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ENVIRONMENTAL AND SOCIAL FACTORS INFLUENCING WILDFIRES IN THE UPPER MIDWEST, UNITED STATES

JEFFREY A. CARDILLE,[1,4] STEPHEN J. VENTURA,[2] AND MONICA G. TURNER[3]

[1]*Environmental Monitoring Program, University of Wisconsin, 1225 W. Dayton Street, 11th Floor: CCR, Madison, Wisconsin 53706 USA*
[2]*Environmental Studies and Soil Science, University of Wisconsin, 1525 Observatory Drive, Madison, Wisconsin 53706 USA*
[3]*Department of Zoology, University of Wisconsin, 432 Birge Hall, Madison, Wisconsin 53706 USA*

Abstract. Although the vast majority of contemporary wildfires in the Upper Midwest of the United States have a human origin, there has been no comprehensive analysis of the roles played by abiotic, biotic, and human factors in determining the spatial patterns of their origins across the region. The Upper Midwest, a 2.8×10^5 km^2 area in the northern, largely forested parts of the states of Minnesota, Wisconsin, and Michigan, contains regions of varied land cover, soil type, human settlement densities, and land management strategies that may influence differences in the observed spatial distribution of wildfires. Using a wide array of satellite- and ground-based data for this region, we investigated the relationship between wildfire activity and environmental and social factors for >18 000 reported fires of all sizes between 1985 and 1995. We worked at two spatial scales to address the following questions: (1) Which abiotic, biotic, and human variables best explained decade-scale regional fire activity during the study period? (2) Did the set of factors related to large fires differ from the set influencing all fires? (3) Did varying the spatial scale of analysis dramatically change the influence of predictive variables? (4) Did the set of factors influencing the number of fires in an area differ from the set of factors influencing the probability of the occurrence of even a single fire?

These data suggest that there is no simple ''Lake States fire regime'' for the Upper Midwest. Instead, interpretation of modern fire patterns depends on both the fire size considered and the measurement of fire activity. Spatial distributions of wildfires using two size thresholds and viewed at two spatial scales are clearly related to a combination of abiotic, biotic, and human factors: no single factor or factor type dominates. However, the significant factors for each question were readily interpretable and consistent with other analyses of natural and human influences on fire patterns in the region. Factors seen as significant at one scale were frequently also significant at the other, indicating the robustness of the analysis across the two spatial resolutions. The methods for conducting this spatially explicit analysis of modern fire patterns (generalized linear regression at multiple scales using long-term wildfire data and a suite of environmental and social variables) should be widely applicable to other areas. Results of this study can serve as the basis for daily, seasonal, or interannual studies as well as the foundation for simulation models of future wildfire distribution.

Key words: fire; forest; generalized linear regression; landscape patterns; Michigan; Midwest; Minnesota; spatial analysis; spatial scale; wildfire; Wisconsin.

INTRODUCTION

Wildfire risk has become a major concern in recent years, particularly where humans live in close proximity to forests (Goldammer 1991, USDA 1996, Greenberg and Bradley 1997, Lavin 1997). The Upper Midwest of the United States has a history of large, costly fires (e.g., Sando and Haines 1972, Simard et al. 1983, Baumgartner and Marty 1988), but no comprehensive study has been made of the factors in the region that influence wildland fires—uncontrolled, wild, or running fires on forest, marsh, or other nonstructural property (Wisconsin 1997). This study assessed the significance of environmental and social factors that may influence the presence and number of wildfires throughout the northern, largely forested parts of Minnesota, Wisconsin, and Michigan.

In much of the upper Midwest, lightning-caused fire and burning by Native Americans played a large role in forest processes during the presettlement period, driving succession and hindering the development of fire-intolerant species (Curtis 1959, Vogl 1971, Frissell 1973, Heinselman 1973, Whitney 1986, Loope 1991, Loope and Anderton 1998, Zhang et al. 1999). Evidence of fire has been found even in areas where fire was not the dominant disturbance (Frelich and Lorimer

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[4] E-mail: cardille@students.wisc.edu

1991). Historical patterns of Native American occupancy are often consistent with fire history patterns (e.g., Batek et al. 1999). In one study, ignition by humans was considered to account for more than half of the presettlement fires (Loope and Anderton 1998). However, the relative influences of climate, fuels, and cultural patterns on presettlement fire regimes in eastern North America, including the Upper Midwest, remain relatively poorly understood due to a lack of relevant historic or paleoecological data (Clark and Royall 1996).

Whereas wildfire origin locations may once have been determined largely by environmental factors, ample evidence indicates that fire occurrence and size are strongly influenced today by human settlement and activity (Main and Haines 1974, Harrington and Donnelly 1978, Stocks et al. 1996). Though lightning remains a major cause of wildfire in the western United States (Marsden 1982, USDA 1987), it plays only a small role in the modern fire regime of the forested region of the Upper Midwest (e.g., Haines et al. 1975). For example, 93% of all fires $>$4 ha in national forests of Minnesota, Wisconsin, and Michigan in 1986 were caused by humans, compared to only 47% of such fires in the full set of U.S. national forests (USDA 1987). Active fire suppression, another major human activity influencing fire sizes and patterns, limits the area burned, can change the overall fire frequency (Clark 1990, Frelich and Lorimer 1991, Kronberg et al. 1998), and may allow species combinations to change (Heinselman 1973, Swain 1980). The pervasive influence of humans on wildfires in the Upper Midwest is best summarized by Heinselman (1981), who said that human impacts of all kinds have ''so greatly lengthened and modified natural fire cycles, that they are no longer relevant'' except to understand presettlement ecosystems and to work with nature reserves.

Attempts to assess wildfire risk in other parts of the world have typically been implemented as Geographic Information System-based overlays (Burgan and Hartford 1988, Chuvieco and Congalton 1989, Julio 1990, Chou et al. 1993, Castro 1994, Salas and Chuvieco 1994, Carapella 1996, Gonzalez-Alonso et al. 1997). However, we chose not to duplicate these methods for the Upper Midwest, as such studies usually are performed at only a single scale using subjective assessment of the influence of local fire factors. In the Upper Midwest and elsewhere, empirical models of wildfire prediction have used weather information to predict variation in fire occurrence per day (Haines and Main 1978, Haines et al. 1983, Martell et al. 1987, 1989, Todd and Kourtz 1991, Garcia Diez et al. 1994), per month (Harrington et al. 1983, Flannigan and Harrington 1988), or per year (Balling et al. 1992).

A few studies have sought to quantify and assess social factors that may also influence fire activity. Donoghue and Main (1985) found that nonmetropolitan population density, a law enforcement measure, and a latitude variable explained about half the annual variation in fire occurrence in an analysis of monthly wildfire frequency in national forests across the eastern United States. Vega Garcia et al. (1995) explored the influence of both geographic and weather-driven variables in a logistic regression that predicted human-caused forest fires in the Whitecourt Forest of Alberta. Although they found that many of their human factors, such as the distances to roads, towns, and campsites did not significantly explain variation in the daily occurrence of human-caused forest fires, their method of multiple logistic regression provided a useful framework for analyzing and assessing the influence of environmental and social variables on measures of fire activity.

This paper presents the first quantitative investigation of biotic, abiotic, and human factors influencing wildfire activity in the northern Great Lakes region between 1985–1995. In particular, we had the following objectives during this study: (1) to determine which abiotic, biotic, and human variables best explained decade-scale fire activity during the study period; (2) to assess whether the set of factors related to large fires differed from the set influencing all fires; (3) to judge whether varying the scale of analysis dramatically changed the influence of predictive variables; and (4) to determine whether the set of factors influencing the number of fires in an area differed from the set of factors influencing the probability of the occurrence of even a single fire.

Methods

Study area

The 2.8×10^5 km^2 study area centered on the northern, forested region in the states of Minnesota, Wisconsin, and Michigan (Fig. 1). It included the part of those counties containing or north of the boundary of the Laurentian Mixed Forest Province (Bailey 1995) where the appropriate state agency or the USDA Forest Service had primary attack responsibility for wildfires. Nearly all forests of the Laurentian Mixed Forest Province have been logged at least once (Pyne 1982). Vegetation includes: upland conifer forests, peatlands, and conifer swamps in northern and eastern Minnesota; aspen parkland and prairie in northwestern Minnesota; and northern hardwood forests, white pine/red pine forests, and jack pine barrens in northern Wisconsin, the Upper Peninsula of Michigan, and the northern Lower Peninsula of Michigan (Albert 1995).

Database development

Two new data sets were used in this study. The first, the Lake States Fire Database (Cardille and Ventura, *in press*), was made from recent fire records (1985–1995) recorded in state and federal databases. The second, the Fire Factor Database, consisted of environmental and social characteristics we believed to be as-

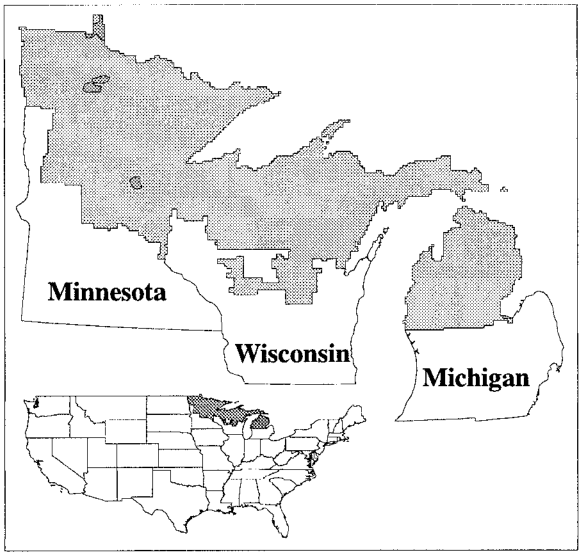

FIG. 1. Study area within Minnesota, Wisconsin, and Michigan for analysis of factors influencing wildfires.

sociated with fire probability and frequency. Observed spatial patterns and the relationships between pattern and process are strongly dependent upon the spatial scale of analysis (Allen and Starr 1982, O'Neill et al. 1986, Turner 1989, Turner et al. 1989, Levin 1992, O'Neill et al. 1996). For example, rare elements on the landscape typically become less well represented as resolution decreases and the representation of spatial complexity may decrease (e.g., Turner et al. 1989, Moody and Woodcock 1995, Cain et al. 1997). Therefore, our study was conducted using data at two resolutions: a ''coarse'' grid of 10-km square cells; and a ''fine'' grid of 5-km cells. The gridded framework permitted the co-registration of a large amount of spatial data; grids at two different resolutions allowed us to determine whether results were robust across these scales. These scales also represented a reasonable level of resolution for a study area that covered such a large spatial extent.

Lake states fire database.—The Lake States Fire Database was produced by combining computerized fire records from the Departments of Natural Resources from Minnesota, Wisconsin, and Michigan with fire data from the USDA Forest Service. This database records the origin point, reported date of origin, and cause of each wildland fire that occurred within the study area between 1985 and 1995. The point of origin of each fire was recorded to the nearest 1.6 km in the database; it contains more than 18 000 records for fires of all sizes.

Since factors influencing all fires might be different from factors influencing only large fires, we used fire size to consider separately those fires larger than two size thresholds. The size of each wildfire was used to stratify the fire database such that the ''all-fire'' set contained all fires with final burned area $\geq$ 0.4 ha, while the ''large-fire'' set contained those $\geq$ 40 ha.

Using the two analysis grids, we constructed eight spatially explicit fire data sets, which together represent broadscale patterns of wildfire activity in the study area during the entire study period. Of these eight, four ''fire occurrence'' data sets were constructed using the following method: for each cell of a given analysis grid, we determined whether one or more fires larger than or equal to a given size threshold (i.e., 0.4 or 40 ha) originated within that cell's boundaries between 1985 and 1995. Cells with at least one such fire were considered ''fire cells'' for that grid and size threshold; this created a set of four binary maps. The remaining four fire data sets were formed by counting the number of fires that originated within each grid cell's borders and satisfied a given size threshold. This created a set of four ''fire counts'' maps with grid cells having values $\geq$ 0.

Although lightning is still an important cause of fires in other parts of the United States (e.g., USDA 1987), Cardille and Ventura (*in press*) found that the vast majority of wildfires recorded in the Lake States Fire Database were caused by humans. Lightning was the cause of only 2.8% of all fires recorded and the cause of only 3.4% of large fires during the study period. Thus, although they may be driven by different factors from human-caused fires, lightning-caused fires were not considered separately for this study.

Fire factor database.—Factors influencing the ignition and growth of wildfires have been very well studied (e.g., Deeming 1977), and we made no attempt to expand upon the rich body of work that seeks to model the behavior of individual fires. To determine which factors should be incorporated into a decade-scale model of fire occurrence and fire counts, we used a conceptual model of wildfire development in the Upper Midwest, including ignition potential and frequency, fire development and spread, probability of a fire being reported, and probability of fire suppression and methods used (Table 1). In this conceptual model, the ignition potential of wildfires is related to both the probability of ignition by natural causes and to human use and access. Fire development and spread are related to fuel abundance and connectivity, soil and vegetation moisture, and weather and climate patterns. We expected that the probability of a fire being reported varies by reporting organization and accessibility of the area, while fire suppression and methods vary by the different management objectives of land ownership in the region, accessibility of land to fire fighting equipment, and the threat to people and structures.

Since the data we sought to predict were the decade-scale spatial patterns of wildfire occurrence and counts, we chose to focus on those factors that (1) were directly measurable in the landscape across the entire study area; (2) could represent, as a single value in each cell, the decade-scale status of some environmental or social

TABLE 1. Conceptual model of wildfire development in the Upper Midwest, with Fire Factor representation.

Wildfire stage	Influences	Fire Factor representation
Ignition potential and frequency	Human use and access	Rail Density Road Density Distance to City Population Density Proportion of Seasonal Units Proportion of Owner-Occupied Units
	Natural causes	Not explicitly represented
Fire development and spread	Soil and vegetation moisture	Available Water Capacity
	Fuel abundance and connectivity	Land Cover Lake Density Stream density
	Weather and climate patterns	Mean March Precipitation Mean August Maximum Temperature Mean June Precipitation
Probability of a fire being reported	Wildfire reporting organization	State
	Area accessibility	Road Density Distance to Nonforest Distance to City
Probability of fire suppression and methods used	Management objectives	National Forest Federal Land—Other State Forest State Land—Other Indian Reservation
	Accessibility of fire fighting equipment	Rail Density Road Density Distance to Nonforest Distance to City
	Threat to people and structures	Population Density National Forest, State Forest and Others

variable; (3) varied substantially across the study area at the two analysis scales; (4) were plausible influences on the ignition potential, growth potential, reportability, or suppression of wildfires; and (5) were not highly correlated in the study area with any other factors.

Elements of the Fire Factor Database were used to represent the influences on wildfires (Table 1). The same factor may influence, for example, both fire ignition potential and the probability of fire suppression (Table 1); to avoid repetition we present each factor below according to whether it is a biotic, abiotic, or human factor.

1. *Biotic factor: Current Land Cover*.—Because some forest types in the Upper Midwest have been associated with higher incidence of fire (e.g., Whitney 1986), and because several studies of fire patterns (e.g., Chuvieco and Congalton 1989, Chou et al. 1993, Castro 1994, Salas and Chuvieco 1994) have included land cover as a factor influencing fire risk, we incorporated an assessment of land cover. Expecting that the land cover would influence wildfires by influencing fire development and spread primarily through variations in fuel abundance and connectivity (Table 1), we obtained the USDA Forest Service forest classification data set (Powell et al. 1992). Derived from NOAA advanced very high resolution radiometer (AVHRR) images and ancillary data, this data set classifies each 1-km pixel into one of the following categories: White-Red-Jack Pine; Spruce–Fir; Oak–Hickory; Elm–Ash–Cottonwood; Maple–Beech–Birch; Aspen–Birch; Nonforest; and Water. The coarse and fine grids were populated with Current Land Cover data following Cardille and Ventura (*in press*) (Table 2).

2. *Abiotic factors: Available Water Capacity (AWC)*.—This factor is defined as ‘‘the volume of water that should be available to plants if the soil, inclusive of rock fragments, were at field capacity’’ (Miller and White 1998). We expected AWC to play a role in fire development and spread through its influence on soil and vegetation moisture (Table 1). Soil moisture conditions have been linked to wildfires in the Upper Midwest (Vogl 1971, Heinselman 1973, Whitney 1986,

TABLE 2. Fire Factors and their grid interpretations methods in the Fire Factor Database.

Fire Factor name	Source for computation	Data source type	Grid interpretation method	Continuous or categorical?
Biotic factor				
Current Land Cover	†	raster	Majority chosen‡	categorical
Abiotic factors				
Available Water Capacity	STATSGO database	polygon	Area weighting§	continuous
Lake Density	Lake coverage	polygon	Total area per grid cell	continuous
Stream Density	Stream coverage	line	Total length per grid cell	continuous
Mean March Precipitation	†	raster	Averaging filter	continuous
Mean August Maximum Temperature	†	raster	Averaging filter	continuous
Mean June Precipitation	†	raster	Averaging filter	continuous
Human factors				
State	State boundaries	polygon	Grid center point	categorical
Rail Density	Railroad coverage	line	Total length per grid cell	continuous
Road Density	Road coverage	line	Total length per grid cell	continuous
Distance to Nonforest	Distance to Nonforest in Current Land Cover	raster	Direct calculation	continuous
Distance to City	City coverage	point	Distance from cell center to nearest city point	continuous
Population Density	Census block coverage	polygon	Area weighting	continuous
Proportion Seasonal Units	(Vacant Units)/(Housing units)	polygon	Area weighting	continuous
Proportion Owner-Occupied Units	(Owner-Occupied Units)/(Housing Units)	polygon	Area weighting	continuous
National Forest	Ownership coverage	polygon	Percentage area per grid cell	categorical‖
Federal Land—Other	Ownership coverage	polygon	Percentage area per grid cell	continuous
State Forest	Ownership coverage	polygon	Percentage area per grid cell	categorical‖
State Land—Other	Ownership coverage	polygon	Percentage area per grid cell	continuous
Indian Reservation	Ownership coverage	polygon	Percentage area per grid cell	categorical‖

† Not computed; obtained directly as raster data.
‡ Ties: selected random pixel.
§ Area weighting assumed uniform density of the item being weighted. For example, if 20% of a 300-person block lay in cell A, and 80% of the block lay in cell B, that block contributed (300×0.20) = 60 to the calculated amount for cell A, and the remaining 240 to the amount for cell B.
‖ Using 50% rule; e.g., if a given cell was ≥ 50% National Forest, it was given a "1" for National Forest.

Loope 1991) and elsewhere (Carapella 1996). In the Upper Midwest, Loope (1991) found that areas with coarser soils (and thus lower AWC) were linked to land covers and surface conditions favoring greater fire frequency. We expected that soils with greater AWC would tend to allow fuel buildup to a point where a larger fire was more probable during the study period. We estimated the Available Water Capacity value to a depth of 1 m for each state soil geographic database (STATSGO) map unit (USDA 1994) following Miller and White (1998). The derived map unit coverage was weighted by area to determine the value of each pixel in both the coarse and fine analysis grids (Table 2).

3. *Abiotic factors: Lake Density.*—Because parts of the study area have a very high density of lakes, we expected that this factor would affect fire development

and spread through its influence on fuel connectivity throughout the study area (Table 1). Because of the several very large lakes in the study area, furthermore, we believed that cells with very high Lake Density values would witness fewer fires as well as fewer large fires. Using the United States Geological Survey's (USGS) 1:100 000 Digital Line Graphs (DLGs), a lake coverage was created for Minnesota, Wisconsin, and Michigan. For each grid size, a Lake Density data set was then created in which the density value in a cell represented the proportion of each cell's area that had been classified as a lake (Table 2).

4. *Abiotic factors: Stream Density*.—We expected that the density of streams in the study area, like the density of lakes, would influence fuel connectivity and might also be an important correlate of typical soil moisture (Table 1). Using USGS 1:100 000 DLGs, a line-based stream coverage was produced. A Stream Density data set was then produced using each analysis grid to determine the total length of stream in each grid cell (Table 2).

5. *Abiotic factors: 30-year Mean Climate Data*.—Daily weather patterns, while reasonable predictors of daily fire activity, may be temporally too fine for a decade-scale study. Daily high temperatures, for example, on adjacent days in an area are very highly correlated and would disrupt the reliability of the regression models; furthermore, variability inherent in the sheer volume of daily data would likely dwarf the explanatory power presented by the other factors in a model.

To match the scale of weather and climate patterns to our decade-scale questions, we used climate variables representing mean monthly values in the study area. The ZedX Corporation (Boalsburg, Pennsylvania, USA) provided gridded data at 1-km spatial resolution for monthly historical climate indicators for the study area. This information was produced as a set of 12 monthly means for 1961–1990 and included Mean Maximum Temperature, Mean Minimum Temperature, and Mean Precipitation. With data for each of 12 months and each of three indicators (e.g., Mean Maximum Temperature for July), this resulted in 36 gridded data sets at each analysis scale.

A factor analysis (Venables and Ripley 1997) of these 36 potential variables indicted that 95% of the climate data variability could be represented by three nearly orthogonal, biologically meaningful climate variables that would serve to represent the variation in the climate data. The three selected climate variables, Mean March Precipitation, Mean August Maximum Temperature, and Mean June Precipitation (Table 2), had several important attributes: they were very highly correlated with the first, second, and third significant factors; they were only very mildly correlated with each other, having no pairwise Pearson correlation above 10% in the set; and they were plausible predictors for questions of climatic influence on decade-scale fire occurrence and fire counts. We expected that in a given 10-km or 5-km cell, the Mean June Precipitation and Mean August Maximum Temperature were related to the relative heat and dryness of summer in an area, which would likely affect fire development and spread (Table 1). This was consistent with Flannigan and Harrington (1988), who found that the monthly maximum temperature correlated well with monthly area burned in Canada between 1953 and 1980. We expected that Mean March Precipitation would influence fire development and spread in the spring, when most fires occur (Cardille and Ventura, *in press*).

6. *Other abiotic factors*.—Although wind conditions are known to influence the spread and suppression of individual wildfires, no decade-scale data on wind conditions were available for this study. Wind conditions, with their high variability in speed and direction through time and across space are quite different from, for example, Lake Density, which is spatially variable but can be reasonably assumed to be temporally stable during the study period. Inclusion of wind would have necessitated using some spatially explicit composite measure of wind for the study period, which was unavailable to us and was found to be of negligible value in explaining monthly area burned in Canada (Flannigan and Harrington 1988). Topographic variation in the study area was also not explicitly incorporated in the analysis: changes in elevation are quite small compared to other well-known fire-prone areas such as the western United States.

7. *Human factors: State*.—We expected that by-state differences in fire reporting may have existed during the study period (Table 1). We also expected that these differences could have extended to the resources available for fire suppression, human access to burnable land during fire-danger periods, or cultural attitudes toward fire. Accordingly, we included a categorical variable for State from an Environmental Systems Research Institute (ESRI) (Redlands, California, USA) state polygon coverage.

8. *Human factors: Rail Density, Road Density*.—Following the historically strong relationship between fire occurrence and railroad sparks (Harrington and Donnelly 1978) and the very high proportion of Upper Midwest wildfires that are caused by humans (Cardille and Ventura, *in press*), we expected Rail Density and Road Density to influence ignition potential and frequency (Table 1). We expected further that the density of the road network would strongly affect the probability of a fire being reported by driving the level of human residents and visitors in an area (Table 1). Since fire suppression equipment is often brought to the scene by road or rail, we also expected the accessibility of fire fighting equipment to be related to these two factors (Table 1). Using USGS 1:100 000 DLGs, a line-based road coverage was produced for the study area and converted using the two analysis grids to Road Density

data sets (Table 2). The same process was used to produce Rail Density data sets (Table 2).

9. *Human factors: Distance to Nonforest*.—We expected that the distance from a grid cell to the nearest area of Nonforest would influence both the likelihood that a fire is discovered and reported as well as the accessibility of a reported fire to the delivery of suppression equipment (Table 1). Although in a univariate analysis Cardille and Ventura (*in press*) found that both all fires and large fires were more frequent on Nonforest, we believed that areas very far from Nonforest might, if a fire were to begin there, tend to become larger than fires nearer to Nonforest. To create this factor, we used the Nonforest cells of the Current Land Cover factor to compute the Distance to Nonforest for each cell at both analysis resolutions (Table 2).

10. *Human factors: Distance to Nearest City Larger Than 10 000 People*.—Following Vega Garcia et al. (1995), who found that the district of their study forest nearest to a large city had a higher daily likelihood of fire, we expected that the distance to a city would influence the human use and accessibility of an area, affecting ignition potential and frequency. The proximity of a city could also be expected to influence the reportability of a fire, and ease of delivering fire suppression equipment to the scene (Table 1). This factor was created using an ESRI point-based coverage of cities of $>$ 10 000 people in the United States, to determine the distance from each cell in the study area to the nearest such city. Where the nearest city was outside the Unites States, an ESRI Canadian city map was used.

11. *Human factors: Population Density*.—Because humans caused the vast majority of wildfires in this region during the study period (Cardille and Ventura, *in press*), a factor expressing the omnipresent effect of population was critical. The influence of human population can be seen in most stages of a reported fire's life cycle (Table 1): the population in an area drives the human use of that area and thus the likelihood that part of that area will be ignited; it influences the probability (through a proxy such as Road Density) that a fire is reported; and the people and property in an area affect the probability of fire suppression and the methods used. To create this factor, block-level data from the 1990 U.S. Bureau of Census population census (U.S. Bureau of the Census 1991) was calculated in each grid cell at both analysis resolutions (Table 2). Because the range of this factor across the study area was several orders of magnitude, we transformed Population Density values using the base 10 logarithm. A small value was added to each cell before calculating the logarithm, to ensure that zero-population cells would not contain a spurious value.

12. *Human factors: Proportion of Seasonal Units, Proportion of Owner-Occupied Units*.—Since most wildfires in the region are caused by local permanent residents (Main and Haines 1974) and since many fires in the region during this period were caused by the accidental ignition of land during refuse burning (Cardille and Ventura, *in press*), we expected that ignition potential and frequency was influenced by the seasonality and ownership of housing across the region (Table 1). Using block-level data from the 1990 U.S. census, the Proportion of Seasonal Units in each grid cell was calculated by dividing the number of vacant units by the total number of housing units in the cell. Census data reveal that in this part of the Upper Midwest, seasonal units account for $\sim$ 90% of vacant housing units in most counties (U.S. Bureau of the Census, 1991). Dividing the number of owner-occupied housing units by the number of occupied units formed the second factor, Proportion of Owner-Occupied Units (Table 2). Grid cells with no housing units (in the first case) or no occupied housing units (in the second) were given a small negative value for the appropriate factor to prevent division by zero.

13. *Human factors: National Forest, State Forest, Indian Reservation*.—We expected that the management objectives of different ownership organizations would directly influence fire suppression effort and methods in the region (Table 1). We believed that ownership status would affect fire fighting philosophy, financial and material resources available at the state and federal levels, and the regional patterns of the distribution of limited suppression resources. Although it is not shown in Table 1, we also believe that ownership status could, through different forest management strategies, perhaps also affect fuel abundance and connectivity and thus the probability of fire development and spread. A univariate analysis of Upper Midwest fire patterns (Cardille and Ventura, *in press*) revealed differences in fire probabilities by ownership: fires during this period were less likely, for example, to occur within national forest boundaries. Using the ownership data set of McGhie et al. (1996), the area of each cell that was National Forest, State Forest, and Indian Reservation was calculated and stored as three separate factors. Interpretation of the polygon coverage for the National Forest factor in both the coarse and fine analysis grids revealed that $>$ 70% of cells had a proportion of National Forest area that was within 10% of either 0 or 1. We judged that this factor was thus more appropriately represented as a binary variable than as a continuously varying density. Grid cells whose area was $>$ 50% National Forest were coded as National Forest. An identical test was used for the State Forest and Indian Reservation variables; as a result, they too were categorized as binary variables.

14. *Human factors: Federal Land—Other, State Land—Other*.—Like the other ownership categories, these two factors were postulated to influence wildfires primarily through differences in fire suppression effort and methods (Table 1). Federal Land—Other represented that land, other than that controlled by the USDA Forest Service, which is managed by the federal

government. This included such classes as National Parks, National Lakeshores, and National Scenic Rivers. Developed from the McGhie et al. (1996) polygon coverage, Federal Land—Other was coded as a continuous variable since substantially $<$ 70% of Federal Land—Other cells were near 0 or 1. State Land—Other represented that land, such as State Parks and State Wilderness Areas, under direct state control but not part of the State Forest system. This factor was developed using the McGhie et al. (1996) data set and was represented as a continuous variable.

15. *Human factors: Other human factors*.—Several other factors that could be expected to influence fire frequency were produced from the block-level census data and considered for addition to the Fire Factor Database; however, because their incorporation would have produced a seriously multicollinear set of predictors, they were not included in the final set of independent variables. These included Housing Unit Density, Vacant Unit Density, Owner-Occupied Unit Density, Renter-Occupied Unit Density, and Population per Housing Unit, each of which was highly correlated with Population Density; and Proportion Renter-Occupied Units, which was highly correlated with Proportion Owner-Occupied Units.

Checks for multicollinearity

In order for the elements of the Fire Factor Database to be useful as independent variables in a regression context, it was necessary to consider only those factors that would not create high levels of multicollinearity (Myers 1990, Menard 1995, Hocking 1996, Ryan 1997). Using the eigenvalue-based method of Myers (1990) and Hocking (1996), we verified that the 15 continuous variables of the Fire Factor Database did not have serious levels of multicollinearity. This included the three representative climate variables chosen through factor analysis, as well as the other continuous variables.

Regression methods

Regression models.—For each of the eight spatially explicit fire data sets created from the Lake States Fire Database, a generalized linear regression model was developed in S-PLUS (MathSoft 1997). The regression models were designed to determine which, if any, of the elements of the Fire Factor Database significantly influenced the broad-scale fire patterns of wildfire activity in the study area. Each model used a fire data set as the dependent variable and the elements of the Fire Factor Database as the independent variables.

Each regression was based on a Binomial, a Poisson, or a Negative Binomial response distribution. For the four regressions involving fire occurrence a logistic model was appropriate (Hosmer and Lemeshow 1989). For models that fit count data, either the Poisson or Negative Binomial model is typically used (Marsden 1982, Lawless 1987, Todd and Kourtz 1991, Liao 1994, Hilborn and Mangel 1997, Venables and Ripley 1997). The Negative Binomial distribution is well suited for count data in which there is an overdispersal of the values, such that the variance exceeds the mean (Venables and Ripley 1997). The Poisson model is usually a better fit for count data in which the variance and mean are roughly equal. Count data for wildfires have been modeled previously using one of these two distributions by Bruce (1960), Martell et al. (1987), and Vega Garcia et al. (1995). Depending on these statistical characteristics for each of the four fire counts data sets, we fit the more appropriate of the two distributions.

Sampling scheme and model fitting.—For each analysis, values from half of the cells at a given scale were randomly chosen for model fitting, while the other half of the cells were kept in reserve for testing. This provided 1297 observations for fitting models at the 10-km resolution and 5483 observations for fitting models at the 5-km resolution. Stepwise regression with backward elimination was used, beginning with the full set of elements of the Fire Factor Database. Significance of each fitted model was evaluated at the 0.01 level using a chi-square test of the likelihood-ratio statistic using the number of estimated coefficients (Hosmer and Lemeshow 1989). To evaluate significance of the coefficients of continuous regression variables, Student's t statistics were used (Venables and Ripley 1997); for each categorical variable, which could assume multiple values and thus did not suit the t test well, a chi-square test was used that evaluated the effect of removing the variable from the regression (Hosmer and Lemeshow 1989). Factors were eliminated from consideration until only those remained with $>$ 0.05 significance.

Prediction and evaluation.—For each model, cells not used in model fitting were used for model prediction and evaluation. For Binomial models, a given cell was predicted to be a fire cell if its predicted probability of fire using the model was $\geq$ 0.5. Evaluation of each Binomial prediction occurred in four forms: first, a 2 $\times$ 2 table was constructed contrasting observed values of fire occurrence with predicted values of fire occurrence in those same cells. This table was evaluated using the Tau_p statistic, which quantifies the improvement in a model's predictive power over a random assignment of values to cells (Ma and Redmond 1995). Second, studentized residuals were computed and evaluated for each predicted fire probability; these residuals measure the departure of a cell's predicted fire probability from the observed value of fire occurrence in that cell, and have values approximating a Normal distribution (Venables and Ripley 1997). We considered studentized residuals with absolute value larger than 1.96 to be significantly large. Third, spatially explicit maps of predicted fire occurrence and predicted fire probability were generated using all cells, for qualitative comparison with the map of observed values of

TABLE 3. Factors influencing fire occurrence and fire counts at 10-km and 5-km resolutions in the northern Great Lakes region.

Factors	All-fire occurrence		Large-fire occurrence		All-fire counts		Large-fire counts	
	10-km	5-km	10-km	5-km	10-km	5-km	10-km	5-km
Biotic								
Current Land Cover	S	S			S	S		
Abiotic								
Available Water Capacity		−		+	−	−		+
Lake Density		−	−	−	−	−		
Stream Density			−				−	
Mean March Precipitation	+	+			+	+		
Mean August Max. Temp.	−	−			−	−		
Mean June Precipitation								
Human								
State	S	S	S	S	S	S		
Rail Density	−					+		
Road Density	+	+		+	+	+	−	
Distance to Nonforest	−	−	−	−	−	−	−	−
Distance to City		+	+	+	+			
Population Density	+	+			+	+		
Proportion Seasonal Units						−		
Proportion Owner-Occupied Units		−			−	−		
National Forest		−			−	−		
Federal Land—Other						+		
State Forest			−	−				
State Land—Other		−						
Indian Reservation		−						

Notes: All eight models were significant at the 0.01 level. Factors not marked for a given model were not significant at the 0.05 level. Significant categorical variables with more than two categories do not have a relevant sign and are denoted as ''S.'' Signs of relevant variables (+ or −) denote the direction of their effect on the dependent variable.

fire occurrence. Fourth, a measure of pseudo-R^2 was calculated (Maddala 1983) for the model.

For each Poisson and Binomial model, spatially explicit maps of predicted fire counts were generated using all cells for qualitative comparison with observed values of fire counts. Studentized residuals were computed and evaluated for each cell used to construct the model, and a measure of pseudo-R^2 was calculated.

RESULTS

Occurrence of fires

All-fire occurrence.—In the multivariate analysis, areas with higher Population Density, higher Road Density, and lower Distance to Nonforest were more likely at both scales to have witnessed a fire during the study period (Table 3, ''All-fire Occurrence'' columns). At the finer scale of analysis, National Forests, Indian Reservations, State Land-Other, and high Lake Density regions (all regions with less frequent human access because of the low number of permanent residents) saw lower all-fire occurrence probability. We interpret the significance and direction of influence of these variables to mean that increased human access raised the probability of fire occurrence in the region. However, although increased access generally increased fire probability, it appears that there was a limit to this effect at the highest levels of human activity: in areas where Rail Density is high, and where Distance to City is low (i.e., very near or in cities) all-fire occurrence probability was diminished. This probability was also significantly affected by Current Land Cover and by State.

In addition to human and biotic factors, two climate factors significantly influenced all-fire occurrence at both analysis scales: areas with higher Mean March Precipitation and areas with lower Mean August Maximum Temperature generally had higher fire probabilities. These climate factors may represent environmental and/or social processes: for example, higher Mean March Precipitation could influence growth of underbrush, which could be related to human-ignited debris fires in April and May, during which $>$ 70% of fires occurred (Cardille and Ventura, *in press*). However, it appears that these climate variables may also play a geographic role. Specifically, Mean March Precipitation increases toward the southeast, and was lowest in the agricultural lands west of the Red Lakes region in Minnesota. In that area, recorded fire occurrence was low (Figs. 2a, 3a). Mean August Maximum Temperature may also be acting as a proxy for geography: in west-central Minnesota, where its value is highest, there was a low incidence of reported fire.

The all-fire occurrence model at the 10-km resolution had a pseudo-R^2 of 0.31, meaning that 31% of the variation in the independent variables was described by the model. Of more value in this context is the model's ability to predict all-fire occurrence, as represented by the Tau_p statistic. The Tau_p value for the all-fire occurrence model at the 10-km resolution was 0.44, in-

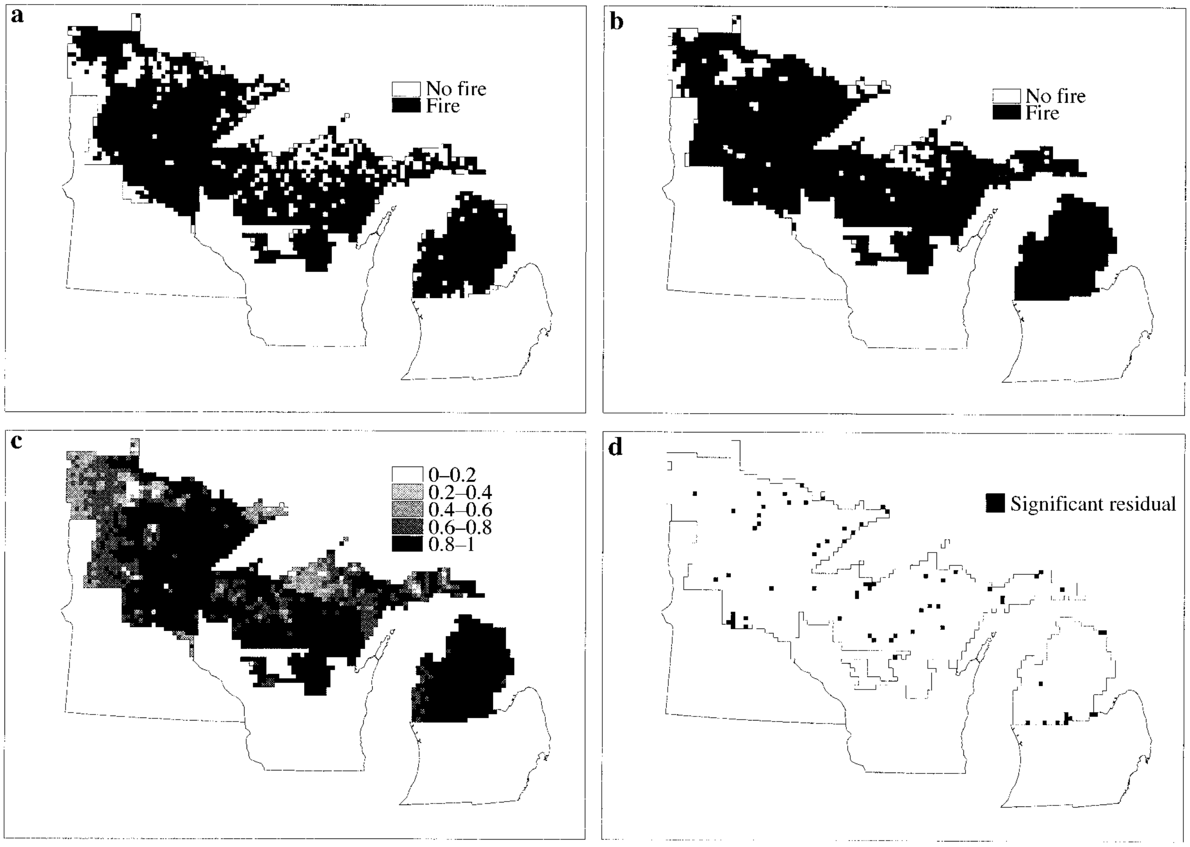

FIG. 2. (a) Observed fire occurrence, 10-km resolution. (b) Predicted binary fire occurrence, 10-km resolution. (c) Continuous prediction of fire occurrence probability, 10-km resolution. (d) Studentized residuals of fire occurrence model, 10-km resolution.

dicating that 44% more pixels were classified correctly than would be expected by random assignment of the same number of fire cells to the study area. At the 10-km resolution, there was good agreement between the observed (Fig. 2a) and predicted (Fig. 2b) binary images, particularly in capturing the high fire probability throughout central Minnesota and the Lower Peninsula of Michigan, as well as the lower incidence of fires in Michigan's Upper Peninsula. On the whole, however, the predicted binary image did not successfully capture fine-scale variation in the observed fire occurrence data, where some isolated cells or pairs of adjacent cells witnessed no fires during the study period. This was particularly true in Wisconsin, although the continuous-prediction image showed that many of these cells had a predicted probability near the 0.5 threshold (Fig. 2c). Where the departure between the model predictions and observed data was statistically significant (Fig. 2d), the model overpredicted the probability of fire. The proportion of these studentized residuals that were significantly large, however, was below 5%.

At the 5-km resolution, although the model's predictions did not have the grainy detail of the observed fire data, there was broad agreement between the observed (Fig. 3a) and predicted (Fig. 3b) binary images. The lack of fires in much of Wisconsin and in the Upper Peninsula of Michigan was well modeled, as was the low fire occurrence on and near the Red Lakes of Minnesota. The binary prediction was poor in the northwest extremes of Minnesota, although this failure is mitigated by the observation that many continuous predictions there (Fig. 3c) were near 0.5, the threshold for predicting all-fire occurrence in a cell. Fewer than 5% of studentized residuals were significantly large (Fig. 3d); these large residuals were seen in overpredictions of fire probability in Minnesota, Wisconsin, and the Lower Peninsula of Michigan, and underpredictions of fire probability in Michigan's Upper Peninsula (Fig. 3d). The pseudo-R^2 value for the 5-km all-fire occurrence model was 0.24, although the model did retain the predictive power seen at the 10-km resolution: the Tau_p value was 0.36.

Large-fire occurrence.—Areas remote from cities, areas near Nonforest, and areas with low Lake Density all had an increased probability of large fire during the study period (Table 3, ''Large-fire Occurrence'' columns). The observed occurrence of large fires was clearly biased toward Minnesota (Fig. 4); this was indicated by the significance of State at both scales. Large fires were less likely on State Forests; this was also

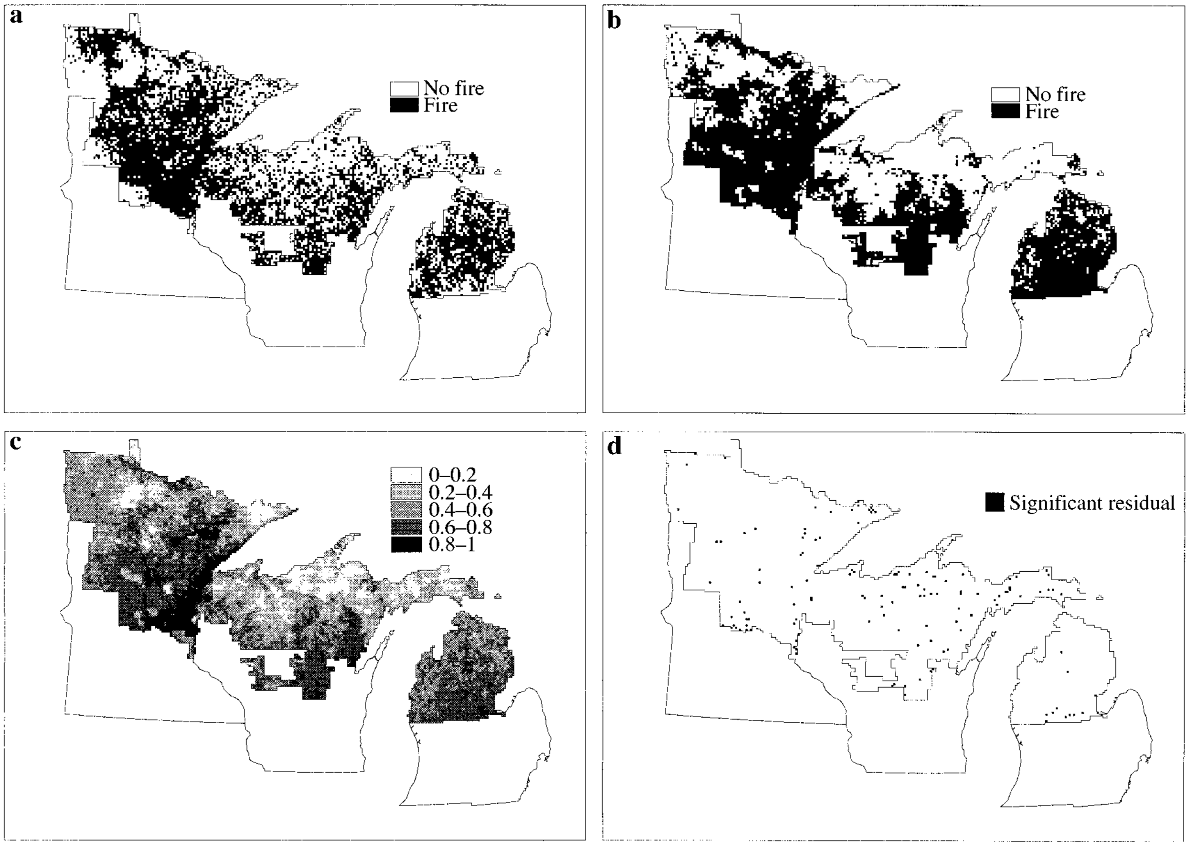

FIG. 3. (a) Observed fire occurrence, 5-km resolution. (b) Predicated binary fire occurrence, 5-km resolution. (c) Continuous prediction of fire occurrence probability, 5-km resolution. (d) Studentized residuals of fire occurrence model, 5-km resolution.

seen in a single-factor analysis of the data (Cardille and Ventura, *in press*). Results of the large-fire occurrence models suggest an interplay between fire ignition probability and fire suppression activity: large-fire probability was increased where more ignitions occur (i.e., on and near Nonforest and in areas with higher Road Density, as seen for all-fire probability), given that the ignition is far enough from infrastructure (i.e., away from cities) that a fire can grow before a major suppression effort can begin.

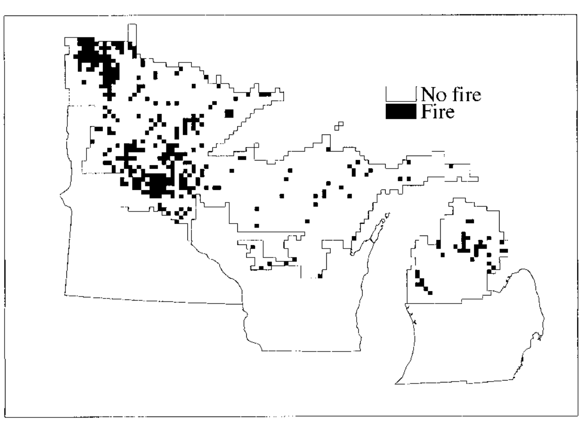

FIG. 4. Observed large-fire occurrence, 10-km resolution.

Although the large-fire probability models were statistically significant at both resolutions, predictive maps at each scale gave poor results. At the 10-km resolution, very few observed large-fire cells were predicted to contain a large fire; however, the model had sufficient predictive power (Tau_p) to classify 42% more cells correctly than would be expected in a random assignment. At the 5-km resolution, the entire study area was predicted to be devoid of large fires, and thus Tau_p was not calculated for this model. Low values of pseudo-R^2 indicate that only a small part of the variance in the independent variables was explained by these large-fire models. The difficulty predicting these rare events may well be due to their low frequency in the landscape, particularly at the 5-km scale where only 5% of the cells contained a reported large fire. Model difficulty may also be due to missing factors from the analysis, or because the model is insufficiently sensitive to the probability of a large fire. It is possible to adjust the 0.5 cutoff level for predicting fire cells (as was done in the daily prediction model of Vega Garcia et al. 1995), although we did not explore that possibility for this analysis.

Fire counts

All-fire counts.—In the final regression model, Population Density and Road Density were positively related to all-fire counts, while National Forests and areas of high Lake Density were associated with a decrease in the number of fires observed during the study period (Table 3, ''All-fire Counts'' columns). These effects were seen at both resolutions.

Generally, the factors seen to be significant in explaining whether a fire occurred in an area were also important in explaining the numbers of fires during the study period (Table 3). In each case where a factor significantly explained fire occurrence at both spatial resolutions (e.g., Mean March Precipitation, Road Density, State), it also influenced fire counts at both resolutions. Furthermore, the signs of these significant factors were almost completely identical between the analyses of fire occurrence and fire counts. As in the models of all-fire occurrence, we interpret these results to mean that increased human access tended to raise the number of fires occurring in an area during the study period.

In addition to the factors already seen as significant in explaining fire occurrence, several factors were important at both resolutions in explaining fire counts. Areas with coarser soils (i.e., with decreased Available Water Capacity) exhibited higher numbers of fires. Also, at both resolutions, higher numbers of fires were seen in those areas where smaller proportions of housing units were occupied by their owners.

The all-fire counts model at the 10-km resolution had a pseudo-R^2 of 0.61, and the model at the 5-km resolution has pseudo-R^2 of 0.45. The Tau_p statistic is not particularly informative for prediction of polytomous variables and thus was not calculated for fire counts models. At both spatial scales, maps of predicted fire counts and significant studentized residuals show that the models captured the broad-scale traits of the observed fire data (Figs. 5 and 6). At the 10-km resolution, the model reflected the low fire counts in Wisconsin and the Upper Peninsula of Michigan, and was generally successful in its fit in central Minnesota and the Lower Peninsula of Michigan (Figs. 5a, b). Fewer than 5% of studentized residuals were large; where the model was significantly incorrect (Fig. 5c), it underpredicted the fire count. Clustering of significant studentized residuals was evident throughout Minnesota, indicating that the model missed several of the high-activity areas there. In Minnesota, although the model successfully captured low fire counts near the Red Lakes and the Superior National Forest, it incorrectly predicted a relatively continuous fire map; observed values were more spatially clustered.

The 5-km model succeeded in predicting the low fire counts in Wisconsin and Michigan's Upper Peninsula, as well as the high level of fire activity in central Minnesota (Figs. 6a, b). However, it missed the focus of fire activity in the north-central Lower Peninsula of Michigan, incorrectly predicting high fire activity in the southeastern-most part of the study area. Similarly, although the model predicted relatively high all-fire count values in central Minnesota, it failed to capture the high values in that area. As a result, although the model roughly captured the spatial pattern of observed fire count values, and although the number of significantly underpredicted all-fire counts was below 5% (Fig. 6c), there was inaccuracy throughout the study area.

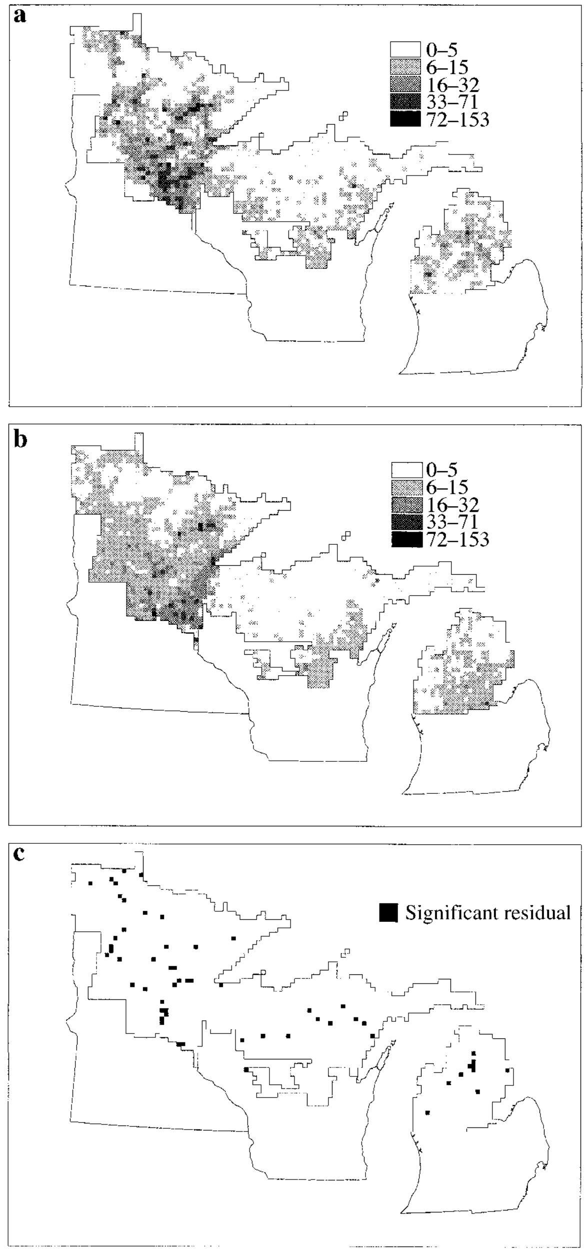

FIG. 5. (a) Observed fire counts, 10-km resolution. (b) Predicted fire counts, 10-km resolution. (c) Studentized residuals of fire counts model, 10-km resolution.

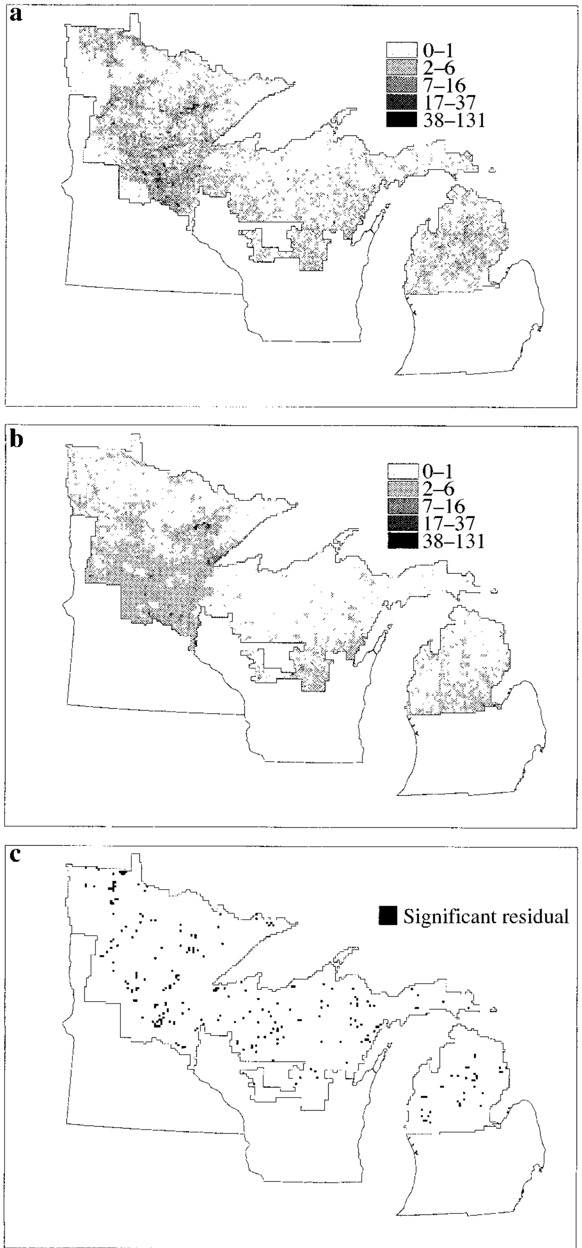

FIG. 6. (a) Observed fire counts, 5-km resolution. (b) Predicted fire counts, 5-km resolution. (c) Studentized residuals of fire counts model, 5-km resolution.

Large-fire counts.—Because of the low proportion of cells witnessing a large fire during the study period, it was not possible to adequately fit a fire count model using data that included both fire cells and nonfire cells. Instead, large-fire count models were fit using half of only those cells in which a large fire was observed during the study period.

On sites near or on Nonforest, counts of large fires (Fig. 7) tended to be higher at both analysis resolutions (Table 3, ''Large-fire Counts'' columns). At the 10-km resolution, counts were also significantly higher in areas of low Stream Density and in areas with low Road Density. At the 5-km resolution, counts were significantly lower in areas of coarser soils.

The 10-km model for large-fire counts, built with 180 large-fire cells and having a pseudo-R^2 of 0.30, suggests an interplay among soil moisture, land cover, and human access. That is, areas with low Stream Density on and near Nonforest are perhaps more susceptible to drying of vegetation and subsequent large fires. These effects are enhanced where there are few roads to support suppression efforts, allowing more large fires to occur.

The 5-km model, built with 253 large-fire cells, having two significant factors (Table 3) and a pseudo-R^2 of 0.13, is less easily explained. In particular, the sign for Available Water Capacity indicates that finer soils with greater available water capacity are associated with higher large-fire counts; it would instead be expected that coarser soils are associated with more large fires. The positive coefficient for Available Water Capacity is, however, consistent with the direction of its significance in predicting large-fire occurrence at the 5-km resolution. The consistency among these unexpected values suggests that the influence of Available Water Capacity deserves further investigation.

DISCUSSION

There is no simple ''Lake States fire regime'' that can be summarized with a single number. Rather, fire patterns differ depending on the fire size considered, the scale of analysis, and the measurement of fire activity. Results of this study suggest that wildfires in the northern Great Lakes region are influenced by biotic, abiotic, and human factors. At each of two fire size thresholds, at two resolutions, for two measures of fire activity, at least two of the three factor types played a significant role in explaining fire variation during the 1985–1995 period.

As expected, the biotic factor Current Land Cover was a significant factor in explaining fire patterns when

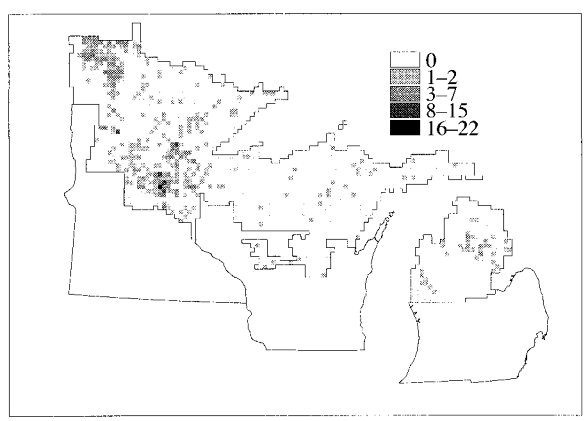

FIG. 7. Observed large-fire counts, 10-km resolution.

all fires were considered; surprisingly, however, it was insignificant in the analysis of the patterns of large fires.

Abiotic factors strongly influenced fire patterns in the northern Great Lakes region during the study period. Areas with high Lake Density, which included areas containing the very large lakes of the region, mostly lacked fires of any size. Stream Density appeared as a negative influence on large-fire occurrence and large-fire counts, perhaps suggesting that streams may serve in the region as natural firebreaks, or that areas with more streams supported soil or vegetation conditions discouraging large fires. Available Water Capacity played a complex role during this study period; its influence was negative for all fires and positive for large fires. These results seem consistent with Loope (1991), who found that areas with lower AWC tended to have greater fire frequency. The climate factors Mean March Precipitation and Mean August Maximum Temperature were significant in several regressions, but may have served as proxies for geographic trends in fire occurrence and fire counts. Although outside the scope of this study, further exploration of these and other climate factors is warranted, either by analyzing the Lake States Fire Database at finer temporal resolution (e.g., seasonal fire occurrence) or by incorporating observed temperature and precipitation data from the study period.

Human factors were significant in each analysis of this study. For predicting patterns for all fires, increases in human access and activity tended to be positively associated with both fire occurrence and counts. For large wildfires, however, it appears that decrease in human access to an area generally increased fire activity. Thus, increases in Road Density could increase several measures of overall fire activity, while a remoteness from those roads was significant in determining the number of large wildfires in areas prone to such fires. Distance to Nonforest was critically correlated with wildfires of the northern Great Lakes region: greater distance was consistently negatively associated with fire activity for each regression at each resolution. Several categories indicating land where human access is managed or relatively limited (such as National Forest and State Forest) were negatively related to fire activity. The tendency for fires of all sizes to occur on and near Nonforest was consistent with its role in a univariate setting (Cardille and Ventura, *in press*). This behavior is probably due to the relative ease of igniting Nonforest fuels as well as the tendency for human population to be higher outside of areas classified as forest at these scales.

Effects of changes in spatial resolution

Nearly all factors significant at the coarser, 10-km scale were also significant at the 5-km scale. For example, the Population Density parameter, which appeared as a positive influence on both all-fire occurrence and all-fire counts (Table 3), was significant at both scales for these two questions. In general, the appearance of a factor at one scale and not the other does not seem to occur frequently enough to indicate that factors were chosen arbitrarily during model development. On the contrary, the frequent pairing of a significant factor across scales of analysis for a given question, combined with the fact that all paired factors had identical signs at both scales, indicate the robustness of the analysis across the two spatial resolutions.

It is noteworthy that for three of the four analyses, more factors are significant at the finer scale than at the coarser. It is expected that with scale changes come differences in important variables (Allen and Starr 1982, O'Neill et al. 1986, Meentemeyer 1989). Although this increase in the number of predictors may be due mostly to the higher degrees of freedom available for statistical fitting at the finer scale, Meentemeyer and Box (1987) predicted that processes at finer scales, as a rule, will tend to be driven by a larger number of factors.

Conclusion

This paper has shown that in addition to biotic and abiotic factors, human settlement and land use are important correlates of fire patterns in and near Lake States forests. The influence of humans on the modern fire patterns of the Upper Midwest is inescapable and should be explicitly considered in future assessments. By investigating both simple and complex measures of fire activity over a decade, we have shown that the factors influencing fire occurrence and fire counts in this region are similar, with robust results across two scales of analysis.

This study, the first in-depth analysis of such data in this region, suggests that many other questions about fire patterns in the Upper Midwest can now be approached. With daily weather and wind data future studies could investigate, for example, the factors that influence measures of fire activity seen in other studies, such as probability of a fire day, fires per day, and probability of a large-fire day. Analyses of the factors underlying seasonal variability of fires of different causes are also now possible.

The factors identified in this study can readily serve as the basis for a spatially explicit simulation model of decade-scale fire activity in the Upper Midwest. Such a model could assist, for example, in projections of future vegetation for habitat management or the possible changes in fire patterns under scenarios of further residential development in the region. Fire suppression planners could benefit directly from the results of this study, particularly if maps of fitted probability were extended to mapping the predicted risk of fires of various sizes.

Finally, the success of this study suggests that while the specific results are not expected to extend to other regions, these methods of logistic regression and spatially explicit analysis of fire activity could be used in other areas having sufficient information about wildfires and the factors that may influence their regional distribution.

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