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Human and biophysical factors influencing modern fire disturbance in northern Wisconsin

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Abstract. Humans cause most wildfires in northern Wisconsin, but interactions between human and biophysical variables affecting fire starts and size are not well understood. We applied classification tree analyses to a 16-year fire database from northern Wisconsin to evaluate the relative importance of human *v.* biophysical variables affecting fire occurrence within (1) all cover types, and (2) within forest types in each of four different fire size groupings (all fires; fires ≥0.4 ha (1 acre); fires ≥4 ha (10 acres); fires ≥16 ha (40 acres)). Housing density was the most important indicator of fire observations. Increasing minimum fire size increased the relative importance of biophysical variables. Key biophysical variables included land cover type, soil moisture indicators, and an index of presettlement fire rotation associated with glacial landforms. Our results indicate the likelihood of fire starts is primarily influenced by human activity in northern Wisconsin, whereas biophysical factors determine whether those fire starts become large fires. Important interactions between human and biophysical variables were observed for nearly all fire types and size thresholds examined. Our results have implications for both ecological restoration and the management of fire risk within historically fire-prone systems currently experiencing rapid rural development.

Additional keywords: anthropogenic fire, biophysical units, modern fire regime, presettlement fire rotation, rural development, wildfire occurrence.

Introduction

Past research has shown that presettlement vegetation and its characteristic fire disturbance regimes were closely tied to glacial landforms in the Great Lakes Region of North America (Brubaker 1975; Cleland *et al*. 2004; Schulte and Mladenoff 2005). For example, sandy outwash plains were historically occupied by pyroclastic vegetation types such as jack pine (*Pinus banksiana*), whereas richer soil types more typical of glacial moraines were occupied by deciduous northern hardwood forest types that rarely burned (Grimm 1984; Whitney 1986). Historical fire regimes may also provide context for the patterns of vegetation and fire disturbances that we observe today (Cleland *et al*. 2004). Yet, historically important biophysical drivers of fire regimes may have less relevance to modern fire patterns due to the often overwhelming influence of modern society on current fire regimes.

Contemporary fires in the Great Lakes region are generally started by humans, responsible for over 97% of fires in recent decades (Cardille *et al*. 2001). A rigorous fire suppression program enforced throughout the region counters these ignitions, but has also reduced the annual area burned relative to presettlement by an order of magnitude (Cleland *et al*. 2004). Hence, frequent but small wildfires define the modern fire regime in the region, though large (400–4000 ha (1000–10 000 acres)) wildfires still occur (Radeloff *et al*. 2000*a*; Walker *et al*. 2003), posing a continuing threat to human safety and property in rural areas. As human-caused wildfire starts are most common around human developments and travel corridors (Cardille *et al*. 2001), the greatest risk of wildfire likely occurs where rural developments overlap with fire-prone ecosystems (Haight *et al*. 2004). In northern Wisconsin, fire-adapted ecosystems such as pine barrens are being converted to hardwood cover types by succession owing to the absence of catastrophic fire (Radeloff *et al*. 2000*a*), and historically common red pine (*Pinus resinosa*)–white pine (*P. strobus*) and white pine–hemlock (*Tsuga canadensis*) systems have never recovered following the exploitative logging period in the late 19th century (Stearns 1997). Restoration for each of these ecosystems will require active management that includes prescribed fire and wildfire (Radeloff *et al*. 2000*a*; Stearns and Likens 2002). Reconciling ecosystem restoration with human safety will require a firm understanding of the human and biophysical factors underlying wildfire patterns of this primarily forested region.

Two interrelated elements of fire behaviour influence wildfire patterns across landscapes: fire *starts* (i.e. fire ignitions that become wildfires) that dictate fire occurrence and frequency, and fire *spread* that affects fire size. Each element may be influenced by both human and biophysical factors. Humans influence the spatial pattern and frequency of fire starts through activity associated with development, transportation networks, and recreation (Cardille *et al*. 2001; Pew and Larsen 2001; Román-Cuesta *et al*. 2003). However, the likelihood of a successful fire start is also dependent in part on biophysical factors such as fuel moisture (Forestry Canada Fire Danger Group 1992), antecedent

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weather (Prestemon *et al*. 2002), and the relative flammability of vegetation and litter as determined by fuel moisture and vegetation type (Frelich and Reich 1995). Humans influence fire spread through aggressive fire detection and suppression, and their efforts may vary in space and time because of road access, priorities associated with human dwellings, and ultimately the allocation of firefighting resources. However, biophysical factors primarily determine the flammability and connectivity of fuels and thus the ability of a fire to spread to adjacent vegetation. For example, dry and continuous conifer canopies can burn as intense, fast-moving crown fires that are difficult to suppress, whereas the crowns of deciduous tree communities seldom burn (Cumming 2001). Tree species also vary in relative flammability of their litter (Frelich and Reich 1995), and tree species distribution is constrained, in part, by soil moisture and nutrient availability (Smith and Huston 1989), and also by past fire regimes and management legacies (Radeloff *et al*. 2000*a*). Non-forested cover types, such as wetlands, cultivated crops, and open fields can also readily burn when dry, and their distribution also depends on both human land use and landform patterns (Radeloff *et al*. 2000*b*). It is the interaction among these social and biophysical drivers that ultimately determine contemporary fire regimes in the region.

Georeferenced fire records collected by state and federal agencies in the upper Midwest, United States, have been previously analysed with respect to climatic, ecological, and human variables to gain insight about the key factors affecting modern fire regimes in the region (Cardille and Ventura 2001; Cardille *et al*. 2001). In parallel, Cleland *et al*. (2004) have developed a synthetic landscape ecosystem classification system that maps biophysical units based on associations of ecological characteristics known to influence historical fire regimes and the biogeography of fire-prone *v.* fire-resistant communities in the same area. This classification correlates well with modern fire return intervals in northern Lower Michigan (Cleland *et al*. 2004). However, a formal analysis of the classified forest fire regimes as they interact with modern, human-dominated fire patterns has not yet been performed.

A common approach to the spatial analysis of modern fire databases is the application of logistic regression (i.e. logit) models to predict fire occurrence with respect to different geographic variables (Vega-Garcia *et al*. 1995; Cardille *et al*. 2001; Pew and Larsen 2001). Though this approach can be powerful in terms of predictability, it is also limited by the classical parametric assumptions of normality, linear relationships, and absence of multicollinearity between independent variables. Relationships between biophysical and social data, particularly in a spatial context, can often be complex, non-linear, and involve high-order interactions. Classification and regression trees are far more flexible in their data requirements and ability to evaluate complicated interactions among variables, and can therefore serve as a useful alternative to classical parametric analyses in exploring relationships within complex datasets (Breiman *et al*. 1984; De'ath and Fabricius 2000).

We used classification trees to evaluate the relative importance of human *v.* biophysical variables on wildfire occurrence and size in northern Wisconsin, USA, using a 16-year fire record database. Specifically, we wished to address whether the historical fire regimes and their underlying drivers (i.e. soil texture, vegetation, etc.) are useful indicators of contemporary fire risk. If so, then biophysical factors historically associated with large and frequent fires should influence fire occurrence, size, or both. We focussed on the state of Wisconsin because its Department of Natural Resources (DNR) consistently recorded the cover type where a given wildfire occurred, allowing us to separate forest wildfires from those wildfires occurring on open land cover types (e.g. agricultural, wetland). Hence our analyses built on previous research of modern fires in the Lake States (Cardille and Ventura 2001; Cardille *et al*. 2001; Cleland *et al*. 2004) by explicitly evaluating the interactions among social and biophysical variables as they affect cover-specific wildfires using non-parametric techniques.

Methods

Study area

We focussed on the Laurentian Mixed Forest Province (McNab and Avers 1994) within northern Wisconsin ($\sim$58 000 km^2), where either the Wisconsin DNR or the US Forest Service had primary wildfire attack responsibility (Fig. 1). The area is primarily forested (67%), with scattered residential areas, seasonal lakeshore development, and low-to-moderate levels of agricultural activity (21%). Topographic relief ranges from flat to gently undulating with elevations ranging between 175 m and 600 m above sea level. The forest composition ranges from northern hardwoods (sugar maple, *Acer saccharum*; American basswood, *Tilia americana*; yellow birch, *Betula alleghaniensis*) on nutrient-rich glacial till to pine- and oak-dominated systems (e.g. jack, red, and white pine; red oak, *Quercus rubra*; pin oak, *Q. ellipsoidalis*) underlain by sandy glacial outwash plains (Curtis 1971). Boreal tree species (e.g. aspen, *Populus* spp.; balsam fir, *Abies balsamea*; white spruce, *Picea glauca*) are also common in this ecological transition zone, as are lowland conifer species (black spruce, *P. mariana*; tamarack, *Larix laricina*) (Pastor and Mladenoff 1992). Forests in the region are actively managed, and more than a third of the land area is in the public domain under

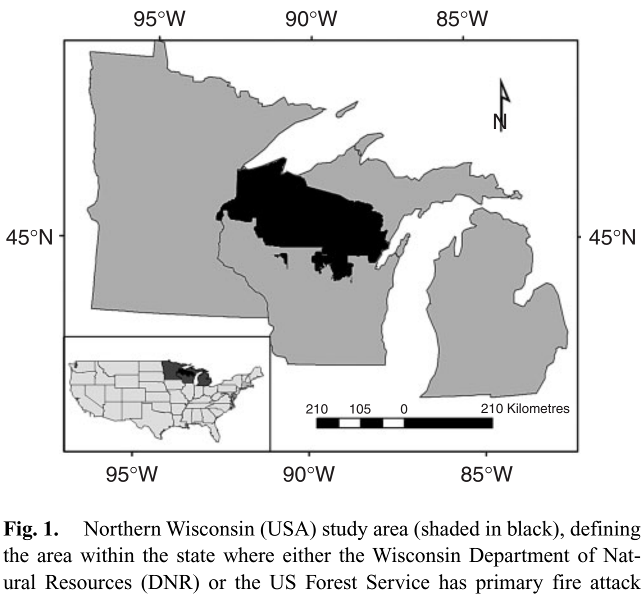

Fig. 1. Northern Wisconsin (USA) study area (shaded in black), defining the area within the state where either the Wisconsin Department of Natural Resources (DNR) or the US Forest Service has primary fire attack responsibility.

federal, state, and county jurisdictions. Agricultural activities include row crops (e.g. corn), hayfields, and dairy pastures.

Wisconsin fire database

We analysed Wisconsin fire records excerpted from the Lake States Fire Database compiled as part of the Great Lakes Ecological Assessment (Cardille and Ventura 2001, http://www.ncrs.fs.fed.us/gla/, accessed 24 July 2007). Each wildfire observation (referred to hereforth as simply *fire observations*) in the database represents a wildfire that was suppressed by either the Wisconsin DNR or the US Forest Service. Between 1985 and 2000, a total of 13 513 fires were recorded in the study area. Because fires controlled by private citizens were not recorded, fire observations should be interpreted as those fires requiring agency suppression rather than all fires *per se*. Nonetheless, state and federal policy is to suppress all wildfires, and the minimum fire size reported was 0.004 ha (0.01 acre), suggesting that most fire starts in the study area are included in the database. Each fire record includes attributes such as fire size, the date and time the fire was observed, the estimated cause of the fire, and the cover type at the origin of the fire (Wisconsin Department of Natural Resources 1996). The origin of each fire was assigned to a square mile (2.59 km^2) area corresponding with a section of the Public Land Survey System (PLSS). Our unit of analysis was therefore a PLSS section, where section boundaries were used to calculate mean values for each biophysical and human factor described below. The majority of fire observations were small (mean = 0.82 ha (2.09 acres)), and only three fires (max = 476 ha (1210 acres)) exceeded the 252 ha (640 acres) section sample unit size. We therefore assumed that fires were contained within a PLSS section. Forest fires were separated from the rest of the database using the cover type listed by the recording agency, where the reported cover type was defined as the major vegetation type within the 4-ha (10-acre) area surrounding the ignition point (Wisconsin Department of Natural Resources 1996).

Biophysical factors

Soil characteristics. Soil texture and moisture influence both vegetation composition and fuel moisture. The US General Soil Map (i.e. STATSGO, http://soildatamart.nrcs.usda.gov/, accessed 24 July 2007) contains general soil association units and soil attributes characterising soils and non-soil areas that were generalised from more detailed soil surveys and other data sources (e.g. topography, climate, satellite imagery). We extracted four soil attributes related to soil moisture and texture from the STATSGO soil polygons: low available water-holding capacity, high available water-holding capacity, soil drainage class, and hydric soil rating. Available water-holding capacity was first averaged across soil layers, weighted by layer depth, for each component of the STATSGO mapping units (Table 1). We then calculated area-weighted averages for each mapping unit, using the percentage of each soil component in the mapping unit as weights. Drainage class refers to the frequency and duration of periods when the soil is free of saturation, and includes seven classes ranging from 'excessive' to 'poor'. Drainage was converted to an ordinal scale, where 1 = poor and 7 = excessive drainage. Hydric rating is a binary variable indicating the presence or absence of hydric soil conditions, and was converted to 0 (not hydric) and 1 (hydric). Both variables were defined at the soil component level, and were therefore calculated as area-weighted averages for the STATSGO mapping units. Because STATSGO polygons are large (median size = 62.3 km^2, minimum = 1.1 km^2, maximum = 748.1 km^2) relative to the PLSS sections, soil variables were simply sampled from the STATSGO polygons using the centroids of the PLSS sections.

SSURGO is the most detailed level of soil mapping done by the US Natural Resources Conservation Service, mapped at scales ranging between 1:12 000 and 1:63 360 (http://soildatamart.nrcs.usda.gov/, accessed 24 July 2007) with mapping units with much finer resolution than the PLSS sections. Although SSURGO data existed for 20 of the 27 counties within the study area, most of the corresponding attribute data is not yet in digital form and therefore could not be used directly in our analyses. However, SSURGO data was used to map presettlement fire rotations, described in the next section.

Presettlement fire rotation. SSURGO soil polygons were assigned one of six presettlement forest replacement fire rotation (FR) categories based on soil texture and drainage, glacial landform and presettlement vegetation following the methods of Cleland *et al*. (2004). These criteria are now being used to map biophysical units for the national fire regime condition class effort and this nomenclature has been adopted in the present research. For example, biophysical units historically dominated by jack pine systems underlain by coarse-textured sandy soils (FR1) experienced frequent, large catastrophic stand-replacing fires (Table 2; Fig. 2). In contrast, biophysical units historically dominated by northern hardwood systems, underlain by fine-textured sandy loam to heavy clay and silt loam soils (FR4) experienced very infrequent stand-replacing fires (Table 2). In the seven counties where SSURGO data was not digitally available, coarser-scale land-type association polygons (Cleland *et al*. 1997) were classified using the same methodology (Cleland *et al*. 2004). When necessary, land-type polygons were subdivided or revised based on soil or historical vegetation criteria.

Presettlement fire rotations were estimated for each biophysical unit using General Land Office (GLO) records from 1836 and 1858. Evidence of fire occurrence was inferred from GLO surveyor notes, recorded along transects of section lines, that included 'burned' or 'blown down' and other indications of recent disturbance such as 'pine thickets', pine and oak barrens, prairies, and so forth (Cleland *et al*. 2004). Historical fire boundaries were determined using ordinary kriging for the interpolation of the fire occurrence data points, with output in the form of a probability map (Maclean and Cleland 2003). Historical fire rotations were determined by calculating the area burned for each biophysical unit category and dividing this area by fifteen (i.e. the time that evidence of fire was assumed to persist) to estimate area burned per year (Cleland *et al*. 2004) (Table 2).

Each biophysical unit class was assigned a value between 1 and 5 corresponding with its ordinal rank in presettlement fire rotation length (i.e. FR1 = 1, FR2 = 2, FR3 = 3, FR4 = 5, Table 2; Fig. 2). Though the presettlement fire rotations of wetland systems differed depending on landscape context (i.e. FR3W wetlands embedded within fire-prone landscapes burned more frequently than FR4W wetlands embedded within fire-resistant landscapes; Cleland *et al*. 2004), the two wetland classes

Table 1. Biophysical and human variables included in our analyses and their predicted influence of fire starts and size

Variable	Abbreviation[A]	Data source[B]	Units	Predicted direction of influence[C]	
				Fire starts	Large fires
Biophysical factors					
Available water-holding capacity (high)	AWCH	STATSGO	Proportion	–	–
Available water-holding capacity (low)	AWCL	STATSGO	Proportion	–	–
Soil drainage class	Drainage	STATSGO	Index	+	+
Hydric soils rating	Hydric	STATSGO	Index	–	–
Presettlement fire rotation	PFR	Cleland *et al*. 2004	Index	–	–
Percentage agriculture and grassland	AG	WISCLAND	Percent	Fire type dependent	
Percentage forest	Forest	WISCLAND	Percent	Fire type dependent	
Percentage water	Water	WISCLAND	Percent	?	–
Percentage wetland	Wetland	WISCLAND	Percent	–	–
Relative forest flammability	RFF	WISCLAND/MRLC	Index	+	+
Stream density	StreamDens	TIGER	$km\ km^{-2}$	–	–
Mean maximum August temperature	AugMaxT	PRISM	°C	+	+
Mean March precipitation	MarPrecip	PRISM	mm	–	–
Mean June precipitation	JunPrecip	PRISM	mm	–	–
Human factors					
Population density (1990)	PopDens90	US Census Bureau	Residents km^{-2}	+	–
Housing density (1990)	HousDens90	US Census Bureau	Homes km^{-2}	+	–
Population change (1990–2000)	PopGrowth	US Census Bureau	Residents km^{-2}	?	?
Housing change (1990–2000)	HouseGrowth	US Census Bureau	Homes km^{-2}	?	?
Percentage of homes occupied by owner	PctOwn	US Census Bureau	Percent	?	?
Percentage of seasonally occupied homes	PctSeas	US Census Bureau	Percent	–	+
Median home value	MedHomeVal	US Census Bureau	US$	–	–
Distance to road	DistRoad	TIGER	km	+	–
Road density	RoadDens	TIGER	$km\ km^{-2}$	+	–
Distance to railroad	DistRail	TIGER	km	+	?
Rail density	RoadRail	TIGER	$km\ km^{-2}$	+	?
Distance to city >10 000 people	DistLgCity	ESRI	km	+	–
Distance to city >1000 people	DistSmCity	ESRI	km	+	–

[A]Abbreviations are used in all subsequent figures.
[B]See sections on *Biophysical factors* and *Human factors* for full data source descriptions.
[C]Positive signs indicate that the variable is predicted to be positively correlated with the likelihood of (1) fire starts, and (2) large fires. See *Predictions* section for full description of predictions.

Table 2. Presettlement fire rotation

This index ranks biophysical units according to their presettlement stand-replacing fire rotation, defined as the length of time required to burn an area equivalent in size to the total area represented by the classified land units. A 'W' in the original classification indicates a wetland-dominated ecosystem (Cleland *et al*. 2004)

Fire rotation classification	Rank	Soil moisture	Dominant presettlement vegetation	Presettlement fire rotation (years)
FR1	1	Xeric	Jack pine and barrens	62
FR2	2	Less xeric	Red and white pine, oak	207
FR3	3	Dry mesic	White pine–hemlock	525
FR3W	4	Hydric	Wetlands adjacent xeric systems	274
FR4W	4	Hydric	Wetlands adjacent mesic systems	1873
FR4	5	Mesic	Northern hardwoods	2128

were lumped together for this analysis and given a value of 4 (i.e. intermediate between FR3 and FR4). We combined these two classes because fire sizes are small relative to presettlement periods owing to suppression efforts, reducing the importance of landscape context on wetland fire rotations (Cleland *et al*. 2004). The resulting classified coverage was converted to a grid raster with 30 × 30-m grid cell resolution, and averaged across all cells within a given PLSS section using the 'zonalstats' function in ArcInfo GRID (Version 8.1, Environmental Systems Research Institute, Inc., Redlands, CA). Water bodies were classified as 'no data', and were therefore ignored (percentage water was included as another variable, defined below). The resulting variable, called presettlement fire rotation, was a real number index value ranging between 1 and 5 (Tables 1, 2).

Current land cover (fuel type). A fuel classification that describes spread rates and potential fire behaviour was not

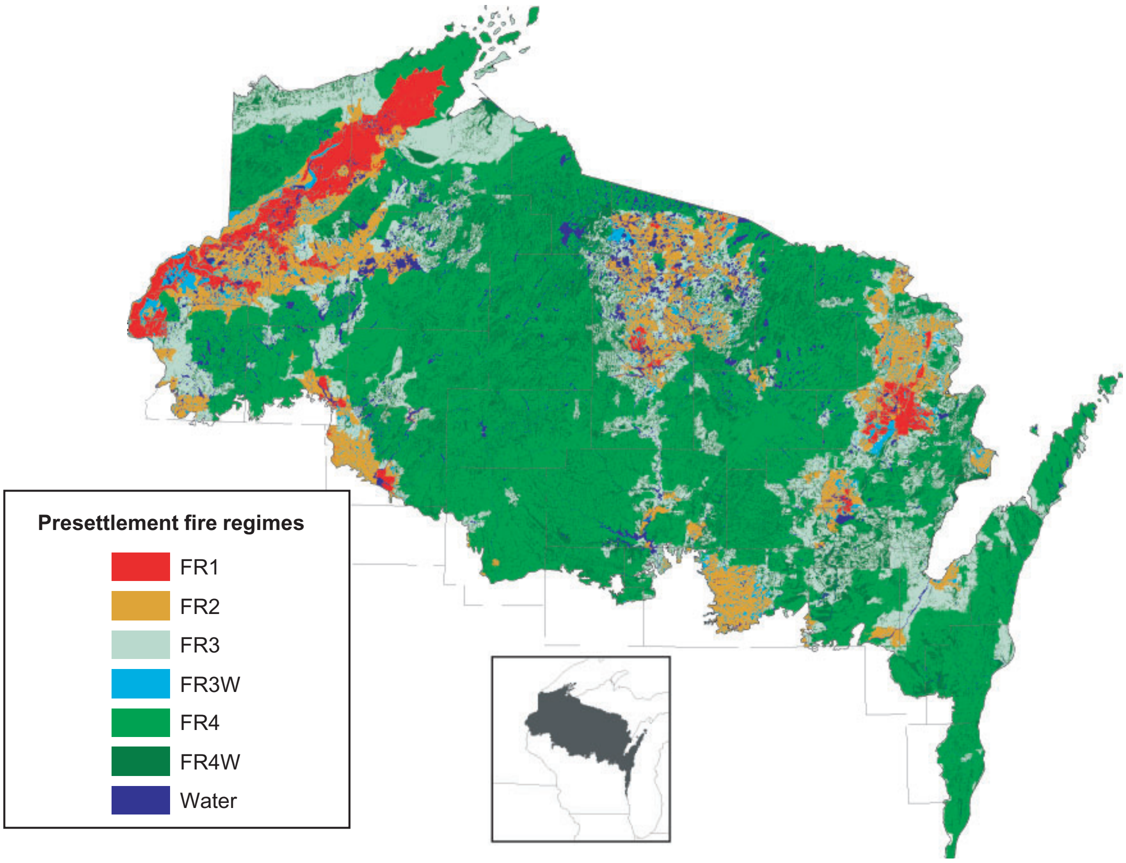

Fig. 2. Presettlement fire rotation classification for the Laurentian Mixed Forest Province of northern Wisconsin. Fire rotation (FR) classes are defined in Table 2.

Table 3. Relative forest flammability

Relative forest flammability is an ordinal ranking that translates classified land cover into potential fire risk. The ranking is based on local expert opinion about how fires might behave within different forest cover types, and fire risk increases with the flammability rank. This index was applied in lieu of a more comprehensive forest fuel dataset

Rank	WISCLAND[A] cover types	Potential fire behaviour and risk
1	Maple, mixed and other broad-leaved, broad-leaved wetlands	Lowest surface fire risk
2	Coniferous and mixed wetlands	Crown fires rare but possible
3	Aspen, oaks, lowland mixed and other coniferous	Surface fire risk or low crown fire risk
4	White spruce, mixed and other coniferous	Moderate crown fire risk
5	Jack pine, red pine, upland mixed and other coniferous	Pine-dominated systems with greatest crown fire risk

[A] State-wide satellite classification of land cover (WISCLAND, http://dnr.wi.gov/maps/gis/datalandcover.html/, accessed 24 July 2007).

available for the study area. We therefore substituted current vegetation for fuel types. Current vegetation was described from 1992 thematic mapper (TM) imagery classified by the Wisconsin Initiative for Statewide Cooperation on Land Cover Analysis and Data (WISCLAND, http://dnr.wi.gov/maps/gis/datalandcover.html/, accessed 24 July 2007). The percentage of four major cover types within each PLSS section was calculated: agricultural and grassland, forest, water, and wetland.

Current forest vegetation was further rank-ordered according to the expected flammability and fire behaviour within the vegetation class as estimated by fire managers in the region (Table 3). One of the WISCLAND classes (mixed or other coniferous) contained both upland and lowland coniferous vegetation types, where fires are expected to behave quite differently. We therefore used the lowland forest class from the 1992 Multi-Resolution Land Characteristics (MRLC) land cover classification (Vogelmann *et al*. 1998) to subdivide the 'mixed or other coniferous' class from WISCLAND into upland and lowland mixed conifers. This ordinal scale, termed relative forest flammability, was assigned to each 30×30 m-pixel of the classified imagery, and averaged across all forested pixels in a given PLSS section, resulting in a real number index value ranging between 1 (least flammable) and 5 (most flammable) (Table 3).

Stream density. Linear water features can potentially affect fire spread, and smaller streams are typically not detected using Landsat TM imagery. A line coverage of streams was obtained from the Wisconsin DNR (Geodisc v3.0; 1998), originally digitised from 1:100 000 US Geological Survey (USGS) digital line graphs (DLGs). We created a stream density raster data layer (km km^{-2}; 100-m resolution) by applying the 'linedensity' function in ArcInfo GRID to the stream coverage, and then averaged the stream density values across all cells within a given PLSS section.

Climate. Cardille *et al*. (2001) found that three biologically meaningful and orthogonal climate variables could represent 95% of the variability in monthly mean precipitation and temperature in our study region: maximum August temperature, March precipitation, and June precipitation. We calculated these variables using climate data from 1961 to 1990 at 2-km^2 resolution (ZedX Corporation, Boalsburg, Pennsylvania, USA). These climatic values were sampled and assigned to PLSS sections using their centroid locations.

Human factors

Human factors evaluated here represented different indicators of human population, development, property values, and access associated with both transportation networks (i.e. roads and railroads) and distance to population centres (Table 1). We used block-level census data from the 1990 census (Radeloff *et al*. 2005) to calculate five variables: population density (residents km^{-2}), housing density (houses km^{-2}), percentage of homes occupied by owners, percentage of seasonally occupied homes, and the median home value (US$). We also calculated population and housing density change between 1990 and 2000 using the methods of Radeloff *et al*. (2005). Census block polygons were converted to 100-m resolution raster layers for each of the variables, which were averaged across all cells within a given PLSS section. The exception was median home value, not available at the block level, calculated instead at the minimum civil division level. In the study area, median size for block polygons was 13.9 ha, whereas the median size for minimum civil divisions was 9323 ha.

Line coverages of railroads and roads were also obtained from the Wisconsin DNR (Geodisc v3.0; 1998), originally digitised from 1:100 000 USGS DLGs. These coverages included a buffer of roads in adjacent Michigan and Minnesota, allowing us to calculate accurate distances to nearest roads and railroads even along state boundaries. We converted the road layer to a binary 100 m-resolution raster layer (i.e. road *v*. non-road), and calculated the Euclidean distance (m) from each cell centre to the nearest road using the Spatial Analyst extension of ArcGIS (v8.1). We then averaged the distance to nearest road values across all cells within a given PLSS section. The same procedure applied to railroads provided a distance-to-railroad data layer. We used the stream density procedure to generate road and railroad density (km km^{-2}; 100-m resolution) data layers.

Distance to nearest population centres can affect levels of human activity (Vega-Garcia *et al*. 1995) and response time for fire personnel (Cardille *et al*. 2001). Distances to the nearest population centres were calculated at two population thresholds: cities with greater than 10 000 people (large cities), and cities with greater than 1000 people (small cities). The 100 m-resolution raster layers of the Euclidean distances from the nearest large and small city, respectively, were calculated in ArcInfo GRID, and these values were averaged across cells within a PLSS for each variable.

Predictions

Biophysical factors listed in Table 1 are dominated by factors hypothesised to spatially influence fuel conditions. Soil attributes from the STATSGO database influence soil moisture, which in turn affects fuel moisture. Factors positively correlated with soil moisture (i.e. available water-holding capacity and proportion of hydric soils) should decrease the likelihood of both starts and large fires, whereas the converse is true for soil drainage (Table 1). Climate can similarly influence soil moisture patterns across space during the fire season, so spring or summer precipitation should negatively influence the likelihood of both fire starts and large fires, while summer temperatures should positively influence these same variables.

Because vegetation patterns have been heavily influenced by human land use, we used current land cover as a surrogate for current fuel type. For forest fires, relative forest flammability should be positively related to the likelihood of fire starts and large fires in forests, but should not be relevant for fires in other cover types. We expected that agricultural and grassland cover types would increase both fire starts and large fire observations relative to forest types, because open habitats are typically more flammable than forests in the region (Cardille and Ventura 2001). We expected the opposite to be true for forest fires, simply because forest fires by definition are constrained to forested land cover. Finally, open water and streams were expected to constrain the ability of fires to spread, and such that their relative coverage should be negatively correlated with the likelihood of large fires. It is not clear how water and streams will influence ignitions; increased relative humidity near water should decrease the likelihood of fire starts, but these variables are also associated with waterfront development and recreational access that may enhance human-caused ignition frequency.

Unlike the biophysical variables, most human variables were expected to have opposite direction of influence on fire starts *v.* large fire occurrence (Table 1), because humans both start fires and suppress them. Hence we expected that fire starts would be positively associated with human access and development variables (i.e. population, housing, road and railroad density), and negatively associated with distance to infrastructure and population centres (i.e. distance to roads, railroads, small and large cities). All fires in the database are suppressed fires, so the most likely human influence on fire size was (1) the time to report a fire start; (2) the time required for fire attack crews to arrive at the scene of a fire; and (3) road access to the fire location. We expected that the time to report a fire should decrease with human presence in the landscape (i.e. population and housing density), response time should increase with distance to population centres, and access to a fire should be positively related to road density (Table 1). The two railroad variables should be unrelated to fire size because suppression resources are not sent via railroad. We had no *a priori* predictions how recent development (i.e. housing and population change from 1990 to 2000) would influence either fire starts or fire size.

Land ownership patterns and residential property values were expected to have different relationships. Owing to harsh continental winters and also a high density of lakes and forests, northern Wisconsin has some of the highest concentrations of seasonal homes in the nation. The primary fire season occurs in late spring (Cardille and Ventura 2001), when many seasonal homes are not occupied. Hence the percentage of owner-occupied homes is expected to positively influence the likelihood of fire starts and negatively influence the likelihood of observing large fires, because proportionally greater human presence should both increase ignition sources and decrease the reporting time, respectively. The converse is expected for the percentage of seasonal homes. Finally, economic status may influence human behaviours related to fires (e.g. Prestemon 2006). For example, debris-burning may be more common in less affluent areas, and arson activity can be related to unemployment levels. We therefore expected fire starts to be negatively associated with median house value.

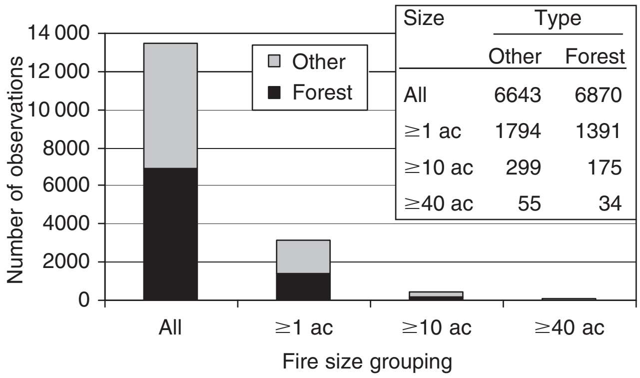

Fig. 3. Number of fire observations by type and size grouping. 'General' fires included both forest fires and fires occurring in other land cover types (gray + black bars), whereas forest fires included only the observations indicated by black bars.

Statistical analysis

Classification and regression trees explain the variation of a single categorical (i.e. classification tree) or numeric (regression tree) variable with respect to one or more explanatory variables that can include both categorical and numeric data types (De'ath and Fabricius 2000). They achieve this by recursively partitioning data into increasingly homogeneous subsets, examining all possible variables, and then selecting the best variable to split each 'parent' group into two 'child' groups or 'nodes' with the lowest 'impurity', a measure of the relative homogeneity of the resulting child nodes (De'ath and Fabricius 2000). Child nodes become new parent nodes that are further split, and the process continues until all of the observations are classified. Terminal nodes are those groups formed at the end of the tree that cannot be split any further. We applied classification tree analyses to binary (fire *v.* non-fire) section observations using the recursive partitioning and regression trees (RPART) library extension (Atkinson and Therneau 2000) to SPLUS 2000 Professional (Release 3, Mathsoft, Inc.).

The recursive nature of classification trees allows them to capture some interactions between variables that are difficult to reconcile using conventional linear methods (Urban 2002). As classification trees partition data according to ranked values, they do not assume any distribution of the data, nor are they sensitive to outliers (Breiman *et al.* 1984; De'ath and Fabricius 2000; Karels *et al.* 2004). However, the partitioning method of classification trees, when applied to continuous explanatory variables, tends to break the data based on gaps in the continuous data (J. Stanovick, pers. comm.). As gaps in the data can be either inherent in the data or due to an insufficient number of observations, it is best to first eliminate the gaps by binning the data into discrete ordinal classes. Finally, unlike parametric multivariate techniques, classification tree analysis is not sensitive to strong correlations among explanatory variables (i.e. collinearity), and in fact can take advantage of collinearity by identifying surrogate variables that can be applied in cases where an explanatory value is missing from a given observation (Breiman *et al.* 1984; De'ath and Fabricius 2000; Karels *et al.* 2004). Additional insights can be gained by examining alternative splitting criteria for a given node, defined by either a different threshold of the same variable or by a different variable (De'ath and Fabricius 2000). Four alternative splitting criteria are output by RPART for each parent node in the tree, rank-ordered by their relative improvement in classification for the resulting child nodes.

We created eight different classification trees reflecting the relative likelihood of observing either fires within all cover types (general fires) or fires that burned specifically within forests (forest fires) within a section according to four different size thresholds:

- all fire observations
- fires ≥0.4 ha (1 acre)
- fires ≥4 ha (10 acres)
- fires ≥16 ha (40 acres)

The number of fire observations decreased exponentially with increasing fire size threshold, with forest fires comprising roughly half of the fire observations within each size grouping (Fig. 3). PLSS sections containing fires meeting each of the above criteria were used as independent fire observations, and sections containing multiple fires were treated as independent observations, essentially weighting the section according to the number of fire observations they contained. For each set of fire observations, we randomly selected an equal number of sections that did not contain fires meeting the same fire size and type criteria. Random selection of non-fire sections was performed separately for each fire type and size combination defined above, because the set of sections without fire observations differed among size and type combinations (e.g. a section may contain a small fire observation, but not one larger than 16 ha (40 acres)). All continuous variables within each resulting dataset were binned into ordinal classes with a target size of 25 observations in each class to remove gaps in the data before analysis. Datasets for general fires ≥16 ha (40 acres) and forest fires ≥16 ha (40 acres) had smaller class sizes, averaging 14 and 8 observations, respectively, to provide an appropriate balance between the number of classes and the number of observations within classes.

A key component in classification tree analyses involves 'pruning' an overlarge tree to an appropriate number of splits, where the degree of pruning depends on the added contribution of new splits as well as the relative interpretability of the resulting tree (Breiman *et al.* 1984). We followed the methods of De'ath and Fabricius (2000) to select the appropriate tree size using 10-fold cross-validation, performed automatically by RPART. Specifically, we selected the tree size with either the minimum cross-validation error (minimum error rule), or the minimum tree size within one standard error of the minimum cross-validation error (1-SE rule). Choice of pruning rules depended on the sample size for the tree, which decreased rapidly with increasing fire size thresholds. Because the minimum cross validation error of classification trees is often imprecisely estimated (Breiman *et al.* 1984), we created a series of 50 classification trees for each fire size and class, and defined the optimum tree size (number of splits) based on the pruning rule and cross-validation results for each tree, and then selected the optimum tree size with the greatest frequency of occurrence within the 50 replicates (De'ath and Fabricius 2000).

The relative importance of the different independent variables was evaluated by their improvement (i.e. decrease) in misclassification error for a given split, as estimated by the relative change in the Gini index of impurity used to determine the split (Atkinson and Therneau 2000). Relative misclassification error (RME) and cross-validation error (CVE) for the final trees were scaled from 0 (no misclassifications) to 1 (null model of 50% misclassifications) (Atkinson and Therneau 2000). CVE was averaged across the 50 replicate trees. Predictions from selected classification trees were mapped by applying the fitted tree object to the independent variables for each PLSS section using the 'predict' function from SPLUS, where predicted values represented the relative probabilities of observing a fire observation given an equal sample of random non-fire observations. Large trees not easily displayed (i.e. trees with >25 splits) were summarised by graphically displaying the relative contribution of each variable, measured as the total decrease in impurity summed across all splits. The direction of influence (i.e. positive or negative) of the variable was also displayed, indicating whether increasing the variable above the threshold value deciding the split increased or decreased the likelihood of observing a fire observation.

Results

Correlations among independent variables

Linear correlations between independent variables across all PLSS sections indicated that several variables were interdependent (Table 4). Despite some very high correlations, all variables were retained in the analyses because even highly correlated variables had subtle differences that improved the classification trees. For example, population growth and housing density were very highly correlated ($\rho > 0.98$), but we found several instances where these two variables were not directly substitutable based on the alternative split information provided by RPART. Most of the strong correlations were expected, including the four soil variables (with each other), the strong positive association between road density and population and housing densities, and the strong negative association between forest and percentage agriculture or grassland cover (Table 4). Others were less obvious. For example, percentage of owner-occupied homes was positively associated with agriculture or grassland cover, and negatively associated with forested land cover (Table 4), indicating a higher proportion of rental and seasonal properties

Table 4. Pearson's correlation coefficients among independent variables

Only those variables with strong correlations (≥0.5, shown in bold) were included in the table. Variable abbreviations are defined in Table 1

	AWCH	AWCL	Drainage	Hydric	AG	Forest	RFF	PFR	PopDens90	HousDens90	PopGrowth	HouseGrowth	PctOwn	PctSeas	DistRoad	RoadDens	DistLgCity	DistSmCity
AugMaxT	−0.12	−0.15	0.17	0.25	0.46	−0.39	−0.21	−0.20	0.04	0.03	0.05	0.01	0.35	−0.37	−0.13	0.10	**−0.67**	−0.14
AWCH		**0.92**	**−0.59**	**−0.66**	−0.02	−0.03	−0.12	0.26	−0.06	−0.07	−0.06	−0.05	0.04	0.01	0.14	−0.17	0.06	0.01
AWCL			**−0.55**	**−0.75**	−0.10	−0.01	0.03	0.11	−0.05	−0.06	−0.06	−0.05	−0.03	0.05	0.14	−0.14	0.09	0.09
Drainage				**0.65**	−0.04	0.09	0.27	−0.47	0.03	0.07	0.07	0.04	−0.19	0.04	−0.20	0.24	−0.06	0.03
Hydric					0.21	−0.06	−0.09	−0.07	0.03	0.03	0.04	0.04	0.12	−0.12	−0.14	0.12	−0.21	−0.11
AG						**−0.86**	−0.34	0.11	0.06	0.02	0.05	0.06	**0.59**	−0.49	−0.28	0.19	−0.49	−0.44
Forest							0.22	−0.03	−0.18	−0.14	−0.06	−0.10	**−0.54**	0.46	0.21	−0.23	0.44	0.45
RFF								**−0.51**	0.02	0.05	0.02	0.00	−0.37	0.22	−0.07	0.16	0.21	0.28
PFR									−0.05	−0.08	−0.09	−0.05	0.22	−0.04	0.17	−0.26	0.08	−0.12
PopDens90										**0.98**	0.08	0.33	0.15	−0.12	−0.12	**0.60**	−0.12	−0.17
HousDens90											0.09	0.29	0.09	−0.07	−0.15	**0.64**	−0.08	−0.15
PopGrowth												**0.69**	0.06	−0.06	−0.09	0.19	−0.07	−0.10
HouseGrowth													0.11	−0.06	−0.08	0.28	−0.06	−0.15
PctOwn														**−0.58**	−0.10	0.07	**−0.55**	**−0.55**
PctSeas															0.14	−0.12	0.46	0.40
DistRoad																**−0.62**	0.12	0.14
RoadDens																	−0.11	−0.16
DistLgCity																		0.19

in forested areas. Presettlement fire rotation was also negatively correlated with relative forest flammability, indicating that current composition (i.e. fuel) characteristics of the forests are still associated, in part, with biophysical constraints imposed by soil type and landform.

Fire starts

The optimal tree size based on the 1-SE rule for general fire observations was 306 splits (RME = 0.31, CVE = 0.46 ± 0.006 s.e.). The first split was defined by a housing density value of 2.09 houses km^{-2}, where PLSS sections with housing densities greater than that value were more likely to contain fire observations. This first split decreased the majority of the misclassification error (39%), suggesting that housing density was by far the most important variable influencing general fire observations starts (Fig. 4*a*). Other relatively important human variables included road density, percentage owner-occupied homes, and distance to railroads (Fig. 4*a*). Important biophysical variables included the percentage of agriculture or grassland cover and relative forest flammability – both variables were positively associated with fire observations (Fig. 4*a*).

Optimal tree size based on the 1-SE rule for forest fire observations was 35 splits (RME = 0.44, CVE = 0.50 ± 0.009 s.e.). Again, housing density of 4.09 houses km^{-2} defined the first split and had the largest reduction in the misclassification error (39% decrease) (Fig. 4*b*). Road density was the next most influential human variable and had a consistently positive relationship with fire observations. The positive influence of forested land and negative influence of agriculture or grassland cover reflected the fact that fires were restricted to forests. Presettlement fire rotation and relative forest flammability were only moderately important predictors of forest fire observations.

Interpreting classification tree diagrams – fires ≥0.4 ha (1 acre)

Classification trees are interpreted as dichotomous keys; the decision variable is shown at each parent node, true statements flow to the left child node. For example in the classification tree created for general fire observations greater than or equal to 0.4 ha (1 acre) in size, the split at the first parent node was determined by the logical expression: population density $< 1.03\ km^{-2}$ (Fig. 5). Data meeting that criterion were less likely to be fire observations and flow to the left child, whereas data not meeting that criterion were more likely to be fire observations and flow to the right child. The vertical length of each branch reflects the reduction in misclassification rate from parent to child nodes. In this example, the first parent node based on population density reduced the majority of misclassification error in the tree. The left child node was split again (i.e. it became a new parent node) based on whether the presettlement fire rotation (a relative index) was greater than 3.27, a value near the midpoint between very short (1) and very long (5) presettlement fire rotations. Data meeting that criterion flowed to the left child node, which in this case was a terminal node predicting non-fire samples. Note that the splitting criterion for new parent nodes should be interpreted in the context of splitting criteria higher in the tree. In this example, the branching structure suggests that, given low population density and a high presettlement fire rotation, there is a very low likelihood of observing a fire greater than or equal to 0.4 ha (1 acre) in size. Nonetheless, 'less than' symbols generally indicated that the variable had a positive influence on fires in this type and size category, and 'greater than' symbols generally indicated that the variable had a negative influence on fires in this type and size category. Examining the remainder of the tree, increasing housing density and road density appeared to increase the likelihood of observing fires, whereas increasing the percentage of owner-occupied homes, distance to railroads, and percentage forest cover appeared to decrease the likelihood of observing fires in this type and size category. The two remaining variables, percentage agriculture and grasslands and August maximum temperature, had both positive and negative relationships with fire. This result may indicate a non-linear relationship. For example, increasing agriculture and grassland cover may increase the likelihood of fires up to a point (e.g. 76%) above which fire risk decreases. Alternatively, it is possible that the model simply over-fitted the data, such that short branches near the terminal nodes may not have had any real predictive power. In the case of August maximum temperature, we found no logical reason to explain the change in direction of influence.

The classification tree for forest fires greater than or equal to 0.4 ha (1 acre) in size was simpler than the previous tree, but similarly dominated by human factors (Fig. 6*a*). Forest fires in this size class were positively associated with road, housing, and population densities, in that order of importance (Fig. 6*a*). Percentage agriculture and grassland cover was again negatively associated with forest fires in this size grouping, though the threshold value for the split was near 50%, suggesting that agricultural and grassland cover types only reduced the likelihood of forest fires when they became the dominant cover type. Surprisingly, small percentages of water actually increased the likelihood of fires in this type and size grouping, perhaps owing to the increased human activity and development along lakeshores.

All four classification trees described thus far shared some common traits. First, the most influential variables were human factors. Second, the direction of influence between most factors, either human or biophysical, and the likelihood of fire observations was very consistent with our predictions for fire starts (compare Table 1 with Fig. 4 and Table 5). A few exceptions included home ownership patterns and percentage water. Comparison of misclassification error among the trees indicated that error increased with decreasing sample size, as expected (Table 6). In particular, classification trees for both general and forest fires greater than or equal to 0.4 ha (1 acre) had difficulty classifying non-fire observations. Nonetheless, misclassification error for the validation data was very similar to the error calculated for the original data, suggesting that the underlying relationships were robust (Table 6).

Larger fires

Classification tree results for larger fires (i.e. ≥4 ha (10 acres) and ≥16 ha (40 acres) size groupings) indicated a fundamental shift in the relative importance of human *v.* biophysical factors, with biophysical factors having greater influence over the likelihood of observing larger fires (Table 5). Land cover type strongly affected larger general fires, where increasing agriculture or grassland cover and decreasing forest cover

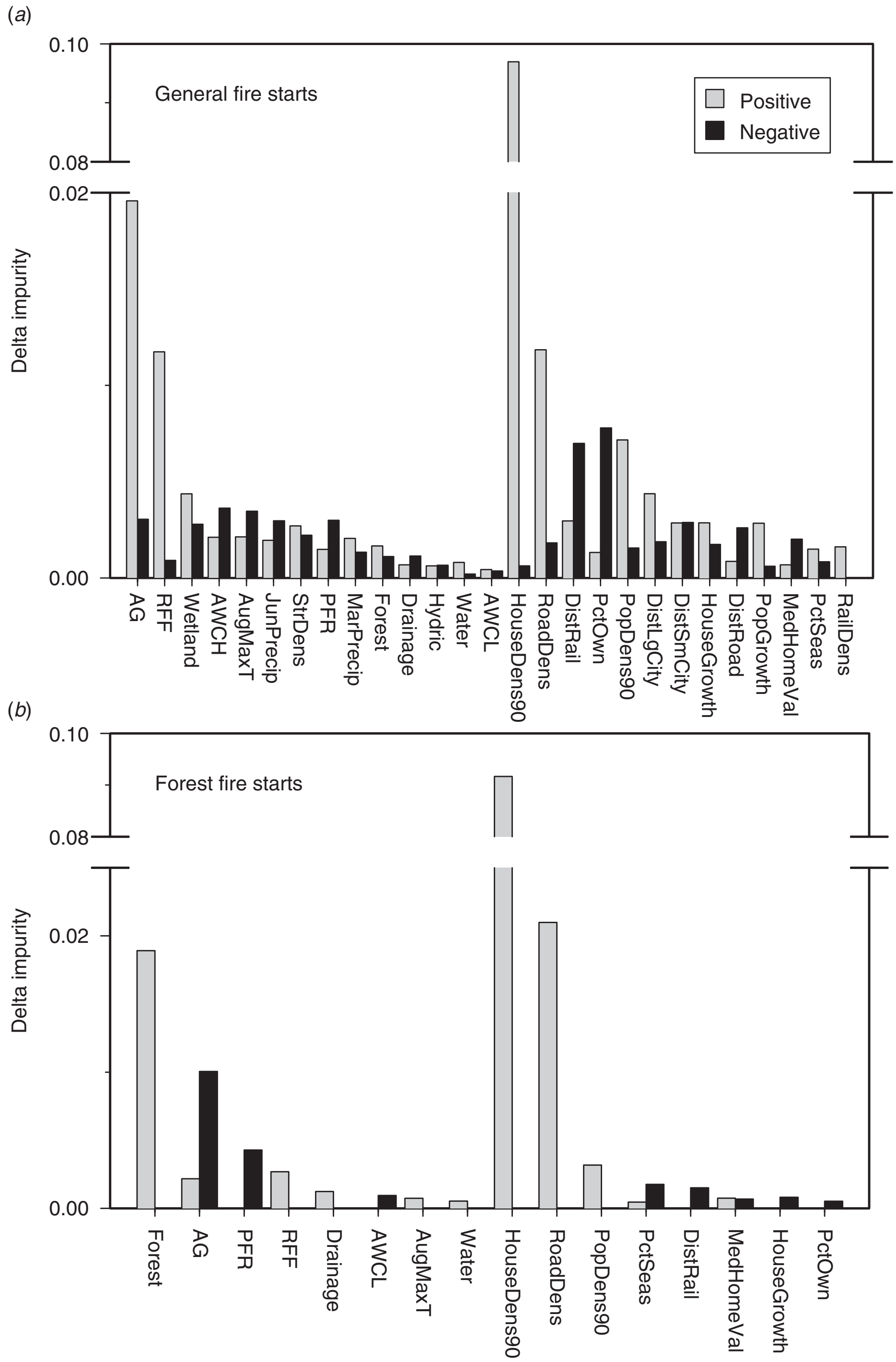

Fig. 4. Relative contribution of each independent variable, measured as the total decrease (delta) in impurity summed across all splits for both (*a*) general (i.e. all) fire observations, and (*b*) forest-specific fire observations. The direction of influence (i.e. positive or negative) of the variable indicates whether increasing the variable above the threshold value deciding the split increased or decreased the likelihood of observing a fire observation. Classification trees had (*a*) 306 for general fire observation and (*b*) 35 splits for fire observation models.

typically (but not always) increased the likelihood of observing larger fires (Table 5). Threshold values for these two variables were consistently low for percentage agriculture and grassland, and high for percentage forest cover (Fig. 7*a*, *b*), possibly because a mixture of land cover types increased fire risk. Population density was an important variable for influencing general fires in the largest size group, but in this case, an increase in population density decreased the likelihood of large fires (Fig. 7*b*),

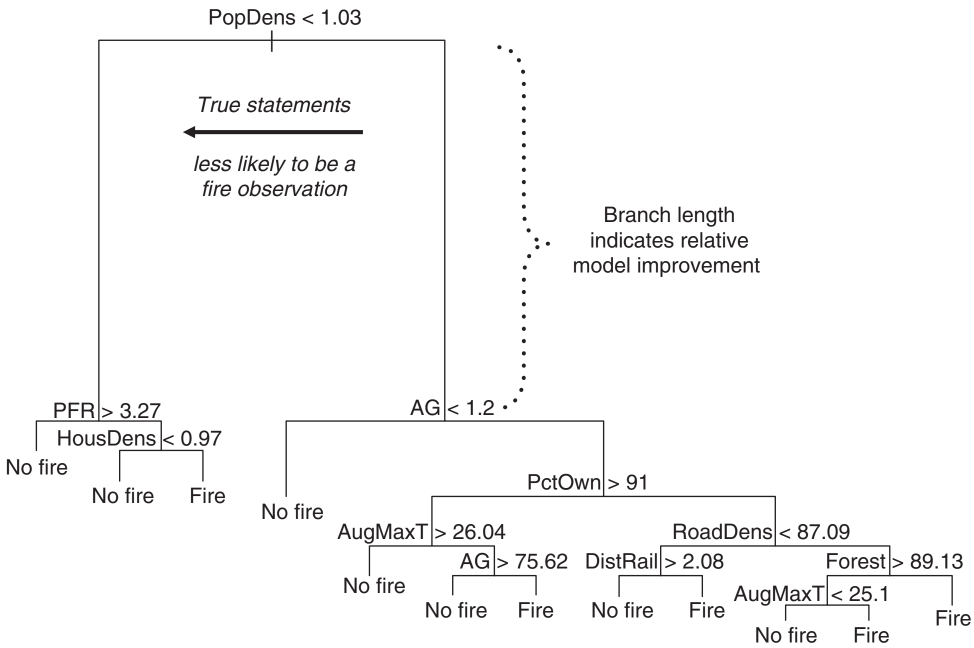

Fig. 5. Interpreting a classification tree – an example using the model for general fires ≥0.4 ha (1 acre). Branch length indicates the relative model improvement (i.e. reduction in misclassification error) accounted for by the split. True statements flow to the left, and the tree is organised so that terminal nodes for non-fire predictions are on left branches, and terminal nodes for fire predictions are on right branches. Variable abbreviations are defined in Table 1.

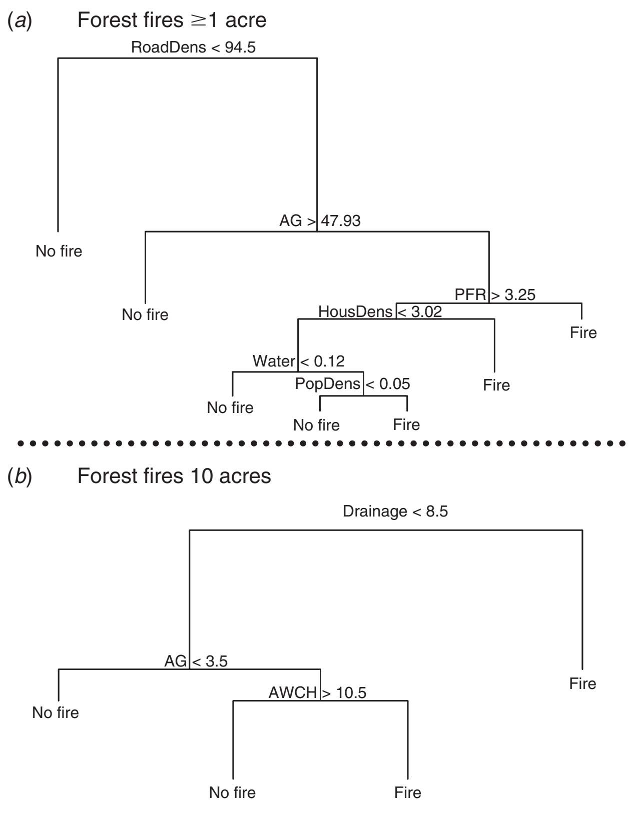

Fig. 6. Classification trees for (*a*) forest fires ≥0.4 ha (1 acre), and (*b*) forest fires ≥4 ha (10 acres). Variable abbreviations are defined in Table 1, and interpretation of the tree diagrams are described in Fig. 5.

consistent with our predictions that human development would be negatively associated with fire size (Table 1).

Larger forest fires were primarily associated with either soil moisture variables or presettlement fire rotation. The likelihood of forest fires greater than or equal to 4 ha (10 acres) increased with soil drainage and decreased with available water-holding capacity (Fig. 6*b*; Table 5). The classification tree for the largest forest fires greater than or equal to 16 ha (40 acres) had only a single split defined by a presettlement fire rotation index value of 2.45 (Table 5).

Discussion

Assuming that the spatial distribution of fire occurrence in the Wisconsin fire database is an unbiased indicator of the risk of fire starts, our results indicate that the likelihood of fire starts is primarily influenced by human activity, whereas biophysical factors determine whether those fire starts increase to larger fire sizes. This distinction provides insight into the interaction between humans and the environment as it affects fire occurrence and size, and suggests a combination of human activity and biophysical attributes contribute to fire risk in the region.

Human factors

Fire occurrence was overwhelmingly affected by housing density, for which population density was a close surrogate (Fig. 4). Cardille *et al.* (2001) did not observe such a strong relationship between fire occurrence and human population in the same region, which may have been due in part to their focus on fires greater than 0.4 ha (1 acre) in size. Nonetheless, the dramatic increase in fire observations with population and housing

Table 5. Direction of influence of independent variables on fire observations in different size and type groupings

The direction of influence (i.e. positive or negative) of the independent variables indicates whether increasing the variable above the threshold value deciding a split in a classification tree increased (+) or decreased (−) the likelihood of observing a fire observation in each of six fire size–fire type groupings. Double symbols indicate a primary split explaining the majority of misclassification error

Variable	GE1	GE10	GE40	GE1	GE10	GE40
Biophysical factors						
Mean maximum August temperature	+, −					
Available water-holding capacity (high)			−		−	
Soil drainage class			+		++	
Percentage agriculture and grassland	+, −	++		−	+	
Percentage forest	−	+	−			
Percentage water				+		
Stream density			−			
Relative forest flammability		+	−			
Presettlement fire rotation	−	−		−		−
Human Factors						
Population density (1990)	++		−	+		
Housing density (1990)	+			+		
Housing change (1990–2000)			−			
Percentage of homes occupied by owner	−					
Percent of seasonally occupied homes		+				
Road density	+			++		
Distance to railroad	−	−				
Distance to city >10 000 people		+				
Statistics						
Number of splits	11	8	9	6	3	1
Relative misclassification error	0.31	0.62	0.36	0.64	0.63	0.62
Cross-validation error	0.46	0.78	0.83	0.72	0.74	0.93
Standard error	0.01	0.03	0.07	0.02	0.05	0.12

Table 6. Classification tree validation results

Percentage of correctly classified observations by fire grouping for both model building and model validation datasets (75 and 25% of total dataset respectively)

Fire grouping	Classified fire obs.	Model building		Model validation	
		N	% correct	N	% correct
All fire observations	No	10 137	85.0	3376	77.6
	Yes	10 150	83.8	3363	75.6
All fires ≥0.4 ha (1 acre)	No	2410	60.0	775	56.1
	Yes	2363	75.7	822	75.7
Forest fire observations	No	5183	81.3	1687	79.0
	Yes	5087	73.9	1783	70.3
Forest fires ≥0.4 ha (1 acre)	No	1030	65.8	361	62.3
	Yes	1037	70.1	354	67.2

development has critical implications for fire risk within the wildland–urban interface (WUI) in this region. The WUI of northern Wisconsin is dominated by 'intermix', i.e. low–medium density rural housing developments where wildland fuels and homes intermingle (Radeloff *et al.* 2000*b*; Haight *et al.* 2004). Primary splits affecting general and forest-specific fire occurrence were 2.09 km^{-2} and 4.09 houses km^{-2}, respectively. Given that each is below the formal definition of WUI intermix (i.e. 6.17 houses km^{-2}; Radeloff *et al.* 2005), our results suggest that a permanent presence of people in the landscape strongly increases the risk of fire occurrence even at low densities.

Other studies of human-caused fires in northern forest ecosystems did not specifically evaluate the effects of human population *per se*, but rather human activities associated with roads, campsites and distance to municipalities (Vega-Garcia *et al.* 1995; Pew and Larsen 2001). Neither of these Canadian studies had the same extent of WUI intermix; hence, indicators of human access to wildland fuel sources were more logical indicators of the frequency of human observations. Our results did show road density as an important variable predicting fire occurrence (Figs 4, 5*a*). However, this variable is correlated with housing density ($\rho = 0.64$, Table 4) and its association with fire occurrence could be due to rural development, human access to wildland fuels, or both.

Studies from subtropical and tropical climates suggest that changes in fire risk associated with drought cycles can overwhelm human effects. Prestemon *et al.* (2002) found little evidence that rural development significantly affected fire

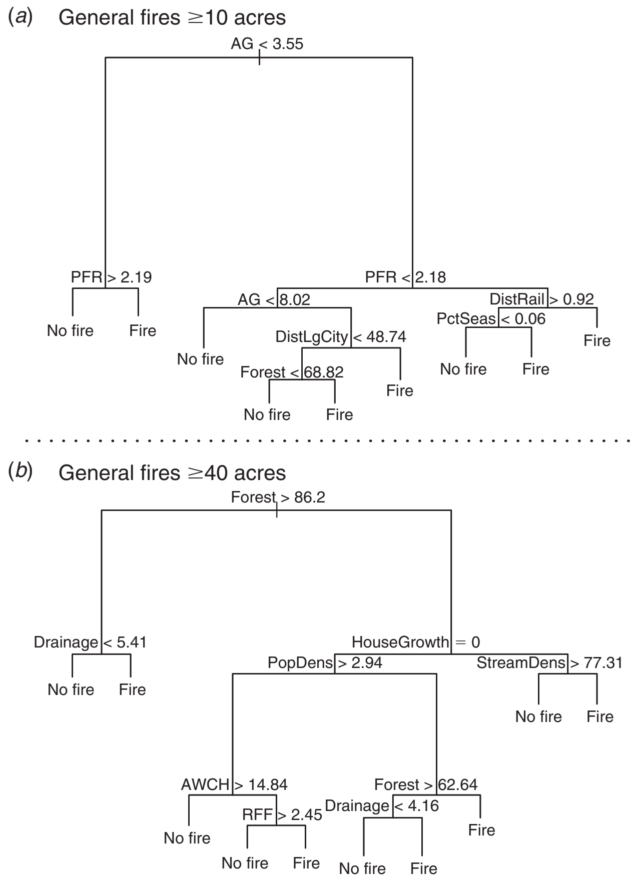

Fig. 7. Classification trees for (*a*) general fires ≥4 ha (10 acres), and (*b*) general fires ≥16 ha (40 acres). Variable abbreviations are defined in Table 1, and interpretation of the tree diagrams are described in Fig. 5.

risk within Florida, though they acknowledge that the county-level resolution of their analyses may have been too coarse to detect any human effects on fires. Similarly, an analysis of a fire database from the tropical Mexican state of Chiapas suggested that the spatial distribution of human populations only affected fire occurrence under extreme drought conditions controlled by the El Niño–Southern Oscillation (Román-Cuesta *et al*. 2003); such drought cycles had similar impacts on fire occurrence in subtropical Florida (Prestemon *et al*. 2002). Although drought cycles are typically less dramatic within northern temperate forests, they do affect fire risk there (Haines *et al*. 1978; Cardille and Ventura 2001). Our analyses did show that soil types susceptible to drought (i.e. high drainage and low available water-holding capacity) increased the likelihood of both fire occurrence and large fires (Fig. 4, Table 5). Clearly the interactions between spatial and temporal drivers of fire risk, such as drought, warrant further investigation in our study region (see *Study limitations and future directions* below).

Classification tree results showing that fire occurrence was positively associated with population, housing, road, and railroad density and negatively associated with distance to railroads and roads were consistent with our predictions that fire starts should be associated factors indicating human presence in the landscape (i.e. human development and infrastructure). Yet human variables explained little in the large fire models – this result was surprising because humans do have a huge influence on fire size via suppression policies enforced throughout the state. There was some evidence that population density was negatively associated with the largest fires (Fig. 7*b*; Table 5), suggesting that isolated homes may be more at risk from large fires, perhaps owing to delays in fire reporting or increased response time. Nonetheless, in general our results indicate that fire suppression activities in the study area are probably not limited by road access, and only somewhat related to the spatial distribution of rural communities.

Biophysical factors

Cardille and Ventura (2001) first documented that fires were both more common and generally larger within non-forest cover types relative to forested cover types in the Lake States. They speculated that open habitats support more flammable vegetation and promote human access to the landscape relative to closed forest conditions. Our results indicated that agricultural and grassland cover (or conversely, the absence of forest cover) was the most important biophysical variable affecting general fire observations in all size groupings. Such cover types are also often associated with rural housing development in the region (Radeloff *et al*. 2000*b*) that may enhance their relative ignition rates. However, the effects of agriculture or grassland or forest cover types were not always consistent with our expectations. For example, the percentage of agriculture and grassland cover types had both positive and negative influences on general fires greater than or equal to 0.4 ha (1 acre), and the percentage of forest cover had a positive influence on general fires greater than or equal to 4 ha (10 acres), despite the fact that the percentage of agriculture and grassland had a strong positive effect in the same classification tree (Table 5). Similarly, the percentage of agriculture and grassland had a positive influence on the likelihood of observing forest fires greater than or equal to 4 ha (10 acres) (Table 5). These results suggest that a mixture of agricultural and forest land cover types may increase fire risk.

Presettlement fire rotation and related indicators of soil moisture (i.e. soil drainage and available water-holding capacity) had very consistent relationships with the likelihood of fires of all types and sizes, and were the most important factors predicting large forest fires (Table 5). This result is consistent with earlier studies in Wisconsin and Michigan associating both historical and current fire regimes with glacial landforms that largely control the spatial distribution of different soil textures (Brubaker 1975; Cleland *et al*. 2004; Schulte and Mladenoff 2005). Our results are also consistent with the findings of Cleland *et al*. (2004), who found that the rank order of contemporary fire rotations was identical to that estimated for presettlement fire rotations in northern Lower Michigan, despite the fact that current fire suppression policies have increased fire rotations by roughly an order of magnitude relative to presettlement periods. Hence our results suggest that biophysical factors (principally soil texture) affecting fire regimes in the past remain important indicators of modern risk in the region.

In contrast, relative forest flammability was only influential for fire starts (Fig. 4), and was surprisingly absent from the majority of forest fire classification trees (Table 5). It is possible that our interpretation of vegetation characteristics that influence fuel conditions and relative fire risk (i.e. Table 3) was not accurate. Most fuel models developed in the United States have focussed on systems further west (Andrews 1986), and although eastern fuel types have received more recent attention (e.g. Scott and Burgan 2005), they are still under development. Still, the largest contemporary fires in Wisconsin are typically associated with crown fires in coniferous systems, especially pines (Radeloff *et al.* 1999), suggesting that fire risk is still associated at least in part with current forest cover. It is more likely that the satellite land cover classification was not precise enough to reliably characterise vegetation characteristics most relevant to forest fuels affecting surface fires. For example, the 'maple' class can contain either red maple systems, more likely to contain more xeric species such as oaks, or sugar maple systems, more likely to contain obligate mesic species such as basswood (WISCLAND, http://dnr.wi.gov/maps/gis/datalandcover.html/, accessed 24 July 2007). Litter decomposition and moisture conditions within each of these systems are expected to be quite different. Further, subtle differences in soil texture can have greater influence on understorey vegetation than the dominant tree cover (Host and Pregitzer 1991). In particular, sedges, bracken fern and ericaceous shrubs associated with dry-mesic forests have very different surface fire potential than succulent herbs within mesic forests that rarely burn. By comparison, the classified biophysical units (i.e. presettlement fire rotation) better account for understorey differences associated with soil texture. Whereas relative forest flammability was correlated with presettlement fire rotation (Table 4), the lack of response from the former may simply be because the latter was a better integrative measure of fire risk.

Human–biophysical interactions

Some counter-intuitive results were likely due to interactions among variables, and potentially seasonal trends that we did not account for directly in our analyses. We expected the likelihood of fire starts to increase with the percentage of owner-occupied homes, and decrease with the percentage of seasonal homes and with increasing distance from either large or small population centres ('cities'). Our classification tree results indicated the contrary, specifically for general fires (Fig. 4*a*; Table 5). Examination of correlations among independent variables reveals that these four variables were interrelated, and also related to land cover (Table 4). Hence regions closer to population centres tend to have more agriculture or grassland cover, a greater percentage of owner-occupied homes, and a correspondingly lower percentage of seasonal homes.

Post hoc interpretation indicated that the classification trees picked up a seasonal human–biophysical interaction that accounts for the above discrepancy between our predictions and results. Monthly fire occurrence and area burned shows the fire season in northern Wisconsin begins in March and ends in November, with April and May being the primary fire months and moderate fire activity occurring in March, June, July and October (Fig. 8). Seasonal patterns of fire occurrence and area burned were nearly identical, but open (i.e. agriculture or grassland) and wetland fires were more prevalent in early spring. Seasonal differences in the relative influence of a given independent variable can be evaluated by averaging the variable across all PLSS sections containing fires by month – if a variable has a

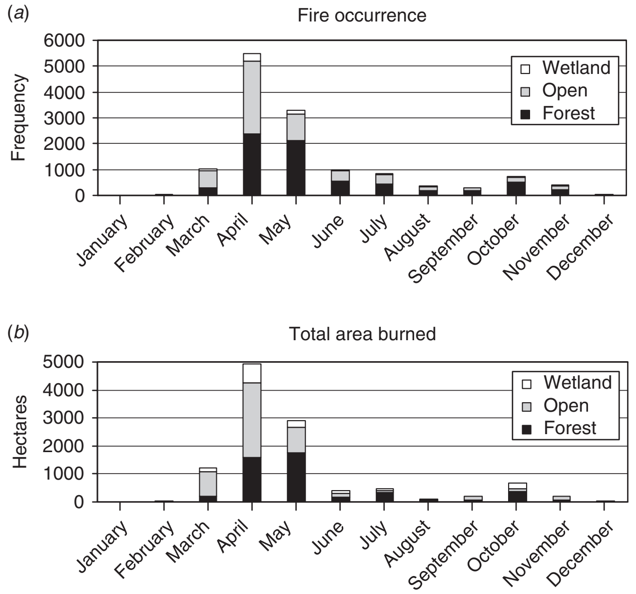

Fig. 8. Monthly summaries of (*a*) fire occurrence, and (*b*) total area burned by the cover type in which the fires occurred.

seasonal influence on fires, we should observe a corresponding change in the average monthly value of that variable for sections containing fires. We found the percentage of agriculture or grassland cover for sections containing fires was highest early in the fire season, and lowest during the period from May through October (Fig. 9), mirroring the seasonal trends for forest cover and consistent with the observed seasonal patterns of fire types (Fig. 8). The seasonal pattern of percentage of owner-occupied homes for sections containing fires was also depressed during the same period, with a corresponding increase in the percentage of seasonal homes for sections containing fires. The above trends suggest that the seasonal residents and other visitors in northern Wisconsin influenced the spatial distribution of fire occurrence from May through October. Our classification trees analysis apparently detected this seasonal interaction, first accounting for the large positive influence of agriculture and grassland on fire observations that occurred predominantly in early spring, and then indicating an influx of fire starts associated with seasonal visitors to the region later in the fire season. This interpretation is consistent with the observed positive influence of water on forest fires greater than or equal to 0.4 ha (1 acre) that likely reflects enhanced ignition rates associated with increased human development and activity along lakeshores (Table 5). This seasonal human–biophysical interaction further provides an alternative explanation for the inconsistent relationships between agriculture or grassland cover, forest cover, and fire occurrence (Table 5).

Study limitations and future directions

The above interactions and previous studies suggest that temporal factors such as weather, seasonality, drought cycles (Prestemon *et al.* 2002; Román-Cuesta *et al.* 2003) and economics (Prestemon 2006) can all influence fire risk in both space and time. Although our results could have been improved by incorporating temporal factors, our classification tree approach

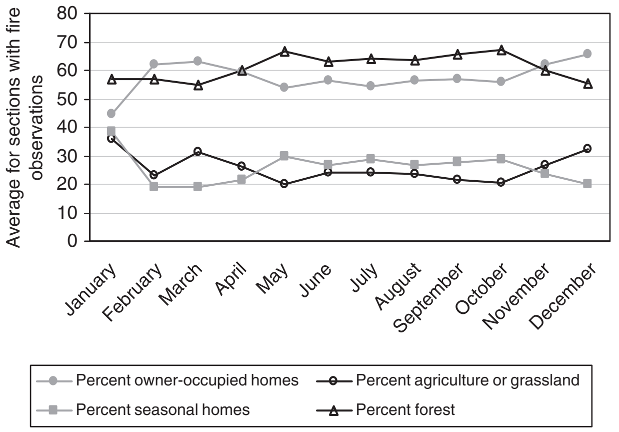

Fig. 9. Values of two land cover variables and two home ownership values averaged across all sections containing fires during each month. Average variables without any seasonal influence on fire occurrence should not fluctuate between months. This graphic suggests the seasonal influence during the period from May through October.

did not lend itself to a combined spatiotemporal analysis. This limitation may also explain why our climate variables were generally not useful (Fig. 4; Table 5). Future work could randomly assign dates to non-fire observations as a way to add temporal attributes such as weather or drought (S. Saunders, unpubl. data). Alternatively, it may be possible to first apply one analysis (e.g. temporal), and then apply the next (e.g. spatial) on the residuals. We suspect that this latter approach may work well for modelling general trends (e.g. seasonality) but will have difficulty addressing spatiotemporal interactions (e.g. Fig. 9).

Our results were also likely influenced by differences in the spatial resolution of both input variables and the fire observations. For example, we found presettlement fire rotations to be more influential than the actual soil variables. One possible explanation for this result is the SSURGO polygons from which presettlement fire rotations were mapped were simply more precise than the generalised STATSGO polygons used to estimate soil attributes. Variables such as drainage class or available water-holding capacity may have been more predictive if mapped at higher spatial resolution. Similarly, median house value could have had greater explanatory power if it were available at the block census level (i.e. higher resolution). Further, the spatial resolution of the fire observations was also poor (i.e. a PLSS section). Some of the factors examined (e.g. distance to road, current vegetation) are likely more relevant at finer spatial scales than that allowed by the fire database. Our results should therefore be interpreted in light of these mismatches in scale between independent and dependent variables.

Conclusions

Our results support the use of biophysical units defined by soil–landform–vegetation associations to identify areas of wildfire risk in northern Wisconsin. This finding is particularly significant because several areas within these fire-prone ecosystems are experiencing significant population growth, particularly in the vicinity of lakes (Radeloff *et al*. 2000*b*). Our analyses suggest that fire frequency will increase with this additional development. Given the relatively low wildfire risk within the broader region (Fig. 2), new residents typically have little appreciation of the fire risks surrounding their homes (R. Hammer, Oregon State University, pers. comm.). Further *post hoc* analyses suggest that seasonal visitors, many of them from urban centres, significantly influence fire risk in the region (Fig. 9). We expect conflicts between the restoration of fire-prone ecosystems, which will require active burning (Radeloff *et al*. 2000*a*; Stearns and Likens 2002), and the protection of human life and property to increase as these lands are further developed, unless proactive steps toward protecting property in these fire-prone regions (e.g. FIREWISE) are taken.

We also recommend that open land cover types, particularly grasslands, should be recognised as important contributors to wildfire risk in the region. Though the study area is primarily forested, our results indicated that even small percentages of agriculture or grassland increased the likelihood of wildfire. Conventional wisdom that pine forests represent the greatest fire risk can therefore be improved by including agriculture and grassland cover types as an additional risk factor.

Finally, we emphasise that the largest, arguably most important, fires are also rare and therefore difficult to predict. Very large fires in the region should occur only when the right combination of weather, fuel moisture, and contiguous fuels allow the wildfire to escape human control. Understanding the drivers underlying human fire starts, fire spread, and suppression efforts will help restrict the future occurrence of catastrophic wildfire events. Whereas classification tree analyses hold promise for evaluating the complex relationships between humans and biophysical variables as they influence fire risk, an approach that addresses both spatial and temporal variation in fire risk, in combination with improved resolution in fire records, should ultimately provide the best insight into fire risk in human-dominated fire regimes.

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