Research Article

Understanding Uncertainty in Broad-Scale Mapping of Historical Vegetation in the Great Lakes Region

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Associate Editor: Joshua Gabriel Cohen

ABSTRACT

In the Great Lakes Region, minor differences in soils and location (e.g., proximity to the Great Lakes) can lead to strong differences in vegetation; thus, the utility of broad-scale mapping often depends on capturing subtle landscape features and local processes. Similarly, vegetation patterns are in part a result of disturbances that have changed drastically over time, therefore mapping efforts must take into account vegetation–fire relationships to various biophysical settings (e.g., landtype associations, climate, and soils). Despite this, too little attention has been given to potential sources of mapping error, which include data limitations, ecological similarity, community classifications, locational error, sample quality, and lack of knowledge of systems—specifically natural disturbance regimes. We used ~23,500 plots with detailed vegetation, soils, and classification information to (1) evaluate LANDFIRE (Landscape Fire and Resource Management Planning Tools) historical vegetation (Biophysical Settings or BpS) classifications, (2) refine these classifications based on detailed soil regime and plant associations, and (3) draft fuzzy set soil-classification gradient maps to evaluate uncertainty in mapping and sources of mapping errors. Locally derived reference plot data often did not agree with LANDFIRE BpS mapping even for classifications generalized broadly by Fire Regime Groups. Our fuzzy methodological approach improves decision-making processes by assessing mapping confidence and highlighting potential sources for errors including classifications themselves. Our mapping efforts suggest that soil drainage and productivity data helped to delineate BpS classifications, which may in turn help stratify Existing Vegetation Types into feasible options.

Index terms: biophysical settings; fuzzy mapping; LANDFIRE; map error; soil gradients

INTRODUCTION

The Great Lakes Region has complex vegetation patterns representing many transitional vegetation types controlled by biotic and abiotic factors such as glacial substrates, water table depth, varying climate, and historical forces including disturbances. Our understanding of historical vegetation patterns and disturbance regimes in the Great Lakes Region are largely derived from General Land Office (GLO) records, forming the basis for regional conservation targets (Comer et al. 1995; Ravenscroft et al. 2010). While invaluable, GLO records are coarse-scale, leaving key knowledge gaps regarding fine-scale historical disturbance and vegetation patterns in many Lake State systems. Nevertheless, the emulation of natural disturbances is increasingly used as a basis for managing natural resources (Hunter 1993; Cleland et al. 2004; Perera et al. 2004), and spatially explicit "all-lands" data that capture relationships between disturbance and vegetation patterns are increasingly important in fire and resource management and being adopted for a variety of applications.

Mapping ecosystems can play an important role in understanding ecosystem processes and relating processes to appropriate spatial scales (Gong et al. 1996; Schaetzl et al. 2013). LANDFIRE, an interagency mapping program that produces comprehensive maps and data describing vegetation, wildland fire, and fuel characteristics for the entire United States, is a good example. Although LANDFIRE vegetation products are mapped at a 30-m pixel resolution, these products are designed primarily to support regional planning efforts. A key concern is that such mid-level land cover maps are of insufficient quality for operational applications in the Great Lakes Region. However, there has never been a systematic evaluation of LANDFIRE data accuracy in this region. Similarly, despite having locally derived, well founded, and regionally available fine-scale data-driven classifications that utilize soil–plant relationships, there has not been an attempt to methodically integrate this knowledge into broad-scale mapping efforts or evaluate mid-level classifications like LANDFIRE's.

LANDFIRE data products provide rich ecological information, particularly the Biophysical Settings (BpS) product. BpS depicts pre-Euro-settlement reference conditions with disturbance explicit in driving ecological change and vegetation patterns. BpS map unit names represent natural plant communities that would become dominant in later stages of successional development considering historical ecological disturbance processes such as fire. BpS predict the proportions of vegetation succession classes under reference conditions using state-and-transition models based on expert derived disturbance probabilities (Yanoff et al. 2007; Rollins 2009). BpS essentially compiles what we know of the historical ecology for various systems and uses expert opinion coupled with topographical and other datasets along with local data where existing vegetation is

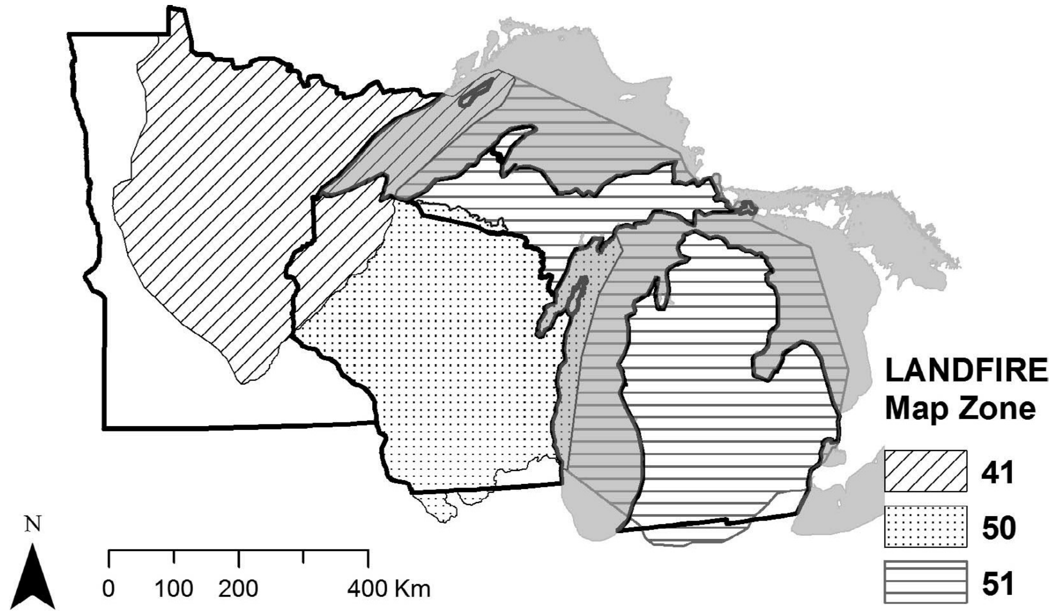

Figure 1.—Great Lakes Region project area: LANDFIRE mapping zones 41, 50, and 51 corresponding to portions of Minnesota, Wisconsin, and Michigan, respectively.

highly departed from historical vegetation (Rollins et al. 2007). Thus, BpS is a conglomerate of published literature, expert opinion, GIS datasets, and, to a degree, local vegetation data.

Mapping efforts that consider both processes and patterns, as BpS does, are incredibly useful but understandably challenging. Basic assumptions of BpS are that reference conditions are, first, understood and, subsequently, can be accurately predicted by modeling and then mapped. This can be problematic in highly altered systems with limited knowledge of historical disturbance regimes, particularly when measures of departure between current and historical conditions are predicted from these same reference conditions, as in the case of LANDFIRE BpS (Yanoff et al. 2007; Ryan and Opperman 2013).

Any map is simply a model or generalization and will contain error (Brown et al. 1999). It is important, however, that the quality of thematic maps be assessed and expressed in a meaningful way, not only to provide insight to the accuracy of the map and its suitability for a particular purpose, but also in understanding error and its likely implications for management planning. This is especially true if potential errors are allowed to propagate (and multiply) through analyses linking the map to other datasets (Janssen and van der Wel 1994; Foody 2002) as is the case with many LANDFIRE spatial data products (Rollins 2009). Biophysical settings, for example, are important precursors to the LANDFIRE project's fire regime products (Rollins 2009). Errors in mapping vegetation communities can arise from many sources including incomplete understanding of community classifications (e.g., in the processes that drive particular communities), ecological similarity (similar physiognomic, diagnostic species), data limitations, locational mapping error, and overall sample quantity for the training and mapping process.

The use of Habitat Types that reflect soil and plant community associations have increasingly become an integral component determining potential vegetation for a given site. There is a long history of using Habitat Typing methodology to understand management options for particular sites (Cajander 1926), including in the Lake States region (Barnes et al. 1982), with understory vegetation often serving as key determinants of site conditions, including nutrient and moisture availability (Kotar 1986; Kotar and Burger 1996a, 1996b; Kotar et al. 2002). Habitat Types are not all that different from defining BpS classifications made using soils and other ancillary data, just at a finer scale. Habitat Type classifications (Kotar and Coffman 1984; Kotar 1988; Kotar and Burger 1996a), and more recently Native Plant Community classifications in the Great Lakes Region (Minnesota Department of Natural Resources 2003), follow the convention of de-emphasizing canopy trees in data analysis based on observations of understory species composition generally being more reflective of site conditons (Aaseng et al. 2011). Similarly, soil characteristics and associated plant communities are primary delineation criteria at finer Land Type and Land Type Phase scales, the patterns of which can provide useful information on the composition of mid-level Land Type Associations (LTAs, 1:250,00 to 1:60,000 map scale) and help generate misclassification corrections where necessary (DeMeo et al. 2001). LANDFIRE classifications, which are based on NatureServe's Ecological Systems (Comer et al. 2003), are landscape-scale or mid-level (LTA) classifications that incorporate biogeographic region, dominant cover type, and disturbance regimes.

We set out to understand sources and magnitude of potential mapping errors within LANDFIRE's historical vegetation (BioPhysical Settings, BpS) mapping in the Great Lakes Region (Figure 1). We also aimed to evaluate the potential to use locally derived soils-based assignment and ancillary data, rather than pixel-based assignment with remotely sensed explanatory data, to inform broad-scale mapping. We did this by (1) quantifying existing classification errors in mid-level (LANDFIRE) vegetation classification data, (2) developing a simple and portable synecological approach to mapping plant communities based on knowledge of soil–plant–community relationships, and (3) using fuzzy set soil–vegetation gradient mapping in an attempt to understand sources of uncertainty and types of errors in vegetation mapping. Modeled Habitat Types exist for portions of Michigan, however we used only field-collected data from Minnesota (NPC plots) and Wisconsin (Habitat Types) to evaluate BpS mapping. Soil regime and fuzzy set mapping were applied to the three states. Our efforts to define mapping errors and provide a basic framework for mapping historical vegetation communities is founded on a simple and sound ecological framework that can be used to improve large-scale mapping efforts by helping to set informed thresholds of allowable amounts and types of error based on the best information available.

METHODS

Study Area

The Great Lakes Region of Minnesota, Wisconsin, and Michigan corresponding to LANDFIRE map zones 41, 50, and 51, respectively, was our study area (Figure 1). Climate, soils, and topography are highly variable across the region. In the north climate is cold and terrain dominated by Precambrian rocks of the Laurentian shield with thin soils and conifer dominated cover types. In southern areas the climate is warmer, soils deeper with more deciduous forest (Schaetzl 2017). Glaciation and proximity to the Great Lakes have strong local controls throughout the region. Snowfall, for example, ranges from 80 cm near Duluth, Minnesota, outside the lake effect zone, to more than 600 cm in areas strongly affected by Lake Superior (Albert 1995; Andresen and Winkler 2009). Relationships between vegetation and glacial features are readily observable with northern hardwood forests tending to occur on glacial moraines, mixed pine (*Pinus* spp.) and oak (*Quercus* spp.) forests on ice-contact features, and red pine (*P. resinosa* Aiton) and jack pine (*P. banksiana* Lamb.) forests on outwash plains (Jordan et al. 2001; Schaetzl 2002).

The primary source of pre-Euro-American settlement vegetation data for our study region that we considered was LANDFIRE's Biophysical Settings (BpS). BpS is based on both current biophysical environment (e.g., aspect, slope, topography, soils) and an approximation of historical disturbance regimes. BpS classifications are based on NatureServe Ecological Systems (Comer et al. 2003) and are linked to vegetation succession models and mapped at 30-m pixel resolution for the entire United States. Although there is no minimum mapping unit for LANDFIRE, products are designed for national to regional scales (100s–1000s ha) and applicability varies by location and specific use (Rollins 2009).

Quantify Classification Error

We used plot-level datasets from two independent ecological classifications to test accuracy of mid-level BpS mapping: Wisconsin Habitat Types and Minnesota's Native Plant Communities. Each system corresponded to a different LANDFIRE mapping zone, which were evaluated separately, allowing us to test accuracy across a wider-range spatial scale. Both classifications were crosswalked to BpS classifications for a common legend. We did this by translating Wisconsin Habitat Types and Class level Minnesota Native Plant Communities (NPC) using detailed documentation of species, ranges, and soil characteristic for various plant communities to LANDFIRE BpS classifications (Appendices A–B; Kotar and Burger 1996a, 1996b; Kotar et al. 2002; Minnesota Department of Natural Resources 2003).

After translating Habitat Type and NPC classifications to the LANDFIRE BpS legend, we conducted accuracy assessments for LANDFIRE zone 41 using NPC plots ($n = 22{,}016$), and zone 50 (Figure 1) using a subset of Wisconsin's Continuous Forest Inventory (CFI) vegetation plots that included Habitat Types and were also found within homogeneous stands >2 ha and located away from ecotones or edges of land cover types ($n = 758$). We used this selection criteria to avoid locational error in both georeferenced data points and LANDFIRE pixels, as well as issues related to fine-level point-in-cell extraction for assessment of mid-level data (The Nature Conservancy 2011). It should be noted that ground verification plots are not without their own sources of error; thus, accuracy assessments should be viewed as indicative rather than definitive. Analyses were conducted in ESRI's Spatial Analyst tool in ArcMap (ArcMap 10.4.1; ESRI, Redlands, California, USA) and Microsoft Access software.

Plot locations (CFI and NPC) were not allocated on an area-weighted basis nor randomly distributed, which presumably could introduce a source of bias; however, the data were appropriate for comparisons in other ways. For example, Minnesota's NPC plots were subjectively located in areas representing native vegetation and distributed as evenly as possible on the landscape to capture a full range of environmental conditions. Both the NPC plot data and classifications thus represent vegetation across an environmental gradient (e.g., soil moisture and types). Most plots were 400 m^2 (100 m^2 plots were used for herbaceous and shrub dominated vegetation), located in homogeneous stands >2 ha in size, and placed as to be representative of the entire stand or classification type. We eliminated NPC plot data collected prior to 1995 to ensure positional accuracy and data quality (J. Almendinger pers. comm.). Continuous Forest Inventory plots in Wisconsin are similar to national Forest Inventory Analysis plots. CFI plots were represented statewide, but limited to state forest lands, with a plot density of one plot per 81 ha of forest.

To address potential problems with locational accuracy and pixelation we examined the datasets with (and without) 60-m radius buffers around the vegetation plots (~11,310 m^2 area) and used a majority rule to determine classifications for buffered plots. If the accuracy of classifications improved by expanding the plot area with buffering, we would expect that error was, at least in part, attributable to pixelation and/or locational accuracy of the georeferenced point locations.

For each plot, we compared the vegetation classification as predicted by the LANDFIRE map, to the classification as determined from the ground verification plot data and collated results into an error matrix (Appendices C–D; Foody 2002). In the error matrices, LANDFIRE classifications were given as rows and ground verification as columns. Diagonal elements in matrices indicate numbers of samples for which the classification

Table 1.—Criteria used in fuzzy set risk map (RMAP) modeling of BpS classifications. Each criterion was weighted based on relative importance of each criterion with weights always summing to 100%.

	Criteria	Description
1	EcoRegion[a]	Bailey ecoregion sections
2	USGS Map Zone	Used if a BpS was restricted to only one map zone (41, 50, or 51)
3	Position Index	Terrain slope position from 0 (flat) to 100 (ridge tops); low values are valley bottoms
4	Drainage Index	Long-term soil wetness developed from taxonomic sub-group interpretations with ordinal ranking (0–99)
5	Productivity Index	Ordinal estimate (0–19) of inherent soil productivity, prior to anthropogenic changes, without water table limitations
6	Slope	Maximum rate of change (percent rise) in elevation via National Elevation Dataset (NED)
7	Aspect	Direction of maximum rate of change in NED elevation from one cell to another (calculated using ASPECT function in Arc)
8	Northiness	Represents slope and aspect; 1000 represents 100% slope facing north, 500 is flat, 1 is 100% slope facing south
9	Eastiness	Based on slope and aspect; 1000 represents 100% slope facing east, 500 is flat, 1 is 100% slope facing west
10	NHD Flow Lines (Streams)	National Hydrology Dataset, NHDPlus, gridded stream network flow lines

[a] Ecoregion was weighted in models based on abundance of indicator species from General Land Office (GLO) data, Bailey (2016).

results agree with the reference data. Off-diagonal elements in each row represent the numbers of plots that have been misclassified (commission error). The off-diagonal elements in each column are those samples omitted by LANDFIRE classifications (omission errors). We derived a measure of the overall classification accuracy from the matrix by dividing the sum of correctly classified pixels (diagonal) by the total number of pixels. We used similar steps to obtain accuracy by individual classifications for both user's (commission error) and producer's (omission error) accuracy. Producer accuracy is a measure of the probability a land cover on the ground is correctly classified, whereas user's accuracy is the probability a pixel labeled as a land-cover class in the map was really this class.

Soil Regime–Plant Association Delineations

Soil taxonomy is generally based on morphological features readily measurable (e.g., horizon type, color, texture) rather than directly on functional properties that influence conditions of plant growth, such as moisture and nutrients (Kotar 1986). Forest Habitat Type identification is based on functional properties (moisture and nutrients; Kotar and Burger 1996a) typically by field examination of understory vegetation within a stand; however, Habitat Types can also be inferred based on soil moisture and nutrient regimes found at a given location. This relationship results from individual Habitat Types having specific moisture and nutrient requirements (Michigan Department of Natural Resources 2006). NPC classes were developed using a similar methodology to Habitat Typing and based on measures of soil moisture and nutrient content. In the development of NPC classifications, canopy trees were removed from data to emphasize understory vegetation, which is more immediately sensitive to, and therefore, more reflective of, habitat conditions than canopy trees (Aaseng et al. 2011). Host and Pregitzer (1992) have also illustrated that specific overstory–ground flora assemblages recur in characteristic landscapes. This is an important feature of Habitat Type classifications in the Great Lakes Region and elsewhere.

Thus, describing a site via the plant community has been demonstrated for fine-scale classification. We use similar methodology to predict plant communities from soils information regionally. Establishing rigorous relationships among soil characteristics and forest species distributions over broad areas is a complex task, as data generally do not exist at the appropriate scales or required spatial extent, particularly when restricted to national datasets (Burger and Kotar 2003; Schaetzl et al. 2009). We established soil–plant relationships over broad scales using a soil drainage index that quantifies long-term soil wetness developed by Schaetzl et al. (2009) for the entire United States. The Drainage Index (DI) reflects the amount of water a soil supplies to plants under natural conditions, over long timescales (Schaetzl et al. 2009). The DI has demonstrated the ability to resolve fine differences between sites (e.g., very dry and dry) and reinforce ecological descriptions and successional pathways that Kotar and Burger (1996a, 1996b) identified across large geographic regions with an ordinal index (Schaetzl et al. 2009). DI has been used to assess linkages between pre-Euro-settlement vegetation and soils based on General Land Office data (Schaetzl and Brown 1996). Similarly, we used an ordinally based Productivity Index (PI) developed at 30-m resolution for the entire United States by Schaetzl et al. (2012). These datasets are tied to county level soil (SSURGO database) map units and delineate soils well across scales (Schaetzl et al. 2009). We used fine-scale methodology for regional mapping by first describing the relationships between drainage and fertility gradients and different BpS classifications and then used this information for fuzzy set mapping across the Great Lakes Region.

Fuzzy Set Mapping to Understand Uncertainty

A major assumption of error matrices is that there is a single correct community classification for each plot. Fuzzy set theory recognizes intrinsic ambiguity and simulation of natural variability (Rapp et al. 2005). The use of fuzzy sets to assess uncertainty in cover maps provides a robust framework for examining unique characteristics of map error (Lowry et al. 2008) and for improving the mapping process. We used an integrated, multi-criteria vegetation mapping method to map BpS classifications and to evaluate sources of error, particularly errors related to class similarity, and ambiguity in the classifications themselves. The mapping framework we used, a national insect and disease risk mapping program (RMAP), was

Table 2.—User and producer percent error between zone 41 Minnesota Native Plant Community (NPC) plot data points ($n = 22{,}805$), zone 50 Wisconsin Continuous Forest Inventory (CFI) data plot data points ($n = 758$), and LANDFIRE BpS classifications with $\geq$10 comparisons. Table also shows impacts of lumping classifications on accuracy for particular classes (lighter font).

	Zone 41				Zone 50			
Biophysical setting	Producer		User		Producer		User	
Laurentian-Acadian Northern Hardwoods Forest	35.2	43	12.8	22	16.1	51	35.0	60
Laurentian-Acadian Northern Hardwoods Forest - Hemlock	4.7		36.5		39.3		27.9	
Laurentian-Acadian Northern Pine(-Oak) Forest	13.9		33.1		64.6	65	23.8	56
Laurentian Pine-Oak Barrens	0.3	69	1.7	59	9.6		27.8	
Laurentian-Acadian Jack Pine Barrens and Forest	91.3		0.4					
North-Central Interior Maple-Basswood Forest	18.5		22.4		12.5		9.1	
North-Central Interior Dry-Mesic Oak Forest and Woodland	3.1		30.5		11.1		40.0	
North-Central Oak Barrens	4.3		2.4					
Boreal Jack Pine-Black Spruce Forest	11.8		30.3					
Boreal Acidic Peatland Systems	39.1		29.2					
Laurentian-Acadian Alkaline Conifer-Hardwood Swamp	8.5		15.2					
Boreal White Spruce-Fir-Hardwood Forest - Inland	22.7		7.7					
Boreal White Spruce-Fir-Hardwood Forest - Coastal	25.2	45	9.7	26	7.7		50	
Boreal White Spruce-Fir-Hardwood Forest - Aspen-Birch	23.6		18.8					
Laurentian-Acadian Floodplain Systems	8.1		7.0					
Eastern Boreal Floodplain	5.5		11.9					
Laurentian-Acadian Shrub-Herbaceous Wetland Systems	17.2		1.3					
North-Central Interior Sand and Gravel Tallgrass Prairie	19.8		34.8					
Northern Tallgrass Prairie	40.0		17.3					
Overall accuracy =	14.2				14.4			

developed by the USDA Forest Service Forest Health Protection Unit and is used by all nine Forest Service regions and 49 states (Krist et al. 2010). RMAP provides a consistent, repeatable, and transparent process through which interactive spatial risk assessments are conducted. In our case, we were interested in the "risk," or rather probability, of a classification occurring based on input parameters. We identified, ranked, and weighted mapping criteria (Table 1) for each BpS classification that determined the likelihood of a classification occurrence. Our goal was to limit the spatial input data to the most important criteria as determined from literature, including LANDFIRE's BpS model documentation, and other classification reference materials (Minnesota Department of Natural Resources 2003; Kost et al. 2007).

In RMAP, we first identified and equally weighted mapping criteria, but weights could be adjusted based on knowledge of their overall importance in determining a BpS classification. We then standardized criteria based on a common evaluation scale from 0 to 10, with 0 representing little or no potential for determining occurrence of a classification and 10 representing highest potential. Standardization allows for comparison of criteria with differing values and relationships assigned. For example, Laurentian-Acadian Jack Pine Barrens and Forest is most abundant on flat outwash plains; thus, the slope criterion was ranked such that flat slopes had high probability (0% slope = 10) and steep slopes less likely (100% slope = 0), with the intervening gradient defined by any number of curves. We conducted similar ranking for drainage (e.g., Laurentian-Acadian Jack Pine Barrens and Forest received high ranking on well-drained, dry soils), productivity, and all other criteria broadly important in determining a classification (Table 1). We ranked the probability of classifications by Ecosubregions (Cleland et al. 2005) based on General Land Office pre-European-settlement forest cover maps for the region (Comer et al. 1995; Schulte and Mladenoff 2001). For example, Laurentian-Acadian Jack Pine Barrens and Forest were given a high rank in ecoregions where jack and red pine were abundant in General Land Office data (e.g., ecoregion 212 Ka = 10). While we ranked ecoregions outside of the known range for a classification low (e.g., Central Interior types in Laurentian-Acadian ecoregions = 0), we did not restrict classifications by range (e.g., a Laurentian type could be mapped in a more southerly Central Interior region and vice versa). We modeled each BpS classification in this way ($n = 30$) using 240-m resolution spatial datasets for computational efficiency; however, all data we considered are nationally available at 30-m resolution. We did not model classifications that were not well represented in the source data or that were generally rare ($n = 15$; e.g., Lakeplain Prairie; Appendix E). We overlaid those types directly from LANDFIRE BpS into our final output map for illustrative purposes only. After we generated weights and standardized values for each criterion, we combined all criteria in a series of weighted overlays representing a final "risk," or probability, assessment. We combined factors within a weighted overlay, or weighted linear combination, by multiplying the factor weight by each criterion value, followed by a summation of the results (Saaty 1977; Krist et al. 2010) where

$$P = \sum W_i X_i$$

P = Potential for "risk"
W_i = weight criterion i
X_i = criterion score of factor i

We produced fuzzy probability maps for each vegetation classification ($n = 30$) with every map pixel scaled between 0 and

Table 3A.—Gradients of Drainage Index (DI) and Productivity Index (PI) data for Wisconsin Habitat Type Groups ($n = 710$).

Habitat Type Group	n (710)	Avg DI	(SD)	Avg PI	(SD)	Soil Regime
VD-D	190	30	18	5	2	DM/P
D-DM	80	35	18	6	2	M/P
DM	54	39	14	7	2	M/P
DM-M	27	48	18	11	2	M/R
M	100	47	13	8	2	M/M
M-WM	128	58	19	7	3	WM/P
N.LOW	112	84	16	12	3	W/R
S.LOW	19	85	9	13	3	W/VR

10. For each classification we then selected pixels with the highest probability of occurrence (values from 8 to 10) and overlaid all 30 modeled BpS classification maps using Arc highest function. We then analyzed overlapping BpS classifications which represented uncertainty in modeling of dynamic and interrelated entities.

RESULTS

Quantify Classification Error

The overall accuracy of the LANDFIRE BpS in relation to verification data was relatively poor with only 14.4% and 14.2% classified in accordance to the plot data in zones 41 and 50, respectively (Table 2; Appendices C–D). Buffering sample plots with a 60-m radius to increase classification areas improved accuracy but only slightly (e.g., from 14.4% to 20% in zone 41), suggesting that issues of plot position in relation to location of classification boundaries and/or issues of pixelation were not the primary cause for misclassification. Classification accuracy was highly variable (Table 2), ranging from producer accuracy <1% (Laurentian Pine-Oak Barrens) to over 90% (Laurentian-Acadian Jack Pine Barrens and Forest). Laurentian-Acadian Jack Pine Barrens and Forest had the highest producer's accuracy of any type (91.3%) and the lowest user's accuracy of any type (0.4%). This finding reflects that mapping of this community was over 91% better than random (it was not omitted where it should occur), but it was routinely mapped in places where it was not, resulting in a user accuracy only 0.4% better than random delineations. There were also differences in accuracy between zones with generally higher producer accuracy in zone 41 and user accuracy in zone 50.

Table 3B.—DI data derived from NPC plot ($n = 12{,}017$) moisture ordinal measure (0–9) for all types.

Moisture	n	Avg DI	SD DI	Moisture Regime
1	674	38.1	17.8	M
2	1025	42.5	18.9	M
3	3419	44.7	19.1	M
4	3382	59.6	19.1	WM
5	909	76.6	17.3	W
6	781	82.2	15.3	W
7	225	84.1	13.8	W
8	1150	83.0	16.3	W
9	452	84.7	15.1	W

Table 3C.—PI data derived from NPC plot ($n = 12{,}017$) productivity ordinal measure (0–9) for all types. DM = dry mesic, M = mesic, WM = wet mesic; P = poor, M = medium, R = rich, VR = very rich productivity. DI ordinal measure 0–99, dry–wet; PI ordinal measure 0–19, least–most productive.

Productivity	n	Avg PI	SD PI	Productivity Regime
0	186	13.6	1.5	VR
1	528	13.2	2.1	VR
2	1963	8.7	4.3	M
3	3278	8.6	3.7	M
4	3010	9.1	3.1	M
5	1271	9.9	2.5	M
6	1084	9.8	2.5	M
7	623	10.3	2.7	M
8	40	12.3	2.2	R
9	34	12.8	2.0	VR

In both regions, combining similar classifications (e.g., Laurentian-Acadian Northern Hardwood Forest and Northern Hardwoods Forest-Hemlock [*Tsuga canadensis*]) resulted in a marked increase in accuracy (Table 2). This is also true for the various pine classifications. Combining all the non-wetland pine types (Laurentian-Acadian Northern Pine Forest, Laurentian-Acadian Northern Pine [-Oak] Forest, Laurentian Pine-Oak Barrens, and Laurentian-Acadian Jack Pine Barrens and Forest) resulted in 69% producer and 59% user accuracy. Although an improvement, accuracy is still below generally recommended accuracy metrics of 70–85% accuracy (Thomlinson et al. 1999; Foody 2002), and confusion within and among these systems was apparent. Half of Laurentian-Acadian Northern Pine (-Oak) Forest, for example, was mapped as Jack Pine Barrens and Forest, and >20% was mapped as Boreal White Spruce-Fir Hardwoods Forest (*Picea glauca–Abies balsamea*); more than what had been correctly mapped as Pine (-Oak).

Soil Regime–Plant Association Delineations

We evaluated moisture and productivity gradients for Habitat Type and NPC Ecological Systems by moisture and nutrient gradient groups (dry/poor–wet/rich) against DI and PI data to assess the level of agreement between data (Table 3A, 3B, 3C). At this broad level a relative gradient was apparent and indices of productivity and drainage were highly correlated with the field-based NPC gradient delineations of moisture and nutrients (Pearson's $r = 0.639$). However, the ecological amplitude was greater than expected for both DI and PI with higher plot data moisture and productivity values in comparison to general DI and PI soil regime groupings (Schaetzl et al. 2009). While the range and mean drainage and productivity values were broader than expected by soil regime group, we were able to split among classification types with relative gradients (Table 4), illustrating the potential utility of DI and PI data for delineating and mapping vegetation communities.

Fuzzy Set Mapping to Understand Uncertainty

We created 30 models, one for each individual BpS based vegetation classification, and produced a fuzzy set map with a probability of a classification between 0 and 10 for every pixel (Figure 2). We did not restrict classifications by map ranges;

Table 4.—Gradients among the Drainage and Productivity Indices for LANDFIRE Biophysical Settings (BpS) as determined from Minnesota Native Plant Community plots ($n = 21{,}409$). Soil regime moisture: DM = dry mesic, M = mesic, WM = wet mesic, W = wet/soil regime productivity: P = poor, M = medium, R = rich, VR = very rich. Drainage Index (DI) ordinal measure 0–99, dry–wet; Productivity Index (PI) ordinal measure 0–19, least–most productive.

BpS	Soil regime	*n*	Avg DI	SD DI	Avg PI	SD PI
Boreal Acidic Peatland Systems	W/R	1894	78	19	11	4
Boreal Jack Pine-Black Spruce Forest	M/M	338	56	21	8	3
Boreal White Spruce-Fir-Hardwood Forest - Aspen-Birch	M/M	1650	54	19	9	3
Boreal White Spruce-Fir-Hardwood Forest - Coastal	WM/M	291	62	21	9	3
Boreal White Spruce-Fir-Hardwood Forest - Inland	M/M	1590	56	20	9	3
Central Interior and Appalachian Floodplain Systems	WM/R	21	67	29	11	4
Central Interior and Appalachian Shrub-Herbaceous Wetland Systems	WM/VR	112	74	26	13	2
Central Interior and Appalachian Swamp Systems	W/VR	53	81	20	13	3
Eastern Boreal Floodplain	W/R	292	82	15	11	3
Eastern Great Plains Tallgrass Aspen Parkland	W/M	7	78	15	10	4
Laurentian Pine-Oak Barrens	M/P	122	41	22	6	3
Laurentian-Acadian Alkaline Conifer-Hardwood Swamp	WM/M	747	72	21	10	4
Laurentian-Acadian Floodplain Systems	W/R	180	78	22	12	4
Laurentian-Acadian Jack Pine Barrens and Forest	DM/P	5863	30	20	5	2
Laurentian-Acadian Northern Hardwoods Forest	M/M	3193	52	15	9	2
Laurentian-Acadian Northern Hardwoods Forest - Hemlock	M/M	62	52	16	8	3
Laurentian-Acadian Northern Pine Forest	M/P	125	40	15	6	2
Laurentian-Acadian Northern Pine(-Oak) Forest	M/P	2783	40	16	7	3
Laurentian-Acadian Shrub-Herbaceous Wetland Systems	W/M	806	82	13	10	4
North-Central Interior Dry-Mesic Oak Forest and Woodland	M/M	399	47	19	10	3
North-Central Interior Maple-Basswood Forest	M/R	476	51	19	11	3
North-Central Interior Oak Savanna	M/R	163	54	22	12	3
North-Central Interior Sand and Gravel Tallgrass Prairie	M/R	61	39	17	11	2
North-Central Oak Barrens	DM/P	90	23	15	6	3
Northern Tallgrass Prairie	WM/VR	91	69	22	13	2
Grand Total		21,409				

however, ranges for high probability classification (8–10) outputs were plausible. Similarly, when we overlaid pixels with the highest probability of occurrence (values from 8 to 10) for all 30 modeled BpS classifications there was relatively little overlap among BpS's, indicating model ability in delineating types even with limited mapping criteria (Figure 3). Most overlap was between two plausible classifications and greater overlap ($\geq$3 classifications) among types was spatially limited (Figure 3). Generally, our mapping areas for various classifications and our maps generally were similar to the LANDFIRE BpS map (Figure 4).

DISCUSSION

Categorical maps are commonly produced to represent complex geographical patterns, making it essential to identify and address classification errors (Gopal and Woodcock 1994). The primary motivation for assessing the accuracy of maps is to understand the frequency, source, and magnitude of mapping errors. This can inform methods for improvements and more accurate end products. LANDFIRE Biophysical Settings (BpS) are used to assess regional vegetation departure and set management priorities at a variety of spatial scales, but caution is generally advised with local data applications. An implied assumption is that inaccuracies in the quantitative models underlying BpS are minor when applied at broad scales (Yanoff et al. 2007). This assumption has not been adequately tested nor have mapping errors been systematically evaluated in the Great Lakes Region to determine the usefulness for mid-level, forest-level purposes.

Locally derived plot data representing native vegetation was often misclassified by LANDFIRE BpS (Table 2). Even classifications generalized broadly by Fire Regime Groups (FRG; Schmidt et al. 2002; Barrett et al. 2010) and over an entire LANDFIRE mapping zone, classification errors were common and carried over into LANDFIRE mapping of current or Existing Vegetation Types (EVT; Figure 5), which apparently have less basis on soil gradients (Appendix F). An example is Laurentian-Acadian Jack Pine Barrens and Forest for which none of the verification plots were correctly mapped (Appendix F) and instead were largely mapped as Boreal Acid Peatlands (40% of plots) and Boreal White Spruce-Fir-Hardwoods (27% of plots). Conceptually, Jack Pine Barrens and Forests should be one of the simpler forest types to map correctly as it occurs primarily within a relatively narrow set of ecological conditions (Comer et al. 1995; Rothstein et al. 2004).

Although many of these misclassifications seem to attribute fire-dependent communities to more mesic, less fire-adapted types (e.g., majority of FRG I communities are mapped as FRG V), errors in the other direction are also common and could be equally problematic for informing forest management, particularly in relation to the use of fire. Grimm (1984) determined that soil drainage was the most important factor controlling vegetation and influencing the probability of fire in Minnesota. Our mapping efforts suggest that soil drainage and productivity data helped to delineate BpS classifications, which may in turn help stratify Existing Vegetation Types into feasible options.

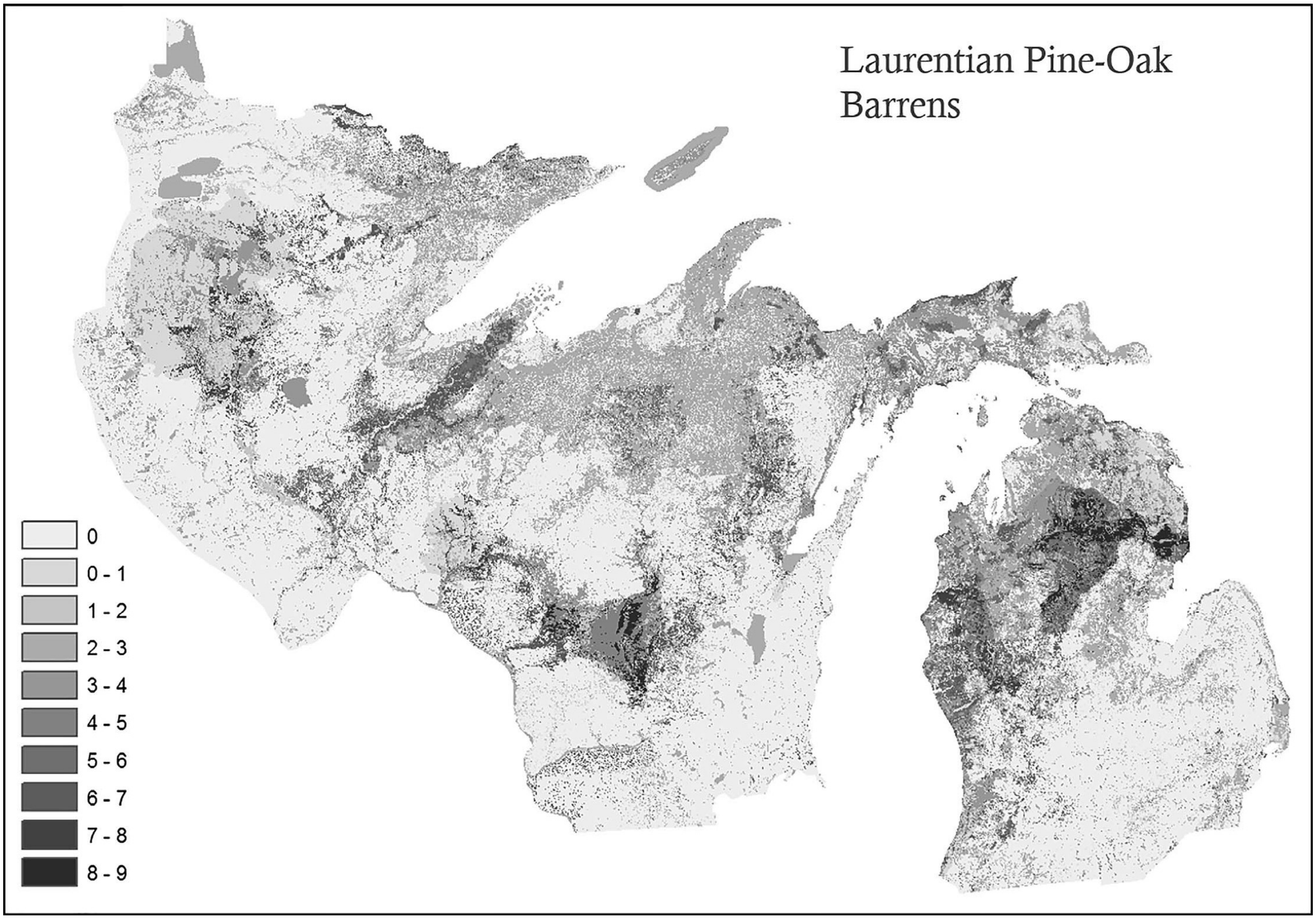

Figure 2.—RMAP modeled likelihood of occurrence (0–10) for Laurentian Pine-Oak Barrens classification in LANDFIRE mapping zones 41, 50, and 51.

Fine-level classifications (like Habitat Types and NPCs) offer flexibility for upward integration within mid-level classifications (e.g., BpS) and a bottom-up approach using basic units derived from soil characteristics and associated plant communities may better reflect the ecology of a site. Soils are important in delineating vegetation communities at a variety of scales. The Laurentian Province 212, for example, separates the northern deciduous coniferous forest biome from the southern oak-hickory-prairie biome, primarily due to broad-scale gradients including soil gradients influenced by Pleistocene glaciation (Cleland et al. 2005). In Michigan, snowfall ranges from 80 cm on the southwest border of the Laurentian province to more than 600 cm in areas strongly affected by Lake Superior (Cleland et al. 2005). Despite high spatial variability of precipitation generally, the association of historical General Land Office (GLO) tree species were strongly related to soil patterns with prominent forest ecotones near distinct till provinces (Barrett et al. 1995).

Our methodology relied on understory species for classification purposes but also for understanding fine-scale soil regime gradients to use for mapping across the Great Lakes Region. Understory species have been emphasized over tree species in development of forest classifications in this region as well as in Europe where forest canopies are viewed as being more widely and directly altered by silvicultural activities than understory species (Westhoff and van der Maarel 1978; Rodwell 1991–2000; Aaseng 2011). The stability, or relatively fast recovery, of ground-layer vegetation following disturbance, and the strong influence of soil on ground-layer flora, has been widely observed (Daubenmire 1976; Wang 2000; Aaseng et al. 2011) and formed the basis for our mapping via gradients of soil drainage and productivity.

LANDFIRE map categories are constructs that may not always lend themselves to physical measurement, and vegetation classification definitions often may not be able to make unambiguous decisions for individual sites. Accuracy assessments are just one tool for understanding error and may have limitations in regional scale analyses particularly in understanding types of error and their causes (Dobson 1992). While traditional accuracy assessments are a tool for understanding error, they rely on hard/binary classification that fails to consider the reality of natural gradients; some Habitat Types or NPCs are very similar ecologically and misclassification of similar habitats is less egregious than dissimilar ones.

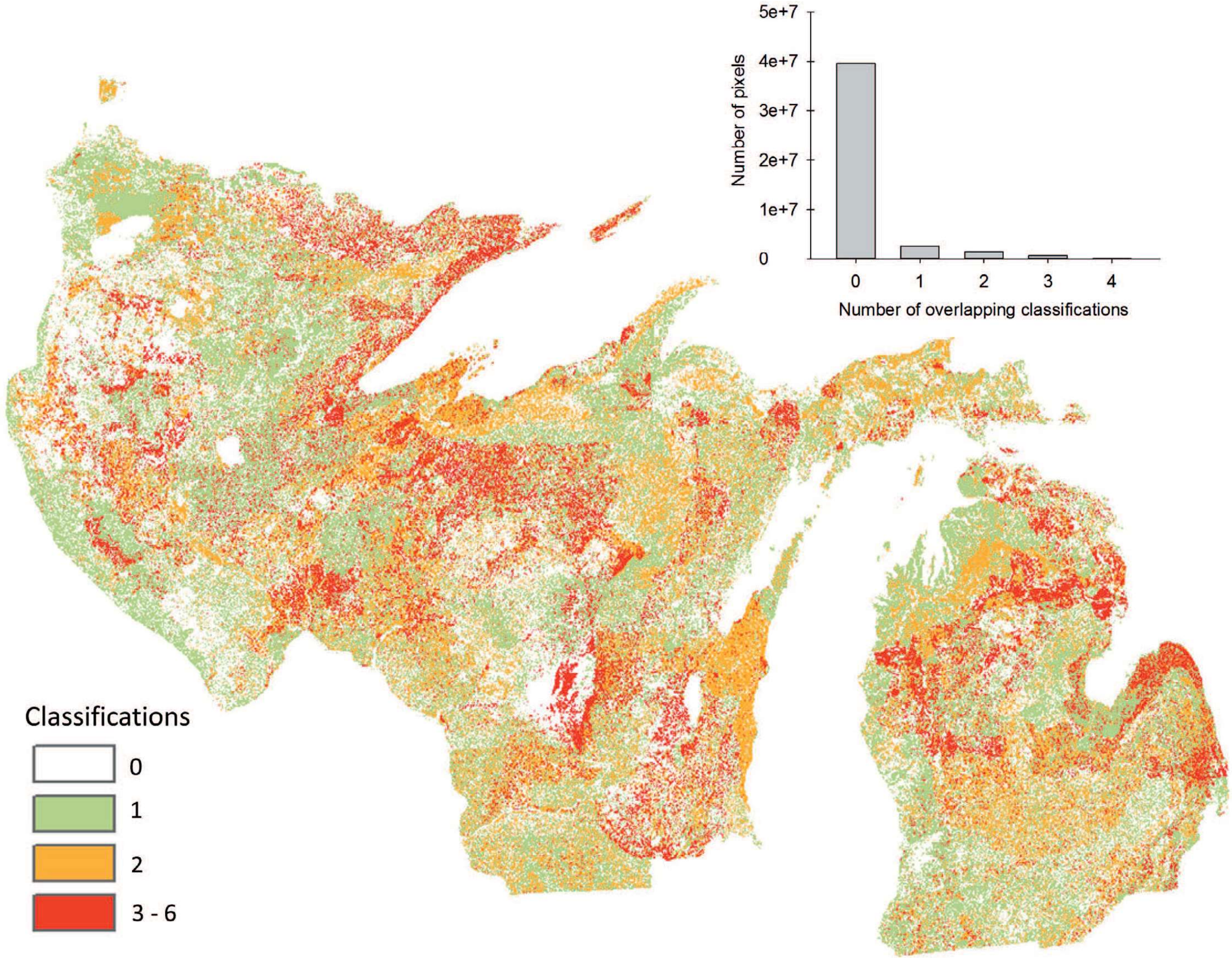

Figure 3.—Overlap among classifications with high (8–10 rank) likelihood of occurrence. Most pixels (240 m) had no overlapping classifications.

We addressed these limitations, at least in part, by explicitly considering uncertainty in making conventional hard class allocations through our use of fuzzy mapping with strength of membership (Figure 2). In our fuzzy membership mapping we started with data that we were most confident *should* determine a particular classification (Table 1). In this framework, data can be added and analyses refined as needed or as information becomes available. In this way, we do not make unnecessary assumptions and can explicitly consider the breadth of communities for mapping. "Hard" classifications based in binary logic, where a pattern is either a full member of a class or not, do not address data that are mixed and imprecise in nature (Shi et al. 2004; Zhang et al. 2004). "Fuzzy" membership that gives partial membership to several classes allows ambiguity to be analyzed and informative. Fuzzy set theory recognizes that category membership is not homogeneous, and some members are better representatives of a category than others and better reflect central tendency, which is itself meaningful (Qi et al. 2006).

Overlap among classification types occurred for a variety of reasons. In some instances, there was high overlap with relatively few classifications. This was the case with Laurentian-Acadian Alkaline Conifer Swamps and Boreal Acid Peatlands, which had substantial overlap, with a greater number of pixels classified as Acid Peatlands and relatively few overlapping pixels of Alkaline Conifer Swamp (Figure 6). The opposite can sometimes be true: although fewer pixels are classified as Alkaline Conifer Swamp overall, a greater proportion of these pixels overlap with Boreal Acid Peatlands. Our mapping reflects LANDFIRE BpS mapping of these types in zone 41 where Boreal Acid Peatlands were overmapped, especially in place of Alkaline Conifer Swamps (Figure 4). This issue can likely only be resolved with data on wetland pH, which helped delineate these peatland types in Minnesota (Minnesota Department of Natural Resources 2003), but generally there is a lack of detailed wetland data necessary to accurately delineate peatland types.

In other situations, we likely do not understand the systems well enough to derive the appropriate processes and patterns

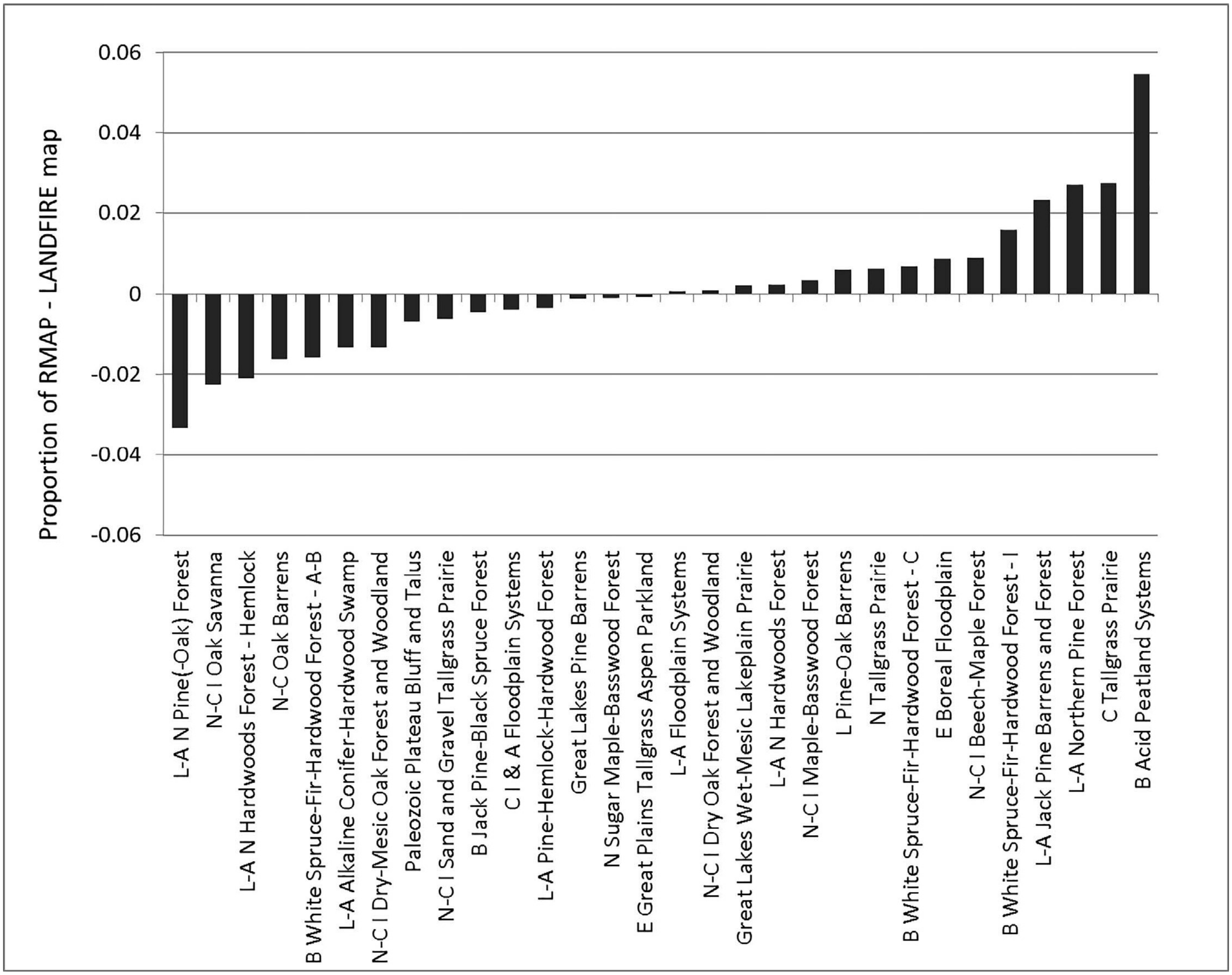

Figure 4.—Comparison between LANDFIRE Biophysical Setting (BpS) and RMAP (high likelihood, 8–10) map areas by vegetation classification type.

important in delineating types, particularly similar types. This seems to be the case with Laurentian-Acadian Northern Pine Forest, which has considerable overlap with the other pine classifications (Figure 7a). Interestingly, this type had greater overlap than the other pine types (e.g., Pine (-Oak); Figure 7b), which may represent its relatively wide ecological gradient. Habitat Typing delineates Laurentian-Acadian Northern Pine Forest as a dry-poor soil regime while Native Plant Communities delineate it as dry-mesic to mesic. LANDFIRE may have split this type out from other pine classifications (e.g., Laurentian-Acadian Northern Pine (-Oak)) when mapping primarily on the presence of fire breaks (e.g., lakes and rivers) but it seems to be underrepresented in LANDFIRE BpS mapping (Figure 4).

In general, we see relatively low levels of overlap among classifications with mapping based primarily on soil regimes. Similarly, overlapping classifications tend to be mostly plausible (e.g., not mapping Pine (-Oak) as Boreal White Spruce-Fir) and show promise for highlighting issues limiting classification accuracy in a spatial framework. Overall, we found notable agreement between LANDFIRE maps and our mapping efforts with limited, nondirectional discrepancies (e.g., mapping xeric communities as mesic or vice versa) between maps (Figure 4).

Additional mapping data can certainly help in mapping various systems; however, it will not address a fundamental lack of understanding of ecological processes driving these systems (e.g., fire regime differences among Jack Pine Barrens and Forest, Pine-Oak Barrens, Pine (-Oak) Forest, and Northern Pine Forest). Ambiguity in the relations between information inputs (e.g., soil–fire–vegetation relationships) and classification type outputs can also result in mapping issues including vague boundaries (Brown 1998). This may be true for many of the pine classifications. It is notable, for example, that LANDFIRE BpS data for Laurentian-Acadian Jack Pine Barrens and Forest was mapped as Pine (-Oak), Pine Oak Barrens, and Northern Pine and a myriad of other types with a low user accuracy (Appendices C–D). Aggregated tree species, like jack pine, are

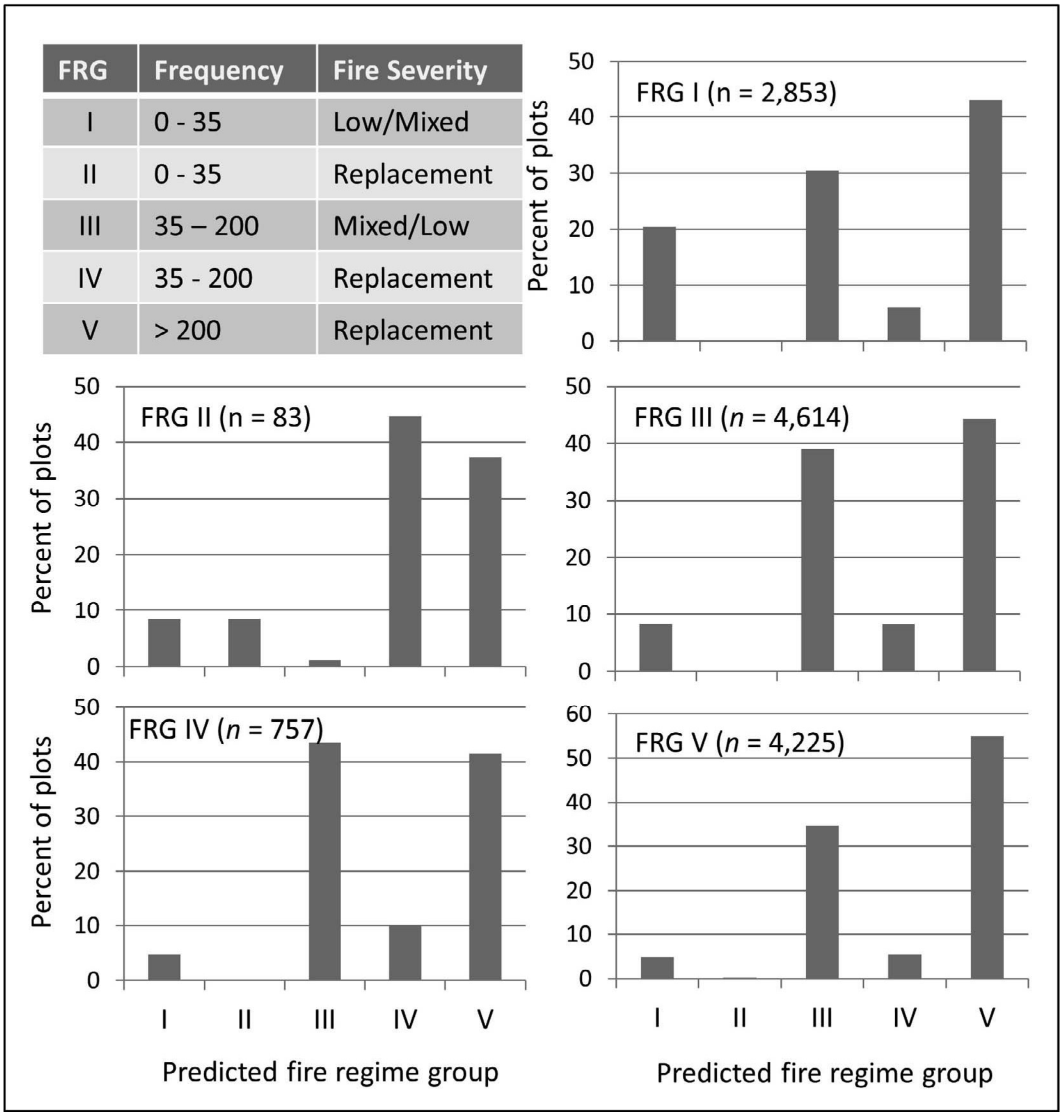

Figure 5.—Comparison of Fire Regime Group (FRG), defined by fire frequency (years) and severity, as predicted by LANDFIRE Existing Vegetation Type (bars) versus Zone 41 Minnesota Native Plant Community plots compiled by FRG ($n = 12{,}532$).

generally mapped more accurately in both location and quantity than widely or sparsely distributed species. We saw similar confusion among types with Laurentian-Acadian Northern Pine (Figure 7a). Improved mapping of fire-dependent communities may also require a better understanding of historical fire regimes for many of these systems. Proxies of fire regimes (e.g., tree-ring, fire-scar, and charcoal records) are woefully lacking in this region and may be necessary for fine-scale understanding of fire and plant community gradients (Stambaugh et al. 2015). There are opportunities to further our understanding of ecological processes and systems including by evaluating potential sources of error in mapping them.

Our mapping efforts, which used a relatively simple system of well-established vegetation–soil relationships and freely available national data, show promise in helping delineate feasible classification options. Similarly, our approach improves decision-making processes by assessing mapping confidence and highlighting potential sources for errors including classifications themselves, all of which can be refined based on identifying sources of uncertainty.

ACKNOWLEDGMENTS

Funding for this work was provided by US Forest Service, Northeast Area State and Private Forestry grant program to the Great Lakes Forest Fire Compact. Further support was provided by the University of Minnesota and the Wisconsin Department of Natural Resources, Science Services. We thank Trent Marty, Jim Barnier, Robert Ziel, and the LANDFIRE Business Leads: Henry Bastion, Frank Fey, Don Long, and TNC partners Jim Smith and Kori Blankenship, for their diligent participation and input on this project. We are indebted to the reviewers of this manuscript who greatly improved its content and delivery. We also thank those who helped field questions, provide data, and technical assistance including Dan Wovcha and John Almendinger – MN, Andy Stoltman and Sally Dahir – WI DNR, as well

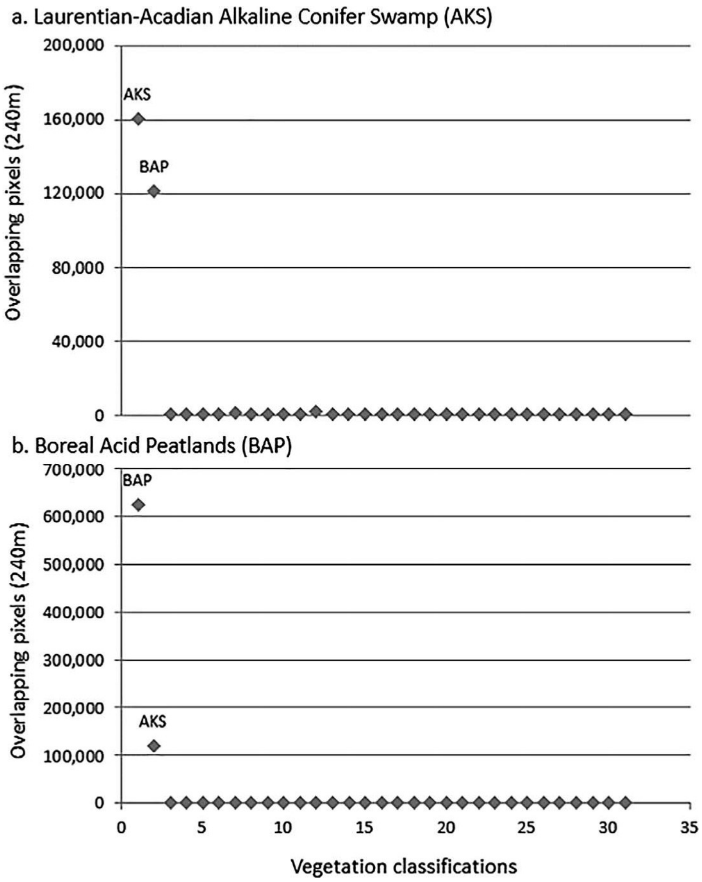

Figure 6.—Overlapping pixels of peatland vegetation types classified with high probability, scaled 8–10, in RMAP model outputs mapped at 240-m resolution. The pixels for the classification in consideration are the total pixels mapped for that type with additional classifications representing overlapping pixels with that type (e.g., >600,000 240-m pixels are classified as Boreal Acid Peatlands [BAP, b]). Label identifiers (AKS; Laurentian-Acadian Alkaline Conifer Swamp; BAP; Boreal Acid Peatlands) were given for types with >0.01% overlap.

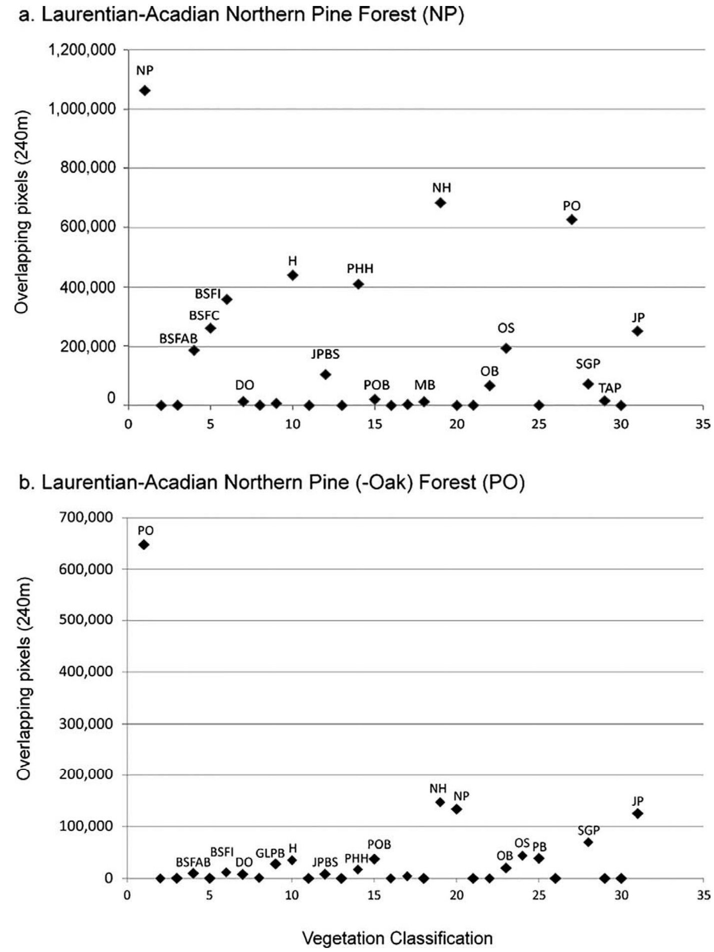

Figure 7.—Pixels classified as Laurentian-Acadian Northern Pine Forest (a) and Laurentian-Acadian Northern Pine (-Oak) Forest (b) with high probability, scaled 8–10, in RMAP model outputs mapped at 240-m resolution. The pixels for the classification in consideration are the total pixels mapped for that type with additional classifications representing overlapping pixels with that type. Laurentian-Acadian Northern Pine (NP) forest (a) had a high degree of overlap with other types whereas Laurentian-Acadian Norther Pine (-Oak, b) had better separation among types. Label identifiers (BSFAB; C; I, Boreal White Spruce-Fir Aspen-Birch; Coastal; Inland, DO; North Central Interior Dry Oak Forest and Woodland, GLBP; Great Lakes Pine Barrens, H; Laurentian-Acadian Northern Hardwoods-Hemlock, JPBS; Boreal Jack Pine-Black Spruce Forest, PHH; Laurentian-Acadian Pine-Hemlock-Hardwood Forest, POB; Laurentian Pine-Oak Barrens, MB; Northern Sugar Maple-Basswood Forest, NH; Laurentian-Acadian Northern Hardwood Forest, OB; North-Central Oak Barrens, OS; North-Central Interior Oak Savanna, PB; Laurentian Pine-Oak Barrens, SGP; North-Central Interior Sand and Gravel Prairie, TAP; Eastern Great Plains Tallgrass Aspen Parkland, and JP; Laurentian-Acadian Jack Pine Barrens and Forest) were given for types with >0.01% overlap.

as Paul Charland and Jerry Szymaniak – FWS. We are particularly indebted to Frank Krist and Mark Zwiefler – USFS FHTET, who helped in innumerable ways.

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