Using terrain attributes to assist remote sensing vegetation mapping of northern Great Plains grasslands
by Jonathan Mark Wheatley

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in Earth Sciences
Montana State University


Abstract:
Certain vegetation types of ecological interest to land-managers can not be reliably distinguished with multispectral remote sensing tools, such as the Landsat thematic mapper, because there is no simple correlation between remote sensing properties of vegetation and botanical classifications such as genus and species. To improve classification accuracy, researchers have employed ancillary information such as digital elevation data and soil survey data to help resolve ambiguities in remote sensing derived vegetation maps. Existing U.S. Forest Service remote sensing methods for large areas (10^4 - 10^6 km^2), developed by Ma and Redmond at the University of Montana, add the primary terrain attributes of elevation and slope to a multispectral image classification. This study explores whether secondary terrain attributes relevant to vegetation, such as topographic wetness indices and incident solar radiation, can be incorporated into the Forest Service classification to improve accuracy. Terrain attributes were computed from 30-meter spatial resolution USGS digital elevation data with the Terrain Analysis Programs for the Environmental Sciences - Grid version (TAPES-G), and the DYNWET and SRAD programs, in a 1700 km^2 test site in the Littie Missouri National Grassland, North Dakota.

When quasi-dynamic topographic wetness index and incident shortwave solar radiation are added to a Ma/Redmond classification containing seven Landsat bands and elevation, little or no improvement in overall classification accuracy occurs: accuracy remains in the 51-57% range for a classification into 13 landcover types. Individual landcover class accuracies are not significantly improved: a large fraction of the total error is found in misclassification of grassland and riparian forest classes. Possible reasons for the lack of improvement include 1) classes with distinct terrain attributes, such as ponderosa pine and badlands, are already distinguished by remote sensing alone, and 2) confused categories with similar remote sensing properties, such as broadleaf forest and cropland, occur on terrain with similar topographic wetness and solar radiation indices. Overall classification accuracy would improve approximately 10% if the two grassland categories were combined into a single class.

The Ma/Redmond method also incorporates a spatial grouping process to merge image pixels into groups appropriate for the scale of the final map. Although overall classification accuracy varies little when the minimum mapping unit is changed from 0.4 to 2.0 ha, spatial aggregation can change the vegetation class of up to two-thirds of the pixels in a map and can dramatically change the spatial pattern of vegetation patches. A minimum mapping unit of 0.8 ha is recommended to retain the spatial structure of the wooded-draw ecosystems of the Little Missouri region.

A predicted riparian zone derived from TAPES-G computed stream channels can be used to improve classification accuracy. This technique has the potential to improve accuracy up to 20% in the Little Missouri study area, because ~12% of the error in the maps is due to riparian vegetation classes occurring outside the riparian buffer, and ~8% of the error is due to non-riparian classes occurring inside the buffer. These errors can be corrected by using the stream buffer to reclassify vegetation to the appropriate riparian or non-riparian class.

# USING TERRAIN ATTRIBUTES TO ASSIST REMOTE SENSING VEGETATION MAPPING OF NORTHERN GREAT PLAINS GRASSLANDS

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APPROVAL

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## ABSTRACT

Certain vegetation types of ecological interest to land-managers can not be reliably distinguished with multispectral remote sensing tools, such as the Landsat thematic mapper, because there is no simple correlation between remote sensing properties of vegetation and botanical classifications such as genus and species. To improve classification accuracy, researchers have employed ancillary information such as digital elevation data and soil survey data to help resolve ambiguities in remote sensing derived vegetation maps. Existing U.S. Forest Service remote sensing methods for large areas ($10^4$-$10^6$ km$^2$), developed by Ma and Redmond at the University of Montana, add the primary terrain attributes of elevation and slope to a multispectral image classification. This study explores whether secondary terrain attributes relevant to vegetation, such as topographic wetness indices and incident solar radiation, can be incorporated into the Forest Service classification to improve accuracy. Terrain attributes were computed from 30-meter spatial resolution USGS digital elevation data with the Terrain Analysis Programs for the Environmental Sciences - Grid version (TAPES-G), and the DYNWET and SRAD programs, in a 1700 km$^2$ test site in the Little Missouri National Grassland, North Dakota.

When quasi-dynamic topographic wetness index and incident shortwave solar radiation are added to a Ma/Redmond classification containing seven Landsat bands and elevation, little or no improvement in overall classification accuracy occurs: accuracy remains in the 51-57% range for a classification into 13 landcover types. Individual landcover class accuracies are not significantly improved: a large fraction of the total error is found in misclassification of grassland and riparian forest classes. Possible reasons for the lack of improvement include 1) classes with distinct terrain attributes, such as ponderosa pine and badlands, are already distinguished by remote sensing alone, and 2) confused categories with similar remote sensing properties, such as broadleaf forest and cropland, occur on terrain with similar topographic wetness and solar radiation indices. Overall classification accuracy would improve approximately 10% if the two grassland categories were combined into a single class.

The Ma/Redmond method also incorporates a spatial grouping process to merge image pixels into groups appropriate for the scale of the final map. Although overall classification accuracy varies little when the minimum mapping unit is changed from 0.4 to 2.0 ha, spatial aggregation can change the vegetation class of up to two-thirds of the pixels in a map and can dramatically change the spatial pattern of vegetation patches. A minimum mapping unit of 0.8 ha is recommended to retain the spatial structure of the wooded-draw ecosystems of the Little Missouri region.

A predicted riparian zone derived from TAPES-G computed stream channels can be used to improve classification accuracy. This technique has the potential to improve accuracy up to 20% in the Little Missouri study area, because ~12% of the error in the maps is due to riparian vegetation classes occurring outside the riparian buffer, and ~8% of the error is due to non-riparian classes occurring inside the buffer. These errors can be corrected by using the stream buffer to reclassify vegetation to the appropriate riparian or non-riparian class.

# CHAPTER ONE

# INTRODUCTION

## Scope and Purpose

> *"A vegetation map not only serves as a record of what exists when it is made, but also as a starting point for the study of changes, whether natural or brought about by human activity. It serves to arouse public interest of a country in its wild vegetation, which ought to be recognised as a national possession not to be lightly destroyed or wasted; and it indicates the localities which are most suitable for the nature reserves which every country should have. ... The making of such maps should be part of the national stock-taking which is the duty of every modern community."*
> Arthur G. Tansley and T.F. Chipp, 1926.

In order to manage natural resources effectively, land managers must know the geographical distribution of landscape components such as vegetation, soils and terrain. The need for natural resource mapping has long been acknowledged (Tansley and Chipp 1926), but until the advent of digital remote sensing and computerized image analysis, the production of detailed resource maps was costly, time consuming and not easily standardized. Such maps were compiled from decades of fieldwork which could not be updated quickly. Remote sensing and GIS now provide the tools for mapping large areas such as an entire National Forest at spatial resolutions as fine as 30 m, and potentially allow these maps to be updated efficiently.

A disadvantage of remote sensing is that it may not be able to distinguish ecologically distinct vegetation types of interest to the land manager. Remote sensing image classification attempts to convert multi-spectral imagery into ecologically meaningful vegetation types. However, there is no simple correlation between vegetation type and spectral signature (Gates 1980), so that considerable confusion arises: dissimilar vegetation types may have similar spectral signatures. Furthermore, a given vegetation type may have a seasonally variable signature. Grasslands in particular show rapid responses to varying precipitation amounts (Pickup et al. 1994). Regardless of future improvements in remote sensing technology, such as imaging spectrometers (Thomas and Ustin 1987), which produce a reflectance spectrum for each pixel in the image, there will always be some inherent confusion between spectral reflectance and vegetation type.

To help resolve confusion in remote sensing maps, additional information may be incorporated into the remote sensing classification in two ways, either in the original statistical clustering method, or in a rule-based classifier. In the former, terrain attributes are treated by the clustering algorithm as additional layers of information that complement the multi-spectral bands of a Landsat image. In a rule-based model, the ecological knowledge of experts is distilled into a series of questions in a decision tree that can be used to clarify vegetation types that are confused in remote sensing images (Bolstad and Lillesand 1992). The advantage of the statistical clustering method is that it does not involve assumptions about the relationship between vegetation and terrain, whereas rule-based classifiers may involve subjective rules and broad assumptions about terrain-vegetation correlations. Often, rule-based classifiers are specific to a particular area, whereas general statistical clustering is less site-dependent.

Terrain parameters, rather than soil or climate variables, are explored in this study, because topographic data are available at an appropriate scale for Landsat images, whereas soil and climate data are not available in this study area. Modern soil surveys are available for less than half of the Little Missouri region studied here, and where 1:20,000 scale soil maps are available, they do not resolve individual wooded valleys and small drainages, but lump together much of the highly dissected badlands as "mixed badlands complex" (Aziz 1989). The climate of western North Dakota does not exhibit the dramatic elevation-induced variations seen in more mountainous terrain: the climate within the study area is quite homogenous (Owenby and Ezell 1992) and is therefore of little use in differentiating vegetation types.

Digital topographic data can be used to calculate terrain parameters of relevance to vegetation. The Topographic Analysis Programs for the Environmental Sciences - Grid version (TAPES-G) suite of programs compute how various geometric terrain parameters such as slope, aspect, curvature, and the upslope area that drains to each point (upslope contributing area, or specific catchment area), and biophysical parameters, such as solar radiation and topographic wetness, vary across a landscape (Gallant and Wilson 1996, Wilson and Gallant 1996a, 1996b). In particular, two vegetation-related parameters may be improvements over the basic parameters of elevation, slope and aspect: 1) the spatial pattern of soil moisture as affected by accumulated waterflow, and 2) solar radiation as affected by topographic shading by nearby features. Both are physical processes not addressed by slope and aspect alone. Thus, one might expect these secondary biophysical parameters to correlate with vegetation better than slope and aspect. Where landcover has been greatly influenced by human activity, such as agriculture, terrain attributes may be less useful in predicting vegetation. However, cropland is constrained by terrain: in the United States, cultivation of steep slopes is discouraged. A time-series of images might also improve vegetation identification, but the temporal dimension could not be explored here, due to the high cost of multiple images of the same area, and also due to the paucity of recent cloud-free imagery during the growing season in parts of the Little Missouri (Dibenedetto, Custer National Forest ecologist, personal communication).

This study explores whether terrain attributes can be used to improve the thematic accuracy of remote sensing landcover maps. The objective is to compare the accuracy of Landsat vegetation maps prepared with and without the use of terrain attributes, to determine whether application of these methods is worthwhile over the entire Little Missouri region. Specifically, two improvements to the existing U.S. Forest Service vegetation classification methods are explored: 1) whether or not the addition of TAPES-G topographic wetness and solar radiation attributes improves the Ma/Redmond (1994b) vegetation classification; and 2) whether or not the use of TAPES-G drainage channels derived from 30 m digital elevation models improves the accuracy of the vegetation maps.

# Literature Review

## Remote Sensing

Landsat multispectral remote sensing attempts to identify vegetation based on its spectral reflectance, measured in the satellite's seven wavelength bands, ranging from blue visible light to far-infrared thermal wavelengths. Generally, green leaves absorb light in the 0.4-0.7 micron wavelength range, but make an abrupt transition to reflectance at .70 micron, scattering light effectively between 0.7 and 1.3 microns (Gates et al. 1965, Ripple 1985). In the semiarid grassland and badlands cover types that are common in the Little Missouri area, the observed reflectance may result from a combination of live vegetation, dead vegetation and bare soil. In addition, the spectral signature may vary due to differing angles of illumination, the health of vegetation (affected by precipitation and grazing), and the seasonal life-cycle of vegetation. The ability of the Landsat thematic mapper to distinguish vegetation types is limited by the spectral and spatial resolution of the detector. Furthermore, remote sensing classification has proven difficult to automate (Lillesand and Keifer 1994).

Accuracy of remote sensing vegetation classification decreases when vegetation is divided into fine categories. Anderson et al. (1976) defined a hierarchy of landcover types: land managers are typically interested in Anderson level III vegetation categories (the species level) but automated classification accuracies for these classes are generally quite low, 65% to 75% (Skidmore and Turner 1988). Accuracy can be increased by grouping vegetation into the very broad classes of Anderson level II, such as conifer versus hardwood forest. Manual photo-interpretation of Landsat images may yield higher accuracies, and these methods are still used for small study areas, but are too time consuming for an area as large as the Little Missouri National Grassland.

Two general types of classification are used, unsupervised and supervised. In the former, the data are clustered into arbitrary categories, but in the latter, ground-truth is used as training data to divide the multidimensional data space into categories based on the observed properties of the training data set (Jensen 1996). Provided that there is adequate, unbiased training data available, the supervised method is far superior to the arbitrary classes of the unsupervised method.

Hutchinson (1982) outlines three ways that additional data layers can be added to remote sensing classification: before, during or after the remote sensing classifier. Ancillary data can be used as a pre-classification stratifier, as additional data dimensions in a maximum likelihood classifier, or as a post-classification sorting of classes. In the first method, the data can be divided into subsets with smaller variance using the ancillary data. In the maximum likelihood method, ancillary data is used to modify the prior probabilities used in the classification. In the post-classification sorting, deterministic rules are used to reassign classes based on ancillary data. Joria and Jorgenson (1996) used ancillary data layers of elevation, slope, landform type, solar radiation and riparian zones, in a post-classification sorting, to assist a classification of 14 landcover types in arctic tundra, but classification accuracy remained at ~50% when these terrain attributes were used.

Numerous statistical clustering methods have been used to group multispectral data into landcover classes, but ultimately, the quantity and quality of ground-truth data used in supervision of vegetation classes may be more important than the classification method used (Congalton 1991). Zhuang et al. (1995) compare minimum distance, maximum-likelihood, and neural network classification accuracy for six landcover classes in a mixed cropland, rangeland and broadleaf forest site in Indiana. The three methods produced similar accuracies (within a 5% range) for each of the landcover classes, with the exception of the bare soil class, where the neural network classifier was 10% more accurate than the other two methods. As with many remote sensing applications, high accuracies of 85-95% were achieved by lumping landcover types into very broad categories, in this case water, bare soil, one forest class, one grassland class and two crop classes.

For this study, the Forest Service was interested in evaluating the impact of adding additional terrain attributes to their existing remote sensing method developed for efficient mapping of very large areas. This method, developed by Ma and Redmond at the University of Montana, is a multi-stage process in which terrain attributes are added after an initial classification of Landsat bands 3, 4 and 5 (Ma and Redmond 1994b). The details of this method are described in Chapter Two.

An alternative approach to identifying vegetation by species is to characterize it by ecological parameters such as leaf area index (LAI) or above ground biomass, which are less arbitrarily related to the plant's spectral reflectance than genus and species. However, establishing a universal relationship between remote sensing spectral indices, such as the normalized infrared minus red difference (NDVI), and ecological parameters has proven difficult. In Great Plains grasslands at Mandan, North Dakota, Aase et al. (1987) found that the relationship between remote sensing vegetation index and leaf area index varied according to the intensity of cattle grazing, making it impossible to translate NDVI into LAI without knowing the grazing intensity. Friedl et al. (1995) report similar problems in the Konza Prairie, Kansas.

In grasslands in particular, the rapid temporal variation of the spectral signature, and the interplay of forces such as drought and grazing have made the mapping of rangeland at large scales problematic. For large areas where automated mapping is necessary, low classification accuracies seem unavoidable using the classification techniques and ancillary data used to date.

Digital Terrain Analysis

With the advent of widely available, inexpensive digital elevation data, there is a need for computerized terrain analysis and automated, standardized landform classification algorithms based on terrain attributes (Dikau 1989). Terrain parameters have already proven useful for hydrologic analysis and erosion modeling (Moore and Nieber 1989, Moore and Hutchinson 1991, Panuska, et al. 1991, Quinn, et al. 1991) . Moore et al. (1993a) and Wilson et al. (1994) have used terrain attributes to aid soil mapping. Moore et al. (1993b) explored how solar radiation and topographic wetness are related to vegetation in south-east Australia. They found that the presence of certain species of Eucalyptus correlated well with the amount of solar radiation, but the presence of Eucalyptus could not be predicted from the distribution of average annual soil water content across the landscape.

Terrain analysis computes properties of a three-dimensional landscape surface. Terrain attributes may be locally defined geometric properties such as slope, curvature and aspect, or cumulative, such as flow direction, upslope contributing area, and flow path length. Secondary, biophysical parameters such as the quantity of solar radiation incident on the land surface, and various topographic wetness indices, can be computed from the primary terrain attributes.

Several terrain analysis software packages are widely used, including the ARC/INFO TOPOGRID and FLOWDIRECTION terrain functions (ESRI Inc. 1995), the TOPMODEL software of Beven et al. (1994), and the Terrain Analysis Programs for the Environmental Sciences (TAPES-G) (Gallant and Wilson 1996). Firstly, in order to have correct drainage patterns, spurious pits in the terrain surface, which may result from DEM defects or undersampling of complex terrain, must be removed. The method of Jensen and Dominque (1988) is the most widely used.

Hydrologic parameters, such as upslope contributing area, depend on the method used to calculate flow direction on the terrain surface. The simplest method, known as deterministic eight-node (D8), used by ARC/INFO, assumes that all the water in a cell flows to a single adjacent cell in the direction of steepest descent (O'Callaghan and Mark, 1984). Two problems arise from this, 1) the divergence of flow on a convex surface is not modeled, and 2) only eight flow directions are permitted, so that flow paths are not smoothly curved, but broken into 45° increments, which does not look "natural", but may be an acceptable approximation. As the spatial pattern of soil moisture may be influenced by divergence in upland areas, a more sophisticated flow algorithm is necessary for this study. The TAPES-G random eight-node (FRho8) algorithm uses the method of Fairfield and Leymarie (1991) which adds Poisson noise to the flow vector to avoid long parallel flow paths, and partitions flow between multiple downhill cells by a weighting based on steepness. This algorithm allows divergence below a user-defined channel initiation threshold, above which divergence is turned off because the flow is assumed to be channeled. Wolock and McCabe (1995) compared maps of specific catchment area computed with both of these algorithms and concluded that the FRho8 flow direction algorithm was superior in predicting the distribution of soil moisture. For some cumulative hydrologic functions, such as predicted stream flow, there may be little difference between the methods.

Beven and Kirkby (1979) proposed a topographic wetness index which approximates the depth to the water table, $w=\ln(a/\tan b)$, where $w$ is wetness index, ln is the natural logarithm, $a$ is the upslope contributing area, tan is the trigonometric tangent, and $b$ is the slope angle in degrees. This index assumes a steady-state subsurface drainage equilibrium, which is rarely the case (Barling et al. 1994). The DYNWET program used here computes a quasi-dynamic wetness index which takes into account variable flow times across a landscape, and the hydrologic conductivity and porosity of the soil. Barling et al. (1994) have found that the quasi-dynamic index better models observed soil moisture in catchments in southeast Australia. Overall, the two methods both predict lower soil moisture on steeper slopes, but the static index is influenced more by upslope contributing area which is largest in drainage channels at the mouth of catchments. Neither static nor dynamic wetness indices incorporate evaporation, vegetation effects such as water uptake, or variation in soil properties and geology across a landscape. Thus, the indices are independent of terrain aspect, which may not be realistic.

Computer programs that calculate incident solar radiation across landscapes include the SOLARFLUX software written in ARC/INFO Macro Language, and the Atmospheric and Topographic Model (ATM), both summarized by Dubayah and Rich (1996), and the SRAD program (Wilson and Gallant 1996b). All three use the efficient topographic shading algorithm of Dozier et al. (1981), and compute the sum of solar radiation computed at intervals throughout the year.

## Study Area Description

The choice of study area arose from the desire of the U.S. Forest Service to map the USFS Northern Region National Grasslands and National Forests of North and South Dakota, a $10^4$ $km^2$ area consisting of the Little Missouri, Grand River/Cedar River and Sheyenne National Grasslands and the Sioux District of the Custer National Forest. Of the grasslands, the Little Missouri (Figure 1) has the largest vertical relief, making it most suitable for terrain analysis; farther east the terrain is very flat and the USGS digital data errors become more troublesome, and the effects of terrain on vegetation are less dramatic. The following criteria were used to select a study area within the Little Missouri. As hydrology is cumulative downhill, the area used in the terrain calculations must consist of complete catchment areas, or the uppermost portions thereof. The grassland area east of the Little Missouri River satisfies this requirement, but 30 m digital data coverage is not complete in the western tributary drainages of the Little Missouri River. The area must also

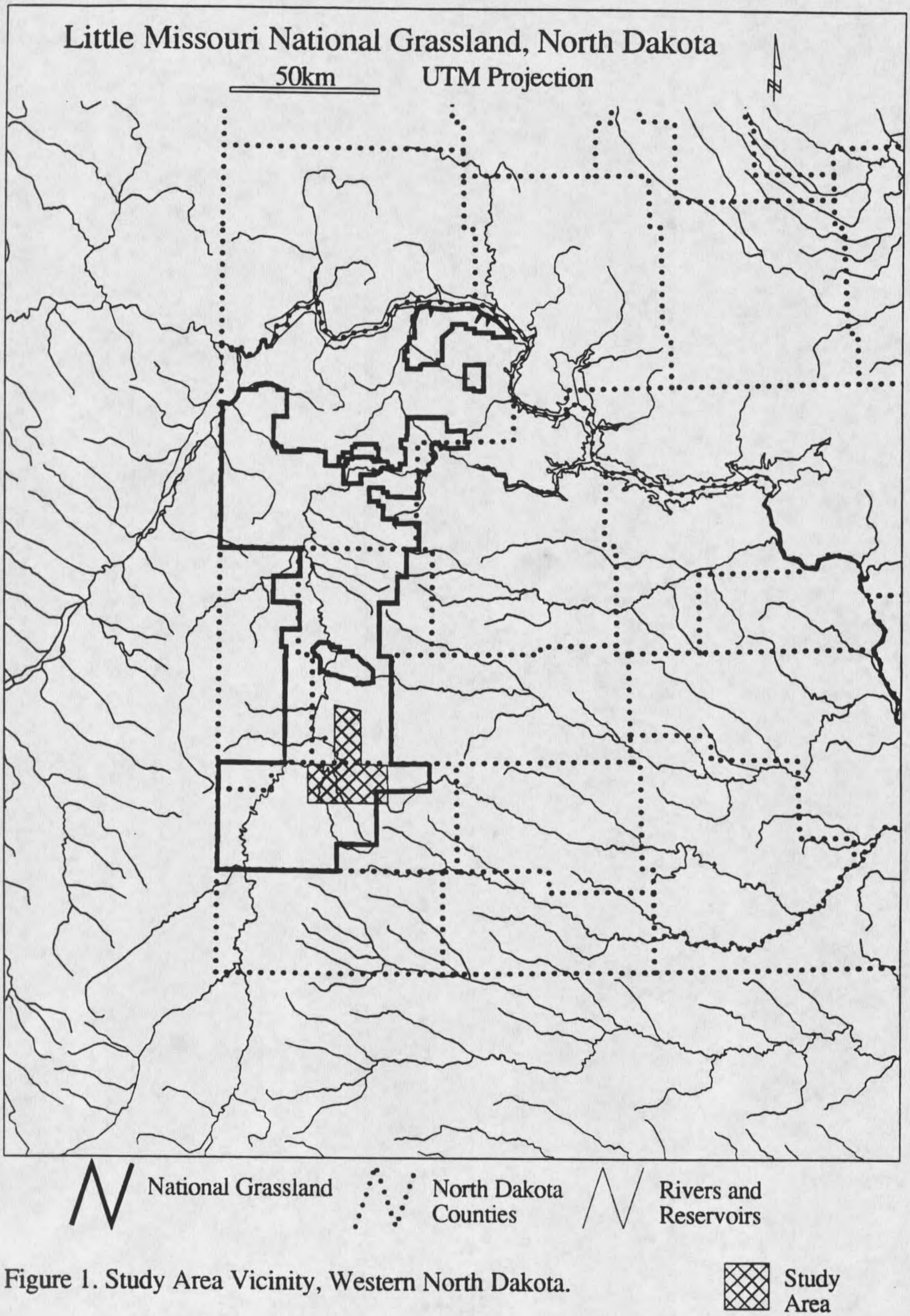


Figure 1. Study Area Vicinity, Western North Dakota.

have adequate ground-truth fieldwork measurements available. Ma and Redmond chose a 700 $km^2$ test area consisting of the Tracy Mountain, Cliffs Plateau, Deep Creek North, Spring Creek and Juniper Spur 7.5 minute USGS quadrangles (cross-hatched in Figure 1). The primary selection criterion was the availability of ground-truth data with which to evaluate classification accuracy: these five quadrangles contained the highest density of ground-truth data in addition to representing the major landscape types of the Little Missouri: rolling uplands which are mostly cropland, wooded draws and badlands, and river floodplains and terraces. The study area contains the Third Creek drainage, on the east side of the Little Missouri River. The northern edge of the study area is truncated at an angle by the northern boundary of the Landsat scene.

## Geology

The erosional processes that created the North Dakota badlands began 600,000 years ago, when the continental ice sheet displaced the Little Missouri River southward into a shorter, steeper channel. The Little Missouri and its tributaries continue to cut into the surrounding plain. The eastern boundary of this erosion bisects the study area, dividing it into two dramatically different physiographic regions, the gently rolling Missouri Slope Upland to the east and the Little Missouri Badlands to the west (Bluemle 1991).

The bedrock is entirely sedimentary, consisting of Upper Cretaceous and Tertiary shale strata. The Bullion Creek Formation, which underlies most of the study area, consists of alternating layers of sandstone, shale and lignite. Flat-topped buttes (monadnocks) of the more resistant sandstone rise 150 m above the surrounding peneplain. Total vertical relief in the study area is less than 250 m. The Little Missouri has incised a channel 100-200 m below the surrounding terrain. Most of the wooded draws have a V-shaped cross-section, but the larger drainages have a floodplain several hundred meters wide. The main stem of the Little Missouri has a floodplain up to one kilometer wide. Pleistocene river terraces, containing material eroded from the Rocky Mountains, cover areas up to 10 $km^2$ near the Little Missouri main stem. A distinctive feature of this area is the presence of naturally fired clay (clinker, locally named "scoria"), which is more erosion resistant than unbaked materials, forming steep-sided knobs 20-40 m high (Bluemle 1991). In places these knobs, together with depressions caused by the collapse of burned lignite beds, form large areas of hummocky terrain. This highly complex terrain is barely resolved at the 30 m cell size of the Landsat images and elevation data.

## Soils

Soil is largely absent in the badlands areas, because the steep slopes are continually eroding. Where the parent materials are sufficiently weathered to be considered soil, Inceptisols and Entisols are common, such as the Cherry series (fine-silty, mixed, frigid Typic Ustochrepts) and Cabbart series (loamy, mixed (calcareous), frigid, shallow Ustic Torriorthents), two of the more common soils in the wooded draws (Thompson 1978). The floodplains of the larger creeks are also classified as Entisols, though they may be deep soils, such as the Korchea series (fine-loamy, mixed (calcareous), frigid Mollic Ustifluvents). The rolling uplands, which are mostly grassland and cropland, contain moderately deep soils such as Entic and Typic Haploborolls.

Most wooded draws are not delineated in the 1:20,000-scale soil survey map of Slope County (Thompson 1978) and large areas of the wooded draws are mapped as the Badlands-Cabbart complex. Flatter upland areas and wide floodplains within the badlands are delineated. It appears that cropland in the rolling uplands is mapped at greater detail. Only the southernmost portion of the study area, in Slope County, has been mapped at this scale. The computerized 1:250,000-scale State Soil Geographic Database (STATSGO) soil maps show even less detail, but they do distinguish broad areas of badlands from the surrounding rolling uplands (U.S. Soil Conservation Service 1993).

## Climate

North Dakota, which is located near the geographic center of North America, has a semiarid mid-latitude steppe climate (BSk in the Koppen classification), where cold dry winters (-15° C mean temperature) alternate with warm summers (21° C mean temperature) that average 120 frost-free days. Precipitation is greatest in the early part of the growing season, when approximately 50% of the annual precipitation of 400 mm occurs in April, May and June, whereas less than 30 mm of precipitation falls in the three mid-winter months (Owenby and Ezell, 1992).

The temporal variation of precipitation from year to year at a given station is far greater than the spatial variation across North Dakota. At Dickinson Experimental Farm, just east of the Little Missouri, annual precipitation has ranged from 170 mm to 800 mm over the 90 year record, 1904-93 (Hydrosphere, Inc. 1993). The rainfall distribution is skewed, with drier than average years occurring more frequently than wetter than average ones. The moisture balance in the growing season shifts dramatically from year to year: at Williston Experimental Farm, the nearest station for which data is complete, a dry year such as 1988 yielded 9 mm precipitation and 290 mm observed pan evaporation in the month of July, whereas in a wet year (1993), the moisture balance was reversed, with 208 mm precipitation and 136 mm observed evaporation (NOAA 1993a). The wet weather was also accompanied by much cooler temperatures, in July 1993 the mean daily maximum was 9.3° C cooler than in July 1988.

The climate is sufficiently arid and hot in the growing season that most tree species are unable to grow on south-facing slopes, with the possible exception of ponderosa pine (*Pinus ponderosa*). Broadleaf trees such as green ash (*Fraxinus pennsylvanica*) and shrubs such as snowberry (*Symphoricarpos occidentalis*) are largely confined to areas near watercourses.

Vegetation

The Little Missouri is a transition zone between western and eastern plant species (Rudd 1951). The region is at the western limit of the range of eastern hardwoods such as green ash *(Fraxinus pennsylvanica*) and bur oak (*Quercus macrocarpa*) and at the eastern limit of western species, such as Rocky Mountain juniper (*Juniperus scopulorum*) and Ponderosa Pine (*Pinus ponderosa*) (Little 1971). Furthermore, the Little Missouri is the southernmost extent of some boreal forest trees such as balsam poplar (*Populus balsamifera*) and paper birch (*Betula papyfira*). Desert plants with ranges centered on the Great Basin, such as cactus (*Opuntia fragilis*), yucca (*Yucca glauca*), saltbush (*Atriplex *sp*.), skunkbrush (*Sacrobatus vermiculatus*), saltgrass (*Distichlis stricta*) and sagebrush (*Artemesia tridentata*) are also widespread in the Little Missouri region (Rudd 1951), though they may not grow in patches large enough to be detected by remote sensing.

Brown (1993) mapped species composition of grasses in the Great Plains and found western wheatgrass (*Agropyron smithii*) and needle-and-thread (*Stipa comata*) to be the most common "cool-season" (C3 photosynthesis path) native grasses in the region, whereas blue grama *(Bouteloua gracilis*) is the only "warm-season" (C4 photosynthesis path) grass that is abundant in the Little Missouri. In the rolling uplands, crested wheatgrass (*Agropyron desertorum*), an introduced bunchgrass from the Russian steppe, was abundantly planted on former cropland abandoned in the drought of the 1930's, to prevent erosion.

# CHAPTER TWO

# DATA SOURCES AND METHODS

## Ground-Truth Data

From 1987 to 1994, the USDA Forest Service made vegetation measurements in the Little Missouri National Grasslands which are suitable for use as ground-truth for remote sensing vegetation classifications. The dominant vegetation species was determined by relative canopy cover at 97 field data points within the five-quadrangle study area. Jeff Dibenedetto, Custer National Forest ecologist, assigned these vegetation types to a Forest Service landcover class (Table 1), and associated each ground-truth point with a vegetation patch visible on the Landsat image. The geographic locations of the vegetation patches were measured on the Landsat image, using the ARC/INFO command CELLVALUE. An additional 76 landcover ground-truth points were derived from 1:24,000-scale airphotos dated August 17, 1981, to increase the sample size for landcover types such as riparian forest that are poorly represented in the field data. Some landcover types such as riparian shrub, sagebrush, and juniper forest, are nevertheless still poorly represented (five points or less) in the combined data-set because they could not be identified on airphotos. The Forest Service landcover classes are defined in Appendix A and the locations of the ground-truth data are given in Appendix B.