

## Spatial and temporal drivers of wildfire occurrence in the context of rural development in northern Wisconsin, USA

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**Abstract.** Most drivers underlying wildfire are dynamic, but at different spatial and temporal scales. We quantified temporal and spatial trends in wildfire patterns over two spatial extents in northern Wisconsin to identify drivers and their change through time. We used spatial point pattern analysis to quantify the spatial pattern of wildfire occurrences, and linear regression to quantify the influence of drought and temporal trends in annual number and mean size of wildfires. Analyses confirmed drought as an important driver of both occurrences and fire size. When both drought and time were incorporated in linear regression models, the number of wildfires showed a declining trend across the full study area, despite housing density increasing in magnitude and spatial extent. Fires caused by campfires and debris-burning did not show any temporal trends. Comparison of spatial models representing biophysical, anthropogenic and combined factors demonstrated human influences on wildfire occurrences, especially human activity, infrastructure and property values. We also identified a non-linear relationship between housing density and wildfire occurrence. Large wildfire occurrence was predicted by similar variables to all occurrences, except the direction of influence changed. Understanding these spatial and temporal drivers of wildfire occurrence has implications for land-use planning, wildfire suppression strategies and ecological goals.

**Additional keywords:** Palmer Drought Severity Index, spatial point pattern analysis.

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### Introduction

Understanding the processes underlying spatial and temporal trends in wildfire patterns is critical for projecting future wildfire risk. Traditionally, biophysical factors such as climate, soil moisture and vegetation types collectively define the fire regime (Schulte *et al.* 2005) and its consequent risk to human life and property. Yet in many areas, humans are the cause of most fires, and human development and activity patterns (both starting and putting out fires) are increasingly overriding the biophysical factors that historically controlled fire regimes (Syphard *et al.* 2007).

Human factors such as housing density, population density and road networks have all been identified as important influences in the spatial distribution of wildfires in places where people tend to start most fires (Maingi and Henry 2007; Sturtevant and Cleland 2007; Syphard *et al.* 2007; Calef *et al.* 2008; Catry *et al.* 2009; Grala and Cooke 2010). In areas where rural development overlaps with fire-prone vegetation, assessing the importance of human and biophysical drivers and their

spatial and temporal patterns is necessary for both current and future wildfire risk assessment.

Most of the drivers underlying wildfire occurrence – whether biophysical or human – are dynamic at different spatial and temporal scales. Drought cycles, climate, vegetation, and human activities and development patterns are all simultaneously changing, but at different spatial and temporal scales. If relationships among wildfires and their underlying drivers remain constant over time, we would simply need to forecast the drivers into the future to understand future wildfire risk. Alternatively, the relationships themselves may change. For example, ignition and suppression patterns can change over time (Guyette *et al.* 2002) owing in part to changing social conditions, which could result in substantially different patterns of wildfire risk. Accounting for such variable relationships is important to the dynamic projection of future wildfire risk under different scenarios of human development, land management and climatic conditions.

Previous research in the Great Lakes region has shown human influence, specifically housing density, to be an

important driver of wildfire occurrence by increasing fire ignition rates (Cardille *et al.* 2001; Sturtevant and Cleland 2007). Given the general increasing trend of housing density in recent decades in northern Wisconsin (US Census Bureau 2002), we hypothesised an increasing trend in wildfire ignitions. Our second hypothesis was that annual area burned in this region would not show a temporal trend, because biophysical variables assert greater influence than human factors in determining large fires (Sturtevant and Cleland 2007), and because higher housing density might lead to faster reporting and suppression, countering the effect of increased ignitions. Our third hypothesis was that these trends would be regulated by climatic conditions, specifically drought, which has been identified by several researchers as increasing wildfire occurrence (Lorimer and Gough 1988; Mitchener and Parker 2005; Xiao and Zhuang 2007; Brown *et al.* 2008; Grala and Cooke 2010). Thorough understanding of these hypothesised drivers of wildfire occurrence should allow the projection of wildfire risk under future alternative human development scenarios.

The objectives of this study were to quantify the temporal and spatial trends in wildfire occurrence in northern Wisconsin, to identify the drivers of these trends, and to assess whether the relationships between underlying drivers and wildfire occurrence vary at different spatial and temporal scales. Accomplishing these objectives will enable the projection of future wildfire risk assuming continued rural development in the region. We expand on earlier research by Sturtevant and Cleland (2007) who applied classification tree analysis to evaluate the relative importance of human and biophysical factors affecting fire occurrence in northern Wisconsin. We add to their analysis by using more fine-scale fire location and spatial covariate data, and adding specific spatial land-use variables that can be projected into the future. We additionally evaluate the temporal component of wildfire occurrences – specifically with respect to the influence of drought on wildfire occurrence and size – to better understand the concurrent influence of human development patterns on wildfire risk. Understanding these spatial and temporal drivers underlying observed wildfire patterns has implications for land-use planning, fire management and ecological restoration (Sturtevant *et al.* 2009), particularly under alternative future climate change and land-management scenarios.

## Methods

### *Study area*

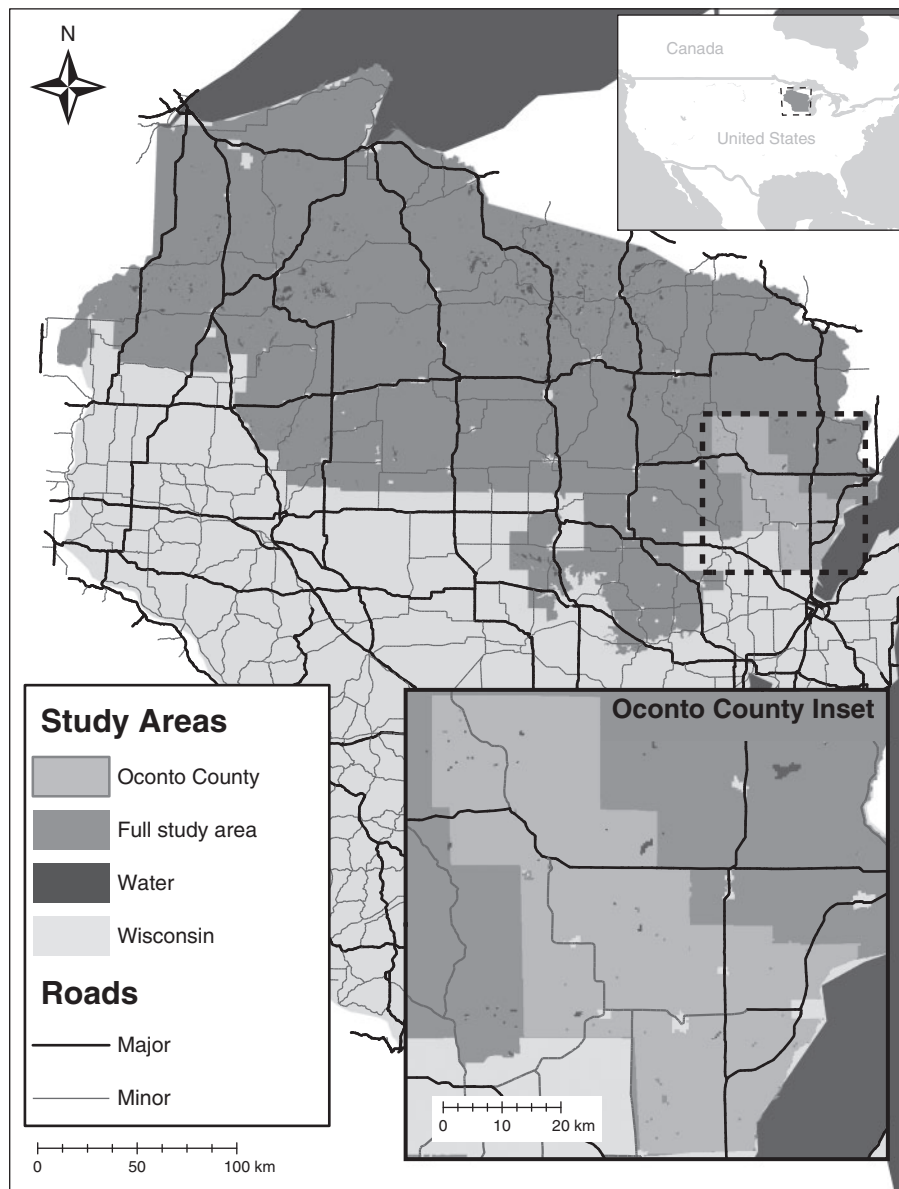
We evaluated wildfire patterns at two spatial extents. The smaller study area was defined by Oconto County, WI (Fig. 1), and contains a mixture of forest, agriculture and developed lands, with the north-western third dominated by forest, including a portion of the Chequamegon–Nicolet National Forest. Developed areas are interspersed throughout the county, including inholdings within the National Forest. All analysis was limited to portions of the county for which the WI Department of Natural Resources (DNR) or the US Forest Service have primary wildfire protection responsibilities. This limitation excludes from analysis many areas within incorporated towns and cities where fire protection is provided by local fire departments. The larger study area, referred to as the ‘full

analysis area’ is defined as the portion of Wisconsin within the Laurentian Mixed Forest Province (McNab and Avers 1994), which includes Oconto County, including only areas with state or federal fire protection. The extent of this study area closely matches the Wisconsin portion of the study area used by Cardille and others (2001). The full analysis area also encompasses a mixture of forest, agriculture and developed lands. Oconto County and the full study area have very similar proportional land-use areas, with two exceptions. The landscapes differ in proportional land area in agriculture (39% Oconto County, 14% full study area) and private forest (21% Oconto County, 48% full study area). Total land areas were  $\sim 2500 \text{ km}^2$  for the Oconto County analysis area and  $\sim 56\,500 \text{ km}^2$  for the full study area.

The fire regime across the full study area is dominated by frequent small fires, and rare large fires, with humans causing most ignitions. The average fire return interval of nearly 8700 years (Sturtevant *et al.* 2009) may imply relatively low fire risk, but within this landscape, the overlap of the human development with sandy glacial landforms that are prone to high-intensity fires creates locally substantial risk for life and property. Approximately 30% of Oconto County lies within the Northeast Sands Ecological Landscape, composed of glacial outwash sand plains that were historically dominated by fire-prone communities of jack pine and oak barrens, with the remaining area in the less fire-prone Forest Transition and Northern Lake Michigan Coastal Landscapes (Wisconsin Department of Natural Resources 2006), historically dominated by northern hardwoods (Sturtevant and Cleland 2007). The average fire return interval within the county was  $\sim 4900$  years over the time period of our fire data (see below). The presettlement fire return interval in this area ranged from 62 years in the jack pine barrens to 2128 years in the northern hardwoods (Sturtevant and Cleland 2007). The overlap of fire-prone landscapes and developed areas makes this an ideal study area for investigating human and biophysical drivers of wildfire.

### *Fire data*

Fire data representing all wildfires suppressed by either federal or state agencies were provided by the WI DNR and the USDA Forest Service (USFS) from 1985 to 2007. Each fire record included fire ignition date, size (acres), cause and location where the wildfire started. State (WI DNR) fire locations were defined by a Public Land Survey System (PLSS) quarter-quarter section (QQ or ‘forty’), which has a standard size of 16.19 ha (40 acres). USFS fire locations were recorded by latitude and longitude coordinates. For the purposes of spatial analysis, where all data were summarised at a QQ-scale (see below), fire locations from both datasets were assigned to the centroid of the QQ in which they were located. Records that appeared in both the DNR and USFS data with matching ignition date, cause, location and size were assumed to be duplicate records for the same fire, and the record was removed from one data source. After removing duplicates, we combined records that had the same ignition date, cause and location (but different size) into one fire record by summing the fire sizes. These records were assumed to be multiple ignitions (usually very small ( $<0.01 \text{ ha}$ )) associated with the same fire event. All analyses were limited to fire records with burned areas greater than or equal to 0.09 ha, the resolution of Landsat imagery from which we estimated much of the spatial



**Fig. 1.** The full study area (Laurentian Mixed Forest Province with state or federal fire protection), and the Oconto County study area (excluding areas of local fire protection). The full study area closely matches the Wisconsin portion of the study area of Cardille *et al.* (2001).

covariate data. This size threshold also represents a reasonable size for inclusion in wildfire risk assessment, by removing the influence of 10 851 very small fires that together represented less than 2% of area burned. Because very small fires were more likely than larger fires to be undetected and unreported (i.e. not consistently represented in our database), excluding the smallest fires from analysis also constrained our analysis to where we had the most complete and consistent data records. The resulting fire dataset contained 9266 wildfires for the full study area, and 790 wildfires for the Oconto County study area (Tables 1, 2).

#### Temporal analysis

We used multiple linear regression models to quantify temporal trends in the annual number of wildfires and mean fire size.

Annual totals for the number of wildfires ( $\geq 0.09$  ha) and area burned were calculated as the sum across fire records for each calendar year. Annual mean fire size was calculated as the total area burned divided by the annual number of fires. We used the statistical program R (R Development Core Team 2008) to perform the linear regressions (*lm* in package *stats*), using the packages *lme4* (Zeileis and Hothorn 2002) and *bbmle* (Bolker 2010) for model evaluation and the package *effects* (Fox 2003) to create the variable effects plots.

Others have identified drought as an important influence on fire regimes (Lorimer and Gough 1988; Mitchener and Parker 2005; Xiao and Zhuang 2007; Brown *et al.* 2008; Grala and Cooke 2010), so we included the Palmer Drought Severity Index (PDSI) as an independent variable in the regression analysis.

**Table 1.** Annual number of fires by cause for fires  $\geq 0.09$  ha, number of fires  $\geq 16.19$  ha (40 acres), mean fire size (ha) and Annual Palmer Drought Severity Index (PDSI) for the full study area

Year	Number of fires $\geq 0.09$ ha									Fires $\geq 16.19$ ha	Mean fire size (ha)	Annual PDSI
	Total	Lightning	Equipment	Smoking	Campfire	Debris-burning	Railroad	Arson	Miscellaneous			
1985	218	19	21	12	5	98	3	27	33	1	4.02	2.36
1986	267	2	21	9	12	83	11	29	100	7	8.45	1.67
1987	629	17	81	32	33	221	53	92	100	8	6.42	-2.35
1988	726	44	117	27	27	198	74	105	134	11	5.50	-2.98
1989	610	4	82	31	30	236	40	78	109	7	4.42	-2.44
1990	627	6	82	37	27	271	25	79	100	10	4.68	0.50
1991	280	2	40	14	6	103	13	40	62	1	3.57	2.34
1992	273	1	39	12	10	93	9	45	64	6	3.89	1.53
1993	270	3	25	9	4	133	23	28	45	3	3.35	1.34
1994	555	11	74	17	21	211	43	84	94	1	3.18	-0.01
1995	434	5	38	10	26	196	25	68	66	0	2.63	0.53
1996	304	3	34	13	13	153	14	30	44	2	3.16	2.62
1997	447	2	40	16	20	237	24	36	72	0	2.24	0.03
1998	497	12	56	19	33	178	11	70	118	6	4.34	-1.09
1999	414	3	61	21	22	153	17	59	78	2	3.45	-0.17
2000	422	5	67	11	14	197	15	35	78	7	4.32	-0.04
2001	194	2	32	8	15	72	2	22	41	0	2.40	0.92
2002	190	3	23	8	7	92	5	13	39	0	2.66	2.18
2003	527	94	66	13	35	175	21	48	75	5	3.88	0.28
2004	275	6	27	11	19	141	5	23	43	3	3.80	0.76
2005	339	0	57	3	17	143	1	36	82	0	2.45	-0.26
2006	352	5	53	4	19	137	4	33	97	3	3.00	-0.59
2007	416	8	62	2	21	132	6	49	136	11	8.86	-1.03
All years	9266	257	1198	339	436	3653	444	1129	1810	94	4.28	0.27

**Table 2.** Annual numbers of fires  $\geq 0.09$  ha, mean fire size (ha) and Annual Palmer Drought Severity Index (PDSI) for Oconto County

Year	Number of fires $\geq 0.09$ ha	Mean fire size (ha)	Annual PDSI
1985	14	1.22	3.13
1986	14	18.53	2.26
1987	46	1.62	-1.91
1988	54	1.77	-2.19
1989	79	5.43	-2.22
1990	39	3.65	0.41
1991	20	10.33	2.52
1992	21	1.08	2.56
1993	24	1.73	2.96
1994	62	4.14	0.17
1995	43	2.77	0.33
1996	33	1.99	2.69
1997	37	2.69	0.30
1998	19	2.92	-0.81
1999	55	5.21	-0.93
2000	36	2.49	-0.35
2001	15	1.38	0.13
2002	22	2.82	2.03
2003	56	2.51	1.63
2004	17	13.49	1.36
2005	27	1.76	-0.30
2006	28	3.02	0.47
2007	29	2.53	-0.29
All years	790	3.69	0.61

PDSI (Palmer 1965) is an index of long-term surface moisture conditions that is commonly used in fire-climate studies (Trouet *et al.* 2006; Xiao and Zhuang 2007) and is readily available at broad spatial scales and over a long time period (Dai *et al.* 2004). Monthly PDSI values for the Wisconsin North-west, North Central, and North-east climate divisions (25 counties covering the northern third of the state) were obtained from the National Climatic Data Center and averaged across months to create average PDSI values representing the full study area. In order to evaluate the seasonal and annual influence of drought, we calculated PDSI averaged for the wildfire season only (March–October) and averaged for the entire year, and applied each version of PDSI in separate regression models. Along with average PDSI, we used the numeric year as the second independent variable in the regressions to quantify temporal trends. Our hypothesised regression models included a null model (intercept only), linear PDSI only, PDSI with linear year, and PDSI with quadratic year. We evaluated each fitted model for residual homoscedasticity, residual normality and absence of statistically significant outliers ( $P < 0.1$ ). Homoscedasticity was evaluated using the Breusch–Pagan test (package *lmtest*; Zeileis and Hothorn 2002), residual normality was evaluated using the Shapiro–Wilk normality test (package *stats*; Royston 1995), and outliers were evaluated using the Bonferroni outlier test (package *car*; Fox 2010). We applied logarithmic transformation of the dependent variable and removal of outliers as necessary to meet these critical regression assumptions. Models

**Table 3. Spatial covariate datasets and sources**

PRISM, Parameter-elevation Regressions on Independent Slopes Model (PRISM Climate Group, Oregon State University, <http://prism.oregonstate.edu>, accessed 16 September 2011); WISCLAND, Wisconsin Initiative for Statewide Cooperation on Landscape Analysis and Data (WISCLAND Land Cover, Wisconsin Department of Natural Resources, <http://dnr.wi.gov/maps/gis/datalandcover.html>, accessed 21 November 2011); SSURGO, Soil Survey Geographic Database (USDA Natural Resources Conservation Service, <http://soildatamart.nrcs.usda.gov>, accessed 26 October 2009); NLCD, National Land Cover Database; TIGER, Topologically Integrated Geographic Encoding and Referencing system (TIGER/Line Files, US Census Bureau, [http://www.census.gov/geo/www/tiger/tigerua/ua\\_tgr2k.html](http://www.census.gov/geo/www/tiger/tigerua/ua_tgr2k.html), accessed 16 September 2011); ESRI, Environmental Systems Research Institute (ESRI Data & Maps, CD-ROM)

Variable	Abbreviation	Data source	Units
<b>Biophysical factors</b>			
Mean maximum August temperature	AugMaxT	PRISM	°C
Mean March precipitation	MarPrecip	PRISM	mm
Mean June precipitation	JunPrecip	PRISM	mm
Presettlement fire rotation majority	FR_Major	Cleland <i>et al.</i> (2004)	Class
Fuel class majority	Fuel_Major	WISCLAND	Class
Soil available water	AvWater	SSURGO	mm
Soil drainage class	Drainage	SSURGO	Class
Percentage water	PctWater	NLCD (Homer <i>et al.</i> 2004)	%
<b>Human factors</b>			
Distance to road	DistRoad	TIGER	m
Distance to railroad	DistRail	TIGER	m
Housing density	HousDens	US Census Bureau (2002)	Homes km <sup>-2</sup>
Distance to city >10 000 people	DistLgCity	ESRI	m
Land use majority	LU	NLCD, US Census Bureau, S. Golding and R. Hammer, unpubl. data	Class
Land-use housing density index <sup>A</sup>	LU_HDI	NLCD, US Census Bureau, S. Golding and R. Hammer, unpubl. data	Index
Population density	PopDen	US Census Bureau (2002)	People km <sup>-2</sup>
Percentage seasonal ownership	PctSeas	US Census Bureau (2002)	%
Median home value	MHVal	US Census Bureau (2002)	US dollars

<sup>A</sup>LU\_HDI is a numerical index (0–4) ranking the land-use classes from lowest to highest housing density.

that did not meet the residual assumptions were dropped from consideration.

For each model, we calculated small-sample Akaike's Information Criterion (AICc) scores and Akaike weights ( $w_i$ ) for model comparison (Burnham and Anderson 1998). AIC is an estimate of the relative Kullback–Leibler (K-L) information loss in a specific model based on the data, and is appropriate for model comparisons among multiple working hypotheses (Burnham and Anderson 2004). A lower AIC score indicates less K-L information loss, and therefore a more plausible model. AIC includes a penalty for the number of estimated parameters, which diminishes overfitting. AICc is a variant of AIC with a correction for finite sample sizes. The Akaike weights, when calculated across a set of models, give the weight of evidence (relative likelihood) that each model is the most plausible of the set (Burnham and Anderson 1998). We identified the most plausible model as the model with the lowest AICc score among all models meeting the assumptions. The temporal regression analysis was performed using the Oconto County and full fire datasets, and using subsets of the data separated by fire cause for the full study area.

#### *Spatial analysis*

We used spatial point pattern analysis to quantify the spatial pattern of wildfire occurrences within Oconto County and for the full analysis area, using the same fire records as the temporal analysis (all fires  $\geq 0.09$  ha). Analysis was performed using the R statistical package *spatstat* (Baddeley and Turner 2005) following the methods of Yang *et al.* (2007). We first used Ripley's

K function to assess the degree of spatial correlation of fire locations. Because the K function showed strong deviance from complete spatial randomness of wildfire occurrences, we modelled the occurrences as an inhomogeneous Poisson process, using spatial covariates (Table 3) to account for the pattern. All spatial covariate data were aggregated at the QQ scale to match the resolution of the fire location data. Continuous variables were summarised as mean values, and categorical variables were summarised as the most common value within each QQ. The modelling process assumes no interactions among neighbouring fire occurrences (Poisson), and that the spatial pattern of occurrences is a result of the spatial heterogeneity of the landscape (inhomogeneous). The inhomogeneous Poisson models to be fit could include any number of spatial covariates in any functional forms. We constructed 14 *a priori* candidate models (Burnham and Anderson 1998; Table 4) using combinations of spatial covariates, generally categorised as biophysical, anthropogenic or a combination of both, based on theorised relationships between the spatial covariates and fire ignitions. For some covariates, we hypothesised multiple functional forms (linear and log for population density and housing density; linear, quadratic, log and categorical for land use), and evaluated multiple versions of the candidate models that separately incorporated each selected functional form. We used AICc for all candidate model comparisons (Burnham and Anderson 1998), identifying the model with the lowest AICc score as the most plausible model. We did not screen covariate combinations for multicollinearity because the AIC method of model comparison penalises the inclusion of covariates that contribute little

additional information, so only the most plausible combinations of variables were selected from among those that were potentially correlated. To quantify the relative strength of evidence for the chosen model, we calculated  $w_i$  for each model (Burnham and Anderson 1998). We used a Monte Carlo test of the L-transformation of Ripley's K function (Baddeley 2008) to assess whether the fit models were appropriate. To assess whether the relative importance of spatial drivers changed through time, we evaluated the candidate models separately for the decades containing 1990 (1985–94) and 2000 (1995–2004). We also evaluated separate candidate models for large fires ( $\geq 16.19$  ha (40 acres)) to assess whether spatial drivers for large fires differed from smaller fires (Sturtevant and Cleland 2007). The 40-acre threshold for large fires was chosen to be consistent with previous analysis (Sturtevant and Cleland 2007), and resulted in a dataset of 94 large fires for the full study area (Table 1).

After evaluating the hypothesised candidate models, we also performed exploratory analysis to provide additional insight into the relative importance of the different covariates. We evaluated a set of models that included all spatial covariates with multiple functional forms ('all-variables' model), for comparison with the candidate models we selected. We did not evaluate all possible combinations of variables, as others have done for exploratory analysis (Murtaugh 2009), owing to the millions of potential combinations. Instead, we assessed the relative contribution of each covariate in the most plausible candidate model and the all-variables model by comparing the change in AICc values caused by the individual removal of each covariate from the model. We performed a model comparison among a set of models that included the full model, and a model representing the full model without each one of the covariates.

The AICc value of the model without a given covariate, when compared with the AICc value of the full model including that covariate, gives a relative rank order of model plausibility given the data. A model with a lower Akaike weight when a covariate is included gives an indication that the inclusion of the covariate does not result in a more plausible model. Candidate and all-variables models were evaluated for Oconto County, but computing constraints limited the full analysis to the candidate models only.

## Results

### *Temporal analysis*

For the analysis of all fire records for both the full study area and Oconto County, the most plausible models for the number of fires and mean fire size (MFS) all included annual PDSI in a linear functional form with a negative coefficient (Figs 2, 3). Because PDSI values relate to the total moisture balance, the negative relationship implied there was a greater number of wildfires and the mean size of the fires increased as drought conditions became more severe. The model of number of fires for the full study area included year as a variable, indicating a negative quadratic temporal trend, with the maximum value in the year 1994. The full study area MFS model included year as a positive quadratic relationship with a general declining trend and the minimum value in the year 2001. The most plausible Oconto County models for numbers of fires and MFS did not include year as a variable, showing no clear temporal trend.

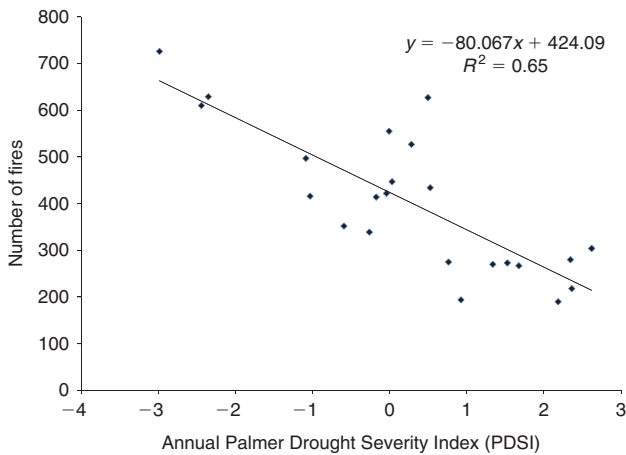
Separating the analysis by fire cause for the full study area provided additional insights into the temporal trends. All of the most plausible models for number of fires included negative linear relationships for either average annual or seasonal PDSI

**Table 4. Candidate models evaluated for spatial analysis. Models were evaluated for both Oconto County and the full study area, unless noted otherwise as 'Full' or 'County'**

See Table 3 for definitions of parameter abbreviations. Abbreviations in parentheses indicate the functional forms considered for each covariate: F for factor, Log for logarithmic, P1 for first-order polynomial, P2 for second-order polynomial

Model	Parameters
Null model	None
Biophysical models	
Ecosystem	FR_Major (F)
Soil	Drainage (P2) + AvWater (P2)
Vegetation	Fuel_Major (F)
Climate (Full)	AugMaxT (P1) + JunPpt (P1) + MarPpt (P1)
Combined Biophysical (County)	Ecosystem + Soil + Vegetation
Combined Biophysical (Full)	Ecosystem + Soil + Vegetation + Climate (Full)
Anthropogenic models	
Infrastructure	DistRoad (Log) + DistRail (Log) + DistLgCity (P1)
Development	LU_HDI (F/Log/P1/P2) + PctSeas (P1) + DistRoad (Log) + DistRail (Log)
Economic	MHVAl (P1) + PctSeas (P1)
Human activity	PopDen (Log/P1) + DistRoad (Log) + DistRail (Log) + DistLgCity (P1) + PctWater (P2)
Combined anthropogenic	Infrastructure + Economic + LU_HDI (F/Log/P1/P2) + PopDen (Log/P1)
Combined models	
Ecosystem + Human activity	Ecosystem + Human activity + Vegetation
Soil + Human activity	Soil + Human activity + Vegetation
Ecosystem + Development	Ecosystem + Development + Vegetation
Soil + Development	Soil + Development + Vegetation
All variables	All covariates

(Fig. 4). The most plausible models for number of fires for campfire, debris-burning and miscellaneous-caused fire did not include temporal trends. Models for all other causes (including lightning) included either a negative linear or quadratic relationship indicating declining wildfire ignitions over time. The regression analysis for mean fire size by cause yielded few cause-specific models including PDSI or year that were more plausible than the corresponding null model, which did not contain either PDSI or year as components (Fig. 5). MFS models



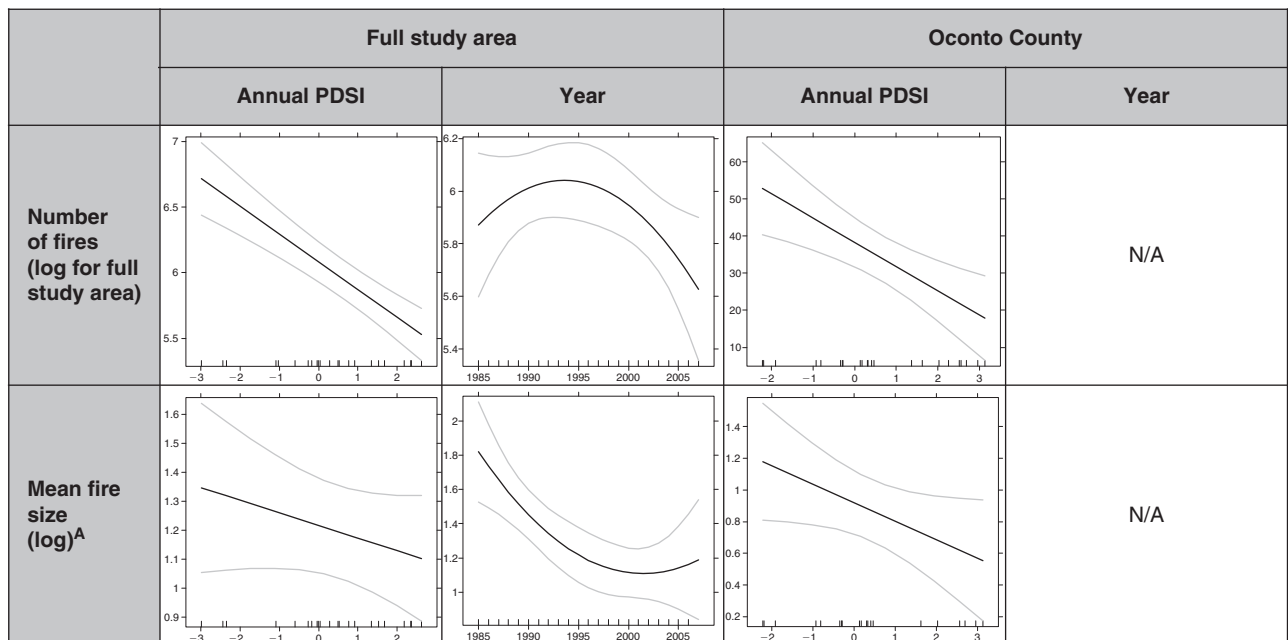
**Fig. 2.** Plot of annual Palmer Drought Severity Index (PDSI) against annual number of fires ( $\geq 0.09$  ha) for the full study area for the years 1985–2007.

for equipment, smoking and arson fires did include average PDSI as a linear relationship. The MFS–PDSI relationship was essentially flat for smoking-caused fires, but negative for equipment and arson fires, as it was for all causes in the number of fires models. MFS from equipment and smoking causes were the only causes to include a temporal trend, having negative linear and quadratic relationships respectively.

*Spatial analysis*

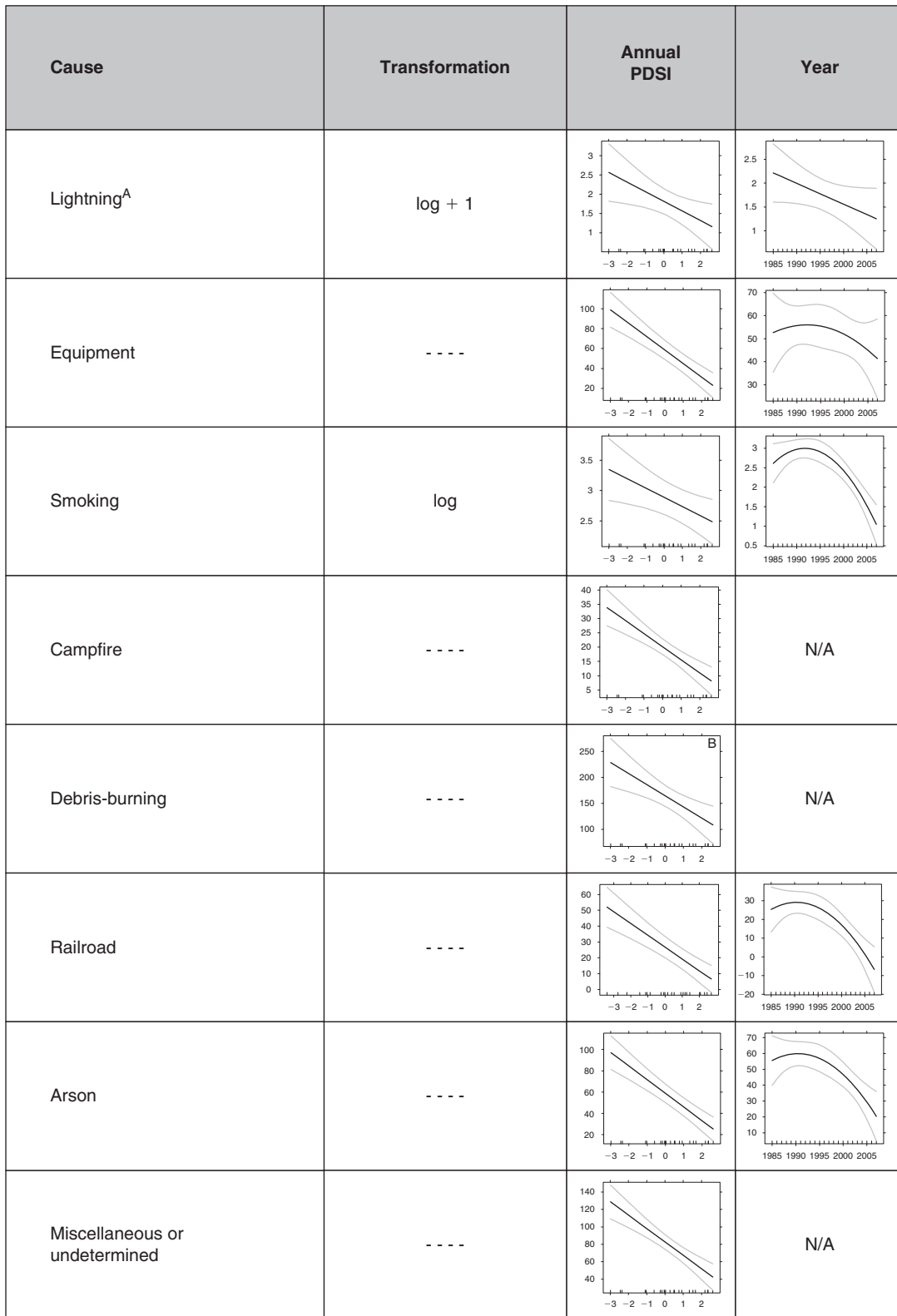
The plot of the estimated K function of the fire occurrences across the full study area (Fig. 6) showed the level of aggregation was higher than the theoretical K function for complete spatial randomness, indicating clustering of wildfire ignitions up to  $\sim 8000$  m, then showed strong disaggregation at larger distances. The simultaneous Monte Carlo tests of the L function showed that all of the chosen most plausible models, for Oconto County and for the full study area, were well within the simulated critical bands. This result indicates that the patterns of data were not significantly different from null inhomogeneous Poisson models based on the fitted models.

The most plausible spatial model for both the full study area ( $w_i = 1.000$ ) and Oconto County ( $w_i = 1.000$ ) was the Combined Anthropogenic, which included covariates with a negative influence on wildfire occurrence (distance to roads, distance to railroads, distance to large cities and median home value) and covariates with positive influence on wildfire occurrence (percentage seasonal ownership and population density) (Table 5). The Combined Anthropogenic model also included the land-use housing density index (LU\_HDI) with a polynomial quadratic form, with a peak maximum value at approximately three,



<sup>A</sup>Years 1986, 1991, 2004 removed as outliers for Oconto County Mean fire size regression

**Fig. 3.** Effects plots for most plausible linear regression models for number of fires ( $\geq 0.09$  ha; log-transformed for full study area) and mean fire size (log-transformed) using the full and Oconto County fire datasets. The solid black lines represent the estimated effects and the grey lines represent 95% confidence intervals. N/A indicates that a component was not included in the model identified as the most plausible (lowest Akaike Information Criteria (AICc)).

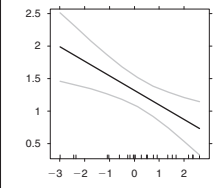
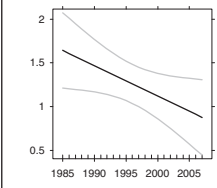
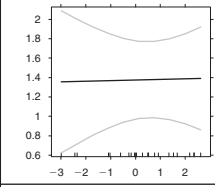
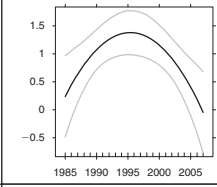
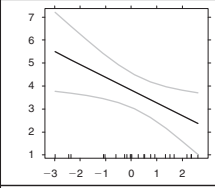


<sup>A</sup>Year 2003 removed as outlier

<sup>B</sup>PDSI averaged for fire season (March–October) only, instead of entire year

**Fig. 4.** Dependent variable transformation and effects plots for most plausible linear regression models for number of fires ( $\geq 0.09$  ha), separated by fire cause. The black lines represent the estimated effects and the grey lines represent 95% confidence intervals. N/A indicates that a component was not included in the model identified as the most plausible (lowest Akaike Information Criteria (AICc)).

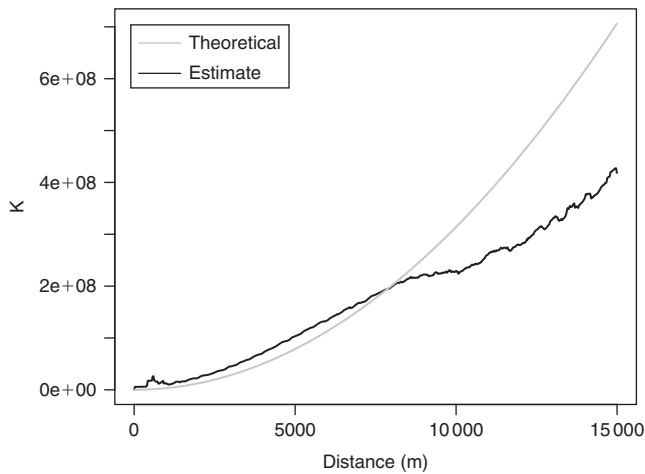


Cause	Transformation	Annual PDSI	Year
Lightning	log + 1	N/A	N/A
Equipment	log		
Smoking	log		
Campfire	----	N/A	N/A
Debris-burning	----	N/A	N/A
Railroad <sup>A</sup>	log	N/A	N/A
Arson	----		N/A
Miscellaneous or undetermined <sup>B</sup>	log	N/A	N/A

<sup>A</sup>Year 2007 removed as outlier

<sup>B</sup>Years 1986, 2007 removed as outliers

**Fig. 5.** Dependent variable transformation and effects plots for most plausible linear regression models for mean fire size, separated by fire cause. The black lines represent the estimated effects and the grey lines represent 95% confidence intervals. N/A indicates that a component was not included in the model identified as the most plausible (lowest Akaike Information Criteria (AICc)).



**Fig. 6.** Estimated Ripley’s K function for fire occurrences in the full study area compared with the theoretical Ripley’s K function that represents complete spatial randomness.

corresponding to the medium housing density class. The models containing only anthropogenic variables had consistently lower AICc scores and were therefore more plausible than models containing only biophysical variables or models containing both anthropogenic and biophysical variables. Looking at only the individual spatial models (not combinations), the Oconto County analysis identified the Economic model as the most plausible ( $w_i = 1.000$ ), and the full study area analysis identified the Human Activity model as the most plausible ( $w_i = 1.000$ ).

The full study area analysis consistently identified the Combined Anthropogenic model as the most plausible for all fires, large fires ( $w_i = 1.000$ ) and fires separated by decade (1990  $w_i = 1.000$ , 2000  $w_i = 1.000$ ). Each of these models incorporated varied forms and decade-specific values for land use or housing density and population density. The repeated selection of the Combined Anthropogenic model suggested that the importance of its constituent spatial drivers was consistent across decades. However, the direction of the coefficients for the covariates was not always consistent, including opposite signs for some covariates between the full study area models for all fires and large fires (Table 5).

Unlike in the full study area, the most plausible Oconto County models for the two separate decades were not the same. For the 1990s, the Soil and Human Activity model was the most plausible ( $w_i = 0.900$ ), whereas for the 2000s, the Combined Anthropogenic model was the most plausible ( $w_i = 1.000$ ). These models shared several covariates (population density, distance to road, distance to railroad and distance to large city), but the 1990 model also included Soil attributes (drainage, available water and percentage water cover) whereas the 2000 model included Economic attributes (median house value, percentage seasonal homes and land-use index). The variability in these decadal models indicated a potential shift in spatial drivers through time that was not apparent for the full study area.

The exploratory analysis evaluating the removal of covariates from the Combined Anthropogenic model for Oconto County indicated that the full model had the highest weight of evidence ( $w_i$ ) when compared with models that had any

**Table 5.** Parameter coefficients from the most plausible model and change in Akaike Information Criteria ( $\Delta AICc$ ) and Akaike weights ( $w_i$ ) from post hoc analysis of a set of models that removed individual covariates from the Oconto County and full study area Combined Anthropogenic models

See Table 3 for definitions of parameter abbreviations. Abbreviations in parentheses indicate the functional forms considered for each covariate: F for factor, Log for logarithmic, P1 for first-order polynomial, P2 for second-order polynomial

Parameter (function)	Coefficient	$\Delta AICc$	$w_i$
<b>Oconto County</b>			
Intercept (full model)	-10.74	0.00	0.959
PctSeas (P1)	0.08	6.31	0.041
DistRail (Log)	-0.15	18.86	<0.001
DistLgCity (P1)	$-2.43 \times 10^{-5}$	24.28	<0.001
LU_HDI (P2)	0.01	40.84	<0.001
LU_HDI^2 (P2)	$-1.29 \times 10^{-5}$	N/A	N/A
DistRoad (log)	-0.53	70.26	<0.001
PopDen (log)	0.02	88.47	<0.001
MHVal (P1)	$-0.22 \times 10^{-5}$	1272.41	<0.001
<b>Full study area</b>			
PctSeas (P1)	$7.60 \times 10^{-4}$	0.00	0.525
Intercept (Full model)	-11.60	0.20	0.475
LU_HDI (P2)	$4.04 \times 10^{-3}$	11.10	<0.001
LU_HDI^2 (P2)	$-6.26 \times 10^{-6}$	N/A	N/A
DistLgCity (P1)	$-4.43 \times 10^{-6}$	130.30	<0.001
DistRail (log)	-0.13	249.40	<0.001
MHVal (P1)	$-2.28 \times 10^{-6}$	1760.90	<0.001
PopDen (log)	0.19	1928.30	<0.001
DistRoad (log)	-0.71	2373.00	<0.001
<b>Full study area – large fires</b>			
LU_HDI (P2)	0.01	0.00	0.597
LU_HDI^2 (P2)	$-7.40 \times 10^{-5}$	N/A	N/A
DistLgCity (P1)	$-4.45 \times 10^{-6}$	2.38	0.182
PctSeas (P1)	-0.01	3.30	0.115
Intercept (Full model)	-15.19	3.49	0.104
DistRail (Log)	-0.28	12.30	0.001
DistRoad (Log)	-0.49	13.41	0.001
MHVal (P1)	$8.27 \times 10^{-6}$	46.27	<0.001
PopDen (Log)	$-1.58 \times 10^{-4}$	81.83	<0.001

covariate removed (Table 5). The model excluding median home value had the lowest  $w_i$ , indicating it was the least plausible model of the set. For the Oconto County 1990 and 2000 decadal models, the models excluding distance to road and median home value had the lowest weights (both 0.000) of evidence respectively. For the 1990 model, the model excluding percentage water had a higher  $w_i$  (0.378) than the full model (0.327), indicating the inclusion of that variable resulted in a less plausible model. In the 2000 model, the model excluding distance to railroads had the highest weight of evidence (0.679), exceeding  $w_i$  for the full model (0.305).

In the all-variables model for Oconto County, the models excluding housing density, distance to large city, August maximum temperature, June precipitation or presettlement fire rotation (FR) class had higher weights of evidence than the full model (0.046), with the model excluding FR class showing the greatest  $w_i$  (0.438). The model excluding median home value

covariate showed the lowest  $w_i$  (0.000), indicating that its removal does not result in a more plausible model.

The removal of individual covariates from the Combined Anthropogenic model for the full study area indicated that the model excluding distance to road had the lowest  $w_i$  near zero, followed closely by the models excluding population density, and then median home value (Table 5). The model excluding percentage seasonal ownership had the highest  $w_i$ , even greater than the full model. The evaluation of models excluding covariates from the Combined Anthropogenic model for large fires identified the models excluding the same three covariates (population density, median home value and distance to road) as having the lowest weights of evidence, with a different rank order. Population density had the lowest  $w_i$ , followed by median home value and then distance to roads (Table 5). Models excluding housing density, distance to large city and percentage seasonal ownership each showed higher weights of evidence than the full model.

## Discussion

Our spatial analysis demonstrates the importance of human influence on wildfire occurrences by the inclusion of anthropogenic, not biophysical covariates in the most plausible models. Syphard and others (2007) also concluded that human factors are increasingly overriding the biophysical influence in fire regimes. Analyses of the full study area consistently demonstrated that distance to roads, population density and median home values (in varying order) were important model components during both of the decades and for large fires. The human influence is not always straightforward, as indicated by a curvilinear response to residential housing density. In both the Oconto County models and the full study area models, the land-use housing density index (LU\_HDI) had a quadratic functional form (Table 5), peaking at the medium housing density class. Syphard *et al.* (2007) reported a similar relationship with population density in California, where fire peaked at intermediate densities, and suggest that thresholds of anthropogenic relationships (e.g. population and housing densities) may be important to fire risk. Because the land-use housing density index, and not housing density itself was included in the most plausible models, it is possible that these land-use classes effectively represent those thresholds, and that the relative frequency of these housing density classes, and not housing density *per se*, account for this finding. Across the two study areas between 1990 and 2000, housing density increased at a nearly equal rate (9.2% Oconto County, 8.9% full study area). At the same time, the area of both the medium- and high-density residential land-use classes decreased (Fig. 7). The decline in these two land-use classes during this time period may partially explain the declining trend in wildfire occurrences across the full study area, but it does not provide an explanation why Oconto County does not exhibit a similar trend. In the interpretation of these housing density trends, it is important to keep in mind that most of the areas with the highest housing density have been excluded from this analysis because they have local, not state or Federal, fire protection. We are therefore missing the high end of this scale, which might influence the relationships between housing density and wildfire occurrences.

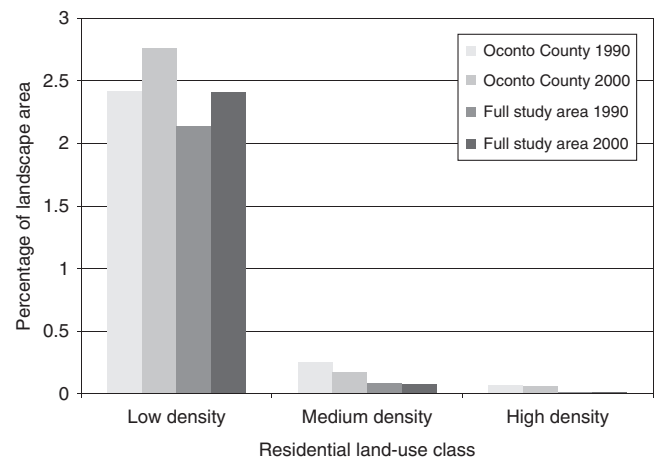


Fig. 7. Percentage of landscape area in the residential land use classes in 1990 and 2000 for Oconto County and the full study area.

Although human influence appears important for both Oconto County and the full study area, there are subtle differences between the two. Within Oconto County, economic variables (e.g. home value) appear to be the strongest drivers, whereas human activity (e.g. population density, road networks) appears to be the strongest driver across the full study area. In particular, median home value appears to be most strongly associated with the spatial pattern of ignitions within Oconto County, but this relationship is not as strong as distance to road and population density across the full study area. Again, the exclusion of areas with local fire protection may account for part of this difference.

Few published studies directly address social factors of wildfire occurrences (but see Prestemon and Butry 2005), but we can speculate on how social factors may have influenced wildfires. For example, median home value may be negatively related to fire occurrence owing to social differences between the occupants of high-value and low-value homes. Areas of high-value homes may be in more urban-suburban settings, have occupants with a more urban background (such as second-home owners) or both, where debris-burning and campfires (for cooking or recreation) are not the norm, whereas areas of low-value homes may be more rural, where debris-burning and campfires are more common. Additionally, the economic cost of trash disposal could contribute to wildfires caused by debris-burning in low-home-value areas, where homeowners (who may include retirees on fixed incomes) might be unable or unwilling to pay for trash disposal at the dump when they can burn it themselves instead. In addition to these accidental fire causes, economic factors such as low wages and poverty, for which home value could serve as a surrogate, have been linked to wildland arson (Prestemon and Butry 2005). Median home value appears to have a stronger influence on fire occurrence in Oconto County than in the full study area, which may indicate that this social difference is greater in Oconto County than elsewhere in the region. The median home values may be surrogates for other characteristics of homeowners that should be explored more directly with additional social science research.

Although the same drivers are important in determining locations of large fires, the relative influences of the drivers are different. The sign of the coefficients for percentage seasonal ownership, median home value and population density switch for large fires relative to the coefficients for all fires. This result is consistent with the findings of Cardille *et al.* (2001) and Sturtevant and Cleland (2007) that large fires have different drivers than small fires, but our results differ in that biophysical factors did not show increased importance for the large fires. The influence of the land-use housing density index also changed for large fires, in that the quadratic form peaks at the lowest values (0–1) of the index, corresponding to areas with no or very low housing density, and declines as the index increases towards the high-density class. These large fires generally represent fires that escape initial control by suppression, which appear to originate in the most remote areas where they may not be quickly reported or suppressed.

Our results indicate that drought is an important driver of the number of wildfire occurrences, and a less important driver of mean fire size. The important influence of drought on fire regimes has been well established by other researchers (Mitchener and Parker 2005; Xiao and Zhuang 2007; Brown *et al.* 2008; Grala and Cooke 2010), and is further supported by the results of our regression analysis. All of the most plausible models for number of wildfires showed strong negative linear relationships with average PDSI, which corresponds with the results of Ruffner and Abrams (1998) that show increased lightning-caused fires in drought years (PDSI < -2.0) in Pennsylvania. In nearly all cases in the present study (92% of models), the models using annual average PDSI had lower AICc values than the models using seasonal average PDSI, which suggests that drought conditions outside the typical fire season may still influence the fire regime during the fire season. Mean fire size appears to be less influenced by drought than the number of fires. PDSI was not included in the most plausible fire size models for the majority of causes, and in the fire size model for all records, the coefficient for PDSI was smaller than in the number of fires model, as well as having larger standard errors. Contrary to Ruffner and Abrams (1998), we did not see an effect of drought on MFS of lightning-caused fires. The precipitation, temperature and climate variables that were important in the models of Cardille *et al.* (2001) did not appear in any of our most plausible models, likely because they operate on a scale that is broader than that of our analysis. Still, the influence of these climate factors is evident from the consistently strong relationship between the annual number of fires and the drought index. Our analysis underscores the importance of accounting for drought as a key driver when trying to evaluate temporal trends that may be related to social and land-use changes.

Despite increasing housing density (in both magnitude and spatial extent) throughout the region, the number of wildfires has been declining in recent years across the study area when accounting for drought influences. This result was contrary to our expectations. Syphard *et al.* (2007) also showed a decline in wildfire occurrence in California corresponding with increasing housing density, though their analysis did not account for drought effects. Because non-anthropogenic (lightning)-caused fires show a declining trend during this

time period (Fig. 4), we speculate that fuel conditions in general have become less favourable to fire ignitions. We also expect that some social factors are contributing to the decreasing wildfire trends in this area among certain causes. Possible social contributors include fire prevention education, fire prevention activities (e.g. fuel treatments), suppression planning, suppression actions and demographic changes. We only evaluated records of fires at least 0.09 ha in size, so it is possible that fires of smaller size, although having a negligible effect on fire risk, would support our original hypothesis of an increasing trend in fire occurrence.

The result that Oconto County did not show any temporal trends of annual fire occurrences (Fig. 3), whereas the full study area did show temporal trends, which indicates that the drivers affecting fire occurrences within the County are not necessarily the same as those working across the full study area. When broken down by specific cause, the relatively small number of wildfires in the County prevents us from evaluating trends for specific fire causes, but we can speculate on what differences may exist between Oconto County and the region at large. The proportions of wildfires due to each cause are fairly similar at both scales, so discrepancies in the frequency of causes are not likely the reason for the difference. The land-use classes and housing density in Oconto County show similar proportional changes to the full study area between decades (Fig. 7), indicating that land-use changes probably do not account for the difference either. However, Oconto County has a larger proportion of area in agricultural land use, which may partially account for its lack of temporal trend in fire occurrences, because other research has shown fires in agricultural land to have different temporal patterns and drivers than forest fires (Sturtevant and Cleland 2007). We suspect that these land-use differences as well as social factors have contributed to the difference in temporal trends between Oconto County and the larger region.

The spatial analysis separated by decade indicates some potentially different drivers between the two time periods in Oconto County. With only two points in time, we cannot draw any definitive conclusions about trends, but the fact that biophysical factors were important in the 1990s but not in the 2000s is interesting nonetheless, and we can speculate why there may be differences. For the parameters that the two decadal models share, the coefficients show similar values, so it appears that the biophysical factors of soil drainage, soil water-holding capacity and percentage of the landscape in water in the 1990s model are replaced by percentage seasonal home ownership and median home value in the 2000s model. This implies that there was a social shift that made these socioeconomic parameters a stronger influence on the pattern of wildfire occurrences, or a biophysical difference that decreased the importance of the biophysical parameters. The 1990 decade had more severe drought conditions, with 2 years below the PDSI threshold for moderate drought (-2), than did the 2000 decade, with no year meeting the drought threshold. As we have seen the importance of drought in the temporal analysis, it is probable that the instances of drought in the 1990 decade increased the importance of the soil parameters (Drainage and AvWater) relative to the human factors. In the decade that followed with less drought, the underlying socioeconomic factors exerted more influence. The full study area models, however, indicate that the

socioeconomic variables were important drivers for both decades for the region as a whole. The differences in spatial drivers in the 1990 decade and the differences in temporal trends between Oconto County and the full study area provide evidence that the underlying drivers of fire occurrence have not always been the same across these two areas.

#### Management implications

When considering future spatial and temporal patterns of ignitions, it is important to identify the covariates that are likely to change over time. Our spatial models were almost completely composed of anthropogenic covariates that are subject to change in the future based on human development patterns. Population changes and development that alter the spatial patterns of these covariates will influence the future spatial pattern of wildfire ignitions. If projections of the future spatial pattern of these covariates were available, they could be used with these models to provide insight into the changes to the spatial patterns of wildfires. Even without specific future predictions, this analysis has identified important human-related drivers of wildfires, which could be the focus of land managers, development planners and others concerned with minimising fire risk in an increasingly human-dominated landscape such as this.

Some of the biophysical factors that we included in our analyses (e.g. soil attributes) could be considered stable into the future, whereas others (e.g. precipitation, fuel class) will be dynamic. Although these biophysical covariates did not appear in our most plausible models, changing biophysical factors are still important to consider in determining future risk. Drought cycles and climate change vary at scales broader than our analysis, but they will influence regional fire patterns. According to the US Global Change Research Program (Easterling and Karl 2000), the Midwestern United States is likely to experience increased temperatures and precipitation over the next century. Because evaporative demand may outpace precipitation when both temperature and precipitation increase (Rind *et al.* 1990), a net result of more drought-like conditions is expected in many areas.

Owing to data availability, our analysis focussed on a relatively short time period of fire history, but we did see some evidence for shifting drivers through time. Over longer time periods, as human development interacts with the surrounding landscape, the relative importance of drivers may change (Guyette *et al.* 2002). Complex social factors are likely to contribute to shifting drivers in this region.

Despite some of the decreasing trends, severe wildfire years can still occur and fires attributed to some causes have not declined. The year 2007 (the last year of available data) was notable for the relatively high area burned and large mean fire size, due to a few very large fires. The most common cause of wildfires in this area, debris-burning, does not show a temporal trend in any of the models. The social factors that are causing declines in other causes are not carrying over to debris-burning, at least not as strongly. Along with campfires, which also do not show a declining trend, debris-burning could be targeted for future prevention education and activities, which can be effective at reducing these types of preventable wildfires (Prestemon *et al.* 2010).

#### Conclusions

Our results provide additional support for drought as an important driver of wildfire occurrences and mean fire size. Once we accounted for the effect of drought, we found that the number of wildfires is declining across the study area, despite increased housing density. Our evaluation of spatial models demonstrated the importance of human influence on wildfire occurrences, especially human activity, infrastructure and property values. Among these influences, we identified a non-linear relationship between housing density and wildfire occurrence. We found that large fires are driven by similar landscape variables to smaller fires, but the influence is often opposite. We discerned subtle differences in drivers between the full study area and Oconto County, which reinforces the need for local information. We speculate that social factors play an important role in both the temporal and spatial drivers of wildfires. These spatial and temporal drivers of wildfire occurrence have important implications for land management, land-use planning, wildfire suppression strategies and ecological goals. Managing forests and other wildlands to meet ecological goals while also accommodating housing growth requires attention to somewhat different factors and processes in the unique landscape of northern Wisconsin where agricultural lands and broadleaf forests mix with fire-dependent Eastern pine barrens.

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