CLASSIFYING AGRICULTURAL LAND IN AN URBAN LANDSCAPE WITH APPLICATION TO WATERFOWL CONSERVATION

by

Daniel Buffett, B.Sc. Biology, Simon Fraser University 1993

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Name:	**Dan Buffett**
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Supervising Committee:

Senior Supervisor	**Dr. Kristina Rothley** Assistant Professor School of Resource and Environmental Management Simon Fraser University
Supervisor	**Dr. Ronald C. Ydenberg** Professor Department of Biological Sciences Simon Fraser University

Date Defended/Approved: ______________________________

ABSTRACT

This project evaluates technical considerations and human resources required to remotely sense agricultural lands and demonstrates how the results can be used for waterfowl conservation. Using a hierarchical decision tree classifier and 3 agricultural classification schemes on Landsat 7 ETM data, the accuracy was calculated for several image transformation techniques. For an 8 class agricultural scheme, the Tasseled Cap transform had a higher overall accuracy (75.1% ± 1.6) than the normalized difference vegetation index (60.6 ± 1.8), second modified soil adjusted vegetation index (60.6 ± 1.8), or arctangent to the simple ratio (59.4% ± 1.8), and had comparable accuracy to the dataset using 84 data layers (77.6% ± 1.5). The decision tree classifier replaced the requirement of raster based classification software and reduced the financial cost by 25%. A classified agricultural map was combined with a species – habitat model for American wigeon to set conservation goals for agricultural lands.

Keywords: Fraser River Delta; decision tree classifier; conservation; remote sensing; Landsat 7; waterfowl

Subject Words: Remote Sensing; British Columbia; crops; agriculture; conservation; waterfowl

EXECUTIVE SUMMARY

Measuring the diversity and extent of agricultural crops is important to society for agriculture and wildlife. In particular, many agricultural areas provide key habitats for migratory birds and mapping these areas provide important information for conservation planning. Key information includes the identification of important agricultural areas and locations where there is a gain or loss of agricultural areas.

This project evaluated the technical considerations, human resource requirements and application of remote sensing of agricultural land within an urban agricultural landscape. The approach demonstrated that Landsat 7 ETM possesses sufficient spectral, spatial and temporal resolution to differentiate agricultural land classes that have high and low value to waterfowl. The Tasseled Cap (TC) had a higher accuracy than the normalized difference vegetation index, second modified soil adjusted vegetation index, or arctangent to the simple ratio, and had comparable accuracy to an 84 data layer that used many transforms including change vector transforms. Using the TC the overall accuracy for a 2 class (permanent crop, temporary crop) was 86.7% ± 1.3% (95% Confidence Interval). The TC transformed classified the vegetation type (graminoid, grass, forb, grain and shrub) with an overall accuracy of 83.1 ± 1.4%, and a vegetation subtype classification (graminoid - active manage, graminoid – passive management, shrub – berry, shrub – nursery, grain, forb – berry, forb –

summer harvest, forb – fall harvest) with an accuracy of 75.1 ± 1.4%. The approach indicated that the four multi-date image had a higher accuracy than the three or single date classification.

A decision tree classifier replaced the need of raster classification software if statistical software and a vector Geographical Information System are available. This modification to the classification method could reduce the financial cost of classification by 25% and significantly reduce the need to learn and operate this software. This can be a significant savings for conservation agencies that have limited funding, expertise and staff time.

To demonstrate the application of remote sensing beyond the production of a map of land use, a series of supply and demand curves were constructed. The supply curves were constructed from a remote sensing agricultural map, while the demand curves were constructed from a species – habitat model. In this demonstration, the species – habitat model for American wigeon and perennial grass indicated that minimum grass requirement had a larger effect on the demand curve that grass species or temperature. When the demand and supply curves were combined a series of conservation habitat goals could be identified.

To improve the application of remote sensing for conservation planning will require the refinement of habitat supply information from remote sensing. Attention should be placed on evaluating less recognized classification methods such as decision trees and artificial neural networks for other land uses beyond

agriculture, explicitly identifying sampling methods and errors and evaluate other satellite systems beyond Landsat 7.

The greater challenge will be the development of species – habitat models and validating the models to determine habitat demand. These models will require resources to develop a model, collect the data to build and validate the model, and identify and reduce uncertainties of the model components. Finally, within a given geographic area, there will be multiple demand curves (from multiple species) that need to be combined with only a limited number of supplied habitats. Ultimately, developing supply and demand curves will improve our ability to rational a scarce habitat if we are to co-exist with other species.

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1.1.1 Importance of Agricultural Lands to Migratory Birds

Agricultural land plays an important role in the survival of migratory birds by providing specific features such as food or corridors within a landscape for dispersal. Along the Pacific Coast, migratory birds travel long distances from northern breeding grounds in the Arctic to wintering areas such as California, Mexico and South America. During the northward trek, it is critical that birds have sufficient energetic reserves to complete their migration and breeding stage of their lifecycle. Therefore, providing food is a key necessity to maintain the future populations of migratory birds.

1.1.2 Importance of Fraser River Delta to Migratory Waterfowl

Along the Pacific Flyway, the Fraser River Delta in British Columbia (BC) is an important site for migratory birds. The Fraser River Delta is the largest estuary in BC and one of the largest along the upper Pacific Coast. It has the highest density of wintering waterfowl, raptors and shorebirds in Canada (Butler and Campbell 1987). Waterfowl forage on plants, invertebrates and seeds in the large natural tidal habitats and remnant crops (e.g. potatoes, carrots), grains, grasses (e.g. annual winter cover crops and perennial forage grasses), seeds and invertebrates on the adjacent agricultural fields. In addition, agricultural fields provide refuge for waterfowl and other migratory birds during storms or during high tides when intertidal habitats are unavailable. Migratory waterfowl species that use agricultural land in the Fraser River Delta include trumpeter swans (*Cygnus buccinator*), lesser snow geese (*Anser c. caerulescens*), American wigeon (*Anas americana*), northern pintail (*A. acuta*), mallard (*A. platrrhynchos*) and green-winged teal (*A. crecca carolinensis*).

1.1.3 Agricultural Land Use Trends in the Fraser River Delta

Land use changes driven by increasing land costs and changing agricultural markets have resulted in an average annual loss of 653 ha of food to migratory waterfowl between 1980 and 1995 in the Fraser River Delta (Slattery et al. 2000). The loss reflects the conversion from traditional agricultural crops such as vegetables, grains, and grasses to non-compatible migratory waterfowl uses of urban development, berries, nurseries and greenhouses. Given the current extent of agricultural land that is compatible with migratory birds and the rate of annual loss, all the agricultural land that provides food for migratory waterfowl is projected to be unavailable to waterfowl by 2025. While the rate of loss will change over the coming years, the timeline underscores the need to conserve agricultural land.

1.2 Measuring Agricultural Land Use

1.2.1 Importance of Measuring Land Use Trends

Given the high rate of agricultural loss to migratory waterfowl, conservation agencies need to monitor the spatial and temporal changes of agricultural land uses. This information enables conservation agencies to prioritize areas for habitat protection and implement conservation initiatives to ensure sufficient agricultural land is maintained for migratory waterfowl. Without adequate monitoring, conservation protection will remain opportunistic. Land use monitoring also provides a metric to determine the amount of habitat presence as well as the rate of habitat gain and loss. Knowing both of these measures enables conservation agencies to determine whether the rate of habitat protection is sufficient. Finally, knowing the location and rate of land use change improves the understanding of the underlying drivers of land use trends, which enables predictions of future trends. For example, agricultural mapping would identify that the conversion of traditional agricultural crops to greenhouses occurs more frequently closer to the coastline. This observation can guide investigations to determine the mechanism causing the change in land use such as the revelation that the moderating effect of water reduces the heating costs for greenhouses causing a preference to situate greenhouses near the coastline. With this information, agencies can strategically determine appropriate conservation actions.

1.2.2 Requirements To Monitor Agriculture Land Use

To monitor agriculture land use, there are four main criteria that the monitoring system should provide:

1. Coverage of the area of interest (i.e. Fraser River Delta)

2. Minimal mapping unit (e.g. less than 1 or 2 ha) that can differentiate between agricultural fields.

3. Ability to differentiate between land use classes (i.e. waterfowl compatible and non-compatible agricultural crops.

4. Feasible to replicate monitoring protocol over time

1.2.3 Limitations of the Current Agriculture Land Use Surveys

In the Fraser River Delta, there are currently two methods used to monitor agricultural land use: 1) Canada Census of Agriculture and 2) field mapping. The Canada Census of Agriculture is a compulsory questionnaire of agricultural operators conducted every five years throughout Canada coordinated by Statistics Canada. In addition, various government and non-government agencies conduct field mapping by staff or contractors that drive a vehicle along public roads and record the different agricultural land uses on maps.

Both of these current methods do not meet all four criteria required to monitor agricultural land use for conservation planning purposes. The Census of Agriculture provides complete spatial coverage and is replicated every 5 years (satisfying #1 and #4 requirements). However, the classes of land uses have changed over the last twenty years making it difficult to separate compatible and non-compatible land uses for migratory waterfowl. In addition, the information is only available at coarse scales (i.e. agriculture regions, divisions, subdivisions), and is not available at the scale of individual agricultural fields. The smallest mapping unit, which is the Greater Vancouver Regional District, is larger than the area of interest (Fraser River Delta) and therefore does not allow differentiation between agricultural fields. In comparison, the field mapping meets the minimal mapping unit and can differentiate between different agricultural land uses (satisfying requirements #2 and #3). However, the field mapping does not have complete coverage of the Fraser River Delta and is not repeated on a regular interval.

To satisfy all four requirements, a third option for monitoring agriculture land use is remote sensing. This option will satisfy the criteria of complete coverage and be repeatable over time. Therefore, the outstanding question (and the focus of this project) is whether the option can meet the minimal mapping unit of individual agricultural fields (requirement #2) and whether it can differentiate between different agricultural land uses (requirement #3).

1.2.4 Remote Sensing Options

There are many remote sensing systems that could be used to monitor agriculture land use. The technical criteria to determine the appropriate remote sensing system (Lunetta and Elvidge 1998) includes:

1. Sufficient spectral resolution – portion of wavelength that can differentiate between the desired land use.
2. Sufficient spatial resolution – information at the scale that can differentiate between agricultural fields.
3. Sufficient temporal resolution – ability to differentiate the phonological change of agricultural crops over time.
4. Availability of Data
5. Cost to acquire the data – (Table 1-1).

Table 1-1: 2006 One Day Satellite Image Cost in the Fraser River Delta.

Satellite Image (Pixel size, # bands)	**# unit**	**Unit**	**Cost per Unit**	**Total Cost**	**Price Source**
Landsat 7 ETM (30m, 8 bands)	1	image	850	$850	www.photosat.ca
Spot 4 (20m, 4 bands)	2	Image	1200	$2,500	www.terraengine.com
Radarsat (8m, 1 band)	1	image	5000	$5,000	www.photosat.ca
IRS (5m, 1 band)	16	map	470	$7,500	www.photosat.ca
Spot 5 (10m, 4 bands)	2700	km^2	3	$8,100	www.terraengine.com
Quickbird (2.5m, 5 bands	2700	km^2	30	$81,000	www.spatialmapping.com
Ikonos (4m, 4 bands)	2700	km^2	25	$67,500	www.photosat.ca

1.3 Research Project Goals and Objectives

To evaluate a remote sensing system, the Landsat 7 ETM satellite was selected because it has the lowest cost per image. Therefore the overall project goal is to determine whether the Landsat 7 satellite can meet the technical criteria (#1 to #4) for monitoring agricultural land use in the Fraser River Delta. In addition to these technical considerations, conservation agencies will need to know the human resources requirements (e.g. technical expertise, amount of staff time) to conduct agriculture land use monitoring. Finally, the project outlines how remote sensing information can assist in setting conservation habitat goals. Therefore the project objectives are:

1) What are the technical considerations to discriminate amongst waterfowl compatible and non-compatible agricultural land use classes? This includes the questions:

    a) Does Landsat 7 ETM possess sufficient spectral, spatial and temporal resolution to differentiate among agricultural land classes?

    b) What is an appropriate image transform (e.g. NDVI, Tasseled Cap) that can differentiate among the different agricultural land use classes?

    c) Is one image or several images within a year needed to differentiate amongst the land use classes?

2) What are the human resources considerations (skills and staff time) required to conduct remote sensing analysis?

3) How can the remote sensing information be used to set conservation habitat goals?

1.4 Project Overview

The document consists of four chapters. Chapter one provides the project background and rationale. Chapter two is an overview of remote sensing theory while Chapter three describes the technical procedures that were used to develop an agriculture land use map for the Fraser River Delta. Chapter four uses the spatial information along with a simple species-habitat model of wigeon and perennial grass to demonstrate how remote sensing information can determine quantitative conservation goals for a specific species of waterfowl.

2 GENERAL REMOTE SENSING CONCEPTS

2.1 General Description of Remote Sensing

Remote sensing is the acquisition and recording of information about objects without being in direct contact with the object (Gibson 2000). Sensors detect wavelengths of light that are reflected or emitted from an object. This concept applies when our eyes (sensor) detect wavelengths of light (red, green, blue) and our brain classifies the information into an image, or when a camera processes the information into a photograph.

Using airplanes or satellites, sensors can be deployed over the earth's surface to measure the reflected wavelengths of light from the ground. Active sensors record energy that originates from the remote sensing system itself, while passive sensors detect energy from the sun. The sun emits electromagnetic radiation in a broad range of wavelengths (e.g. visible, infrared, thermal, ultraviolet, microwave), however only visible, infrared and ultraviolet radiation wavelengths are transmitted through the earth's atmosphere and reach the surface of the earth (Gibson 2000). Therefore the final amount and type of wavelength recorded by the sensor is a function of the amount of emitted radiation, the type of radiation that penetrates the atmosphere, the reflective properties of the object (e.g. building, crop or forest), atmospheric effects and the type of sensor.

The physical properties of the object significantly affect the type of radiation reflected from the object and can change over time. For example, changes in the structure of plant cells change the type of reflected radiation. While healthy vegetation reflects green light (one portion of the visible spectrum) it also reflects near-infrared radiation. As plants loose chlorophyll throughout the year (senescence), the reflection of near infrared decreases while the visible increases (Gibson 2000). In comparison, anthropogenic surfaces (e.g. buildings, roads) have high reflectance in both the near infrared and visible spectrums reflection and are constant over time. These radiation differences can be used to differentiate between different land uses such as agriculture crops.

In general, each sensor is designed to detect a specific range of radiation in the electromagnetic spectrum. In some satellite systems, there is only one sensor that measures a narrow range (band) of wavelengths (e.g. Radar satellite measures only microwaves). In other satellites such as the Landsat 7 ETM there are multiple sensors that detect radiation in the visible band (0.4 - 0.7 μm), near infrared (0.7 – 1.0 μm), mid-infrared (1.0 – 3.0 μm), and thermal bands (3.0 - 15μm).

2.2 Remote Sensing Steps to Measure Land Use

There are four basic steps in remote sensing to determine land use: data pre-processing, image transformation, pattern recognition, and error assessment. The pre-processing step is a series of data manipulations to correct for impacts that degrade the data and prepare the data for the upcoming steps. Potential impacts include sensor degradation, loss of data, image distortions affecting the geometry of the data, as well as solar illumination and other atmospheric impacts that can scatter, absorb or interact with the data.

Image transformation consists of a number of techniques that increases the ability to distinguish between features of interest (Lillesand and Kiefer 2000). This step modifies the value of individual pixels, or adjacent pixels or combines multiple layers of information. One example is contrast stretching, in which the range of the recorded sensor data (e.g. 10 to 80 units) is stretched over a larger range (e.g. 0-255 units). A second example is a common transformation called the Normalized Difference Vegetative Index (NDVI), which combines the near infrared wavelengths and visible red wavelengths in a ratio. A third example is the Tasseled Cap (Crist and Cicone 1984) that reduces the 6 bands (3 visible, 1 near infrared and 2 mid infrared) of the Landsat TM satellite into 4 dimensions; soil reflectance (brightness), greenness, wetness and noise. Finally another type of transform is the Principle Component Analysis (PCA) that transforms data based on the variance of the data into a smaller number of rotated dimensions that explain a majority of the variability in the original data.

Following image transformation, pattern recognition (also know as classification), establishes a relationship between a pattern (i.e. reflectance value) of a feature and a class label such as potato field (Tso and Mather 2001). The more common pattern recognition techniques are one-to-one relationship between a class and a label (hard classification). This includes labels that are known (supervised classification: where regions of known land cover types are provided as input) or unknown (unsupervised classification: where statistics are used to identify distinctly different regions). Other less common techniques include artificial neural networks, knowledge based methods that simulate the human brain’s inference mechanism (Tso and Mather 2001) such as decision trees or one-to-many relationships (fuzzy classification) between a pattern and label.

The final but critical step is the assessment of error that is incorporated into data through the pre-processing, image transformation and pattern recognition steps. Quantifying error assists in the identification and correction of error sources and provides a metric to compare various techniques (Congalton and Green 1999). Errors between the pattern and class labels can be attributed to 1) reference data, 2) sensitivity of the classification scheme to observer variability, 3) inappropriate use of remote sensing techniques, 4) pre-processing error, 5) inappropriate sampling scheme, and 6) operator error (Congalton and Green 1999, Foody 2002). Crist and Deitner 2000 also include topological errors such as incorrect boundaries (duplicate, overshoot, undershoot, sliver polygons), and temporal errors due to the time difference between collecting reference data and remotely sensed data. In most remote sensing projects, a reference dataset (derived from a secondary data source) is compared to the pattern recognition step by an error matrix, which provides the accuracy for each label. It is also recommended that additional information should be provided such as sampling design, confidence in the ground data labels, classification protocols and lineage of the data sets (Foody 2002).

3 CLASSIFYING AGRICULTURAL LAND IN AN URBAN LANDSCAPE USING LANDSAT 7 IMAGES

3.1 Overview

Landsat 7 ETM images were acquired that temporally covered the growing cycle of agricultural crops within the urban agricultural landscape of the Fraser River Delta over a single season. After correcting for geometric and radiometric distortions, several image transforms were prepared and evaluated to detect agricultural land uses that are compatible with waterfowl and not compatible with waterfowl. See5 (Quinlan 2005), a hierarchical decision tree classifier, was used to classify satellite images rather than the more commonly used maximum likelihood classifier algorithm. Error matrices and confidence intervals were prepared for each image transform based on three agricultural classification schemes (growing life cycle, vegetation type, vegetation sub-type). Based on the measures of accuracy, the best image transform was identified and recommendations for future work are proposed.

3.2 Methods

3.2.1 Study site

The study site is the agricultural land within the Corporation of Delta (49^0 12’ latitude, 123^0 1’ longitude) of the Fraser River Delta, which is located in the southwest portion of British Columbia, Canada. Located at approximately sea level along the coast, the area has a seasonally mild climate and was formed by thousands of years of sediment deposition from the Fraser River. Because of the fertile soils, it supports a significant diversity of agricultural crops including vegetables, grain, forage (grass), nurseries and berry crops. The variation in crops also creates a variable cropping schedule where at any given time different fields are cultivated, planted, harvested or fallowed (no cultivation or planting) throughout the spring, summer and fall. The combination of crop variety, cropping schedule and relatively small field sizes (average field size is 7.8 ha ± SD 8.2 ha) will create heterogeneous units that change over time and space and therefore challenge the traditional remote sensing classification techniques.

3.2.2 Data

3.2.2.1 Satellite Image

Satellite Landsat 7 ETM image archives were queried to select multiple images during the agricultural growing season between 1999 and 2000 which corresponded to years in which reference field data was available. Cloud-free (less than 10% cloud covering an image) image dates that covered the study area over an entire agricultural crop cycle were: June 28 2000, July 30 2000, September 16 2000 and January 22, 2001. In 2002, the satellite data was purchased from Resource GIS and Imaging Ltd, who provided georeferenced Landsat 7 ETM images using 25 m digital elevation model. All 8 Landsat bands were provided in greyscale in a UTM zone 10 projection, NAD83 datum and as a TIF image format.

3.2.2.2 Orthophoto

A 1995 color orthophoto provided a background for the display of spatial information and was the reference base to geometrically correct the satellite image and reference data. The orthophoto was a georefenced color 1m pixel in a UTM zone 10 projection, NAD83 datum and TIF image format.

3.2.2.3 Reference Data

A georefenced vector dataset of permanent agricultural field boundaries was provided with attributes of field size. Agriculture & Agri-Food Canada developed permanent agricultural field boundaries through photo interpretation using the 1995 color orthophoto. Field boundaries were formed at fences, roads or trees, or other permanent boundaries, however a change in crop type did not constituent a boundary as that boundary could change on an annual basis. The data also functioned as a mask to remove any non agricultural lands from the classification process.

Using the permanent field boundaries as a base map, staff from Agriculture & Agri-Food Canada collected agricultural field crop information in the summer of 2000. Staff drove along roads in July, identified agricultural crops and assigned a crop code (Appendix 1) for each crop type to each field. If a field contained multiple crops, the location of each crop boundary was identified using a measurement wheel from a known point on the map to create multiple fields. Data entry staff digitized additional fields if necessary and attributed a field code to each field polygon. The information was created in MapInfo in a BC Albers projection, NAD 83 datum and subsequently exported into an ESRI interchange file (e00).

3.2.3 Pre-processing

3.2.3.1 Geometric correction

All satellite images were visually checked and displayed to check consistent geometric registration. Several landmarks with defined boundaries (e.g. roads) that were visible in both the orthophoto and satellite images were identified. The distance was measured between the same landmark in the orthophoto and satellite image. If the distance was more than 30m (approximately 1 Landsat pixel) the orhtophoto was geometrically corrected. Since the orthophoto had the finest spatial resolution and highest positional accuracy (1m), all satellite images were georeferenced to the orthophoto. A total of 12 ground control points (GCP) were chosen that represented intersection of roads and intersection of road and waterways (Appendix 2). Using the georeferencing function of ER Mapper (ER Mapper 2003), each satellite image was geometrically corrected using the 12 GCP allowing a tolerance of up to 1.0 root mean square (rms). Each image was re-sampled using the nearest neighbour and a 25m pixel size. After completion of the geometric correction, all satellite images were viewed with the orthophoto to ensure that previously selected ground control points and boundaries were within 1 pixel (approximately 30m).

In addition to the satellite images, the reference data (field boundaries with agricultural crops) were overlaid on the 1995 orthophoto. Field boundaries were viewed at the 1:5,000 scale in Acrview 3.2 (Environmental Systems Research Inc. 2000) and if the difference between the vector field boundary and raster field boundary was greater than 5m, the vector field boundary was moved to be consistent with the raster field boundaries in the 1995 orthophoto. Additional database work included the removal of small sliver polygons (error polygons created from an intersection of two or more overlapping polygons) and records that did not have a spatial polygon.

3.2.3.2 Radiometric correction

Radiometric correction was required to adjust for reflectance differences that occur between image dates due to changes in the atmosphere and earth-sun position. The approach was based on Oetter et al. 2001 in which a defined control set of pixels were determined that have limited change in reflectance values over time (e.g. forest, roads, water). The magnitude of the reflectance change in each band for the no change pixels was calculated, followed by the development and application of a regression equation specific to each band of each image.

To develop a set of no change pixels, polygons representing potential no-change areas of forests, roads and water were identified and digitized. A total of

20.2 ha were located (14.02 ha forest, 3.36 ha water, 2.83 ha water). The reference image was identified as the June 2000 image because the image would have the largest range of reflectance values corresponding to the month with the most amount of light. Each of the bands (1, 2, 3, 4, 5, 7) for each of the image dates (July, Sept, Jan) was subtracted from the corresponding bands (1,2,3,4,5,7) of the June reference image to create difference images (Coppin and Bauer 1996, Oetter et al. 2001). For each of the difference images, an unsupervised classification was conducted using the default of 5 classes and the termination of the classification when 95% of the pixels remain unchanged within the classes. If the 5 classes did not reach the 95% threshold, then the procedure was repeated for 3, 4, 6, or 7 classes until the 95% threshold was met. For each of the difference images, the class that contained the majority of no-change pixels was designated as the optimal class of the unsupervised classification. The optimum no-change pixels were selected by constructing a query to select only those pixels that were within the optimal class of each difference band. The optimal no-change pixels were divided equally into a set to develop the linear regression equation (training no-change pixels) and a set to test the accuracy of the regression model (testing no-change pixels). Upon validation of the regression equations against the testing no-change pixels, the linear regression equations were applied to each of the bands for each of the image dates (July, Sept, Jan) resulting in a radiometric normalized image for each band of each image.

3.2.4 Image Transforms

3.2.4.1 Traditional Image Transforms

Four image transforms were identified for evaluation of agriculture land uses. One of the common image transforms is the Tasseled Cap (Crist and Cicone 1984), which creates 4 transforms that correspond to brightness, greenness, wetness and noise. The normalized difference vegetation index (NDVI) is also a common transform to determine vegetation types. Two additional vegetative indices were also evaluated: Second Modified Soil Adjusted Vegetation Index (MSAVI2) (Qi et al. 1994) as well as the arctangent to the simple ratio vegetative index (RVI) which Spencer and Spry 1999 proposed might provide better results than the NDVI or MSAVI2. The formulas for each of the image transforms are provided in Table 3-1.

Table 3-1: Equations for Image Transform

Name	**Formula**
TC1-Brightness	B1*0.3037 + B2*0.2793 + B3*0.4743 + B4*0.5585 + B5*0.5082 + B7*0.1863
TC2-Greenness	B1*-0.2848 + B2*-0.2435 + B3*-0.5436 + B4*0.7243 + B5*0.0840 + B7*-0.1800
TC3-Wetness	B1*0.1509 + B2*0.1973 + B3*0.3279 + B4*0.3406 + B5*-0.7112 + B7*-0.4572
NDVI	$\frac{B4-B3}{B4+B3}$
MSAVI2	$\frac{(2*B4+1)-\sqrt{(2*B4+1)^2-8*(B4-B3)}}{2}$
Arctangent RVI	$\arctan\left(\frac{B4}{B3}\right)$

B1=(ETM band1, visible blue), B2=(ETM band 2, visible green), B3=(ETM band 3-visible red), B4=(ETM band 4, near infrared), B5=(ETM Band 5, mid infrared), B7=(ETM band 7, mid infrared)

3.2.4.2 Change Vector Transforms

In addition to the four standard image transforms, change vector transforms were also calculated that measure the change in magnitude of a transform between two or more image dates. Pax-Lenney et al. 1996 suggested the use of max NDVI, range NDVI and a combined max-range NDVI rather than NDVI alone. Uchida 2001 used the temporal changes in NDVI to discriminate agricultural land use and Seto et al. 2002 suggested a similar concept for Tasseled Cap. Therefore, using this concept the maximum, range and combined max-range $\left(NDVI_{\max} * NDVI_{range} * \frac{\sqrt{2}}{2}\right)$ for both the Tasseled Cap and NDVI for each of the bands for the following temporal combinations (June, July, Sept, Jan), (June, July, Sept), and (June, Sept) were calculated.

3.2.4.3 Reducing Redundancy of Image Transforms

A total of 84 data layers were created and the challenge was to reduce the number of data layers while maintaining high classification accuracy. Starting with 84 data layers, data layers were removed and the classification process was repeated. Each subset of data layers was termed a trial. Two methods were used to identify potential data layers to remove: First, data layers with a correlation greater than 0.90 were selected for removal. Second, the See5 (Quinlan 2005) decision tree classifier identified data layers that were not used or had only minor contribution to the classification. When a decision tree constructs the nodes to partition the data into homogenous sets, some of the data layers were not used. In addition, the software provides a relative ranking of each of the data layers based on estimated percentage increase in error rate if the data layer was removed from the classification. Using these two methods, potential data layers were removed resulting in a total of 26 trials.

3.2.5 Classification

3.2.5.1 Agricultural Land Use Classes

The initial land use class was based on the classification scheme of the reference agricultural crop data. Crop classes were removed if they were not a specific agricultural crop (i.e. unknown use, use outside agriculture, other agriculture use), or if a specific sub class did not meet the minimal size of 6.25 ha (i.e. other berry, nursery crop, residue, celery, culinary herb, leek). The minimal size was based on the minimal requirement of 100 sample points (100 * 25m pixels = 6.25 ha) to provide 50 training pixels and 50 pixels for accuracy assessment. The agricultural crop classes used in the reference data were subsequently combined into a classification scheme to meet the project goals (identify waterfowl compatible and incompatible crops).

3.2.5.2 Crop Calendar

To inform the development of an agricultural land use classification scheme, a crop calendar was constructed and clustering analysis was conducted. A crop calendar provides the phenology (life cycle) of agricultural crops and can identify the agricultural crops that could be differentiated from other crops based on changes in color or plant coverage of the soil. A local farmer was interviewed on December 17, 2003 who had extensive knowledge of a diversity of agricultural crops. The information included the planting date and harvesting date of each crop, along with monthly estimates of the crop coverage of the ground surface (measured in quartile percent). Additional information included the date of ploughing and when subsequent winter crops were grown (e.g. winter cover crops). As part of the process to acquire information from human subjects, an ethical approval from Simon Fraser University was approved for this interview.

3.2.5.3 Clustering Analysis

Cluster analysis was completed based on the classes used in the training data. Cluster analysis uses algorithms that clusters objects into statistically similar categories based on attribute(s) of each object. Using the test and accuracy values of all the transforms, clustering analysis was completed using JMP (SAS 2003). Using the K-means option (where the number of clusters had to be specified), the process was repeated using 2, 3, 5, and 10 clusters.

3.2.5.4 Decision Tree Classifier

A decision tree classification was used instead of the traditional maximum likelihood supervised classification. Decision tree classifiers combine the training data into homogenous datasets by developing a series of sequential rules (based on the training data) at various decision points (nodes) that partition the data into incremental homogenous datasets (Brown de Colstoun et al. 2003). The decision tree classifications can provide a higher accuracy than the traditional maximum likelihood algorithm for multi-spectral data, can be quickly computed and can handle both qualitative and quantitative data, and provide easy to interpret outputs (Pal and Mather 2003, Rogan et al. 2002). A commercial software version of a decision tree classifier, See5 (Quinlan 2005) was used that could classify large databases and use the results to create a map of agriculture land use.

3.2.6 Accuracy Assessment

Accuracy assessment data was available for the entire study area, enabling stratification by crop type (40 crops) and random sampling of the individual pixels. For each agricultural crop a minimum of 50 samples were used based on the recommendation that 50 samples for accuracy assessment is a good approximation when there are less than 12 categories (Congalton and Green 1999). For crops with limited samples (e.g. curcurbit, mixed nursery, lettuce, fruit, carrot), 50 random selected sample points were obtained, and 75 randomly selected sample points for the remainder of the crop types. Upon completion of the classification, an error matrix including calculation of user, producer and overall accuracy along with a confidence interval (Congalton and Green 1999) was constructed for each of the classification levels and trials . Other measures of map accuracy (e.g. normalized error matrix, Kappa statistic) were not used because of bias and imprecise accuracy estimates created by normalizing the error matrix (Stehman 2004) and the requirement of independence samples to assess each classifier to calculate the Kappa statistic (Foody 2004).

3.3 Results

3.3.1 Pre-Processing

3.3.1.1 Geometric Correction

In several instances the distance between the same landmark for bands within an image date and between image dates was nearly 200 m. Therefore all Landsat bands were geometrically corrected to the 1995 orthophoto. Using 12 GCP (Appendix 2), we had an average root mean square (ms) value of 0.45 +/- 0.08 and a range of rms values between 0.27 and 0.61 pixels (Table 3-2).

Table 3-2: Geometric Correction Root Mean Square Values

Image Date	Band	Mean	SD	Low	High
Jun 28, 2000	B1	0.47	0.19	0.18	0.82
	B2	0.50	0.24	0.11	0.83
	B3	0.55	0.28	0.04	0.96
	B4	0.40	0.16	0.15	0.58
	B5	0.50	0.22	0.16	0.95
	B7	0.57	0.23	0.19	0.90
	B8	0.40	0.13	0.16	0.57
Jul 30, 2000	B1	0.61	0.20	0.15	0.87
	B2	0.46	0.16	0.14	0.66
	B3	0.53	0.25	0.14	0.89
	B4	0.51	0.16	0.34	0.90
	B5	0.34	0.14	0.14	0.58
	B7	0.37	0.12	0.18	0.56
	B8	0.43	0.20	0.21	0.90
Sep 16, 2000	B1	0.34	0.16	0.13	0.57
	B2	0.40	0.17	0.15	0.66
	B3	0.27	0.11	0.06	0.46
	B4	0.33	0.12	0.17	0.51
	B5	0.36	0.15	0.15	0.67
	B7	0.41	0.21	0.05	0.75
	B8	0.54	0.30	0.05	0.95
Jan 22, 2001	B1	0.54	0.30	0.06	0.92
	B2	0.45	0.19	0.26	0.78
	B3	0.51	0.23	0.28	1.06
	B4	0.40	0.20	0.2	0.90
	B5	0.45	0.19	0.19	0.86
	B7	0.48	0.23	0.16	0.79
	B8	0.45	0.32	0.02	0.93
Overall		**0.45**	**0.08**	**0.27**	**0.61**

When the boundaries of the georeferenced vector dataset of permanent field boundaries were compared to the 1995 orthophoto, the field polygons were approximately 20-30 metres east of fields in the 1995 orthophoto. To correct this dataset, all the vector field boundaries were manually adjusted to ensure there was less than a 5 metre difference between the two datasets. Six sliver polygons and any records that did not have a corresponding spatial boundary were removed resulting in a total of 2,128 agricultural field polygons.

3.3.1.2 Radiometric Correction

A total of 624 no-change pixels were selected for each image date from roads, forests and water (Table 3-3). In the July and September images, most of the no-change pixels were within one or two classes, however in the January image, the no-change pixels were difficult to statistically differentiate and were present within most of the classes. The optimum no-change pixels totalled 412, 411 and 350 (Table 3-4) for the image dates of July, September and January respectively. For each of the bands and image date combinations, the optimum set provided a better fit than the non-optimum pixels (Figure 3-1) based on the R^2 value. This supported the approach of using the difference image for each band and conducting an unsupervised classification of all the image pixels to allow the selection of optimum no-change pixels.

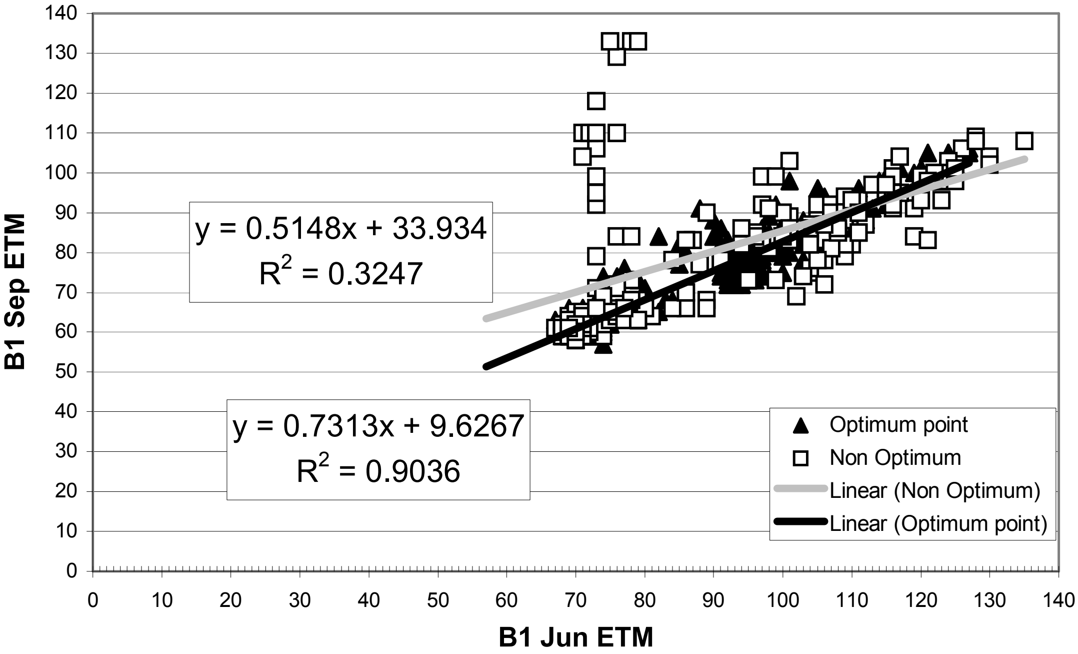
Table 3-3: Membership of No-Change Pixels after Unsupervised Classification of Difference Image.

Image Date	Band	Total Classes	Classes without any No-change pixels	Classes with some No-change pixels	Classes with most No-change pixels
Jul 30, 2000	B1	5	1,2,3	4	5
	B2	5	1,2,3	4	5
	B3	3	1	2	3
	B4	7	3,7	1,2	4,5,6
	B5	6	1,2,3,4	5	6
	B7	3	1	2	3
Sep 16, 2000	B1	5	4,5	1,3	2
	B2	5	4,5	1,3	2
	B3	5	4,5	1,3	2
	B4	5	5	1,3,4	2
	B5	5	4,5	3	1,2
	B7	5	5	1,4	2,3
Jan 22, 2001	B1	7	1	2,7	3,4,5,6
	B2	5	-	1,5	2,3,4
	B3	8	-	1,2,3,8	4,5,6,7
	B4	8	-	1	2,3,4,5,6,7,8
	B5	10	-	1,2,3,4	5,6,7,8,9,10
	B7	9	1	2,3,4	5,6,7,8,9

Table 3-4: Total and Optimum Number of No-Change Pixels

Image Date	Total # Pixels	# Optimum Pixels	# Optimum Forest	# Optimum Road	# Optimum Water
July	624	412	129	118	165
September	624	411	148	115	148
January	624	350	87	80	183

Figure 3-1: Optimum and Non-Optimum Training Pixels for B1 September.



For each of the bands and image date combinations, the radiometric correction regression equations (BXn) had slopes ranging from 0.113 to 1.052 and intercepts ranging from –11.220 to 32.014 (Table 3-5). The coefficients for the radiometric correction (Model R^2) ranged from 0.145 to 0.970. The testing pixels were applied to the normalized images with the expectation that the testing regressions (BXn’) would have a slope near 1 and the Y intercept near 0. The testing slopes had ranges from 0.804 to 1.317 and the intercepts ranged from – 20.418 to 3.591 with a coefficient of correction (R^2) ranging from 0.159 to 0.975. The results indicate that the regression equations effectively corrected the variations due to radiometric impacts for the July and September band-image combinations, however the January band-image combinations were not improved with the radiometric correction given a larger variation in slope and Y intercepts.

Table 3-5: Radiometric Correction Model and Testing Equation

Image Date	Model Regression	Model R^2	Test Regression	Testing R^2
Jul 30, 2000	B1n=1.039*b1 – 11.220	0.942	B1n’=1.028*b1 - 1.692	0.939
	B2n=1.052*b2 – 9.378	0.966	B2n’=0.986*b2 + 1.101	0.958
	B3n=1.002*b3 – 5.628	0.970	B3n’=0.990*b3 + 0.438	0.965
	B4n=0.942*b4 + 0.002	0.969	B4n’=1.001*b4 - 0.778	0.975
	B5n=0.935*b5 + 1.357	0.924	B5n’=1.024*b5 - 2.058	0.969
	B7n=0.929*b7 + 1.644	0.941	B7n’=0.997*b7 - 1.248	0.972
Sep 16, 2000	B1n=0.740*b1 + 8.747	0.915	B1n’=0.978*b1+ 2.384	0.892
	B2n=0.763*b2 + 3.707	0.893	B2n’=1.014*b1 - 0.250	0.895
	B3n=0.755*b3 + 4.195	0.906	B3n’=1.002*b3 + 0.883	0.908
	B4n=0.912*b4 + 7.687	0.969	B4n’=1.017*b4 + 0.636	0.978
	B5n=0.689*b5 + 2.978	0.895	B5n’=0.992*b5 + 0.545	0.869
	B7n=0.740*b7 + 2.259	0.931	B7n’=1.003*b7 – 0.755	0.906
Jan 22, 2001	B1n=0.147*b1 + 32.014	0.301	B1n’=0.929*b1 + 6.846	0.313
	B2n=0.118*b2 + 21.917	0.202	B2n’=1.317*b2 – 20.418	0.321
	B3n=0.113*b3 + 18.593	0.145	B3n’=1.088*b3 – 3.699	0.159
	B4n=0.278*b4 + 10.195	0.747	B4n’=1.057*b4 – 2.912	0.745
	B5n=0.256*b5 + 6.678	0.830	B5n’=0.952*b5 + 1.068	0.772
	B7n=0.267*b7 + 7.244	0.726	B7n’=0.804*b7 + 3.591	0.671

3.3.2 Image Transforms

A total of 84 data layers (Table 3-6) were created for each pixel based on 24 individual bands (Bands 1-7 for each of each of 4 image dates), 12 ratios (NDVI, MSAVI2, arctan for each of 4 image dates), 12 Tasseled Cap (TC1, TC2, TC3 for each of 4 image dates) and 36 vector change transforms ($NDVI_{max}$, $NDVI_{range,}$,$NDVI_{max-range,}$ TC_{max} and TC_{range})

Table 3-6: Image Transforms Evaluated

Transform Type	Number of Transforms	Transform Label
Individual Bands	24	Jun (B1a, B2a, B3a, B4a, B5a, B7a), Jul (B1b, B2b, B3b, B4b, B5b, B7b), Sep (B1c, B2c, B3c, B4c, B5c, B7c) and Jan (B1d, B2d, B3d, B4d, B5d, B7d)
Ratios (NDVI, MSAVI2, Arctan RVI)	12	Jun (NDVIa, MSAVI2a, Atan RVIa), Jul (NDVIb, MSAVI2b, Atan RVIb), Sep (NDVIc, MSAVI2c, Atan RVIc), and Jan (NDVId, MSAVI2d, Atan RVId)
Tasseled Cap	12	Jun (TC1a, TC2a, TC3a), Jul (TC1b, TC2b, TC3b), Sep (TC1c, TC2c, TC3c), Jan (TC1d, TC2d, TC3d),
Change Vector - NDVI	12	Range (NDVIRGabcd, NDVIRGabc, NDVIRGacd, NDVIRGac), Max (NDVIMXabcd, NDVIMXabc, NDVIMXacd, NDVMXac), Max-Range (NDVCMRabcd, NDVCMRabc, NDVCMRacd, NDVCMRac)
Change Vector - TC	24	Range (TC1RGabcd, TC1RGabc, TC1Rgacd, TC1RGac, TC2RGabcd, TC2RGabc, TC2Rgacd, TC2RGac, TC3RGabcd, TC3RGabc, TC3Rgacd, TC3RGac) Max (TC1MXabcd, TC1MXabc, TC1MXacd, TC1Mxac, TC2MXabcd, TC2MXabc, TC2Macd, TC2Mxac, TC3MXabcd, TC3MXabc, TC3Mxacd, TC3Mxac

Date codes: June(a), July(b), September(c) and January (d)

3.3.2.1 Reducing Redundancy Between Transforms

To identify transforms that could be removed from the 84 layer dataset, correlations were produced for all the transforms (Appendix 4). Transforms that had a very strong correlation defined as higher than 0.90 (Table 3-7) included several of the ratios (NDVI, MSAVI2, TC2, ATAN, AtanRVI) for all the image dates (Jun, Jul, sep and Jan) and the vector change (Max value for TC2 and NDVI, Range and Range-max). Using the information from the correlations, the transforms that had a high correlation were sequentially removed from the 84 layer dataset and the classification was completed for all three levels of the classification scheme (life cycle, vegetation, vegetation subtype).

Table 3-7: Image Transforms with Strong Correlations (0.90 – 1.00)

Ratios with Positive Correlation
NDVa-TC2a, MS2a-TC2a, MS2a-NDVa, B2a-TC1a, ATANa-TC2a, ATANa-NDVa, ATANa-MS2a, B2a-B3a, B1a-B3a, B1a-B2a, NDVc-TC2c, MS2c-TC2c, ATANc-TC2c, MS2c-NDVc, ATANc-NDVc, ATANc-MS2c, NDVd-TC2d, MS2d-TC2d, ATANd-TC2d, ATANd-NDVd, ATANd-MS2d, NDVb-TC2b, MS2b-TC2b, ATANb-TC2b, ATANb-NDVb, ATANb-MS2b, MS2b-NDVb,
Vector Change with Positive Correlation
TC3MXabcd-TC3jan, NDCMRabcd-NDVRGabcd, NDVCMRabc-NDVRDabc, NDVMXabc-NDVMXabcd, TC2MXabcd-NDVMXabcd, TC2MXabcd-NDVMXabc, TC2MXabc-NDVMXabcd, TC2MXabc-NDVMXabc, TC2MXabc-TC2MXabcd, TC2MXac-NDVMXac, TC2RGabcd-NDVRDabcd, TC2RGabc-NDVRGabc, TC2RGac-NDVRDac, TC1MXac-TC1MXabc
Ratios with Negative Correlation
B3a-TC2a, B3a-NDVa, B3a-MS2a, ATANa-B3a

Date codes: June(a), July(b), September(c) and January (d)

3.3.3 Agricultural Classification Scheme

3.3.3.1 Training and testing points

The selection of training and testing points required a minimal of 100 random points (50 training, 50 testing) and an optimal set of 150 random points (75 training, 75 testing) for each of the agricultural land uses. The total study area contained a total of 119,337 potential sampling points based on a 25 metre grid. The attribute information associated with each sample point in Arcview (ESRI 2000) was exported and manipulated using JMP (SAS 2003). Key procedures include randomly sample 75 training and 75 test points for each of the classes, attribute the points (as training, testing points) and export the data as text format into the classification software. For the majority of agricultural crops, 150 sample points were used however for some crops 150 sample points were not available. Therefore for these crops, 50% were used for training and the remaining for testing for mixed nursery (90 records), lettuce (89 records), fruit (118 records) and carrot (120 records) crops.

3.3.3.2 Initial Agricultural Land Classes

From the training data, a total of 40 agricultural use crops had sufficient sampling sizes (minimum 6.25 ha). These classes (Table 3-8) formed the preliminary land use classes that could be combined based on further refinement.

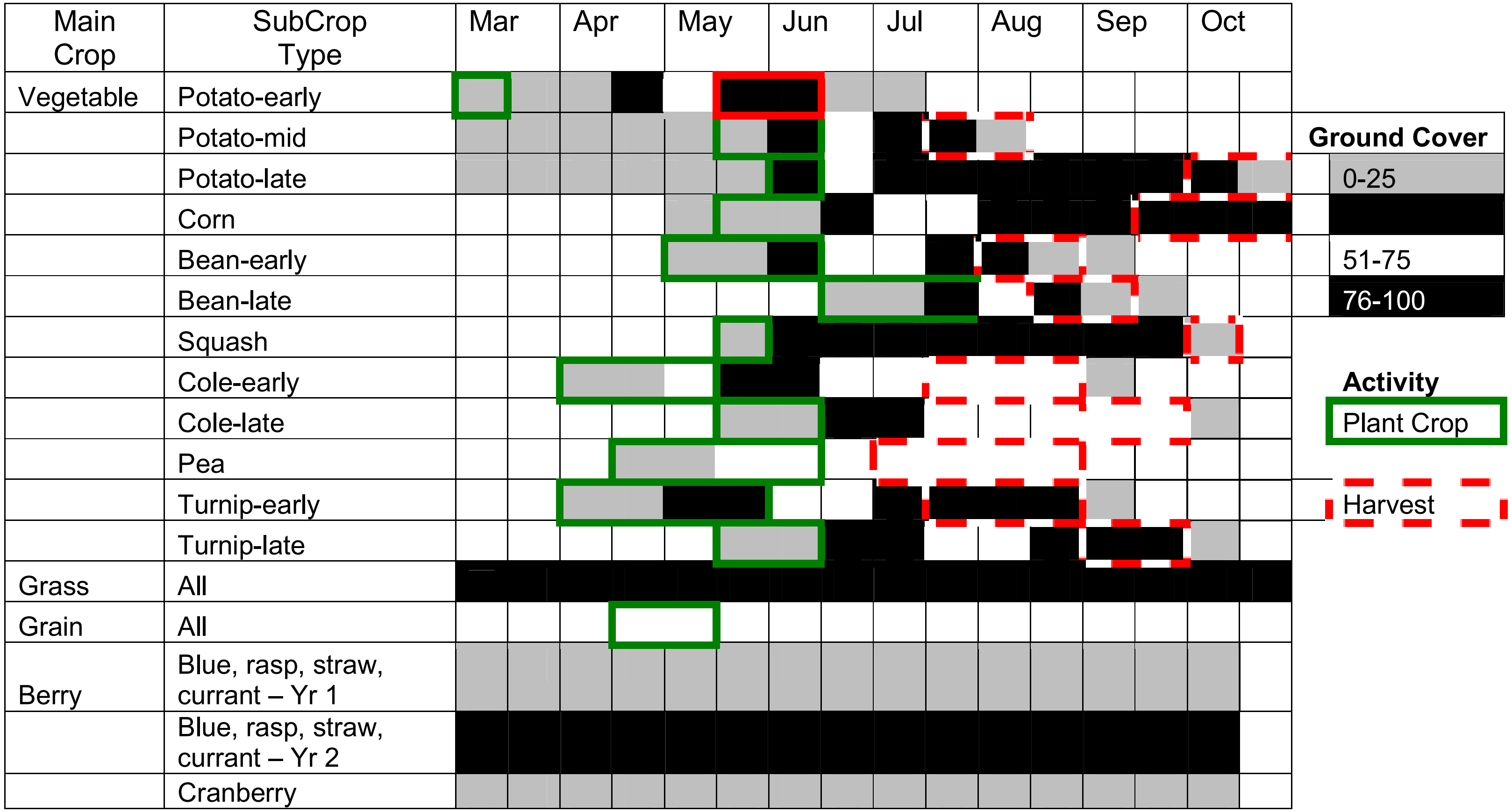
Table 3-8: Potential Agricultural Crops

General Crop Class	Crop Class
Berry – Small Fruit	Blueberry, cranberry, currant, raspberry, strawberry
Grain	Barley, oats, wheat, other grain
Grass – Forage	Clover, forage, overgrown pasture, pasture, turf
Nursery	Mixed
Orchard	Fruit
Uncultivated	Bare, bare and weedy, summer cover, summer fallow, weedy
Vegetable	Bean, beet, carrot, cole, corn, cucurbit, lettuce, mixed vegetable, onion, pea, potato, pumpkin, specialty, squash, turnip, vegetable
Wild Land	Grassland, mixed wild land, set-aside

3.3.3.3 Crop Calendar

A crop calendar (Table 3-9) identified the time periods where potential differentiation of crops may exist based on changes in the reflectance of radiation. Based on the crop calendar it did not appear probable that differentiation was possible between individual crops given the spatial and temporal overlap between crops. As a result, a large amount of spectral confusion was expected between individual crops. However, a few individual crops may be differentiable such as corn. Several crops such as grass and berries had consistent reflectance values throughout the year while vegetable and grain crops had changing reflectance values throughout the year. Several of the non-vegetable crops such as grasses (forage, pasture, overgrown), as well as grain subtypes (oats, wheat, barley, other) had similar percent crop cover and had a lower expected chance of differentiating amongst the crops.

Table 3-9: Crop Calendar



Main Crop	SubCrop Type	Mar		Apr		May		Jun		Jul		Aug		Sep		Oct	
Vegetable	Potato-early	▨	▨	▨	■		■	■	▨	▨							
	Potato-mid	▨	▨	▨	▨	▨	▨	■		■	■	▨					
	Potato-late	▨	▨	▨	▨	▨	▨	■		■	■	■	■	■	■	■	▨
	Corn					▨	▨	▨	■			■	■	■	■	■	■
	Bean-early					▨	▨	■			■	■	▨	▨			
	Bean-late								▨	▨	■		■	▨	▨		
	Squash						▨	■	■	■	■	■	■	■	■	▨	
	Cole-early			▨	▨		■	■						▨			
	Cole-late						▨	▨	■	■						▨	
	Pea				▨	▨											
	Turnip-early			▨	▨	■	■			■	■	■	■	▨			
	Turnip-late						▨	▨	■	■			■	■	■	▨	
Grass	All	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
Grain	All																
Berry	Blue, rasp, straw, currant – Yr 1	▨	▨	▨	▨	▨	▨	▨	▨	▨	▨	▨	▨	▨	▨	▨	
	Blue, rasp, straw, currant – Yr 2	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	
	Cranberry	▨	▨	▨	▨	▨	▨	▨	▨	▨	▨	▨	▨	▨	▨	▨	

Ground Cover

▨	0-25
■	
	51-75
■	76-100

Activity

🟩 Plant Crop

🟥 Harvest

3.3.3.4 Cluster Analysis

Cluster analysis was performed in JMP (SAS 2003), using 40 potential crops and approximately 100 sample pixels for each crop. For each crop, all 84 data layers were used as inputs in the analysis. Cluster analysis was repeated for 2, 3, 5, 10 clusters and the results were analysed whether more than 75% of the samples for each crop were categorized into one class (Appendix 3). If less than 75% of the samples were in one class then the crop was assigned to a mixed category (Table 3-10, Table 3-11, Table 3-12, Table 3-13). As the number of clusters increased, more of the crops were classified as mixed. However the 2 and 3 cluster analysis separated the crops into 2 categories: Those crops that were re-planted each year e.g. vegetables (temporary crops) and those crops that did not require replanting after each harvest e.g. perennial grass, shrubs (permanent crops). These definitions are consistent with the Food and Agricultural Organization (FAO 2005).

Table 3-10: 3 Class Cluster Analysis

Crops were assigned to a class if more than 75% of the samples were clustered into one class, otherwise the crop was assigned to mixed class.

Class	Land Classes
A	bare & weedy, bean, beet, cole, corn, cucurbit, onion, pea, potato, specialty, squash, turnip, weedy
B	blueberry, clover, cranberry, forage, fruit, grain, grassland, mixed wild land, overgrown pasture, pasture, set aside, summer cover, summer fallow, turf
Mixed	bare, barley, carrot, currant, lettuce, mixed nursery, mixed vegetable, oats, pumpkin, raspberry, strawberry, vegetable, wheat

Table 3-11: 3 Cluster Analysis

Crops were assigned to a class if more than 75% of the samples were clustered into one class, otherwise the crop was assigned to mixed class.

Class	Land Classes
A	bare, bare & weedy, bean, beet, cole, corn, cucurbit, onion, pea, potato, specialty, squash, turnip
B	blueberry, clover, cranberry, foragem fruit, grain, grassland, mixed wildland, overgrown, pasture, pasture, setaside, summer cover, turf, weedy
C	--
Mixed	barley, carrot, currant, lettuce, mixed nursery, mixed vegetable, oats, pumpkin, raspberry, strawberry, summer fallow, vegetable, wheat

Table 3-12: 6 Class Cluster analysis

Crops were assigned to a class if more than 75% of the samples were clustered into one class, otherwise the crop was assigned to mixed class.

Class	Land Classes
A	--
B	onion
C	grain
D	beet, corn
E	blueberry, cranberry, fruit
Mixed	bare, bare & weedy, barley, carrot, clover, cole, curcurbit, currant, forage, grassland, lettuce, mixed nursery, mixed vegetable, mixed wildland, oats, overgrown pasture, pasture, pea, potato, pumpkin, raspberry, set aside, specialty, squash, strawberry, summer cover, summer fallow, turf, turnip, vegetable, weedy wheat

Table 3-13: 11 Class Cluster analysis

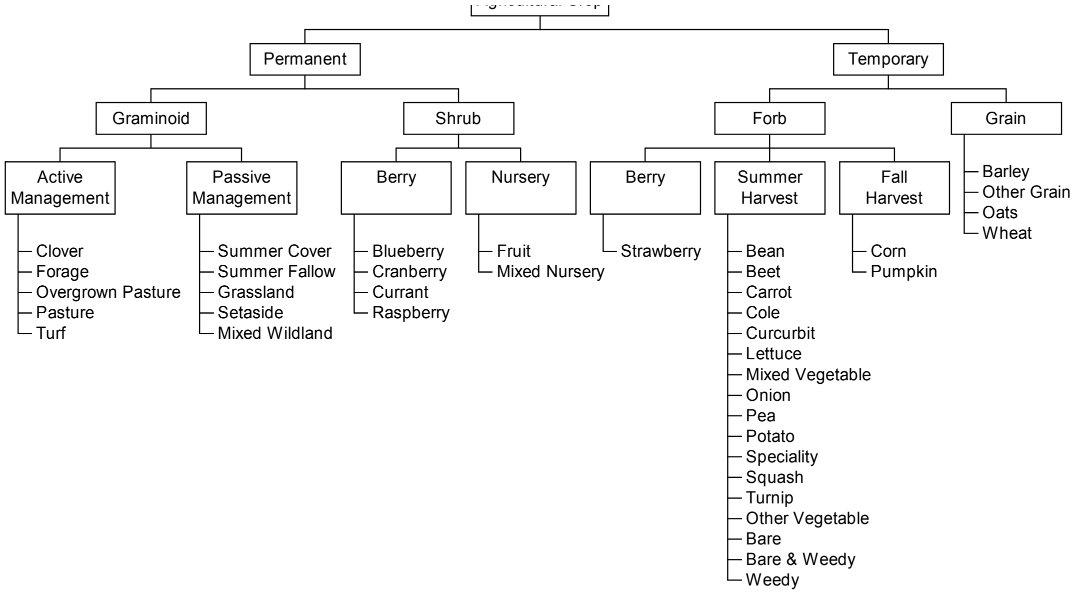
Crops were assigned to a class if more than 75% of the samples were clustered into one class, otherwise the crop was assigned to mixed class.

Class	Land Classes
A	cranberry
B	--
C	--
D	pea
E	--
F	grain
G	beet, corn
H	--
I	onion
J	--
Mixed	bare, bare & weedy, barley, beet, carrot, clover, cole, curcurbit, currant, cranberry, forage, fruitgrassland, lettuce, mixed nursery, mixed vegetable, mixed wildland, oats, overgrown pasture, pasture, pea, potato, pumpkin, raspberry, set aside, specialty, squash, strawberry, summer cover, summer fallow, turf, turnip, vegetable, weedy wheat

3.3.3.5 Final Agricultural Classification Scheme

Three agricultural classifications were constructed using information from the crop calendar and clustering analysis. The crop calendar identified a significant amount of temporal overlap between planting dates and harvesting dates of different types of vegetables indicating differentiation of individual crops would be difficult. Clustering analysis statistically separated agricultural crops into two groups that presented temporal and permanent crops. This division formed the first node of separation between crops. Subsequent review of the information from both of these information sources guided the final nested hierarchical classification (Figure 3-2). The first level is the growing life cycle (permanent, temporary), the second level is main vegetation type (graminoid, shrub, forb and grain) and the third level is the vegetation sub-type (graminoid-active managed, graminoid-passive managed, shrub-berry, shrub-nursery, forb-berry, forb summer harvest and forb fall harvest).

Figure 3-2: Final Agricultural Land Classes and Agricultural Crop



3.3.3.6 Trials and Image Transforms

Twenty six trials representing different combination of transforms were completed for the three agricultural classes from 88% to 48% (Table 3-14). The first trial included all 84 data layers while trials 2 to 6 were datasets in which transforms with high correlations were removed. Additional transforms were removed based on the transform that the decision tree software identified as not required (trial 7) and for the transforms that had less than 1% use in the decision tree (trial 8). To contrast the top down approach of beginning with all datasets, individual transforms without change vectors (trial 9 to 12) were also calculated. Trials 13 and 14 compared the difference between using all data except change vector and a trial with change vector only. To determine the relative contribution of the temporal data, trials 15 to 18 used data only from the images of June, July, September and January respectively. Trials 19 to 22 include temporal data where only 3 of the 4 image dates were used and finally trials 23 to 26 used only single image dates.

Table 3-14: Description of Image Transforms and Trials.

Trial	Number of Datasets			Data Layer Description
	LC	**V**	**VS**	
1	84	84	84	All data layers
2	72	72	72	Remove MS2, ARV, NDVCMR
3	60	60	60	Remove MS2, ARV, NDVCMR, TC2
4	60	60	60	Remove MS2, ARV, NDVCMR, NDV
5	39	39	39	Remove MS2, ARV, NDVCMR, TC2, all July dates
6	39	39	39	Remove MS2, ARV, NDVCMR, NDV, all July dates
7	28	23	39	Remove datasets identified as winnowed in See5
8	19	14	39	Remove datasets with less than 1% importance in See5
9	4	4	4	NDV only (no change vector)
10	12	12	12	TC only (no change vector)
11	4	4	4	MS2 only (no change vector)
12	4	4	4	Arv only (no change vector)
13	48	48	48	All layers except change vector
14	36	36	36	Change Vector only
15	12	12	12	June layers (no change vector)
16	12	12	12	July layers (no change vector)
17	12	12	12	September layers (no change vector)
18	12	12	12	January layers (no change vector)
19	9	9	9	TC (no June data)
20	9	9	9	TC (no July data)
21	9	9	9	TC (no September data)
22	9	9	9	TC (no January data)
23	3	3	3	TC (June data only)
24	3	3	3	TC (July data only)
25	3	3	3	TC (September data only)
26	3	3	3	TC (January data only)

LC: Life cycle, V: Vegetation type, VS: Vegetation Subtype

3.3.4 Accuracy Assessment

3.3.4.1 Overall Accuracy

As more data layers were removed from the dataset, the overall accuracy decreased for all 3 classification schemes (Table 3-15). However, individual transforms (e.g. NDVI, Arctan RVI, MSAVI2) generally had lower accuracy except for the Tasseled Cap, which had a high level of accuracy for all 3 levels of the agricultural classification scheme (86.7% ± 1.3, 83.1% ± 1.4, 75.1% ± 1.6). This accuracy was comparable to the trial using all 84 data layers (88.5 ± 1.2, 84.4 ± 1.3, 77.6 ± 1.5). Considering the 95% confidence intervals, it can be concluded that no difference in accuracy can be detected between the 12 data layer Tasseled Cap and using all 84 data layers in the study area for all three classification scheme. An overall accuracy of 85% is generally the accepted threshold between acceptable and unacceptable results (Congalton and Green 1999). Therefore the Tasseled Cap was used to develop the agricultural land use map of the study area for all three agricultural classification schemes (Life Cycle Figure 3-3, Vegetation Figure 3-4, Vegetation subtype Figure 3-5).

Comparing individual transforms, the Tasseled Cap dataset had a higher level of accuracy than the three other individual transforms. In fact the other three transforms (NDVI, Arctan RVI, MSAVI2) all classified with a similar accuracy. When comparing transforms over time, it appears that the January transforms had a lower accuracy for all three classifications (69.4 ± 1.7, 62.2 ± 1.8, 51.5 ± 1.8) than the dates in June (80.4 ± 1.5, 70.3 ± 1.7, 57.0 ± 1.8), July

(73.4 ± 1.6, 66.1 ± 1.7, 55.3 ± 1.8) or September (79.4 ± 1.5, 69.1 ± 1.7, 59.1 ± 1.8). Comparing the accuracy of all datasets (88.5 ± 1.2, 84.4 ± 1.3, 77.6 ± 1.5) to the trial which did not have any change vectors (87.4 ± 1.2, 83.9 ± 1.4, 76.5 ± 1.6) indicates that the change vectors did not increase accuracy.

Table 3-15: Overall Accuracy (%) and 95% Confidence Interval.

Trial	Data Layer Description	Level 1 Life Cycle	Level 2 Vegetation Type	Level 3 Vegetation Sub-Type
1	All data layers	88.5 ± 1.2	84.4 ± 1.3	77.6 ± 1.5
2	All data except MS2, ARV, NDVCMR	88.4 ± 1.2	83.7 ± 1.4	76.1 ± 1.6
3	All data except MS2, ARV, NDVCMR, TC2	89.0 ± 1.2	83.1 ± 1.4	77.2 ± 1.5
4	All data except MS2, ARV, NDVCMR, NDV	86.4 ± 1.3	83.6 ± 1.4	75.9 ± 1.2
5	All data except MS2, ARV, NDVCMR, TC2, all July dates	86.2 ± 1.3	80.8 ± 1.5	75.1 ± 1.6
6	All data except MS2, ARV, NDVCMR, NDV, all July dates	86.0 ± 1.3	81.1 ± 1.4	73.9 ± 1.6
7	All data except data identified as winnowed in See5	87.0 ± 1.2	81.1 ± 1.4	74.0 ± 1.6
8	All data except data with less than 1% importance in See5	85.8 ± 1.3	79.9 ± 1.5	74.0 ± 1.6
9	NDV	78.3 ± 1.5	71.5 ± 1.7	60.6 ± 1.8
10	TC	86.7 ± 1.3	83.1 ± 1.4	75.1 ± 1.6
11	MS2	77.9 ± 1.5	71.0 ± 1.7	60.6 ± 1.8
12	Arv	79.7 ± 1.5	69.1 ± 1.7	59.4 ± 1.8
13	All layers except change vector	87.4 ± 1.2	83.9 ± 1.4	76.5 ± 1.6
14	Change Vector only	83.0 ± 1.4	77.8 ± 1.5	68.6 ± 1.7
15	All June Transforms	80.4 ± 1.5	70.3 ± 1.7	57.0 ± 1.8
16	All July Transforms	73.4 ± 1.6	66.1 ± 1.7	55.3 ± 1.8
17	All September Transforms	79.4 ± 1.5	69.1 ± 1.7	59.1 ± 1.8
18	All January Transforms	69.4 ± 1.7	62.2 ± 1.8	51.5 ± 1.8
19	TC (no Jun image)	83.8 ± 1.4	78.6 ± 1.5	70.5 ± 1.7
20	TC (no July image)	85.4 ± 1.3	80.8 ± 1.5	71.9 ± 1.7
21	TC (no September image)	82.9 ± 1.4	80.0 ± 1.5	69.2 ± 1.7
22	TC (no January image)	85.1 ± 1.3	80.3 ± 1.5	72.0 ± 1.6
23	TC (June image only)	79.2 ± 1.5	66.1 ± 1.7	52.9 ± 1.8
24	TC (July image only)	68.3 ± 1.7	61.1 ± 1.8	47.5 ± 1.8
25	TC (September image only)	72.4 ± 1.7	63.8 ± 1.8	52.2 ± 1.8
26	TC (January image only)	67.8 ± 1.7	60.2 ± 1.7	47.5 ± 1.8

In general there was a decrease in accuracy as the number of image dates were reduced. For the Level 2 classification scheme (vegetation type), the overall accuracy for TC was 83.1% ± 1.4 when all four image dates were used. However when one of the image dates was removed, the accuracy ranged between 78.6% ± 1.5 and 80.8% ± 1.5 depending on which image date was removed. When only one image date was used, the overall accuracy was further reduced to a range between 60.2% ± 1.7 and 66.1% ± 1.7 depending on the image date.

Figure 3-3. 2000 Agricultural Land Classification (Level 1 Class – Crop Life Cycle)

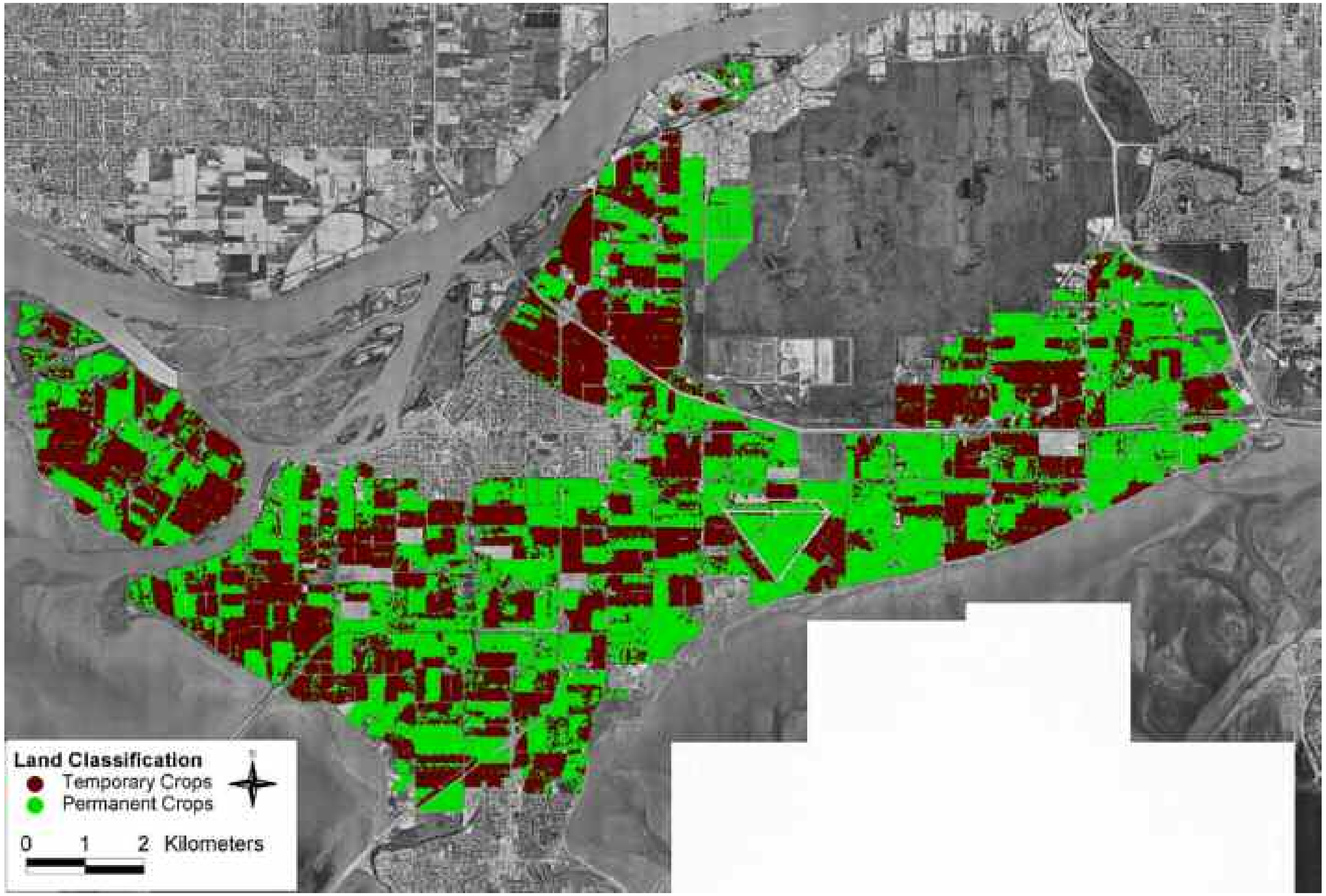


Figure 3-4: 2000 Agricultural Land Classification (Level 2 Class – Vegetation type).

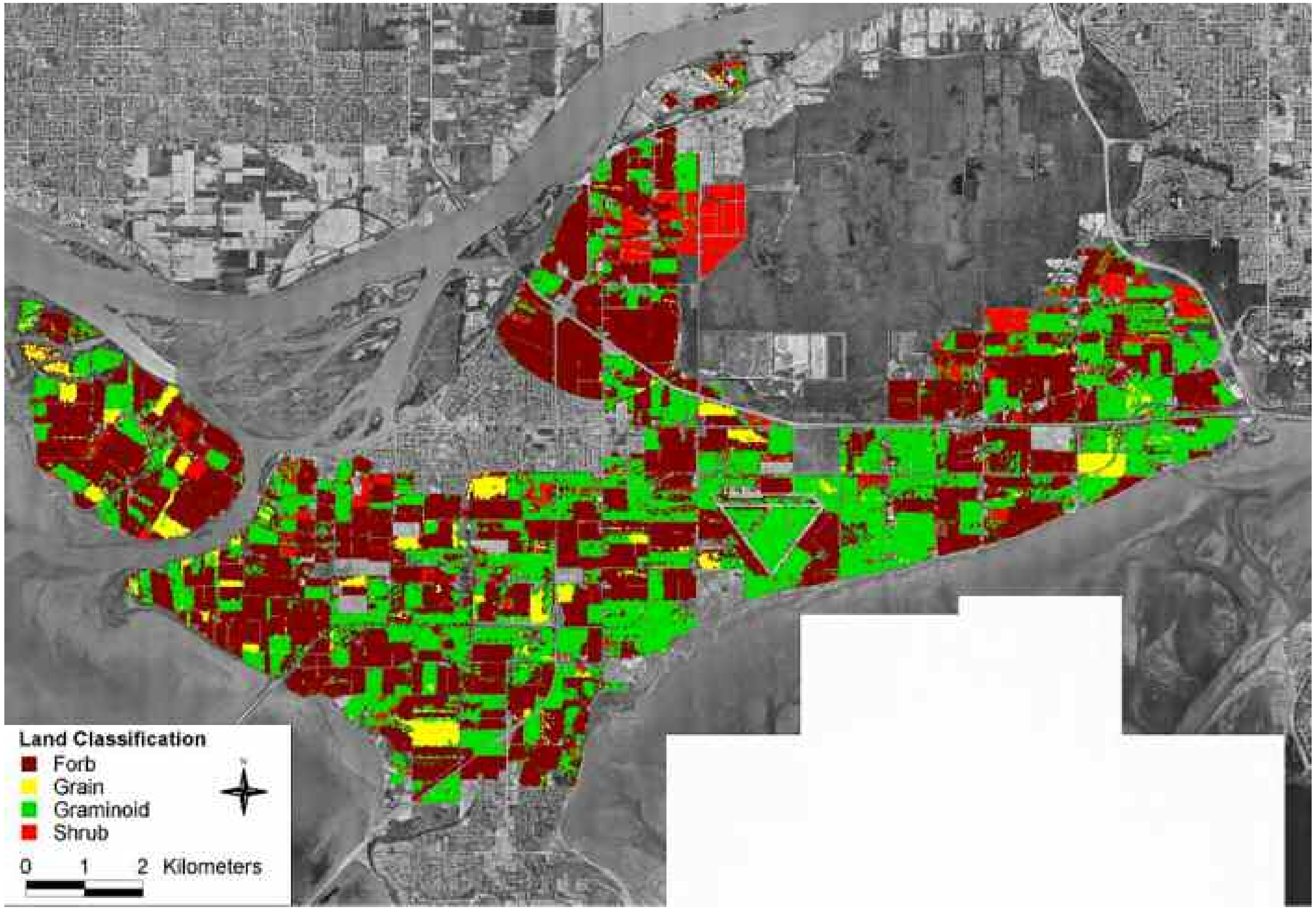
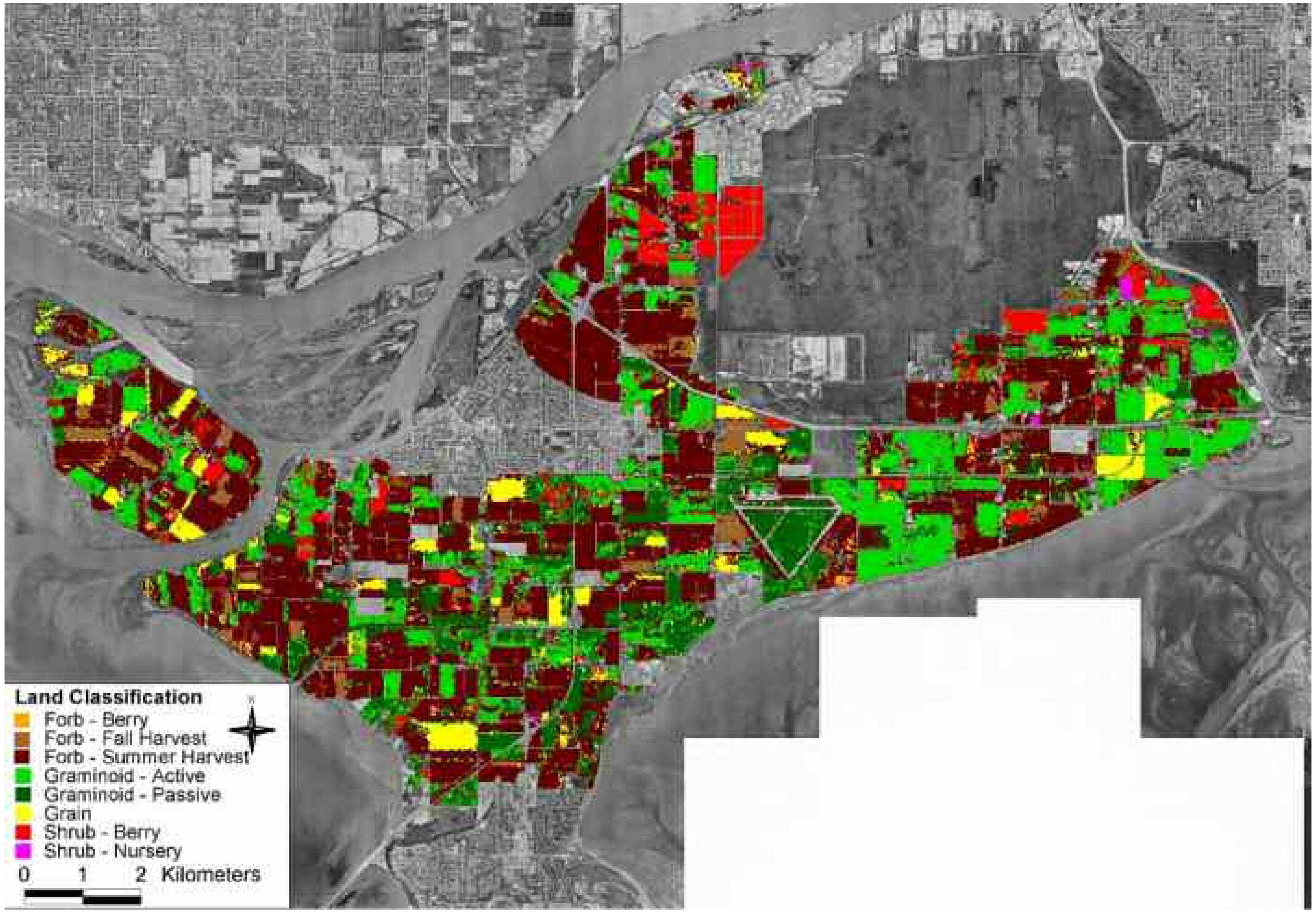


Figure 3-5: 2000 Agricultural Land Classification (Level 3 Class – Vegetation Subtype).



3.3.4.2 Accuracy of Level 1 Classification Scheme (Crop Life Cycle)

The complete error matrices for the level one classification (Agricultural Crop Life cycle: permanent crops versus temporary crops) were constructed for all 26 trials (Appendix 5). Error matrices for trials 1 (all data) and trial 10 (Tasseled Cap) are provided below (Table 3-16) for comparison. Both User and Producer Accuracies were above 85% in Trials 1 to 8 and similar for both permanent and temporary agricultural crops. However, the accuracy ranged from 68% to 82% in trials 11 to 16, indicating lower accuracy. Similar to the overall accuracy, the user accuracy did not differ given the confidence interval between the 84 data layers of Trial 1 (UA_{perm}= 90.1% ±1.1%, UA_{Temp} = 86.8% ±1.3%) and 12 data layers of Trial 10 (UA_{perm}= 87.9% ±1.2%, UA_{Temp} = 85.3% ±1.3%) that used the Tasseled Cap transform.

Table 3-16: Level 1 Error Matrices (Crop Life Cycle)

Error Matrixes for Trial 1 and 10 are provided below. The reference and map data values are the number of samples, however user and producer accuracies are corrected for bias using map marginal proportions (π_{Perm}=0.51, π_{Temp}=0.49)

Trial 1		Reference Data			
	Class	Perm	Temp	Total	User Acc ±CI
Map Data	Perm	1253	138	1391	90.1% 1.1%
	Temp	201	1317	1518	86.8% 1.3%
	Total	1454	1455	2909	
	Prod Acc ±CI	87.7% 1.5%	89.3% 1.5%		Overall Acc 88.5% 1.2%

Trial 10		Reference Data			
	Class	Perm	Temp	Total	User Acc ±CI
Map Data	Perm	1233	169	1402	87.9% 1.2%
	Temp	221	1286	1507	85.3% 1.3%
	Total	1454	1455	2909	
	Prod Acc ±CI	86.3% 1.5%	87.1% 1.6%		Overall Acc 86.7% 1.3%

3.3.4.3 Accuracy of Level 2 Classification Scheme (Vegetation Type)

Using the second agricultural classification scheme of vegetation type (shrub, graminoid, grain and forb) the error matrices were constructed for all 26 trials (Appendix 6). As datasets were removed, both the producer's accuracy and the user' accuracy decreased for all classes (Table 3-17). Similar to the first agricultural classification, both the producers and user's accuracy decreased as data sets were removed, however the Tasseled Cap transform (Trial 10) again performed well and was comparable to Trial 1 where all 84 datasets were used. While the User Accuracy remained high (i.e. above 80%) for all four classes (shrub, graminoid, grain and forb), the Producers Accuracy was high for graminoids and forbs in Trial 10 (PA_{Gram}= 86.5% ±2.0%, PA_{Forb} = 91.3% ±1.4%) but much lower for shrubs and grain (PA_{Shrub}= 53.7% ±4.4%, PA_{Grain} = 56.1% ±5.3%). Based on the reference data, it appears that several of the reference samples that were shrubs (25%) and grain (19%) were classified as the forb class.

Table 3-17: Level 2 Error Matrices (Vegetation Type)

Error Matrices for Trial 1 and 10 are provided below and the values are the number of samples, however user and producer accuracies are corrected for bias using map marginal proportions (π_{Shrub} =0.072, $\pi_{\mathrm{Graminoid}}$=0.352, π_{Grain} =0.046, π_{Forb}=0.529).

Trial 1			**Reference Data**					
	Class	**Shrub**	**Gram**	**Grain**	**Forb**	**Total**	**User Acc**	**'±CI**
Map Data	**Shrub**	276	34	5	35	350	78.9%	1.5%
	Gram	42	617	29	55	743	83.0%	1.4%
	Grain	3	10	207	8	228	90.8%	1.1%
	Forb	83	89	59	1357	1588	85.5%	1.3%
	Total	404	750	300	1455	2909		
	Prod Acc	54.1%	88.3%	55.1%	92.8%		**Overall Acc**	
	'±CI	4.5%	1.9%	5.0%	1.3%		84.4%	1.3%

Trial 10			**Reference Data**					
	Class	**Shrub**	**Gram**	**Grain**	**Forb**	**Total**	**User Acc**	**'±CI**
Map Data	**Shrub**	268	24	13	31	336	79.8%	1.5%
	Gram	32	596	22	67	717	83.1%	1.4%
	Grain	2	15	209	12	238	87.8%	1.2%
	Forb	102	115	56	1345	1618	83.1%	1.4%
	Total	404	750	300	1455	2909		
	Prod Acc	53.7%	86.5%	56.1%	91.3%		**Overall Acc**	
	'±CI	4.4%	2.0%	5.3%	1.4%		83.1%	1.4%

3.3.4.4 Accuracy of Level 3 Classification Scheme (Vegetation Sub-Type)

The level 3 classification, consisted of the agricultural classes: graminoid - active management, graminoid – passive management, shrubs – berry, shrubs – nursery, grain, forb - summer harvest crops and forb – fall harvested crops. The error matrices were constructed for all 26 trials (Appendix 7). Similar to the previous classifications, the overall, producer's and user's accuracy generally declined as the number of datasets was reduced (Trials 1 to 8). The trials that used one transform (Trials 9 to 16) were much lower except for the Tasseled Cap transform (Trial 10) which had comparable accuracies with Trial 1 (Table 3-18, Table 3-19). In Trial 1 the User Accuracies varied between (70.6% ± 1.7% for Shrub-berry and 86.3% ±1.3% for Grain) while the Producer Accuracies varied between (27.9% ± 7.9% for Shrub-Nursery and 92.1% ± 1.5% for Forb-Summer Harvest). In Trial 10, the User Accuracies varied between (64.3% ± 1.8% for Shrub-berry and 86.3% ±1.3% for Grain) while the Producer Accuracies varied between (28.3% ± 7.9% for Shrub-Nursery and 92.1% ± 1.5% for Forb-Summer Harvest). The differences between the User and Producer's Accuracies between Trial 1 and 10 were within the confidence intervals except for the User Accuracy of Graminoid – Active (decreased 7.4%), Shrub – Berry (increased 4.9%), and Forb – Berry (decreased 7.1%). Reviewing the matrices for confusion between classes revealed that the highest confusion for all the classes occurred when samples were classified as Forb-Summer harvest when they were in reality in other classes. In addition, confusion existed between the two graminoid classes (active and passive management).

Table 3-18: Level 3 Error Matrix Trial 1 (Vegetation Sub-Type)

Error Matrix for Trial 1 (below) with values that are the number of samples, however user and producer accuracies are corrected for bias using map marginal proportions ($\pi_{\text{Gram-Active}}$=0.209, $\pi_{\text{Gram - Passive}}$=0.130, $\pi_{\text{Shrub-Berry}}$ =0.070, $\pi_{\text{Shrub-Nursery}}$=0.006, π_{Grain} =0.056, $\pi_{\text{Forb-Berry}}$=0.005, $\pi_{\text{Forb-Summer Harvest}}$ =0.483, $\pi_{\text{Forb-Fall Harvest}}$=0.041).

Trial 1		**Reference Data**										
Map Data	**Class**	**Gram Active**	**Gram Passive**	**Shrub Berry**	**Shrub Nursery**	**Grain**	**Forb Berry**	**Forb Sum Harvest**	**Forb Fall Harvest**	**Total**	**User Acc ±CI**	
	Gram Active	237	23	13	3	8	4	20	8	316	75.0%	1.6%
	Gram Passive	40	291	7	2	16	2	19	5	382	76.2%	1.6%
	Shrub Berry	25	13	211	7	6	9	24	4	299	70.6%	1.7%
	Shrub Nursery	1	1	4	67	2	0	5	0	80	83.8%	1.4%
	Grain	11	8	5	1	214	0	7	2	248	86.3%	1.3%
	Forb Berry	0	1	1	0	1	20	5	0	28	71.4%	1.7%
	Forb Sum Harv	59	36	56	24	50	38	1137	40	1440	79.0%	1.5%
	Forb Fall Harv	2	2	3	0	3	2	13	91	116	78.4%	1.5%
	Total	375	375	300	104	300	75	1230	150	2909		
	Prod Acc	78.7%	74.9%	60.4%	27.9%	61.4%	16.8%	92.1%	59.5%		**Overall Acc ±CI**	
	±CI	3.0%	3.9%	5.3%	7.9%	5.2%	5.8%	1.5%	6.4%		77.6%	1.5%

Table 3-19: Level 3 Error Matrix Trial 10 (Vegetation Sub-Type).

Error Matrix for Trial 10 (below) with values that are the number of samples, however user and producer accuracies are corrected for bias using map marginal proportions ($\pi_{\text{Gram-Active}}$=0.209, $\pi_{\text{Gram - Passive}}$=0.130, $\pi_{\text{Shrub-Berry}}$ =0.070, $\pi_{\text{Shrub-Nursery}}$=0.006, π_{Grain} =0.056, $\pi_{\text{Forb-Berry}}$=0.005, $\pi_{\text{Forb-Summer Harvest}}$ =0.483, $\pi_{\text{Forb-Fall Harvest}}$=0.041).

Trial 10		**Reference Data**									
	Class	**Gram Active**	**Gram Passive**	**Shrub Berry**	**Shrub Nursery**	**Grain**	**Forb Berry**	**Forb Summer Harvest**	**Forb Fall Harvest**	**Total**	**User Acc ±CI**
Map Data	**Gram Active**	234	47	15	3	11	2	22	12	346	67.6% 1.7%
	Gram Passive	45	285	2	0	9	0	26	6	373	76.4% 1.6%
	Shrub Berry	11	9	203	5	4	8	27	2	269	75.5% 1.6%
	Shrub Nursery	4	0	4	67	2	0	2	0	79	84.8% 1.3%
	Grain	10	7	3	1	207	0	11	0	239	86.6% 1.3%
	Forb Berry	3	2	1	0	0	18	4	0	28	64.3% 1.8%
	Forb Sum Harv	63	25	72	28	65	46	1127	52	1478	76.3% 1.6%
	Forb Fall Harv	5	0	0	0	2	1	11	78	97	80.4% 1.5%
	Total	375	375	300	104	300	75	1230	150	2909	
	Prod Acc ±CI	76.1% 3.2%	70.8% 3.8%	60.6% 5.0%	28.3% 7.9%	59.4% 5.0%	15.5% 6.1%	90.7% 1.6%	55.0% 5.9%		**Overall Acc ±CI** 75.1% 1.6%

3.3.4.5 Assessing Reference Data

One other independent dataset was available for a small portion of the study site, which provided a method to assess the primary reference data. The data was collected in the fall for fields that were planted with a winter cover crop. This secondary assessment data contained 148 polygons of the 2129 polygons (7.0%) of the study area and were mostly fields that would be part of the grain or forb class. Based on the results (Table 3-20), there was an overall agreement for 69.6% of the classes with a range between 46.7% and 93.8% for the grain and forb classes.

Table 3-20: Error Matrix Between Primary and Secondary Reference Data

The Secondary Reference Data is a subset (8%) of the Reference Data and was collected mainly on vegetable fields, that correspond to the Forb-Summer Harvest and Forb-Fall Harvest fields. The User and Producer Accuracies were not corrected for bias.

		Primary Reference Data (Agriculture Canada)								
	Class	**Gram Active**	**Gram Passive**	**Shrub Berry**	**Grain**	**Forb Berry**	**Forb Summer Harvest**	**Forb Fall Harvest**	**Total**	**User Acc**
Secondary Reference Data	**Gram Active**	2	0	0	0	0	1	0	3	66.7%
	Gram Passive	0	0	0	0	0	0	0	0	--
	Shrub Berry	0	0	2	0	0	0	0	2	100.0%
	Grain	2	1	0	7	0	1	0	11	63.6%
	Forb Berry	0	1	0	0	0	1	0	2	0.0%
	Forb Sum Harv	16	10	1	8	0	90	2	129	70.9%
	Forb Fall Harv	0	0	0	0	0	1	2	3	66.7%
	Total	20	12	3	15	0	96	4	148	
	Prod Acc	10.0%	0.0%	66.7%	46.7%	--	93.7%	50.0%		**Overall Acc** 69.6%

3.3.5 Resources Required for the Project

The project used a personal computer (IBM compatible, Pentium 4 with 512 MB RAM on a Microsoft Windows Millennium operating system), several software programs, and data valued at approximately $20,000 (Table 3-21). The main software used was ER Mapper (ER Mapper 2003) for raster remote sensing, ArcView (ESRI 2000) for map and vector analysis, and See5 (Quinlan 2005) for the decision tree classification. Additional software JMP (SAS 2003) and Microsoft Excel © 2000 was also used to conduct supplementary analysis and convert data between the main software packages. A significant amount of time was required to learn ER Mapper (ER Mapper 2003) and to understand the assumptions of the software. Only a limited amount of time was required to learn See5 (Quinlan 2005) and ArcView (ESRI 2000). However previous experience with ArcView (ESRI 2000) underestimated the amount of learning time and it is estimated the learning time for an inexperienced person would be between the time require to learn ER Mapper (ER Mapper 2003) and See5 (Quinlan 2005).

Table 3-21: Resources Used in the Project

Resource	Resource Type	Approximate Cost (Cdn)	Use in Project	Time Use
Hardware	PC Computer	$1,000		
Software	ER Mapper (ver 5.0)	$5,000	Geometric correction, unsupervised classification of no change units	25%
	ArcView (ver 3.2)	$2,500	Attributing data, map preparation, data manipulation	25%
	See5 (ver 2.02)	$1,000	Classification, matrix	10%
	MS Excel (ver 2000)	$500	Radiometric formula, data prep for See5	20%
	JMP (ver 5.0.1)	$1,200	Correlation, cluster analysis	20%
Data	Landsat 7 Data	$4,000		
	Reference Data	$5,000		
Total		$20,200		

Time use is based on an estimated amount of time require to learn and use the software.

3.4 Discussion

3.4.1 Pre-Processing

The project demonstrated the importance of conducting the pre-processing steps when classifying land from remote sensing data. While the satellite images were specified to be orthorectified to 25m, the misalignment of landmarks was nearly 200m for some of the images. While the variation was smaller within a single image date (for all bands), the variation was greater among image dates. Without ensuring a consistent geometric registration, there will be a lower accuracy between reference and classified map especially in areas such as the study area where agricultural fields are relatively small and have a higher crop diversity than other agricultural areas such as the Canadian Prairies.

The radiometric correction technique using no-change pixels to determine a regression equation (Oetter et al. 2001) was useful to normalize all the image dates without the need for knowledge of the satellite sensor parameters or reflectance values collected on the ground. This approach is useful for historical remote sensing information because no satellite sensor parameter information is required. Based on the regression equation, roads had lower variation of reflectance values while forests and water had higher variation. While it was expected that water would have higher variation (due to turbidity changes, water depth changes), the higher variation was not expected for the coniferous trees in the study area. Once the optimal no-change pixels were identified, the method to develop the regression equations required basic technical skills.

3.4.2 Agricultural Land Classes

In the majority of land cover classification projects; the land classification scheme is developed a priori. In this project, the desired land classification scheme was modified based on information from the crop calendar and cluster analysis. Using information from both sources, informed the decisions to group specific crops that would provide higher accuracy given the project goal to discriminate between agricultural land classes that were beneficial to waterfowl (e.g. grass, grain and vegetables) and those that had limited value to waterfowl (e.g. nursery and berry crops).

3.4.3 Determining an Effective Image Transform

In this study area, the Tasseled Cap transform was the most effective image transform for determining waterfowl compatible agricultural crops, based on the accuracy value and low number of input data layers required (three for each of the four image dates). To achieve the objectives of the project, the Tasseled Cap transform performed better than the vegetation indices (NDVI, ArcTan, MS2) and as well as the trials that used combinations of all data layers. While the use of change vectors have been demonstrated in other studies, the data in this project did not support the importance of change vectors for the vegetation indices.

Before accepting the conclusion that an image transform is a good classifier, there are several components that should be evaluated. The first component is whether more than one image transform (e.g. NDVI, Tasseled Cap) was evaluated on the same data set, time period and classification approach. The second component is to review the overall, Producers and User Accuracy. While two image transforms may have the same overall accuracy, they may differ on the Producers and User's Accuracy of the individual classes. Thirdly, a measure of variance or statistical difference of the accuracies should be provided with the accuracy measures. Finally, detailed methods should be provided to allow the reader to evaluate the sampling design. All four of these components are provided in the report so that readers can assess the error and determine the confidence in the conclusions of the report.

3.4.4 Importance of Multi-Date Images

The importance of multiple image dates has been identified in land use projects, especially for land uses that change within a season. In the study area, the land use of the agricultural crops changed over time and therefore multi-date images should be important. Based on the four images used in this project, it was demonstrated that all four images were required as the accuracy decreased beyond the confidence intervals as successive image dates were removed. However, it was not determined whether additional image dates would have increased the accuracy. Therefore all four image dates in the agricultural classification for all 3 levels of the classification scheme were necessary to classify agricultural land.

3.4.5 Estimation of Errors

The assessment of a classification approach is not complete with a description of the potential errors. Potential errors can be divided into four categories based on Congalton and Green 1999. The first category is the assumption that the reference data is 100% accurate given potential errors in the spatial registration of the data, data entry errors, poor classification scheme, temporal change between reference and remotely sensed information and incorrect labelling. Given a subset of the reference data had only 69.9% agreement with the secondary reference data, it illuminates the prominence of this error in both reference datasets. Spatial registration of the datasets was conducted with less than a 0.5 RMS per pixel indicating this error component should be low. However, errors could also be generated from data entry errors or the mislabelling of agricultural crops in the field. The temporal difference between the reference datasets was approximately 3 months and considered to be a small contribution to the error.

The second category of error is the sensitivity of the classification scheme to observer variability. In this project both field boundaries and crop types were discrete and consistent over time and space and therefore this error is assumed to be low. In more natural habitats, categories (e.g. 10% cover, 40% cover) and their boundaries are continuous data, which increases this type of error. The inability for remote sensing technology to discriminate between land classes forms the third category of errors. Using information from the crop calendar as well as the cluster analysis directed the development of a classification scheme. If the project evaluated individual agricultural crops, then based on information from the crop calendar and cluster analysis, this error would be much larger. However for this project the contribution of this type of error is assessed to be low. The final category of error is gross mapping errors such as spectral confusion between two different land classes (e.g. exposed soil and roads that may have similar spectral reflectance values). Based on a visual review of the final maps, this error is also expected to be small as only agricultural fields were part of the data and other cover such as roads, forests, water were removed from the data.

In addition to Congalton and Green 1999, other authors have advocated that a detailed method section is required to assess the accuracy of classification results for bias (Hammond and Verbyla 1996). This can include a review of sample sizes and sampling methods. In the project, a minimum of 50 stratified (by agricultural crop) samples for each of the training and accuracy data was used, which is consistent with the recommended sample size when there are less than 12 classification categories (Congalton and Green 1999). Secondly, the reference data covered the entire study area allowing any pixel to be selected. If the selection of reference from the training data is not independent, then this creates a positive bias and overestimates accuracy (Hammond and Verbyla 1996). The sampling design also enabled any pixel in a field to be selected and therefore avoided the bias of selecting the middle of the field where the remotely sensed data would be the most homogenous. When only homogenous pixels are chosen, it biases the data and again overestimates the accuracy (Hammond and Verbyla 1996). Therefore, considering the potential sources of error, it is concluded that the largest contributor to error in this project is the reference dataset caused by data entry error or incorrect labelling of agricultural crops in the field.

3.4.6 Resources Required for the Project

The second objective of the project was to determine the human resources required to conduct remote sensing. The result section identified the combination of hardware, software and data that is required for remote sensing. While a significant amount of the cost is required to purchase hardware, software and data ($20,000) there is also a significant amount of human resources (i.e.

time) required to learn the techniques of the program, understand the assumptions, and use the software.

Based on the experience in the project and the recent technological advancements in software, a significant amount of time (and corresponding cost) can be reduced by removing the raster remote sensing software. This would reduce the total capital cost by $5,000, reducing the capital cost by about 25% and would also reduce the amount of software learning by a similar amount. The use of the See5 (Quinlan 2005) decision tree classifier replaced the need for a raster remote sensing software that uses the maximum likelihood classifier. The geometric correction of the datasets that was completed using the raster based remote sensing software can now be completed using ArcGIS (ESRI 2005). The only remaining procedure to replace in the raster remote sensing software is the unsupervised classification of the no-change pixels that could be replicated in a statistical software program (e.g. JMP SAS 2003). If the remote sensing software was no longer required, then there should also be a corresponding reducing in the amount and time allocated for data conversions. Therefore removing ER Mapper (ER Mapper 2003) and MS Excel © 2000 should reduce the capital cost by 27% (20,200 to $14,700) with a similar corresponding reduction in human resources.

During the project after several classification trials JMP (SAS 2003) was determined to be better software for manipulating data than MS Excel © 2000 or Arcview (ESRI 2000). JMP (SAS 2003) could more efficiently manipulate the large database, create new fields and attribute the fields better than MS Excel ©

2000 or Arcview 3.2 (ESRI 2000). MS Excel © 2000 is limited to 65,535 records and it's ability to randomly sample a subset of data based on an attribute in a field is inferior to JMP (SAS 2003). While scripts are available in Arcview 3.2 (ESRI 2000) to randomly sample large databases, the program is significantly slower than the statistical program.

3.5 Conclusion

3.5.1 Accomplishment of Project Goals

The project achieved the first goal to determine the technical considerations that discriminate amongst waterfowl compatible and non-compatible agricultural land use classes. The approach demonstrates that Landsat 7 ETM does possess sufficient spectral, spatial and temporal resolution to differentiate among agricultural land classes that are compatible with waterfowl at two classification levels. At the level of vegetation type (graminoid, grass, forb, grain and shrub) the overall accuracy was 83.1 ± 1.4%, while at the vegetation subtype (graminoid - active manage, graminoid – passive management, shrub – berry, shrub – nursery, grain, forb – berry, forb – summer harvest, forb – fall harvest) had an overall accuracy of 75.1 ± 1.4%.

The project evaluated different types of image transforms and found that the Tasseled Cap transform performed better than the other individual transforms (MSAVI2, Arctan RVI, NDVI) and comparable to the approach of using a combination of these vegetation indices and other vector change transforms.

Multi-image dates were important for the classification of agricultural land, and in particular all four image dates were required to maintain an acceptable overall accuracy. Finally, the use of decision tree classifier provided a relatively simple approach for classification, completed the classification quickly and provided additional data about the importance of specific datasets that could not be obtained in other traditional supervised or unsupervised classifications.

The second goal of the project (determine the resources required to conduct remote sensing analysis) was also achieved. The estimated cost to conduct the agricultural land use was approximately $20,000. The use of a decision tree classifier along with current GIS vector based software and statistical package can also eliminate the need of raster based GIS software. This has important implications as there will be a significant reduction in the learning time required for the raster-based GIS software. As most conservation agencies have staff familiar with vector based GIS software, the only software that would require some understanding is the decision tree classification software.

3.5.2 Recommendations for Further Research

From the results provided in this report, there are three main recommendations for future work. The project supports the further work of using decision tree methods for agricultural classification. However, additional work is required to replicate beyond agricultural land cover to general land cover and compare to the traditional approaches of the maximum likelihood classifier. The methodology and results also support a more simplified method by replacing the raster based remote sensing program with the decision tree classifier (See5 Quinlan 2005) and using an analytical statistical program (e.g. JMP SAS 2003) to compute the band ratios and manipulate data. The third recommendation is to evaluate other satellite systems (e.g. Spot), which have a better spatial resolution (e.g. Landsat 30m, Spot 10m) but less of a spectral resolution (e.g. Landsat 7 bands vs Spot 4 bands), especially as the scan line corrector failed on the Landsat 7 Satellite in 2003.

4 APPLICATION OF AGRICULTURAL LAND CLASSIFICATON ON THE CONSERVATION OF AMERICAN WIGEON IN THE FRASER RIVER DELTA

4.1 Introduction

Information from habitat supply and demand curves can assist conservation agencies in setting habitat conservation goals. Using a series of supply and demand curves allow conservation agencies to better understand tradeoffs between ecological and social considerations. In the previous chapter, the remote sensing methods produced a map of the spatial locations of agricultural crops. Using the map, additional calculations with the data can produce multiple habitat supply curves and advance the utility of remote sensing beyond the production of maps. In this chapter, several demand curves are produced from a species – habitat model. A species – habitat model is a method to better understand how species relate to their environment and can be a simple or complex model. The model is based on American wigeon (*Anas americana*) and perennial grass, which is one of the agricultural classes of graminoid from chapter 3. The supply and demand curves are combed on a graph to identify the amount of perennial grass to be conserved based on a specific population of wigeon.

American wigeon were chosen to serve as a proxy for migratory birds in the model because of their relative importance in the study area and association with agricultural perennial grass fields. The American wigeon is a species of continental concern and received a priority rating of high (North American Waterfowl Management Plan 2004) for the Pacific Coast based on a 6-step scale that ranged from high to low. Locally, American wigeon is one of the four most abundant wintering waterfowl in the Fraser River Delta along with the other species: mallard, northern pintail and green-winged teal. Wigeon are herbivores that forage on plants in the intertidal zone as well as the perennial grass fields on farms. Its high use of perennial grass fields that can be mapped with remote sensing was another contributing factor for this species to be used in a species – habitat model.

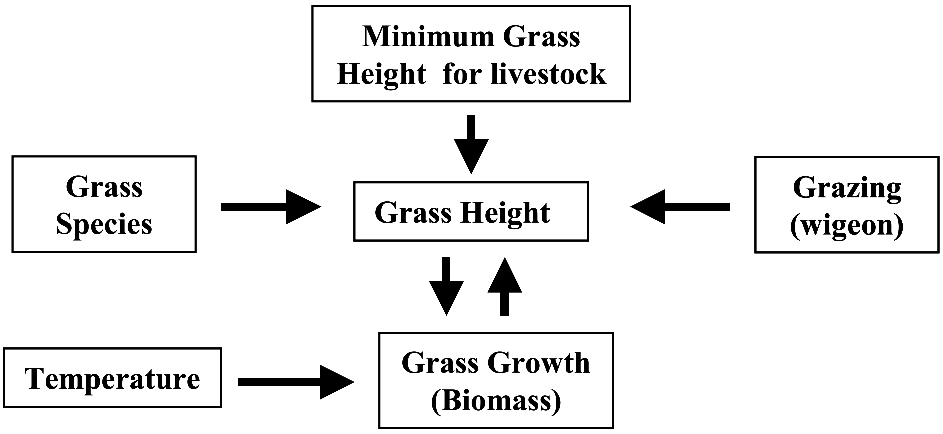
To develop the model, the first step was to determine the key parameters that affect habitat selection of the American wigeon. There are three main factors that influence habitat selection in grazing waterfowl species: grass quality (Mayhew and Houston 1999), grass quantity (Vickery et al. 1997), and disturbance (Prins and Ydenberg 1985). Durant et al. 2004 found that there is a trade off between grass quality and quantity for Eurasian wigeon (*Anas penelope*), which are similar to American wigeon in terms of size, habitat use (herbivore) and weight. The main difference between the species is their distribution, where as Eurasian wigeon mainly occur in Europe and Asia, American wigeon reside in North America. For the purposes of this project, only grass quantity is considered as a driver of habitat selection. The metric of grass quantity (i.e. hectares) can be assessed with remote sensing through maps.

4.2 Methods

4.2.1 Overall Model Description

A model was constructed to simulate the relationship between grass quantity and consumption of perennial grass by wigeon. The factors within the model include the rate of grass growth affected by temperature, height of grass, population of wigeon, minimum height of grass to be maintained on the agricultural field and growth characteristic of grass species (Figure 4-1). The model was assembled in Microsoft Excel © 2000 with the following variable parameters: three temperature profiles, six population levels of wigeon, two species of grass and six minimum heights of grass required to be maintained. The output was the area of perennial grassland (ha) required to sustain a given wigeon population based on energetic calculations.

Figure 4-1: Model Overview



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4.2.2 Grass Growth Sub-models

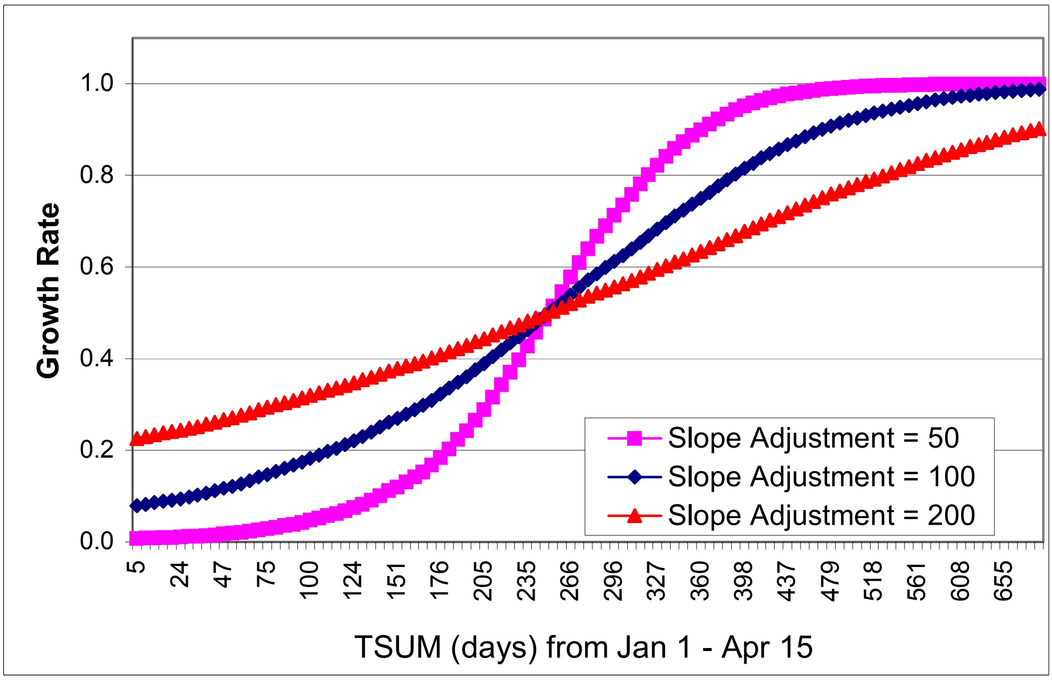
The grass growth model consisted of two main factors: temperature and height of grass. While other factors determining grass growth include light, rainfall, level of nitrogen (Barrett et al. 2005), the purpose of the project is to demonstrate a simple application of a species – habitat model. Therefore, other factors affecting grass growth were not incorporated into the model.

4.2.2.1 Temperature (TSUM) Sub-model

The temperature sum (TSUM) variable is the accumulated mean daily temperatures (in °C) above zero beginning on January 1. This metric assumes that a certain amount of accumulated heat (as opposed to a certain daily temperature) is required to initiate plant processes such as growth, flowering etc. In the study area, grass becomes dormant in the winter and does not grow until the late winter (i.e. February). Therefore January 1 was used as the starting point to ensure the starting point begins prior to any plant growth. In the study area, the TSUM value between 200 and 300 represents the accumulated heat level that is sufficient for plants to absorb nutrients and initiate above ground growth (Bittman et al. 1999). The timeline of the model extends from January 1 to April 15, which includes the period when the wigeon forage predominately in the agricultural fields (February and March) and when wigeon leave the study area to migrate north (April).

To emulate the grass growth curves, a standard sigmoid curve was used $y = \frac{1}{1+e^{-x}}$, where y = grass growth rate (GR) and x = TSUM. Based on observations of the grass growing parameters in the study area, the sigmoid curve was shifted so that there was zero growth on January 1, fifty percent grass growth rate occurred at TSUM = 250, and maximal growth (1.0) on April 15. To incorporate potential impacts of the slope on the grass growth, a slope adjustment factor was incorporated into the formula to provide variables in the model. Values for the slope(s) were 200, 100 and 50 (Figure 4-2) representing linear, gentle sigmoid and sigmoid grass growth rate respectively. The final growth formula was $GR_{TSUM} = \frac{1}{1+e^{-(\frac{x-250}{s})}}$ where s = slope factor and X = TSUM.

Figure 4-2: Slope Adjustment Factors of TSUM Grass Growth Model



4.2.2.2 Grass Height Sub-model

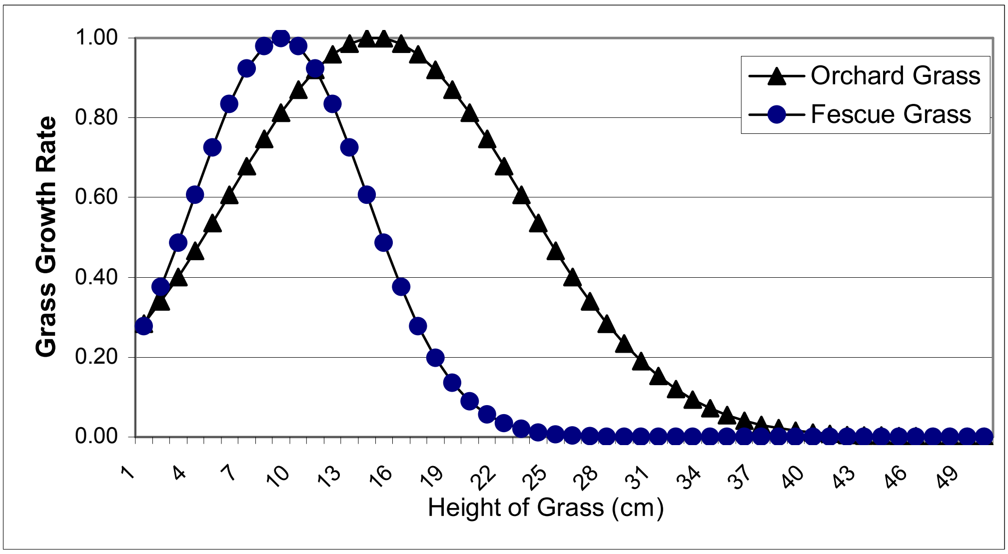
The second component of the model is the influence of grass height on the growth rate of grass. In general grass growth rate increases with height until an optimal height is achieved and then grass growth rate decreases, that is similar to a bell shaped curve $y = \frac{e^{-\frac{x^2}{2}}}{\sigma\sqrt{2\pi}}$. The bell curve formula was rescaled to match the GR_{TSUM} range between 0 and 1.0. The growth rate due to grass height $GR_{HOG} = \frac{e^{-\frac{(x-\mu)^2}{2(\sigma)^2}}}{\sigma\sqrt{2\pi}}$, is a function of the height of grass (x), the height of grass where growth rate is maximum (μ), and the standard deviation of the grass height (σ). To determine the maximum growth height and standard deviation parameters, recommendations from a forage production manual was utilized for the two main grass species (fescue, ryegrass) in the study area. These species represent the two main grasses: warm season and cool season grasses. The recommendations provided the optimal forage production and quality conditions at which the grass should be harvested (Table 4-1). The midpoint of the height range was the maximal height (μ), while the height range provided the standard deviation (σ). Using the parameters in the GR_{HOG} create two grass growth curves based on height of grass (Figure 4-3).

Table 4-1: Grass Growth Parameters for Grass Height Submodel.

Grass Species	**Fescue**	**Orchard Grass**
Grass Type	Warm Season	Cool Season
Optimal Pre-harvest height	12.7 – 15.2	20.3 – 25.4
Optimal Post-harvest height	2.5 – 5.0	10.1 – 12.7
Height at max growth (x) (average of pre-harvest height)	14.0	23.0
Range of height (SD) (range of pre-harvest height)	5.0	8.5

Source: **http://www.caf.wvu.edu/~forage/growth.htm**

Figure 4-3: Grass Growth Rate for Two Grass Species



4.2.2.3 Combining Growth Rate Sub Models

The overall growth rate (GR_{TOTAL}) is the product of the growth rates from the temperature and grass height sub-models $(GR_{TOTAL} = GR_{TSUM}\ X\ GR_{HOG})$, where the growth rate units are cm / day. The assumption is both sub models contribute equally to the overall growth rate and that the maximal growth rate is 1 cm per day. In south coastal British Columbia, the maximal spring forage growth rate is approximately 15-20 cm over a 15-20 day period (Bittman et al. 1999), which is approximately 1 cm/day.

To calculate the total height of grass on a specific day, the height of grass on the previous day (HOG_{t0}) is summed with the height of grass (HOG_{t1}) on the current day, which is the product of growth rate (GR_{TOTAL}) multiplied by 1 day.

$HOG_{TOTAL}[cm] = HOG_{t0}[cm] + (GR_{TOTAL} * 1\, day[cm])$.

To calculate the total biomass of grass on the fields, the current height of grass is multiplied by the area of grass and density in the following formula: $Biomass_{Available}[kg] = (HOG_{Total}[cm]) * Area_{fGrass}[ha] * Grass_{density}\left[\frac{kg}{ha * cm}\right]$. Where

$HOG_{Total}[cm]$ = Current height of grass,

$Area_{Grass}[ha]$ = Total area of perennial grass calculated

$Grass_{density}$ = 72 kg/ha*cm, which is calculated from the assumption that 20 - 25 cm of grass contains between 1200 and 2000 kg/ha (Bittman et al. 1999).

4.2.2.4 Wigeon Compensatory Sub Model

The third sub-model incorporates the compensatory response of the grass grazed by wigeon. When a grass is defoliated (i.e. grazed), the plant response can include positive or negative changes to growth rate, total biomass, or final biomass (Ferraro and Oesterheld 2002, VanderGraaf et al. 2005). Percival and Houston 1992 found that waterfowl grazing affect plant biomass, while other studies demonstrate that waterfowl modify their grazing response to optimize plant quality (Mayhew and Houston 1999, Prins et al. 1980, Bos 2002). Therefore waterfowl grazing and the subsequent plant response are strongly linked together.

In this sub-model, a population of wigeon reduce the plant height through grazing. The reduction of plant height is an input to the grass height sub-model (Section 4.2.2.2), which affects the plant growth rate. Prior to grazing, if the plant height is above the height of maximum growth rate, then the reduction in plant height will increase the growth rate. Conversely, if the plant height is below the height of maximum growth rate, then the reduction in plant height will decrease the growth rate. This sub-model incorporates a dynamic component to the model instead of relying on the total production of grass without the impact of grazing waterfowl.

To relate the amount of biomass of grass in agricultural fields (kg) to the grass height model (cm), the amount of biomass grazed and consumed by wigeon ($BM_{Consumed}$) is calculated from the population of wigeon, the energetic requirement of wigeon, and the energetic value of grass by the formula:

$$BM_{Consumed}[kg] = AMWI_{total}[\#] * \frac{DER_{amwi}[kJ/bird]}{EV_{grass}[kJ/g]} * \frac{1kg}{1000g}$$, where

$AMWI_{total}[\#]$ = The population level of American wigeon.

$DER_{amwi}[kJ/bird]$ = Daily Energetic Requirement for an American wigeon (630 kJ/bird/day), Source: (Mayhew 1988).

$EV_{grass}[kJ/g]$ = Energetic Value of grass (7.11 kJ/g of grass, Source: Buffett unpublished 2006

To calculate the biomass remaining on agricultural fields after a grazing event (BM_{Remain}), is the amount of biomass grazed subtracted from the amount of biomass present on the previous day: $BM_{Remain}[kg] = BM_{available}[kg] - BM_{Consumed}[kg]$. The remaining biomass after a grazing event is converted to an equivalent of grass height $HOG_{t2}[cm] =$ using the previous constants of total field area and grass density: $HOG_{t2}[cm] = \dfrac{BM_{\mathrm{Re}\,main}[kg]}{Area_{forage}[ha] * Grass_{density}\left[\dfrac{kg}{ha * cm}\right]}$. The result is the input for the grass height model for the next day.

4.2.3 Habitat Demand and Simulation Model

All three sub-models were assembled in Microsoft Excel © 2000. Simulation scenarios were completed using the Solver application in Microsoft Excel © 2000 to determine the minimum amount of grass area required to sustain a given wigeon population for a given temperature profile, grass species type and minimum height of grass. The output was a number of demand curves of the amount of grass area (ha) required to sustain a given wigeon population.

While the temperature profile, grass type and wigeon population reflect the biological dimension of the model, the minimum height of grass incorporates a social dimension. The increase in grass consumption by wigeon reduces the amount of grass available for livestock consumption and demonstrates the social dimension of balancing needs of wildlife with the needs of agriculture. The model output was constrained by a set of minimum grass heights to be maintained through each scenario to reflect the amount of grass required to feed livestock such as cows and cattle.

Therefore a total of 4 parameters were varied in the model (Table 4-2) to create a series of demand curves required to sustain a given population of wigeon. In addition to the demand curves that represent the amount of grass required, the supply of grass was also determined. Using the remote sensing output (Chapter 3) for the class of graminoid fields that were actively managed, a supply curve was created. Two additional scenarios of supply curves incorporated the impact of fragmentation if wigeon were unable to use the outer 25m or 50m of a field.

Table 4-2: Simulation Model Variables

Parameter	**Values**
Grass Species	Fescue, Orchard
TSUM Slope	50, 100, 200
Wigeon Population	0, 25,000, 50,000, 75000, 100,000, 125,000, 150,000
Minimum Grass Height (cm)	0, 2, 4, 6, 8, 10

4.3 Results

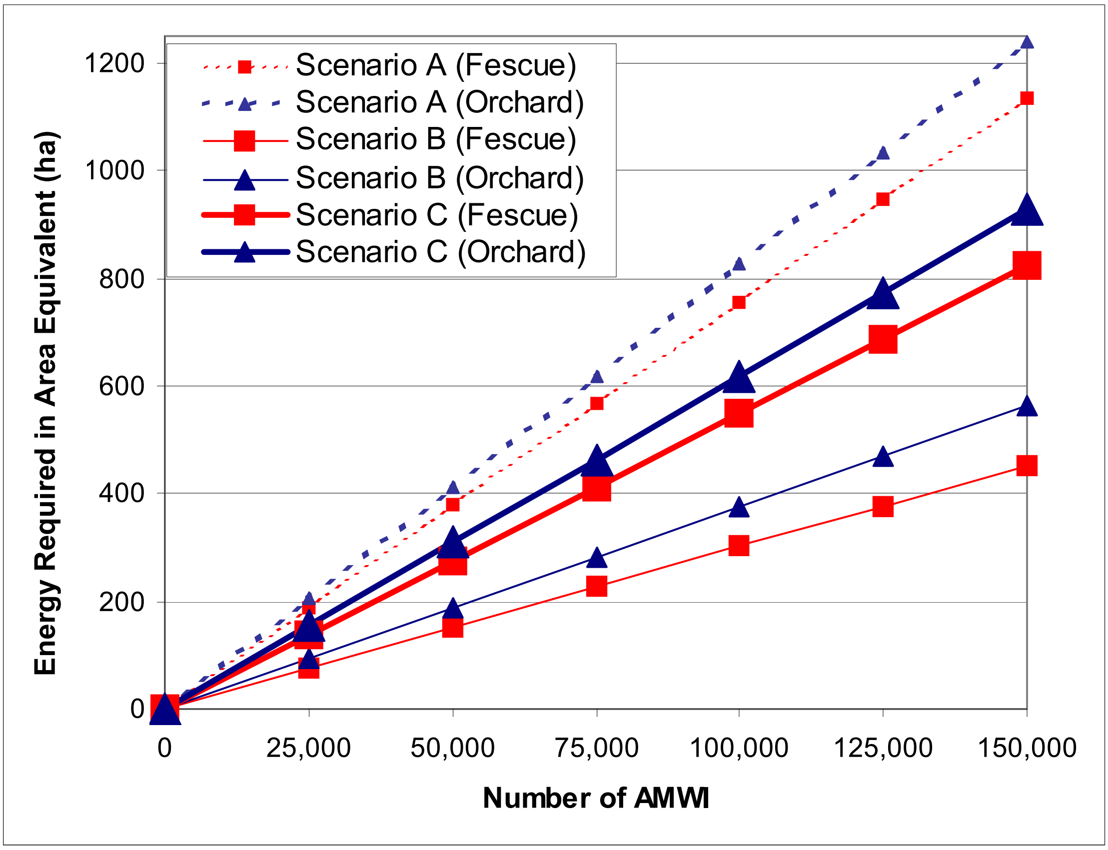
4.3.1 Influence of Grass Species

Three different scenarios (Table 4-3) illustrated the differences between the grass species (Figure 4-4). The amount of area for Fescue grass was consistently lower than Orchard grass in all scenarios indicating that more Fescue grass is required to support a given population of wigeon.

Table 4-3: Scenario Parameters for Fescue and Orchard Grass Species.

Scenario	Tsum	Minimum Grass Height (cm)	Fescue Equation	Orchard Equation
A	50	6	y = 189.0x – 189.0	y = 206.5x – 206.7
B	200	6	y = 75.5x – 75.7	y = 93.6x – 93.6
C	200	10	y = 137.2x – 137.4	y = 154.6x – 154.6

Figure 4-4: Amount of Grass Required for Two Grass Species in Three Scenarios.



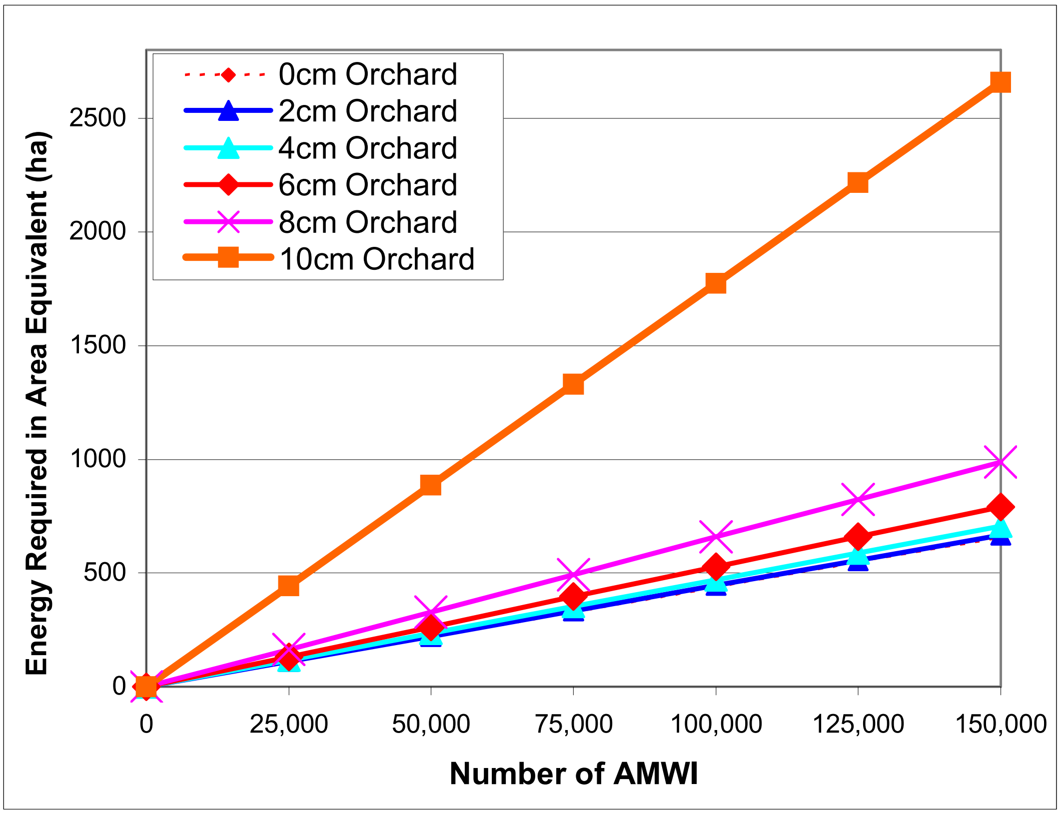
4.3.2 Influence of Minimum Grass Height

Grass height had a significant influence on the amount of grass required to sustain a population of wigeon. As the required minimum height of grass increased, there was a corresponding increase in the total area of grass required (Figure 4-5). This relationship is expected because as the minimum height of grass increased, there is less grass per unit area available for wigeon. Therefore wigeon required more area to graze.

The second influence of grass height is on growth rate. As the minimum grass height approached the optimal height for growth rate (e.g. 10cm), the area of grass to sustain wigeon substantially increased. As the grass height increased beyond the optimal height, the growth rate is suppressed. Therefore when wigeon graze the grass, the re-growth of grass occurs at a lower rate. Since a lower amount of grass is produced for a given unit area of grass, a proportional larger area of grass is required to sustain the same wigeon population. These results and the results from the three scenarios (Table 4-3) suggest that the effect of minimum grass height has a larger impact on the area required than TSUM or grass species.

Figure 4-5: Area (ha) of Grass Required to Support Wigeon

All curves are Orchard Grass with a slope factor of 100. The height of grass is the minimum height of grass required to be maintained and is therefore is the amount of grass that is not available for wigeon grazing.



4.3.3 Supply of Perennial Grass

The supply lines (amount of grass present) was created using the remote sensing methods using the actively managed graminoid class (from Chapter 3) within the study area (Figure 4-6). Using the spatial map of grass fields, a total of 1410 ha of grass were available for wigeon. Two additional supply lines were created by incorporating a field edge effect on the assumption that wigeon would not use the outer 25m and 50m of a field due to disturbance. The impact of edge effect creates a substantial decrease of the amount of grass fields (Table 4-4) by reducing the total amount of grass to 832 ha (25m buffer) and 448 ha (50m buffer).

Figure 4-6: Actively Managed Graminoid Fields Within the Study Area.

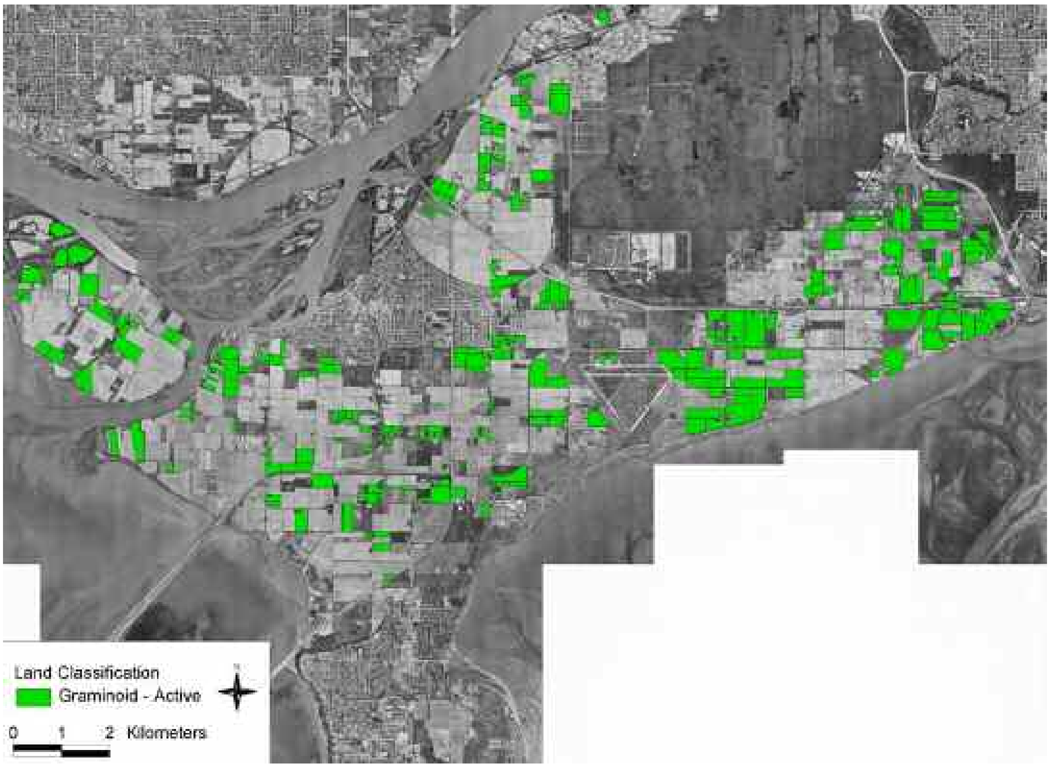


Table 4-4: Impact of Edge Effect on Abundance of Grass

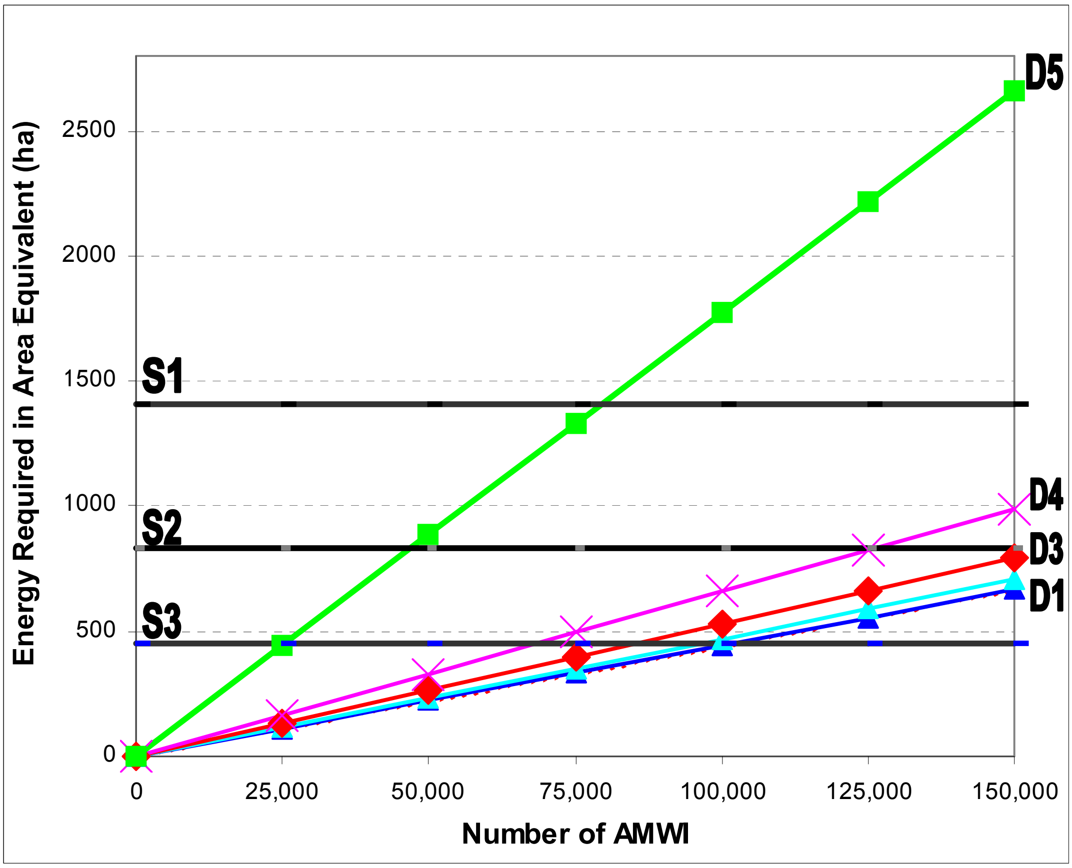
Edge Effect	Area (ha)
None	1410
25m	832
50m	440

4.3.4 Combining Supply and Demand Lines

Combing the supply information of grass fields, with the demand lines from the species – habitat model, creates a number of potential habitat goals for conservation. The specific habitat goal is dependent on the number of wigeon, the desired demand line representing minimal grass height and the estimated supply of grass (Figure 4-7). For example, at an estimated population of 75,000 wigeon, and the assumption that a minimum height of grass required for livestock is 10cm, then approximately 1450 ha of grass is required to maintain the energetic requirements of wigeon. Based on the remote sensing mapping, there already exists approximately 1,500 ha of perennial grass if there is no field edge effect on wigeon. However, if there exists a 25m edge effect then approximately 832 ha of grass is available for wigeon. Since the required amount of grass (for 75,000 wigeon and minimum 10 cm grass height) is approximately 1450 ha, there is a deficit of 618 ha (1450 ha required minus 832 ha available). Therefore, to achieve the goals either more grass must be produced on the landscape or the assumption of 75,000 wigeon or minimum grass height of 10cm need to be reduced in order to balance the supply and demand lines.

Figure 4-7: Supply and Demand of Grass for American Wigeon

Three demand lines (S1: no edge, S2: 25m buffer, S3: 50m buffer) and supply lines of grass of minimum height of orchard grass (D1: 2cm, D2: 4cm, D3: 6cm, D4: 8cm, D5: 10cm)



4.4 Discussion and Conclusions

Creating a species – habitat model provides conservation agencies with a mechanism to develop demand curves that can be combined with supply curves from remote sensing to set habitat goals for wildlife. In this chapter a species – habitat model was constructed by identifying the factors that affect the amount of habitat (e.g. grass) and the use of habitat (e.g. consumption of the grass). Subsequently, the relationship between the various factors was defined to create a model. In this demonstration of American wigeon, the factors include temperature and grass height to determine the amount of habitat, while the consumption of grass was a function of the amount of grass consumed per wigeon (using energy equivalents) and the population of wigeon. The model was constructed with an output of the amount of habitat (ha) required to sustain a given population of wigeon based on the grass species (Fescue, Orchard), temperature, or minimum height of grass (0 cm, 2 cm, 4 cm, 6cm, 8 cm, 10 cm) that was required to be maintained throughout the season from January 1 to April 15.

In general a model is an incomplete abstraction of various factors and additional validation is required to improve the model. The grass growth sub-model (temperature, grass height) should be validated against empirical data to determine the effect of temperature and grass height as well as the relationship between these two factors on the rate of grass growth. Other factors such as the amount of light, rainfall and level of nitrogen, which can affect grass growth, should also be determined whether they have a large or small affect on grass growth.

The information from the species – habitat model can be used to determine conservation goals for habitat and provide an estimate to the question “How much habitat is enough?” Using the model, several scenarios can be developed using a mix of model parameters. For example, if the desired wigeon population to maintain is 100,000 birds and the goal is to maintain a minimum of 10 cm of grass on fields throughout the period of January 1 to April 15, then

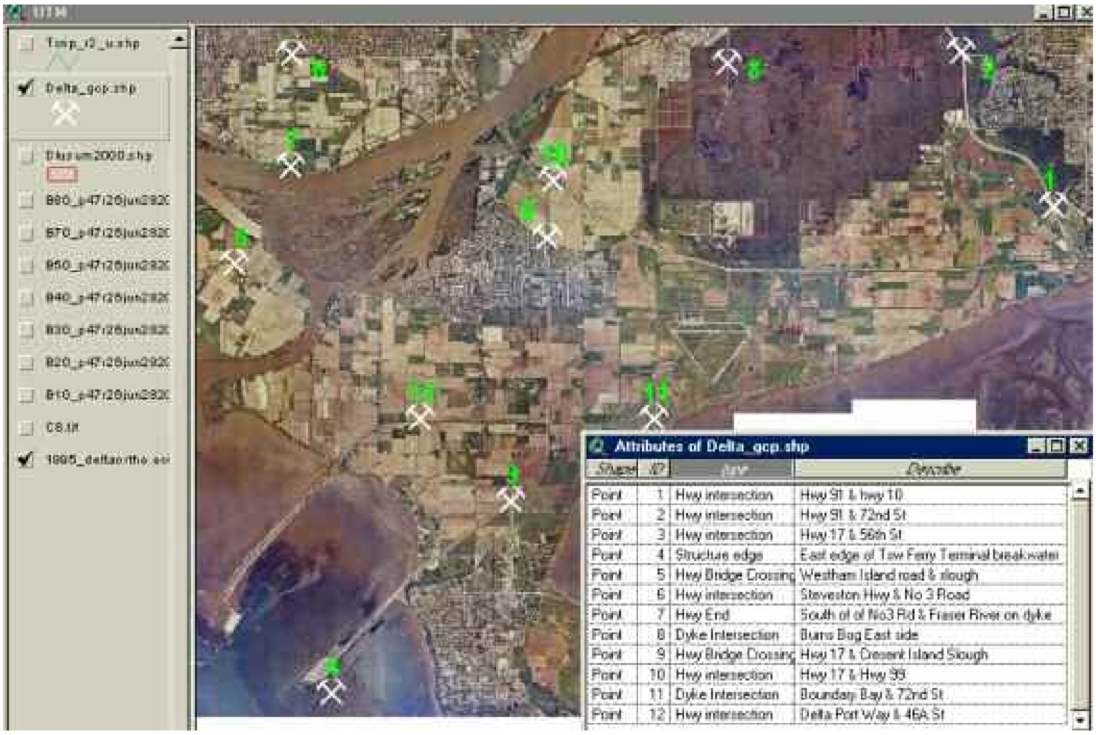
1,773 ha of grass is required to be protected. However, the current supply of grass estimated by remote sensing is 1,410 ha, therefore there is a deficit of 363 ha of grass for this scenario. Options to address the shortfall include accepting a lower population of wigeon, increasing the growth rate of grass by management (e.g. addition of nitrogen), creating an additional 363 ha of grass or providing alternate food for wigeon such as eelgrass in the adjacent intertidal habitat.

APPENDICES

Appendix 1. Agricultural Land Use Codes

- A. Vegetable
  - A1. Potato
  - A2. Pea
  - A3. Cole
  - A4. Corn
  - A5. Squash
  - A6. Bean
  - A7. Lettuce
  - A8. Carrot
  - A9. Celery
  - A10. Onion
  - A11. Beet
  - A12. Pumpkin
  - A13. Turnip
  - A14. Mixed vegetable
  - A15. Specialty
  - A16. Cucurbit
  - A17. Leek
  - A18. Culinary herb
  - A19. Pepper
- B. Grass/forage
  - B1. Pasture
  - B2. Forage
  - B3. Alfalfa
  - B4. Clover
  - B5. Turf
  - B6. Winter cover
  - B7. Overgrown pasture
- C. Grain
  - C1. Wheat
  - C2. Canola
  - C3. Barley
  - C4. Winter wheat
  - C5. Fall rye
  - C6. Spring barley
  - C7. Oats
  - C8. Mixed
  - C9. Annual rye grass
  - C10. Spring wheat
  - C11. Sudan grass
  - C12. Winter barley
  - C13. Trial
- D. Berry/small fruit
  - D1. Currant
  - D2. Strawberry
  - D3. Blueberry
  - D4. Raspberry
  - D5. Blackberry
  - D6. Cranberry
  - D7. Grape
  - D8. Other
- E. Orchard
  - E1. Fruit
  - E2. Nuts
  - E3. Other
- F. Nursery Crop
  - F1. X-mas trees
  - F2. Ornamental
  - F3. Fruit
  - F4. Mixed
  - F5. Perennial
- G. Other agriculture crop
  - G1. Greenhouse
  - G2. Other
  - G3. Livestock
  - G4. Flower
- H. Wild land
  - H1. Woods/Tree
  - H2. Grassland
  - H3. Shrub
  - H4. Marsh
  - H5. Mixed
  - H6. Set aside
- I. Uncultivated
  - I1. Bare
  - I2. Summer fallow
  - I7. Summer cover
  - I3. Crop residue
  - I4. Weedy
  - I8. Refuse
  - I5. Crop residue
  - I6. Bare and weedy
  - I9. Crop residue and weedy
- J. Unknown Crop
- K. Unknown Use
- L. Use Outside Agriculture

Appendix 2. Location of Control Points for Geometric Correction



Attributes of Delta_gcp.shp

Shape	ID	Type	Describe
Point	1	Hwy intersection	Hwy 91 & hwy 10
Point	2	Hwy intersection	Hwy 91 & 72nd St
Point	3	Hwy intersection	Hwy 17 & 56th St
Point	4	Structure edge	East edge of Tsw Ferry Terminal breakwater
Point	5	Hwy Bridge Crossing	Westham Island road & slough
Point	6	Hwy intersection	Steveston Hwy & No 3 Road
Point	7	Hwy End	South of of No3 Rd & Fraser River on dyke
Point	8	Dyke Intersection	Burns Bog East side
Point	9	Hwy Bridge Crossing	Hwy 17 & Cresent Island Slough
Point	10	Hwy intersection	Hwy 17 & Hwy 99
Point	11	Dyke Intersection	Boundary Bay & 72nd St
Point	12	Hwy intersection	Delta Port Way & 46A St

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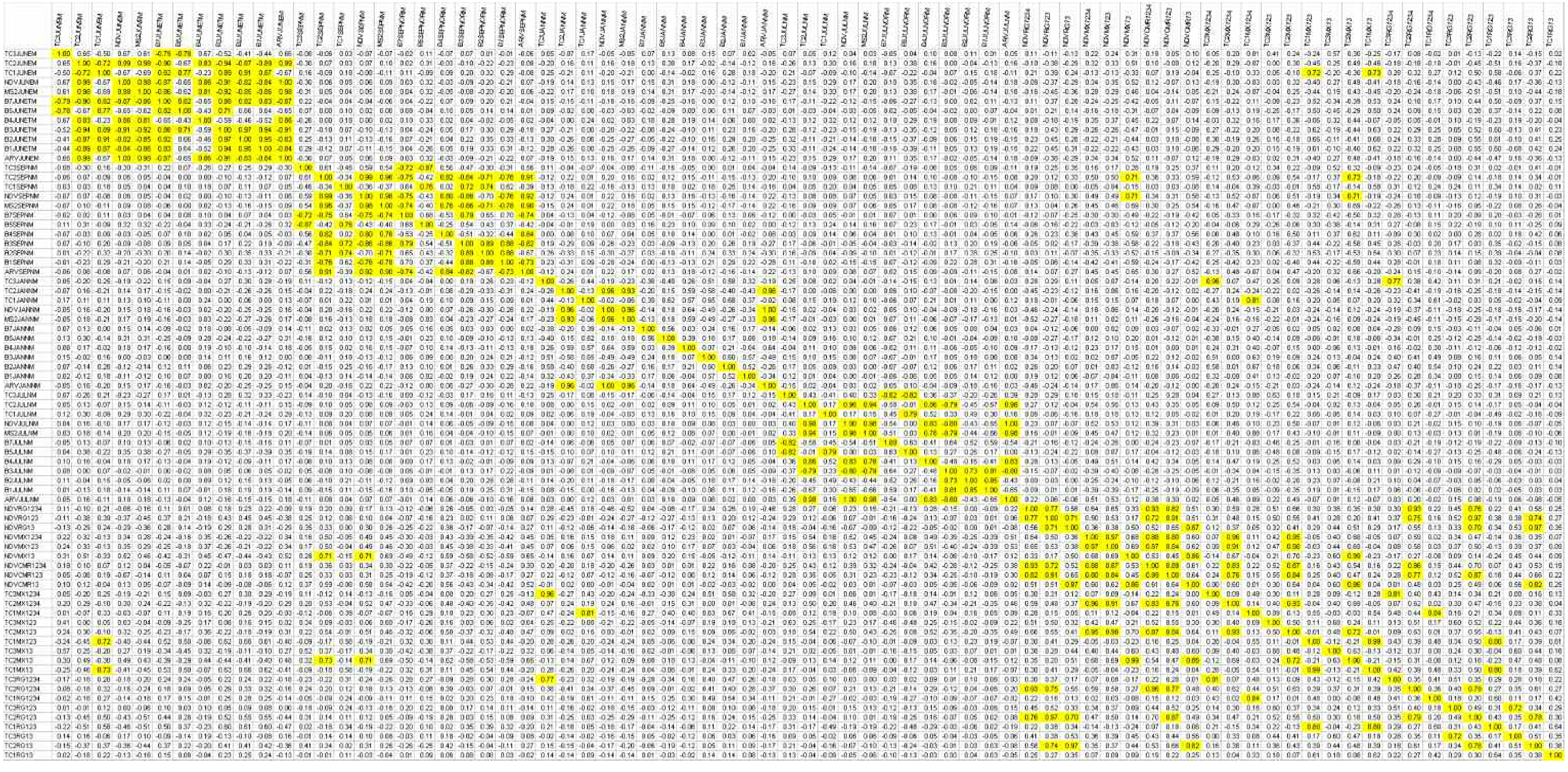
Appendix 3. Output of Cluster Analysis

# of Clusters	2		3			5					10									
Crop Type	A	B	A	B	C	A	B	C	D	E	A	B	C	D	E	F	G	H	I	J
Bare	73	27	0	73	27	0	2	29	43	26	2	15	0	37	3	0	43	0	0	0
Bare and Weedy	77	23	0	77	23	0	20	4	75	1	19	1	0	1	74	0	5	0	0	0
Barley	51	49	0	51	49	0	9	42	10	39	9	37	0	37	14	0	3	0	0	0
Bean	93	7	0	93	7	0	3	50	43	3	3	3	0	63	17	0	14	0	0	0
Beet	89	11	0	89	11	0	5	81	9	5	3	4	0	11	77	0	5	0	0	0
Blueberry	17	83	0	17	83	0	77	1	20	3	75	3	0	1	0	0	21	0	0	0
Carrot	45	55	0	47	53	0	43	4	41	12	42	12	0	3	26	0	18	0	0	0
Clover	3	97	0	3	97	0	16	0	3	81	15	80	0	1	0	0	3	1	0	0
Cole	75	25	0	75	25	0	7	37	33	23	5	11	1	20	43	0	20	0	0	0
Corn	83	17	0	83	17	0	20	48	31	1	15	1	0	2	79	0	3	0	0	0
Cranberry	8	92	0	8	92	0	91	1	7	1	91	0	0	1	0	0	8	0	0	0
Cucurbit	88	12	0	88	12	0	7	15	73	5	6	3	0	6	42	0	43	0	0	1
Currant	65	35	0	65	35	0	23	10	55	12	22	13	0	13	2	0	51	0	0	0
Forage	13	87	0	13	87	0	75	9	3	13	73	13	0	5	7	0	3	0	0	0
Fruit	14	86	0	14	86	0	84	5	8	3	84	3	0	9	1	0	4	0	0	0
Grain	2	98	0	2	98	0	5	1	0	95	5	94	0	1	0	0	0	0	0	0
Grassland	15	85	0	15	85	0	20	13	4	63	19	61	0	14	0	0	6	0	0	0
Lettuce	46	54	0	46	54	0	39	4	53	3	35	3	0	4	0	0	57	0	0	0
Mixed Nursery Crop	56	44	13	46	41	13	42	17	27	1	40	0	0	17	2	8	27	0	3	3
Mixed Vegetable	39	61	0	41	59	0	47	7	40	5	46	3	0	1	21	0	29	0	0	0
Mixed Wild Land	6	94	0	6	94	0	27	1	4	67	25	67	0	1	1	0	6	0	0	0
Oats	36	64	0	36	64	0	13	28	11	49	14	47	0	23	5	0	11	0	0	0
Onion	95	5	0	95	5	0	5	70	25	0	5	0	0	73	5	0	17	0	0	0
Overgrown Pasture	14	86	0	14	86	0	26	4	9	61	23	65	0	3	2	0	8	0	0	0
Pasture	9	91	0	9	91	0	68	5	7	21	67	21	1	3	1	0	7	0	0	0
Pea	93	7	0	93	7	0	2	85	6	7	2	1	0	92	3	0	1	0	0	0
Potato	79	21	0	79	21	0	3	61	11	25	1	15	0	59	12	0	12	0	0	0
Pumpkin	78	22	0	78	22	0	21	67	9	3	19	3	0	57	19	0	1	0	0	0
Raspbery	59	41	0	59	41	0	33	27	32	7	33	6	0	27	12	0	22	0	0	0
Set Aside	5	95	0	5	95	0	7	3	3	88	7	87	0	3	0	0	3	0	0	0
Specialty	83	17	0	83	17	0	5	30	59	6	5	5	0	13	35	0	41	0	0	0
Squash	89	11	0	89	11	0	6	71	20	3	8	3	0	27	54	0	9	0	0	0
Strawberry	71	29	0	71	29	0	20	7	65	8	21	4	0	6	11	0	59	0	0	0
Summer Cover	21	79	0	21	79	0	16	14	11	59	14	59	0	3	15	0	10	0	0	0
Summer Fallow	27	73	0	27	73	0	0	0	26	74	0	66	0	1	0	0	33	0	0	0
Turf	22	78	0	22	78	0	74	3	16	7	70	2	0	3	16	0	9	0	0	0
Turnip	89	11	0	89	11	0	4	47	41	8	3	3	0	11	63	0	20	0	0	0
Vegetable	72	28	0	73	27	0	6	8	76	10	7	4	0	2	22	0	65	0	0	0
Weedy	84	16	0	84	16	0	13	15	69	3	13	2	0	2	17	0	65	0	0	0
Wheat	51	49	0	51	49	0	5	30	18	47	5	37	0	1	46	0	11	0	0	0

Appendix 4. Correlation Between Image Transforms

Cells highlighted in yellow indicated a strong correlation (greater then 0.70 or less than –0.70)



Appendix 5. Error Matrices for Level 1 Classification (Trials 1 to 26)

Error matrix contains number of samples, however user and producer accuracies are corrected for bias using map marginal proportions (π_{Perm}=0.51, π_{Temp}=0.49)

	Trial 1	Reference Data			
	Class	Perm	Temp	Total	User Acc ±CI
Map Data	Perm	1253	138	1391	90.1% 1.1%
	Temp	201	1317	1518	86.8% 1.3%
	Total	1454	1455	2909	
	Prod Acc ±CI	87.7% 1.5%	89.3% 1.5%		Overall Acc 88.5% 1.2%

	Trial 2	Reference Data			
	Class	Perm	Temp	Total	User Acc ±CI
Map Data	Perm	1252	138	1390	90.1% 1.1%
	Temp	202	1317	1519	86.7% 1.3%
	Total	1454	1455	2909	
	Prod Acc ±CI	87.7% 1.5%	89.3% 1.5%		Overall Acc 88.4% 1.2%

	Trial 3	Reference Data			
	Class	Perm	Temp	Total	User Acc ±CI
Map Data	Perm	1270	138	1408	90.2% 1.1%
	Temp	184	1317	1501	87.7% 1.2%
	Total	1454	1455	2909	
	Prod Acc ±CI	88.5% 1.5%	89.5% 1.5%		Overall Acc 89.0% 1.2%

Trial 4		Reference Data			
	Class	**Perm**	**Temp**	**Total**	**User Acc ±CI**
Map Data	**Perm**	1229	174	1403	87.6% 1.2%
	Temp	225	1281	1506	85.1% 1.3%
	Total	1454	1455	2909	
	Prod Acc ±CI	86.0% 1.5%	86.7% 1.6%		**Overall Acc** 86.4% 1.3%

Trial 5		Reference Data			
	Class	**Perm**	**Temp**	**Total**	**User Acc ±CI**
Map Data	**Perm**	1238	187	1425	86.9% 1.3%
	Temp	216	1268	1484	85.4% 1.3%
	Total	1454	1455	2909	
	Prod Acc ±CI	86.2% 1.5%	86.1% 1.6%		**Overall Acc** 86.2% 1.3%

Trial 6		Reference Data			
	Class	**Perm**	**Temp**	**Total**	**User Acc ±CI**
Map Data	**Perm**	1208	166	1374	87.9% 1.2%
	Temp	246	1289	1535	84.0% 1.4%
	Total	1454	1455	2909	
	Prod Acc ±CI	85.2% 1.6%	86.9% 1.6%		**Overall Acc** 86.0% 1.3%

Trial 7		Reference Data			
	Class	**Perm**	**Temp**	**Total**	**User Acc ±CI**
Map Data	**Perm**	1222	152	1374	88.9% 1.2%
	Temp	232	1303	1535	84.9% 1.3%
	Total	1454	1455	2909	
	Prod Acc ±CI	86.1% 1.5%	88.0% 1.6%		**Overall Acc** 87.0% 1.2%

Trial 8 **Reference Data**

	Class	Perm	Temp	Total	User Acc ±CI	
Map Data	Perm	1214	177	1391	87.3%	1.2%
	Temp	240	1278	1518	84.2%	1.4%
	Total	1454	1455	2909		
	Prod Acc ±CI	85.3% 1.6%	86.3% 1.6%		Overall Acc 85.8%	1.3%

Trial 9 **Reference Data**

	Class	Perm	Temp	Total	User Acc ±CI	
Map Data	Perm	1106	286	1392	79.5%	1.5%
	Temp	348	1169	1517	77.1%	1.6%
	Total	1454	1455	2909		
	Prod Acc ±CI	78.4% 1.7%	78.1% 1.8%		Overall Acc 78.3%	1.5%

Trial 10 **Reference Data**

	Class	Perm	Temp	Total	User Acc ±CI	
Map Data	Perm	1233	169	1402	87.9%	1.2%
	Temp	221	1286	1507	85.3%	1.3%
	Total	1454	1455	2909		
	Prod Acc ±CI	86.3% 1.5%	87.1% 1.6%		Overall Acc 86.7%	1.3%

Trial 11 **Reference Data**

	Class	Perm	Temp	Total	User Acc ±CI	
Map Data	Perm	1098	289	1387	79.2%	1.5%
	Temp	356	1166	1522	76.6%	1.6%
	Total	1454	1455	2909		
	Prod Acc ±CI	78.0% 1.7%	77.8% 1.8%		Overall Acc 77.9%	1.5%

Trial 12		Reference Data				
	Class	**Perm**	**Temp**	**Total**	**User Acc ±CI**	
Map Data	**Perm**	1100	244	1344	81.8%	1.4%
	Temp	354	1211	1565	77.4%	1.6%
	Total	1454	1455	2909		
	Prod Acc ±CI	79.1% 1.7%	80.3% 1.8%		**Overall Acc** 79.7%	1.5%

Trial 13		Reference Data				
	Class	**Perm**	**Temp**	**Total**	**User Acc ±CI**	
Map Data	**Perm**	1241	157	1398	88.8%	1.2%
	Temp	213	1298	1511	85.9%	1.3%
	Total	1454	1455	2909		
	Prod Acc ±CI	86.8% 1.5%	87.9% 1.6%		**Overall Acc** 87.4%	1.2%

Trial 14		Reference Data				
	Class	**Perm**	**Temp**	**Total**	**User Acc ±CI**	
Map Data	**Perm**	1179	221	1400	84.2%	1.4%
	Temp	275	1234	1509	81.9%	1.4%
	Total	1454	1455	2909		
	Prod Acc ±CI	82.9% 1.6%	83.2% 1.7%		**Overall Acc** 83.0%	1.4%

Trial 15		Reference Data				
	Class	**Perm**	**Temp**	**Total**	**User Acc ±CI**	
Map Data	**Perm**	1061	197	1258	84.3%	1.3%
	Temp	393	1258	1651	76.2%	1.6%
	Total	1454	1455	2909		
	Prod Acc ±CI	78.8% 1.6%	82.3% 1.8%		**Overall Acc** 80.4%	1.5%

	Trial 16	**Reference Data**				
	Class	**Perm**	**Temp**	**Total**	**User Acc ±CI**	
Map Data	**Perm**	1074	393	1467	73.2%	1.6%
	Temp	380	1062	1442	73.6%	1.6%
	Total	1454	1455	2909		
	Prod Acc	74.4%	72.4%		**Overall Acc**	
	±CI	1.8%	1.8%		73.4%	1.6%

	Trial 17	**Reference Data**				
	Class	**Perm**	**Temp**	**Total**	**User Acc ±CI**	
Map Data	**Perm**	1135	281	1416	80.2%	1.5%
	Temp	319	1174	1493	78.6%	1.5%
	Total	1454	1455	2909		
	Prod Acc	79.7%	79.1%		**Overall Acc**	
	±CI	1.7%	1.8%		79.4%	1.5%

	Trial 18	**Reference Data**				
	Class	**Perm**	**Temp**	**Total**	**User Acc ±CI**	
Map Data	**Perm**	866	322	1188	72.9%	1.6%
	Temp	588	1133	1721	65.8%	1.8%
	Total	1454	1455	2909		
	Prod Acc	69.1%	69.8%		**Overall Acc**	
	±CI	1.7%	2.0%		69.4%	1.7%

	Trial 19	**Reference Data**				
	Class	**Perm**	**Temp**	**Total**	**User Acc ±CI**	
Map Data	**Perm**	1195	213	1408	84.9%	1.3%
	Temp	259	1242	1501	82.7%	1.4%
	Total	1454	1455	2909		
	Prod Acc	83.8%	83.9%		**Overall Acc**	
	±CI	1.6%	1.7%		83.8%	1.4%

Trial 20 **Reference Data**

	Class	Perm	Temp	Total	User Acc ±CI	
Map Data	Perm	1199	175	1374	87.3%	1.2%
	Temp	255	1280	1535	83.4%	1.4%
	Total	1454	1455	2909		
	Prod Acc ±CI	84.6% 1.6%	86.2% 1.6%		Overall Acc 85.4%	 1.3%

Trial 21 **Reference Data**

	Class	Perm	Temp	Total	User Acc ±CI	
Map Data	Perm	1127	182	1309	86.1%	1.3%
	Temp	327	1273	1600	79.6%	1.5%
	Total	1454	1455	2909		
	Prod Acc ±CI	81.5% 1.6%	84.5% 1.7%		Overall Acc 82.9%	 1.4%

Trial 22 **Reference Data**

	Class	Perm	Temp	Total	User Acc ±CI	
Map Data	Perm	1218	199	1417	86.0%	1.3%
	Temp	236	1256	1492	84.2%	1.4%
	Total	1454	1455	2909		
	Prod Acc ±CI	85.1% 1.6%	85.1% 1.7%		Overall Acc 85.1%	 1.3%

Trial 23 **Reference Data**

	Class	Perm	Temp	Total	User Acc ±CI	
Map Data	Perm	977	169	1146	85.3%	1.3%
	Temp	477	1286	1763	72.9%	1.6%
	Total	1454	1455	2909		
	Prod Acc ±CI	76.8% 1.6%	82.5% 1.9%		Overall Acc 79.2%	 1.5%

	Trial 24	**Reference Data**				
	Class	**Perm**	**Temp**	**Total**	**User Acc ±CI**	
Map Data	**Perm**	983	451	1434	68.5%	1.7%
	Temp	471	1004	1475	68.1%	1.7%
	Total	1454	1455	2909		
	Prod Acc ±CI	69.2% 1.8%	67.4% 1.9%		**Overall Acc** 68.3%	1.7%

	Trial 25	**Reference Data**				
	Class	**Perm**	**Temp**	**Total**	**User Acc ±CI**	
Map Data	**Perm**	969	326	1295	74.8%	1.6%
	Temp	485	1129	1614	70.0%	1.7%
	Total	1454	1455	2909		
	Prod Acc ±CI	72.3% 1.7%	72.6% 1.9%		**Overall Acc** 72.4%	1.7%

	Trial 26	**Reference Data**				
	Class	**Perm**	**Temp**	**Total**	**User Acc ±CI**	
Map Data	**Perm**	786	305	1091	72.0%	1.7%
	Temp	668	1150	1818	63.3%	1.8%
	Total	1454	1455	2909		
	Prod Acc ±CI	67.3% 1.7%	68.3% 2.0%		**Overall Acc** 67.8%	1.7%

Appendix 6. Error Matrices for Level 2 Classification (Trials 1 to 26)

Error matrix contains number of samples, however user and producer accuracies are corrected for bias using map marginal proportions (π_{Shrub} =0.072, $\pi_{\mathrm{Graminoid}}$=0.352, π_{Grain} =0.046, π_{Forb}=0.529)

	Trial 1		Reference Data					
	Class	**Shrub**	**Gram**	**Grain**	**Forb**	**Total**	**User Acc**	**'±CI**
Map Data	**Shrub**	276	34	5	35	350	78.9%	1.5%
	Gram	42	617	29	55	743	83.0%	1.4%
	Grain	3	10	207	8	228	90.8%	1.1%
	Forb	83	89	59	1357	1588	85.5%	1.3%
	Total	404	750	300	1455	2909		
	Prod Acc	54.1%	88.3%	55.1%	92.8%		**Overall Acc**	
	'±CI	4.5%	1.9%	5.0%	1.3%		84.4%	1.3%

	Trial 2		Reference Data					
	Class	**Shrub**	**Gram**	**Grain**	**Forb**	**Total**	**User Acc**	**'±CI**
Map Data	**Shrub**	272	37	9	39	357	76.2%	1.6%
	Gram	33	605	26	62	726	83.3%	1.4%
	Grain	3	12	205	5	225	91.1%	1.1%
	Forb	96	96	60	1349	1601	84.3%	1.4%
	Total	404	750	300	1455	2909		
	Prod Acc	53.1%	87.6%	55.3%	92.0%		**Overall Acc**	
	'±CI	4.5%	1.9%	5.0%	1.3%		83.7%	1.4%

Trial 3		Reference Data						
	Class	**Shrub**	**Gram**	**Grain**	**Forb**	**Total**	**User Acc**	**'±CI**
Map Data	**Shrub**	277	30	5	43	355	78.0%	1.5%
	Gram	38	603	28	65	734	82.2%	1.4%
	Grain	3	12	201	9	225	89.3%	1.1%
	Forb	86	105	66	1338	1595	83.9%	1.4%
	Total	404	750	300	1455	2909		
	Prod Acc	54.2%	87.0%	53.3%	91.4%		**Overall Acc**	
	'±CI	4.5%	2.0%	5.0%	1.4%		83.1%	1.4%

Trial 4		Reference Data						
	Class	**Shrub**	**Gram**	**Grain**	**Forb**	**Total**	**User Acc**	**'±CI**
Map Data	**Shrub**	278	32	12	37	359	77.4%	1.5%
	Gram	33	607	28	61	729	83.3%	1.4%
	Grain	1	12	198	11	222	89.2%	1.2%
	Forb	92	99	62	1346	1599	84.2%	1.4%
	Total	404	750	300	1455	2909		
	Prod Acc	54.4%	87.5%	53.2%	91.9%		**Overall Acc**	
	'±CI	4.5%	1.9%	5.0%	1.3%		83.6%	1.4%

	Trial 5			Reference Data				
	Class	Shrub	Gram	Grain	Forb	Total	User Acc	'±CI
Map Data	Shrub	248	34	10	45	337	73.6%	1.6%
	Gram	36	597	37	79	749	79.7%	1.5%
	Grain	0	19	181	7	207	87.4%	1.2%
	Forb	120	100	72	1324	1616	81.9%	1.4%
	Total	404	750	300	1455	2909		
	Prod Acc	48.5%	86.4%	48.5%	90.0%		Overall Acc	
	'±CI	4.3%	2.0%	4.7%	1.5%		80.8%	1.5%

	Trial 6			Reference Data				
	Class	Shrub	Gram	Grain	Forb	Total	User Acc	'±CI
Map Data	Shrub	262	32	5	46	345	75.9%	1.6%
	Gram	37	606	41	86	770	78.7%	1.5%
	Grain	0	15	184	11	210	87.6%	1.2%
	Forb	105	97	70	1312	1584	82.8%	1.4%
	Total	404	750	300	1455	2909		
	Prod Acc	51.2%	86.7%	48.5%	89.5%		Overall Acc	
	'±CI	4.4%	2.0%	4.6%	1.5%		81.1%	1.4%

Trial 7 **Reference Data**

	Class	Shrub	Gram	Grain	Forb	Total	User Acc	'±CI
Map Data	**Shrub**	262	32	5	46	345	75.9%	1.6%
	Gram	37	606	41	86	770	78.7%	1.5%
	Grain	0	15	184	11	210	87.6%	1.2%
	Forb	105	97	70	1312	1584	82.8%	1.4%
	Total	404	750	300	1455	2909		
	Prod Acc	51.2%	86.7%	48.5%	89.5%		**Overall Acc**	
	'±CI	4.4%	2.0%	4.6%	1.5%		81.1%	1.4%

Trial 8 **Reference Data**

	Class	Shrub	Gram	Grain	Forb	Total	User Acc	'±CI
Map Data	**Shrub**	246	38	8	50	342	71.9%	1.7%
	Gram	40	580	46	75	741	78.3%	1.5%
	Grain	1	19	179	12	211	84.8%	1.3%
	Forb	117	113	67	1318	1615	81.6%	1.4%
	Total	404	750	300	1455	2909		
	Prod Acc	47.3%	84.8%	46.4%	89.9%		**Overall Acc**	
	'±CI	4.3%	2.1%	4.6%	1.5%		79.9%	1.5%

	Trial 9			Reference Data				
	Class	**Shrub**	**Gram**	**Grain**	**Forb**	**Total**	**User Acc**	**'±CI**
Map Data	**Shrub**	180	64	9	39	292	61.6%	1.8%
	Gram	67	487	58	106	718	67.8%	1.7%
	Grain	5	36	136	26	203	67.0%	1.7%
	Forb	152	163	97	1284	1696	75.7%	1.6%
	Total	404	750	300	1455	2909		
	Prod Acc	35.3%	76.1%	33.8%	85.6%		**Overall Acc**	
	'±CI	3.8%	2.4%	4.2%	1.7%		71.5%	1.7%

	Trial 10			Reference Data				
	Class	**Shrub**	**Gram**	**Grain**	**Forb**	**Total**	**User Acc**	**'±CI**
Map Data	**Shrub**	268	24	13	31	336	79.8%	1.5%
	Gram	32	596	22	67	717	83.1%	1.4%
	Grain	2	15	209	12	238	87.8%	1.2%
	Forb	102	115	56	1345	1618	83.1%	1.4%
	Total	404	750	300	1455	2909		
	Prod Acc	53.7%	86.5%	56.1%	91.3%		**Overall Acc**	
	'±CI	4.4%	2.0%	5.3%	1.4%		83.1%	1.4%

Trial 11				Reference Data				
	Class	**Shrub**	**Gram**	**Grain**	**Forb**	**Total**	**User Acc**	**'±CI**
Map Data	**Shrub**	174	52	13	49	288	60.4%	1.8%
	Gram	70	489	51	101	711	68.8%	1.7%
	Grain	6	33	127	30	196	64.8%	1.8%
	Forb	154	176	109	1275	1714	74.4%	1.6%
	Total	404	750	300	1455	2909		
	Prod Acc	34.2%	76.3%	32.6%	85.0%		**Overall Acc**	
	'±CI	3.7%	2.4%	4.2%	1.7%		71.0%	1.7%

Trial 12				Reference Data				
	Class	**Shrub**	**Gram**	**Grain**	**Forb**	**Total**	**User Acc**	**'±CI**
Map Data	**Shrub**	144	58	13	55	270	53.3%	1.8%
	Gram	71	476	62	99	708	67.2%	1.7%
	Grain	4	37	109	16	166	65.7%	1.8%
	Forb	185	179	116	1285	1765	72.8%	1.7%
	Total	404	750	300	1455	2909		
	Prod Acc	29.4%	74.9%	30.6%	84.9%		**Overall Acc**	
	'±CI	3.6%	2.4%	3.9%	1.7%		69.1%	1.7%

Trial 13	Reference Data							
	Class	Shrub	Gram	Grain	Forb	Total	User Acc	±CI
Map Data	**Shrub**	269	38	4	33	344	78.2%	1.5%
	Gram	37	615	27	62	741	83.0%	1.4%
	Grain	2	8	206	7	223	92.4%	1.0%
	Forb	96	89	63	1353	1601	84.5%	1.3%
	Total	404	750	300	1455	2909		
	Prod Acc	53.1%	88.2%	55.4%	92.2%		**Overall Acc**	
	±CI	4.4%	1.9%	5.0%	1.3%		83.9%	1.4%

Trial 14	Reference Data							
	Class	Shrub	Gram	Grain	Forb	Total	User Acc	±CI
Map Data	**Shrub**	234	45	7	50	336	69.6%	1.7%
	Gram	60	551	27	91	729	75.6%	1.6%
	Grain	0	14	184	15	213	76.4%	1.3%
	Forb	110	140	82	1299	1631	79.6%	1.5%
	Total	404	750	300	1455	2909		
	Prod Acc	43.6%	82.1%	49.4%	87.9%		**Overall Acc**	
	±CI	4.1%	2.2%	4.8%	1.6%		77.8%	1.5%

Trial 15 **Reference Data**

	Class	Shrub	Gram	Grain	Forb	Total	User Acc	'±CI
Map Data	**Shrub**	142	59	7	46	254	55.9%	1.8%
	Gram	95	528	76	111	810	65.2%	1.8%
	Grain	2	24	103	12	141	73.0%	1.6%
	Forb	165	139	114	1286	1704	75.5%	1.6%
	Total	404	750	300	1455	2909		
	Prod Acc	30.1%	77.2%	32.5%	86.0%		**Overall Acc**	
	'±CI	3.5%	2.5%	3.7%	1.7%		70.3%	1.7%

Trial 16 **Reference Data**

	Class	Shrub	Gram	Grain	Forb	Total	User Acc	'±CI
Map Data	**Shrub**	138	43	15	52	248	55.6%	1.8%
	Gram	112	495	33	162	802	61.7%	1.8%
	Grain	20	11	106	49	186	57.0%	1.8%
	Forb	134	201	146	1192	1673	71.2%	1.7%
	Total	404	750	300	1455	2909		
	Prod Acc	29.3%	73.4%	28.9%	79.3%		**Overall Acc**	
	'±CI	3.5%	2.6%	4.2%	1.8%		66.1%	1.7%

Trial 17		Reference Data						
	Class	**Shrub**	**Gram**	**Grain**	**Forb**	**Total**	**User Acc**	**'±CI**
Map Data	**Shrub**	167	51	16	49	283	59.0%	1.8%
	Gram	79	453	41	132	705	64.3%	1.8%
	Grain	18	34	156	26	234	66.7%	1.7%
	Forb	140	212	87	1248	1687	74.0%	1.6%
	Total	404	750	300	1455	2909		
	Prod Acc	32.8%	72.4%	37.4%	82.4%		**Overall Acc**	
	'±CI	3.7%	2.5%	4.7%	1.7%		69.1%	1.7%

Trial 18		Reference Data						
	Class	**Shrub**	**Gram**	**Grain**	**Forb**	**Total**	**User Acc**	**'±CI**
Map Data	**Shrub**	166	28	13	42	249	66.7%	1.7%
	Gram	49	355	38	114	556	63.8%	1.8%
	Grain	17	22	36	43	118	30.5%	1.7%
	Forb	172	345	213	1256	1986	63.2%	1.8%
	Total	404	750	300	1455	2909		
	Prod Acc	36.5%	67.4%	14.4%	76.8%		**Overall Acc**	
	'±CI	3.6%	2.5%	3.5%	2.0%		62.2%	1.8%

Trial 19 **Reference Data**

	Class	Shrub	Gram	Grain	Forb	Total	User Acc	'±CI
Map Data	**Shrub**	240	37	6	37	320	75.0%	1.6%
	Gram	44	540	21	77	682	79.2%	1.5%
	Grain	4	11	186	21	222	83.8%	1.4%
	Forb	116	162	87	1320	1685	78.3%	1.5%
	Total	404	750	300	1455	2909		
	Prod Acc	47.3%	81.9%	49.6%	88.8%		**Overall Acc**	
	'±CI	4.2%	2.2%	4.9%	1.5%		78.6%	1.5%

Trial 20 **Reference Data**

	Class	Shrub	Gram	Grain	Forb	Total	User Acc	'±CI
Map Data	**Shrub**	232	26	14	35	307	75.6%	1.6%
	Gram	26	595	30	75	726	82.0%	1.4%
	Grain	3	22	184	14	223	82.5%	1.4%
	Forb	143	107	72	1331	1653	80.5%	1.5%
	Total	404	750	300	1455	2909		
	Prod Acc	47.9%	86.5%	48.4%	90.0%		**Overall Acc**	
	'±CI	4.2%	2.0%	4.9%	1.5%		80.8%	1.5%

Trial 21			Reference Data					
	Class	Shrub	Gram	Grain	Forb	Total	User Acc	'±CI
Map Data	Shrub	253	34	10	45	342	74.0%	1.6%
	Gram	42	606	48	91	787	77.0%	1.6%
	Grain	2	15	160	8	185	86.5%	1.3%
	Forb	107	95	82	1311	1595	82.2%	1.4%
	Total	404	750	300	1455	2909		
	Prod Acc	49.3%	86.5%	44.2%	89.3%		Overall Acc	
	'±CI	4.3%	2.1%	4.3%	1.5%		80.0%	1.5%

Trial 22			Reference Data					
	Class	Shrub	Gram	Grain	Forb	Total	User Acc	'±CI
Map Data	Shrub	243	48	12	47	350	69.4%	1.7%
	Gram	53	569	24	76	722	78.8%	1.5%
	Grain	2	17	199	11	229	86.9%	1.3%
	Forb	106	116	65	1321	1608	82.2%	1.4%
	Total	404	750	300	1455	2909		
	Prod Acc	45.0%	84.3%	53.2%	89.9%		Overall Acc	
	'±CI	4.2%	2.1%	5.1%	1.5%		80.3%	1.5%

Trial 23 **Reference Data**

	Class	Shrub	Gram	Grain	Forb	Total	User Acc	'±CI
Map Data	**Shrub**	90	46	6	13	155	58.1%	1.8%
	Gram	124	512	102	152	890	57.5%	1.8%
	Grain	4	31	66	4	105	62.9%	1.8%
	Forb	186	161	126	1286	1759	73.1%	1.6%
	Total	404	750	300	1455	2909		
	Prod Acc	28.1%	70.8%	26.5%	85.1%		**Overall Acc**	
	'±CI	3.2%	2.6%	3.5%	1.7%		66.1%	1.7%

Trial 24 **Reference Data**

	Class	Shrub	Gram	Grain	Forb	Total	User Acc	'±CI
Map Data	**Shrub**	79	26	13	50	168	47.0%	1.9%
	Gram	125	463	38	187	813	56.9%	1.8%
	Grain	14	12	83	40	149	55.7%	1.8%
	Forb	186	249	166	1178	1779	66.2%	1.8%
	Total	404	750	300	1455	2909		
	Prod Acc	22.9%	69.3%	26.6%	75.3%		**Overall Acc**	
	'±CI	3.2%	2.7%	4.0%	1.9%		61.1%	1.8%

	Trial 25			Reference Data				
	Class	**Shrub**	**Gram**	**Grain**	**Forb**	**Total**	**User Acc**	**'±CI**
Map Data	**Shrub**	94	53	11	30	188	50.0%	1.9%
	Gram	86	420	43	152	701	59.9%	1.8%
	Grain	32	28	134	43	237	56.5%	1.8%
	Forb	192	249	112	1230	1783	69.0%	1.7%
	Total	404	750	300	1455	2909		
	Prod Acc	25.3%	67.9%	30.8%	79.1%		**Overall Acc**	
	'±CI	3.3%	2.6%	4.5%	1.8%		63.8%	1.8%

	Trial 26			Reference Data				
	Class	**Shrub**	**Gram**	**Grain**	**Forb**	**Total**	**User Acc**	**'±CI**
Map Data	**Shrub**	150	21	7	32	210	71.4%	1.7%
	Gram	49	332	25	112	518	64.1%	1.8%
	Grain	8	13	11	11	43	25.6%	1.6%
	Forb	197	384	257	1300	2138	60.8%	1.8%
	Total	404	750	300	1455	2909		
	Prod Acc	36.2%	66.0%	12.5%	76.5%		**Overall Acc**	
	'±CI	3.4%	2.4%	3.5%	2.0%		61.1%	1.8%

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Appendix 7. Error Matrices for Level 3 Classification (Trials 1 to 26)

Error matrix contains number of samples, however user and producer accuracies are corrected for bias using map marginal proportions ($\pi_{Gram-Active}$=0.209, $\pi_{Gram - Passive}$=0.130, $\pi_{Shrub-Berry}$ =0.070, $\pi_{Shrub-Nursery}$=0.006, π_{Grain} =0.056, $\pi_{Forb-Berry}$=0.005, $\pi_{Forb-Summer Harvest}$ =0.483, $\pi_{Forb-Fall Harvest}$=0.041).

Trial 1		Reference Data										
	Class	**Gram Active**	**Gram Passive**	**Shrub Berry**	**Shrub Nursery**	**Grain**	**Forb Berry**	**Forb Sum Harvest**	**Forb Fall Harvest**	**Total**	**User Acc ±CI**	
Map Data	**Gram Active**	237	23	13	3	8	4	20	8	316	75.0%	1.6%
	Gram Passive	40	291	7	2	16	2	19	5	382	76.2%	1.6%
	Shrub Berry	25	13	211	7	6	9	24	4	299	70.6%	1.7%
	Shrub Nursery	1	1	4	67	2	0	5	0	80	83.8%	1.4%
	Grain	11	8	5	1	214	0	7	2	248	86.3%	1.3%
	Forb Berry	0	1	1	0	1	20	5	0	28	71.4%	1.7%
	Forb Sum Harv	59	36	56	24	50	38	1137	40	1440	79.0%	1.5%
	Forb Fall Harv	2	2	3	0	3	2	13	91	116	78.4%	1.5%
	Total	375	375	300	104	300	75	1230	150	2909		
	Prod Acc	78.7%	74.9%	60.4%	27.9%	61.4%	16.8%	92.1%	59.5%		**Overall Acc ±CI**	
	±CI	3.0%	3.9%	5.3%	7.9%	5.2%	5.8%	1.5%	6.4%		77.6%	1.5%

Trial 2		Reference Data										
	Class	**Gram Active**	**Gram Passive**	**Shrub Berry**	**Shrub Nursery**	**Grain**	**Forb Berry**	**Forb Summer Harvest**	**Forb Fall Harvest**	**Total**	**User Acc ±CI**	
Map Data	**Gram Active**	232	36	20	5	13	2	18	10	336	69.0%	1.7%
	Gram Passive	45	281	12	1	7	1	18	3	368	76.4%	1.6%
	Shrub Berry	18	13	208	5	6	8	25	4	287	72.5%	1.7%
	Shrub Nursery	0	1	2	67	4	0	2	0	76	88.2%	1.2%
	Grain	11	6	4	1	213	0	12	2	249	85.5%	1.3%
	Forb Berry	4	0	1	0	1	25	4	0	35	71.4%	1.7%
	Forb Sum Harv	62	37	53	25	54	37	1138	51	1457	78.1%	1.5%
	Forb Fall Harv	3	1	0	0	2	2	13	80	101	79.2%	1.5%
	Total	375	375	300	104	300	75	1230	150	2909		
	Prod Acc	76.2%	71.4%	58.9%	28.0%	60.5%	18.7%	92.1%	55.8%		**Overall Acc ±CI**	
	±CI	3.2%	3.8%	5.1%	7.4%	5.2%	6.5%	1.5%	6.1%		76.1%	1.6%

Trial 3		Reference Data										
	Class	Gram Active	Gram Passive	Shrub Berry	Shrub Nursery	Grain	Forb Berry	Forb Summer Harvest	Forb Fall Harvest	Total	User Acc ±CI	
Map Data	Gram Active	245	31	17	6	16	1	23	7	346	70.8%	1.7%
	Gram Passive	34	291	7	1	11	0	20	6	370	78.6%	1.5%
	Shrub Berry	21	10	199	8	4	7	23	3	275	72.4%	1.7%
	Shrub Nursery	2	1	2	61	2	0	1	0	69	88.4%	1.2%
	Grain	15	10	3	1	210	1	8	1	249	84.3%	1.3%
	Forb Berry	1	0	0	2	1	30	7	1	42	73.1%	1.7%
	Forb Sum Harv	54	32	71	25	52	33	1140	38	1445	78.9%	1.5%
	Forb Fall Harv	3	0	1	0	4	3	8	94	113	83.2%	1.4%
	Total	375	375	300	104	300	75	1230	150	2909		
	Prod Acc	78.7%	74.9%	57.4%	25.7%	58.3%	20.6%	92.1%	62.9%		Overall Acc ±CI	
	±CI	3.1%	3.8%	5.0%	6.7%	5.1%	7.2%	1.5%	6.3%		77.2%	1.5%

Trial 4		**Reference Data**										
Map Data	**Class**	**Gram Active**	**Gram Passive**	**Shrub Berry**	**Shrub Nursery**	**Grain**	**Forb Berry**	**Forb Summer Harvest**	**Forb Fall Harvest**	**Total**	**User Acc ±CI**	
	Gram Active	225	29	18	6	15	2	25	6	326	69.0%	1.7%
	Gram Passive	40	284	8	2	12	3	19	5	373	76.1%	1.6%
	Shrub Berry	22	14	212	8	4	7	24	5	296	71.6%	1.7%
	Shrub Nursery	2	1	5	58	5	0	2	1	74	78.4%	1.5%
	Grain	14	6	2	0	209	0	13	4	248	84.3%	1.3%
	Forb Berry	0	0	1	0	2	27	7	0	37	73.0%	1.6%
	Forb Sum Harv	68	41	54	30	51	33	1130	41	1448	78.0%	1.5%
	Forb Fall Harv	4	0	0	0	2	3	10	88	107	82.2%	1.4%
	Total	375	375	300	104	300	75	1230	150	2909		
	Prod Acc	75.6%	72.8%	60.1%	21.7%	58.7%	19.5%	91.2%	61.0%		**Overall Acc ±CI**	
	±CI	3.2%	3.9%	5.2%	6.5%	5.1%	6.6%	1.5%	6.3%		75.9%	1.6%

Trial 5		**Reference Data**										
	Class	**Gram Active**	**Gram Passive**	**Shrub Berry**	**Shrub Nursery**	**Grain**	**Forb Berry**	**Forb Summer Harvest**	**Forb Fall Harvest**	**Total**	**User Acc ±CI**	
Map Data	**Gram Active**	227	27	10	6	10	4	26	8	318	71.4%	1.7%
	Gram Passive	38	283	6	2	16	1	17	6	369	76.7%	1.6%
	Shrub Berry	24	9	195	7	7	11	27	5	285	68.4%	1.7%
	Shrub Nursery	5	3	9	60	3	0	6	0	86	69.8%	1.7%
	Grain	18	19	4	0	198	0	8	2	249	79.5%	1.5%
	Forb Berry	1	0	0	1	1	20	11	1	35	58.8%	1.8%
	Forb Sum Harv	60	34	74	28	64	36	1125	51	1472	76.4%	1.6%
	Forb Fall Harv	2	0	2	0	1	3	10	77	95	81.1%	1.5%
	Total	375	375	300	104	300	75	1230	150	2909		
	Prod Acc	77.1%	73.7%	57.6%	20.5%	55.4%	14.0%	90.7%	56.2%		**Overall Acc ±CI**	
	±CI	3.1%	3.9%	5.3%	7.1%	5.1%	6.2%	1.6%	6.0%		75.1%	1.6%

Trial 6		**Reference Data**										
Map Data	**Class**	**Gram Active**	**Gram Passive**	**Shrub Berry**	**Shrub Nursery**	**Grain**	**Forb Berry**	**Forb Summer Harvest**	**Forb Fall Harvest**	**Total**	**User Acc ±CI**	
	Gram Active	217	32	13	7	12	2	21	10	314	69.1%	1.7%
	Gram Passive	49	286	9	0	18	0	22	7	391	73.1%	1.6%
	Shrub Berry	20	7	184	3	6	9	25	5	259	71.0%	1.7%
	Shrub Nursery	2	1	6	57	3	0	3	0	72	79.2%	1.5%
	Grain	16	8	0	0	193	0	6	2	225	85.8%	1.3%
	Forb Berry	2	2	1	0	1	26	9	0	41	63.4%	1.8%
	Forb Sum Harv	64	39	87	37	65	35	1126	44	1497	75.2%	1.6%
	Forb Fall Harv	5	0	0	0	2	3	18	82	110	74.5%	1.6%
	Total	375	375	300	104	300	75	1230	150	2909		
	Prod Acc	74.9%	71.4%	55.3%	20.9%	56.0%	17.4%	90.6%	54.8%		**Overall Acc ±CI**	
	±CI	3.2%	4.0%	5.0%	6.2%	4.9%	6.9%	1.6%	6.3%		73.9%	1.6%

Trial 7		Reference Data										
Map Data	Class	Gram Active	Gram Passive	Shrub Berry	Shrub Nursery	Grain	Forb Berry	Forb Summer Harvest	Forb Fall Harvest	Total	User Acc ±CI	
	Gram Active	224	31	12	5	16	1	23	12	324	69.1%	1.7%
	Gram Passive	41	293	10	1	13	0	19	6	383	76.5%	1.6%
	Shrub Berry	20	6	192	4	5	9	29	3	268	71.6%	1.7%
	Shrub Nursery	1	1	1	57	1	0	1	0	62	91.9%	1.0%
	Grain	17	11	1	2	193	0	13	2	239	80.8%	1.5%
	Forb Berry	1	2	2	0	1	26	6	0	38	68.4%	1.7%
	Forb Sum Harv	69	31	82	35	69	37	1118	52	1493	74.9%	1.6%
	Forb Fall Harv	2	0	0	0	2	2	21	75	102	73.5%	1.6%
	Total	375	375	300	104	300	75	1230	150	2909		
	Prod Acc	75.7%	74.2%	56.8%	24.6%	53.4%	18.9%	89.7%	51.8%		Overall Acc ±CI	
	±CI	3.2%	3.8%	5.0%	6.0%	4.9%	6.9%	1.6%	6.1%		74.0%	1.6%

Trial 8		Reference Data										
Map Data	Class	Gram Active	Gram Passive	Shrub Berry	Shrub Nursery	Grain	Forb Berry	Forb Summer Harvest	Forb Fall Harvest	Total	User Acc ±CI	
	Gram Active	224	31	12	5	16	1	23	12	324	69.1%	1.7%
	Gram Passive	41	293	10	1	13	0	19	6	383	76.5%	1.6%
	Shrub Berry	20	6	192	4	5	9	29	3	268	71.6%	1.7%
	Shrub Nursery	1	1	1	57	1	0	1	0	62	91.9%	1.0%
	Grain	17	11	1	2	193	0	13	2	239	80.8%	1.5%
	Forb Berry	1	2	2	0	1	26	6	0	38	68.4%	1.7%
	Forb Sum Harv	69	31	82	35	69	37	1118	52	1493	74.9%	1.6%
	Forb Fall Harv	2	0	0	0	2	2	21	75	102	73.5%	1.6%
	Total	375	375	300	104	300	75	1230	150	2909		
	Prod Acc	75.7%	74.2%	56.8%	24.6%	53.4%	18.9%	89.7%	51.8%		Overall Acc ±CI	
	±CI	3.2%	3.8%	5.0%	6.0%	4.9%	6.9%	1.6%	6.1%		74.0%	1.6%

Trial 9		Reference Data									
	Class	Gram Active	Gram Passive	Shrub Berry	Shrub Nursery	Grain	Forb Berry	Forb Summer Harvest	Forb Fall Harvest	Total	User Acc ±CI
Map Data	Gram Active	169	41	45	4	19	7	38	8	331	51.1% 1.9%
	Gram Passive	51	225	15	4	29	3	36	8	371	60.6% 1.8%
	Shrub Berry	37	13	119	16	9	4	47	6	251	47.4% 1.9%
	Shrub Nursery	11	0	12	43	1	0	10	0	77	55.8% 1.8%
	Grain	16	23	7	2	148	1	37	0	234	63.2% 1.8%
	Forb Berry	5	1	3	0	2	9	8	0	28	32.1% 1.7%
	Forb Sum Harv	78	69	99	34	86	51	1029	81	1527	67.4% 1.7%
	Forb Fall Harv	8	3	0	1	6	0	25	47	90	52.2% 1.9%
	Total	375	375	300	104	300	75	1230	150	2909	51.1% 1.9%
	Prod Acc	63.3%	57.4%	32.8%	13.9%	39.1%	7.0%	81.8%	37.7%		Overall Acc ±CI
	±CI	3.8%	4.1%	4.4%	6.0%	4.6%	5.0%	2.0%	6.1%		60.6% 1.8%

Trial 10		Reference Data										
Map Data	Class	Gram Active	Gram Passive	Shrub Berry	Shrub Nursery	Grain	Forb Berry	Forb Summer Harvest	Forb Fall Harvest	Total	User Acc ±CI	
	Gram Active	234	47	15	3	11	2	22	12	346	67.6%	1.7%
	Gram Passive	45	285	2	0	9	0	26	6	373	76.4%	1.6%
	Shrub Berry	11	9	203	5	4	8	27	2	269	75.5%	1.6%
	Shrub Nursery	4	0	4	67	2	0	2	0	79	84.8%	1.3%
	Grain	10	7	3	1	207	0	11	0	239	86.6%	1.3%
	Forb Berry	3	2	1	0	0	18	4	0	28	64.3%	1.8%
	Forb Sum Harv	63	25	72	28	65	46	1127	52	1478	76.3%	1.6%
	Forb Fall Harv	5	0	0	0	2	1	11	78	97	80.4%	1.5%
	Total	375	375	300	104	300	75	1230	150	2909	67.6%	1.7%
	Prod Acc	76.1%	70.8%	60.6%	28.3%	59.4%	15.5%	90.7%	55.0%		Overall Acc ±CI	
	±CI	3.2%	3.8%	5.0%	7.9%	5.0%	6.1%	1.6%	5.9%		75.1%	1.6%

Trial 11		Reference Data										
	Class	**Gram Active**	**Gram Passive**	**Shrub Berry**	**Shrub Nursery**	**Grain**	**Forb Berry**	**Forb Summer Harvest**	**Forb Fall Harvest**	**Total**	**User Acc ±CI**	
Map Data	**Gram Active**	169	39	49	3	13	6	40	8	327	51.7%	1.9%
	Gram Passive	47	229	17	2	32	2	27	6	362	63.3%	1.8%
	Shrub Berry	40	15	111	15	8	2	40	10	241	46.1%	1.8%
	Shrub Nursery	7	2	14	39	1	2	5	1	71	54.9%	1.8%
	Grain	17	22	9	2	145	1	37	0	233	62.2%	1.8%
	Forb Berry	3	0	2	0	3	9	13	0	30	30.0%	1.7%
	Forb Sum Harv	81	65	97	43	91	53	1043	81	1554	67.1%	1.7%
	Forb Fall Harv	11	3	1	0	7	0	25	44	91	48.4%	1.9%
	Total	375	375	300	104	300	75	1230	150	2909		
	Prod Acc	62.9%	59.3%	31.1%	13.3%	39.1%	6.8%	82.3%	35.8%		**Overall Acc ±CI**	
	±CI	3.7%	4.1%	4.3%	5.9%	4.7%	5.2%	2.0%	6.2%		60.6%	1.8%

Trial 12		Reference Data									
	Class	**Gram Active**	**Gram Passive**	**Shrub Berry**	**Shrub Nursery**	**Grain**	**Forb Berry**	**Forb Summer Harvest**	**Forb Fall Harvest**	**Total**	**User Acc ±CI**
Map Data	**Gram Active**	164	39	56	9	23	3	56	7	357	45.9% 1.8%
	Gram Passive	44	226	15	1	34	3	32	6	361	62.6% 1.8%
	Shrub Berry	40	11	111	12	11	2	36	11	234	47.4% 1.9%
	Shrub Nursery	7	3	17	36	3	2	10	0	78	46.2% 1.8%
	Grain	22	29	6	2	143	2	41	0	245	58.4% 1.8%
	Forb Berry	0	1	1	0	2	14	10	0	28	50.0% 1.9%
	Forb Sum Harv	91	64	91	44	83	48	1017	79	1517	67.0% 1.7%
	Forb Fall Harv	7	2	3	0	1	1	28	47	89	52.8% 1.9%
	Total	375	375	300	104	300	75	1230	150	2909	
	Prod Acc	59.5%	59.9%	31.8%	10.2%	36.6%	11.9%	80.2%	38.3%		**Overall Acc ±CI**
	±CI	3.9%	4.1%	4.3%	5.3%	4.7%	6.0%	2.0%	6.2%		59.4% 1.8%

Trial 13		Reference Data										
	Class	Gram Active	Gram Passive	Shrub Berry	Shrub Nursery	Grain	Forb Berry	Forb Summer Harvest	Forb Fall Harvest	Total	User Acc ±CI	
Map Data	Gram Active	219	30	18	5	12	2	19	6	311	70.4%	1.7%
	Gram Passive	49	284	4	0	9	1	16	6	369	77.0%	1.6%
	Shrub Berry	23	10	219	8	4	8	27	3	302	72.5%	1.7%
	Shrub Nursery	3	0	5	61	2	0	2	0	73	83.6%	1.4%
	Grain	13	7	2	3	214	0	11	3	253	84.6%	1.3%
	Forb Berry	0	0	0	0	0	22	3	0	25	88.0%	1.2%
	Forb Sum Harv	63	44	50	27	55	39	1144	41	1463	78.2%	1.5%
	Forb Fall Harv	5	0	2	0	4	3	8	91	113	80.5%	1.5%
	Total	375	375	300	104	300	75	1230	150	2909		
	Prod Acc	75.3%	72.2%	61.7%	24.8%	59.7%	21.2%	92.4%	61.0%		Overall Acc ±CI	
	±CI	3.2%	3.8%	5.2%	6.9%	5.2%	5.6%	1.4%	6.4%		76.5%	1.6%

Trial 14		Reference Data										
	Class	**Gram Active**	**Gram Passive**	**Shrub Berry**	**Shrub Nursery**	**Grain**	**Forb Berry**	**Forb Summer Harvest**	**Forb Fall Harvest**	**Total**	**User Acc ±CI**	
Map Data	**Gram Active**	217	33	26	11	21	3	37	10	358	60.6%	1.8%
	Gram Passive	34	239	8	3	24	2	33	9	352	67.9%	1.7%
	Shrub Berry	23	15	179	3	3	12	40	3	278	64.4%	1.8%
	Shrub Nursery	3	1	4	53	1	0	4	0	66	80.3%	1.5%
	Grain	11	12	3	1	183	1	29	4	244	75.0%	1.6%
	Forb Berry	1	0	3	1	2	14	6	0	27	51.9%	1.9%
	Forb Sum Harv	84	73	77	32	65	43	1070	59	1503	71.2%	1.7%
	Forb Fall Harv	2	2	0	0	1	0	11	65	81	80.2%	1.5%
	Total	375	375	300	104	300	75	1230	150	2909		
	Prod Acc	72.0%	63.7%	50.4%	19.8%	48.9%	12.4%	85.6%	52.4%		**Overall Acc ±CI**	
	±CI	3.5%	4.0%	5.0%	5.7%	4.9%	6.0%	1.8%	5.7%		68.6%	1.7%

Trial 15		Reference Data										
Map Data	Class	Gram Active	Gram Passive	Shrub Berry	Shrub Nursery	Grain	Forb Berry	Forb Summer Harvest	Forb Fall Harvest	Total	User Acc ±CI	
	Gram Active	160	70	38	2	29	5	39	8	351	45.6%	1.8%
	Gram Passive	71	196	45	1	37	1	41	10	402	48.8%	1.9%
	Shrub Berry	27	24	95	4	7	6	47	11	221	43.0%	1.8%
	Shrub Nursery	14	3	10	50	1	0	11	0	89	56.2%	1.8%
	Grain	16	28	5	1	117	2	25	3	197	59.4%	1.8%
	Forb Berry	3	2	2	0	1	8	8	0	24	33.3%	1.7%
	Forb Sum Harv	81	51	90	46	103	53	1042	84	1550	67.2%	1.7%
	Forb Fall Harv	3	1	15	0	5	0	17	34	75	45.3%	1.8%
	Total	375	375	300	104	300	75	1230	150	2909		
	Prod Acc	59.7%	46.0%	28.4%	15.8%	33.3%	7.4%	82.2%	32.4%		Overall Acc ±CI	
	±CI	3.9%	4.1%	4.2%	6.8%	4.2%	5.2%	2.0%	6.0%		57.0%	1.8%

Trial 16		Reference Data										
	Class	**Gram Active**	**Gram Passive**	**Shrub Berry**	**Shrub Nursery**	**Grain**	**Forb Berry**	**Forb Summer Harvest**	**Forb Fall Harvest**	**Total**	**User Acc ±CI**	
Map Data	**Gram Active**	155	72	56	8	10	4	49	16	370	41.9%	1.8%
	Gram Passive	60	169	21	5	19	0	52	2	328	51.5%	1.9%
	Shrub Berry	22	21	88	5	12	2	52	11	213	41.3%	1.8%
	Shrub Nursery	11	6	5	53	4	4	16	4	103	51.5%	1.9%
	Grain	17	6	16	4	136	0	41	13	233	58.4%	1.8%
	Forb Berry	1	0	6	0	0	5	8	0	20	25.0%	1.6%
	Forb Sum Harv	94	99	104	29	108	60	993	51	1538	64.6%	1.8%
	Forb Fall Harv	15	2	4	0	11	0	19	53	104	51.0%	1.9%
	Total	375	375	300	104	300	75	1230	150	2909		
	Prod Acc	55.1%	45.2%	26.6%	14.1%	37.0%	5.7%	78.4%	38.8%		**Overall Acc ±CI**	
	±CI	4.0%	3.9%	4.1%	6.6%	4.7%	4.9%	2.1%	6.4%		55.3%	1.8%

Trial 17		Reference Data										
	Class	Gram Active	Gram Passive	Shrub Berry	Shrub Nursery	Grain	Forb Berry	Forb Summer Harvest	Forb Fall Harvest	Total	User Acc ±CI	
Map Data	Gram Active	155	55	30	19	13	2	39	17	330	47.0%	1.9%
	Gram Passive	56	175	23	10	28	7	39	10	348	50.3%	1.9%
	Shrub Berry	27	18	122	6	11	5	29	8	226	54.0%	1.8%
	Shrub Nursery	18	5	3	35	1	0	11	1	74	47.3%	1.9%
	Grain	13	27	12	3	171	5	36	2	269	63.6%	1.8%
	Forb Berry	3	2	1	1	1	10	14	0	32	31.3%	1.7%
	Forb Sum Harv	96	87	96	29	73	45	1039	59	1524	68.2%	1.7%
	Forb Fall Harv	7	6	13	1	2	1	23	53	106	50.0%	1.9%
	Total	375	375	300	104	300	75	1230	150	2909		
	Prod Acc	59.5%	46.0%	36.5%	9.0%	43.4%	7.3%	82.9%	36.0%		Overall Acc ±CI	
	±CI	3.9%	4.0%	4.4%	4.5%	5.1%	5.4%	1.9%	6.1%		59.1%	1.8%

Trial 18		Reference Data										
	Class	**Gram Active**	**Gram Passive**	**Shrub Berry**	**Shrub Nursery**	**Grain**	**Forb Berry**	**Forb Summer Harvest**	**Forb Fall Harvest**	**Total**	**User Acc ±CI**	
Map Data	**Gram Active**	154	29	15	23	18	9	58	8	314	49.0%	1.9%
	Gram Passive	40	147	7	3	22	5	49	14	287	51.2%	1.9%
	Shrub Berry	11	15	138	8	12	8	41	5	238	58.0%	1.8%
	Shrub Nursery	8	0	4	34	2	0	10	1	59	57.6%	1.8%
	Grain	18	15	19	3	56	7	69	15	202	27.7%	1.7%
	Forb Berry	4	3	1	1	6	5	2	0	22	22.7%	1.6%
	Forb Sum Harv	139	164	111	32	174	40	977	90	1727	56.6%	1.8%
	Forb Fall Harv	1	2	5	0	10	1	24	17	60	28.3%	1.7%
	Total	375	375	300	104	300	75	1230	150	2909		
	Prod Acc	60.3%	46.7%	43.2%	10.4%	15.8%	4.7%	71.3%	21.4%		**Overall Acc ±CI**	
	±CI	3.8%	4.1%	4.8%	4.3%	3.7%	4.4%	2.2%	5.7%		51.5%	1.8%

Trial 19		Reference Data										
	Class	**Gram Active**	**Gram Passive**	**Shrub Berry**	**Shrub Nursery**	**Grain**	**Forb Berry**	**Forb Summer Harvest**	**Forb Fall Harvest**	**Total**	**User Acc ±CI**	
Map Data	**Gram Active**	206	35	22	4	16	0	30	13	326	63.2%	1.8%
	Gram Passive	40	249	14	5	11	2	34	2	357	69.7%	1.7%
	Shrub Berry	25	19	176	7	7	9	24	2	269	65.4%	1.8%
	Shrub Nursery	4	0	4	54	4	1	6	0	73	74.0%	1.6%
	Grain	9	6	5	5	190	1	24	0	240	79.2%	1.5%
	Forb Berry	3	3	1	0	0	21	10	0	38	55.3%	1.8%
	Forb Sum Harv	79	58	76	29	71	39	1091	44	1487	73.4%	1.6%
	Forb Fall Harv	9	5	2	0	1	2	11	89	119	74.8%	1.6%
	Total	375	375	300	104	300	75	1230	150	2909		
	Prod Acc	71.5%	64.5%	49.8%	20.4%	52.6%	15.0%	87.8%	56.1%		**Overall Acc ±CI**	
	±CI	3.4%	4.0%	4.9%	6.6%	5.0%	6.9%	1.7%	6.4%		70.5%	1.7%

Trial 20		Reference Data										
Map Data	Class	Gram Active	Gram Passive	Shrub Berry	Shrub Nursery	Grain	Forb Berry	Forb Summer Harvest	Forb Fall Harvest	Total	User Acc ±CI	
	Gram Active	223	30	10	10	11	5	29	11	329	67.8%	1.7%
	Gram Passive	48	284	7	1	17	1	28	6	392	72.4%	1.7%
	Shrub Berry	10	10	174	8	4	11	29	4	250	69.6%	1.7%
	Shrub Nursery	6	0	1	54	3	0	4	0	68	79.4%	1.5%
	Grain	14	10	5	1	197	0	19	2	248	79.4%	1.5%
	Forb Berry	1	1	2	1	1	12	7	0	25	48.0%	1.9%
	Forb Sum Harv	70	37	98	29	65	42	1096	55	1492	73.5%	1.6%
	Forb Fall Harv	3	3	3	0	2	4	18	72	105	68.6%	1.7%
	Total	375	375	300	104	300	75	1230	150	2909		
	Prod Acc	75.4%	71.5%	53.1%	19.8%	55.2%	10.6%	87.9%	49.7%		Overall Acc ±CI	
	±CI	3.2%	4.0%	4.9%	5.8%	5.1%	5.5%	1.7%	6.2%		71.9%	1.7%

Trial 21		**Reference Data**										
	Class	**Gram Active**	**Gram Passive**	**Shrub Berry**	**Shrub Nursery**	**Grain**	**Forb Berry**	**Forb Summer Harvest**	**Forb Fall Harvest**	**Total**	**User Acc ±CI**	
Map Data	**Gram Active**	199	32	31	11	20	5	33	3	334	59.6%	1.8%
	Gram Passive	57	275	6	5	18	0	24	5	390	70.5%	1.7%
	Shrub Berry	28	10	172	3	4	8	37	6	268	64.2%	1.8%
	Shrub Nursery	6	1	5	54	1	0	6	1	74	73.0%	1.6%
	Grain	14	10	10	3	177	0	13	8	235	75.3%	1.6%
	Forb Berry	3	0	0	0	1	10	9	1	24	43.5%	1.8%
	Forb Sum Harv	63	47	74	28	74	50	1090	59	1485	73.4%	1.6%
	Forb Fall Harv	5	0	2	0	5	2	18	67	99	67.7%	1.7%
	Total	375	375	300	104	300	75	1230	150	2909		
	Prod Acc	70.1%	69.4%	47.8%	18.2%	47.8%	9.1%	87.3%	51.2%		**Overall Acc ±CI**	
	±CI	3.5%	4.0%	4.8%	5.9%	4.8%	5.4%	1.7%	6.4%		69.2%	1.7%

Trial 22		Reference Data										
	Class	**Gram Active**	**Gram Passive**	**Shrub Berry**	**Shrub Nursery**	**Grain**	**Forb Berry**	**Forb Summer Harvest**	**Forb Fall Harvest**	**Total**	**User Acc ±CI**	
Map Data	**Gram Active**	214	50	32	9	11	5	27	10	358	59.8%	1.8%
	Gram Passive	48	260	8	1	9	3	14	2	345	75.4%	1.6%
	Shrub Berry	26	19	180	8	9	1	36	4	283	63.6%	1.8%
	Shrub Nursery	8	1	4	53	2	2	5	0	75	70.7%	1.7%
	Grain	10	8	3	1	200	0	14	0	236	84.7%	1.3%
	Forb Berry	2	1	0	0	2	19	5	0	29	65.5%	1.8%
	Forb Sum Harv	62	36	67	32	66	44	1122	54	1483	75.7%	1.6%
	Forb Fall Harv	5	0	6	0	1	1	7	80	100	80.0%	1.5%
	Total	375	375	300	104	300	75	1230	150	2909		
	Prod Acc	71.4%	67.2%	48.7%	18.4%	57.9%	15.5%	90.7%	56.5%		**Overall Acc ±CI**	
	±CI	3.5%	3.8%	4.9%	6.2%	5.0%	5.9%	1.6%	6.1%		72.0%	1.6%

Trial 23		Reference Data										
Map Data	Class	Gram Active	Gram Passive	Shrub Berry	Shrub Nursery	Grain	Forb Berry	Forb Summer Harvest	Forb Fall Harvest	Total	User Acc ±CI	
	Gram Active	130	51	46	6	28	4	44	7	316	41.1%	1.8%
	Gram Passive	87	183	53	1	42	4	47	8	425	43.1%	1.8%
	Shrub Berry	16	27	48	1	12	3	18	6	131	36.6%	1.8%
	Shrub Nursery	9	5	11	42	0	1	8	0	76	55.3%	1.8%
	Grain	27	44	13	0	96	0	15	4	199	48.2%	1.9%
	Forb Berry	0	0	0	1	1	4	1	1	8	57.1%	1.9%
	Forb Sum Harv	105	65	118	51	121	59	1083	96	1698	63.8%	1.8%
	Forb Fall Harv	1	0	11	2	0	0	14	28	56	50.0%	1.9%
	Total	375	375	300	104	300	75	1230	150	2909		
	Prod Acc	53.8%	41.3%	21.7%	13.1%	27.0%	10.7%	81.7%	34.5%		Overall Acc ±CI	
	±CI	4.0%	4.1%	3.7%	5.7%	4.1%	5.4%	2.0%	5.9%		52.9%	1.8%

Trial 24		Reference Data										
Map Data	Class	Gram Active	Gram Passive	Shrub Berry	Shrub Nursery	Grain	Forb Berry	Forb Summer Harvest	Forb Fall Harvest	Total	User Acc ±CI	
	Gram Active	136	73	60	12	9	7	78	20	395	34.4%	1.8%
	Gram Passive	61	155	23	5	19	4	64	8	339	45.7%	1.8%
	Shrub Berry	16	7	33	8	20	1	40	10	135	24.4%	1.6%
	Shrub Nursery	15	8	9	40	1	3	12	2	90	44.4%	1.8%
	Grain	6	2	20	1	88	1	37	8	163	54.0%	1.8%
	Forb Berry	0	0	1	0	0	0	1	0	2	0.0%	0.0%
	Forb Sum Harv	114	125	144	37	149	59	965	63	1656	58.3%	1.8%
	Forb Fall Harv	27	5	10	1	14	0	33	39	129	30.2%	1.7%
	Total	375	375	300	104	300	75	1230	150	2909		
	Prod Acc	48.5%	42.1%	15.2%	9.8%	30.0%	0.0%	71.3%	23.5%		Overall Acc ±CI	
	±CI	4.2%	4.0%	3.5%	5.2%	4.1%	0.0%	2.2%	6.0%		47.5%	1.8%

Trial 25		Reference Data										
Map Data	**Class**	**Gram Active**	**Gram Passive**	**Shrub Berry**	**Shrub Nursery**	**Grain**	**Forb Berry**	**Forb Summer Harvest**	**Forb Fall Harvest**	**Total**	**User Acc ±CI**	
	Gram Active	161	65	23	17	13	5	61	19	364	44.2%	1.8%
	Gram Passive	54	131	29	8	29	9	56	11	327	40.1%	1.8%
	Shrub Berry	33	20	91	6	9	5	43	12	219	41.6%	1.8%
	Shrub Nursery	17	4	6	27	6	0	9	1	70	38.6%	1.8%
	Grain	8	21	26	11	139	4	56	1	266	52.3%	1.9%
	Forb Berry	2	3	1	0	0	2	6	0	14	14.3%	1.3%
	Forb Sum Harv	93	127	109	34	103	48	988	82	1584	62.4%	1.8%
	Forb Fall Harv	7	4	15	1	1	2	11	24	65	36.9%	1.8%
	Total	375	375	300	104	300	75	1230	150	2909		
	Prod Acc	57.5%	36.4%	28.3%	7.4%	34.9%	3.0%	76.4%	25.3%		**Overall Acc ±CI**	
	±CI	3.9%	4.0%	4.3%	4.4%	4.9%	3.7%	2.1%	5.6%		52.2%	1.8%

Trial 26		Reference Data										
Map Data	Class	Gram Active	Gram Passive	Shrub Berry	Shrub Nursery	Grain	Forb Berry	Forb Summer Harvest	Forb Fall Harvest	Total	User Acc ±CI	
	Gram Active	133	32	22	22	20	7	71	6	313	42.5%	1.8%
	Gram Passive	43	119	15	2	17	6	22	5	229	52.0%	1.9%
	Shrub Berry	19	8	109	9	14	8	42	4	213	51.2%	1.9%
	Shrub Nursery	8	1	5	31	5	0	10	0	60	51.7%	1.9%
	Grain	13	18	15	2	32	3	52	3	138	23.2%	1.6%
	Forb Berry	2	3	5	1	1	1	4	3	20	5.9%	0.8%
	Forb Sum Harv	156	194	128	37	200	48	1009	120	1892	53.3%	1.8%
	Forb Fall Harv	1	0	1	0	11	2	20	9	44	20.5%	1.5%
	Total	375	375	300	104	300	75	1230	150	2909		
	Prod Acc	53.3%	45.2%	35.7%	9.3%	12.6%	1.0%	69.0%	17.3%		Overall Acc ±CI	
	±CI	3.9%	3.9%	4.5%	4.3%	3.4%	2.2%	2.3%	5.8%		47.5%	1.8%

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