study area

The eastern states of New Jersey, Ohio and Pennsylvania (NJOHPA) encompass 244 315 km^2. Elevation ranges from 1 m below sea level to 978 m above and based on the 2006 National Land Cover Dataset 46.3% of the area is forested, whereas 38.8, 14.5 and 1.2% is non-forested, urban and water. Historically, these states were predominantly characterised by oak–hickory or oak–pine forest types with pre-suppression fire return intervals of $<$30 years for southern Ohio, and an average of 14 years for New Jersey (Abrams 2000). Prior to European settlement, fires were the result of lightning or were purposely set by Native Americans as a means to manage resources (Abrams and Nowacki 1992; Abrams 2000). Centuries of development, landuse change and fire exclusion have resulted in forests characterised by dense understoreys, heavy fuel loads and altered fire regimes (Nowacki and Abrams 2008). Although human activities have played a dominant role in shaping the current fire regime, site conditions are also critically important in creating the conditions favourable to wildfires. For example, Givnish (1981) indicates that site conditions, specifically coarse soil texture and low fertility, in the New Jersey Pine Barrens region contribute to wildfires by creating drier soils and more fire-prone vegetation.

Wildfire records occurring between 2000 and 2009 were obtained from three state agencies (New Jersey Division of Parks and Forestry, Ohio Department of Natural Resources – Division of Forestry, Pennsylvania Department of Conservation and Natural Resources – Bureau of Forestry) and one federal source, the US Geological Survey's Geospatial Multi-Agency Coordination (GeoMAC) (see http://geomac.gov/index.shtml, accessed September 2011). Only records that were georeferenced and contained the attributes of date or time, area burnt and cause were used. Although latitude and longitude were reported as point locations, these coordinates may only rarely represent the point of ignition. The 4847 usable records were made compatible by generalising the reported cause, based on The New Jersey Forest Fire Service Incident Reporting System. Thus, the final causes were reclassified to campfires, children, debris burning, equipment, incendiary, lightning, railroad or cigarette smoking. For our hazard model, four uncorrelated environmental variables (Pearson's correlation coefficient ranging from −0.26 to 0.28) were selected via model contribution from a suite of potential variables on terrain, climate and human influences. These variables (described below) were derived from GIS data and comprised an Integrated Moisture Index (IMI) value, mean Palmer Modified Drought Index (PMDI) value, percentage forest cover and WUI classification. A GIS was used to process the data and produce grid coverages at 30-m resolution for each predictor and response variable. Final grid coverages were converted to an ASCII format to be read into the Maxent software.

Integrated Moisture Index

Terrain is a key component of any fire hazard modelling and we assumed the IMI – as an index of long-term soil moisture potential for rolling topography common in our study area – to be representative of the terrain influence within the model. It is based on topographic shading, flow accumulation of water downslope, curvature and soil water-holding capacity, and has been related spatially to soil fertility, productivity, fire intensity and species composition (Iverson *et al.* 1996, 1997; 2004, 2008). IMI was calculated from a US Geological Survey 10-m digital elevation model (DEM) and soil data from the Soil Survey Geographic (SSURGO) database (Natural Resources Conservation Service, United States Department of Agriculture 2008) for each state. The method described in Iverson *et al.* (1997) was modified to incorporate an infinite directional algorithm, TauDEM v4.0 (Utah State University, Logan, UT, USA), to calculate flow direction and accumulation (Tarboton 1997) of soil moisture. Hillshade and curvature were also derived from the DEM. Available water-holding capacity (AWC) to a depth of 150 cm was generated from SSURGO county soil survey data. For each county, the dissolved map unit symbol produced by the Soil Data Viewer (version 5.2) was converted to a 30-m grid. For each state, the county grids were combined using a mosaicking technique to produce a seamless coverage for the region. Using a weighted summation developed by Iverson *et al.* (1996), we

Table 1. Generalised WUI class values used in Maxent model

WUI	Non-WUI	Non-vegetated or agriculture	Uninhabited or no vegetation	Water
Low-density interface	Very low-density vegetated	Very low-density no vegetation	Uninhabited or no vegetation	Water
Medium-density interface	Uninhabited vegetated	Low density no vegetation		
High-density interface		Medium density no vegetation		
Low-density intermix		High density no vegetation		
Medium-density intermix				
High-density intermix				

combined the four grid coverages to generate an IMI following this equation:

$$\text{IMI} = (\text{curvature} \times 0.1 + \text{flow accumulation} \times 0.3 + \text{hillshade} \times 0.4 + \text{AWC} \times 0.2)$$

The resulting grid can contain values ranging from 0 to 100; however, IMI values were reclassified to dry (<35), intermediate (35–50) and mesic (>50) for the Maxent model because reported wildfire locations occurred within a range of IMI values.

Palmer Modified Drought Index

The PMDI was assumed to represent an integrated variable pertaining to the climate influence in the model. Mean monthly PMDI data for the period of 1895–2009 were obtained from the National Climatic Data Center. Due to limitations of the original Palmer Drought Severity Index described in Alley (1984), the modified version (Heddinghaus and Sabol 1991) was used. Monthly PMDI values for the period 2000–09 were averaged and mapped for each of the 23 climate divisions within NJOHPA. A single set of 12 monthly means were calculated by averaging the 10 PMDI numeric values used to determine drought classifications for each year within the study period to provide a long-term value. For example, numeric PMDI values for January 2000–09 were averaged for inclusion into the model. The climate divisions consist of an aggregation of counties so that any derived outputs will show these coarse boundaries.

Forest cover

Most wildfires occurred on land having percentage forest cover >10%; thus, we assumed that forest cover captures the vegetative influence within the model. Percentage forest cover grids were obtained from LANDFIRE data (The National Map, LANDFIRE 2007). Two 30-m coverages encompassing NJOHPA were mosaicked together and the state boundaries were used to remove values beyond the extent of the region. The data values consisted of forest cover classified in 10% intervals, which also helped to distinguish forested from non-forested lands.

Wildland–urban interface

The WUI is intended to capture the interaction between the landscape and humans. Many methods have been used to map WUI (Platt 2010) based on various definitions of land use and the interface zones. The Spatial Analysis for Conservation and Sustainability (SILVIS) Laboratory at the University of Wisconsin–Madison used a ratio of housing density (1 structure per 16 ha) to the proportion of wildland vegetation (>50% for intermix and <50%, but within 2.4 km of a 500-ha area with >75% vegetation for interface) per area (Radeloff *et al.* 2005) to create a data layer developed from 2000 Census data and 1992 National Land Cover Dataset values. Vector classifications were obtained for each state and converted to a 30-m grid and reclassified to WUI, non-WUI vegetative, non-vegetative or agriculture, uninhabited–no vegetation and water (Table 1).

Maxent

Maximum entropy is a density estimation method based on a probability distribution (Phillips and Dudík 2008) and is ideal for modelling presence-only data (Elith *et al.* 2011). Because the wildfire records are locations that have burnt, and it cannot be determined whether a neighbouring area was also suitable to burn at that time, it is appropriate to assume the data represent presence-only. Maxent, using only presence records, has been shown to provide better estimates of probability as compared with other statistical tools (e.g. GLM, tree ensembles) that rely on absences as well for their best estimates (Bar Massada *et al.* 2012). The Maxent model relates samples from a distribution within a spatial extent to environmental variables at the same extent (Phillips *et al.* 2004). Maxent explores this environmental relationship by estimating a distribution that is close to uniform with the constraint that the value for each environmental variable under the estimated distribution is expected to match its empirical average (Phillips *et al.* 2004). It has been used to identify locations of Sudden Oak Death (Crocker and Garbelotto 2010; Václavík *et al.* 2010), estimate species distributions (Phillips *et al.* 2006) and map the environmental space of wildfires (Parisien and Moritz 2009).

We used Maxent (version 3.3.2), a Java application developed by Phillips *et al.* (see http://www.cs.princeton.edu/~schapire/maxent, accessed 5 December 2012), to calculate the relative probability of fire occurrences for a 12-month period (2000–09) using maximum entropy. Wildfire records with a size class ≥0.1 ha and from the following ignition sources were selected for use in the analysis: campfire, children, debris burning, equipment, incendiary, lightning, railroad or smoking. We chose these categories and sizes in an attempt to exclude potential 'non-wildfires', such as reported 'wildfires' that could actually be debris-burning fires that did not result in an out-of-control wildfire. Although we tried to control for 'non-wildfire' records, 510 false alarms were documented among the three state agencies during the study's time period.

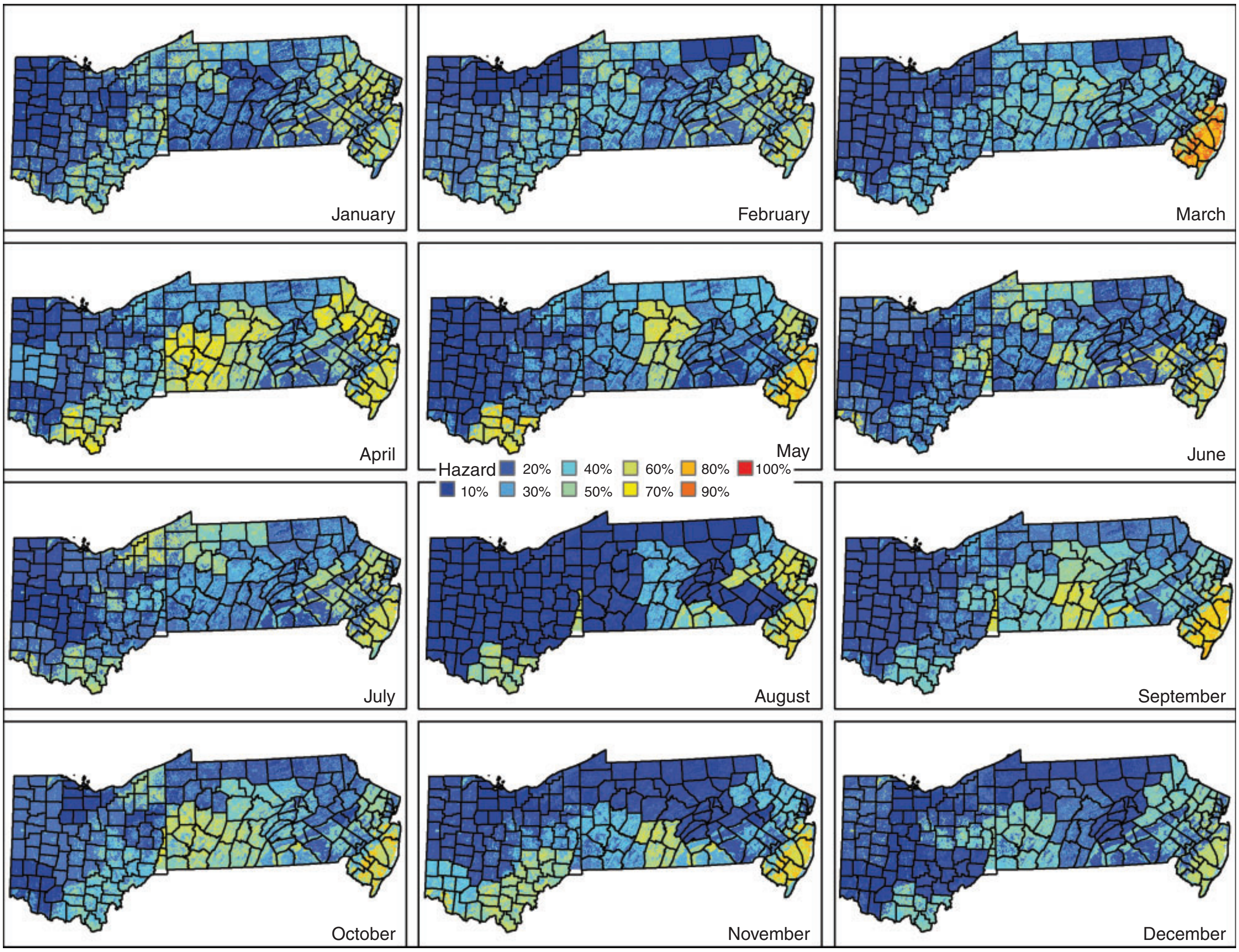

Fig. 1. Average of 10 maximum entropy probability distributions for monthly wildfire hazards developed from reported wildfire (2000–09 ignoring year of occurrence) and four environmental predictors. Visual assessments of each model shows temporal variations at 30-m grid cells with county boundaries overlaid for reference.

Maxent was parameterised with a total of 4847 wildfire records ignoring the year of occurrence and environmental data consisting of 30-m grids of percentage forest cover, IMI, mean PMDI (month of fire, as values 1 month before the reported fire were not significant) and WUI classification, all of which were set to categorical classes except mean PMDI. Within the Maxent software, the options for response curves, jackknife and random seed were set to true. The response curve option generates graphs indicating the predicted probability based on the values of each environmental predictor. The jackknife option, which measures the contribution that is unique to a specific variable, systematically omits one predictor variable to determine the best model, and thus it rebuilds models by excluding the variable of interest. The random seed option results in a unique random subset of the training data during each iteration. Maxent also reduces overfitting with a regularisation multiplier that limits the algorithm from modelling the data too closely (Parisien and Moritz 2009). The default value of 1 was used, as Parisien and Moritz (2009) found it to produce the best results.

Ten replications with 25% of each month's records being randomly withheld for testing were run with bootstrapping of each replicate. The number of sample points varied for each month whereas 10 000 background points were used to characterise the predictor variables. Output was a logistic ASCII file containing the mean relative probability distribution for each month and for each 30-m grid cell. These data were mapped for the entire study area (Fig. 1) and at a finer extent for the Pine Barrens of New Jersey (Fig. 2). The jackknife option provides a measure of percentage contribution for each predictor variable and is determined from the Maxent algorithm, which relates the gain in model performance to the inclusion of each variable. However, this assessment is sensitive to the model parameters and influenced by highly correlated variables.

Hazard maps

Four variables (IMI, mean PMDI, percentage forest cover and WUI classification) were used to calculate the relative probability of fire occurrences using maximum entropy and reported wildfires in NJOHPA. Each variable was created at a 30-m resolution, which serves to preserve the original data values and reduces the potential of multiple wildfire records occurring in

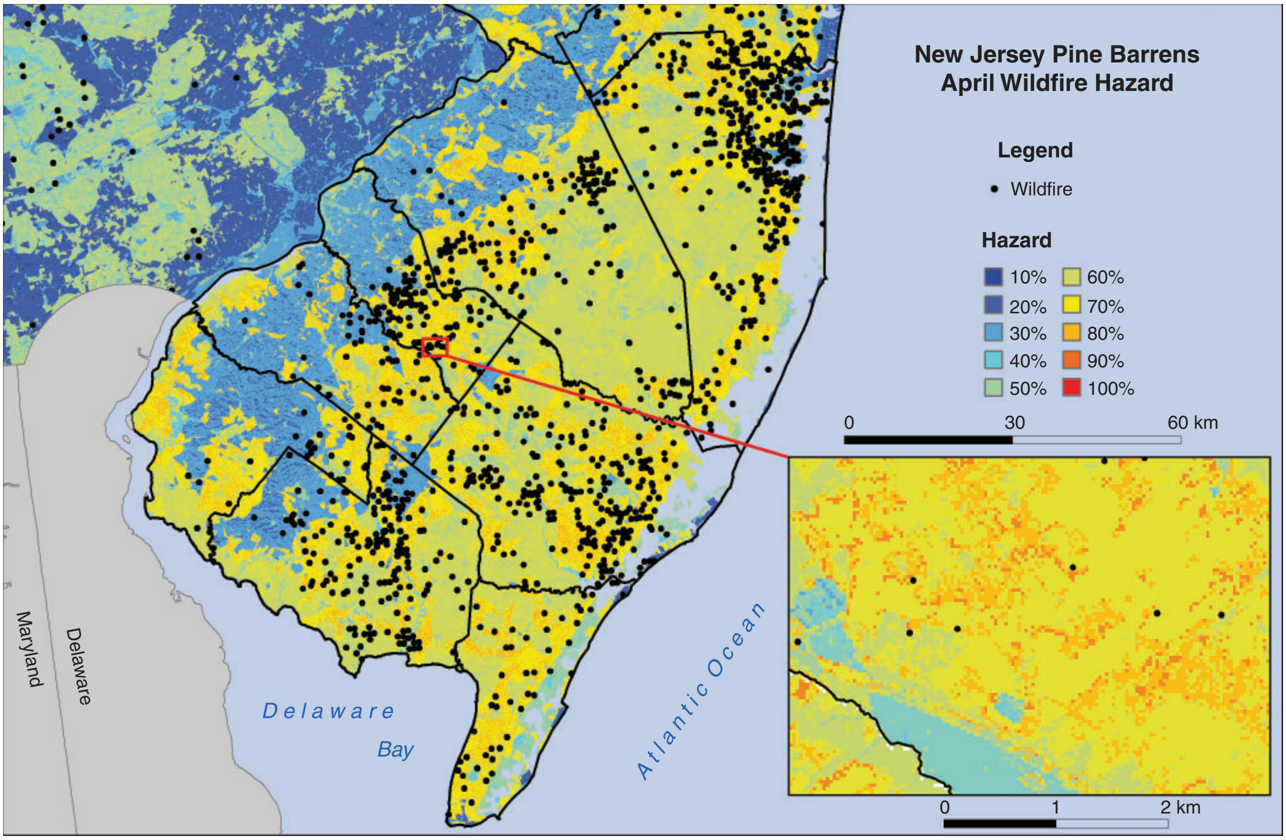

Fig. 2. Average maximum entropy probability distribution of wildfire hazard with reported fires occurring during April 2000–09 overlaid for the New Jersey Pine Barrens region. Inset shows the finescale variability of the 30-m hazard values and the locations of reported wildfires.

the same grid cell; however, the drought index values originated from coarse-scale climate divisions (aggregation of counties), which are visible in the final hazard values.

The average of 10 simulated relative probability distributions for each month and a mean annual and spring (March, April and May; Figs 1–3 of the Supplementary material) probabilities (derived by averaging monthly model output) were used to assess the hazard of reported wildfires (2000–09). Fires used to generate the hazard maps were overlaid within a GIS by month (ignoring the year of occurrence), and probability values were extracted for each fire to assess the accuracy of the monthly and annual models. Additionally, records of 523 wildfires occurring during 2010 but not included in the models were used as a means to evaluate their accuracy by assessing the probability values at their reported locations. We assessed model performance by determining the proportion of fires captured by the monthly or annual models in the higher-probability classes. AUC values of the mean monthly models were also used to evaluate model performance.

An assessment of state and federally owned land was conducted to determine hazard levels for portions of the region that are under different management objectives. Because most records occurred during the spring, the number of reported springtime wildfires (March, April and May during 2000–09) within each state was compared with the number contained by state-owned forests and parks, along with National Forests, Parks and Department of Defence lands. Additionally, mean hazard values for each IMI class on forested land (derived from the 2006 NLCD) and WUI classes were examined to gain insight related to landscape patterns and hazard values.

Results

Historical trends

Historical (1895–1999) records of mean monthly PMDI indicate that near-normal to dry conditions were the general trend for NJOHPA (Fig. 3*a*). During the 2000–09 decade, however, near-normal to wet conditions were reported (Fig. 3*b*), despite the fact that 16 580 wildfires were reported, of which 4847 were ≥0.1 ha and of discernable causes. The leading causes of these wildfires during 2000–09 were 'incendiary behavior' (Fig. 4), followed by 'debris burning'. Fig. 4 also indicates that the wildfire occurrences were temporally bimodal, with most fires occurring in spring and autumn. According to IMI values, 68.4% of the 4847 wildfires were located on dry sites whereas 25.3 and 6.3% were on intermediate and mesic sites. Locations were also distributed among all LANDFIRE percentage forest cover classes with 44% occurring in cells classified as having ≥10% forest cover.

April had the highest number of occurrences (1664) for the study area (Table 2) whereas New Jersey reported the most wildfires (2259) among the three states (Table 3).

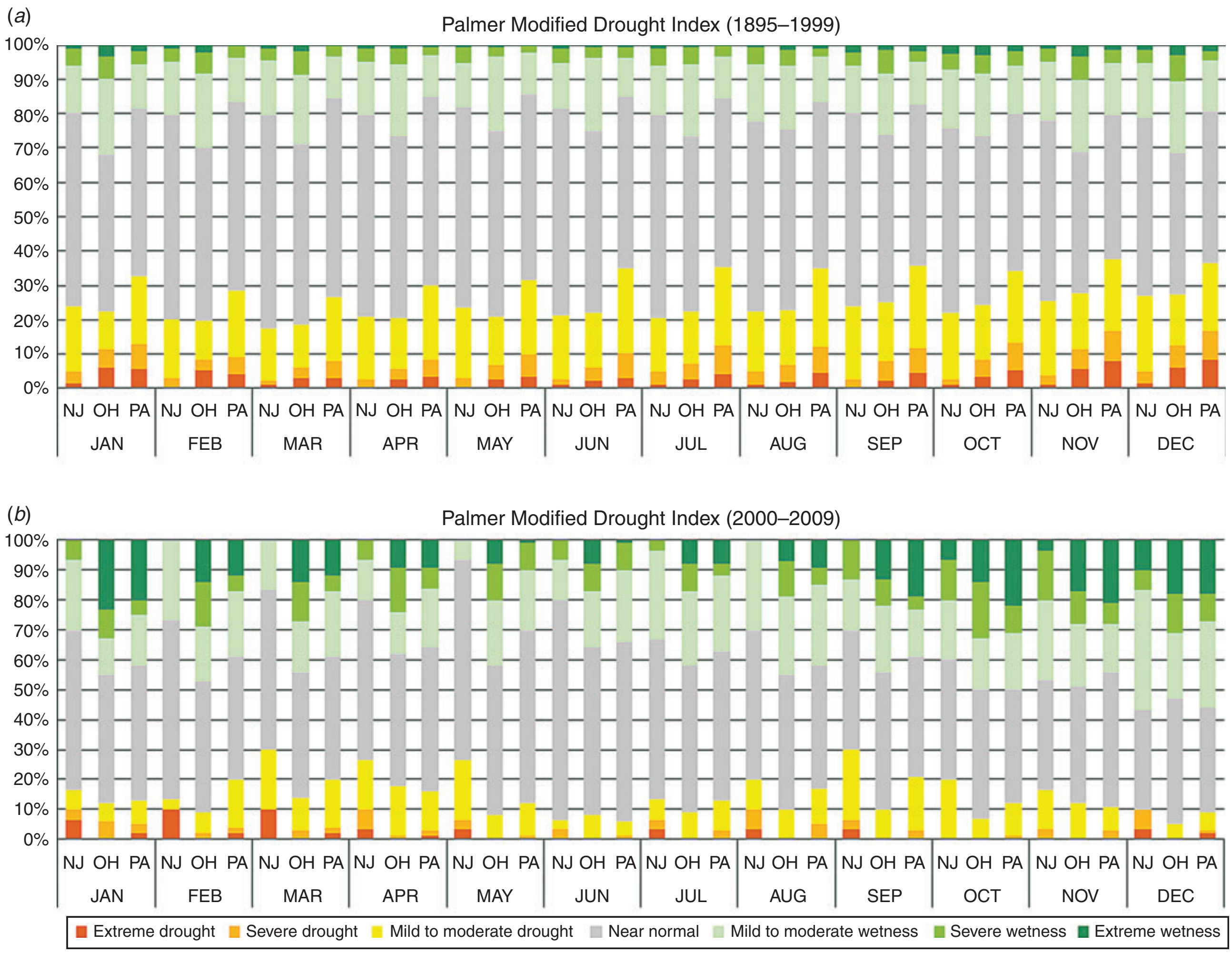

Fig. 3. Historical and current trends of observed drought conditions by month for each state, 1895–2009.

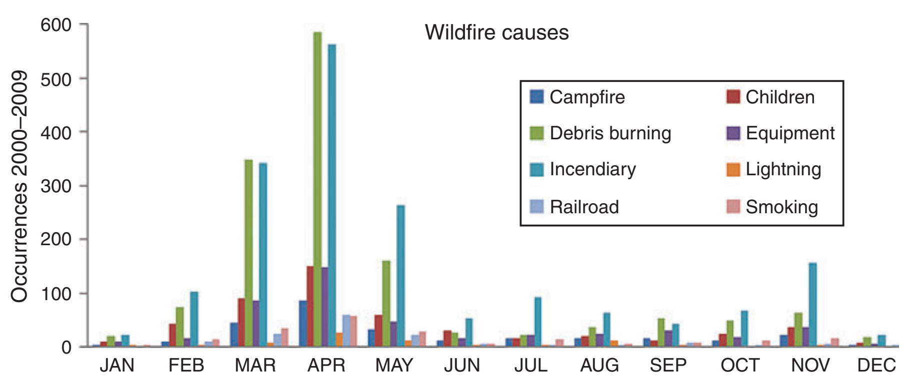

Fig. 4. Wildfire occurrences ≥0.1 ha by cause for the states of New Jersey, Ohio and Pennsylvania between 2000 and 2009.

The region of the Pine Barrens appeared to have more reported wildfires than the rest of the state, which made for a good location to show the spatial variability of hazard probabilities (Fig. 2). The hazard models do not consider fire size or area burnt, thus each 30-m cell contains a probabilistic value that a wildfire ignition could occur, derived from the locations of known fires and the environmental predictors at those sites.

Table 2. Monthly wildfire occurrences during 2000–09 for monthly and annual (in parentheses) hazard probability classes calculated from Maxent models

Monthly hazard values suggest a higher accuracy for the total fires >50% when compared with the average annual probability

Hazard probability	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
10%	2 (2)	3 (2)	7 (13)	25 (32)	4 (7)	3 (1)	4 (2)	13 (2)	3 (5)	8 (2)	8 (2)	3 (2)
20%	6 (1)	17 (11)	97 (61)	59 (122)	30 (34)	19 (1)	21 (9)	7 (9)	12 (9)	7 (10)	27 (10)	6 (0)
30%	1 (4)	34 (28)	84 (146)	164 (333)	127 (121)	9 (20)	18 (22)	6 (26)	15 (30)	13 (20)	28 (44)	8 (6)
40%	6 (10)	28 (35)	121 (147)	177 (364)	63 (128)	22 (11)	6 (20)	14 (24)	32 (26)	37 (25)	48 (43)	0 (9)
50%	9 (10)	37 (30)	237 (170)	235 (305)	27 (94)	12 (22)	16 (17)	27 (25)	30 (26)	13 (21)	35 (40)	4 (13)
60%	20 (12)	45 (40)	112 (146)	379 (171)	59 (51)	26 (18)	35 (11)	21 (20)	18 (20)	51 (32)	47 (53)	14 (5)
70%	17 (12)	33 (65)	57 (147)	465 (152)	122 (76)	17 (35)	15 (40)	35 (25)	15 (30)	5 (36)	61 (72)	19 (14)
80%	5 (15)	72 (58)	74 (132)	160 (185)	158 (106)	40 (40)	68 (62)	46 (43)	32 (19)	48 (36)	69 (69)	7 (11)
90%	0 (0)	0 (0)	163 (0)	0 (0)	27 (0)	0 (0)	0 (0)	5 (0)	8 (0)	0 (0)	10 (0)	0 (0)
100%	0 (0)	0 (0)	10 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Total	66	269	962	1664	617	148	183	174	165	182	333	61

Table 3. Area for each state, state-owned land (forest and park), National Forest Service (NFS), National Park Service (NPS) and Department of Defence (DOD) land is presented along with the number of reported spring (March, April and May) and annual (in parentheses) wildfires (2000–09)

Additionally, the mean hazard probability for each land owner is included for the spring and annual (parentheses) models

State	NJ	OH	PA
Area (km^2)			
Total	20 116	106 870	117 329
State-owned land	1316	819	9115
NFS	–	3455	2901
NPS	292	139	331
DOD	257	362	452
Fires >0.1 ha			
Total	1225 (2259)	317 (504)	1716 (2089)
State-owned land	57 (95)	2 (8)	104 (141)
NFS	– (–)	33 (89)	25 (34)
NPS	7 (8)	0 (0)	7 (8)
DOD	9 (18)	0 (1)	1 (2)
Mean hazard			
Total	0.49 (0.46)	0.19 (0.19)	0.31 (0.27)
State-owned land	0.48 (0.46)	0.33 (0.30)	0.34 (0.24)
NFS	– (–)	0.34 (0.31)	0.30 (0.24)
NPS	0.36 (0.31)	0.23 (0.22)	0.34 (0.31)
DOD	0.62 (0.56)	0.21 (0.26)	0.27 (0.32)

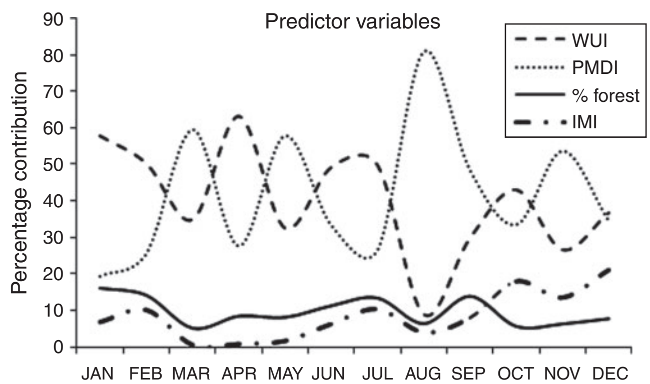

Fig. 5. Mean percentage contribution for each environmental variable among 10 Maxent iterations.

Model evaluation

Maxent uses presence-only data, which prevents an analysis of the true commission error. However, a more robust method to analyse the accuracy of predictions is to evaluate the area under the curve (AUC) of the receiver operating characteristics (ROC) curve, where values >0.5 are generally accepted as better than random. Values of AUC were between 0.764 and 0.872 for monthly averages of 10 iterations. In addition to calculating AUC, Maxent determines the percentage contribution of each predictor variable within the model; the two dominant variables according to their contribution were WUI and PMDI (Fig. 5). An alternative measure of variable importance is the jackknife of regularised training gain plots (Fig. 6). When each of the four predictor variables were evaluated via the jackknife analysis, PMDI was the most influential for the months of March, May, August, September and November, whereas WUI was more important for the months of January, February, April, June and July (Fig. 6). Overall, the models predicted, in most months, a higher proportion of wildfire occurrences (based on >50% probability of fire) than the mean annual distribution (Table 2). For example, 1664 fires were reported during April between 2000 and 2009. The monthly model predicted 1004 fires with a probability >50%, and 660 falling below this threshold. For the same month, the mean annual hazard values captured only 508 fires with a probability >50%, whereas 1156 were below. There may be locations throughout our study area where a threshold <50% is appropriate, however further analysis should be conducted to validate model performance. The monthly hazard maps with an overlay of reported wildfires (Fig. 7) illustrate the annual variation in probabilities, as the PMDI values and reported wildfire locations change throughout the year. Visually, most of the wildfires fall in the higher probability classes, even though the 50% cutoff does not capture many of the fires. The maps produced from this research can be validated only as new data are made available. With a limited number of reported fires (523) and PMDI values from 2010, our model predicted only 40% of

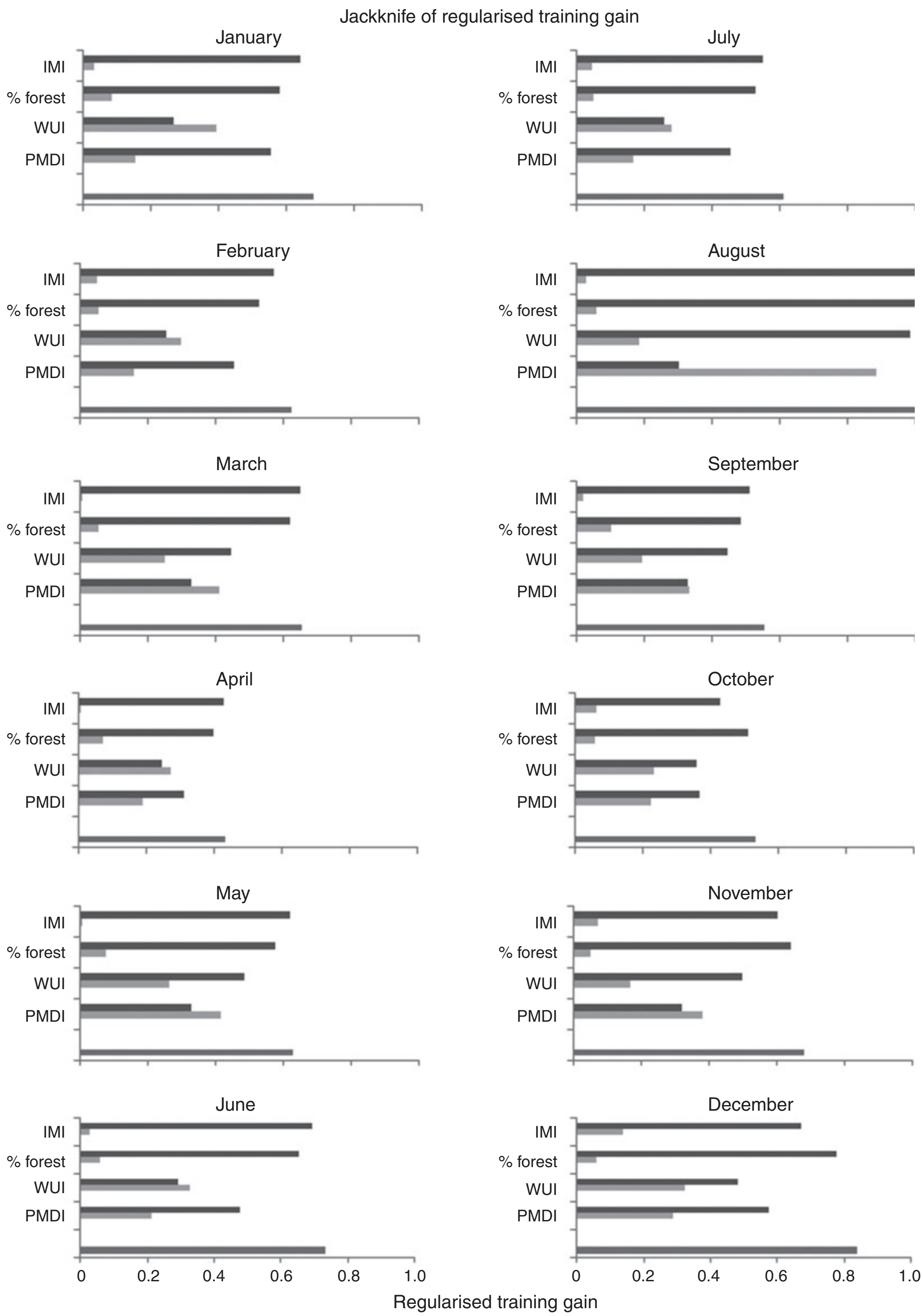

Fig. 6. Monthly plots of jackknife regularised training gains for predictor variables. Model performance without variable (dark grey), performance with only variable (light grey) and performance with all variables (medium grey).

the occurrences with a hazard value >50%; but with a cutoff of >30%, it captured 70% of the occurrences. PMDI values in 2010 were near-normal to wet from January to March and near-normal to mildly dry from April to August (with the exception of NJ's remaining near-normal to wet until June). The small number of wildfires reported in 2010 and the PMDI values' departure from near-normal conditions suggest that more fire records might be needed to evaluate the model's performance.

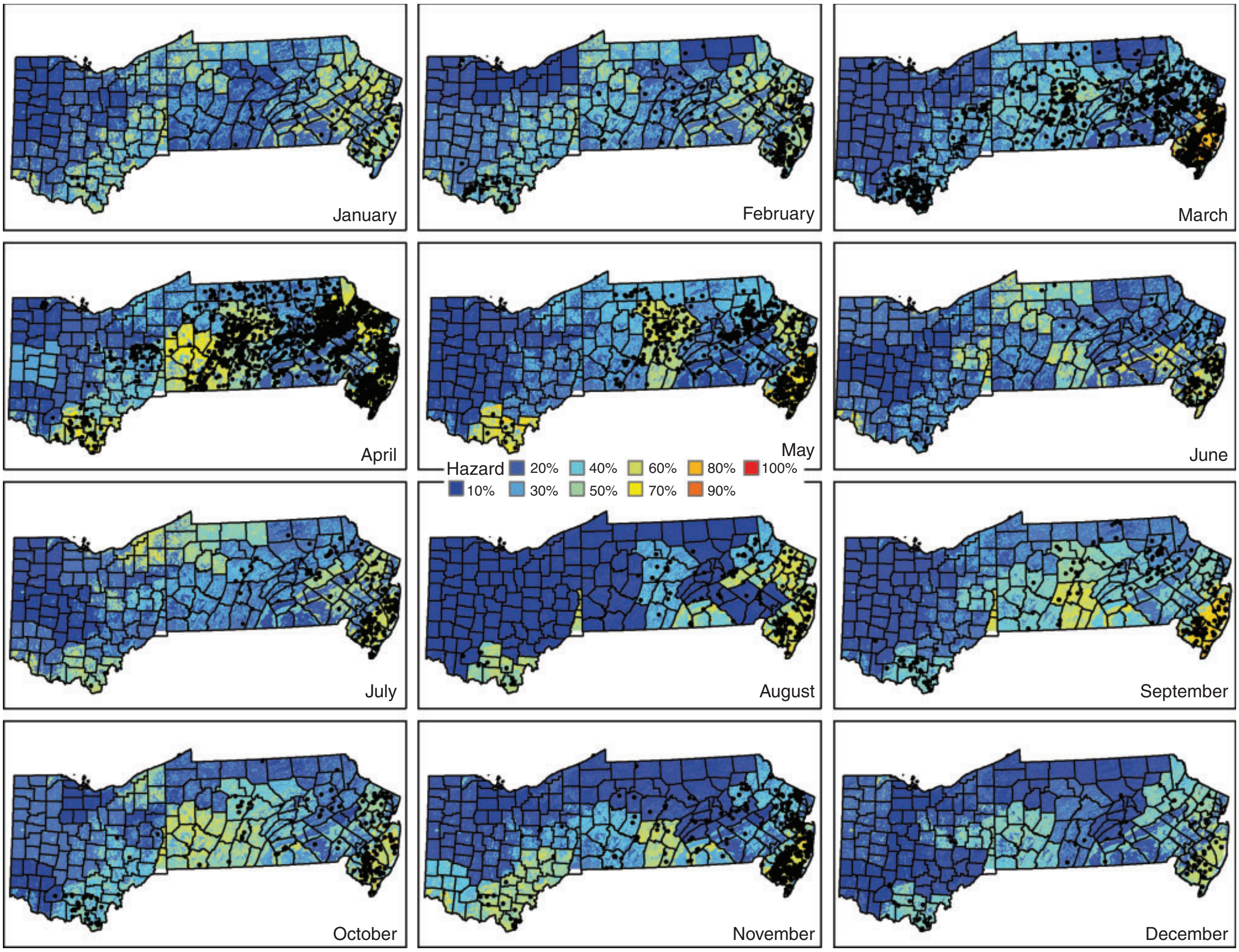

Fig. 7. Average monthly maximum entropy probability distributions of wildfire hazard at 30-m grid cells with monthly reported fires (2000–09) overlaid for accuracy assessment and county boundaries for reference.

Table 4. Average monthly and annual probability of wildfire hazard for IMI (on forested land) and WUI classes

	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	Annual
IMI													
DRY	0.30	0.32	0.30	0.40	0.34	0.29	0.35	0.21	0.37	0.42	0.33	0.32	0.33
INTERMEDIATE	0.22	0.23	0.28	0.38	0.32	0.21	0.21	0.15	0.29	0.25	0.21	0.14	0.24
MESIC	0.17	0.13	0.25	0.33	0.25	0.19	0.23	0.12	0.24	0.21	0.11	0.11	0.20
WUI													
WUI	0.45	0.45	0.44	0.52	0.40	0.42	0.43	0.26	0.41	0.46	0.36	0.34	0.41
Non-veg Agriculture	0.10	0.14	0.14	0.13	0.08	0.10	0.11	0.08	0.13	0.15	0.15	0.08	0.12
Non-WUI Veg	0.22	0.24	0.27	0.37	0.35	0.24	0.30	0.18	0.35	0.30	0.25	0.23	0.28
Uninhabited No Veg	0.47	0.34	0.20	0.28	0.31	0.32	0.20	0.19	0.27	0.28	0.31	0.47	0.30
WATER	0.45	0.28	0.17	0.27	0.32	0.31	0.50	0.23	0.38	0.34	0.37	0.37	0.33

For each state the area, number of reported spring (March–May) and total wildfires $\geq$0.1 ha, and mean spring and annual probabilities are reported for the state, state-owned land (forest and park) and National Forest Service, National Parks Service and Department of Defence (DOD) lands (Table 3). With the exception of DOD land in Ohio and Pennsylvania, mean spring hazard probabilities were higher than the mean annual value.

Mean monthly and annual probability values were higher among drier IMI cells that were also classified as forested by the 2006 NLCD (Table 4). Half of the months had a mean probability ≥ the annual value. Similarly, mean monthly probability values among WUI cells were usually higher between months. Values during August were typically lower among IMI and WUI classes and correspond to a high contribution from PMDI within the model.

Discussion

Wildfires in the eastern states of New Jersey, Ohio and Pennsylvania tended to occur in regions that are predominantly vegetated and have low- to medium-density development. In contrast to risk models developed in the western US by Calkin *et al.* (2010) for Oregon, Bar Massada *et al.* (2009) for a portion of north-western Wisconsin using FARSITE, or Thompson *et al.* (2011) at a national scale using simulated wildfires based on reported large wildfires to assess risk, our approach uses reported finescale wildfires (≥0.1 ha) and site conditions to statistically model the probability of suitable conditions for wildfire ignitions in the eastern US. Our methodology is similar to that of Parisien and Moritz (2009), but with a major difference in running Maxent monthly as opposed to annualising fire records and climate data. Another key difference is the scale at which environmental predictors where included in the model: 30-m rather than 1-km resolution. We assume that this finescale approach is important to help inform local management decisions, especially in the eastern US, as the relationships between fire occurrences and predictor variables often operate at such scales. As Openshaw (1983) showed, aggregation of data into larger zones can artificially increase correlation within the data, thus using the native resolution of each dataset, or converting vector data to a compatible resolution is preferred. Because we are modelling suitable conditions for wildfire ignitions, not fire spread, spatial dependency issues with finescale data are minimised.

Within the western US, risk assessments derived from the spread of a few large fires have been shown to accurately model the total area burnt (Calkin *et al.* 2010). However, wildfires in the eastern US behave quite differently in that more small fires (10 671 records between 2000 and 2009 from all causes with size <121.5 ha) were observed in our study area. Many of these small fires are possibly related to the influences from the WUI, where increased housing density can lead to more fires, but the surrounding infrastructure enables a faster response from firefighters (Bar Massada *et al.* 2009). Another difference between our study region and the western US is that only a small portion of each state is owned by state or federal agencies. Few wildfires were reported on public land during springtime and annually compared with the rest of the study region. However, both state and federal agencies are responsible for wildfires on public and surrounding private lands.

Because the fire records are point locations and represent presence-only data (as the stochastic nature of ignitions makes it difficult to determine whether surrounding sites could have burnt), some assumptions were made. Reported locations may not necessarily represent the ignition site but were assumed to be representative of local site conditions within a 30-m pixel. We also assumed that weather conditions (PMDI) averaged for the entire month represented conditions suitable to fire occurrences for that entire month. We chose to model based on monthly data because weekly PMDI data were not available over the entire study area and because insufficient fire records were available to model at a weekly resolution. However, we realise that this assumption may under-represent periods of extreme conditions or over-represent the time when conditions conducive to ignition may be present, because fire-prone conditions can appear and disappear easily within a calendar month. Therefore, up-to-date fire danger ratings should be used to assess current conditions, as our results represent the long-term trend of hazards in the near future. We also recognise that the resulting output maps will often distinctly show the coarse-resolution boundaries (multiple counties) when there are variations among the PMDI averages.

In addition to providing information related to the potential hazard of wildfires, the Maxent models offer insight into the weights of the four predictor variables driving the models. Knowing the monthly dynamics of these variables can help managers make informed decisions by considering how current conditions vary from the long-term ones in the models. The two dominant variables are WUI and PMDI (Fig. 5), which is not surprising because the majority of reported wildfires occurred in rural areas intermingled with housing under near-normal to dry conditions. The temporal variation of these two variables reveals an alternating level of importance within the models during the first half of the year, followed by higher contributions from PMDI from August through December (Fig. 5). This pattern could indicate that ignition sources (within WUI) relate more to human activities, whereas favourable conditions of drying (PMDI) are related to atmospheric conditions such as humidity that are dominant in the second half of the year. The increased contribution from IMI during October–December supports this hypothesis, as for each month, dry sites had a higher proportion of fire hazard. In contrast, the IMI of the site has essentially no influence in the spring (March–May), when most soils have the potential to be very wet and the moisture content of surface litter is probably tied more to humidity rather than the overall moisture regime of the soils.

Although the monthly models have been shown to perform better than a single annual model for most months, these models may under-estimate the probability of wildfire occurrence due to recent PMDI values being departed from the historical trend (Fig. 3). Given that future climates are expected to be warmer and drier for some regions, our models will be relevant for short-term planning, i.e. annual or biannual forecasting. An advantage to the methods used to produce monthly probability maps is that three of the four environmental predictors are static, with only PMDI values and current reported wildfires needing to be updated within the models.

Conclusions

Wildfires pose a serious threat to property and resources, and managers are faced with important decisions, especially with limited resources available. Hazard and risk mapping can provide supplemental information on which to base resource allocations. Verification of long-term trends related to wildfire conditions could provide some clarity when assessing the uncertainty of risk. The current study aims to provide a tool to spatially project the hazard of wildfires across three states.

It incorporates both the long-term nature of soil moisture at the fine scale (30 m) as well as the dynamic nature of the current climatic conditions, albeit at a coarse resolution (climate divisions at monthly intervals). The system would obviously be improved with finer scale data of climate conditions (e.g. PMDI), both spatially and temporally, but these data were not yet available.

Although hazard and risk mapping can provide insight into the potential long-term distribution of wildfires, managers and property owners need to continually assess local site conditions as small changes are beyond the scope of the models. Additionally, human behaviour cannot accurately be modelled; fires resulting from malicious intentions or accidents can occur throughout the region when conditions are suitable. However, education and preventative measures can mitigate some threat to personal property within the WUI regardless of the risk or hazard levels; for example, communities could reduce burning debris, a dominant cause of the reported fires, with such measures.

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References

Abrams MD (2000) Fire and the ecological history of oak forests in the eastern United States. In 'Proceedings: Workshop on Fire, People, and the Central Hardwoods Landscape', 12–14 March 2000, Richmond, KY. (Ed. DA Yaussy) USDA Forest Service, Northeastern Research Station, General Technical Report NE-274, pp. 46–55. (Newtown Square, PA)

Abrams MD, Nowacki GJ (1992) Historical variation in fire, oak recruitment, and post-logging accelerated succession in central Pennsylvania. *Bulletin of the Torrey Botanical Club* **119**(1), 19–28. doi:10.2307/2996916

Alley WM (1984) The Palmer Drought Severity Index: limitations and assumptions. *Journal of Climate and Applied Meteorology* **23**, 1100–1109. doi:10.1175/1520-0450(1984)023<1100:TPDSIL>2.0.CO;2

Bar Massada A, Radeloff VC, Stewart SI, Hawbaker TJ (2009) Wildfire risk in the wildland–urban interface: a simulation study in northwestern Wisconsin. *Forest Ecology and Management* **258**, 1990–1999. doi:10.1016/J.FORECO.2009.07.051

Bar Massada A, Syphard AD, Stewart SI, Radeloff VC (2012) Wildfire ignition-distribution modelling: a comparative study in the Huron–Manistee National Forest, Michigan, USA. *International Journal of Wildland Fire* . doi:10.1071/WF11178

Calkin DE, Ager AA, Gilbertson-Day J (Eds) (2010) Wildfire risk and hazard: procedures for the first approximation. USDA Forest Service, Rocky Mountain Research Station, General Technical Report RMRS-GTR-235. (Fort Collins, CO)

Cardille JA, Ventura SJ (2001) Occurrence of wildfire in the northern Great Lakes Region: effects of land cover and land ownership assessed at multiple scales. *International Journal of Wildland Fire* **10**, 145–154. doi:10.1071/WF01010

Cohen J (2000) Preventing disaster: home ignitability in the wildland–urban interface. *Journal of Forestry* **98**, 15–21.

Crocker E, Garbelotto M (2010) Phosphonate treatment to control *Phytophthora cinnamomi* infection of Ione Manzanita, *A. myrtifolia*. In 'Proceedings of the Sudden Oak Death Fourth Science Symposium', 15–18 June 2009, Santa Cruz, CA. (Eds SJ Frankel, JT Kliejunas, KM Palmieri) USDA Forest Service, Pacific Southwest Research Station, General Technical Report PSW-GTR-229, p. 307. (Albany, CA)

Dale VH, Joyce LA, McNulty S, Neilson RP, Ayres MP, Flannigan DM, Hanson PJ, Irland LC, Lugo AE, Peterson CJ, Simberloff D, Swanson FJ, Stocks BJ, Wotton BM (2001) Climate change and forest disturbances. *Bioscience* **51**, 723–734. doi:10.1641/0006-3568(2001)051[0723:CCAFD]2.0.CO;2

Elith J, Phillips SJ, Hastie T, Dudk M, Chee YE, Yates CJ (2011) A statistical explanation of MaxEnt for ecologists. *Diversity & Distributions* **17**, 43–57. doi:10.1111/J.1472-4642.2010.00725.X

Givnish TJ (1981) Serotiny, geography, and fire in the Pine Barrens of New Jersey. *Evolution* **35**(1), 101–123. doi:10.2307/2407945

Heddinghaus TR, Sabol P (1991) A review of the Palmer Drought Severity Index and where do we go from here? In 'Proceedings of the Seventh Conference on Applied Climatology', 10–13 September 1991, Salt Lake City, UT. pp. 242–246. (American Meteorological Society: Boston, MA)

Iverson LR, Scott CT, Dale ME, Prasad A (1996) Development of an Integrated Moisture Index for predicting species composition. In 'Caring for the Forest: Research in a Changing World, Statistics, Mathematics and Computers, Proceedings of the Meeting of IUFRO S4.11–00', 6–12 August 1995, Tampere, Finland. (Eds M Kohl, GZ Gertner) pp. 101–116. (Swiss Federal Institute for Forest, Snow and Landscape Research: Birmensdorf, Switzerland)

Iverson LR, Dale ME, Scott CT, Prasad A (1997) A GIS-derived integrated moisture index to predict forest composition and productivity in Ohio forests. *Landscape Ecology* **12**, 331–348. doi:10.1023/A:1007989813501

Iverson LR, Yaussy DA, Rebbeck J, Hutchinson TL, Long R, Prasad AM (2004) A comparison of thermocouples and temperature paints to monitor spatial and temporal characteristics of landscape-scale prescribed fires. *International Journal of Wildland Fire* **13**, 311–322. doi:10.1071/WF03063

Iverson LR, Hutchinson TF, Prasad AM, Peters M (2008) Thinning, fire, and oak regeneration across a hetergeneous landscape in the eastern US: 7-year results. *Forest Ecology and Management* **255**, 3035–3050. doi:10.1016/J.FORECO.2007.09.088

Keane RE, Drury SA, Karau EC, Hessburg PF, Reynolds KM (2010) A method for mapping fire hazard and risk across multiple scales and its application in fire management. *Ecological Modelling* **221**, 2–18. doi:10.1016/J.ECOLMODEL.2008.10.022

Lein JK, Stump NI (2009) Assessing wildfire potential within the wildland–urban interface: a southeastern Ohio example. *Applied Geography* **29**, 21–34. doi:10.1016/J.APGEOG.2008.06.002

Malamud BD, Millington JDA, Perry GLW (2005) Characterizing wildfire regimes in the United States. *Proceedings of the National Academy of Sciences of the United States of America* **102**(13), 4694–4699. doi:10.1073/PNAS.0500880102

Natural Resources Conservation Service, United States Department of Agriculture (2008) Soil surveys of New Jersey, Ohio, Pennsylvania, and West Virginia. Available at http://soildatamart.nrcs.usda.gov/State.aspx [Verified 5 December 2012]

Nowacki GJ, Abrams MD (2008) The demise of fire and 'mesophication' of forests in the eastern United States. *Bioscience* **58**, 123–138. doi:10.1641/B580207

Openshaw S (1983) 'The Modifiable Areal Unit Problem', Vol. 38 of Concepts and Techniques in Modern Geography (CATMOG). (Geo Books: Norwich, UK)

Parisien MA, Moritz MA (2009) Environmental controls on the distribution of wildfire at multiple spatial scales. *Ecological Monographs* **79**(1), 127–154. doi:10.1890/07-1289.1

Phillips SJ, Dudík M (2008) Modeling of species distributions with Maxent: new extensions and a comprehensive evaluation. *Ecography* **31**, 161–175. doi:10.1111/J.0906-7590.2008.5203.X

Phillips SJ, Dudík M, Schapire RE (2004) A maximum entropy approach to species distribution modeling. In 'Proceedings of the Twenty-first International Conference on Machine Learning', 4–8 July 2004, Banff, AB, Canada. (Eds R Greiner, D Schuurmans) pp. 655–662. (AMC Press: New York)

Phillips SJ, Anderson RP, Schapire RE (2006) Maximum entropy modeling of species geographic distributions. *Ecological Modelling* **190**, 231–259. doi:10.1016/J.ECOLMODEL.2005.03.026

Platt RV (2010) The wildland–urban interface: evaluating the definition effect. *Journal of Forestry* **108**(1), 9–15.

Radeloff VC, Hammer RB, Stewart SI, Fried JS, Holocomb SS, McKeefry JF (2005) The wildland–urban interface in the United States. *Ecological Applications* **15**(3), 799–805. doi:10.1890/04-1413

Syphard AD, Radeloff VC, Keeley JE, Hawbaker TJ, Clayton MK, Stewart SI, Hammer RB (2007) Human influence on California fire regimes. *Ecological Applications* **17**(5), 1388–1402. doi:10.1890/06-1128.1

Tarboton DG (1997) A new method for the determination of flow directions and contributing areas in grid digital elevation models. *Water Resources Research* **33**, 309–319. doi:10.1029/96WR03137

The National Map, LANDFIRE (2007) LANDFIRE National Forest Canopy Cover layer. US Department of Interior, Geological Survey. Available at http://gisdata.usgs.net/website/landfire/ [Verified 5 December 2012]

Thompson MP, Calkin DE, Finney MA, Ager AA, Gilbertson-Day JW (2011) Integrated national-scale assessment of wildfire risk to human and ecological values. *Stochastic Environmental Research and Risk Assessment* **25**, 761–780. doi:10.1007/S00477-011-0461-0

US Forest Service Northeastern Area State and Private Forestry (2010) Northeast wildfire risk assessment. Available at http://www.na.fs.fed.us/fire/pubs/northeast_wildfire_risk_assess10_lr.pdf [Verified 5 December 2012]

Václavík T, Kanaskie A, Goheen E, Ohmann J, Hansen E, Meentemeyer R (2010) Mapping the risk of sudden oak death in Oregon: prioritizing locations for early detection and eradication. In 'Proceedings of the Sudden Oak Death Fourth Science Symposium', 15–18 June 2009, Santa Cruz, CA. (Eds SJ Frankel, JT Kliejunas, KM Palmieri) pp. 126–132. USDA Forest Service, Pacific Southwest Research Station, General Technical Report PSW-GTR-229. (Albany, CA)