MAPPING FOREST CANOPY DISTURBANCE IN THE UPPER GREAT LAKES, USA

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Abstract—A map of forest canopy disturbance was generated for Michigan, Wisconsin, and most of Minnesota using 42 Landsat time series stacks (LTSS) and a vegetation change tracker (VCTw) algorithm. Corresponding winter imagery was used to reduce commission errors of forest disturbance by identifying areas of persistent snow cover. The resulting disturbance age map was classed into 5-year age classes and then used to attribute age to forested pixels within the National Land Cover Database of 2011. Overall map classification accuracy was 84.9 percent when using Forest Inventory and Analysis data as reference. User's and producer's accuracies were high for persistent forest, nonforest, and water, but low for disturbed forest 5-year age classes, likely due to rarity of forest canopy disturbance on the landscape and confusion among 5-year age classes in both map and reference data sets.

Forest canopy disturbance is defined in this study as any event, natural or anthropogenic, that reduces tree canopy cover to the extent that there is a change in the dominant age cohort. Such disturbance events, or lack thereof, provide both benefits and challenges to a variety of forest ecosystem functions. Forest disturbance provides important habitat for early successional forest-associated wildlife species such as American woodcock (*Scolopax minor*), Kirtland's warbler (*Septophaga kirtlandii*), white-tailed deer (*Odocoileus virginianus*), and many other species. In contrast, increased water turbidity and phosphorous have been linked to increased forest canopy disturbance (Seilheimer et al. 2013). Forest canopy disturbance also provides inroads for invasive plant species, especially following timber harvesting activities if proper care is not taken to eliminate seeds and spores from logging equipment and subsequent vehicle traffic.

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The USDA Forest Service, Forest Inventory and Analysis (FIA) program produces data, information, and knowledge on many characteristics of forest composition and structure. FIA attributes affected by or indicative of forest canopy disturbance include condition-level attributes of stand age, disturbance, treatment, and stand-size (tree diameter) class; and tree-level attributes of damage, mortality, and removal. These FIA attributes provide area estimates of forest canopy disturbance and stand age class, but do not fully meet the needs for spatially explicit land management information. Existing upper Great Lakes geospatial data sets also do not allow regionally consistent assessment of amount and configuration of forest canopy disturbance across a wide range of spatial scales.

METHODS

We analyzed spectral-temporal data within several Landsat time series stacks (LTSS) to identify spatially explicit forest canopy disturbance. The vegetation change tracker (VCT) algorithm (Huang et al. 2010) was employed to track spectral data of individual pixel locations throughout these LTSS. VCT identifies trajectories in these data and flags departures from stable forest as disturbance events. The USDA Forest Service Northern Research Station (NRS)

in collaboration with the agency's Remote Sensing Applications Center adapted VCT by incorporating winter Landsat imagery of seasonally persistent snow-cover to reduce commission errors of forest disturbance (VCTw) (Stueve et al. 2011). We applied VCTw to Landsat Thematic Mapper and Enhanced Thematic Mapper Plus imagery dating from 1987 to 2010 to map forest canopy disturbance across 42 Landsat scenes encompassing the intersection of Minnesota, Wisconsin, and Michigan with Bird Conservation Regions (BCR) 12 and 23 (Fig. 1). These scenes were then mosaicked together following a procedure which assigns precedence in overlapping areas based on the consistency of each scene with neighboring scenes (Nelson et al., in prep.[2]). The resulting forest canopy disturbance map was relabeled into 5-year forest age classes based on year of disturbance (1990-1994, 1995-1999, 2000-2004, 2005-2009) plus one class of persisting forest (no disturbance since 1990) (Fig. 2).

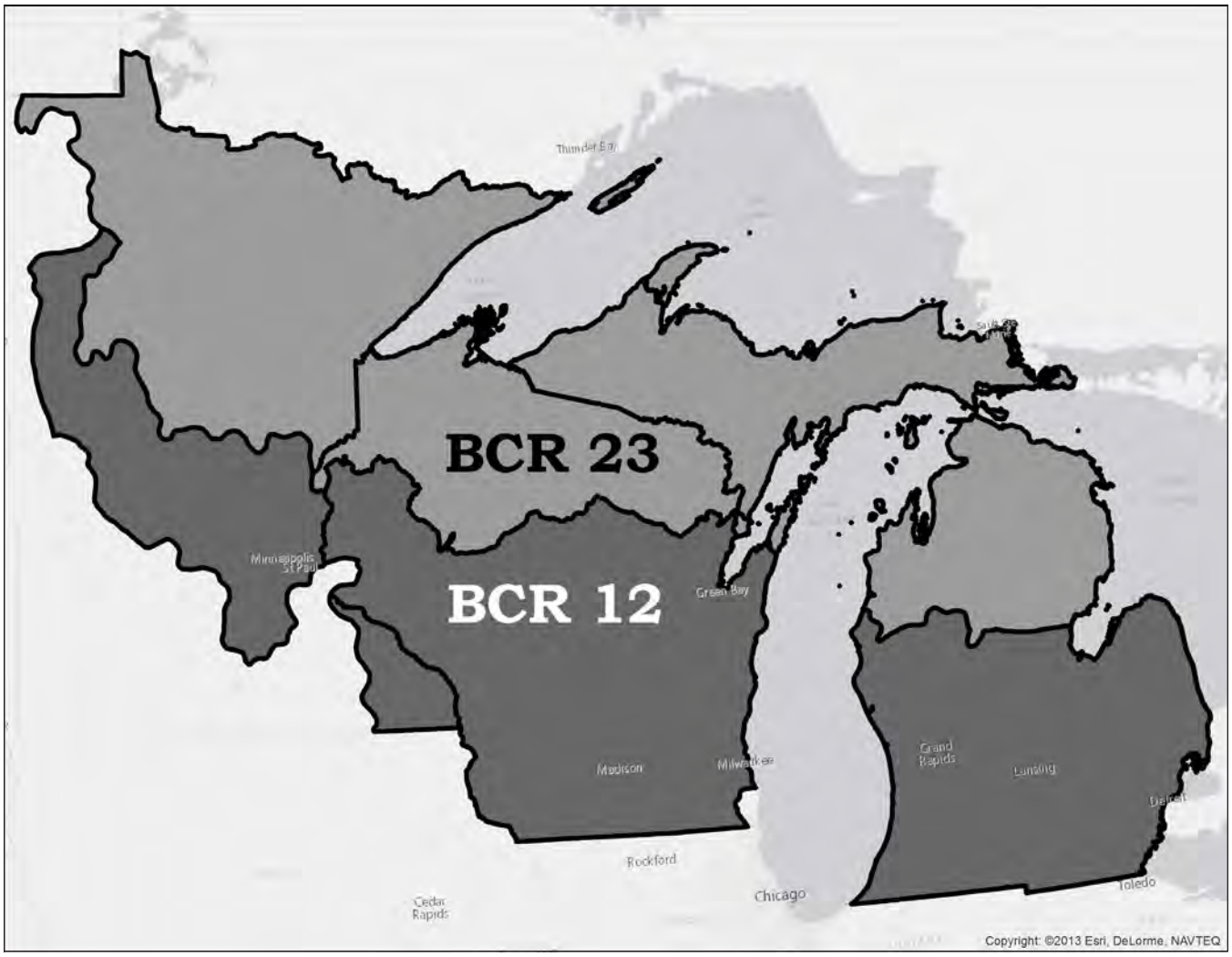

Figure 1.—Study area, consisting of the intersection of Michigan, Minnesota, and Wisconsin, with Bird Conservation Regions (BCRs) 12 and 23. Data sources: North American Bird Conservation Initiative (BCRs, with revisions), Esri (state boundaries, basemap).

[2] Nelson, M.D.; Houseman, I.W.; Stueve, K.M.; Perry, C.H. In preparation. Effects of satellite image mosaic precedence on consistency and accuracy of forest canopy disturbance mapping.

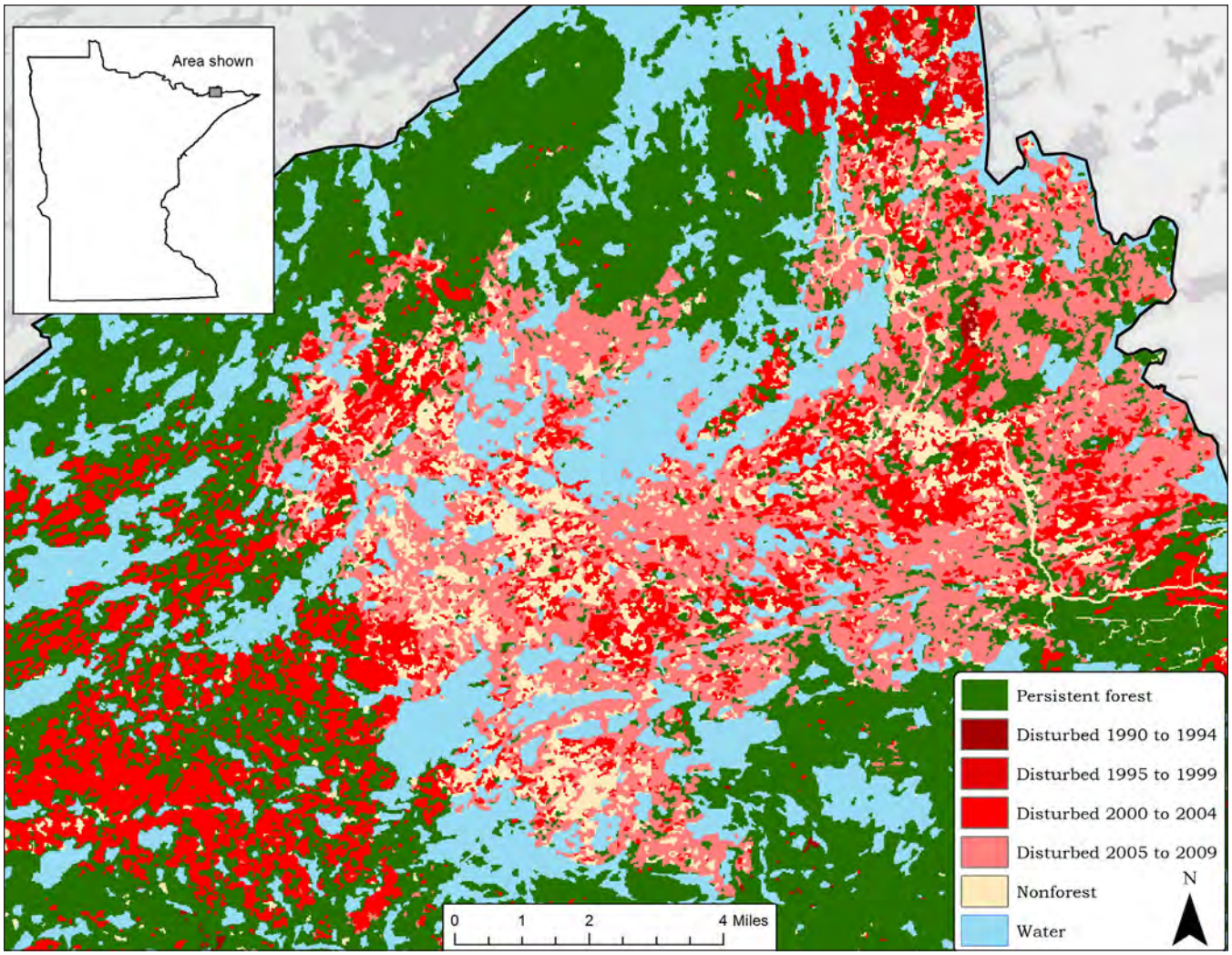

Figure 2.—Map subset shows a portion of the Boundary Waters Canoe Area Wilderness in northern Minnesota illustrating widespread canopy disturbance caused by a severe storm event on 4 July 1999, followed by the Cavity and Ham Lakes fires of 2006 and 2007. Data sources: Nelson et al. (in prep.; land cover and forest age classes), Esri (state boundaries, basemap).

To allow for the inclusion of forest type in subsequent analyses, VCTw-based forest age classes were assigned to deciduous, evergreen, and mixed forest, and woody wetlands pixels in the 2011 National Land Cover Database (NLCD2011) (Homer et al. 2015). Despite the inclusion of winter imagery in VCTw, preliminary analysis indicated that NLCD2011 provides better accuracies of persistent general land use classes (forest, nonforest, water). As such, NLCD2011 forest pixels that were not associated with VCTw age data were labeled as forest of persisting age class.

A subset of shrub/scrub and grassland/herbaceous pixels in NLCD2011 were reclassed as forest when corresponding VCTw pixels were classed as young forest (0-20 years of age); these pixels were labeled as 'other' forest type and were assigned to their corresponding VCTw-based age class. Co-registration disagreement between the NLCD and VCTw maps occasionally resulted in age class assignment to only a portion of an NLCD2011 forest patch, creating a thin strip having no age class along the NLCD2011 forest edge. Areas less than two pixels wide within these strips were assigned to the age class of the largest neighboring NLCD2011 forest patch. Finally, all patches smaller than four pixels were aggregated into their nearest

neighbor, resulting in a four pixel minimum mapping unit (MMU) for the dataset. This MMU (0.36 ha) is similar to the minimum patch size required to meet FIA's definition of forest land (0.4047 ha).

The accuracy of the resulting raster data set was assessed by comparing the mapped age classes to 27,219 FIA plots located within the study area, and following "good practices" prescribed in Olofsson et al. (2014). To avoid complications involved with assigning classes to mixed condition plots and mixed pixel samples, only FIA single condition central subplots were co-located with individual pixels (Chen and Stow 2002). The percentage of FIA plots omitted for not having single condition central subplots was 2.7, 4.2, and 4.5 percent in Minnesota, Michigan, and Wisconsin, respectively. Mapped age classes were subsequently compared with corresponding FIA field age following methods described in Nelson et al.[3] Results were used to populate confusion matrices with proportion estimates weighted by proportion of area mapped in each class (Olofsson et al. 2014; Table 1), from which metrics of accuracy were estimated. Post-stratified area estimates and corresponding 95 percent confidence intervals were produced from the FIA field data using the map classes as strata, per Olofsson et al. (2014).

RESULTS

Overall classification accuracy for the study-wide assessment was 84.9 percent (±0.42 percent, based on 95 percent confidence intervals; Table 1). Overall accuracy was 89.54 percent (±0.36 percent) after aggregating forest into a single class (forest, nonforest, water; confusion matrix not shown).

We estimated 216,563 (±1,532) km^2 of forest land area, and 26,635 (±1,134) km^2 of forest canopy disturbance within the 20-year window (1990-2009). About 12 percent of forest area was disturbed between 1990 and 2009; 8.5 percent in Michigan, 10.9 percent in Wisconsin, and 16.2 percent in the Minnesota portion of the study region.

[3] Nelson, M.D.; Tavernia, B.G.; Garner, J.D.; and Perry, C.H. In preparation. Geospatial modeling and validation of recent forest canopy disturbance in the Upper Great Lakes, USA.

In general, producer's accuracies tended to decrease and user's accuracies tended to increase with decreasing proportion of the respective class on the landscape and with time since disturbance. Each of the 5-year increment disturbed forest classes occupied less than 1 percent of the study area, and their corresponding accuracies were low, ranging from 15-31 percent for producer's accuracies and 39-45 percent for user's accuracies.

DISCUSSION AND CONCLUSION

We applied the VCTw forest canopy disturbance algorithm to several Landsat LTSS and NLCD2011 data to map forest canopy disturbance, persisting forest, nonforest, and water within Minnesota, Wisconsin, and Michigan portions of BCRs 12 and 23 in the western Great Lakes. The proportion of forest area experiencing canopy disturbance within the past 20 years varied among states. Using FIA data for validation, the resulting map had relatively high overall accuracy when including all seven classes, but low producer's and user's accuracies for the 5-year age classes (Table 1), which were rare on the landscape and subject to confusion with other 5-year age classes. There was a discernable trend in both the user's and producer's accuracy of the disturbed forest classes, with accuracy tending to decrease as time since disturbance increases. This may be attributable to varying rates of recovery following disturbance, creating difficulty for FIA field crew assignment of field age to older forest conditions, thus affecting the veracity of the FIA plot data set used for map validation. Additional details on mapping, validation methods, and results by various subareas are reported in Nelson et al.[2]

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Table 1. Confusion matrix and estimates of classification accuracy (overall, user's, producer's) for forest disturbance age classes, persistent forest, nonforest, and water. Matrix cell values are presented as estimated area proportions weighted by the proportion of area mapped in each class, as recommended in Olofsson et al. (2014).

Map categories	Reference categories								
	Persistent forest	Forest disturbed 1990 to 1994	Forest disturbed 1995 to 1999	Forest disturbed 2000 to 2004	Forest disturbed 2005 to 2009	Nonforest	Water	Total	User's Accuracy
Persistent forest	0.401	0.010	0.009	0.007	0.005	0.051	0.003	0.486	0.824
Forest disturbed 1990 to 1994	0.002	0.003	0.001	0.000	0.000	0.000	0.000	0.006	0.426
Forest disturbed 1995 to 1999	0.002	0.001	0.003	0.001	0.000	0.001	0.000	0.008	0.446
Forest disturbed 2000 to 2004	0.002	0.000	0.001	0.004	0.001	0.001	0.000	0.009	0.408
Forest disturbed 2005 to 2009	0.003	0.000	0.000	0.001	0.003	0.001	0.000	0.008	0.388
Nonforest	0.028	0.002	0.004	0.003	0.002	0.393	0.003	0.435	0.904
Water	0.001	0.000	0.000	0.000	0.000	0.004	0.043	0.048	0.895
Total	0.439	0.016	0.018	0.016	0.011	0.451	0.049	1.000	
Producer's accuracy	0.915	0.150	0.172	0.239	0.306	0.870	0.874		0.849

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