Mapping Range of Natural Variation Ecosystem Classes for the Northern Superior Uplands: Draft Map and Analytical Methods

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Introduction

Our primary goal was to create a map of generalized ecological potential for the 8 range of natural variation (RNV) ecosystem classes for the Northern Superior Uplands ecological section (Frelich 1999). The natural range of variability has been shown to be a useful concept for both evaluating the extent of change from historical conditions and for creating tangible models of sustainable ecosystems (Morgan et al. 1994).

At present, the finest level of ecological classification that exists for the Northern Superior Uplands is the Land Type Association (LTA). Our objective was to create a map that nests within the current ecological classification system and shows some of the potential variability of upland and lowland habitats within LTAs.

We mapped the 8 ecosystem classes based on the relationship between sample vegetation data representing these broad habitat classes and a suite of environmental variables representing soil, landform and climate patterns in the Northern Superior Uplands. In this report we document our methods, data sources and initial results including an accuracy assessment.

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%. Decision tree models have also proven to be useful for landscape scale ecosystem classification (Moore et al. 1991, Lynn et al. 1995). Host et al. (1996) integrated soil, landform and climate data in GIS to create an LTA level ecosystem classification for northwestern Wisconsin.

On the Chippewa National Forest relatively fine scale mapping was accomplished using digital soil series data, bearing tree data, surveyor line notes, and an existing phase level classification integrated within a GIS (D. Shadis, pers. comm.).

The Boise Cascade Corporation mapped habitat type classes for a portion of the Northern Minnesota and Ontario Peatlands (MNOPS) using a decision tree modeling approach utilizing the relationships between habitat type samples and soil characteristics, surficial geology, topographic variables, climate, presettlement vegetation, and other predictive variables (Kernohan and Dunning 1998). They reported user's accuracies ranging from 13 to 76%, with an overall accuracy of 60%.

In the Northern Superior Uplands, soil, landform and climate data are relatively coarse with minimum mapping units ranging from 16 to 100 ha. Forest inventory and satellite based classifications are the only synoptic vegetation databases. Given these limitations, we developed an approach that integrates the climate and physiographic data into a composite map which nests within existing Land Type Association boundaries. We then used association analysis methods to relate RNV classes as represented by

vegetation sample data to the composite physiographic map units. Based on this association analysis, we developed decision rules that classify each map unit into the highest probability RNV class.

Classification of vegetation sample data into RNV classes

In order to develop a vegetation sample database of sufficient size and spatial distribution, we acquired data from five sources (Table 1.). Forest inventory data were initially filtered based on the criteria listed in Table 1. We classified this data into RNV types through a two-stage process. First, we cross-classified Natural Heritage Program Native Plant Community Classes into the eight RNV types. This was done in consultation with NHP and CBS staff. We then developed classification criteria based primarily on woody plant composition and structure from NHP native plant community descriptions (Rusterholtz 1999) and NSU releve data. For the MN DNR and FIA data, we used relative abundance of tree species as the primary classification variable. We could not derive detailed relative abundance values from the Superior National Forest data, so cover type and species composition data were used. Natural Heritage program releve points were coded into RNV classes based on the cross-classification of Native Plant Communities to RNV classes. Since sufficient inventory or other vegetation data were not available for the Boundary Waters Canoe Area Wilderness, we used classified satellite data for this region.

Table 1. Vegetation data sources and attributes used for classification into RNV types.

Data Source	Classification Attributes	Initial Screening Criteria	N
MN DNR Phase2 Inventory	Relative Volume by Species Shrub/Groundlayer Data, Cover Type	Natural Regeneration Field Inventory, >= 40 years age	6400
FIA Re-measurement Points	Relative Basal area by species Cover type	Natural Regeneration Field Inventory >= 40 years age	1245
Superior National Forest Inventory	Primary-secondary cover type Primary-secondary species	Field Inventory >= 40 years age	13900
Natural Heritage Program Releve	Native Plant Community Classes	None	298
Classified Satellite Data BWCAW, P.Wolter NRRI	Species composition	Similarity to RNV classes, Patches > 1 ha	5836
		Total	27679

Creation of composite physiographic-climate map units

We assembled available spatial data on soils, landform, topography and climate (Table 2). Minnesota Soil Atlas classes were converted to ordinal values to allow for multivariate analysis. We used principal components analysis on each of 3 major groups of data: climate, soil characteristics, and topography. Based on PCA factor loadings we selected the following variables: soil drainage, elevation, pH, aspect, and maximum temperature. These variables were put in an iterative clustering program (isoclus) to produce composite soil-topographic-climate units. This map was then merged with a categorical soil or landform map (Geomorphology of MN, Cummings-Grigal Soil Associations, Land Type Associations). This was done to add additional information and

spatial resolution to the original map units. Units less than $10km^2$ were merged with surrounding values based on majority of neighborhood pixel values. The 3 final composite maps contained from 110 to 180 map units for the Northern Superior Uplands.

Table 2. Environmental variables used to create composite map units.

Data Source	Attributes	Resolution	Minimum mapping unit
Minnesota Soil Atlas	Drainage, Texture, pH Depth of rooting zone	1ha	16ha
Cummings-Grigal Soil Associations	Texture+material	1ha	5km2
Geomorphology of MN	Geomorphic and sedimentary Associations	1ha	16ha
Land Type Associations	Soil-landform units	1ha	5km2
Zedex Climate data	Mean growing season minimum, maximum temperature, Precipitation	1km2	1km2
USGS digital elevation Model	elevation, slope, aspect, topographic position	1ha	1ha

Data Analysis

Spatial resolution of input data

Predictive spatial variables were used as grid cells at a resolution of 100 m per side (1ha). Positional accuracy of vegetation data in the form of sample points may vary from 30 to as much as 200 m. Given this variability, vegetation point data represented 4 ha in area (4 100 m grid cells).

Upland-lowland stratification

We used National Wetlands Inventory data to stratify upland and lowland areas prior to analysis. Upland and lowland areas were classified separately and then merged.

Uplands were identified at the NWI system level (U). Other areas identified as open water or wetland were masked out. The upland mask included some unclassified wetlands that were not interpretable from aerial photography.

Areas classified under the forested wetland category include palustrine systems defined as forested and scrub/shrub that are not defined as permanently flooded. Areas defined as upland, open water, emergent, or otherwise not dominated by woody plants were masked out. The following codes to define forested wetland/semi-terrestrial forest: System = Palustrine (P), class1 = forested (FO), scrub shrub (SS), wreg (water regime modifier) = A (temporarily flooded), B (saturated), C (seasonally flooded), J (intermittently flooded).

GIS processing

Upland and lowland areas were analyzed separately based on the upland-lowland masks derived from the National Wetlands inventory. For each sample vegetation patch

the majority value of the physiographic-climate composite was output, identified by the patch id. The sample sizes were 14,100 and 11,000 for uplands and lowlands respectively.

Association analysis

Association analysis has proven to be a useful technique for examining relationships between vegetation classes and soils, landforms and topography in northern lake states forests (Pastor and Broschart 1989, White and Mladenoff 1994). The electivity index (Jacobs 1974, Jenkins (1979) a form of association analysis, has been shown to be useful for landscape level classifications. Brown et al. (1999) used the electivity index to classify white pine blister rust hazard for the mixed forest province of Minnesota based on the relationship between sample blister rust occurrence and climate and topography.

In order to test the hypothesis that ecosystem types are not randomly distributed across the landscape with respect to topography, climate, and soil-landform properties, we used the electivity index of Jacobs (1974) and Jenkins (1979):

[1] $$E_{ij} = \ln \frac{(r_{ij})(1-p_j)}{(p_j)(1-r_{ij})}$$

Where E_{ij} is the electivity for ecosystem type *i* on spatial variable class *j* (physiographic-climate composite). r_{ij} is the proportion of ecosystem type *i* on variable class *j*, and p_j is the proportion of the variable that occurs in class *j*. We used this index to determine if there is a non-random positive or negative association between ecosystem classes and physiographic-climate composite map units.

Because electivity values for different classes do not have the same distribution, electivity values were relativized to the maximum value for each class. In order to classify physiographic-climate units, we developed decision rules based on the relative values and the variability of electivity values for each class. We used 2 values to classify map units: M_{ij}, the relativized electivity value for RNV class *i* on map unit *j*, and $S_{i_}$, the ratio of M_{ij} to the mean plus 1 standard deviation for RNV class *i*. In the first iteration, each map unit was assigned the class of the maximum electivity value. We then identified cases where one or more values were within 5% of the maximum. In these cases, the map unit was coded to the RNV class with the highest $S_{i_}$ value. This ensures that the values from the right tail or positive end of the distribution were chosen. In most cases, the maximum relativized electivity value for each map unit also had the highest $S_{i_}$ value.

We classified 3 maps with this method; each based on the original physiographic-climate composite and 1 of three categorical overlays: Cummings-Grigal Soil Associations, Geomorphology of Mn, and Land Type Associations. These 3 maps were evaluated for accuracy based on sample data withheld from analysis.

Bearing tree data

GLO bearing tree data have proven to be useful for assessing pre-European settlement forest composition and structure and the subsequent changes with settlement (Grimm 1984, White and Mladenoff 1994) and for estimating wind and fire disturbance frequencies (Canham and Loucks 1984, Whitney 1986). Bearing tree analysis was a key component in determining the disturbance frequencies for the Northern Superior Uplands (Frelich 1999).

We used the bearing tree data primarily to cross check our data samples and analysis. First, we compared our samples points using electivity analysis with the bearing tree species at the nearest section corner, with a maximum distance of 300 m. This showed whether our classified sample points had any residual relationships with bearing tree species.

We then analyzed the bearing tree data to determine if tree species showed similar distributions to our current sample data when analyzed in relation to the physiographic-climate composite map. In this analysis, the mean number of bearing trees by species was calculated for each map unit. Based on these values we calculated electivity by tree species for each map unit. Species distributions and electivity values were examined visually and compared with current sample data. We then classified composite map units based on bearing tree composition and electivity scores in a similar fashion to the sample data, however decision rules were less formal. Species composition was based that of the 8 RNV classes. For example, when both white pine and red pine had high relative electivity values for a map unit, we examined the other species and their electivity values to determine classification. If white cedar, balsam fir, white spruce or northern hardwood species were present with positive electivity scores, then the map unit would be classified as mesic white pine-red pine.

Accuracy assessment

In order to assess classification accuracy, we withheld 20% of the original sample data as a test data set. We also used the Gap Analysis Program classification as a test data set, however this data is not truly independent from our sample data as some of the same inventory data in our sample set was used as training data for this Landsat based classification (T. Aunan Pers. comm.). We used standard methods outlined by Congalton (1991) to calculate overall, producer's and user's accuracies. Because this map classifies the potential distribution of RNV classes, and map units have low resolution compared with Landsat or aerial photo based classification, accuracy assessment is problematic. In light of this, we applied methods used by Lynn et al. (1995) which may correct for some of the error generated by differences in potential versus actual vegetation and true misclassification.

Results and Discussion

Classification and accuracy assessment

We compared accuracy levels for classifications based on 3 different physiograhic-climate composite maps. The map that included LTAs performed the best in overall accuracy and was selected for further analysis. Initial assessment showed that the jack pine-aspen-oak had very low accuracy (producer's 23 %, user's 17%) and was confused with the jack pine-black spruce, mesic aspen-birch-spruce-fir and dry-mesic white pine-red pine classes. We then re-classified these map units based on the next highest electivity value. However, we left one area centered on Voyageurs National Park as jack pine-aspen-oak because the more precise releve data identified this type in that area. There was also significant confusion between mesic white pine-red pine and dry-mesic white pine-red pine, as 33% of the mesic pine samples were classified into the dry-mesic class (Table 4a). This is due in part to the difficulties in separating the mesic from the dry-mesic type based on information in the inventory data.

Table 3. Area for Range of Natural Variation ecosystem classes in the Northern Superior Uplands

NSU Classification	Hectares	% Area
Sugar maple	234,046	9.7
Mesic white pine-red pine	234,124	9.7
Dry-mesic white pine-red pine	380,821	15.8
Lowland Conifer	431,473	17.9
Rich swamp	103,633	4.3
Mesic birch-aspen-spruce-fir	401,567	16.6
Jack pine-black spruce	376,530	15.6
Jack pine-aspen-oak	33,478	1.4
Water	211,779	8.8
Non-forested wetland	8,841	0.4

Accuracy assessment for the revised classification with 7 classes using the 20% test data set is shown in table 4. Overall accuracy was 61%. Producer's accuracy, the probability that a test pixel was correctly classified ranged from 24 to 96%. Four classes had values over 60% (Sugar maple, dry-mesic white pine-red pine, lowland conifer, and jack pine. User's accuracy, defined as the probability that a classified pixel actually represents that category on the ground, varied from 25 (mesic-white pine-red pine) to 94% (lowland conifer). We also analyzed accuracy using the Gap Analysis Program data (Table 5.) Because we could not reliably separate mesic white pine-red pine from dry-mesic white pine-red pine within the Gap data, these classes were lumped for this analysis. Results show a similar pattern, with an overall accuracy of 57% and similar patterns in the producer's and user's accuracies. The error rates reported for this study are similar to those reported in other studies (Palik et al. 2000, Kernohan and Dunning 1998, Allen and Wilson 1991).

Table 4. Accuracy assessment using Northern Superior Uplands RNV ecosystem classes and 20% of sample data withheld from analysis.

a) Producer's Accuracy

	Sample data						
NSU Classification	Sugar Maple	Mesic white pine/red pine	Dry-mesic white pine/red pine	Lowland conifer	Rich swamp	Mesic aspen-birch-spruce-fir	Jack pine
Sugar Maple	**70**	3	5	0	0	8	1
Mesic white pine/red pine	7	**41**	9	0	0	7	8
Dry-mesic white pine/red pine	1	33	**62**	0	0	16	21
Lowland conifer	0	0	0	**96**	72	0	0
Rich swamp	0	0	0	4	**28**	0	0
Mesic aspen-birch-spruce-fir	17	8	7	0	0	**24**	8
Jack pine	5	16	17	0	0	45	**62**

b) User's Accuracy

	Sugar Maple	Mesic white pine/red pine	Dry-mesic white pine/red pine	Lowland conifer	Rich swamp	Mesic aspen-birch-spruce-fir	Jack pine
Sugar Maple	**56**	2	8	0	0	33	2
Mesic white pine/red pine	6	**25**	16	0	0	30	23
Dry-mesic white pine/red pine	0	8	**40**	0	0	27	25
Lowland conifer	0	0	0	**94**	6	0	0
Rich swamp	0	0	0	62	**38**	0	0
Mesic aspen-birch-spruce-fir	9	3	7	0	0	**66**	15
Jack pine	1	2	7	0	0	46	**44**

overall Accuracy: **61**%

Because this map estimates the potential distribution of RNV classes, and map units have low resolution compared with Landsat or aerial photo based classification, accuracy assessment should be viewed somewhat differently. This map predicts the predominant or highest probability RNV class for a given map unit. Because these are coarse level units (minimum size of 10km^2), and vegetation samples are at a finer resolution (approximately 1ha minimum size) it is very likely that other types will occur within a given map unit. Mesic aspen-birch-spruce-fir makes up 26% of the sample data (Table 5) and is well distributed in the study area. When selecting a random sample from the landscape, we are 5 times more likely to pick a sample of mesic aspen-birch-spruce-fir than of mesic-white pine-red pine. By scaling the error rates of the producer's matrix by their probability of occurrence (Lynn et al. 1995), we see that 19% of the 36% total error is due to misclassification of mesic-aspen-birch-spruce-fir (Table 6). This shows that, proportionately, this type accounts for most of the error, as this type is broadly distributed and shows less affinity to composite physiographic map units.

The user's matrix (Table 4b) can also be interpreted in different ways. If we look at this from the standpoint of potential vegetation, we see that 30% of mesic white pine-red pine and 46% of jack pine is currently in mesic aspen-birch-spruce-fir. While some of this is due to misclassification, much of this may be due land use history and current management practices.

Table 5. Accuracy assessment using Gap Analysis program data recoded into native ecosystem types.

a) Producer's Accuracy

	Gap Analysis Program Classification					
NSU Classification	Sugar Maple	white pine/red pine	Lowland conifer	Rich swamp	Mesic aspen-birch-spruce-fir	Jack pine
Sugar Maple	**70**	4	0	0	9	1
white pine/red pine	7	**55**	0	0	36	32
Lowland conifer	0	0	**88**	76	0	0
Rich swamp	0	0	12	**24**	0	0
Mesic aspen-birch-spruce-fir	22	15	0	0	**27**	8
Jack pine	1	26	0	0	28	**59**

b) User's Accuracy

	Sugar Maple	white pine/red pine	Lowland conifer	Rich swamp	Mesic aspen-birch-spruce-fir	Jack pine
Sugar Maple	**67**	8	0	0	23	3
white pine/red pine	2	**37**	0	0	29	32
Lowland conifer	0	0	**65**	35	0	0
Rich swamp	0	0	45	**55**	0	0
Mesic aspen-birch-spruce-fir	15	22	0	0	**46**	17
Jack pine	0	18	0	0	22	**60**

Overall accuracy: **57**%

Table 6. Producer's error estimates scaled by sampling probability.

NSU Classification	Scaled error estimate	Estimated probability of occurrence
Sugar Maple	1.30	0.04
Mesic white pine/red pine	2.12	0.04
Dry-mesic white pine/red pine	3.43	0.09
Lowland conifer	0.93	0.34
Rich swamp	2.25	0.05
Mesic aspen-birch-spruce-fir	19.46	0.26
Jack pine	6.87	0.18
Total error	36.37	

Bearing tree analysis

Electivity analysis of bearing trees at corners within 300 m of current sample points showed that there some relatively strong residual relationships with bearing tree samples. Jack pine bearing trees were positively associated with both jack pine types. Red pine bearing trees had a strong positive association with the dry-mesic white pine-red pine types and also showed a positive association with the mesic pine type. White pine was more strongly associated with the mesic type. Maple and yellow birch bearing trees had the highest associations with the sugar maple type. Paper birch, fir and white cedar bearing trees showed positive associations with the mesic aspen-birch-spruce-fir class. Fir and white cedar also had a positive associations with the sugar maple type indicating that current sugar maple dominated sites may have had a greater conifer component at the time of settlement. White cedar and black ash had relatively high positive associations with rich swamp, while tamarack and black spruce were the only bearing tree species positively associated with lowland conifer.

Table 7. Electivity scores for sample data classified into RNV types and bearing tree species

	Bearing tree species												
RNV class	jack pine	red pine	white pine	Pine	paper birch	aspen	yellow birch	Fir	Maple	Cedar	black ash	spruce	tamarack
Jack pine-hardwood	0.51	0.44	0.00	0.25	-0.06	0.22	-0.54	-0.42	-2.54	-0.62	-1.59	0.04	-0.23
Jack pine-black spruce	0.44	-0.25	-0.17	0.57	-0.17	-0.04	-0.64	-0.40	-3.40	-0.90	-3.14	0.08	-0.14
Dry-mesic white pine-red pine	0.54	1.37	0.54	0.10	-0.22	0.38	0.66	-0.33	-2.00	-0.52	-0.26	-0.51	-0.31
mesic white pine-red pine	-0.13	0.76	1.04	1.10	0.24	0.36	0.70	-0.24	-2.00	-0.99	0.22	-0.43	-0.55
mesic-aspen-birch-fir-spruce	-0.57	-0.59	0.21	-0.20	0.39	-0.02	0.21	0.48	0.33	0.36	0.19	-0.17	-0.26
Sugar maple	-2.90	-0.83	-0.14	-1.40	0.41	-0.20	0.91	0.64	2.70	0.60	0.78	-0.35	-1.36
Rich swamp	-1.12	-0.43	0.11	-0.72	0.09	0.23	0.51	0.30	0.47	0.87	1.88	-0.31	0.06
Lowland conifer	0.00	-0.60	-0.80	-0.30	-0.39	-0.33	-0.93	-0.41	-2.00	-0.39	-1.37	0.31	0.41

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Table 8. Cross tabulation comparison of NSU classifications based on current vegetation data versus GLO bearing tree data.

a) Producer's

NSU current classification	Sugar Maple	Mesic white pine/red pine	Dry-mesic white pine/red pine	Mesic aspen-birch-spruce-fir	Jack pine
		Bearing tree based classification			
Sugar Maple	**99**	17	4	8	0
Mesic white pine/red pine	0	**42**	11	13	5
Dry-mesic white pine-red pine	0	12	**76**	3	28
Mesic aspen-birch-spruce-fir	1	24	1	**66**	2
Jack pine	0	5	9	10	**64**

b) User's

	Sugar Maple	Mesic white	Dry-mesic white	Mesic aspen-birch-	Jack pine
Sugar Maple	**59**	20	4	17	0
Mesic white pine/red pine	0	**49**	12	27	11
Dry-mesic white pine/red pine	0	8	**50**	4	38
Mesic aspen-birch-	0	16	0	**80**	3
Jack pine	0	3	5	12	**79**
			Overall accuracy		**66 %**

We also created a map based on electivity relationships of bearing tree species and the composite physiographic map. A cross tabulation of the map based on current data versus the bearing tree based classification for upland types is presented in Table 8 in the same format as the accuracy assessment tables. Overall agreement between the 2 maps is 66%. Agreement is strongest in the sugar maple, mesic-aspen-birch-spruce-fir and jack pine classes. Of the area classified as sugar maple by the bearing tree data, 99% was classified as sugar maple using current vegetation data (Table 8a). However, of the total area classified as sugar maple by the current data, 59% was classified as sugar maple by the bearing tree data, with mesic white pine and mesic aspen-birch-spruce-fir accounting for 37% of the area (Table 8b). This would suggest that sugar maple might have expanded to occupy other mesic sites in the post-settlement landscape. Similarly, of the total area classified as mesic-white pine-red pine by the bearing trees, the current data classified 42% the same, while sugar maple and mesic aspen-birch-spruce-fir account for

41%. This may indicate that sugar maple and mesic-aspen-birch-spruce-fir occupy former mesic white pine-red pine areas

These results show that in general, sample data and analysis based on current vegetation data for the NSU revealed ecological potential similar to that of the bearing tree data. However, there are some important differences, particularly with respect to the distribution of the mesic white pine-red pine, sugar maple and mesic aspen-birch-spruce-fir types.

Conclusions

Our primary goal was to create a map showing the potential distribution of RNV ecosystem classes for the Northern Superior Uplands ecological section. In spite of the coarse nature of the available spatial data, and the difficulties in classifying forest inventory data into these RNV types, we believe that we have created a map that can be used for landscape scale planning in this region. This map is relatively coarse, and primarily shows the general distribution of these classes. However, by classifying upland and lowland areas separately, and by integrating spatial databases on soils, landform, topography and climate, this map demonstrates the potential variability within Land Type Associations.

Assessing the accuracy of potential vegetation classifications is difficult at best. There are a number of sources of error, including differences between potential versus current vegetation, difficulty in classifying sample data, and differences between the map unit resolution (coarse) and sample data (fine). Given these difficulties, this map is reasonable estimation of the potential distribution of these RNV ecosystem types.

We have also used the GLO bearing tree data in our analysis. Our analysis shows that while there are differences, there are also strong similarities that indicate that the current sample data reveal similar relationships to the composite physiographic map when compared with the bearing tree data.

Finally, we note that this is a first attempt at this type of classification for the NSU. Future efforts will benefit from both finer scale spatial data and higher quality vegetation data.

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