Development of Procedures to Assess Brushland Resources for Woody Biomass Energy Markets

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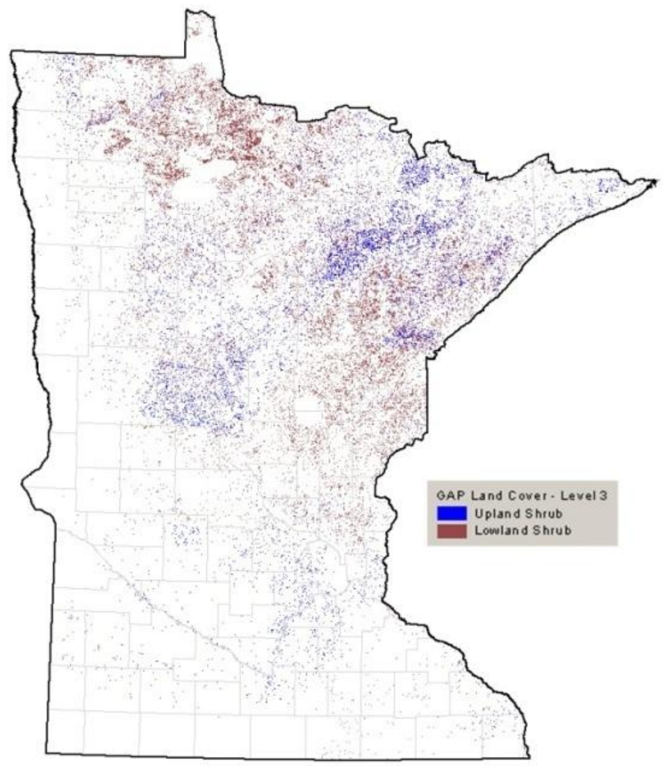

Figure 1. Upland and lowland brushland sites in Minnesota.

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Executive Summary

Brushlands have the potential to provide biomass for energy particularly in northern regions where these land types are common. A pilot project was proposed to assess shrubland density over a several county area using a combination of on-site biomass measurements and remote sensing techniques. This project was done as two sections by different organizations. This first section of research was done cooperatively by the Minnesota Department of Natural Resources and the UM-Duluth, Natural Resources Research Institute and the second section was done exclusively by the Minnesota Department of Natural Resources, Forest Resource Assessment Unit.

The goal of the first task, described in Section 1 of the report, is to conduct on-site biomass assessments and conduct interpretation of aerial photography to develop a dataset of brushland polygons where on-site biomass estimates were made. Brushland areas within selected larger Permanent Sampling Units (PSUs) were delineated on aerial photographs and subsequently sampled to estimate standing biomass on these sites. Plot data were used to estimate shrub biomass using existing biomass estimation equations that provide a means to convert stem dimensional data into estimates of oven-dry biomass. These data were summed across plots within each polygon to arrive at biomass estimates within low, medium and high polygons as delineated through ocular interpretation of aerial photography. The average oven-dry biomass of polygons classified as low, medium and high through photo-interpretation is 0.76, 5.3 and 8.3 tons per acre, respectively. Delineation of poorly-stocked, low-biomass areas through photo-interpretation is potentially useful as a “first-cut” elimination of those areas that are likely to be too low in biomass to warrant further investigation. Evaluation of polygon classification showed that average stand height has the greatest influence on ocular classification.

In addition to analyses of shrub biomass within individual polygons, we digitized areas of each of the polygons present with the PSUs to estimate the average biomass on an area basis on each PSU. Having the distribution of low, medium and high polygons in terms of area, a coarse estimate of the average biomass on brushland sites is possible. Through this method, the weighted average biomass on brushland polygons is estimated to be 4.27 dry tons per acre. Using estimates of the average biomass on brushland sites and applying the result to the statewide lowland brush acreage produces a resulting total statewide standing biomass estimate of 10,065,531 dry tons. It should be noted that upland brushland acreage accounts for an additional 667,593 acres, or roughly 22 percent of the total brushland acreage statewide. Assuming biomass density is the same as lowland brush types, this resource has the potential to account for an additional 2.8 million dry tons. If brushland types could be managed on a fifteen year rotation, annual estimated biomass availability is roughly 670,000 dry tons. However, many of the sites that were measured have undergone significant mortality with cycles of dieback and regrowth occurring. In order to adequately understand annual biomass production, long-term studies of growth rates after shearing are needed. Estimates of biomass growth during the early stages of stand regeneration would provide a more complete picture of the potential growth rate of these lands due to the fact that younger stands are more vigorous and do not have significant biomass losses due to mortality. A network of permanent plots with periodic biomass measurements would be needed to more accurately determine annual growth patterns on these regenerating sites.

The data generated in the first research task was then used as a basis for analysis of satellite imagery classification, described in this report under Section 2. Supervised and unsupervised classifications were performed using field-measured data from the summer of 2008 generated through on-site sampling described in Section 1 and existing inventory data. Results were fair to poor for an early supervised attempt using an object oriented classifier and only the new field data, which was minimal to inadequate for the purpose. A limitation of this dataset is the relatively low prevalence of medium and high biomass area which limits the contrast among the three classifications; low, medium and high biomass areas. Also, this analysis was done at the polygon-level whereas the Landsat TM data occur as multi-band data in 30 meter pixels. Review of aerial photography of the areas used in this analysis showed the high inherent variability within brushland polygons. Given the fact that 30 meter pixel Landsat TM data were used in this analysis, the variability among individual pixels within a given brushland polygon is problematic. Classification and analysis of individual pixels would likely provide better agreement between on-site measurements and TM data but it is highly impractical and very expensive to produce a dataset of on-the-ground measurements that would correspond to TM data at a 30 meter resolution. Also, greater restriction in selection of polygons based on uniformity would likely increase the accuracy of classification.

Other attempts used existing inventory data for training and the new field data for accuracy assessment. This analysis was done using a larger dataset of DNR-FIM inventory data which provides ocular estimates of shrub biomass on 412 brushland sites; again in low, medium and high density classifications. Similar supervised classifications using this expanded data set showed improved accuracies. The best results were obtained using unsupervised methods with signature refinement. These preliminary results show that remote sensing techniques hold promise for identifying high density shrub resources that would be eligible for management as biomass fuels statewide. These techniques combined with follow up interpretation of aerial photography could provide a useful tool to determine the relative biomass density on a particular site. At a minimum, a combination of remote sensing techniques and subsequent review of aerial photography would be useful to eliminate sites likely to be too low in biomass density to facilitate economical harvest on these sites.

Given the fact that brushland height is correlated to shrub biomass and high biomass density classifications were generally found to correspond to areas of greater height, other techniques such Light Detection and Ranging (LIDAR) may hold promise to provide more accurate estimates of biomass on these sites. However, LIDAR data are currently very expensive and are not available statewide or in large geographic zones at this time.

Introduction

Development of new forms of alternate energy has the potential to greatly increase demand for all types of biomass including woody and herbaceous material. An opportunity that has been identified in Minnesota is the potentially large biomass resource represented by brushland habitats. These sites are typically comprised of shrub species such as willow, alder and hazel. While these lands are significant in acreage in the state, estimates of biomass density and tonnages have not attracted attention in the past due to low price for biomass, expected high costs of harvesting and relatively low value of this small-diameter resource.

In addition to value for biomass production, managers of public lands have expressed interest in improving brushlands for Sharptail Grouse, a species favoring open habitats. Habitat improvement is accomplished on these sites by shearing shrub material using bulldozers fitted with shear blades. Due to lack of markets, this material is typically burned on-site thereby producing no revenue through biomass sales. The lack of revenue and high treatment costs have limited the amount of acreage that can be treated in a given year. In light of budget constraints, habitat improvement will likely be dependent on increasing biomass sales from these lands.

Up to this point, the lack of markets and lack of accurate data on biomass amounts has limited the options to sell brushland biomass. The intent of this project is to develop techniques to assess biomass volumes using a combination of satellite imagery, aerial photography and on-site biomass measurements.

This report is organized in two sections, the first describing on-site sampling that was done to develop estimates of biomass with the sampling sites. The second section describes the process of using the information produced in on-site sampling to test the application of remote sensing techniques to brushland biomass estimation.

SECTION I. Sampling Procedure to Evaluate Brushland Biomass

Methods

The sampling procedure was developed using aerial photographs of randomly-selected Primary Sampling Units (PSU) as part of the Minnesota Comprehensive Wetland Assessment, Monitoring and Mapping strategy (CWAMMS) program. Apparently stocked brushland areas within the square-mile PSU sites were photo-interpreted and typed according to an ocular estimate of density; low, medium and high.   Once these polygons were delineated, an on-site evaluation of biomass was done by selecting two polygons within each of the three density classes for a total of six polygons selected for sampling within each PSU. A total of 44 PSUs were selected for sampling out of a total of over 100 candidate PSUs across Minnesota. The 44 PSUs contained a total of 128 individual polygons (Fig. 2). Not all PSUs had all density classes present on site.

Plot Sampling

Polygons were sampled by establishing two measurement plots on which shrub dimensional data were collected. Plot size was determined by diameter of the shrubs on each plot. In the case of shrubs less than one inch diameter-at-breast-height (DBH), a 1/100 acre plot was established. All stems were tallied and the average diameter and height of the shrubs was estimated. In the case of shrubs greater than one inch in diameter and less than 4.9 inches DBH, diameters were collected on all stems on the plot and an average height was estimated. In the case of shrubs greater than five inches in DBH, diameter data were collected and the height of the tallest stem was measured. Heights of all other stems in this size class were estimated. In this way, estimation of biomass across all diameter ranges was possible.

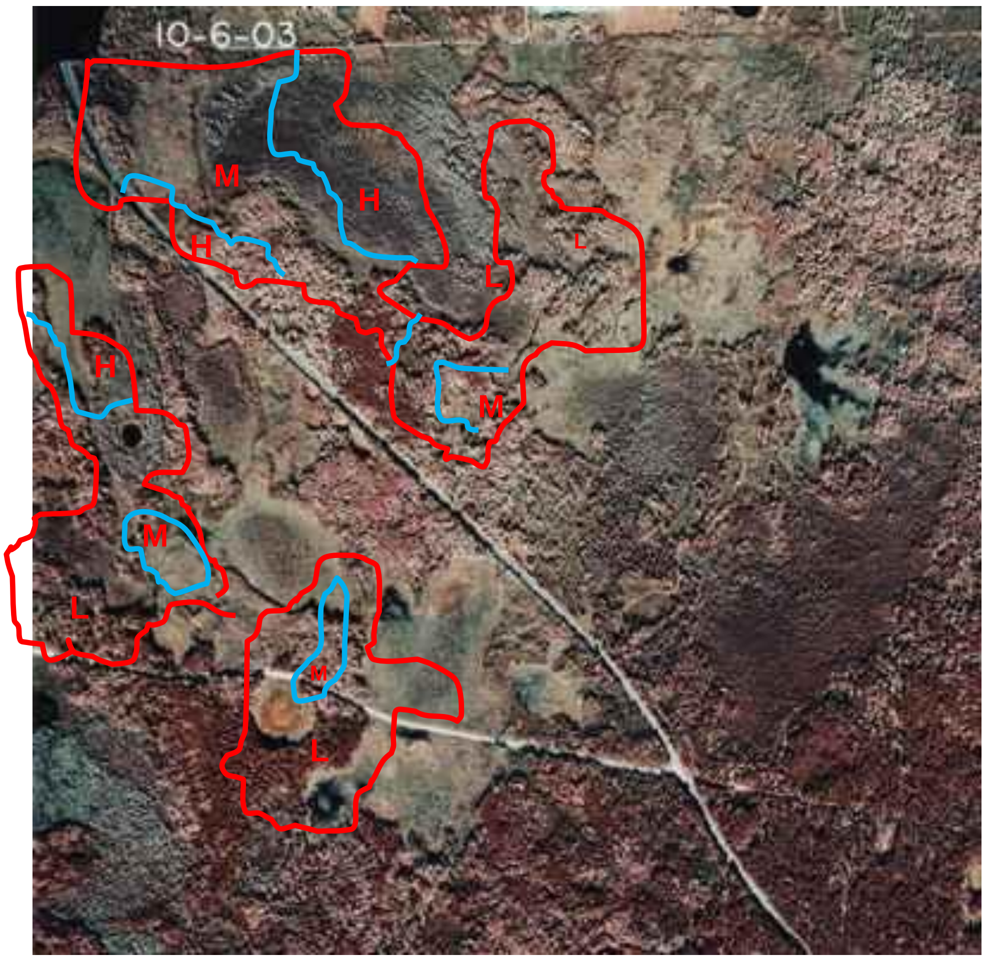


Figure 2. Example PSU with brushland delineations.

Biomass Estimation

All data were entered into computer files and allometric equations were used to estimate individual stem biomass. Using pre-existing brushland biomass data collected from individual stems of brushland species, we evaluated a set of published and unpublished (NRRI previous project) equations for use in this project. These equations included biomasss estimation methods from a variety of sources. We found a composite equation of the form: oven-dry biomass in grams = e^(2.383*ln(diameter @ 15cms)+4.032) to exhibit the best fit across all diameter ranges. This equation was applied to all stems which resulted in an estimate of the biomass for each individual stem. Individual stem biomass was summed for each plot and polygon to produce an estimate of biomass on an area basis, in this case, oven-dry tons per acre.

Results

The average oven-dry biomass of polygons classified as low, medium and high through photo-interpretation was 0.76, 5.3 and 8.3 tons per acre, respectively (Figure 3). As is evident in the Figure 3, delineation of poorly-stocked, low-biomass areas through photo-interpretation is potentially useful as a "first-cut" elimination of those areas that are likely to be too low in biomass to warrant further investigation. Evaluation of polygon classification showed that average stand height has the greatest influence on ocular classification. Polygons delineated as medium and high were characterized by a more rough appearance, likely related to larger crown sizes of individual stems in these areas.

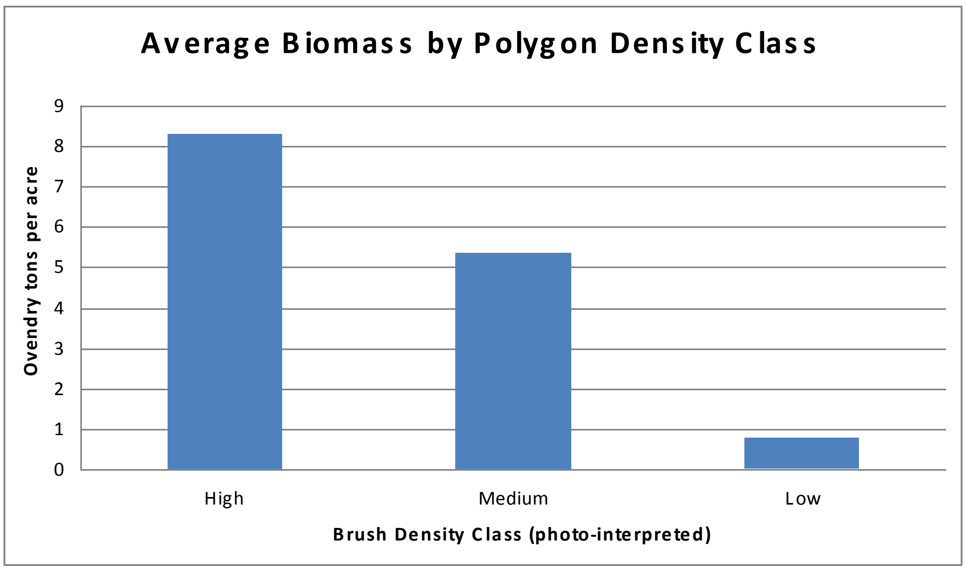


Figure 3. Average biomass of polygons within PSUs as determined by on-site measurement.

Because the intent of this project was to test and develop methodologies for assessment of brushland biomass, the sampling scheme was designed to balance low, medium and high areas. By virtue of this design, we did not, however, produce estimates of the total acreage within each of these classes on each PSU. That is a different question that can only be addressed by more detailed evaluation of all polygons within each PSU across a sampling of PSUs. In order to more accurately assess the average biomass on a given landscape, the distribution of biomass density classes must be known. This requires photo-interpretation of all brushland polygons within a given PSU and digitization of those polygons to arrive at estimates of the total biomass available on a site. The initial phase of the project produced a dataset of all brushland polygons in the PSUs typed according to our brushland density classification. Having this dataset, we digitized all polygons on aerial photographs on the 43 PSUs that have been sampled to produce estimates of total brushland biomass on each PSU. We will use the resulting data describing the distribution of biomass density among polygons and apply this information to statewide brushland acreage as estimated using the GAP Level 3 data. Statewide satellite data are briefly described below.

Estimation of Statewide Brushland Acreage

The Minnesota GAP satellite data was used to estimate the acreage of brushland in Minnesota. The distribution of brushland is shown graphically in Figure 1 at the beginning of this report. Satellite classification of vegetative cover is not an exact science and misclassification of vegetation types is inevitable. For example, separation of brushland from regenerating forest is very difficult and can lead to an overestimate of brushland acreage. The Minnesota Department of Natural Resources has conducted an analysis of the accuracy of the Minnesota GAP data. After completion of the accuracy assessment, the percent of land that was misclassified as upland and lowland brush are published by brushland type and management unit. We used these adjustments by brushland type (upland vs. lowland) and management unit to arrive at a more conservative estimate of brushland acreage. Brushland acreage adjusted according to the accuracy assessment for all units is shown in table 1.

Table 1. Cumulative brushland acreage by unit and brush type in Minnesota adjusted for accuracy assessment.

	Adjustment		Adjusted Acres	
Sub-Section Name	Upland Brush	Lowland Brush	Upland Brush	Lowland Brush
Agassiz Lowlands	65%	59%	14936	388858
Red River Prairie	30%	58%	967	7583
Aspen Parklands	30%	100%	11984	162575
Border Lakes	45%	64%	61884	62080
Littlefork-Vermillion Uplands	100%	100%	49434	171373
North Shore Highlands	81%	100%	58492	166589
Chippewa Plains	100%	100%	54818	208021
Laurentian Uplands	100%	100%	26650	52661
St. Louis Moraines	35%	75%	25707	118268
Nashwauk Uplands	100%	100%	148260	78077
Hardwood Hills	50%	60%	35432	57294
Tamarack Lowlands	100%	100%	46131	282103
Toimi Uplands	100%	100%	26202	60432
Pine Moraines & Outwash Plains	41%	75%	61598	93522
Mille Lacs Uplands	100%	100%	10670	326155
Glacial Lake Superior Plain	100%	100%	983	8388
Minnesota River Prairie	10%	100%	4923	17235
Anoka Sand Plain	60%	80%	5545	57161
St. Croix Moraine		80%		50
Big Woods		80%		7923
St. Paul-Baldwin Plains		80%		2263
Coteau Moraines	100%		9629	
Oak Savanna	33%	100%	1417	12371
The Blufflands	75%	100%	10836	10124
Rochester Plateau	33%	100%	397	3817
Inner Coteau	100%		700	
Total			667593	2354924

As shown above, the total adjusted brushland acreage in Minnesota is 3,022,517 acres.

As mentioned above, on-the-ground assessment of biomass by plot sampling on 43 PSUs was done. Using biomass estimates from plot sampling in each polygon within the PSUs, we digitized the area of each polygon to provide an estimate of the weighted-average shrub biomass occurring on these sites. A total of 129 polygons were digitized from the 43 PSUs. These data were taken in composite to evaluate the areal distribution of high, medium and low biomass polygons. The distribution by acreage is 23, 53 and 24 percent in low, medium and high-biomass polygons, respectively. The weighted average biomass on brushland polygons is estimated to be 4.27 dry tons per acre. Using estimates of the average biomass on brushland sites and applying the result to the statewide lowland brush acreage produces a resulting total statewide biomass estimate of 10,065,531 dry tons. It should be noted that upland brushland acreage accounts for an additional 667,593 acres, or roughly 22 percent of the total brushland acreage statewide. Assuming biomass density is the same as lowland, this resource has the potential to account for an additional 2.8 million dry tons.

The biomass density on any particular site will affect the economics of production by virtue of the fact that higher brushland density will require less moving of equipment to individual sites and likely higher productivity of equipment in a given unit of time. As mentioned above, approximately one fourth of the brushland polygons had 8 tons per acre, only a portion of sites will likely meet the criteria for economic production of biomass. Therefore, the economically-accessible acreage is likely to be only a portion of the total brushland resource due to a large amount of the land base being too low in biomass to warrant moving of equipment and setup of the harvesting operation.

Assuming that brushland types could be managed on a fifteen year rotation, annual estimated biomass availability is roughly 670,000 dry tons. However, many of the sites that were measured have undergone significant mortality with cycles of dieback and regrowth occurring. In order to adequately understand annual biomass production, long-term studies of growth rates after shearing are needed. Estimates of biomass growth during the early stages of stand regeneration would provide a more complete picture of the potential growth rate of these lands due to the fact that younger stands are more vigorous and do not have significant biomass losses due to mortality. A network of permanent plots with periodic biomass measurements would be needed to more accurately determine annual growth patterns on these sites.

At this time, costs of shearing and grinding are known or can be estimated with reasonable certainty. However, the unknown cost factor in brushland harvesting is the cost of collecting sheared material. Shrub biomass is left in windrows as a result of the shearing operation. A mechanism is needed to collect this biomass and transport it to a chipper or grinder near a roadside. As part of a cooperative project funded by the US Department of Energy and the Laurentian Energy Authority, we have modified a standard forestry forwarder and will begin field-testing of this equipment on sites that have been recently sheared. We are cooperating with the Minnesota DNR and the U.S. Fish and Wildlife Service to identify sites where trials of this modified forwarder will be done.

Section II. Remote Sensing Assessment of Shrub Lands in North-central MN

Methods

Using data collected from on-site measurements, biomass estimates of each of the polygons were used to test traditional remote sensing classification methods. The polygons were subdivided and labeled as low, medium, and high shrub density classes based on visual inspection and the field measurements. We took the lines and notes from the edited air photos and digitized them into a GIS format for further analysis.

Landsat TM data with 30 meter pixel resolution offered the best possibility for an inexpensive large area analysis. An initial selection of a path 28, row 27 landsat "scene" covering multiple counties and 16 psu's in North-central MN was made (Figure 1).
The landsat scene selected for this analysis was dated August 3, 2006 and contained 6 bands of data including visual and infrared wavelengths at a 30 meter spatial resolution. This was the latest cloud free scene in our collection for that scene location. Shrub lands do not experience much change over time and this 2 year old image should represent current conditions for the most part.

Figure 1. Landsat scene footprint within a context of county boundaries and psu's sampled.

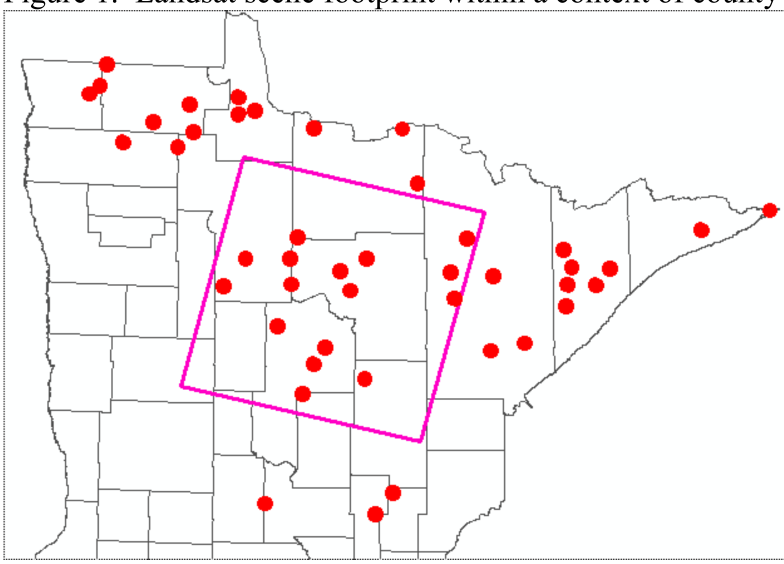


Image classification was only going to be applied to state owned lands identified as "lowland brush" in the current FIM database of forest inventory. A set of these polygons was built from area tiles, selected and clipped for the footprint of path 28, row 27.

There were a total of 38 polygons within the 16 psu's encompassed by the scene boundary. A random number was generated for each polygon and the group was separated into training and accuracy assessment polygons randomly. The following table shows the distribution of shrub densities within the samples:

Table 1: Distribution of training and accuracy assessment samples within the field measured polygons.

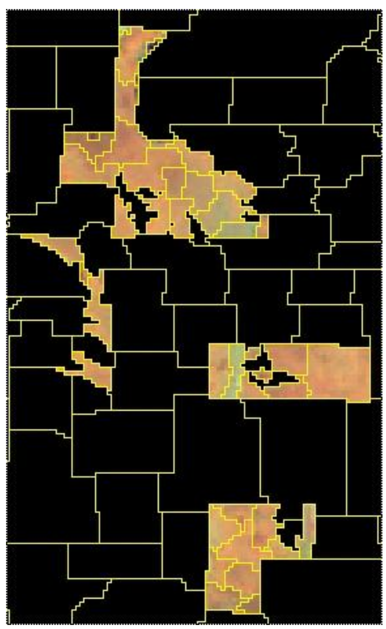
Density class	Training samples	Accuracy Assessment Samples	Total
Low	13	12	25
Medium	3	3	6
High	4	3	7

Field data collection is one of the largest expenses for any remote sensing project. Splitting out half of this data as accuracy assessment limits the amount of training data. More is usually better. This study area contained too few field measured polygons with medium and high densities to adequately cover the variability of species and conditions for these classes. This limitation will affect results seen later.

Classification attempts

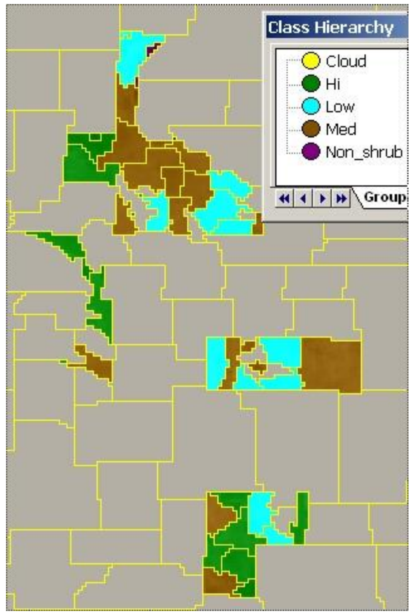
One method of image classification (supervised) involves using the computer to label pixels or objects based on statistical similarity to a set of known quantities (the training samples in this case). The first attempt used an object oriented approach implemented through Definiens Professional Earth software. Attempts to apply image segmentation for the purpose of building objects for the entire scene failed for lack of memory. It was necessary to reduce the areal extent of the data. An “area of interest” (aoi) was generated just outside the 16 psu’s containing sample data and the satellite data was clipped to that extent. An additional reduction in data was accomplished by subsetting the image data with an aoi of just the training (field-measured) data merged with all the state “lowland brush” areas. This allowed the image segmentation routine to build objects (Figure 2) of fine enough detail to be useful for classification. These objects were built using a relative
scale of 7, color component of 0.8 (inverse shape of 0.2), and a compactness component of 0.6 (inverse smoothness of 0.4).

Figure 2. Image segmentation of a subset of satellite imagery for “lowland brush”.



A classification scheme was defined as 5 classes including low, medium and high shrub densities as well as cloud and non-shrub. The nearest neighbor rule for classification used the mean of all 6 spectral bands as well as the standard deviation of band 4 as a hint of a texture measure. Training samples were selected visually from the training polygons that were field measured. The object oriented classification was run and results (Figure 3) exported to an Erdas Imagine “.img” format for accuracy assessment purposes.

Figure 3. Classification results using object oriented classifier.



The “zonal attributes” tool of Erdas Imagine was used to calculate the majority composition of classification values (excluding cloud and non-shrub) for the accuracy assessment polygons. The results of the accuracy assessment are shown in Table 2. The overall accuracy of 22% is low. This could be due to a number of factors including too few field measured training/accuracy assessment polygons, a lack of homogeneity within the training polygons, high variability within density classes for different species of shrub, or a poor choice of imagery and/or classification technique. Shrub is a tough target for a coarse resolution sensor and the low accuracy is not unexpected.

Table 2. Accuracy assessment for field-measured polygons split into Training/Accuracy Assessment.

		Classified Image				
		Low	Medium	High	Row Total	Omission Error %
Reference	Low	3	7	2	12	75%
Image	Medium	2	1	0	3	67%
	High	3	0	0	3	100%
Col. Total		8	8	2	18	
Commission Error %		63%	88%	100%		22%Overall Accuracy

Altering techniques may improve classification accuracy without acquiring more field data. Another attempt was made using a filtered set of the FIM inventory “lowland brush” category as training data instead of the field-measured areas. This also allows for using all the field-measured polygons for accuracy assessment. The selection criteria for training samples was “survey year” > 1997 and a “recon” level of 3 to 5 (ground checked with 1’ of snow or less). This yielded 42, 191, and 179 training polygons of “shrub density” low, medium and high respectively. These density classes are from the FIM inventory and defined differently than for the current project, but hopefully are useful as a relative scale.

Sample objects were selected in Definiens Earth as before and a new classification was run using the same classification scheme and nearest neighbor criteria. The zonal majority was again calculated for the now expanded set of accuracy assessment polygons that were field measured and the results appear in Table 3.

Table 3. Error matrix for classification using selected FIM data for training and field measured polygons as reference.

		Classified Image			Row Total	Omission Error %
		Low	Medium	High		
Reference	Low	3	12	10	25	88%
Image	Medium	0	6	0	6	0%
	High	0	2	5	7	29%
Col. Total		3	20	15	38	
Commission Error %		0%	70%	67%		37%Overall Accuracy

An attempt was made at this point to improve the accuracy further by adjusting samples based on a visual interpretation of aerial photography. Classification results were reviewed and those objects judged to be in error were identified as samples for the subjectively more appropriate class. This procedure was continued iteratively until diminishing returns caused the analyst to stop. The final classification was again exported and a zonal majority calculated. The results are shown in the error matrix in Table 4. Accuracy improved slightly over the unrefined samples above.

Table 4. Error matrix for classification using selected FIM data for training and field measured polygons as reference with visual interpretation for improved training samples.

		Classified Image			Row Total	Omission Error %
		Low	Medium	High		
Reference	Low	7	14	4	25	72%
Image	Medium	1	5	0	6	17%
	High	2	2	3	7	57%
Col. Total		10	21	7	38	
Commission Error %		30%	76%	57%		39%Overall Accuracy

A second type of image classification was attempted to see how it compared to the object oriented approach used previously. This approach uses individual pixels as the basis of classification instead of objects and lets the computer create the training signatures within each density class. This is called unsupervised classification. Resource Assessment used a form of pixel based classification earlier in the GAP analysis project. These same iterative guided clustering techniques were applied to the current project.

The same group of training polygons from the FIM “lowland brush” class was used. AOI’s were built by density class and used as a mask to create a group of 11 signatures for each density class through the unsupervised classification tool in ERDAS “imagine” software. The assumption is that the sub-signatures will adequately represent the
variability in the training set. This variability may include different shrub species, clouds, forest, and density classes other than the training set label. Each signature was visually interpreted over aerial photography and labeled as one of the 6 classes (forest was added to the 5 used in previous analyses) or

some combination thereof if it seemed confused between multiple classes. These confused classes can be deleted, merged, or further refined in continued analyses.

All 33 signatures from the 3 density classes of shrub were merged into one signature file and a Jefferies-Matusita seperability measure was calculated. Signature pairs that were most similar were merged and labeled according to the most appropriate class or majority/minority classes derived from visual interpretation. In most cases, the merged signatures had the same density class from visual interpretation, regardless of the training set of origin. A final signature set of 22 individual signatures was used to classify the population of FIM "lowland brush" and field-measured pixels. The final classification was recoded to the 6 class scheme (Figure 4). Accuracy assessment was calculated as in previous attempts and results are shown in table 5. Overall classification accuracy was
again somewhat improved at 50%. Further improvements in accuracy may be possible with a more precise breakdown of some confused signatures into finer sub-signatures.

Figure 4. Pixel based unsupervised classification within "Lowland Brush" polygons over satellite imagery.

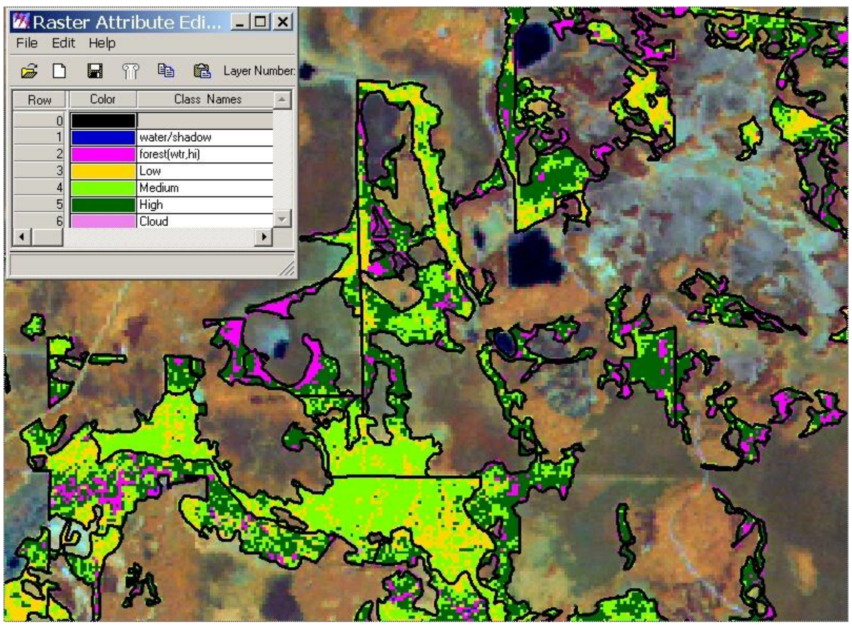


Table 5. Guided clustering of CSA used for training with field measured used for Accuracy Assessment

		Classified Image				
		Low	Medium	High	Row Total	Omission Error %
Reference	Low	13	7	5	25	48%
Image	Medium	1	1	4	6	83%
	High	2	0	5	7	29%
Col. Total		16	8	14	38	
Commission Error %		19%	88%	64%		50% Overall Accuracy

Discussion

The results indicate how problematic this kind of information is to obtain accurately with remote sensing capabilities over large areas. Air photo interpretation would probably produce more promising results for small areas, but is prohibitively expensive in interpretation costs for such a low value product. There are a number of issues worth exploring in order to understand what's possible with available technology.

Good sample or training data would help achieve a higher level of accuracy. A combination of high homogeneity and large numbers of samples to cover the variability in the population is important. Our training sample numbers for medium and high density for the first run of this pilot were only 3 and 4, which are probably contributing to our initial low accuracy in the first attempt at classification. Figure 5 shows the variability that can be found in 4 examples from our training/accuracy assessment set over color infrared photography. How this variability is seen at 30-meter satellite resolution is shown in Figure 6. Displayed bands are near infrared (4), mid infrared (5), and red (3) that tends to allow good visual discrimination of vegetation types. This high variability can have a significant effect on the average spectral values for objects based on the scale of the segmentation used.

Figure 5. Examples of training and accuracy assessment polygons derived from the wetland monitoring data.

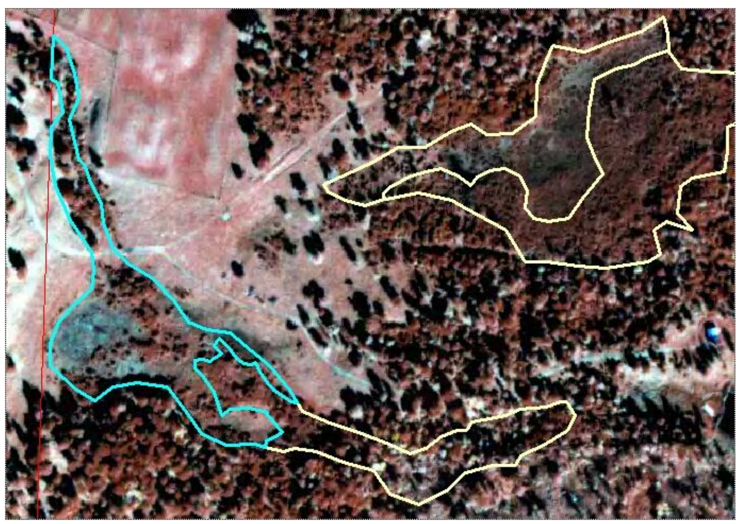
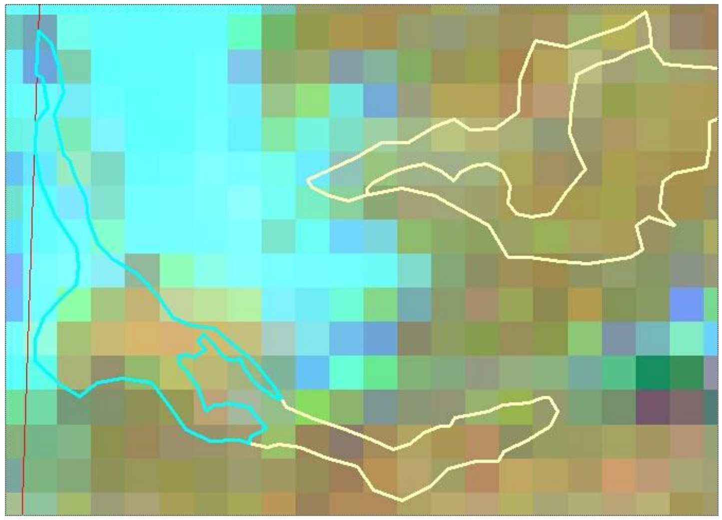


Figure 6. Training and accuracy assessment polygons over 30-meter resolution satellite imagery viewed as bands 4,5,3 (RGB).

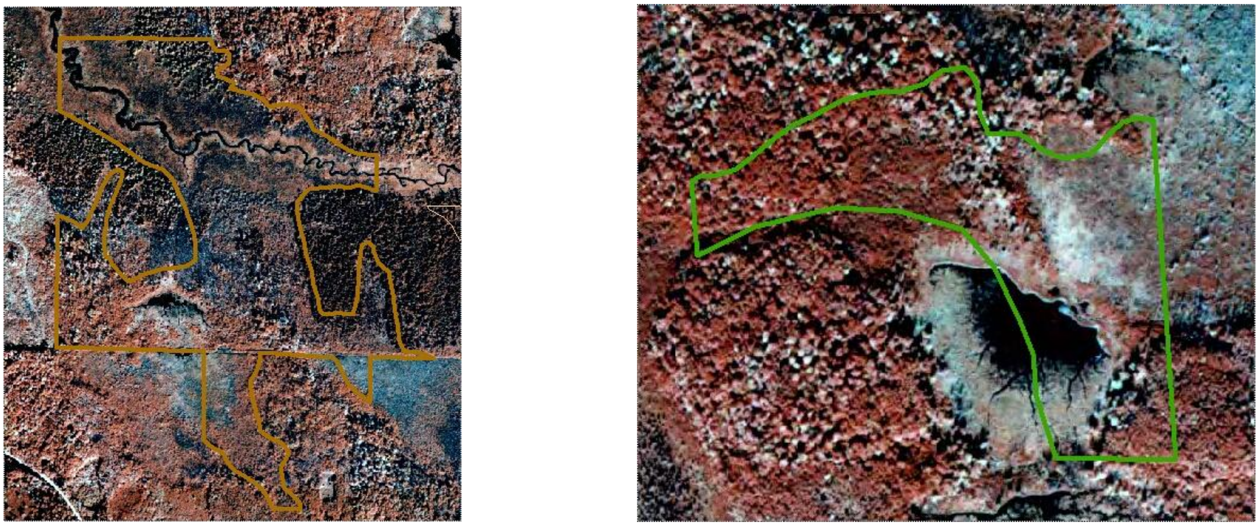


More homogeneous training and accuracy assessment polygons (Figure 7) would certainly help alleviate some of the confusion generated by having mixed types shifting average values away from a pure response.

Figure 7. Example of a more homogeneous training/accuracy assessment polygon.

High variability within the training polygons will certainly affect the results in an object oriented approach because the classification is based on an average value for the entire polygon. It is easy to see how an average for a polygon similar to Figure 8 would not give consistent accuracies.

Figure 8. Two examples of "worst case" high variability in a training polygon from the existing inventory data of "lowland brush".



It is easy to see how average spectral values from these 2 polygons, which include forest, various classes of shrub, wetland grass, and water may not be the best for developing a good signature for high density (above) or medium density (left). One advantage to the guided clustering in a pixel approach is that this variability is broken out into numerous sub-signatures and not averaged for each polygon. All pixels from a group or many polygons are considered together.

This pilot only used one source of imagery. It may be possible to improve results by using different imagery with higher spatial resolution or some combination of photography and satellite imagery to more effectively discriminate shrub densities. We have employed this multi-image capability in the FIM re-inventory project with some success from the segmentation perspective. It would still need to be tested to see if classification accuracies would improve. We could also use multi-season satellite imagery in some combination to better identify shrub species differences, which may improve our density classes as well.

The down side to these approaches is the increased analysis time and consequent expense. Most of the imagery necessary is already in DNR possession or available at no cost from USGS as of January 1, 2009. Higher spatial resolution would also lead to much greater data volumes per unit area. This may necessitate smaller data chunks processed separately and combining of results after the fact.

Overall the pilot shows the potential for segregating lowland shrub densities to some level of accuracy. This process requires considerable expense in planning, field data acquisition, and image analyses. Using existing state inventory data as a surrogate for field data collection would allow considerable savings if data differences could be resolved to some acceptable level. This would facilitate expansion of the classification to a statewide effort, since we would have state inventory data as training for most of the state with a much reduced fieldwork expense. It would be necessary to have a good shrub mask for all ownerships in an expanded effort. This could be produced independently of the shrub density classification or borrowed from other federal or state efforts based on level of accuracy required. The shrub/forest distinction can be very blurry in Minnesota where vegetation types can have a wide gradation based on moisture regimes on the western edge of many species ranges.

Appendix A

Using the Data to Develop Brushland Volume Estimates

Because biomass from brushlands is likely to be a low value product, it will be useful to have a method for appraising approximate volumes on a site with a minimum of field work. Data in this report can be used to calculate estimates for brushland biomass volume on a given site. Follow these steps.

- Use aerial photos and local knowledge of shrub types to delineate areas and determine acreages of "high", "medium" and "low" density brush on a site. An example of sites delineated into density classes by aerial photo interpretation can be found on page 5.
- Total the acreage for each density class.
- Multiply the average dry ton volume for high density sites (8.3 tons per acre) times the total acreage of high shrub density for the site. Then, do the same for medium (5.3 dry tons/ acre) and low density (0.76 dry tons/acre) sites.
- Add the total volumes together.
- A rough conversion can be made to green tons by doubling the dry ton figure.

Availability Considerations

The reader needs to use caution when using the information in this report to develop volume estimates. Biomass volumes will only be partially recoverable. Breakage, small size and other handling difficulties will limit how much brush biomass can be recovered from a site. Additionally, guidelines for retaining some residue on site for soil nutrient maintenance, habitat and water quality concerns limit amount of brush biomass that should be utilized from a site. The Minnesota Forest Resources Council (MFRC) brushlands harvesting guidelines can be found at:
http://www.frc.state.mn.us/FMgdline/Guidebook.html

Estimate Accuracy

The reader should be aware that brushland biomass volume estimates will have wide variability. However they may prove acceptable considering the normally low product value of brush biomass vs. the expense of additional field time to derive more accurate estimates.