Land Cover Classification and Mapping

in the Bighorn Basin, Wyoming

Map Area 1 Results

Final Report for the Wyoming Game and Fish Department and

Wyoming Game and Fish Commission

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Executive Summary

This report documents classification and mapping results for priority area 1 of the Cody Region and Yellowstone National Park land cover remote sensing project. Extensive field collected reference data representing the range of plant communities and habitat types comprising the Bighorn Basin have been analyzed to produce a classification of land cover types based on the Wyoming Game and Fish Department (WGFD) Wildlife Observation System (WOS). Corresponding land cover classes were subsequently spatially modeled using a non-parametric Classification and Regression Tree (CART) algorithm that integrated spectral data from Landsat Thematic Mapper satellite and National Aerial Photography Program imagery, spectral indices designed to enhance the signal and response of vegetation, and a variety of ancillary environmental data derived predominantly from digital elevation models hypothesized to be significant ecological drivers of plant distributions.

A total of 56 land cover classes were identified and modeled for the Absaroka Front Area of the Bighorn Basin. An additional eight anthropogenic types, including areas disturbed by oil extraction, mining, and agriculture, were delineated using external data, interpretations of high resolution imagery, and other modeling methods. CART based land cover classes and anthropogenic classes were spatially merged and the combined map was processed using a customized aggregation routine that generated a final map of land cover classes with a target spatial resolution or minimum mapping unit (MMU) size of 2 acres.

Comprehensive accuracy assessment using independent test data was not performed due to funding and logistical constraints associated with additional field surveys required for the collection of independent test data. A variety of methods were used to provisionally evaluate map accuracy including re-substitution, cross-validation using randomized subsets of reference data, and partitioning techniques to generate independent test data. Resulting overall model accuracy ranged from a lower limit of 67% to an upper limit of 87%. Prediction errors associated with individual cover classes were variable. Causes of prediction error are attributed to the quantity of training and test data available in particular classes, the quality or accuracy of the reference data, and variation in the biology and ecological amplitude of species comprising individual cover classes.

Future efforts to improve modeling performance may include additional field data collection to increase training data sample sizes for selected cover classes, further research into the effectiveness of supplementary explanatory variables or alternative combinations of variables, and an investigation of the influence of spatial scale on prediction accuracy.

Product deliverables include this final report and geospatial data representing the final CART based land cover model for Area 1 of the Bighorn Basin in 30 meter raster format.

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Table of Contents

List of Tables

List of Figures

Introduction

The Wyoming Geographic Information Science Center (WyGISC) of the University of Wyoming has been contracted by the Wyoming Game and Fish Department (WGFD) to develop a map of dominant land cover types for the WGFD Cody Region in northwest Wyoming and Yellowstone National Park. The principle objectives of this study are to develop a standardized classification of land cover types for the Cody Region based on and compatible with existing land cover classification systems utilized by WGFD managers and other state and federal agencies, and to produce corresponding geospatial data and maps describing the current spatial extent and distribution of land cover classes within the study area. Project efforts will provide baseline, spatially-explicit habitat information that may support and inform future management and conservation initiatives.

Map production in this study involves the classification of remotely sensed imagery using ancillary topographic data and a statistical algorithm. The classification and mapping process is complex and relies on a sufficient availability of field collected reference data and intensive image processing and model building efforts. Major components of the mapping process include field surveys to collect reference or training data, a comprehensive lab review of the field data to produce a classification scheme and standardized reference data, selection and processing of explanatory spectral and environmental variables, training or calibration of a chosen classification algorithm with the reference samples, spatial extrapolation of the trained algorithm across the study area to produce a thematic map, and development of some preliminary measures describing map accuracy. Existing field survey data located within the study area and acquired from previous vegetation projects, including the Governor’s Sage Grouse Conservation Initiative (Rodemaker et al. 2009), were used to supplement field reference data collected specifically for this mapping effort.

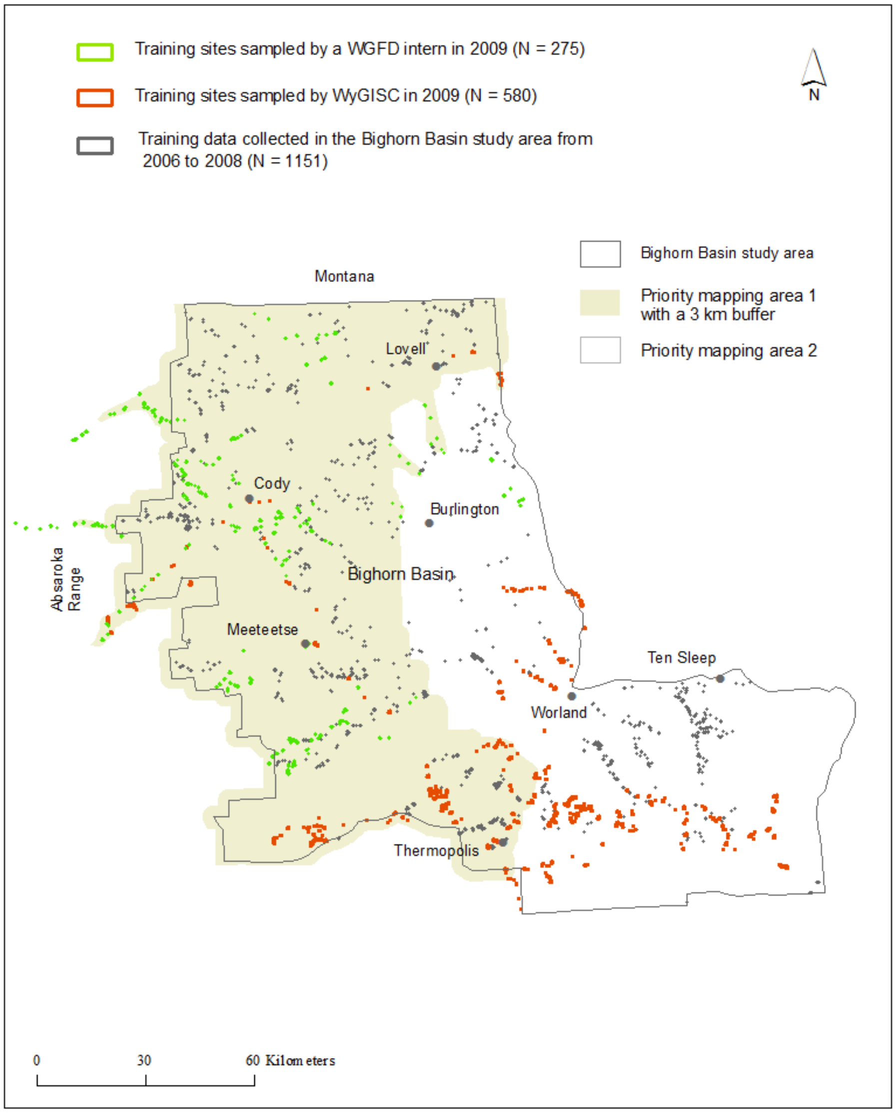
The Cody Region study area was subdivided into 5 priority map zones in order to effectively allocate resources and funding. Initial project efforts are focused on the Bighorn Basin portion, which is comprised of two priority map areas (see Figure 1). This report summarizes field survey and model development results for Area 1 of the Bighorn Basin.

Methods

Study area

Map Area 1 of the Bighorn Basin is approximately bounded by the city of Thermopolis in the southeast, the foothills of the Absaroka Range on the west, and the Montana state boundary to the north (Figure 1). The original mapping area boundary was extended or buffered by an average of three kilometers to the west, east, and south in order to increase training data sample sizes and facilitate the aggregation of future map products from adjacent mapping zones. The total areal extent of Area 1, including buffer regions, is 1,024,356 ha or 2,531,239 acres.

Figure 1: Bighorn Basin study area and field survey locations



Field data collection

Field surveys for this project in the Bighorn Basin have been ongoing since 2006. A total of 764 sites within Area 1 were sampled between 2006 and 2008 by Wyoming Game and Fish Department (WGFD) interns, Bureau of Land Management (BLM) personal, and Wyoming Geographic Information Science Center (WyGISC) staff (Figure 1).

Existing data were synthesized in the spring of 2009 to identify sample size adequacy for subsequent modeling efforts. An Access database was designed and constructed for data storage and retrieval, and to facilitate more efficient data management and statistical analyzes.

A comprehensive species list for the state of Wyoming (Fertig 2003) was obtained from the Wyoming Natural Diversity Database (WYNDD) of the University of Wyoming and incorporated into the Access database to standardize species nomenclature and identification. The species list was synthesized using taxonomy described by Dorn (2001). Preliminary data analyses were conducted to identify, both, under-sampled land cover types, as well as spatial gaps in data coverage for the Bighorn Basin study area. For example, data summaries revealed inadequate sample sizes for most woodland and grassland types, as well as low sample sizes for some shrubland types including mountain big sage (*Artemisia tridentata* subsp. *vaseyana*) and plains silver sage (*Artemisia cana* subsp. *cana*) classes.

Field protocols for surveys conducted in 2009 were adopted from previous survey work in order to maintain data consistency and allow the integration of field data from all survey years for subsequent modeling efforts. Specifically, field samples were subjectively and opportunistically located based on data requirements (existing low sample size) and site accessibly. Surveys were therefore predominantly conducted on publicly owned land that could be freely accessed. In some instances, private land owners were approached in the field to gain access permission or local information regarding roads or vegetation patterns. The owner of a large private ranch in the southern portion of mapping Area 1 (Frank Robbins) was contacted by phone to gain access permission.

Precise field sample locations were documented with Trimble GEO Explorer GPS receivers and site photographs. The WyGISC crew recorded a minimum of 4 photos at each plot location to help identify the spatial variability and extent of each sampled community and to delimit adjacent habitat types. Basic environmental and habitat data were collected including slope, aspect, terrain curvature, color of upper soil horizons, and estimates of the relative extent of abiotic ground cover components. Supplemental descriptive observations of stand condition, impacts of past or ongoing disturbance, and habitat heterogeneity were recorded. Floristic data were also collected. The dominant or characteristic plant species characterizing a given community were identified to species level when possible and their associated abundances were quantified with visual estimates of foliar cover. Corresponding preliminary land cover types were then identified by the surveyor including a corresponding ranking of sampling and classification confidence. In addition, the surveyor digitized the spatial extent of an associated training polygon in a GIS environment based on the GPS captured sample location, field observations, and interpretations of corresponding 1.0 meter USDA National Agriculture Imagery Program (NAIP) ortho-photography and 30 meter Landsat TM remotely sensed imagery.

Model Development

Algorithm Selection

A Classification and Regression Tree (CART; Breiman et al. 1984) algorithm was selected for this modeling effort. CART methods recursively partition training samples into dichotomous groups or tree branches. Data sorting at branch nodes is governed by the selection of a single explanatory variable that maximizes homogeneity in the partitioned training data (Segurado and Araujo 2004; Garzon et al. 2006; Chan and Paelinckx 2008). Successive binary splitting produces a classification tree, whose branch architecture corresponds to the most favorable combination of explanatory variables that quantify the habitat conditions and spectral response of particular plant species or land cover types.

CART algorithms are non-parametric classifiers that do not rely on statistical parameters, such as mean vector or variance, to separate or classify cover types (Lu and Weng 2007). CART classifiers are therefore not constrained by assumptions concerning the data distributions of explanatory variables and are able to incorporate non-normally distributed environmental and GIS-derived layers. Previous research has suggested that non-parametric classifiers may improve land cover classification accuracy compared with parametric or purely spectral classifiers (Lawrence et al. 2004; Lu and Weng 2007).

Spatial Scale

Model performance and resulting map accuracy strongly depend on the scale of the study (Nagendra 2001). The extent of the mapping area, the spatial pattern and variability of land cover classes, and the spatial resolution of the explanatory variables interact to determine the capacity of the classification algorithm to discriminate classes. The spectral and environmental variability associated with individual cover classes increases with increasing study area size. Previous large regional-scale mapping efforts have successfully delimited relatively coarse land cover classes using moderate resolution spectral data including Landsat imagery (Rodemaker and Driese 2006; Lu and Weng 2007; Sivanpillai 2008; Jenkins 2009). However, map accuracy also depends on relationships between the areal extent of individual cover types on the ground, termed patch size, and the spatial resolution or pixel size of the model (Woodcock and Strahler 1987). Individual pixels that significantly exceed patch size will tend to minimize associated local spectral variance. Nagendra (2001) argues that optimal pixel size for mapping should be significantly smaller than the maximum patch size of target cover classes in order to capture the associated spectral variability within those classes. Bighorn Basin cover types are highly variable in terms of patch size. Patch sizes for low density woodland or savanna classes, such as associations between *Juniperus osteosperma* (Utah juniper) and *Pinus flexilis* (limber pine), typically exceed patch sizes for uniform grassland and riparian types. A pixel size of 30 x 30 meters was selected for this modeling effort in order to capture the spectral variability of most target land cover types occurring within the Bighorn study area and to match the spatial resolution of Landsat TM data.

Processing of Field Data

An important component of the model building process includes a systematic review of the field samples to ensure spatially accurate and spectrally uniform training polygons and an associated consistent and reproducible classification of training polygon attributes (land cover types). Classification of field data was based on the WGFD Wildlife Observation System (WOS) Classification, version 1997, refined to include closure classes representing ‘low’, ‘medium’, and ‘high’ foliar cover for selected land cover classes.

High spectral variance associated with poorly digitized polygons or misclassified types may degrade model performance and final map accuracy. All field data were therefore systematically reviewed in the lab. Final homogenous training areas and associated cover types were generated from interpretations of stand floristic composition, field descriptions of habitat variability and condition, an interpretation of Landsat spectral signatures, and inspections of NAIP imagery, field photographs, and ancillary information including topographic data. Heterogeneous training samples or ambiguous types were excluded from further analyses and subsequent model development. This rigorous comprehensive final review ensures that training data collected by multiple observes over a time span of several years are standardized for integration into a single predictive land cover model.

Selection and Processing of Explanatory Variables

Specific explanatory variables used in the CART model were selected based on data availability, appropriate spatial resolution, and their hypothesized influence on or control over species distributions. Decreased classification accuracies have been associated with model over-fitting or the use of too many variables with redundant or correlated information (Price et al. 2002). A relatively parsimonious model was thus constructed from spectral data, a digital elevation model, and several derived variables (see Table 1).

Table 1: Independent or explanatory variables used to predict land cover in the Bighorn Basin

Explanatory variable	**Data type**	**Units**
Spectral data		
Reflectance spectra (Landsat TM; 6 bands)	continuous	0-255 DN / band
Image texture metric (NAIP CIR; 3 bands)	continuous	none
Soil adjusted vegetation index (Landsat TM; SAVI)	continuous	none
Ancillary topographic and floristic data		
Aspect	categorical	9 classes

Explanatory variable	Data type	Units
Digital elevation model (SRTM DEM)	continuous	meter
Floodplain model	categorical	10 classes
Landform position model	categorical	10 classes
Physiognomic model	categorical	6 classes
Slope	continuous	percent
Terrain curvature	continuous	none
Topographic surface roughness	continuous	none

Spectral data used in the CART model include moderate resolution Landsat Thematic Mapper (TM) imagery. Landsat TM images encompassing the Bighorn Basin study area were obtained from the USGS Earth Resources Observation and Science (EROS) Center (http://eros.usgs.gov/#/Find_Data/Products_and_Data_Available/Satellite_Products). The Landsat TM images were acquired on the 23 June 2009, and have a spectral resolution of 6 wavelength bands and a spatial resolution or pixel size of 30 meters. Atmospheric and radiometric corrections were not applied to the Landsat TM data since imagery were obtained for a single date (Lu and Weng 2007).

Image texture indices were also computed to capture spectral variability associated with habitat and floristic heterogeneity at a sub-pixel level. Measures of image texture have been previously shown to improve the classification accuracy of habitat models in semi-arid environments (St-Louis et al. 2006). Image texture indices were derived from a 30 x 30 meter moving windows analysis of high spatial resolution ortho-photography which generated statistical parameters (mean, standard deviation, and mean of NDVI) quantifying variation in image brightness. The ortho-photography was obtained from the USDA National Agriculture Imagery Program (NAIP; http://www.fsa.usda.gov/FSA/apfoapp?area=home&subject=prog&topic=nai) and has 3 wavelength bands (green, red, and near-infrared) and a spatial resolution of 1.0 meter. Computed image texture metrics were subsequently resampled to a spatial resolution of 30 meters to correspond with the selected scale of other explanatory variables.

In order to enhance the spectral response of vegetation and help delimit landscape variation in plant densities and composition, a soil adjusted vegetation index (SAVI; Huete 1988) was computed from the Landsat TM spectral data. SAVI represents a Normalized Difference Vegetation Index (NDVI) modified with a correction factor that minimizes affects related to spatial variability in soil brightness.

Distributions of plant species are determined by various biotic and abiotic factors. Environmental conditions that sustain or limit the ranges of particular species or associations of co-occurring species determine an organism's ecological niche (Brown et al. 1996). Successful modeling of species occurrences thus requires data describing critical range-limiting environmental gradients. Data quantifying many potentially important ecological controls are, however, not available at sufficiently detailed spatial scales. For example, climate data from sources such as Daymet (Edwards et al. 205), are only available at relatively coarse spatial resolutions of 1000 meters. We therefore derived several topographical variables to serve as proxy variables for hypothesized direct environmental controls such as moisture availability (Table 1). All derived proxy variables were computed from elevation data acquired by NASA's Shuttle Radar Topography Mission (SRTM) in February 2000. The SRTM data were collected using Interferometric Synthetic Aperture Radar (IFSAR) and have a spatial resolution of 30 meters. We obtained the SRTM digital elevation model (DEM) from the USGS EROS Data Center (http://eros.usgs.gov/#/Find_Data/Products_and_Data_Available/SRTM_DTED). We performed additional processing in ERDAS Imagine 9.3 using a moving windows mean focal filter to recompute anomalous elevation values, such as sinks or pixels lacking data, with the mean elevation data of spatially adjacent pixels.

Variables representing slope, aspect, and terrain curvature were subsequently derived from the modified SRTM DEM using standard tools in Spatial Analyst (ArcGIS 9.3, ESRI, Redlands, CA). A surface roughness index was also generated using a moving windows analysis that computed the standard deviation of elevation values within a specified window extent. Landform categories, simulating site moisture gradients, were derived from a spatial model incorporating slope, aspect, geographic location, elevation, flow direction, flow accumulation, and other interpolated data (Manis et al. 2001). Finally, a model of riparian habitats was constructed to predict the spatial extent of floodplain areas associated with both perennial and ephemeral stream channels. Channel locations were first modeled from topographic data using the SRTM DEM and standard hydrology tools available in ESRI Spatial Analyst (Figure 2). Potential riparian habitat extent was subsequently delineated for classified stream orders by using a path distance tool with an input slope raster serving as a cost function. Various terrain slope thresholds were iteratively defined to delimit maximum floodplain boundaries (Figure 3).

Figure 2: Stream channel locations computed from a modified SRTM DEM.

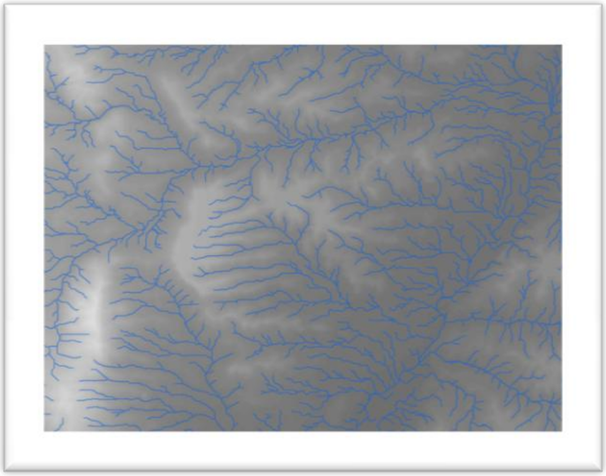
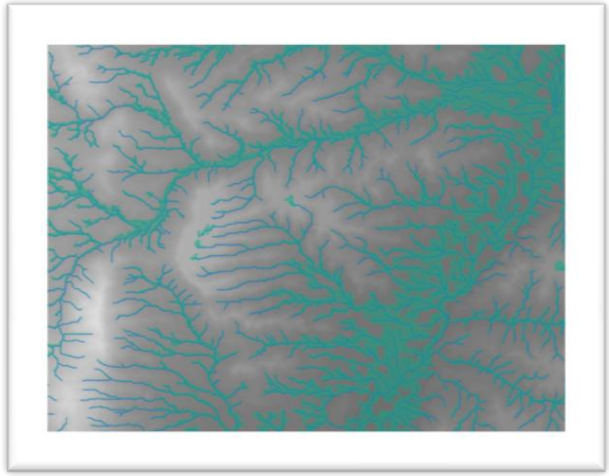
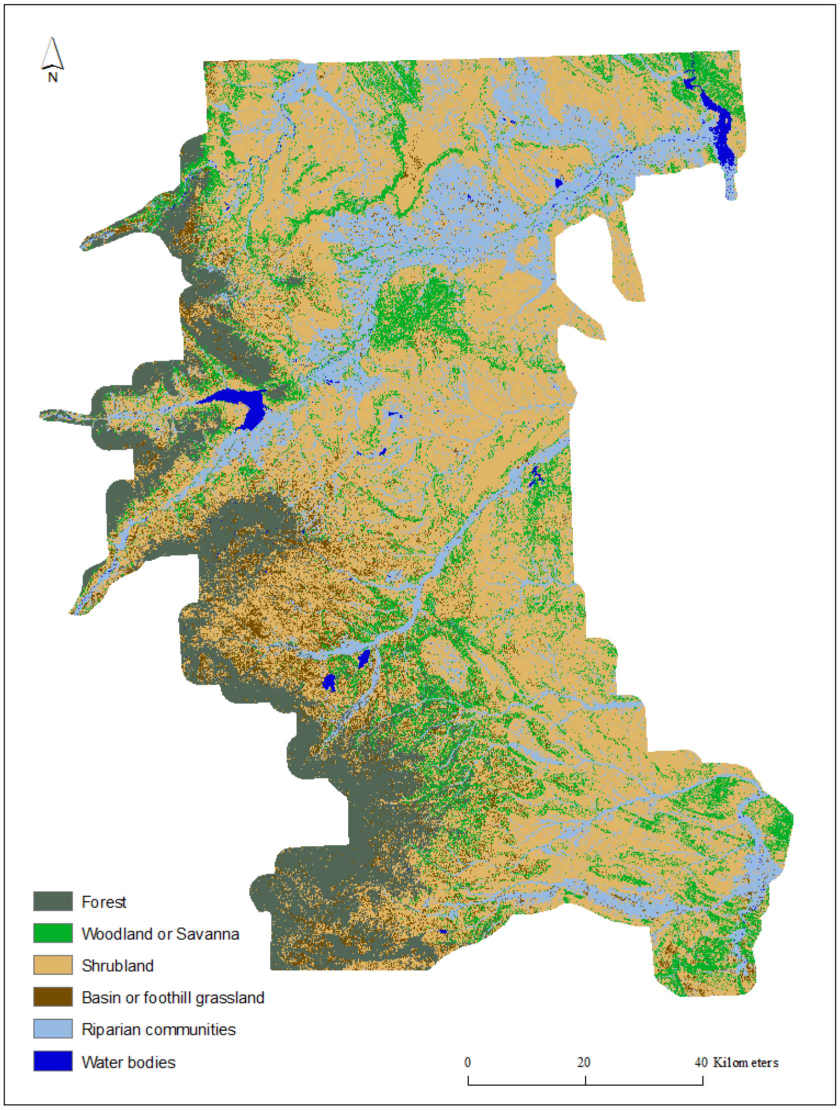


Figure 3: Riparian or floodplain extent predicted from slope and elevation data.



An additional floristically-based explanatory variable was constructed based on a physiognomic classification of the field collected training data. Plant physiognomy is a coarse level biological classification of the dominant species comprising a given plant community based on their morphological characteristics and their functional and evolutionary adaptations (Pillar and Orloci 1993). Physiognomic groups are partially determined by environmental gradients and growth-limiting conditions. Physiognomic classes may be heterogeneous and consist of phylogenetically unrelated organisms. A physiognomic classification system was developed for the Bighorn Basin that categorizes plant assemblages based on their environmental adaptations. Specific classes developed include high elevation forest, open woodland and savanna, xeric shrubland, mesic or riparian dependent communities, and upland herbaceous plant assemblages. All training polygons were reviewed and assigned a corresponding physiognomic class. A model of physiognomic types for the Bighorn Basin was then constructed by calibrating a CART algorithm with the reclassified training data and the previously described explanatory variables (Figure 4). The resulting physiognomic model was used as an additional explanatory variable in the subsequent land cover modeling process.

Figure 4: Physiognomic classification model for Area 1 of the Bighorn Basin



Model Construction and Map Output

Model building consists of training a statistical classification algorithm with reference data that are attributed with the values of the selected explanatory variables so that a rule-set is produced that is capable of correctly classifying land cover types over a defined area of analysis (Guisan and Zimmermann 2000). In this study, processed training data were used to fit a CART algorithm. The CART classifier was then used to categorize land cover types on a pixel by pixel basis, based on the spectral and environmental conditions present in corresponding pixels.

The CART classifier was constructed using See5/C5.0 statistical software (Quinlan 1993). The spatial extraction of the CART classifier to produce an output map of land cover types was performed using an ERDAS Imagine 9.3 classification toolset developed and provided by the USGS National Land Cover Database program.

Land cover predictions generated by the CART model were subjectively evaluated based on field observations of the study area and quantitatively assessed using a set of computed error measures. Quantitative error indices were calculated using a partitioned subset of the original training data that was withheld from model construction in order to provide an unbiased test data set. Specifically, the test data were derived from the original field data by withholding approximately 20% of training polygons for selected classes with more than 5 independent polygons available for model development. An error matrix was constructed from the test data in order to quantify overall and individual map class accuracies (Congalton et al. 1983; Fielding and Bell 1997; Lu and Weng 2007). The error matrix relates actual land cover classes derived from field observations with predictions generated by the CART algorithm. The matrix was constructed with predicted classes constituting matrix columns and reference or test data defining matrix rows. Diagonal elements of the matrix represent pixels correctly classified by the model. Off-diagonal elements represent model misclassification rates and are used to compute indices of commission and omission error (Congalton 1991). Commission error quantifies the percentage of model pixels in a given class incorrectly classified according to the test data, and omission error represents the percentage of pixels in a given class within the reference data that were not correctly predicted by CART. Overall map accuracy is computed from the ratio of correctly classified pixels (diagonal elements in the matrix) to the total number of test pixels evaluated. In addition, the proportion of training pixels in each map class correctly predicted by the CART algorithm was computed to quantify a supplemental, non-independent measure of classification accuracy.

Limited data availability constrained the utility of the test data to provide a definitive or comprehensive assessment of final map accuracy. The test data were mainly used to guide iterative model development by identifying low map accuracies for selected land cover classes. Specifically, error measures were analyzed to identify weakly predicted land cover types at each stage of model development. Associated training samples were then reviewed and ambiguous types were spatially or thematically revised. Supplemental training data were also generated for selected cover types with low accuracies based on interpretations of remotely sensed imagery. Revised training data were then used to recalibrate the CART classifier and generate an improved model output. Error measures were recalculated to evaluate corresponding changes in model performance.

Anthropogenic Cover Classes

Anthropogenically modified or developed areas were delineated independently of the CART modeling process (Table 2). For example, agricultural classes, urban boundaries, and ranch facilities were digitized from an interpretation of high resolution NAIP imagery. Road locations were mapped using data obtained from the 2009 U.S. Census TIGER database (http://www.census.gov/geo/www/tiger). Areas disturbed by recent oil extraction were modeled based on GPS data identifying the approximate locations of past oil related operations. GPS data were obtained from Holly Copeland at the Nature Conservancy's Lander office who synthesized and edited data distributed by the Wyoming Oil and Gas Conservation Commission (http://wogccms.state.wy.us/). Various NDVI thresholds were applied to 150 meter buffer regions surrounding the GPS point locations in order to delimit disturbed areas from adjacent natural vegetation. Minor errors associated with predicted oil pad locations may be attributed to spatial errors in the original source GPS data and high spectral similarity between areas of past oil related disturbance and the current surrounding vegetation, often characterized by sparse cover of *Atriplex gardneri*. Anthropogenic types were subsequently combined with final model predictions generated by the CART classifier using mosaic tools in ERDAS Imagine.

Table 2: Map classes derived from external data, image interpretation, or other modeling methods

Map class	**Class code**	**Mapped area (ha)**	**Source**
11.20 Irrigated Agricultural Field	196	82,271	Image interpretation
11.60 Dry-land Pastures	197	6,671	Image interpretation
11.91 Ranch-Farm Facilities	201	2,039	Image interpretation
99.10 Roads and Rail Roads	213	64,654	TIGER Census data 2009
99.20 Mining Areas	214	12	Image interpretation
99.80 Oil and Gas Developments	218	2,622	NDVI threshold model applied to Landsat imagery; WOGCC data
99.90 Urban/Industrial Land	220	1,656	Image interpretation

Aggregation of CART Output into 2 Acre Minimum Mapping Units

The spatial scale of the map output from the CART classifier matches the 30 m resolution of the explanatory variables. In order to produce a final map product with a target minimum mapping unit (MMU) scale of 2 acres, a generalization or aggregation analysis was performed using ESRI software and a VBA script (Rodemaker and Driese 2006). The aggregation routine clusters contiguous pixels within individual cover classes into region groups, computes the areal extent of these resulting regions, and spatially aggregates or appends individual regions that do not meet MMU targets (2 acres or 9 pixels) with their most ecologically similar neighboring regions. Degrees of ecological similarity are determined systemically by reclassifying regions according to a physiognomic classification system and subsequently ranking the similarity between regions based on relationships between physiognomic classes, which are defined a priori (Table 3). Final land cover classes for all pixels comprising newly aggregated regions are determined by majority rule. Aggregation analyses are iterative until all regions exceed the MMU target of 2 acres.

Table 3: Matrix of relative ecological similarity for 13 physiognomic classes used in the aggregation analysis. Similarity rankings range from 1 (minimum) to 13 (maximum).

	Conifer Forest	Deciduous forest	Woodland	Desert Shrubs	Sagebrush - Grassland	Mountain Shrubs	Riparian Shrubs	Grass-like Types	Marsh-Swanp Wetlands	Aquatic Types	Cropland - Agriculture	Other Non-vegetated	Human or Disturbed Areas
Conifer Forest	13	12	12	1	3	6	7	1	4	3	2	2	5
Deciduous Forest	12	13	11	6	4	9	9	2	7	6	6	1	4
Woodland	11	11	13	5	8	11	6	5	3	2	3	4	3
Desert Shrubs	1	5	5	13	10	7	2	7	2	1	1	8	7
Sagebrush-Grassland	4	7	8	12	13	10	4	12	6	8	8	6	8
Mountain Shrubs	10	10	10	7	11	13	11	9	10	9	5	3	2
Riparian Shrub	9	9	9	9	9	12	13	11	12	11	7	5	1
Grass-like Types	8	8	7	11	12	8	8	13	9	10	11	7	9
Marsh-Swamp Wetlands	7	6	6	8	2	5	12	10	13	12	9	9	6
Aquatic Cover Types	6	4	4	3	1	4	10	6	11	13	4	10	10
Cropland-Agricultural Land	2	3	3	2	6	3	5	8	8	7	13	11	11
Other Non-Vegetated Types	5	1	2	10	7	1	1	4	1	5	10	13	12
Human or Disturbed Areas	3	2	1	4	5	2	3	3	5	4	12	12	13

Results and Discussion

Field survey results from 2009

Field surveys in 2009 were conducted by a WGFD intern (Maddie Ruble, supervised by Jerry Altermatt) and a staff ecologist from WyGISC. The WGFD intern surveyed a total of 275 sites between the end of May and the middle of August. A majority of sites (205) visited by the intern were located within priority Map Area 1 of the Bighorn Basin (Figure 1). The WyGISC ecologist surveyed an additional 580 sites between the middle of August and the end of October. Data collected by WyGISC were predominantly distributed across the southern portions of the Bighorn Basin with 233 plots located in priority Map Area 1 and the remaining 347 plots located in Area 2.

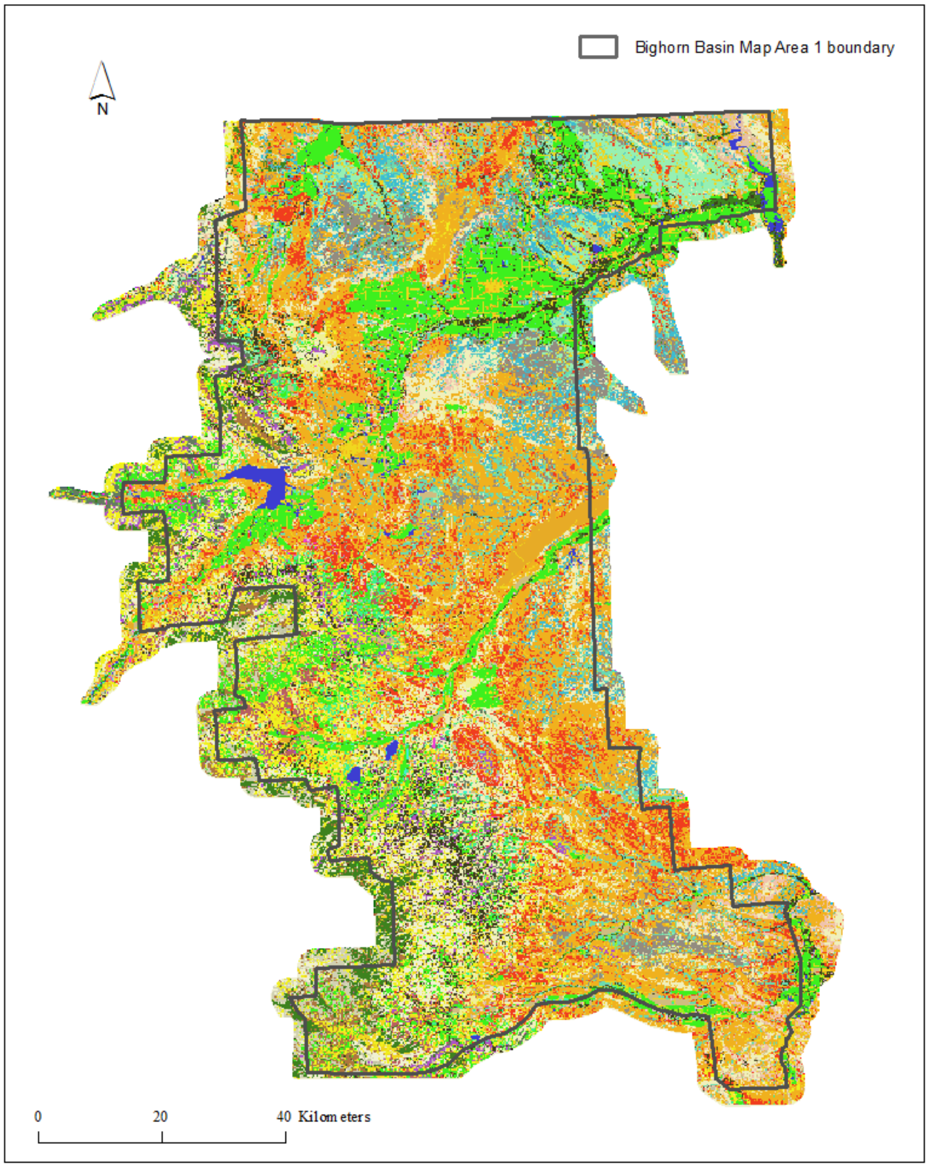
Model Construction

A systematic review of all available field data, including samples collected prior to 2009, produced a total of 922 training polygons and an associated 3,150 training pixels (Table 4) for calibration of the CART based land cover model. Approximately 15 percent of the original field samples were excluded from model building due to high sample spectral variance associated with high habitat heterogeneity, or an ambiguous classification of cover type.

The WGFD Wildlife Observation System was modified slightly to accommodate observed and sampled vegetation patterns in the Bighorn Basin. Specifically, field samples associated with Foothills Grassland were reclassified and combined with Basin Grassland training data in order to increase associated sample sizes. Sampled grassland communities also frequently supported low (1%) to moderate (<5%) cover of fringe sage (*Artemisia frigida*). Fringe sage cover tended to increase with increasing levels of livestock disturbance. Highly disturbed grasslands with low cover of native graminoid species and high cover of fringe sage were reclassified as Fringe Sage types. Additionally, highly degraded sites strongly dominated by non-native herbaceous species, such as *Bassia scoparia* or *Salsola kali*, were classified as Forb types. Degraded riparian areas dominated by Russian olive (*Elaeagnus angustifolia*) were classified as Other or Mixed Deciduous Forest.

A total of 24 model iterations were performed by recursively refining the field training data and by adding ancillary information from image interpretation or external sources. The final CART model delineated 56 land cover classes (Table 4). Predicted land cover classes generated by the CART classifier were spatially merged with an additional 8 classes delineating locations of agriculture, mining, oil extraction, urban areas, and roads (Table 2). The resulting combined pixel level map was processed using an aggregation routine that reclassified and aggregated individual and clusters of pixels according to rankings of ecological similarity to produce a final map with a 2 acre MMU resolution (Figure 5).

Figure 5: Final aggregated map of 64 land cover classes in Area 1 of the Bighorn Basin with a 2 acre MMU resolution.



Model Performance

Other researchers have argued that unbiased, robust measures of model performance and map accuracy depend on the availability of independent test data that were not used in model building (Fielding and Bell 1997). For this study, independent data for testing were not collected due to high monetary costs and time requirements associated with additional field surveys. Map accuracy is therefore evaluated using a variety of approaches including a resubstitution method that uses the same data for both training and testing (Stockwell 1992), a cross-validated error computation using randomized subsets of data (Osborne and Tigar 1992), statistical analyses of a partitioned test dataset (Fielding and Bell 1997), and a subjective review of the CART output and potential sources of error based on field observations and expert opinion.

Re-substitution

Re-substitution does not utilize independent or partitioned test data. The same data used for model training are used for model evaluation. The proportion of training cases in each land cover class correctly classified by the CART classifier serves as measure of map class accuracy. The re-substitution method provides a lower boundary for estimates of prediction error since independent data are not used (Fielding and Bell 1997). Resulting re-substitution based map class accuracies for the final Bighorn model generally exceed 90% (Table 4). The Juniper – Limber Woodland type had the lowest map class accuracy with 89% of associated training data correctly predicted.

Cross-validation

A cross-validation procedure was used to compute an index of overall classification accuracy. In this study, cross-validation was based on a modified k-fold partitioning method (Stockwell 1992) that generates random subsets or blocks of training data selected from the original total training dataset. Each block is comprised of an equal number of random samples with an equal class distribution. Each block is sequentially reserved as a hold-out test dataset while the remaining samples are used to construct independent CART models. Each model iteration or trial is subsequently evaluated using the reserved test data block. In this method, each training sample is used once as a test case. Overall prediction accuracy for a classifier that uses all available training data is estimated as the average cross-validated accuracy for each trial model. Cross-validated model accuracy averaged over 10 random partitions or blocks of the Bighorn Area 1 training data is 86.7%.

Partitioned Test Data Metrics

A total of 439 pixels were partitioned from the original training data and reserved for model evaluation. These pixels were not used in model construction and therefore provide an independent test dataset. Test data sample sizes per cover class ranged from 2 to 90 pixels (Table 4). A total of 38 classes were not evaluated with test data due to small samples sizes associated with the original training data. Corresponding omission and commission errors are highly variable, but are generally highest for classes with few test data (less than 10 samples). Small test data sample sizes limit definitive conclusions regarding map class accuracies, but low prediction accuracy in these classes may be attributed to a paucity of associated training data. Prediction errors were lowest for Juniper – Limber Woodland, Greasewood – Sage Shrubland, Wyoming Sage Shrubland, and Basin Sage Shrubland classes, all of which were intensively field sampled and had large training data sample sizes. Overall map accuracy based on the proportion of correctly predicted test pixels is 67%, which may be constitute an upper boundary of prediction error due to the small sample size of the test data.

Review and Summary of Model Output

Montane and subalpine land cover classes are generally restricted to upper elevations along the western perimeter of Map Area 1 in the Bighorn Basin. Corresponding classes were under-sampled due to their limited areal extent within the study area and difficult access. Limited training data sample sizes suggest that associated model predictions may be less reliable. Future field sampling of similar cover types in the Absaroka Range should be used to revise model output in high elevation regions of Area 1.

Previous studies have correlated model performance with the environmental distribution or ecological amplitude of a target species or cover type (Hernandez et al. 2006; Buechling and Tobalske 2007). Prediction errors produced by classification algorithms such CART are minimized when species are restricted to relatively narrow habitats that can be precisely quantified by the statistical model. Generalist species with broader distributions and wider environmental tolerances are more difficult to predict. A review of the Bighorn model results supports these conclusions. Cover types comprised of species with specific habitat preferences were apparently modeled with high accuracy including Juniper – Limber Woodlands, which are restricted to rock outcrops and narrow ridges, Greasewood and Greasewood – Sage Shrublands, which are generally confined to mesic soils in riparian zones, and Gardner Saltbush – Sage Shrublands, which are associated with extremely xeric, clay soils at the lower elevations of the Bighorn Basin. Black Sagebrush (*Artemisia nova*), in contrast, was less accurately predicted even though this species has a relatively narrow ecological niche characterized by shallow soils and rocky environments on mesas, hilltops, and plateaus. Small training data sample sizes may explain high error rates for this class, but again, limited test data hinder definitive conclusions regarding prediction accuracy.

Wyoming Big Sagebrush (*Artemisia tridentata* var. *wyomingensis*) is a generalist species with a broad ecological distribution that was, however, modeled with relatively high prediction success according to omission and commission indices derived from the independent test data (Table 4). A majority of the prediction errors associated with Wyoming Big Sage is attributed to a misclassification of the correct cover class (low, medium, or high), as quantified by field data. Approximately 25% of low cover Wyoming Sage was classified as medium cover, and 30% of medium cover Wyoming Sage was classified by the model as either low or high cover Wyoming Sage. These classification errors may be correlated with high habitat and plant community heterogeneity, which results in a large variation in associated spectral responses. Additional causes of prediction error may include interpretation errors associated with the training or test data (Lu and Weng 2007). Specifically, sage abundance or cover levels within training pixels may have been imprecisely estimated by field observers.

Table 4: Land cover classes predicted by the final CART model and associated indices of classification accuracy

Map class	Class code	Mapped area (ha)	Training data		Independent test data		
			No of pixels	% of pixels correctly predicted	No of pixels	Omission Error %	Commission Error %
01.10.1 Lodgepole Pine 20-32%	3	12,679	16	100	0		
01.10.2 Lodgepole Pine 33-67%	4	2,513	19	95	0		
01.20.1 Douglas Fir 20-32%	11	239	6	100	0		
01.20.2 Douglas Fir 33-67%	12	9,659	46	100	8	37.5	0
01.30.1 Spruce-Subalpine Fir 20-32%	19	843	4	100	0		
1.30.2 Spruce-Subalpine Fir 33-67%	20	2,204	11	100	0		
01.40.2 Ponderosa Pine 33-67%	24	894	4	100	0		
01.60.1 Limber Pine 20-32%	39	36,994	49	98	10	0	0

Map class	Class code	Mapped area (ha)	Training data		Independent test data		
			No of pixels	% of pixels correctly predicted	No of pixels	Omission Error %	Commission Error %
01.60.2 Limber Pine 33-67%	40	1,121	9	100	0		
01.61.1 Limber Pine-Douglas Fir 20-32%	43	14,194	20	100	0		
01.61.2 Limber Pine-Douglas Fir 33-67%	44	9,180	15	100	0		
Mixed Conifer-Juniper 20-32%	51	8,938	34	100	2	50	0
Mixed Conifer-Juniper 33-67%	52	2,605	16	100	0		
01.90.1 Mixed Conifer-Dominant 20-32%	55	1,780	4	100	0		
01.90.2 Mixed Conifer-Dominant 33-67%	56	25,817	62	100	5	0	37.5
01.94.2 Conifer-Aspen 33-67%	60	13,401	4	100	0		
02.10.1 Aspen 20-32%	69	2,195	7	100	0		
02.10.2 Aspen 33-67%	70	2,375	10	100	0		

Map class	Class code	Mapped area (ha)	Training data		Independent test data		
			No of pixels	% of pixels correctly predicted	No of pixels	Omission Error %	Commission Error %
02.30.1 Cottonwood-Riparian 20-32%	77	1,315	25	92	2	100	0
02.30.2 Cottonwood-Riparian 33-67%	78	8,231	73	100	7	0	22.2
02.80.2 Other or Mixed Deciduous Forest 33-67%	82	206	6	100	0		
03.20 Juniper	88	884	36	100	0		
03.21 Juniper-Sage	91	21,924	91	90	6	0	25
03.22 Juniper-Mountain Mahogany	92	3,391	39	100	0		
03.35 Juniper-Limber Pine	94	79,869	295	89	34	14.7	0
04.20 Greasewood	101	4,843	61	98	3	33	60
04.21 Greasewood-Sagebrush	102	50,895	141	96	42	16.7	12.5
04.41 Gardner Saltbush	104	31,629	99	95	17	52.9	0

Map class	Class code	Mapped area (ha)	Training data		Independent test data		
			No of pixels	% of pixels correctly predicted	No of pixels	Omission Error %	Commission Error %
04.45 Saltbush-Sagebrush	105	38,464	89	97	18	22.2	17.6
04.60 Birdfoot Sage	107	124	5	100	0		
04.70 Mixed Desert Shrubs	108	35,577	41	98	14	0	0
05.11.1 Basin Big Sagebrush 5-15%	115	3,980	4	100	4	100	0
05.11.2 Basin Big Sagebrush 16-25%	116	3,035	36	100	5	100	100
05.11.3 Basin Big Sagebrush >25%	117	2,625	18	94	3	100	0
05.12.1 Wyoming Big Sagebrush 5-15%	119	266,315	468	95	86	29.1	40.2
05.12.2 Wyoming Big Sagebrush 16-25%	120	91,596	282	96	90	43.3	43.3
05.12.3 Wyoming Big Sagebrush >25%	121	5,823	74	100	6	100	100
05.13.1 Mountain Big Sagebrush 5-15%	123	14,345	34	100	0		

Map class	Class code	Mapped area (ha)	Training data		Independent test data		
			No of pixels	% of pixels correctly predicted	No of pixels	Omission Error %	Commission Error %
05.13.2 Mountain Big Sagebrush 16-25%	124	28,442	58	100	11	72.7	72.7
05.13.3 Mountain Big Sagebrush >25%	125	4,666	23	100	5	100	0
05.14 Black Sagebrush	126	5,141	52	96	8	100	0
05.16 Wyoming Three-tip Sagebrush	128	4,948	17	100	0		
05.19 Plains Silver Sagebrush	131	10,422	12	100	0		
05.20 Rabbitbrush	132	11,976	25	96	0		
05.33 Fringed Sage	144	11,231	31	100	0		
06.10 Willow	148	3,080	20	100	0		
06.70 Tamarisk	150	15,576	32	100	0		
07.20.1 Basin Grassland 7.5-20%	157	5,922	28	100	6	16.7	0

Map class	Class code	Mapped area (ha)	Training data		Independent test data		
			No of pixels	% of pixels correctly predicted	No of pixels	Omission Error %	Commission Error %
07.20.2 Basin Grassland 21-40%	158	33,880	124	98	36	11.1	11.1
07.20.3 Basin Grassland >40%	159	11,000	67	100	9	44.4	44.4
07.60 Riparian/Wet Meadow	169	6,444	36	100	0		
07.80.2 Annual Grassland 21-40%	173	143	8	100	0		
07.91.1 Forb 7.5-20% cover	176	3,925	4	100	0		
10.10 Water-Lentic or Standing	189	7,562	230	100	0		
12.90 Bare Ground	207	25,346	63	95	2	0	0
99.50 Burned Areas	216	24,431	67	97	0		
Total		**1,026,835**	**3,150**		**439**		

Conclusions

A non-parametric classification algorithm, calibrated with approximately 3,150 training pixels derived from 922 distinct field-sampled reference sites, was used to produce a moderate resolution map of land cover types for Area 1 of the Bighorn Basin. A total of 64 land cover classes were modeled across the study area. Resulting overall classification accuracy, evaluated using a variety of methods including analyses of randomized and partitioned test datasets, ranges from a lower limit of 67% to an upper limit of 87%. Classification errors associated with individual land cover classes were variable and attributed to the quantity of training and test data available, the quality of the field collected training data, and the biology and ecological amplitude of component species comprising individual cover classes.

Future efforts to improve classification accuracy may include an exploration of the effects of spatial scale on individual map class accuracies, collection of supplemental field reference data to improve under-sampled cover classes, and further research into the effectiveness of additional explanatory variables or alternative combinations of variables.

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