Geospatial Modeling of Native Plant Communities of Minnesota's Laurentian Mixed Forest

Terry Brown, Paul Meysembourg, and George Host

Natural Resources Research Institute

University of Minnesota Duluth

Duluth, MN

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Background

The MFRC Landscape Program recognizes several distinct regional landscapes, formed by integrating the natural physiographic and climatic regions of the state with social and economic objectives. These landscapes have served as focal points for regional planning efforts involving multiple groups of stakeholders. While the landscape regions have unique issues and potentials, they all have common data needs. Foremost among these is an assessment of landscape potential, which is required to formulate desired future conditions.

To date, numerous efforts studies have been conducted to map landscape potential – these efforts typically integrate spatial data in a Geographic Information System (GIS) with forest compositional and structural information from remote sensing (e.g. Landsat; Wolter et al 1995, airphoto interpretations) or field inventories. White and Host (2000) created a landscape ecosystem map for the Northern Superior Uplands based on a spatial analysis of GIS data layers known to be important determinants or correlates of forest type distribution, including soils, elevation, landtype associations, climate, and numerous other factors. Subsequently, Host et al. (2006) mapped Native Plant Communities (NPCs) for the northern landscape, a landscape dominated by extensive peatland systems.

In the late 1990's, David Shadis, soil scientist and ECS coordinator for the Chippewa National Forest created a map of the Drift and Lake Plains (DLP) Section. This map however, was at a much coarser resolution than the previously mentioned mapping efforts. Moreover, since the initial DLP maps were developed, the MN DNR published the *Field Guide to Native Plant Communities of the Laurentian Mixed Forest Province* (MN DNR 2003). For both strategic and tactical planning purposes, there is a strong need to produce a map of the DLP and other unmapped forested lands of the state using MN DNR Native Plant Community classification and based on a common, consistent and cross-boundary set of geospatial data.

The specific objectives of this proposal were to:

1) Integrate a suite of geospatial data layers to predict potential Native Plant Communities of the Drift and Lake Plains and Western and Southern Superior Uplands ecological sections, with a spatial resolution similar to the Minnesota-Ontario Peatlands and Northern Superior Uplands NPC maps map and based on the DNR classification of Native Plant Communities.

2) In support of the Landscape Committee planning efforts, summarize acreages of Native Plant Communities by Ownership (MFRC 2010); provide other reports in consultation with Committee members.

Methods

Overview

This project has two major parts, the development of a new map of potential NPCs for the Drift and Lake Plains (DLP), Western Superior Uplands (WSU) and Southern Superior Uplands (SSU) Ecological

Sections , and the integration of that new map with previously developed maps for the Northern Superior Uplands (NSU - White and Host 2000) and Minnesota Ontario Peatlands (MOP - Host et al. 2006). This was followed by post-processing to improve map accuracy and provide summarizations of NPC areas by ownership and other variables.

The overall methods followed this sequence of analyses:

- Develop new DLP potential NPC map
    - collect section wide input data sets
    - build classification tree model
    - apply model to landscape
- Integrate with NSU and MOP maps and post-process
    - crosswalk NSU forest types to NPC classes/systems
    - combine NSU, MOP, and DLP maps
    - apply rules to improve classifications
    - add ownership and other information
    - summarize results

Analytical methods

A variety of methods have been used to map habitat or native ecosystem types. Allen and Wilson (1991), and Palik et al. (2000) used Discriminant Functions analysis with vegetation data and environmental variables to map potential vegetation with overall accuracies of approximately 60%. Host et al. (1996) integrated soil, landform and climate data in GIS to create an LTA level ecosystem classification for northwestern Wisconsin. Decision tree models have also proven to be useful for landscape scale ecosystem classification (Moore et al. 1991, Lynn et al. 1995), and are used in the present study to predict NPC classes based on a broad suite of environmental data. Detailed description of decision tree methods can be found here:

http://en.wikipedia.org/wiki/Decision_tree_learning

In this analysis, we used the **rpart** recursive partitioning function available in the R statistical language to generate a model to assign NPC classes to 30 x 30 m grid cells across the Northern Minnesota Drift and Lake Plains and Western and Southern Superior Uplands ecological Sections.

To maximise the model's predictive accuracy, as measured against a subset of the data withheld for testing, an unusual application of the **rpart** function was used. The minimum node size (minimum number of observations considered necessary to add a node to the model) and the minimum split benefit (minimum improvement in model accuracy considered necessary to justify further splitting a node) were both set to very low values. This forced the **rpart** method to produce a very detailed model with hundreds of nodes. Because of this the model should be seen as a numerical construct for classifying the landscape, and not as a representation of the mechanistic structure of the factors driving NPC distribution.

Model Inputs

Relevee Data

A shapefile and database of MN DNR relevee plots was supplied by Dan Hanson with the MN Department of Natural Resources Ecological Land Classification Program. [File DNR NPC OBSERVATIONS 2011]. Of the 7,382 relevee points in the three Section study area, 3523 were 'classified' relevee points, i.e. were identified in the field through the ECS program. Only these classified relevee plots were used in this analysis. Approximately 125 records were dropped because the same coordinate was reported more than once, or multiple systems were reported for the same coordinate.

The numbers of relevee plots varied substantially among NPCs, both at the system and class levels. To provide sufficient data for model development, we included only upland classes with more than 40 records. We only included lowland systems with more than 20 records; this excluded Open Peatlands, Floodplain Forests, Marsh Systems from being included in this phase of the analysis. Predictions of Open Peatlands were subsequently added based on GAP data.

NPC Systems and # of verified relevee plots

NPC System	# relevees
AP	108
FD	1161
FF	15
FP	128
MH	1750
MR	7
OP	17
WF	139
WM	73

NPC Classes and # of verified relevee plots

NPC Class	# relevees	NPC Class	# relevees	NPC Class	# relevees	NPC Class	# relevees	NPC Class	# relevees
FDc12	13	MHc26	408	APn80	56	FPn62	7	WFn53	11
FDc23	77	MHc36	111	APn81	36	FPn63	26	WFn55	67
FDc24	173	MHc37	15	APn90	9	FPn72	12	WFn64	58
FDc25	15	MHc47	79	APn91	7	FPn73	30	WFs57	3
FDc34	300	MHn35	512			FPn82	50		
FDn12	43	MHn44	445	FFn57	14	FPs63	3	WMn82	73
FDn22	3	MHn45	2	FFn67	1				
FDn32	16	MHn46	120			MRn83	7		
FDn33	374	MHn47	58						
FDn43	140					OPn81	11		
FDs36	3					OPn91	1		
FDs37	4					OPn92	5		

Landscape Characterization of Relevee Plots

The landscape at each relevee point was characterized by summarizing GIS grid data for the 3 x 3 cell (90 x 90 m) neighborhood of each point. This information was extracted from grids with a Python program using the GDAL open source raster GIS software. For continuous variables (slope, rainfall, etc.) the mean was calculated, for categorical variables (landcover class, soil type etc.) the majority class was determined. The strength of the majority (9 of 9, or 5 of 9, etc.) was also determined to check for weak majorities. Most points had a clear local majority.

The following landscape characteristics were used (descriptions are copied from metadata of original datasets):

DEP_ASRL Depth to any soil restrictive layer:

From SSURGO soils data.

A "restrictive layer" is a nearly continuous layer that has one or more physical, chemical, or thermal properties that significantly impede the movement of water and air through the soil or that restrict roots or otherwise provide an unfavorable root environment. Examples are bedrock, cemented layers, dense layers, and frozen layers. This theme presents the depth to any type of restrictive layer that is described for each map unit. If more than one type of restrictive layer is described for an individual soil type, the depth to the shallowest one is presented. If no restrictive layer is described in a map unit, it is represented by the "> 200" depth class.

DEP_WT Depth to water table:

From SSURGO soils data.

"Water table" refers to a saturated zone in the soil. It occurs during specified months. Estimates of the upper limit are based mainly on observations of the water table at selected sites and on evidence of a saturated zone, namely grayish colors (redoximorphic features) in the soil. A saturated zone that lasts for less than a month is not considered a water table.

DRAIN_rcl3 Drainage class:

From SSSURGO soils data.

"Drainage class (natural)" refers to the frequency and duration of wet periods under conditions similar to those under which the soil formed. Alterations of the water regime by human activities, either through drainage or irrigation, are not a consideration unless they have significantly changed the morphology of the soil. Seven classes of natural soil drainage are recognized-excessively drained, somewhat excessively drained, well drained, moderately well drained, somewhat poorly drained, poorly drained, and very poorly drained. These classes are defined in the "Soil Survey Manual."

ECEC Effective cation-exchange capacity:

From SSURGO soils data.

Effective cation-exchange capacity refers to the sum of extractable cations plus aluminum expressed in terms of milliequivalents per 100 grams of soil. It is determined for soils that have pH of less than 5.5. Soils having a low cation-exchange capacity (CEC) hold fewer cations and may require more frequent applications of fertilizer than soils having a high cation-exchange capacity. The ability to retain cations reduces the hazard of ground-water pollution. Effective CEC is a measure of CEC that is particularly useful in areas where the ion-exchange capacity of the soil is largely a result of variable charge components, such as allophane, kaolinite, hydrous iron and aluminum oxides, and organic matter, which result in a CEC that is not a fixed number but a function of pH.

ECS_SUBSEC ECS Subsection:

MNDNR Data Deli dataset L280000030201

Ecological Classification System sub-sections.

FROSTFREE Frost-free days:

The term "frost-free days" refers to the expected number of days between the last freezing temperature (0 degrees Celsius) in spring (January-July) and the first freezing temperature in fall (August-December). The number of days is based on the probability that the values for the standard "normal" period of 1961 to 1990 will be exceeded in 5 years out of 10.

GEO_ASSOC Geomorphic association:

MNDNR Data Deli dataset L280000062101

KFACTOR_FL K factor, Whole Soil:

From SSURGO soils data.

Erosion factor K indicates the susceptibility of a soil to sheet and rill erosion by water. Factor K is one of six factors used in the Universal Soil Loss Equation (USLE) and the Revised Universal Soil Loss

Equation (RUSLE) to predict the average annual rate of soil loss by sheet and rill erosion in tons per acre per year. The estimates are based primarily on percentage of silt, sand, and organic matter and on soil structure and saturated hydraulic conductivity (Ksat). Values of K range from 0.02 to 0.69. Other factors being equal, the higher the value, the more susceptible the soil is to sheet and rill erosion by water.

ORG_MATTER Organic matter:

From SSURGO soils data.

Organic matter is the plant and animal residue in the soil at various stages of decomposition. The estimated content of organic matter is expressed as a percentage, by weight, of the soil material that is less than 2 millimeters in diameter.

The content of organic matter in a soil can be maintained by returning crop residue to the soil. Organic matter has a positive effect on available water capacity, water infiltration, soil organism activity, and tilth. It is a source of nitrogen and other nutrients for crops and soil organisms. An irregular distribution of organic carbon with depth may indicate different episodes of soil deposition or soil formation. Soils that are very high in organic matter have poor engineering properties and subside upon drying.

PRESETVEG_2 PLS Corners with Presettlement Vegetation Information:

MNDNR Data Deli dataset L250000022103

A point database storing information on vegetation type information and general location of bearing trees used in conjunction with the original Public Land Survey (PLS). This database contains the actual location of section corners, rather than the location of the bearing trees themselves. The data are derived from land surveyor notes, which include descriptions of vegetation and landscape characteristics along survey transects. This database is described in greater detail in the publication: Minnesota's Bearing Tree Database, by John Almendinger, Biological Report No. 56, Minnesota Department of Natural Resources, 1997.'

SURFRANK Surface texture:

Texture is given in the standard terms used by the U.S. Department of Agriculture. These terms are defined according to percentages of sand, silt, and clay in the fraction of the soil that is less than 2 millimeters in diameter. "Loam," for example, is soil that is 7 to 27 percent clay, 28 to 50 percent silt, and less than 52 percent sand. If the content of particles coarser than sand is 15 percent or more, an appropriate modifier is added, for example, "gravelly."

Classified into 8 ordered levels for this project.

SURF_PH pH (1 to 1 water):

Soil reaction is a measure of acidity or alkalinity. It is important in selecting crops and other plants, in evaluating soil amendments for fertility and stabilization, and in determining the risk of corrosion. In general, soils that are either highly alkaline or highly acid are likely to be very corrosive to steel. The most common soil laboratory measurement of pH is the 1:1 water method. A crushed soil sample is mixed with an equal amount of water, and a measurement is made of the suspension.

AWC Available water capacity:

Available water capacity (AWC) refers to the quantity of water that the soil is capable of storing for use by plants. The capacity for water storage is given in centimeters of water per centimeter of soil for each soil layer. The capacity varies, depending on soil properties that affect retention of water. The most important properties are the content of organic matter, soil texture, bulk density, and soil structure, with corrections for salinity and rock fragments. Available water capacity is an important factor in the choice of plants or crops to be grown and in the design and management of irrigation systems. It is not an estimate of the quantity of water actually available to plants at any given time.

CTI_1 Composite Topographic Index:

A combined measure of upstream area and slope, as described be Gessler et al., 1995.

img 2006 NLCD:

2006 National Land Cover Data (NLCD) was downloaded from http://www.mrlc.gov/nlcd06_data.php. Classes present in the study area: Barren, Crops, Deciduous, Emergent Wetlands, Evergreen, Grassland/Herbaceous, High Dev., Low Dev., Med. Dev., Mixed, NoClass, Open Space, Pasture/Hay, Shrub/Scrub, Water, Woody Wetlands.

maxt_08 Maximum August temperature:

Grid data from McKenney et al. 2006.

mint_01 Minimum January temperature:

Grid data from McKenney et al. 2006.

pcppet12mos Net annual precip:

Grid data from McKenney et al. 2006.

psys Predicted NPC System:

Upland only - NPC class prediction was improved when a **rpart** model run was used to predict NPC system, and the predicted system was used as an input, even though the system prediction was not 100% accurate. The **rpart** modeling system described here was used to predict NPC_**SYSTEM**, and then this was fed back into the model for NPC_**CLASS**.

sdist Aspect (degrees from south, 0-180):

DEM derived aspect, recalculated as degrees from south, sdist = abs(180-aspect), to eliminate the wrap around effect from 360 to 0. Degrees from south is an index of solar exposure.

slope Slope:

DEM derived local slope.

uclus24* Upland LTA cluster:

For uplands, the upland cluster from Brown and Host, 2009, was used as an input. These clusters are similar to ECS subsections but driven by a slightly different set of variables, and so potentially useful as an alternative partitioning.

wclus24* Lowland LTA cluster:

For lowlands, the lowland cluster from Brown and Host, 2009, was used as an input. These clusters are similar to ECS subsections but driven by a slightly different set of variables, and so potentially useful as an alternative partitioning.

Decision tree model

Separate **rpart** models were developed for uplands and lowlands. The **rpart** control parameter was set to

```
rpart.control(minbucket=5, cp=0.001)
```

which allows both the creation of very small nodes (nodes representing very few observations, i.e. 5) and nodes which contribute very little improvement, by themselves, to the model fit. The **rpart** models generated with different model calculation parameters were compared by withholding 15% of the relevee points for testing, and then looking at the error rate in the classification of those 15% with the model derived for the 85%. The cumulative effect of the parameters was to give the best error level on the withheld 15%, so an overly complex model produced by these parameters was used in preference to simpler models which gave a weaker fit.

The model inputs for the upland model were:

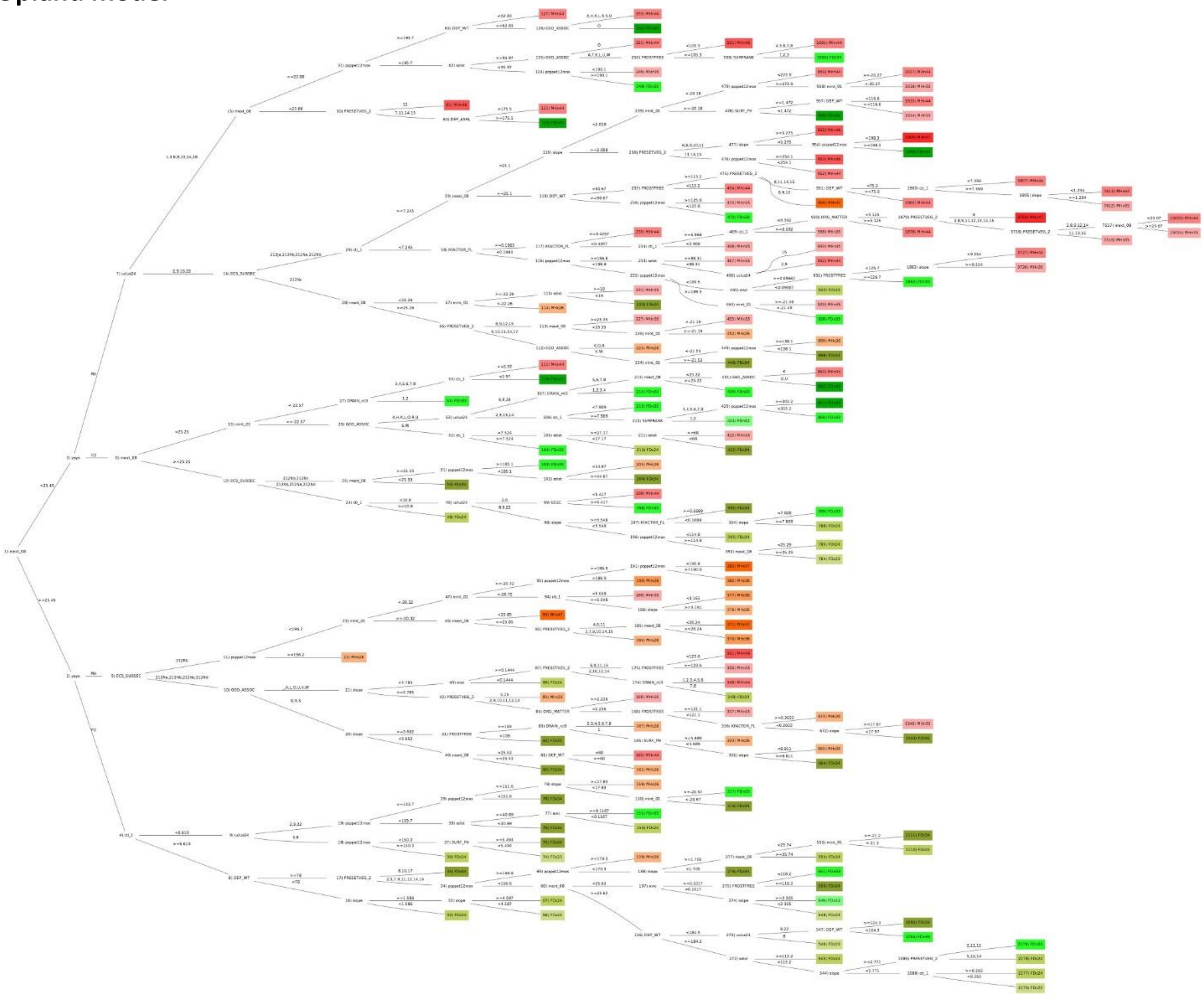
```
aModel = RESPONSE ~ (
 + DRAIN_rcl3    + PRESETVEG_2  + uclus24   + psys       + ECS_SUBSEC  + GEO_ASSOC  + SURF_PH      +
ORG_MATTER   + ECEC    + FROSTFREE      + DEP_ASRL     + DEP_WT    + KFACTOR_FL    + sdist       +
slope    + cti_1         + SURFRANK     + awc   + maxt_08       + mint_01      + pcppet12mos
)
```

The model inputs for the lowland model were:

```
aModel = RESPONSE ~ (

  + DRAIN_rcl3     + PRESETVEG_2  + img    + wclus24       + ECS_SUBSEC   + GEO_ASSOC    +
SURF_PH       + ORG_MATTER   + ECEC    + FROSTFREE     + DEP_ASRL     + DEP_WT
  + KFACTOR_FL    + sdist       + slope    + cti_1         + SURFRANK     + awc
  + maxt_08       + mint_01      + pcppet12mos
)
```

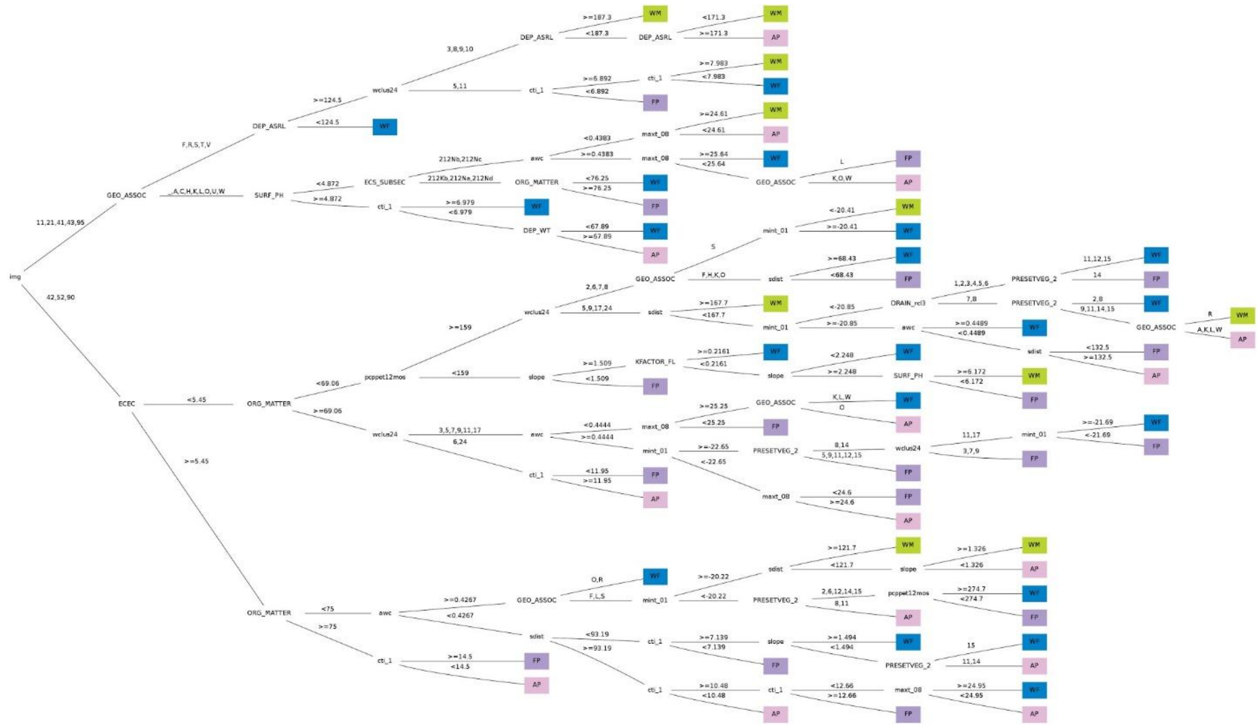
Upland model



High resolution version:
http://gisdata.nrri.umn.edu/projects/NPC2012/20131226/upland_model.png

R's textual representation:
http://gisdata.nrri.umn.edu/projects/NPC2012/20131226/upland_model.txt

Lowland model



High resolution version:
http://gisdata.nrri.umn.edu/projects/NPC2012/20131226/lowland_model.png

R's textual representation:
http://gisdata.nrri.umn.edu/projects/NPC2012/20131226/lowland_model.txt

Mapping model predictions across the landscape

A Python script was created to map model predictions onto the landscape. Python code was written using the open source GDAL raster libraries and numpy Python extensions. The study region was broken into tiles with adjustment to minimize misalignment between input layers. A binary 1/0 grid was used to partition the landscape based on each of the splits from the **rpart** output.

The upland and lowland **rpart** models predicted NPCs for every pixel on the landscape, and an upland/lowland mask applied to assign the correct NPC. In previous work the National Wetland Inventory (NWI) upland class had been used to split the landscape into uplands and lowlands. A preliminary analysis of results indicated that NWI upland class classified too much lowland forest as upland, which is reasonable as the NWI is wetland centric, not forest centric.

For this reason, we developed a scoring system to more accurately classify lowland and upland pixels.

A pixel received one point for each of the following cases:

- NWI class is not upland
- Compound Topographic Index (CTI) > 7.569
- SSURGO Drainage class is 6 or 7 (poorly to very poorly drained)
- MN DNR GAP classification reports a wetland class

This gives a possible score of 0-4 inclusive. Grid cells with scores of 2 or higher were considered to be lowland.

Integrating NPC predictions across Ecological Sections

The modeling described above applies only to the new work done to map the DLP, WSU, and SSU ecosections (referred to below as "DLP" for brevity). The Python script apply_rules.py, performed the following steps to integrate the new work with previous MOP and NSU work.

The NSU map created by White and Host (2000) classified map polygons according to Range of Natural Variation Ecosystem classes (also called Landscape Ecosystems) described in Frelich 1999. These classes predated the MN DNR Native Plant Community classes. To create a crosswalk between the two classification schemes, we assessed the percentages of relevee plots within the Landscape Ecosystem classes, and selected the dominant system and class.

While MHn45 was the dominant class (30% of relevees), MHn35 and MNn44 were also well represented, at 19 and 15% of relevees, respectively. Because MHn35 occurs on dry mesic sites and MHn44 is wet mesic, we further discriminated these two classes based on slope position, with ridgetops and upper slopes classified as MNn35 and lower slopes as classified as MHn44.

Table 1. Crosswalk of Landscape Ecosystems to NPC Systems and Classes for the Northern Superior Uplands.

Landscape Ecosystem (Frelich RNV classes)	NPC System	NPC Class
Mesic Northern Hardwood-Conifer	MH	MHn45
Mesic Conifer-white,red pine (north shore)	FD	FDn43
Dry-mesic conifer-white-red pine (bwcaw)	FD	FDn43
Near boreal mesic-paper birch,aspen,b. spruce, b. fir	FD	FDn43
Near boreal dry forest-jack pine, b. spruce	FD	FDn32
Near boreal dry forest-jack pine, aspen, pin oak, bur oak	FD	---
Wet mesic-boreal hardwood-conifer	MH	MNn44
Lowland conifer-black spruce	FP	FPn62
Rich swamp-white cedar, black ash	WF	---

--- not enough data to identify Class

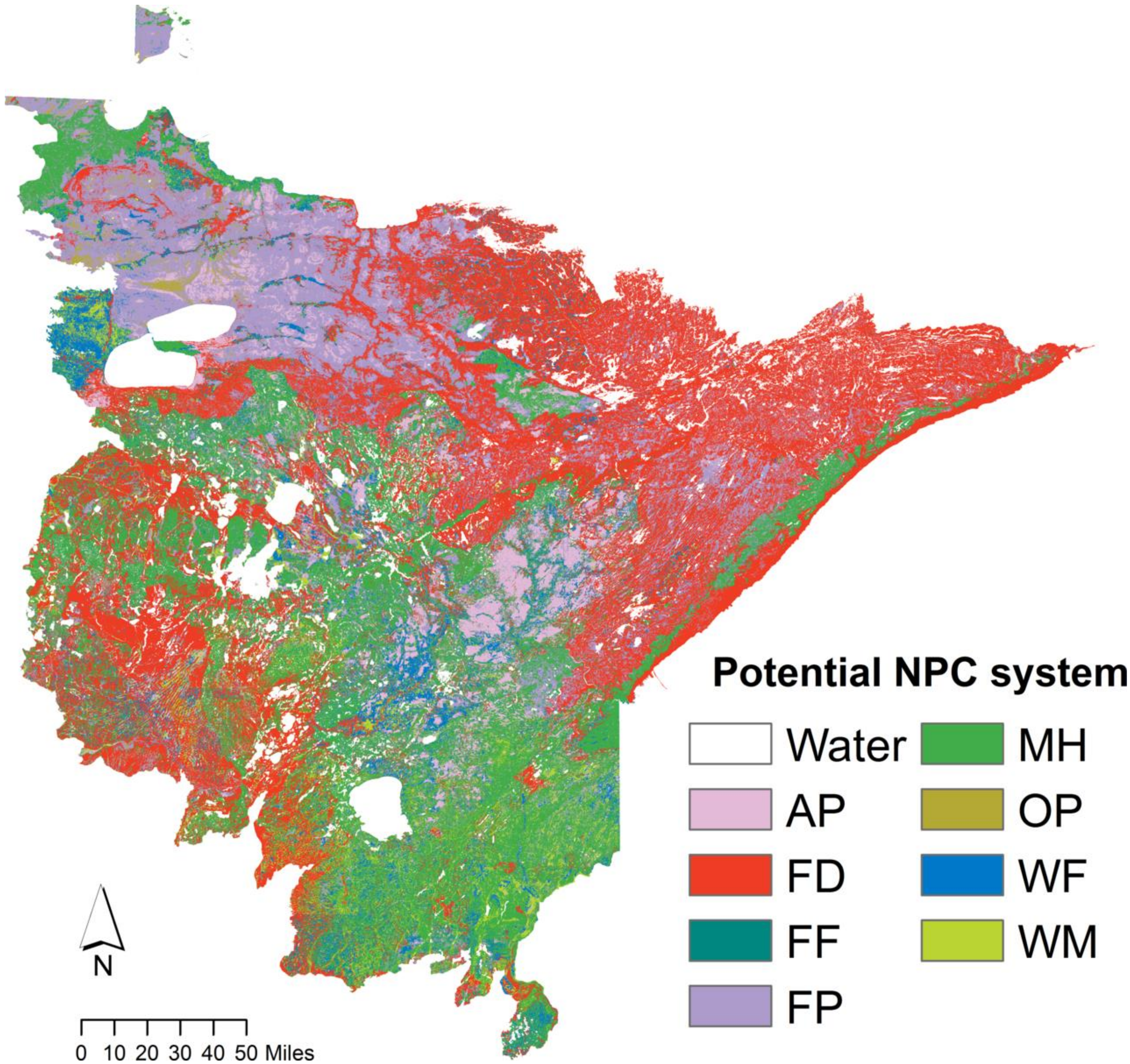
Final maps were made according to the following steps:

1. Fill missing data in the DLP upland model output, using ArcGIS Nibble command. Missing data occurred where combinations of classes not encountered in landcover data around the releveepoints were seen, typically developed classes.
2. Fill missing data in the DLP lowland model output.
3. Merge DLP upland and lowland data using the "Upland / lowland separation" rules described above.
4. Bring in MOP data, adapt class values to match / extend classes seen in DLP data.
5. Fill missing data in MOP data.
6. Bring in crosswalked NSU data, adapt class values to match / extend classes seen in DLP data.
7. Fill missing data in NSU data.
8. Merge DLP, NSU, and MOP data.
9. Collapse data to NPC SYSTEM level.
10. Extract modeled NPC systems at relevee points prior to applying rules.
11. Apply rules to address systems not modeled well because of data limitations:
    a. GAP "Black Ash" class in modeled NPC AP or FP class → WF
    b. GAP "Stagnant (anything)" class → AP
    c. GAP "Broadleaf sedge" class in modeled NPC FP class → OP
    d. GAP "Broadleaf sedge" class in modeled NPC WF class → WM
    e. GAP "Lowland Deciduous Shrub" class in modeled NPC WF class → WM
    f. GAP "Maple / Basswood" class → MH
12. Extract modeled NPC systems at relevee points after applying rules.
13. Tabulate relevee vs modeled NPC system errors before and after rule application.
14. Burn in water from lakes > 10,000 square meters from the DNR's 100k lakes and streams data. This was done after pre and post rule relevee point extraction to avoid noise created by layer alignment issues when relevee points near small water bodies are reclassed as water.
15. Tabulate NPC systems by landscape region, county, owner, and subsection.

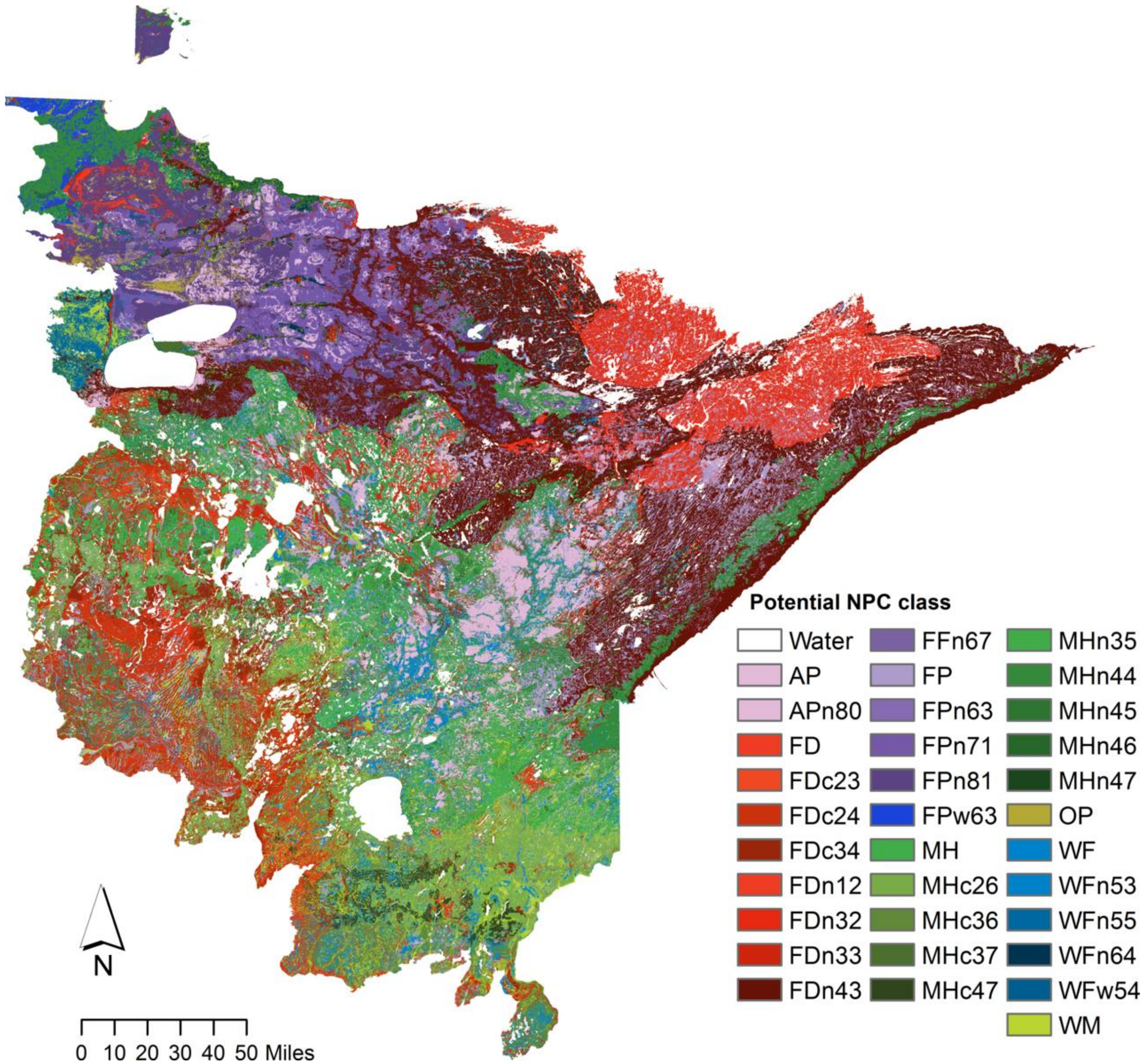
apply_rules.py is available at
http://gisdata.nrri.umn.edu/projects/NPC2012/20131226/apply_rules.py.html.

Results

The end products of the analyses are grid-based maps of the most likely NPC class and system for each pixel. The maps shown below are available in ArcGIS grids, PNG and PDF formats, using the supplied links.



Larger version: http://gisdata.nrri.umn.edu/projects/NPC2012/20131226/System.png



Larger version: http://gisdata.nrri.umn.edu/projects/NPC2012/20131226/Class.png

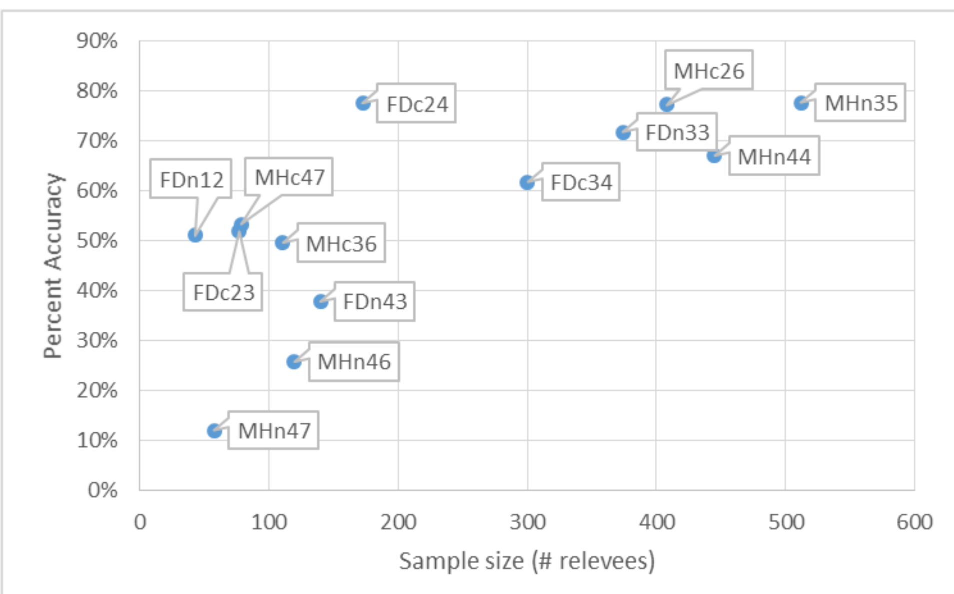
The grid file for the NPC classification can be downloaded here:
http://gisdata.nrri.umn.edu/projects/NPC2012/20131226/PotentialNPC_20131226.zip

RPart Model Accuracy Assessment for Upland Classes

The overall classification accuracy for upland relevees based on the **rpart** model alone at the class level was 65%. The most accurately classified NPCs were MHn35, MHc26 and FDc24, all with 77-78% Producer's accuracy (errors of commission). In many cases, the commissions were of very similar classes, for example, calling an MHn35 an MHn44, or vice versa. But there was also instances of FD classes being placed in the MH system, a more important misclassification.

		Relevee Class														
		FDc23	FDc24	FDc34	FDn12	FDn33	FDn43	MHc26	MHc36	MHc47	MHn35	MHn44	MHn46	MHn47	Total	Producers's accuracy (omission error)
Model Predicted Class	FDc23	40	8	4	0	2	1	0	0	0	1	2	0	0	58	69%
	FDc24	12	134	15	0	8	0	3	0	1	4	11	2	1	191	70%
	FDc34	6	10	185	0	29	0	20	2	0	12	5	3	0	272	68%
	FDn12	0	0	0	22	4	7	0	0	0	0	0	0	0	33	67%
	FDn33	10	10	16	16	268	22	5	0	0	15	26	3	1	392	68%
	FDn43	0	0	0	0	5	53	1	0	0	1	15	2	2	79	67%
	MHc26	2	7	35	0	7	3	315	38	22	33	4	16	2	484	65%
	MHc36	0	0	3	0	0	0	10	55	13	2	1	3	0	87	63%
	MHc47	0	0	1	0	1	0	12	10	42	2	2	3	0	73	58%
	MHn35	4	2	26	1	22	17	31	3	1	397	72	24	28	628	63%
	MHn44	3	2	14	4	26	33	8	3	0	36	298	33	13	473	63%
	MHn46	0	0	1	0	2	4	3	0	0	8	9	31	4	62	50%
	MHn47	0	0	0	0	0	0	0	0	0	1	0	0	7	8	88%
	Total	77	173	300	43	374	140	408	111	79	512	445	120	58	2840	
																65%
User's Accuracy (Commission error)		52%	77%	62%	51%	72%	38%	77%	50%	53%	78%	67%	26%	12%		

Classification accuracy was related to sample size – in general, NPC Classes represented by 150 or more samples had accuracies of 60-80%, whereas fewer than 150 relevees produced accuracies < 55%.



NPC System -level Accuracy Assessment for rpart Model

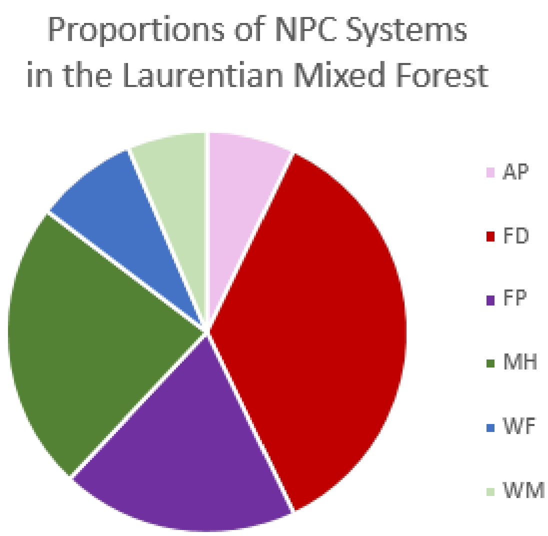
Overall accuracy of the **rpart** model was 59%. In general, producer's accuracy for lowland systems was relatively low, due primarily to confusion within (rather than among) lowland classes, with particular confusion between forested and acid peatlands. The NPC field guide notes that "The floristic differences between forested and open AP communities are subtle because of low species diversity in the AP System as a whole and because trees, when present, are usually sparse, making the boundary between forested and open AP communities diffuse." (MN DNR 2003). We attempted a soil pH < > 5.5 to discriminate these systems, but the SSURGO data is not sufficiently resolved to use this factor.

		Relevee System								
		AP	FD	FP	MH	OP	WF	WM	Total	Producer's accuracy (omission error)
	AP	261	56	95	70	41	65	27	615	42%
	FD	48	4040	110	1137	24	249	49	5657	71%
Model	FP	360	460	774	328	156	428	169	2675	29%
Predicted	MH	26	772	28	3039	7	139	34	4045	75%
System	OP	5		9	1	33	4	16	68	49%
	WF	55	156	117	297	31	267	73	996	27%
	WM	44	54	49	101	61	62	141	512	28%
	Total	799	5538	1182	4973	353	1214	509	14568	
User's Accuracy (Commission error)		33%	73%	65%	61%	9%	22%	28%		59%

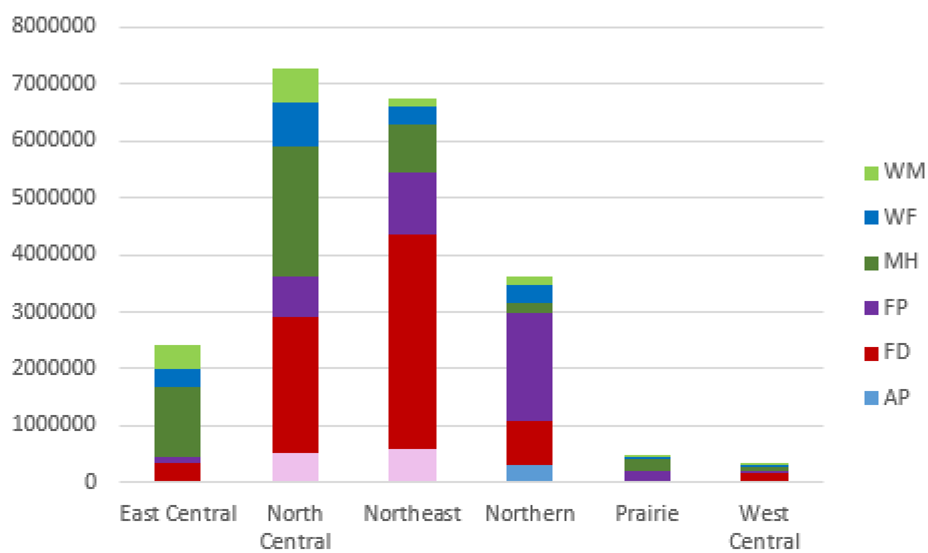
Classification accuracy of upland systems was better, 75% and 71% for MH and FD Systems, respectively, for omission error. Again there was a strong relationship between system-level classification accuracy and numbers of relevees.

Area Summaries

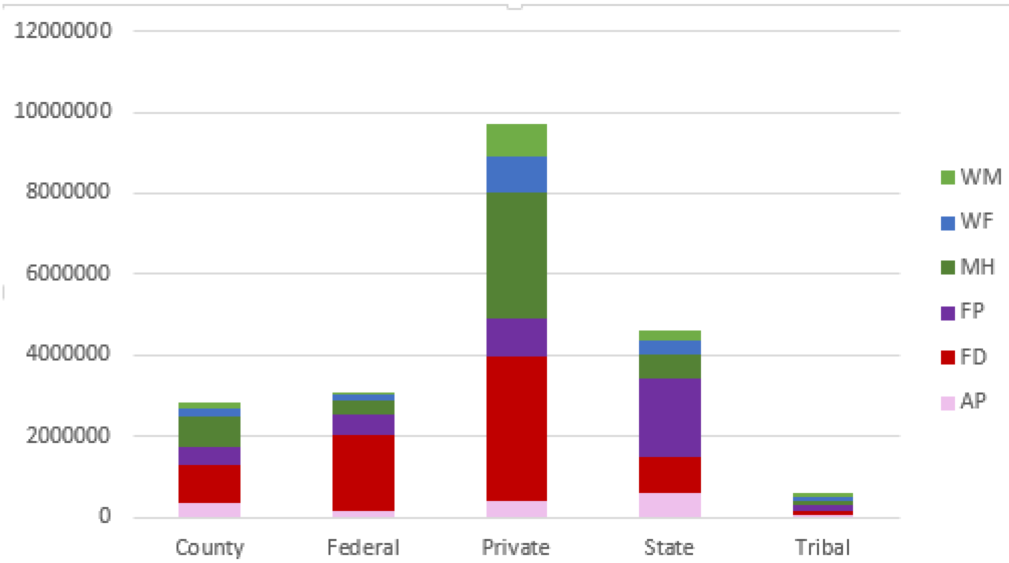
The Laurentian Mixed Forest has an area of approximately 23 million acres. Just over half of the potential NPCs in this area (53%) are upland, with Fire Dependent (FD) and Mesic Hardwood forest systems comprising 32 and 21% of the area, respectively. Lowland systems occupy the 47% of the landscape, with Forested Peatlands being the dominant lowland type (17%). Wet Forest and Wet Meadow account for 13% of the area and open water occupies 9%.



The MFRC Landscape Regions vary in their proportions of NPC Systems. Half of the Northeast Landscape, or roughly 3.8 million acres, is dominated by Fire Dependent Systems. The North Central landscape region has nearly equal proportions of FD and MH systems. The Northern Landscape is dominated by peatland ecosystems, these were predominantly classified as Forested Peatlands, although it was difficult to discriminate among Forested, Acid, and Open Peatlands.



Almost half (48%) of the Laurentian Mixed Forest is in Private ownership. The State, Federal and County manage 21%, 15% and 13% of the area, respectively. Across the Laurentian Mixed Forest as a whole, the Upland forests are predominately in private land ownership – 17% of Fire Dependent and 15% of Mesic Hardwoods. The State of Minnesota is the largest owner of Forested Peatlands (9%), and the Federal Government manages a large proportion of FD forests (9%).



These proportions vary among Landscape Regions, however, with the Northeast Region having nearly equal proportions of Private and Federal ownership, and the Northern region with a large proportion of State land holdings. Consequently, Native Plant Communities also vary greatly across ownerships. In the North Central Region, the upland forest systems are predominately in private ownership. In the Northeast region, 43% of Fire Dependent forests are under Federal ownership, but almost 60% of Mesic Hardwoods are on Private lands. The Northern landscape, has significant State ownership of peatland systems, although the County manage a large proportion of Fire Dependent forests.

Caveats and Interpretations

This map represents the **most probable native plant community** to occur in a landscape position, based primarily on the relationships between DNR relevee plots and a suite of environmental variables. The accuracy of the model is influenced by a number of factors, including the spatial and classification accuracy of the relevees themselves, scale and accuracy of the environmental data, and the ability of the recursive partition method to identify relationships between these two data sets.

An important factor influencing classification accuracy was the difficulty in separating upland and lowland landscape positions. As noted above, the map was created in several steps: the model was run across the entire LMP to predict the most probable upland NPC, then rerun to predict the most probable lowland type. An upland/lowland mask used to merge these two model runs. Basing the upland/lowland mask simply on the National Wetland Inventory gave high rates of misclassification. Accuracy issues with the NWI are well-known, and NWI polygons are relatively coarse compared to the 30 m resolution of the input data. We attempted to correct this by incorporating other data layers, such as the Poorly and Somewhat Poorly Drained soil drainage categories of the SSURGO data, the classification of lowland types by the MN DNR GAP program, and the Compound Topographic Index (CTI), an indicator of potential soils moisture. This strategy ameliorated but did not fully resolve confusion between upland and lowland sites, or more correctly, the broad areas of transitions between clearly upland and clearly lowland areas.

The class predicted for the grid cell containing a relevé point using GIS may not match the class predicted for the point using the model. The model predictions were made using the mean or majority of the 3x3 cell neighborhood of the point, whereas the cell level predictions in the map are made for single cells. The 3x3 cell neighborhoods were used to minimize point / grid alignment issues in model generation. The effects of this difference can sometimes be seen where a relevé point is close to the edge of a "stand" boundary. Furthermore, because of the map smoothing described in “Post model grid processing”, the grid cell containing a relevé point may not have the the NPC system or class value originally calculated by the model for that grid cell.

The maps are delivered at full (30 m) resolution, which give a very high level of apparent spatial resolution, certainly more than in warranted by the scale of input data layers (soil series polygons, Marschner map, etc) and the various sources of error noted above. This is by intent to allow end users to make their own decisions on the degree to which the map should be generalized (e.g. with 3x3 or 5x5 pixel filters, calculating the dominant NPC within a polygon of interest, etc).

Lastly, the map covers the entire region independent of current land use, so it does not directly incorporate land conversion to urban or agricultural land use. Cities, roads and farmlands could be ‘burned in’ to the map using the National Land Cover Dataset or similar land use/land cover GIS layers.

The intent of developing this map across the LMF was to provide support for broad scale regional planning exercises (specifically the Forest Resources Council Landscape Program), and is of variable accuracy at fine spatial scales; some portions of the landscape are modelled well, others poorly. Discriminating Acid and Open Peatlands, for example, was difficult and classification accuracy between these two classes was low. As a result, the maps are best used for large scale assessments, or, at the site level, as exploratory tools to be used in conjunction with other data sources. They do not substitute for field assessment, and should not be used as a sole source of information for site-level management. The map is however, a first attempt at mapping the entirety of the Laurentian Mixed Forest Province. It resolves a long-standing spatial resolution issue of the Drift and Lake Plains, creates new maps for the Western and Southern Superior Uplands, and provide a crosswalk with the NSU classification. As such, it provides a base map for successive refinement as new remote and field based data become available.

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