



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

© Copyright by Jonathan Mark Wheatley (1996)

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 km²), 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 km² 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.

**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-BOZEMAN
Bozeman, Montana**

August 1996

N398
W5601

APPROVAL

of a thesis submitted by

Jonathan Mark Wheatley

This thesis has been read by each member of the thesis committee and has been found to be satisfactory regarding content, English usage, format, citations, bibliographic style, and consistency, and is ready for submission to the College of Graduate Studies.

Oct 4, 1996
Date

John P. Wil
Chairperson, Graduate Committee

Approved for the Major Department

Sept 30, 1996
Date

W. Andrew Marans
Head, Major Department

Approved for the College of Graduate Studies

RL Brown
Date

10/23/96
Graduate Dean

STATEMENT OF PERMISSION TO USE

In presenting this thesis in partial fulfillment of the requirements for a master's degree at Montana State University-Bozeman, I agree that the Library shall make it available to borrowers under rules of the Library.

If I have indicated my intention to copyright this thesis by including a copyright notice page, copying is allowable only for scholarly purposes, consistent with "fair use" as prescribed in the U.S. Copyright Law. Requests for permission for extended quotation from or reproduction of this thesis in whole or parts may be granted only by the copyright holder.

Signature

Jonathan Wheatley

Date

8/31/96

ACKNOWLEDGMENTS

This work was funded by the U.S. Forest Service Northern Region. Landsat images, digital elevation models and ecological fieldwork were provided by the Custer National Forest, which manages the National Grasslands of the Dakotas. Jeff Dibenedetto was my invaluable guide to the ecology of the Little Missouri: he aided every stage of this project with very helpful advice. Roland Redmond and Zhenkui Ma at the University of Montana performed all the remote sensing data processing, accuracy assessment and calculation of stream buffers for this study, and also gave us many useful suggestions. Damian Spangrud charted a course through the Sargasso Sea of ARC/INFO Macro Language, providing assistance that greatly enhanced my data analysis. Lou Glassy, programmer extraordinaire, installed and debugged the TAPES-G terrain analysis software at MSU, and provided excellent UNIX assistance.

I wish to thank my thesis committee for their helpful suggestions, and my advisor, John Wilson, who initiated this project and who created a highly successful Geographic Information and Analysis Center at Montana State University Bozeman, which made this work possible.

TABLE OF CONTENTS

	Page
1. INTRODUCTION	1
Scope and Purpose	1
Literature Review	5
Remote Sensing	5
Digital Terrain Analysis	8
Study Area Description	11
Geology	13
Soils	14
Climate	15
Vegetation	16
2. DATA SOURCES AND METHODS	18
Ground-Truth Data	18
Landsat Thematic Mapper Imagery	19
Digital Elevation Models (DEM)	20
Terrain Analysis (TAPES-G)	23
Quasi-Dynamic Soil Wetness Index (DYNWET)	24
Solar Radiation Modeling (SRAD)	25
Ma/Redmond Remote Sensing Methods	26
Accuracy Assessment	28
3. RESULTS AND DISCUSSION	30
Terrain Attribute Values at Ground-Truth Locations	30
Terrain Attribute Maps	35
Classification Accuracy	43
Landcover Maps Incorporating Terrain Attributes in Classification	49

TABLE OF CONTENTS-Continued

Comparison of Stream Buffers Derived from TAPES-G Drainage Channels and DLG Data	56
Using a Stream Elevation Buffer to Improve Vegetation Classification	60
 4. CONCLUSIONS	 63
 REFERENCES CITED	 68
 APPENDICES	 75
Appendix A - Description of Forest Service Landcover Types	76
Appendix B - Terrain Attribute Values at Ground-Truth Locations	79
Appendix C - Metadata and Parameter Files for TAPES-G Programs	84

LIST OF TABLES

Table	Page
1. U.S. Forest Service Codes and Sample Sizes of Landcover Classes	19
2. Overall Classification Accuracy	44
3. Error Matrices for the Nine Classifications	45-47
4. Percent Agreement in a Pixel-by-Pixel Comparison of Landcover Maps	55
5. Fraction of Upland Vegetation Inside the TAPES-G Derived Stream Buffer, and Fraction of the Riparian Vegetation Outside the Stream Buffer	61

LIST OF FIGURES

Figure	Page
1. Study Area Vicinity, Western North Dakota	12
2. Shaded Relief Elevation Map	21
3. Elevation Map	31
4. Minimum, Maximum and Median Elevation by Landcover Type	32
5. Minimum, Maximum and Median Slope by Landcover Type	32
6. Minimum, Maximum and Median Upslope Contributing Area by Landcover Type	33
7. Minimum, Maximum and Median Steady-State Wetness Index by Landcover Type	33
8. Minimum, Maximum and Median Quasi-Dynamic Wetness Index by Landcover Type	34
9. Minimum, Maximum and Median Solar Radiation by Landcover Type	34
10. Slope Computed by TAPES-G	36
11. Aspect Computed by TAPES-G	37
12.. Upslope Contributing Area Computed by TAPES-G	38
13. Steady-State Wetness Index Computed from TAPES-G Output	39
14. Quasi-Dynamic Wetness Index Computed by DYNWET	40
15. Average Annual Solar Radiation Computed by SRAD	41
16. Landcover Map Using Landsat Data plus Elevation; Minimum Mapping Unit 0.4 hectare	50
17. Landcover Map Using Landsat Data plus Elevation and Quasi-Dynamic Wetness Index; Minimum Mapping Unit 0.4 hectare	51

LIST OF FIGURES-Continued

Figure		Page
18.	Landcover Map Using Landsat Data plus Elevation, Quasi-Dynamic Wetness Index and Solar Radiation; Minimum Mapping Unit 0.4 hectare	52
19.	Landcover Map Using Landsat Data plus Elevation, Quasi-Dynamic Wetness Index and Solar Radiation; Minimum Mapping Unit 0.8 hectare	53
20.	Landcover Map, Using Landsat Data plus Elevation, Quasi-Dynamic Wetness Index and Solar Radiation; Minimum Mapping Unit 2.0 hectare	54
21.	Stream Elevation Buffer Computed From TAPES-G Stream Channels	57
22.	Stream Elevation Buffer Computed From USGS 1:100,000-Scale Digital Line Graph	58
23.	Overlap Between Stream Buffers Derived from TAPES-G and DLG Data	59

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 km²), 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 km² 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 Dominique (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 km² 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

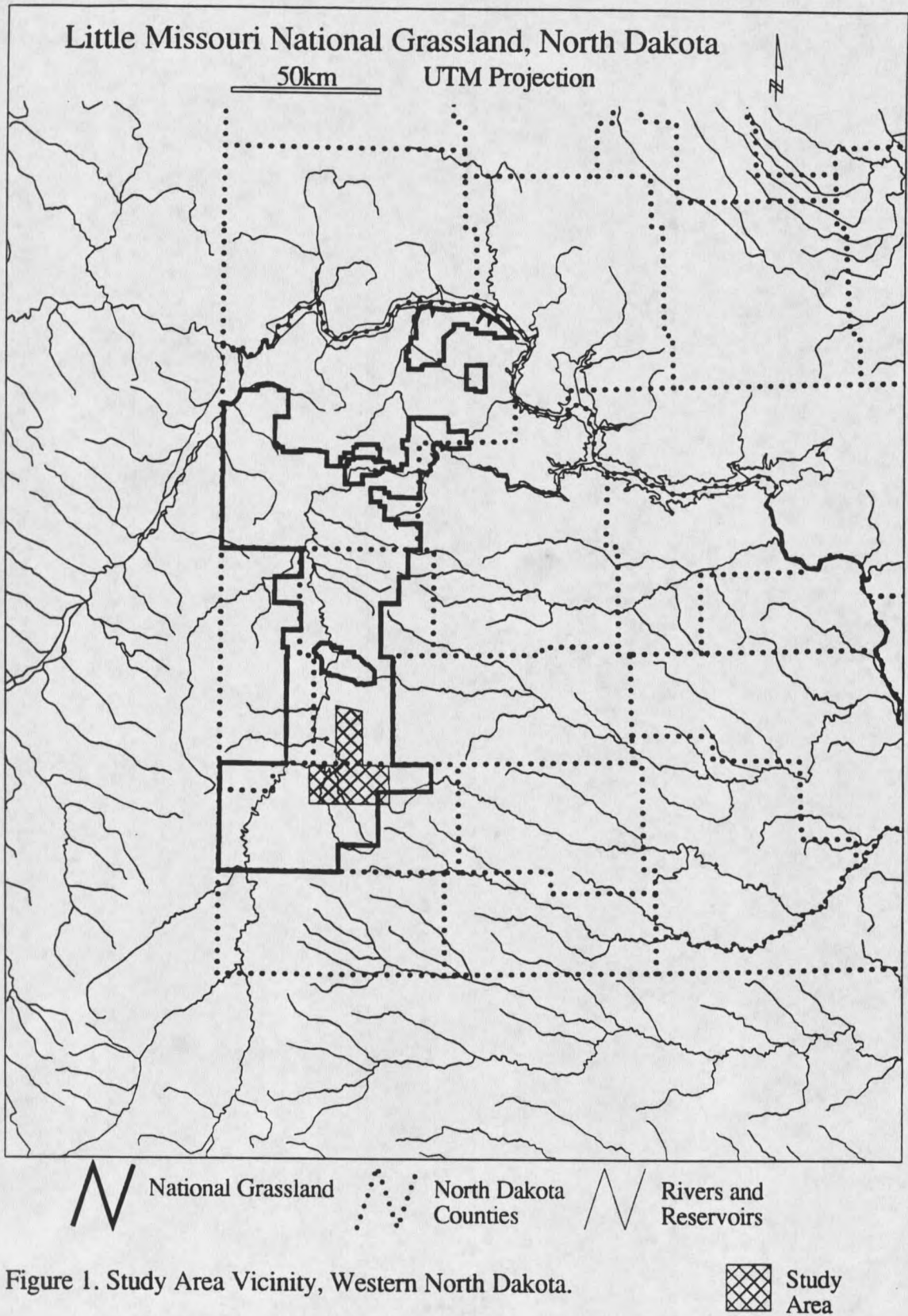


Figure 1. Study Area Vicinity, Western North Dakota.

have adequate ground-truth fieldwork measurements available. Ma and Redmond chose a 700 km² 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 km² 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 (Bluemler 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 papyrifera*). Desert plants with ranges centered on the Great Basin, such as cactus (*Opuntia fragilis*), yucca (*Yucca glauca*), saltbush (*Atriplex*

sp.), skunkbrush (*Sarcobatus vermiculatus*), saltgrass (*Distichlis stricta*) and sagebrush (*Artemisia 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.

Table 1. U.S. Forest Service Codes and Sample Sizes of Landcover Classes.

USFS Code	Landcover Class	Number of Ground Truth Points
2100	Cropland, cultivated pasture and hay	18
3110	Low grass/low cover	24
3111	Low grass/moderate cover	21
3201	Mesic upland shrub	10
3309	Silver sage	5
4102	Upland broadleaf forest	12
4206	Ponderosa pine forest	8
4214	Rocky Mountain juniper forest	5
5000	Water	3
6102	Riparian broadleaf forest	40
6201	Riparian grass and forb	9
6202	Riparian shrub	5
7601	Badland	13

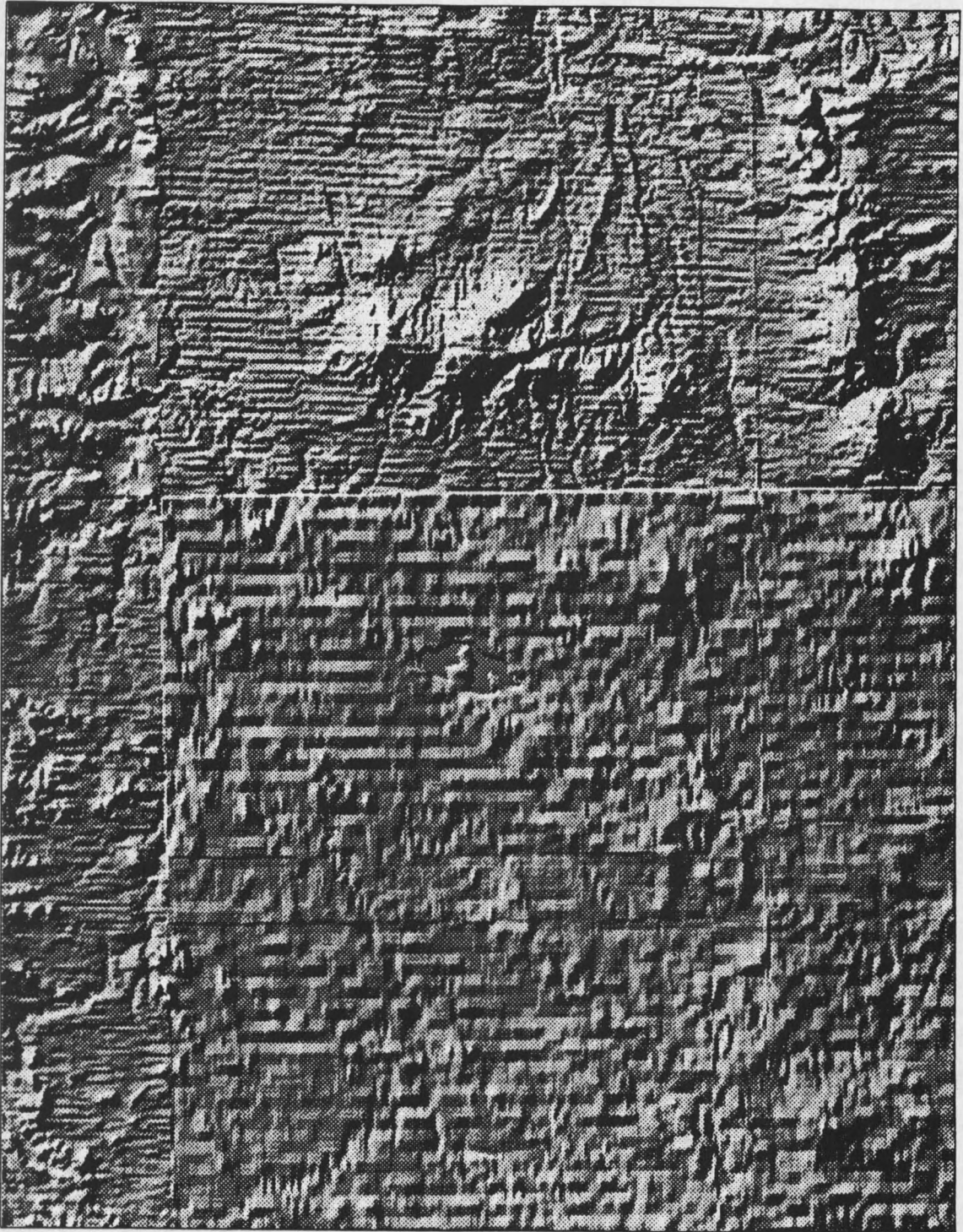
Landsat Thematic Mapper Imagery

A cloud-free Landsat thematic mapper image (path 34, row 28) covering the study area on July 5, 1989 was used for this study. No more recent cloud-free images in the growing season were available for the southern Little Missouri area at the start (1992) of this study (Dibenedetto, Custer National Forest ecologist, personal communication). The image was terrain-corrected and georeferenced to an Albers conical equal area projection by Hughes STX Aerospace Corporation. Ma and Redmond (1992) have measured the spatial accuracy of this terrain correction in western Montana, and have found it to be

accurate to well within the 30 m pixel size.

Digital Elevation Models (DEM)

Five 30 m resolution USGS 7.5 arc-minute quadrangles were joined using ARC/INFO GRID to provide full coverage of the study area; this mosaic was then linearly interpolated from the original Universal Transverse Mercator (UTM) projection to the same Albers projection as the Landsat image, using the ARC Version 7 PROJECT command. Although the digital elevation data conforms to USGS map accuracy level one, which allows a mean elevation error of 7 m in a 7.5 minute quadrangle (U.S. Geological Survey 1993), the systematic and spatially patterned nature of the error can sometimes be confused with real terrain features in an area such as the Little Missouri where the total vertical relief is as little as 20 m in some quadrangles. Several examples of the types of error that can occur in USGS elevation data are illustrated in Figure 2, which shows a 16x22 km area located at the southern boundary of the study area. Portions of six 7.5 arc-minute quadrangles are included. Three types of error are noticeable: 1) a quasi-periodic "ripple" of 250-300 m wavelength and up to 7 m amplitude, oriented roughly, but not exactly, east-west, 2) a quasi-random lumpiness of approximately 20 ha patch size, which varies in amplitude from quadrangle to quadrangle, and 3) linear discontinuities of up to 15 m in elevation, running north-south and east-west, which often, but not always, agree with quadrangle boundaries. The amplitude of all three types of error varies substantially from quadrangle to quadrangle; the orientation and spatial frequency varies less dramatically.



2km

UTM Projection

Figure 2. Shaded Relief Elevation Map. USGS digital elevation data errors are visible as horizontal stripes.



Over water bodies, such as reservoirs, the errors have apparently been removed by the USGS, as they are not present.

The ripple originated from USGS manual profiling of photogrammetric stereomodels (U.S. Geological Survey 1993) and is actually modulated by terrain: human operators made negative errors (resulting in lower elevations) when scanning in an uphill direction, and positive errors when scanning downhill (Band 1993), so that the phase of the ripple is altered by terrain. This error pattern is therefore difficult to remove using standard de-stripping algorithms such as Fourier filtering (Simpson et al. 1995). If the ripple were a perfect sinusoid superimposed on terrain, it could simply be subtracted from the DEM, but the variable amplitude, wavelength and phase make this impossible. A disadvantage of the commonly used rectangular box-average method of stripe removal (Brown and Bara 1994) is that it removes real terrain features, such as some east-west trending wooded draws in the Little Missouri region. The 30 m resolution USGS DEMs are by far the best elevation data that are available in the Little Missouri region, so precise quantification and correction of the errors, or the side effects of ripple removal methods, cannot be undertaken, because there is no reference data. For this reason, no attempt was made to remove the DEM errors in this study. The lower resolution, three arc-second USGS elevation data contain equally problematic systematic data errors of larger magnitude.

For the purposes of terrain analysis, the most troublesome systematic DEM errors are those which mimic real terrain features such as small drainage channels and swales, for example the east-west ripple troughs can be confused with real east-west trending drainages. Fortunately, some DEM errors are compensated for by the depression-filling capability of

the TAPES-G terrain analysis software, discussed in the next section.

Terrain Analysis (TAPES-G)

The TAPES-G software computes various geometric surface parameters such as slope, aspect and curvatures parallel and perpendicular to the flow direction; and water accumulation parameters such as upslope contributing area, flow path length and width, from raster elevation data (Gallant and Wilson 1996). The TAPES-G program includes an option to compute a depressionless terrain surface according to the method of Jensen and Dominique (1988), to remove depressions in the raw DEM due to elevation errors such as the ripple pattern, and from the terrain being insufficiently resolved at the 30 m cell size of the DEM. For example, the narrow wooded draws in the Little Missouri region are only a few cells wide, so the bottom of the channel is not always sampled, producing a chain of "spurious pits" along the drainage path. Once the depressionless DEM has been calculated, TAPES-G allows the user to select one of several flow direction algorithms. This study used the FRho8 method (Fairfield and Leymarie 1991), with divergence enabled below a user-specified catchment size, described below. Some flow algorithms, such as the ARC/INFO FLOWDIRECTION command, do not realistically model divergent flow on convex surfaces.

On a convex surface, water flow diverges unless channeled. TAPES-G allows the user to specify a threshold catchment area above which the water is assumed to flow in a stream channel. This threshold varies depending on the climate and terrain. One way to set

the threshold for a particular region is to examine 1:24,000-scale topographic maps and by trial and error adjust the TAPES-G threshold to match the stream channels shown on the map.

For this study area, a threshold of $2.0 \times 10^5 \text{ m}^2$ was chosen to provide the best match to the topographic maps. It should be noted that the USGS stream lines on maps are not totally consistent with catchment area, as they are derived from photo-interpretation. Therefore, the agreement between TAPES-G channels and 1:24,000-scale hydrography is not uniform across a quadrangle, thus the catchment area threshold is approximate. Another approach is to adjust the TAPES-G threshold to give channels that correspond to the pattern of woody draw vegetation seen in the Landsat image. This yields a lower catchment area threshold, $1.0 \times 10^5 \text{ m}^2$, because wooded draw vegetation occurs in drainages smaller than those containing stream lines on topographic maps. One disadvantage of the lower threshold is that some spurious channels are caused by the DEM errors. Typically, these spurious channels trend east-west in the orientation of the "ripple" error, but sometimes north-south quadrangle boundaries produce errors as well.

Quasi-Dynamic Topographic Wetness Index (DYNWET)

The DYNWET program uses the methods of Barling et al. (1994) to compute a topographic wetness index from the slope and upslope contributing area outputs of the TAPES-G program. Additionally, DYNWET uses soil and climate properties such as average soil depth, saturated hydraulic conductivity, drainable porosity and average drainage

time between rainfall events. These were approximated for the Little Missouri study area by using the soil survey of Thompson (1978) to estimate a mean soil depth of 0.5 m, and a most abundant soil texture of silt loam. A hydrologic conductivity of 15 mm hr^{-1} (Rawls and Brakensiek 1989), and a drainable porosity equal to 25% of the soil volume (Ratliff et al. 1983), are representative for this soil texture. In reality, soil properties vary across the landscape, but the version of DYNWET implemented for this study assumes that they can be approximated by these spatial averages. A mean drainage time of 10 days was chosen to reflect the typical interval between major precipitation events in the semi-arid climate of the Little Missouri region.

Solar Radiation Modeling (SRAD)

The SRAD module of TAPES-G computes shortwave (visible) and longwave (infrared) radiation budgets at each point in the digital representation of terrain. For this study, only the incoming shortwave solar radiation was used, because the other components of the radiation budget depend on vegetative cover and to use them in the determination of remote sensing vegetation type would involve circular reasoning. SRAD uses a three-component approximation of the sky brightness function: it computes the sum of direct solar radiation (affected by topographic shading), plus a circumsolar component scattered from within a few degrees of the solar direction, plus the wider-angle diffuse reflected sunlight from clouds and blue sky (Wilson and Gallant 1996b). To compute this diffuse component, TAPES requires an input parameter, called β , that represents the mean transmission

coefficient for sunlight passing through clouds. The β parameter was calculated from 1961-90 mean solar radiation and percent-of-possible-sunshine measured at the nearest solar station to the Little Missouri, which is Bismarck, ND (NOAA 1993b). Monthly mean values of β are input to SRAD. In this study, incident radiation was computed at four 90-day intervals throughout the year, then added to obtain the mean annual total solar radiation incident on the terrain surface. This annual average radiation is dominated by the summer months when incident solar radiation is greatest.

Ma-Redmond Remote Sensing Methods

This method is a multi-step process developed for mapping large (10^4 - 10^6 km²) areas, where automated classification of entire Landsat scenes in a computationally efficient manner is necessary. The first step applies an unsupervised clustering algorithm (Ma and Redmond 1994a) which is closely related to the widely used color-quantization scheme for approximating three-color composite images in a single 8-bit color image (Heckert 1982). The resulting vegetation classes are color-coded to resemble their appearance in a red-green-blue (RGB) color composite of the three bands, allowing easy visual inspection of the classification, and comparisons with the original image.

In the second step, image pixels are spatially grouped into an ecologically relevant patch size, to eliminate the visual confusion of "salt-and-pepper" pixels. Vegetation classes that do not occur in patches as large as the minimum mapping unit are eliminated, resulting in fewer classes in the aggregated image. A compromise must be made between map clarity

and detail; care must be taken to avoid removing ecologically important features such as riparian corridors, which are prevalent in the Little Missouri region. The aggregation algorithm used here was developed by Ford et al. (1993) at the University of Montana, although similar aggregation tools are now available in ARC GRID Version 7. An additional advantage of aggregation is that it greatly speeds subsequent computation and reduces data storage requirements because later classifications are performed on the grouped regions of pixels rather than individual image pixels. Using the ARC GRID REGIONGROUP command, these regions are treated as single data points in subsequent data analysis. The remaining four Landsat bands (1, 2, 6, and 7), plus the selected terrain attributes are averaged within each vegetation region to obtain mean attribute values for each vegetation patch.

The third step in the Ma-Redmond process is a supervised non-parametric classification which assigns the grouped vegetation patches to the nearest ground-truth point in the multidimensional parameter space which includes seven Landsat bands plus the selected terrain attributes (Ma and Redmond 1994b). In this study, 8, 9 or 10 data layers are used, depending on how many terrain attributes are included in the classification. The advantage of this 'nearest member of group' classification is that it does not depend on any assumptions about the statistical distribution of parameters. Some cumulative terrain parameters, such as upslope contributing area and the wetness indices, are not normally distributed.

A fourth, optional step uses a stream buffer defined by an elevation threshold above stream level to delineate riparian areas (Ma and Righter 1994). The stream channels can be

input either from USGS digital line graph (DLG) hydrography data, or from drainage channels computed by terrain analysis software such as TAPES-G, and the buffer is calculated from the same digital elevation data (DEM) used for other terrain analysis. In this study, Ma and Redmond selected an elevation difference of 5 m above stream level to define riparian areas. Where they are incorrectly identified, Forest Service vegetation classes can be reclassified to correspond to the appropriate riparian or upland designation based on presence inside or outside the stream buffer, thus reducing error in the vegetation map.

Zhenkui Ma and Roland Redmond at the University of Montana Cooperative Wildlife Research Unit performed all image classification, spatial aggregation, error assessment and stream buffer calculations for this project.

Accuracy Assessment

Because the 'nearest member of group' method always yields correct identifications at the ground truth locations, accuracy of the classifications can not be measured by overlaying the ground-truth points on a classified image, because agreement would be 100%. Instead, accuracy assessment was made by a process called 'bootstrapping', in which a ground-truth point is removed and a classification made using the remainder of the points. This process is repeated for each ground-truth point in turn, resulting in 173 classifications for this ground-truth sample. By tabulating which ground-truth points were correctly identified using the remainder of the data sample, Ma and Redmond produced the error matrices reported in this study.

Both the total accuracy of the classification and the accuracies for individual landcover categories are of interest. Furthermore, a pixel-by-pixel comparison of the landcover maps yields a percent agreement between any pair of maps, indicating how much the addition of terrain attributes, or a change in the size of the minimum mapping unit, affects the maps. The percent agreement is computed with the ARC GRID CON function, which can be applied to either the vegetation maps or the stream buffers in raster (image) format. The vector representation of stream buffers given to us by our collaborators was converted to the ARC GRID raster format with the POLYGRID command.

CHAPTER THREE

RESULTS AND DISCUSSION

Terrain Attribute Values at Ground Truth Locations

Terrain parameters were computed for an area somewhat larger than the five-quadrangle remote sensing area (Figure 3), in order to insure that cumulative hydrologic parameters were complete. The only parts of the TAPES-G upslope contributing area map which do not have complete catchment coverage are the one cell wide drainage channels of the Little Missouri River and two of its tributaries. DEM data were not available for the upper part of these catchments. These channels have very large values of upslope contributing area by the time they enter the study area, and the channels are not resolved in the remote sensing image, so this has a negligible effect on the final classification accuracy. Upslope contributing area at the locations of all ground truth points is based on complete elevation data.

All terrain attributes except slope have a large amount of overlap between landcover classes (Figures 4-9). In particular, both secondary attributes (quasi-dynamic wetness and solar radiation) used in this study show a very large overlap between vegetation classes (Figures 7-8). Small ranges in small sample sizes ($N \leq 5$) may simply reflect a lack of data, however a large range in a small sample size does provide evidence of a large variance. Classes 3309 (sagebrush), 4214 (juniper forest), 6202 (riparian shrub) have a sample size of five or less. The quasi-dynamic wetness indices reach similar maximum values of 2.64-2.67 in all classes except 4214 (juniper forest) and three classes (3110, 4102, 7601) span the entire

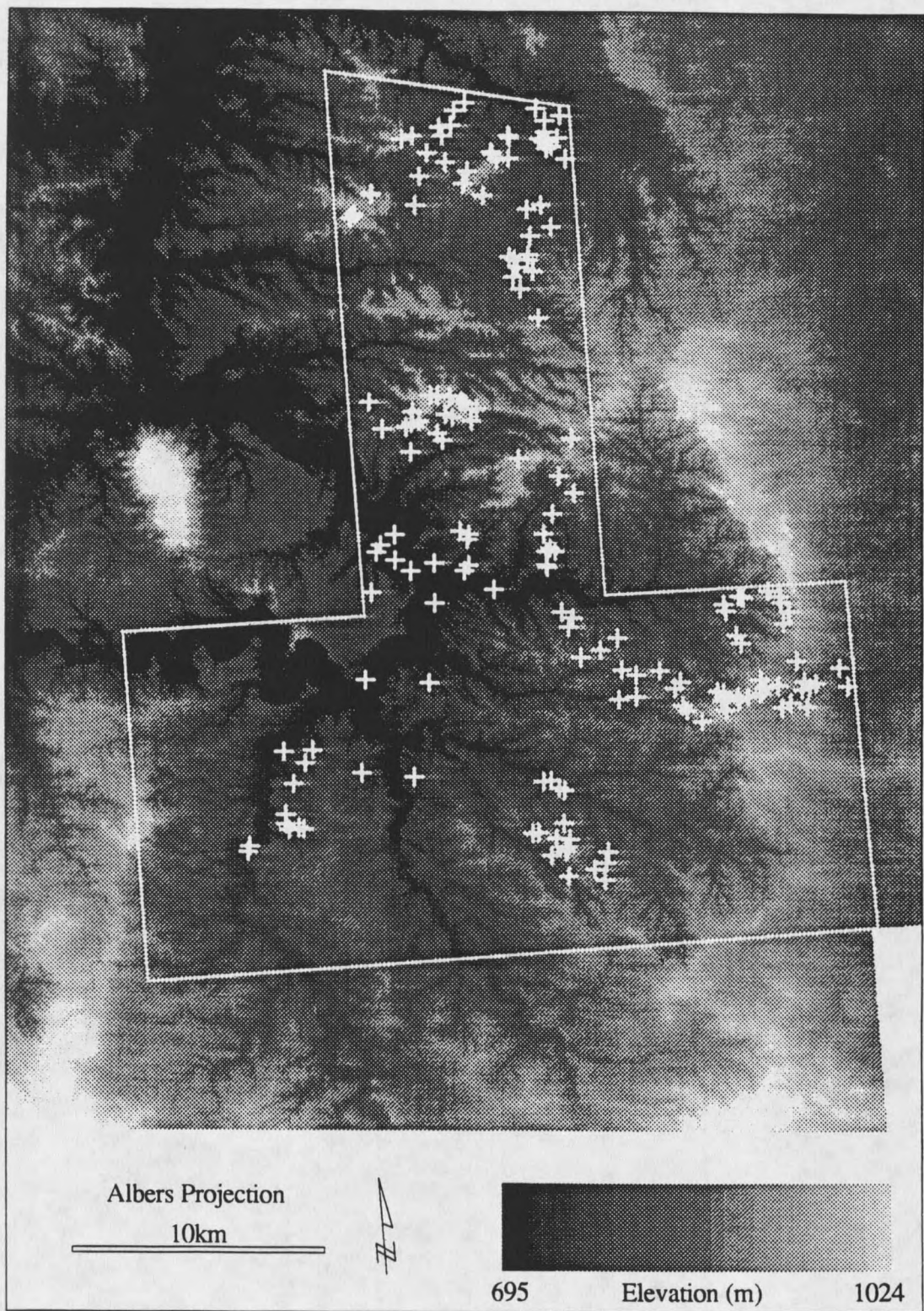


Figure 3. Elevation. Plusses indicate locations of ground-truth data. The remote sensing coverage is outlined in white.

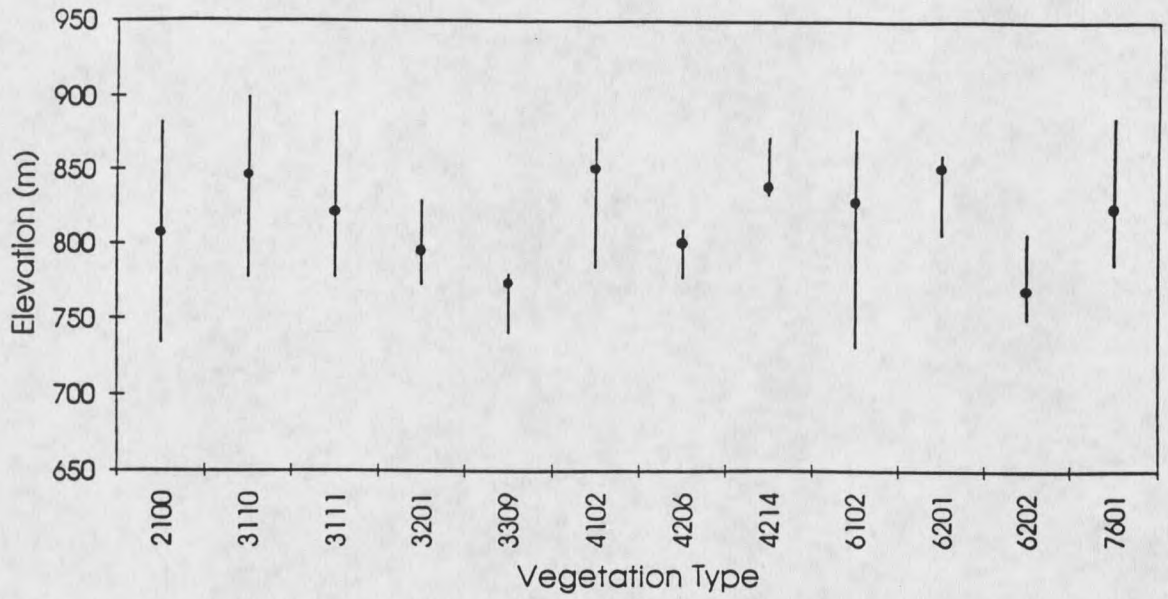


Figure 4. Minimum, Maximum and Median Elevation by Landcover Type.

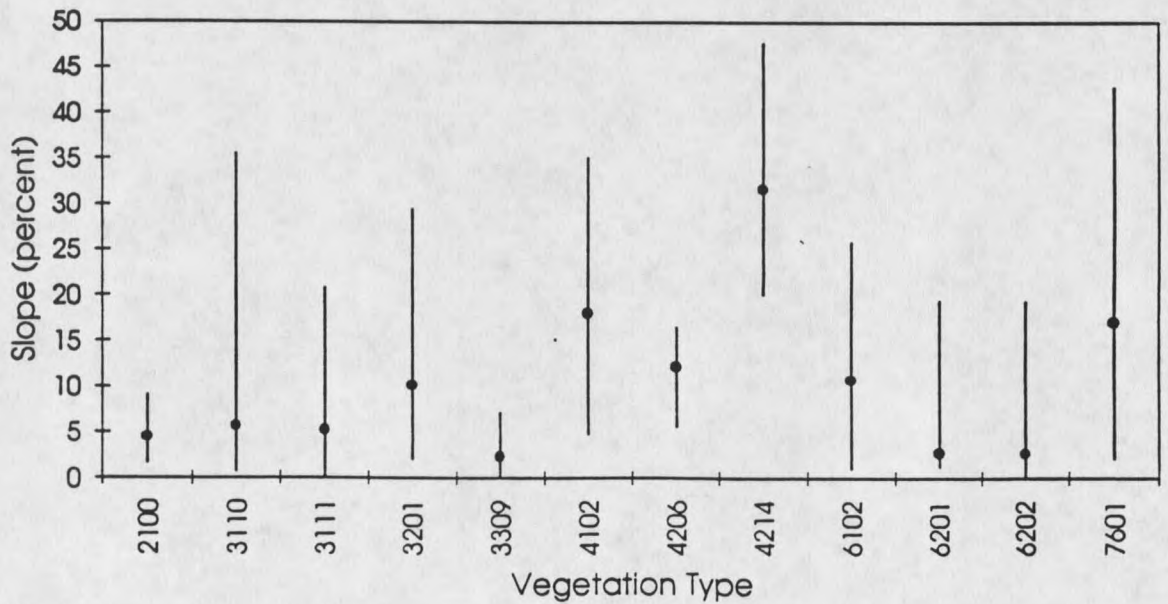


Figure 5. Minimum, Maximum and Median Slope by Landcover Type.

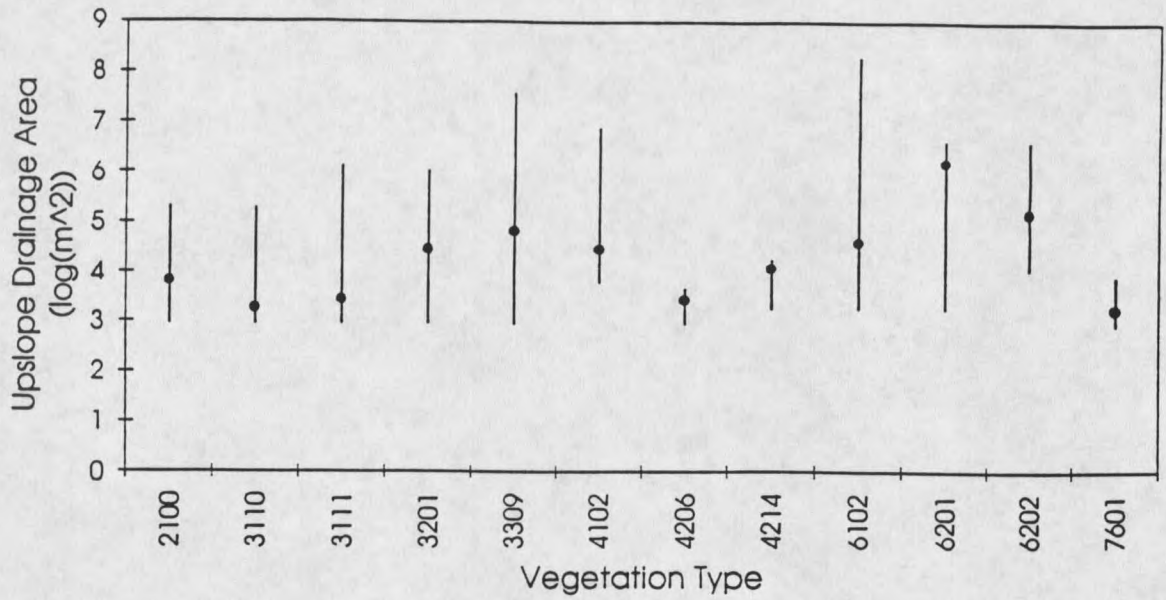


Figure 6. Minimum, Maximum and Median Upslope Contributing Area by Landcover Type.

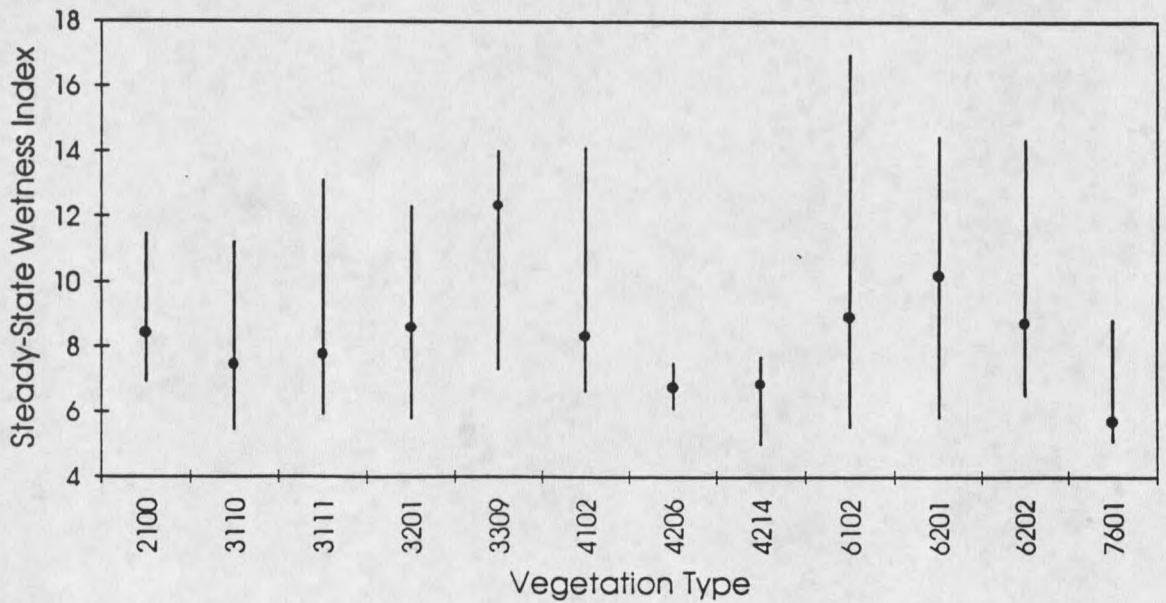


Figure 7. Minimum, Maximum and Median Steady-State Wetness Index by Landcover Type.

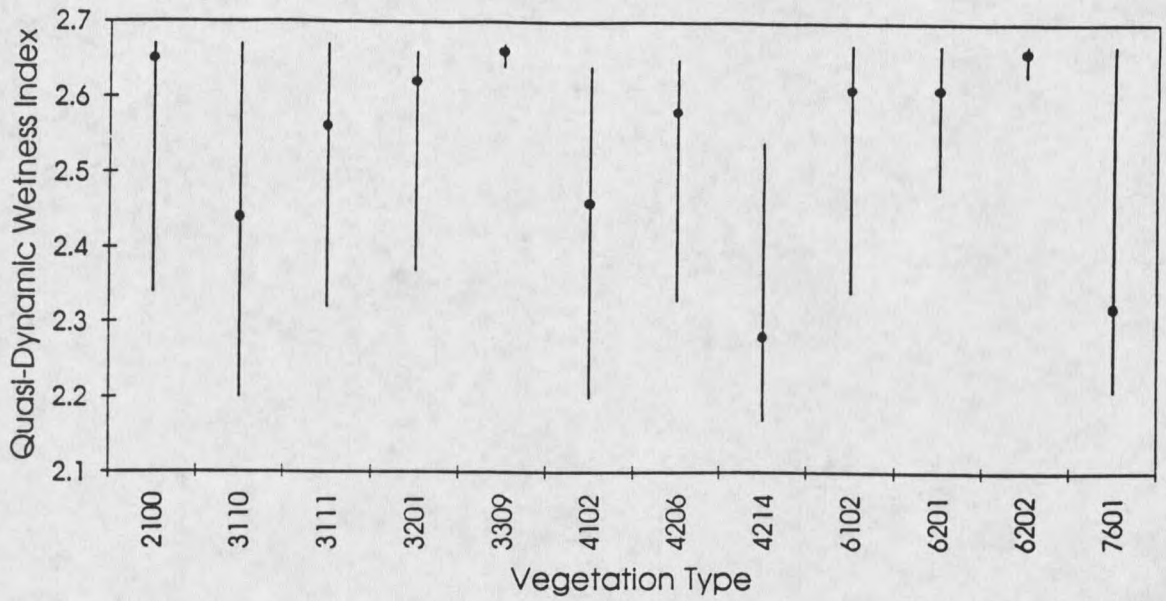


Figure 8. Minimum, Maximum and Median Quasi-Dynamic Wetness Index by Landcover Type.

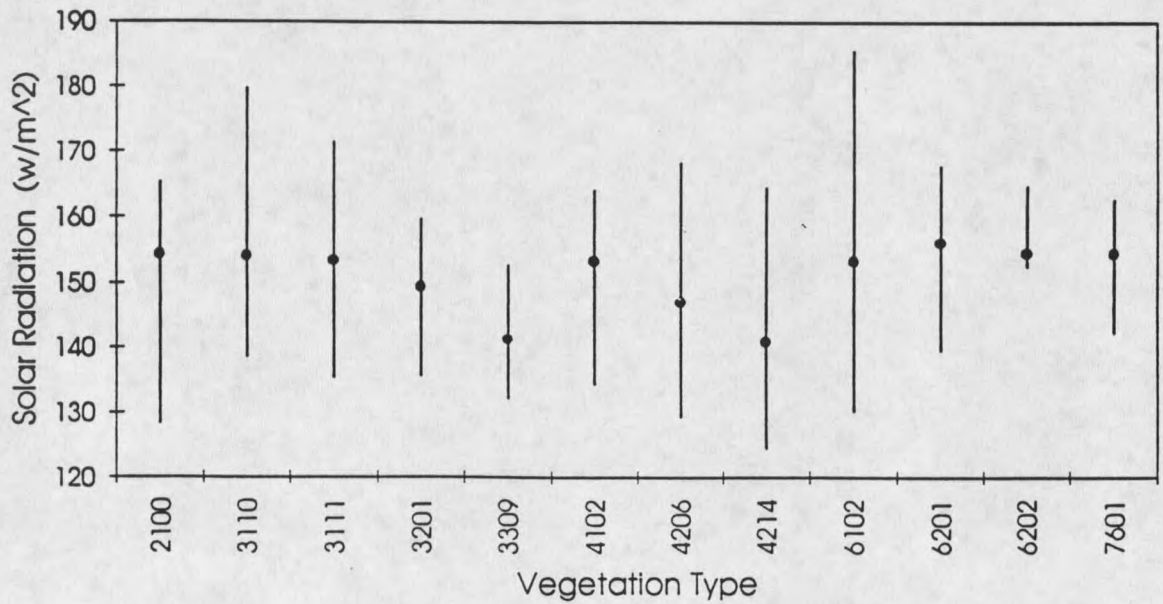


Figure 9. Minimum, Maximum and Median Solar Radiation by Landcover Type.

range of 2.21-2.67 (Figure 8). Thus, vegetation classes are not well separated by this parameter, and this may be reflected in the slight reduction in classification accuracy when it is added to the Landsat data. In particular, some of the most seriously confused classes in Landsat data, 2100 (cropland) and 6102 (riparian broadleaf forest) show largely overlapping distributions in both quasi-dynamic wetness index and solar radiation. If steady-state wetness (Figure 7) were substituted for quasi-dynamic wetness (Figure 8), a similar overlap exists between cropland and riparian forest. In the case of solar radiation (Figure 9), the riparian forest class has the largest range of values.

In contrast, the primary attribute slope (Figure 5), used in the standard Ma/Redmond method, does exhibit interesting variations between classes. None of the 18 cropland points occurs on a slope greater than 10%, whereas upland vegetation types such as 3201 (upland shrub), 4102 (upland broadleaf forest) and 4214 (juniper forest) grow on slopes up to 29%, 35% and 48% respectively. Thus, the slope parameter does show less overlap between some classes than the secondary terrain attributes used in this study. However, the riparian categories also include maximum slopes of 19-26%. These steep riparian areas occur in rugged terrain in the headwaters of drainages.

Terrain Attribute Maps

Output grids from TAPES-G, DYNWET and SRAD are shown in Figures 10-15. The differences between the gently rolling upland areas at the eastern edge of the study area and the more rugged wooded draw and badlands terrain in the western two-thirds of the study area are well shown in most of the terrain attribute maps. Flat areas, shown in dark

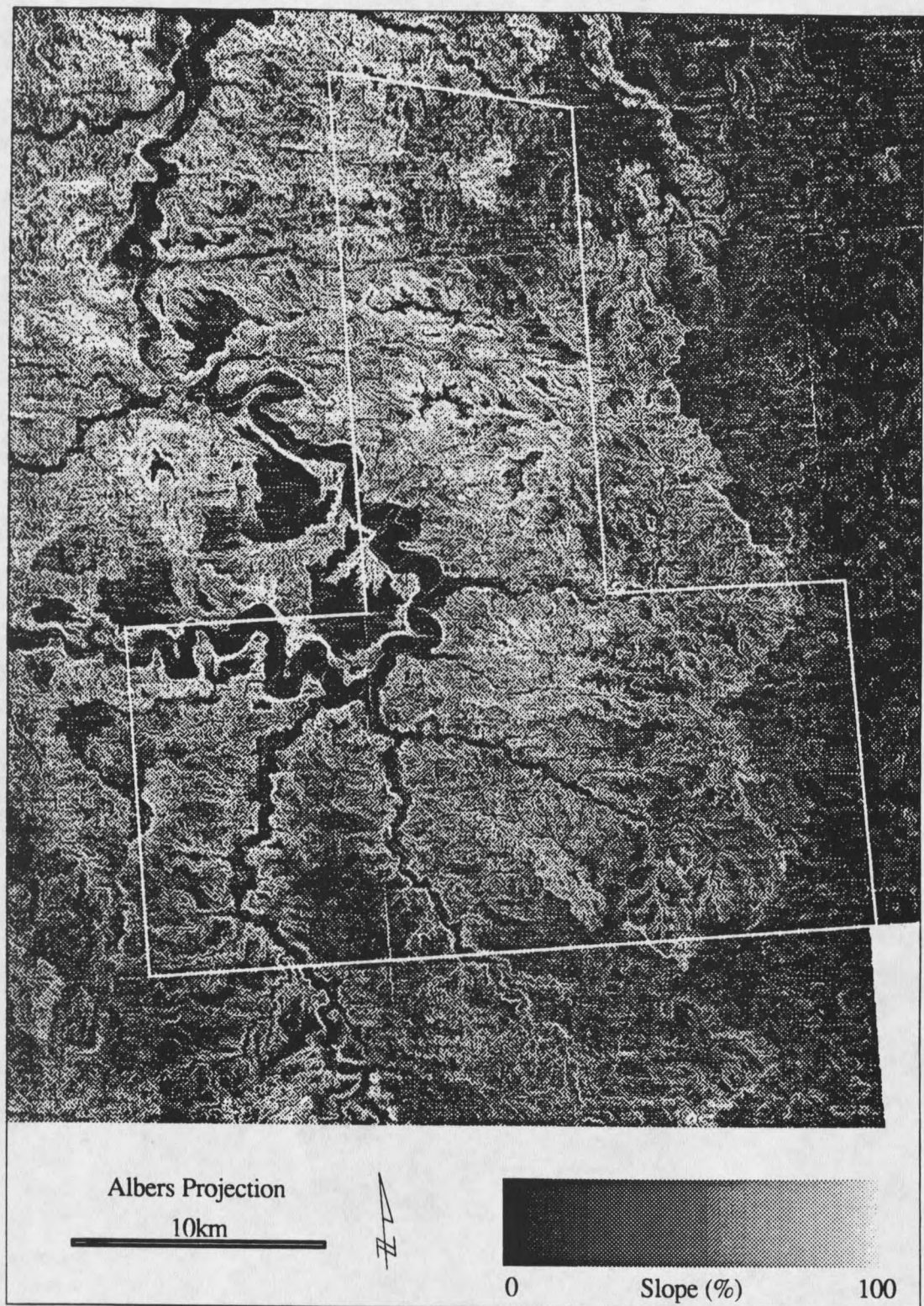


Figure 10. Slope Computed by TAPESG.

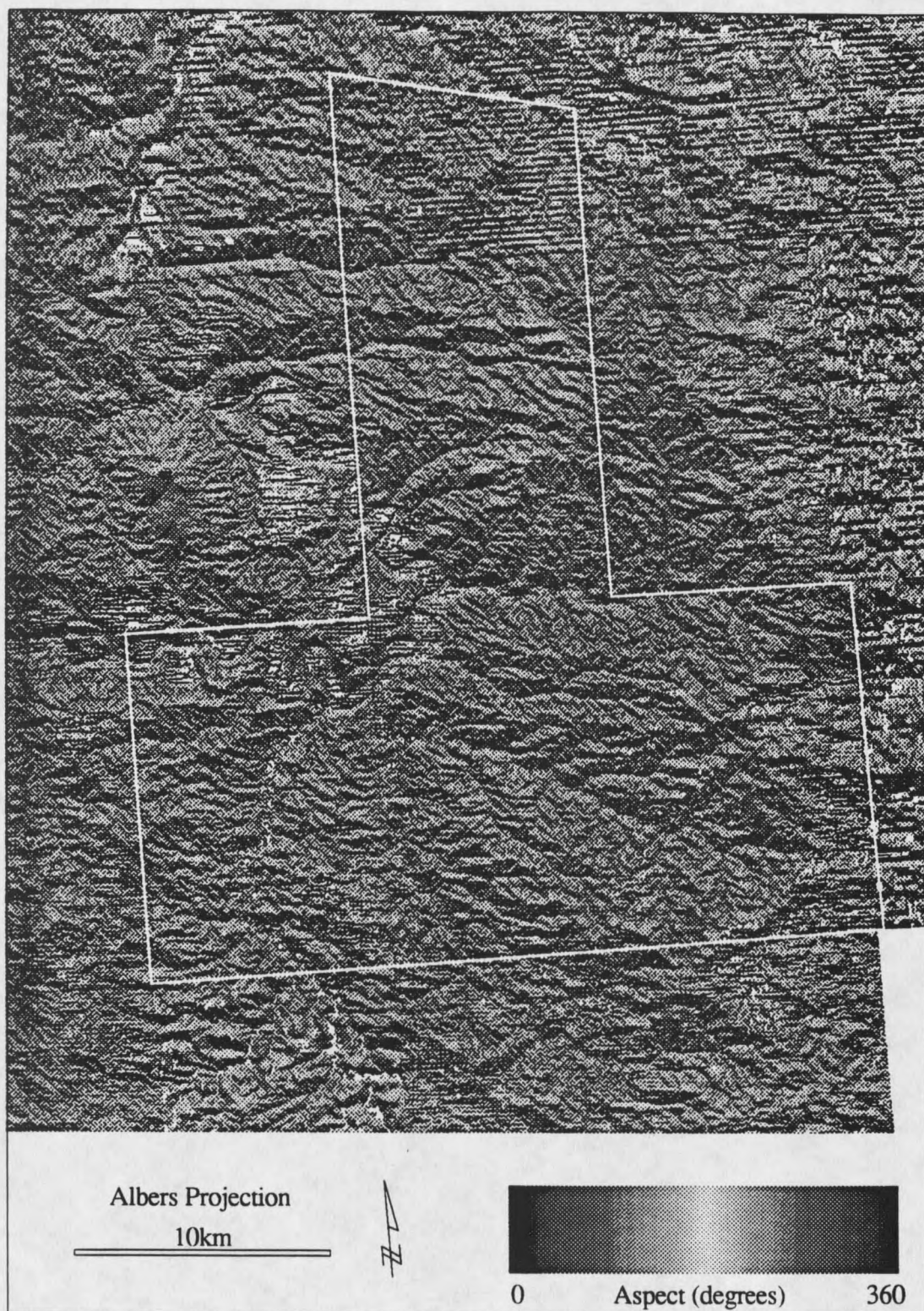


Figure 11. Aspect Computed by TAPESG.



Figure 12. Upslope Contributing Area (sq. meters) Computed by TAPESG.



Figure 13. Steady-State Wetness Index Computed From TAPES-G Output.

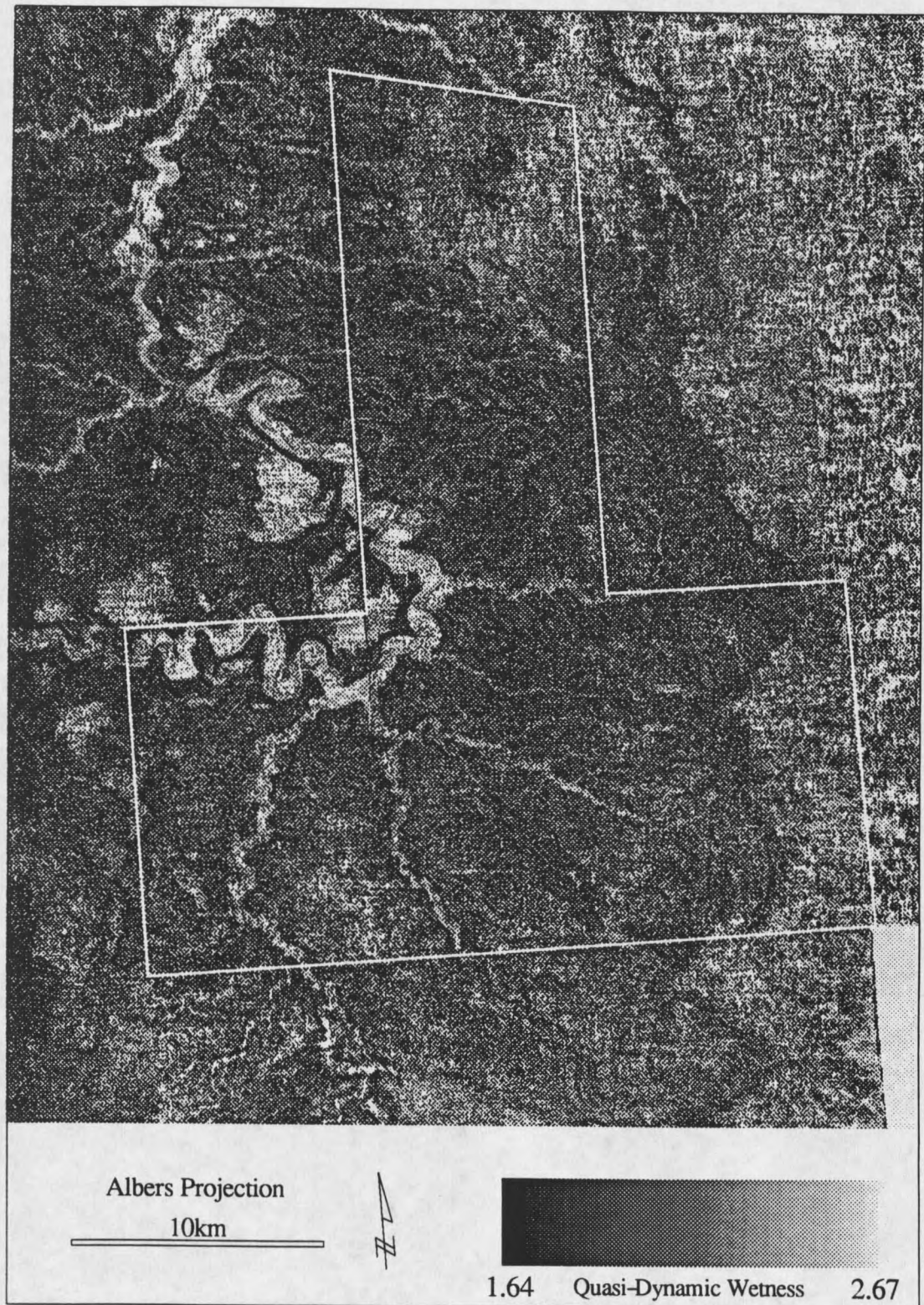


Figure 14. Quasi-Dynamic Wetness Index Computed by DYNWET.

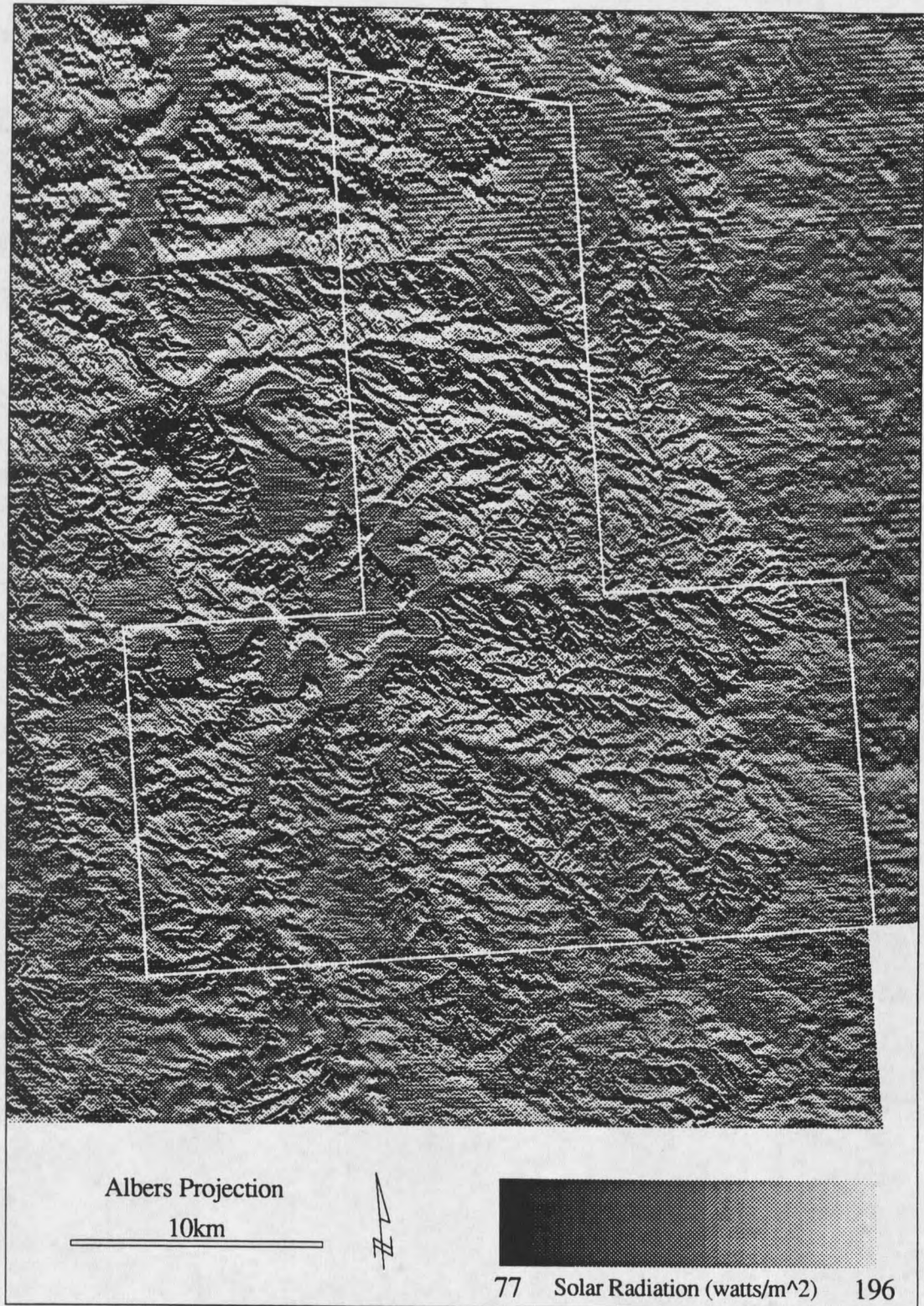


Figure 15. Average Annual Solar Radiation Computed by SRAD.

tones, such as floodplains, river terraces, and depressions in rolling upland, are clearly visible in the slope map (Figure 10), and also as areas of high wetness (light tones) in both the steady-state and quasi-dynamic wetness indices (Figures 13-14). The distribution of both wetness indices follows a pattern of high wetness in flatter terrain and lower wetness on steeper slopes (Figures 10, 13 and 14). High values of wetness index occur in both riparian and cropland areas.

Steeper terrain, such as river bluffs, hillsides, and badlands are shown in lighter tones in the slope map, and appear as areas of low topographic wetness (dark tones) in Figures 13-14. The abrupt transition between the rolling uplands in the east, and the highly dissected Little Missouri drainage to the west, is particularly prominent in the slope map.

The aspect and solar radiation maps (Figures 11 and 15) reveal similar patterns, however topographic shading on north-facing slopes produces a more complex spatial pattern in the solar radiation map. In the aspect map, pure white indicates an undefined aspect, which occurs in regions where the slope is zero. In the solar radiation map (Figure 15), north facing slopes receiving $80\text{-}100 \text{ Wm}^{-2}$ average annual solar radiation are shown in dark tones, whereas southern exposures receive $150\text{-}190 \text{ Wm}^{-2}$, and are shown in lighter tones. In the rugged badland terrain (center), more variation in radiation intensity is seen, compared with the more gentle rolling upland terrain at right. Figure 15 also shows a high-frequency ripple in elevation over part of the study area, plus a more pronounced low-frequency ripple in the northern and eastern quadrangles outside the study area.

In the upslope contributing area map (Figure 12), ridgelines appear as dark areas (low upslope contributing area), and valleys, floodplains and depressions appear lighter (high

upslope contributing area). Elevation data quality is dramatically lower in the northern and eastern quadrangles, as evidenced by the abundant spurious linear drainage features trending east-west. Other discontinuities at quadrangle boundaries are visible at center left in Figure 12, where the flat river terraces and floodplains are truncated by an elevation jump across a quadrangle boundary. The upslope contributing area map shows large upslope drainage areas in both rolling uplands and wooded draws.

Classification Accuracy

Three classifications were compared, 1) all seven Landsat bands plus elevation, 2) seven Landsat bands plus elevation, plus dynamic wetness index, and 3) seven Landsat bands plus elevation, plus dynamic wetness index and incoming shortwave solar radiation. Each classification was spatially aggregated to 0.4, 0.8 and 2.0 ha minimum mapping units, making nine classifications in all, shown in Table 2. In the 0.4 ha merge, overall classification accuracies remained roughly constant with the addition of wetness index and solar radiation: accuracy varied from 51-54%. In the 0.8 ha merge, accuracy declined from 57% to 56% with the addition of wetness index, and further declined to 53% with the addition of solar radiation. In the 2.0 ha merge, accuracy remained nearly constant at 56-57% in all three cases.

Similarly, there is little difference in accuracy when comparing the three sizes of spatial aggregation: accuracy remains at 53-57% at the 0.8 and 2.0 ha minimum mapping units, suggesting that there may be no disadvantage to using the larger mapping unit. However, in other areas of the Little Missouri region, Ma and Redmond (personal

communication) have noticed a loss of continuity in riparian corridors at a 2.0 ha aggregation, but this is not evident from the limited ground-truth sample used in this study area.

Table 2. Overall Classification Accuracy.

0.4 ha Minimum Mapping Unit	Accuracy(%)
Landsat, elevation	53.8
Landsat, elevation, quasi-dynamic wetness	50.9
Landsat, elevation, quasi-dynamic wetness, solar radiation	53.8
0.8 ha Minimum Mapping Unit	Accuracy(%)
Landsat, elevation	57.2
Landsat, elevation, quasi-dynamic wetness	56.1
Landsat, elevation, quasi-dynamic wetness, solar radiation	53.2
2.0 ha Minimum Mapping Unit	Accuracy(%)
Landsat, elevation	57.2
Landsat, elevation, quasi-dynamic wetness	57.2
Landsat, elevation, quasi-dynamic wetness, solar radiation	56.1

Error matrices are shown in Table 3, with USFS numeric landcover codes (2100-7601) identified in Table 1. Correct identifications of the 13 landcover classes fall along the diagonal, incorrect classifications fall elsewhere. Individual landcover classes showed little change in accuracy with the addition of terrain attributes, and altering the minimum mapping unit also had little effect. Cropland showed no accuracy improvement with the addition of terrain attributes, and the 2.0 ha minimum mapping unit reduced accuracy slightly. Cropland was frequently misclassified as riparian classes of forest and shrubland. The two grassland

Table 3. Error Matrices for the Nine Classifications. Vegetation codes identified in Table 1.
Mapping unit 0.4 ha. Landsat, elevation.

	2100	3110	3111	3201	3309	4102	4206	4214	5000	6102	6201	6202	7601	Total	%Correct
2100	12	0	0	0	0	1	0	0	0	0	2	2	1	18	67
3110	0	16	8	0	0	0	0	0	0	0	0	0	0	24	67
3111	0	13	7	1	0	0	0	0	0	0	0	0	0	21	33
3201	0	0	1	0	2	1	2	0	0	3	1	0	0	10	0
3309	0	0	1	1	3	0	0	0	0	0	0	0	0	5	60
4102	0	0	0	0	0	3	1	0	0	7	0	1	0	12	25
4206	0	0	0	1	0	0	7	0	0	0	0	0	0	8	88
4214	0	0	1	0	0	1	0	3	0	0	0	0	0	5	60
5000	0	0	0	0	0	0	0	0	3	0	0	0	0	3	100
6102	0	0	0	0	0	8	0	0	0	24	4	4	0	40	60
6201	1	0	0	2	0	0	0	0	0	3	2	1	0	9	22
6202	1	0	0	0	0	1	0	0	0	3	0	0	0	5	0
7601	0	0	0	0	0	0	0	0	0	0	0	0	13	13	100
Total	14	29	18	5	5	15	10	3	3	40	9	8	14	173	
	85	55	38	0	60	20	70	100	100	60	22	0	92	%Correct	

Mapping unit 0.4 ha. Landsat, elevation, wetness index.

	2100	3110	3111	3201	3309	4102	4206	4214	5000	6102	6201	6202	7601	Total	%Correct
2100	11	0	1	0	0	2	0	0	0	0	1	2	1	18	61
3110	0	16	7	0	0	0	0	0	0	1	0	0	0	24	67
3111	0	13	7	1	0	0	0	0	0	0	0	0	0	21	33
3201	0	0	0	1	3	1	1	0	0	4	0	0	0	10	10
3309	0	0	0	1	3	0	0	0	0	0	1	0	0	5	60
4102	0	0	0	1	0	1	1	0	0	8	0	1	0	12	8
4206	0	0	0	1	0	0	7	0	0	0	0	0	0	8	88
4214	0	0	1	0	0	1	0	3	0	0	0	0	0	5	60
5000	0	0	0	0	0	0	0	0	3	0	0	0	0	3	100
6102	0	0	0	3	0	7	0	0	0	21	4	5	0	40	53
6201	0	0	0	2	0	1	0	0	0	2	3	1	0	9	33
6202	1	0	0	0	0	1	0	0	0	3	0	0	0	5	0
7601	1	0	0	0	0	0	0	0	0	0	0	0	12	13	92
Total	13	29	16	10	6	14	9	3	3	39	9	9	13	173	
	84	55	43	10	50	7	77	100	100	53	33	0	92	%Correct	

Mapping unit 0.4 ha. Landsat, elevation, wetness index, solar radiation.

	2100	3110	3111	3201	3309	4102	4206	4214	5000	6102	6201	6202	7601	Total	%Correct
2100	12	0	1	0	0	1	0	0	0	0	2	1	1	18	67
3110	0	17	6	0	0	0	0	0	0	1	0	0	0	24	71
3111	0	13	6	0	1	0	0	0	0	1	0	0	0	21	290
3201	0	0	0	2	2	0	1	0	0	4	1	0	0	10	20
3309	0	0	0	1	3	0	0	0	0	0	1	0	0	5	60
4102	0	0	0	1	0	2	1	0	0	6	1	1	0	12	17
4206	0	0	0	1	0	0	7	0	0	0	0	0	0	8	88
4214	0	0	1	1	0	0	2	0	0	1	0	0	0	5	0
5000	0	0	0	0	0	0	0	0	3	0	0	0	0	3	100
6102	0	0	1	3	1	2	0	0	0	27	3	3	0	40	68
6201	0	0	0	1	1	2	0	0	0	2	2	1	0	9	22
6202	1	0	0	0	0	1	0	0	0	3	0	0	0	5	0
7601	1	0	0	0	0	0	0	0	0	0	0	0	12	13	92
Total	14	30	15	10	8	8	11	0	3	45	10	6	13	173	
	85	56	40	20	37	25	63	0	100	60	20	0	92	%Correct	

Table 3, Continued.

Mapping unit 0.8 ha. Landsat, elevation.

	2100	3110	3111	3201	3309	4102	4206	4214	5000	6102	6201	6202	7601	Total	%Correct
2100	13	0	1	0	0	1	0	0	0	0	01	1	1	18	72
3110	0	17	6	0	0	0	0	0	0	0	1	0	0	24	71
3111	0	11	9	0	0	0	0	0	0	0	1	0	0	21	43
3201	0	0	0	2	1	0	1	0	0	5	1	0	0	10	20
3309	0	0	0	1	4	0	0	0	0	0	0	0	0	5	80
4102	1	0	0	0	0	3	1	0	0	6	1	0	0	12	25
4206	0	0	0	0	1	0	7	0	0	0	0	0	0	8	88
4214	0	0	1	0	0	0	0	4	0	0	0	0	0	5	80
5000	0	0	0	0	0	0	0	0	3	0	0	0	0	3	100
6102	0	0	1	3	1	10	0	0	0	19	4	2	0	40	48
6201	0	0	1	0	0	0	0	0	0	3	4	1	0	9	44
6202	1	0	0	0	0	0	0	0	0	1	1	2	0	5	40
7601	1	0	0	0	0	0	0	0	0	0	0	0	12	13	92
Total	16	28	19	6	7	14	9	4	3	34	14	6	13	173	
	81	60	47	33	57	21	77	100	100	55	28	33	92	%Correct	

Mapping unit 0.8 ha. Landsat, elevation, wetness index.

	2100	3110	3111	3201	3309	4102	4206	4214	5000	6102	6201	6202	7601	Total	%Correct
2100	13	0	1	0	0	1	0	0	0	0	1	1	1	18	72
3110	0	17	5	0	0	0	0	0	0	0	2	0	0	24	71
3111	0	11	9	0	0	0	0	0	0	0	1	0	0	21	43
3201	0	0	0	1	2	0	1	0	0	5	1	0	0	10	10
3309	0	0	0	1	4	0	0	0	0	0	0	0	0	5	80
4102	1	0	0	0	0	3	1	0	0	6	1	0	0	12	25
4206	0	0	0	0	0	1	0	7	0	0	0	0	0	8	88
4214	0	0	1	0	0	0	0	4	0	0	0	0	0	5	80
5000	0	0	0	0	0	0	0	0	3	0	0	0	0	3	100
6102	0	1	1	4	1	8	0	0	0	17	5	3	0	40	43
6201	0	1	1	0	0	0	0	0	0	2	4	1	0	9	44
6202	1	0	0	0	0	0	0	0	0	1	1	2	0	5	40
7601	0	0	0	0	0	0	0	0	0	0	0	0	13	13	100
Total	15	30	18	6	8	12	9	4	3	31	16	7	14	173	
	86	56	50	16	50	25	77	100	100	54	25	28	92	%Correct	

Mapping unit 0.8 ha. Landsat, elevation, wetness index, solar radiation.

	2100	3110	3111	3201	3309	4102	4206	4214	5000	6102	6201	6202	7601	Total	%Correct
2100	13	0	1	0	0	1	0	0	0	0	1	1	1	18	72
3110	0	14	9	0	0	0	0	0	0	0	1	0	0	24	58
3111	0	11	8	0	1	0	0	0	0	0	1	0	0	21	38
3201	0	0	1	2	1	0	1	0	0	5	0	0	0	10	20
3309	0	0	0	1	3	0	0	0	0	0	1	0	0	5	60
4102	0	0	0	0	0	2	1	0	0	9	0	0	0	12	17
4206	0	0	0	0	1	1	6	0	0	0	0	0	0	8	75
4214	0	0	1	0	0	1	2	0	0	1	0	0	0	5	0
5000	0	0	0	0	0	0	0	0	3	0	0	0	0	3	100
6102	0	1	0	3	1	4	0	0	0	24	4	3	0	40	60
6201	0	1	1	0	0	0	0	0	0	4	2	1	0	9	22
6202	1	0	0	0	0	0	0	0	0	1	1	2	0	5	40
7601	0	0	0	0	0	0	0	0	0	0	0	0	13	13	100
Total	14	27	21	6	7	9	10	0	3	44	11	7	14	173	
	92	51	38	33	42	22	60	0	100	54	18	28	92	%Correct	

Table 3, Continued.

Mapping unit 2.0 ha. Landsat, elevation.

2100	3110	3111	3201	3309	4102	4206	4214	5000	6102	6201	6202	7601	Total	%Correct
2100	11	0	1	0	0	1	0	0	3	1	0	1	18	61
3110	0	15	4	0	0	0	0	1	2	0	0	2	24	63
3111	0	11	6	1	0	0	0	0	1	0	0	2	21	29
3201	0	1	1	5	0	1	0	0	2	0	0	0	10	50
3309	0	0	1	0	3	0	0	0	0	1	0	0	5	60
4102	0	0	0	3	0	2	0	1	5	0	1	0	12	17
4206	0	0	0	1	0	0	7	0	0	0	0	0	8	88
4214	0	0	0	0	0	0	5	0	0	0	0	0	5	100
5000	0	0	0	0	0	1	1	0	1	0	0	0	3	33
6102	3	1	1	1	0	4	0	0	0	26	2	2	40	65
6201	2	0	0	0	0	0	0	0	2	5	0	0	9	56
6202	1	0	0	0	0	0	0	0	1	1	2	0	5	40
7601	1	0	1	0	0	0	0	0	0	0	0	11	13	85
Total	18	28	15	11	3	9	8	5	3	42	10	5	173	
61	53	40	45	100	22	87	100	33	61	50	40	68	%Correct	

Mapping unit 2.0 ha. Landsat, elevation, wetness index.

2100	3110	3111	3201	3309	4102	4206	4214	5000	6102	6201	6202	7601	Total	%Correct
2100	10	0	1	0	0	0	0	0	4	1	1	1	18	56
3110	0	16	4	0	1	0	0	1	1	0	0	1	24	67
3111	0	12	5	1	0	0	0	0	1	0	0	2	21	24
3201	0	0	2	5	0	1	0	0	2	0	0	0	10	50
3309	0	0	1	0	3	0	0	0	0	1	0	0	5	60
4102	0	0	0	2	0	4	0	1	5	0	0	0	12	33
4206	0	0	0	0	0	7	0	0	1	0	0	0	8	88
4214	0	0	0	0	0	0	5	0	0	0	0	0	5	100
5000	0	0	0	0	0	1	1	0	1	0	0	0	3	33
6102	4	1	1	2	0	5	0	0	0	25	0	2	40	63
6201	2	0	0	0	0	0	0	0	2	5	0	0	9	56
6202	1	0	0	0	0	0	0	0	1	1	2	0	5	40
7601	1	0	1	0	0	0	0	0	0	0	0	11	13	85
Total	18	29	15	10	4	11	8	5	3	42	8	5	173	
56	55	33	50	75	36	88	100	33	60	63	40	73	%Correct	

Mapping unit 2.0 ha. Landsat, elevation, wetness index, solar radiation.

2100	3110	3111	3201	3309	4102	4206	4214	5000	6102	6201	6202	7601	Total	%Correct
2100	10	0	1	0	0	1	0	0	3	2	0	1	18	56
3110	0	17	4	0	1	0	0	1	1	0	0	0	24	71
3111	0	11	6	1	0	0	0	0	1	0	0	2	21	29
3201	0	2	1	4	0	1	0	0	1	1	0	0	10	40
3309	0	0	0	1	3	0	0	0	1	0	0	0	5	60
4102	1	0	0	2	0	2	0	1	5	0	1	0	12	17
4206	0	0	0	0	0	7	0	0	0	1	0	0	8	88
4214	0	0	0	0	0	2	1	2	0	0	0	0	5	40
5000	0	0	0	1	1	0	0	1	0	0	0	0	3	33
6102	3	1	1	2	0	4	0	0	0	26	1	2	40	65
6201	1	0	0	0	0	1	0	0	2	5	0	0	9	56
6202	1	0	0	0	0	0	0	0	0	1	3	0	5	60
7601	1	0	1	0	0	0	0	0	0	0	0	11	13	85
Total	17	31	14	11	5	10	9	2	3	40	11	6	173	
58	54	42	36	60	20	77	100	33	65	45	50	78	%Correct	

classes were frequently confused, though the identification of low-cover grass (3110) was higher than for high-cover grass. Merging the two classes would result in approximately a 10% increase in total accuracy, raising the accuracy of a single grassland class to >75% at all three spatial scales. The upland shrub category (3201) was frequently confused with riparian forest, but not confused with riparian shrub. Accuracy improved when the minimum mapping unit was increased to 2.0 ha. Upland forest (4102) was most frequently confused with riparian forest (6102), but the addition of terrain attributes did not affect the generally low accuracy of <30%. Broadleaf riparian forest (6102), does show a slight accuracy improvement with the addition of terrain attributes. Confusion between riparian and upland forest in the Little Missouri is not surprising as the dominant vegetation is green ash in both cases. Confusion between broadleaf shrubs and broadleaf trees is also to be expected, because they may have similar spectral signatures.

In the 0.4 ha aggregation, accuracy increased from 60% to 65% out of 40 points, and the 0.8 ha aggregation improved from 48% to 60%. At the 2.0 ha minimum mapping unit, accuracy remained 65%, both with and without terrain attributes. Riparian forest was frequently misclassified as upland forest. Potentially, eliminating the confusion between riparian and upland forest could improve total accuracy by 5-10%. Additional errors were caused by riparian forest misclassified to non-forest riparian categories. Overall accuracy of the classification could be raised to 75%, if the two grassland categories are merged, and the confusion between upland and riparian classes resolved.

Landcover Maps Incorporating Terrain Attributes in Classification

The complete study area landcover map is too detailed to be reduced to an 8.5x11 inch page size; a representative portion of the area is shown as an example in Figures 16-20. This region is located in the southeast of the study area. Some confusion between cropland and riparian ash remains in all cases, for example, the rectangular cultivated fields at lower right in the figures are misclassified as riparian ash or riparian shrub, even when terrain attributes are added to the classification. Changing the spatial aggregation from 0.4 ha to 0.8 ha altered some map unit identifications, but many misclassifications remain.

Although overall classification accuracy varies little between different terrain attribute combinations and spatial scales, a pixel-by-pixel comparison of the vegetation maps shows substantial differences between them. Percent agreement between the 36 unique combinations of the nine maps is shown in Table 4. The addition of terrain attributes results in an agreement of 67-89%, which means that up to 33% of the pixels in the map can change with the addition of a single secondary terrain attribute. Figure 16-18 show how the classification changes with the addition of terrain attributes, for the 0.4 ha mapping unit. Varying the minimum mapping unit produces even lower agreement, only 34-44%. In other words, between 56% and 66% of the pixels changed when changing the aggregation from 0.4 to 0.8 or 2.0 ha. This is evident in Figures 18-20, where the spatial pattern of the vegetation patches varies greatly according to the spatial scale. Ultimately, the choice of spatial scale is a matter of user preference, but as the aggregation process cannot be reversed, it may be advisable to underestimate the size of mapping unit, to preserve ecologically valuable information in small vegetation patches.

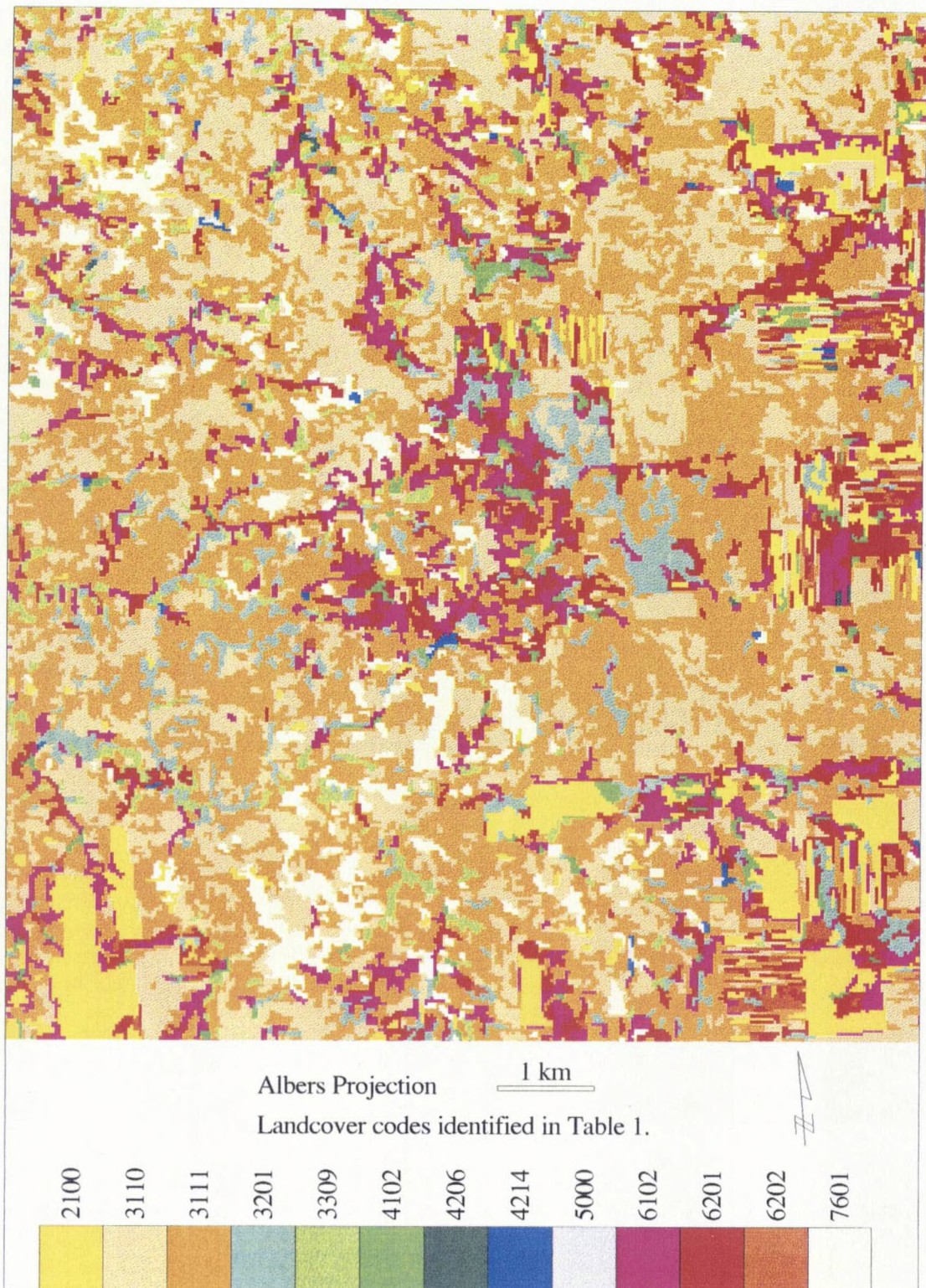


Figure 16. Landcover Map Using Landsat Data Plus Elevation; Minimum Mapping Unit 0.4 hectare.

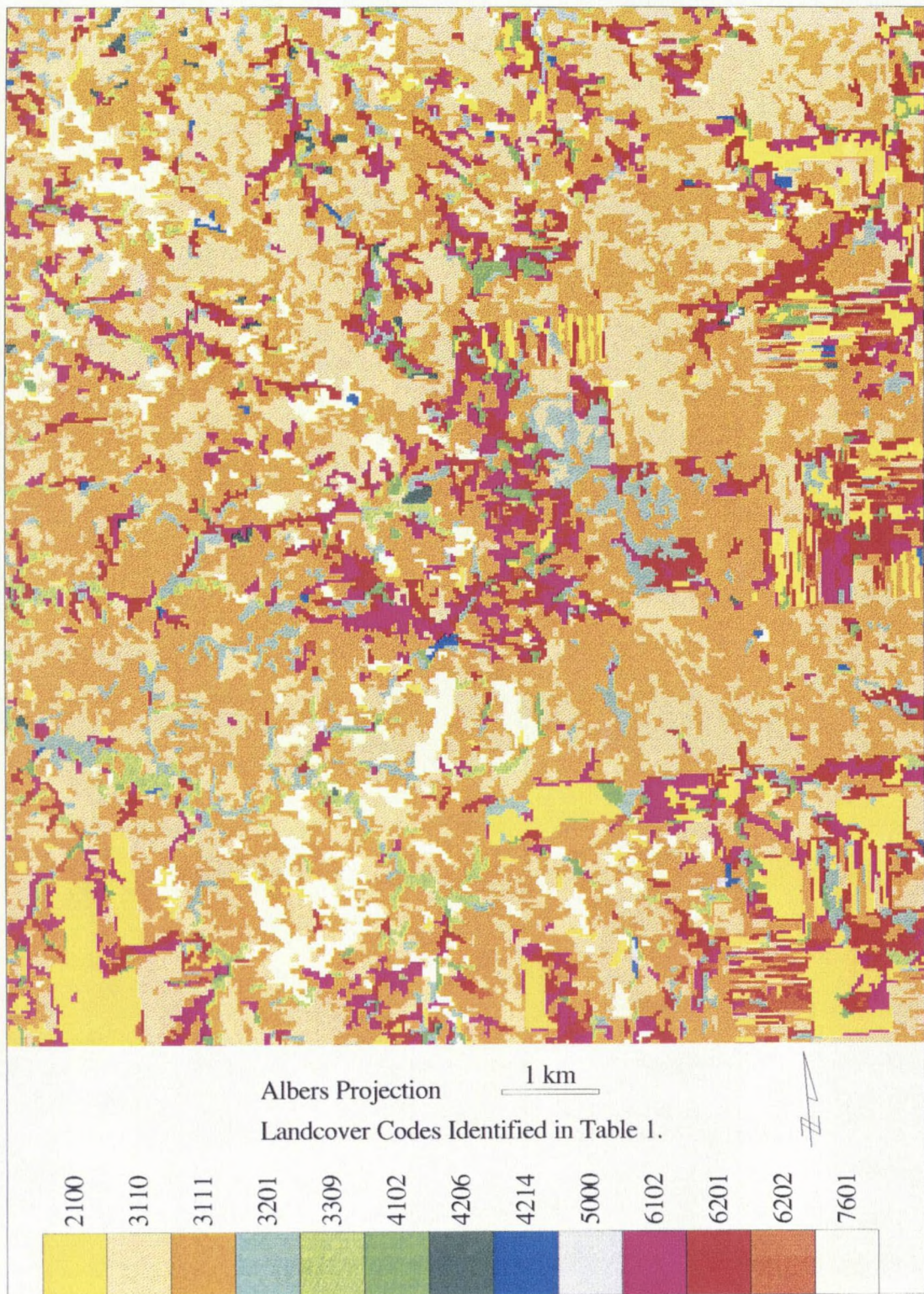


Figure 17. Landcover Map Using Landsat Data Plus Elevation and Quasi-Dynamic Wetness Index; Minimum Mapping Unit 0.4 hectare.

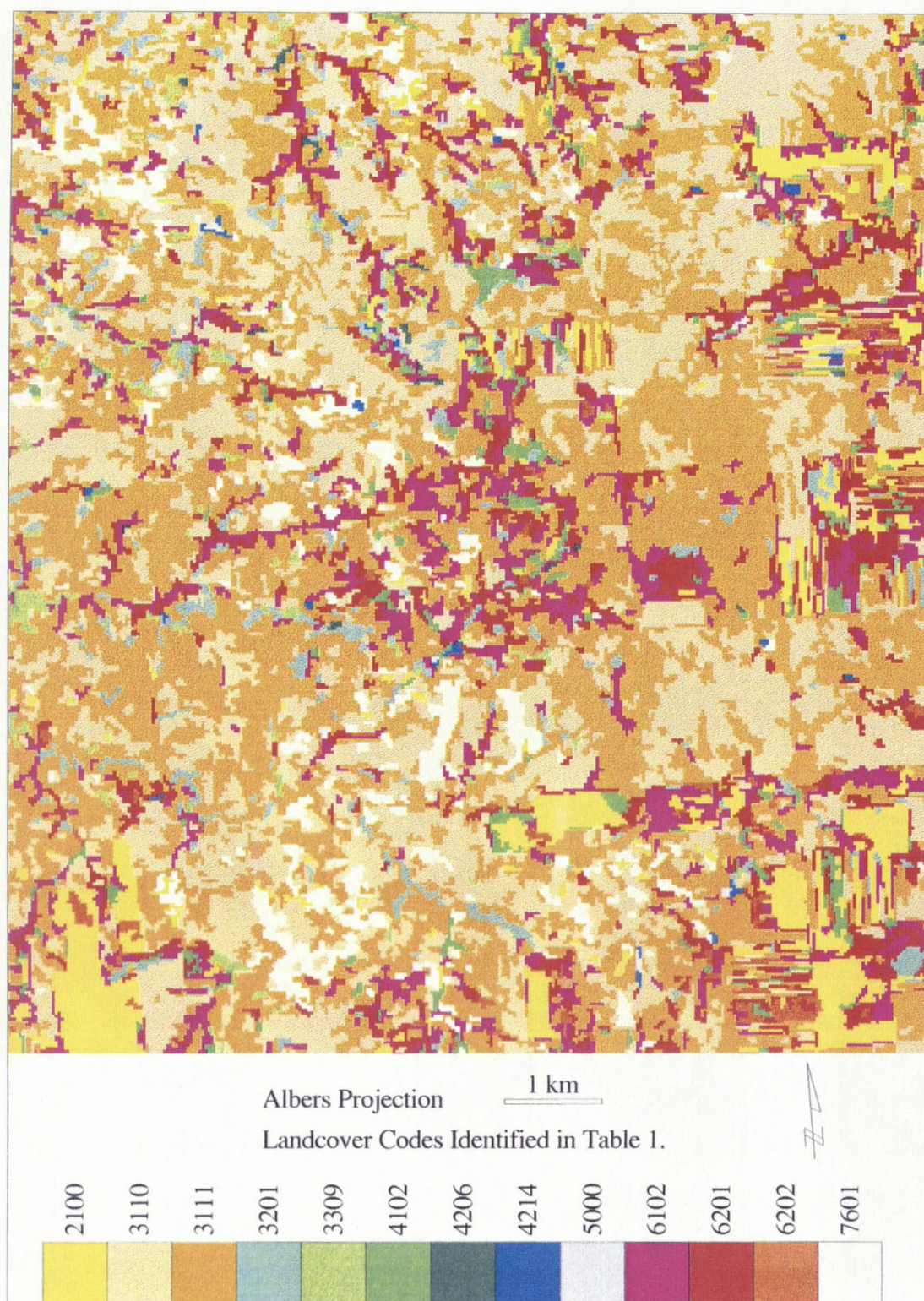


Figure 18. Landcover Map Using Landsat Data Plus Elevation, Quasi-Dynamic Wetness Index and Solar Radiation; Minimum Mapping Unit 0.4 hectare.

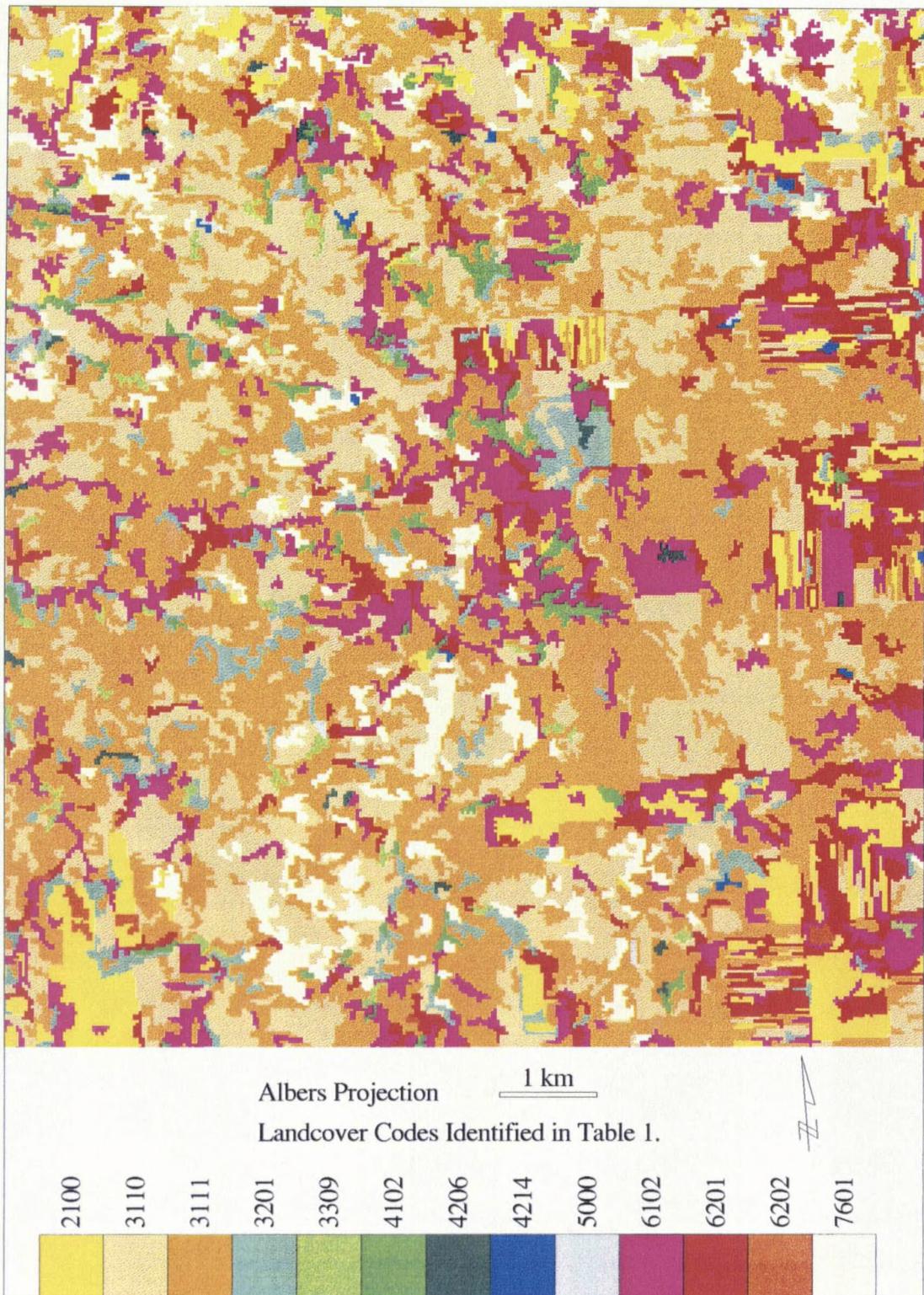


Figure 19. Landcover Map Using Landsat Data Plus Elevation, Quasi-Dynamic Wetness Index and Solar Radiation; Minimum Mapping Unit 0.8 hectare.

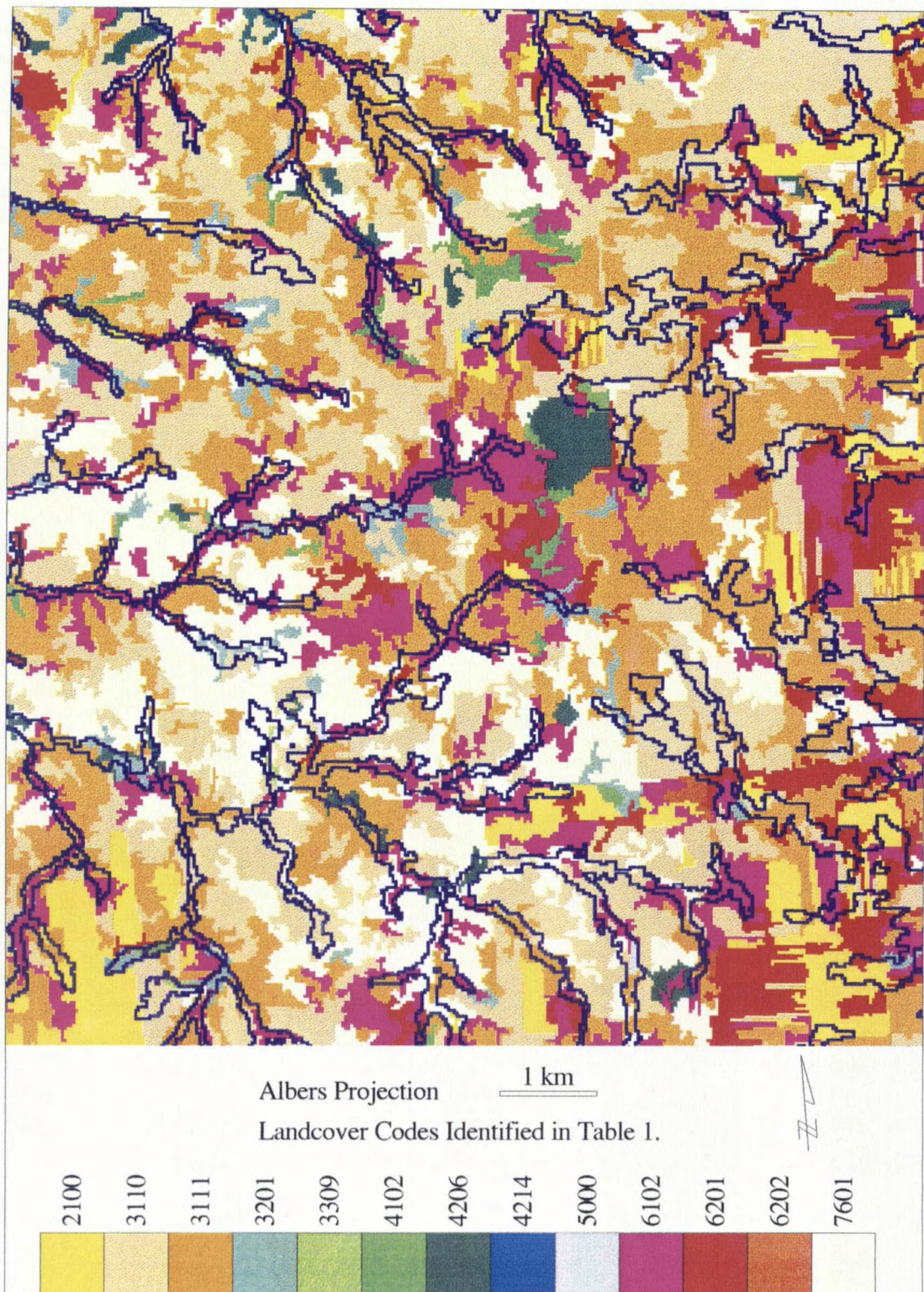


Figure 20. Landcover Map Using Landsat Data Plus Elevation, Quasi-Dynamic Wetness Index and Solar Radiation; Minimum Mapping Unit 2.0 hectare. Stream Buffer Shown in Blue.

	L1	W1	S1	L2	W2	S2	L5	W5	S5
L1	--								
W1	84.8	--							
S1	67.1	69.8	--						
L2	41.7	41.2	39.9	--					
W2	41.8	42.8	40.5	87.5	--				
S2	39.9	39.2	41.3	70.3	73.8	--			
L5	43.2	43.1	40.9	36.8	36.8	35.6	--		
W5	43.2	43.8	41.7	36.4	37.5	35.9	89.4	--	
S5	40.9	41.7	42.0	34.4	35.9	39.0	69.6	71.6	--

L -- Landsat plus elevation

W -- Landsat plus elevation and quasi-dynamic wetness index

S -- Landsat plus elevation, quasi-dynamic wetness index, and solar radiation

1,2,5 -- Minimum Mapping Units of 0.4, 0.8 and 2.0 ha (1, 2 and 5 ac)

Comparison of Stream Buffers Derived from TAPES-G Channels and USGS DLG Data

Given the lack of improvement from incorporating terrain attributes directly into the classification process, other methods for using terrain attributes to improve map accuracy were investigated. Because many of the Forest Service vegetation classes are defined as upland or riparian, the stream elevation buffer of Ma and Righter (1994) can be used to distinguish vegetation classes with similar spectral signatures, such as upland broadleaf forest and riparian broadleaf forest, which may consist of the same vegetation species (e.g. green ash, *Fraxinus pennsylvanica*), growing in different landscape positions.

The elevation buffer is applied to stream channels, which can be obtained either as USGS digital line graph data, or calculated from digital elevation models by the TAPES-G software. At present, high resolution USGS digital hydrography data at 1:24,000-scale is not available for the Little Missouri region, and the available 1:100,000-scale data does not have a high enough drainage density to delineate many of the wooded-draws of interest in this study. Therefore, we investigate the use of TAPES-G stream channels as input to the stream buffer calculation. An advantage of the TAPES-G stream channels is that their drainage density can be adjusted to produce optimum agreement with riparian vegetation seen in the Landsat image.

Figures 21-23 show in black the TAPES-G buffer, the 1:100,000 scale USGS digital line graph buffer, and their overlap. The TAPES-G buffer, which was chosen to match 1:24,000-scale hydrography on paper 7.5 minute quadrangles (digital data were not available), shows more first order tributaries in the headwaters of drainages. In the low-relief areas (at

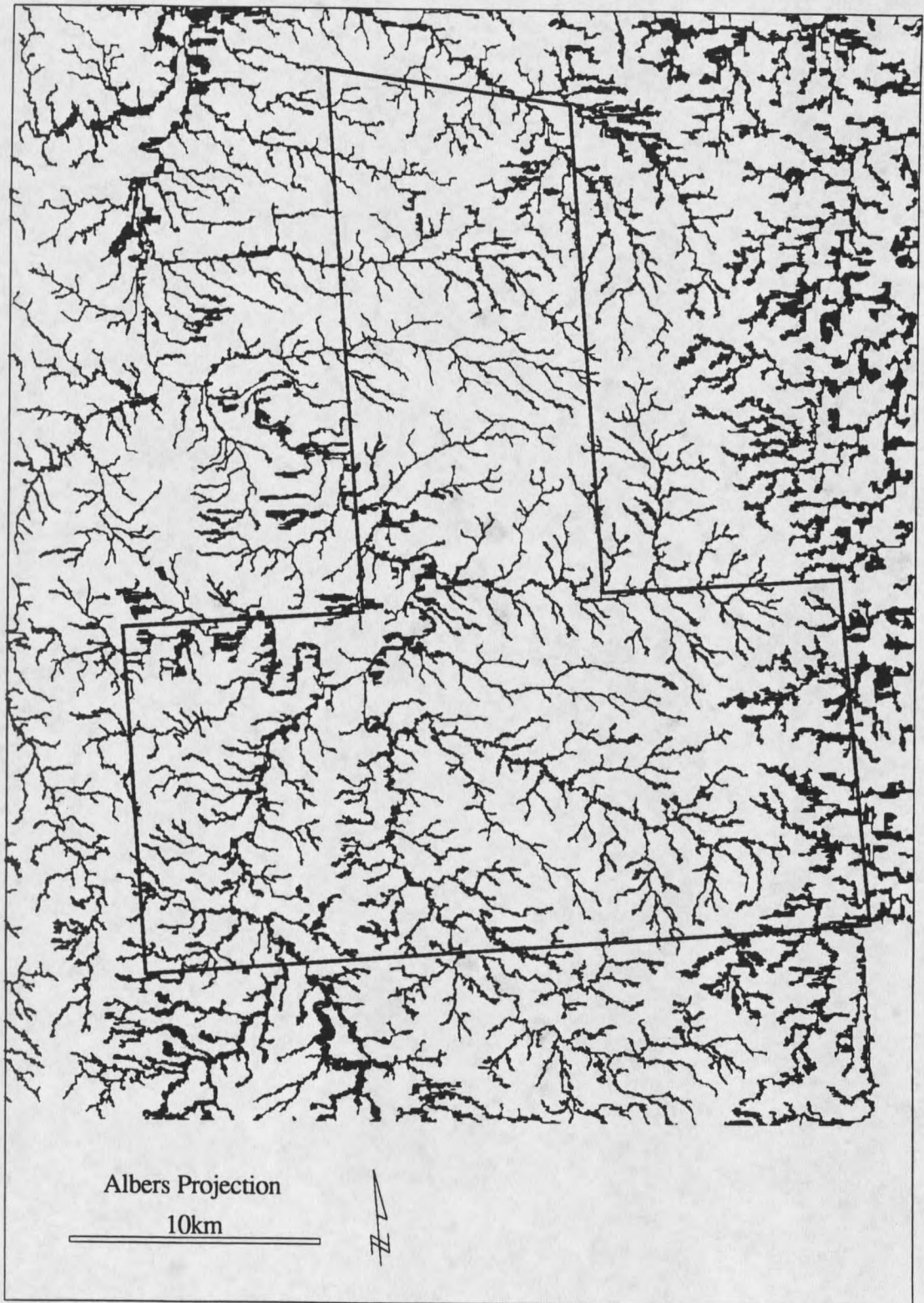


Figure 21. Stream Elevation Buffer Computed From TAPES-G Stream Channels. The catchment area threshold for these channels is 0.2 sq. km.

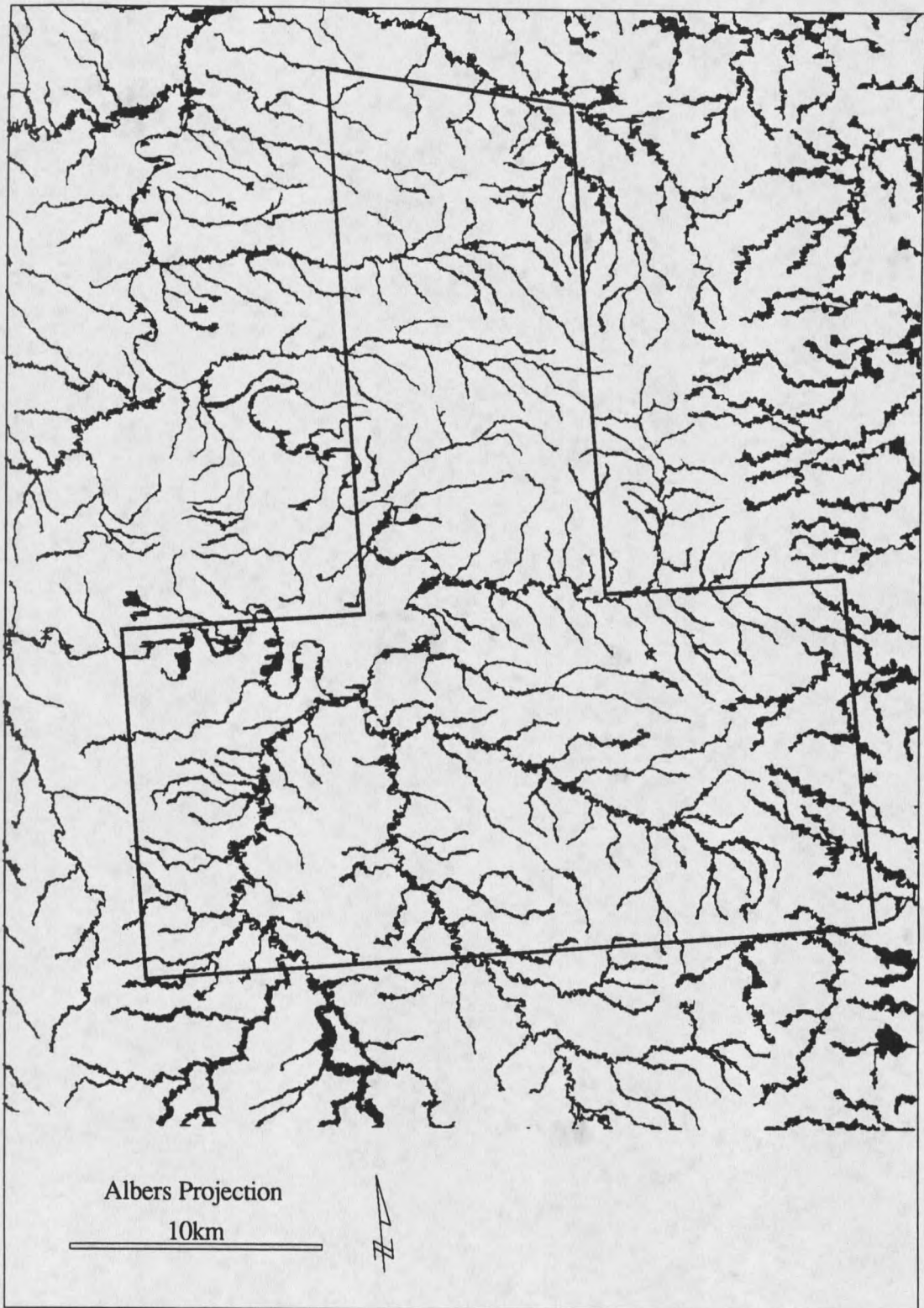


Figure 22. Stream Elevation Buffer Computed From 1:100,000-Scale USGS Digital Line Graph Data.

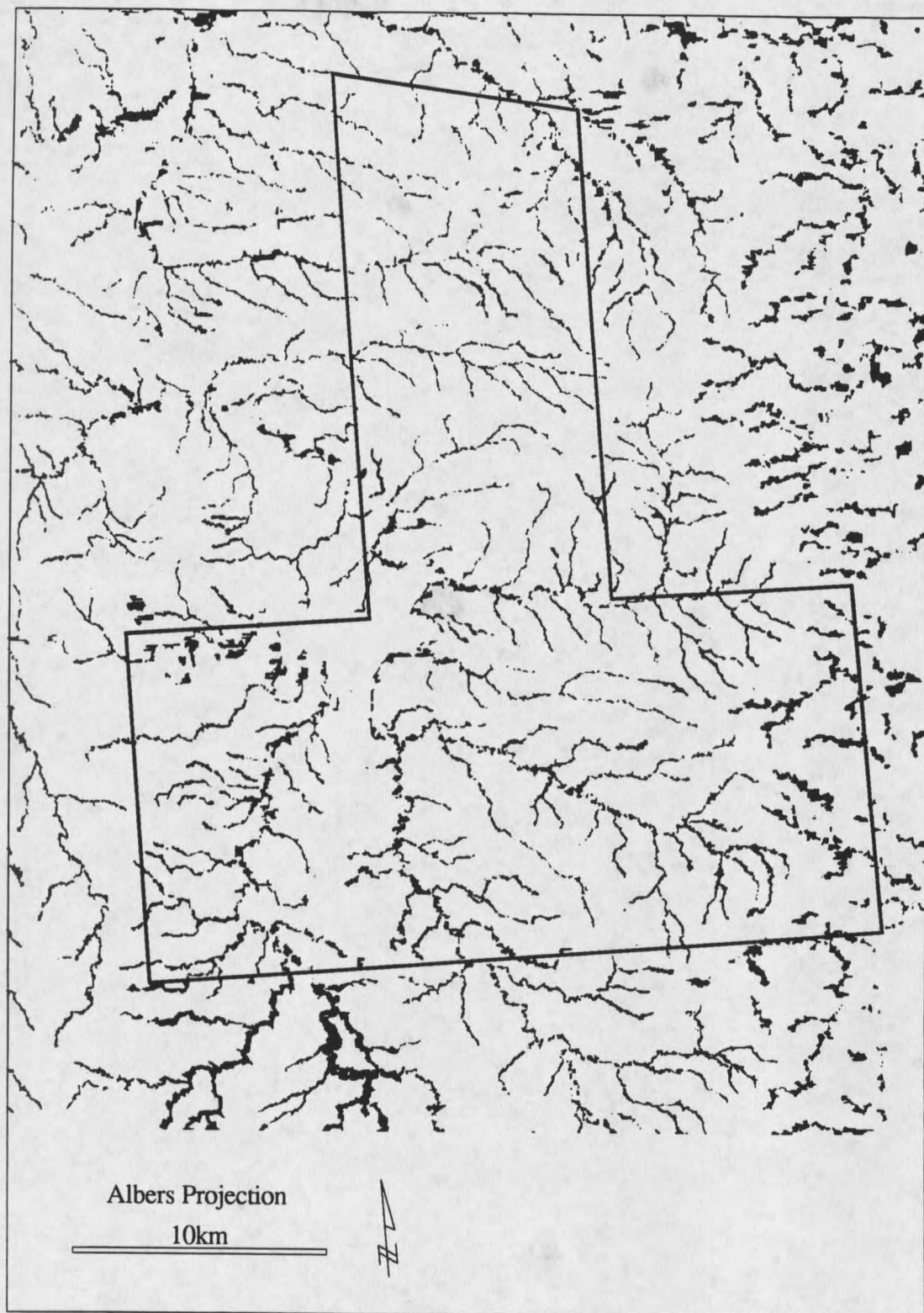


Figure 23. Overlap Between Stream Buffers Derived From TAPES-G and DLG Data.

right in the figures), the buffers are affected by DEM error, which produces spurious drainages trending east-west. Overall, 16.0% of the 1700 km² terrain analysis area is within the TAPES-G buffer, compared with 11.4% for the DLG buffer. The two buffers overlap in 6.9% of the total study area, shown in black in Figure 23. Including agreement in areas outside the buffer, overall agreement between the two grids is 86.5%. Agreement is generally good in the middle sections of well-defined wooded-draw drainages, but worse in the source areas, and in flatter rolling upland terrain.

Using a Stream Elevation Buffer to Improve Vegetation Classification

The stream elevation buffer has the potential to increase classification accuracy substantially in all nine maps, because much of the error results from confusion between upland and riparian vegetation classes, which can be reclassified according to whether they are inside or outside the stream buffer. The remaining vegetation classes (e.g. cropland or silver sage) do not carry a riparian or upland designation, and cannot be reassigned using the stream buffer. Four upland classes can be unambiguously reclassified to riparian equivalents if they occur inside a riparian buffer: the grassland classes 3110 and 3111 can be reclassified to riparian grassland (6201), upland shrub (3201) can be reclassified to riparian shrub (6202), and upland broadleaf forest (4102) can be reclassified to riparian broadleaf forest (6102). In the nine maps, between 7.4% and 8.2% of the total area of the 'T' shaped remote sensing coverage consists of upland classes within the TAPES-G derived riparian buffer (Table 5). In addition, two riparian classes (6102 and 6202) can be unambiguously reclassified to their

Table 5. Fraction of Upland Vegetation Inside the TAPES-G Derived Stream Buffer, and Fraction of Riparian Vegetation Outside the Stream Buffer.

	Upland Vegetation Inside Buffer (%)	Riparian Vegetation Outside Buffer (%)	Sum(%)
L1	8.1	9.8	17.9
W1	8.0	10.1	18.1
S1	8.1	11.3	19.4
L2	8.0	15.2	23.3
W2	8.2	14.2	22.4
S2	8.1	14.5	22.6
L5	7.6	13.1	20.7
W5	7.7	13.3	21.0
S5	7.4	13.6	21.0

Percentages are of the total area in the five quadrangle study site.

L -- Landsat plus elevation
W -- Landsat plus elevation and quasi-dynamic wetness index
S -- Landsat plus elevation, quasi-dynamic wetness index, and solar radiation
1,2,5 -- Minimum Mapping Units of 0.4, 0.8 and 2.0 hectare (1, 2 and 5 acre)

upland equivalents, and riparian grassland (6201) could be reclassified to moderate-cover grass (3111), if this class occurs outside the riparian buffer. Between 9.8% and 15.2% of the map area consists of these riparian classes occurring outside the riparian buffer. Adding the two possible improvements, the TAPES-G derived stream buffer has the potential to improve accuracy of the vegetation classification by 18-23%, assuming that a stream elevation buffer can be created which accurately models what ecologists would consider to be riparian areas. Currently, the Forest Service does not have a riparian delineation for this study area, therefore this agreement can not be measured quantitatively. Qualitatively, the 5 m elevation buffer

employed here produces buffers that are too wide (up to 0.5 km) in areas of low relief, such as river terraces and rolling upland (at right in Figures 20 and 21). This may overestimate the amount of riparian vegetation. Thus we may expect a smaller overall improvement in accuracy if the stream elevation buffer were used to reclassify the maps, perhaps on the order of 10%, which would raise overall classification accuracies to 65% for 13 landcover classes.

CHAPTER 4

CONCLUSIONS

The negligible improvement in classification accuracy gained by adding quasi-dynamic topographic wetness index and solar radiation to Landsat data does not justify their use in remote sensing vegetation mapping, but the use of riparian buffers to distinguish between riparian and upland vegetation classes may be worth the considerable effort involved in computing terrain attributes. Before applying terrain analysis to a large Forest Service management area such as the entire Little Missouri National Grasslands, the following issues should be investigated: 1) assess DEM error over the entire Little Missouri region and examine how it propagates into terrain attributes, 2) determine whether terrain attributes can be incorporated into the initial stage of the Ma/Redmond method, 3) explore more sophisticated wetness indices which incorporate the effects of terrain aspect, such as the WET module of TAPES-G, 4) compare the stream elevation buffer with a Forest Service riparian delineation based on airphotos or field mapping, and 5) alter the buffer algorithm to make the elevation threshold a function of local vertical relief or upslope drainage area, to better tailor the buffer to the terrain.

USGS DEM error varies greatly from quadrangle to quadrangle, and may produce unacceptable errors in terrain attributes in the rolling upland areas of the Little Missouri, whereas the five quadrangle area used in this study consists mostly of rugged wooded-draw terrain where errors are minor. Modeling how spatially patterned systematic elevation error

propagates into terrain attributes is a sparsely researched area, but Spangrud et al. (1995) have shown that derived terrain attributes are highly sensitive to subtle modifications of elevation data. In the Little Missouri region, the USGS elevation data is by far the best available: quantification of errors is hampered by the lack of a reference data set of accurate elevations with which to compare USGS data. Nevertheless, visual inspection of terrain attribute maps can give an excellent qualitative impression of whether the linear patterns of DEM error obliterate terrain features.

A possible improvement to the Ma/Redmond method might be to include terrain attributes in the initial classification stage, in contrast to defining vegetation patches from Landsat bands 3, 4 and 5 only. At large minimum mapping units, terrain attributes are averaged over a large area, which may diminish their impact on the classification process. Dividing the initial classification into classes based on terrain attributes may improve accuracy.

A more sophisticated wetness index which incorporates the effects of aspect might be more successful in discerning vegetation types. The WET module of TAPES-G incorporates SRAD output into a wetness index, but the program was not implemented at MSU in time for this study.

Before proceeding with a stream buffer calculation over a larger area, a comparison of the TAPES-G derived buffer with a Forest Service delineation of riparian areas is recommended. In order to optimize this agreement, two parameters may be adjusted in the buffer calculation: 1) the channel initiation threshold specified in TAPES-G affects the density of drainage channels, and 2) the height above stream level specified in the buffer algorithm

affects the width of the buffers. Adjusting these thresholds to correspond to observed riparian vegetation may result in a more useful stream buffer.

The calculated stream buffer illustrated in Figure 21 suggests that a single height above stream level for the entire area may not be able to generate suitable buffers in both the rolling upland and wooded-draw physiographies: an improvement would be to make the buffer height above stream level a function of the local vertical relief. In areas of large vertical relief, the height above stream level used to define the buffer could be increased; in areas of low relief, this threshold height could be reduced. Similarly, the roughness (vertical relief divided by area) of each catchment could be computed and used to adjust the buffer threshold for streams within these catchments. The threshold could alternatively be scaled by upslope drainage area.

A combination of one or more of these improvements to the terrain analysis methods may improve results. Furthermore, additional data such as a larger ground truth sample, new data layers such as geology, soils and property ownership, or a time series of Landsat images might also be helpful in resolving confusion between vegetation classes.

The accuracy of the Ma/Redmond method might improve with larger ground-truth sample sizes in the post-aggregation classification for landcover classes poorly represented in this study, but the grassland identification remained poor despite a total of 45 ground-truth points in two grassland classes. Grouping together some low-accuracy classes, such as the two grassland classes, or the shrub and forest classes, would increase accuracy substantially.

Additional data layers such as soil properties and property ownership might be of some use in improving accuracy. However, Moore et al. (1993a) have demonstrated a strong

correlation between terrain and soil properties, so soil mapping may not add much new information. Furthermore, in the rugged wooded draw terrain of the Little Missouri, soils have not been mapped in county soil surveys at sufficient spatial resolution to distinguish the individual small drainages that affect vegetation patterns (Thompson 1978). In other National Forests where geologic parent material is more diverse than in the Little Missouri, soil mapping might improve classification accuracy when incorporated into the classification, however, few mountainous National Forests have detailed soil surveys. Property ownership maps might be of use in identifying cropland, which occurs almost exclusively on private land. However, riparian areas also occur on private land, meandering through the complex checkerboard pattern of land ownership in the Little Missouri, making identification by property ownership difficult.

A time-series of Landsat images throughout the growing season might help resolve some of the confusion between cropland and broadleaf forest, because cropland may exhibit rapid changes in spectral signature due to ploughing and harvest, compared with the more constant signature of broadleaf forest in the summer months. Time-series remote sensing has improved accuracy in other large-scale mapping projects (Fuller et al. 1994, Pickup et al. 1993), but in the Konza Prairie, Kansas, a grassland site similar to the Little Missouri, Oleson et al. (1995) found that cropland and forest had a considerable overlap in spectral signature at all times during the May to October growing season.

Although remote sensing classification accuracy is less than ideal in the landscape of the northern Great Plains, satellite mapping remains the best way of mapping large areas of National Grassland in the Dakotas, because field mapping and airphoto interpretation are too

time-consuming at this scale. East of the Little Missouri, in locations with less vertical relief, such as the Grand River/Cedar River and Sheyenne National Grasslands, terrain analysis may be less useful, as the spatially patterned DEM errors may overwhelm terrain features. Alternatively, terrain attributes may be of more use in the mountainous National Forests of the Rockies, where vertical relief is larger.

ci

REFERENCES CITED

Aase, J.K., Frank, A.B., and Lorenz, R.J. 1987. Radiometric Reflectance Measurements of Northern Great Plains Rangeland and Crested Wheatgrass Pastures. *Journal of Range Management* 40(4):299-302.

Anderson, J.R., Hardy, E.E., Roach, J.T., and Witmer, R.E. 1976. A Land Use and Land Cover Classification System for Use with Remote Sensing Data. *Geological Survey Professional Paper 964*. Washington, D.C.: USGS.

Aziz, F.P. 1989. *Soil Survey of Golden Valley County, North Dakota*. Washington, D.C.: Soil Conservation Service.

Band, L.E. 1993. Extraction of Channel Networks and Topographic Parameters from Digital Elevation Data. In *Channel Network Hydrology*, ed. K. Beven and M.J. Kirkby, pp. 17-42. New York: John Wiley.

Barling, R.D., Moore, I.D., and Grayson, R.B. 1994. A Quasi-Dynamic Wetness Index for Characterizing the Spatial Distribution of Zones of Surface Saturation and Soil Water Content. *Water Resources Research* 30(4):1029-1044.

Beven, K.J., and Kirkby, M.J. 1979. A Physically-Based Variable Contributing Area Model of Basin Hydrology. *Hydrological Sciences Bulletin* 24:43-69.

Beven, K.J., Quinn, R., Romanowicz, R., Freer, J., Fisher, J., and Lamb, R. 1994. *TOPMODEL and GRIDATB, a Users Guide*. Lancaster, UK: Lancaster University Center for Research on Environmental Systems.

Bluemle, J.P. 1975. *Guide to the Geology of Southwest North Dakota*. Bismarck, ND: North Dakota Geological Survey, Educational Series No. 8.

Bolstad, P.V., and Lillesand, T.M. 1992. Rule-based Classification Models: Flexible Integration of Satellite Imagery and Thematic Spatial Data. *Photogrammetric Engineering and Remote Sensing* 58:965-971.

Brown, D.A. 1993. Early Nineteenth-Century Grasslands of the Midcontinent Plains. *Annals of the American Association of Geographers* 84(4):589-612.

Brown, D.G., and Bara, T.J. 1994. Recognition and Reduction of Systematic Error in Elevation and Derivative Surfaces from 7.5 Minute DEMs. *Photogrammetric Engineering and Remote Sensing* 60(2):189-194.

Congalton, R.G. 1991. A Review of Assessing the Accuracy of Classification of Remotely Sensed Data. *Remote Sensing of Environment* 37(1):35-46.

Dikau R. 1989. The Application of Digital Relief Models to Landform Analysis in Geomorphology. In *Three Dimensional Applications in GIS*, ed. J. Raper, pp. 51-77. New York: Taylor and Francis.

Dozier, J., Bruno, J., and Downey, P. 1981. A Faster Solution to the Horizon Problem. *Computers and Geosciences* 7:145-51.

Dubayah, R., and Rich, P.M. 1996. GIS-Based Solar Radiation Modeling. In *GIS and Environmental Modeling, Progress and Research Issues*, ed. M.F. Goodchild and six others, pp.129-134. Fort Collins, Colorado: GIS World, Inc.

ESRI, Inc. 1995. *ARC/INFO Command Reference, Version 7.0*. Redlands, CA: Environmental Systems Research Institute, Inc.

Fairfield, J., and Leymarie, P. 1991. Drainage Networks from Grid Digital Elevation Models. *Water Resources Research* 27(5):709-717.

Ford, R., Ma, Z. and Redmond, R.L. 1993. *Aggregation of Image Classification Units for Mapping Large Areas*. Missoula, MT: Wildlife Spatial Analysis Lab, Montana Cooperative Wildlife Research Unit.

Fuller, R.M., Groom, G.B. and Jones, A.R. 1994. The Land Cover Map of Great Britain: An Automated Classification of Landsat TM Data. *Photogrammetric Engineering and Remote Sensing* 60(5):553-562.

Friedl, M.A., Davis, F.W., Michaelsen, J., and Moritz, M.A. 1995. Scaling and Uncertainty in the Relationship Between the NDVI and Land Surface Biophysical Variables: An Analysis Using a Scene Simulation Model and Data From FIFE. *Remote Sensing of Environment* 54:233-246.

Gallant, J.C., and Wilson, J.P. 1996. TAPES-G: A Grid-based Terrain Analysis Program for the Environmental Sciences. *Computers and Geosciences*, in press.

Gates, D.M. 1980. *Biophysical Ecology*. New York: Springer Verlag.

Gates, D.M., Keegan, H.J., Schleter, J.C., and Weidner, V.R. 1965. Spectral Properties of Plants. *Applied Optics* 4:11-20.

Heckert, P. 1982. Color Image Quantization for Frame Buffer Display. *Computer Graphics* 16(3):297.

Hutchinson, C.F. 1982. Techniques for Combining Landsat and Ancillary Data for Digital Classification Improvement. *Photogrammetric Engineering and Remote Sensing* 48(1):123.

- Hydrosphere, Inc. 1993. *Climatedata West 2* (cd-rom). Boulder, Colorado: Hydrosphere, Inc.
- Jensen, J.R. 1996. *Introductory Digital Image Processing, A Remote Sensing Perspective*. New York: Prentice-Hall.
- Jensen, S.K., and Dominique, J.O. 1988. Extraction of Topographic Structure from Digital Elevation Data for GIS Analysis. *Photogrammetric Engineering and Remote Sensing* 54(11):1593-1600.
- Joria, P., and Jorgenson, J. 1996. Comparison of Three Methods for Mapping Tundra with Landsat Digital Data. *Photogrammetric Engineering and Remote Sensing* 62(2):163-169.
- Lillesand, T.M., and Kiefer, R.W. 1994. *Remote Sensing and Image Interpretation*. New York: John Wiley and Sons.
- Little, E.L. 1971. *Atlas of United States Trees*. Washington, D.C.: U.S. Department of Agriculture.
- Ma, Z. and Redmond, R.L. 1992. Spatial Accuracy of Landsat TM Terrain Correction. *Gap Analysis Bulletin* 3:12-13.
- Ma, Z. and Redmond, R.L. 1993. *Using Landsat TM Data and a GIS to Classify and Map Existing Vegetation*. Missoula, MT: Wildlife Spatial Analysis Lab, Montana Cooperative Wildlife Research Unit.
- Ma, Z. and Redmond, R.L. 1994a. *Using a Color Palette for an Unsupervised Classification of Remote Sensing Imagery*. Missoula, MT: Wildlife Spatial Analysis Lab, Montana Cooperative Wildlife Research Unit.
- Ma, Z. and Redmond, R.L. 1994b. *Integration of Remote Sensing and GIS to Classify Multisource Data for Mapping Vegetation Across the State of Montana*. Missoula, MT: Wildlife Spatial Analysis Lab, Montana Cooperative Wildlife Research Unit.
- Ma, Z. and Righter, R. 1994. *A Method for Modeling Riparian Distribution in Mountainous Terrain*. Missoula, MT: Wildlife Spatial Analysis Lab, Montana Cooperative Wildlife Research Unit.
- Moore, I.D., and Hutchinson, M.F. 1991. *Spatial Extension of Hydrologic Process Modelling*. Perth, Australia: International Hydrology and Water Resources Symposium.
- Moore, I.D., and Nieber, J.L. 1989. Landscape Assessment of Soil Erosion and Nonpoint Source Pollution. *Journal of the Minnesota Academy of Sciences* 55(1):18-25.

- Moore, I.D., Gessler, P.E., Nielsen, G.A. and Peterson G.A. 1993a. Soil Attribute Prediction Using Terrain Analysis. *Soil Science Society of America Journal* 57(2):443-452.
- Moore, I.D., Norton, T.W., and Williams, J.E. 1993b. Modelling Environmental Heterogeneity in Forested Landscapes. *Journal of Hydrology* 150:717-747.
- NOAA. 1993a. *Climatological Data, North Dakota*. Asheville, North Carolina: National Oceanic and Atmospheric Administration.
- NOAA. 1993b. *Local Climatological Data Annual Summary, with Comparative Data, Bismarck, North Dakota*. Asheville, North Carolina: National Oceanic and Atmospheric Administration.
- O'Callaghan, J.F., and Mark, D.M. 1984. The Extraction of Drainage Networks from Digital Elevation Data. *Computer Vision, Graphics, and Image Processing* 28:323-344.
- Oleson, K.W., Sarlin, S., Garrison, J., Smith, S., Privette, J. and Emery, W. 1995. Unmixing Multiple Land-Cover Type Reflectances from Coarse Spatial Resolution Satellite Data. *Remote Sensing of Environment* 54:98-112.
- Owenby, J.R., and Ezell, D.S. 1992. *Monthly Station Normals of Temperature, Precipitation, and Heating and Cooling Degree Days, 1961-90, North Dakota*. Asheville, North Carolina: National Oceanic and Atmospheric Administration.
- Panuska, J.C., Moore, I.D., and Kramer, L.A. 1991. Terrain Analysis: Integration Into the Agricultural Nonpoint Source (AGNPS) Pollution Model. *Journal of Soil and Water Conservation* 46(1):59-64.
- Pickup G., Bastin, G.N., and Chewings V.H. 1994. Remote Sensing-Based Condition Assessment for Nonequilibrium Rangelands under Large-Scale Commercial Grazing. *Ecological Applications* 4(3):497-517.
- Pickup G., Chewings V.H. and Nelson, D.J. 1993. Estimating Changes in Vegetation Cover over Time in Arid Rangelands Using Landsat MSS Data. *Remote Sensing of Environment* 43:243-63.
- Quinn, P.F., Beven, K.J., Chevalier, P., and Planchon, O. 1991. The Prediction of Hillslope Paths for Distributed Hydrologic Modeling Using Digital Terrain Models. *Hydrological Processes* 5(1):59-79.
- Ratliff, L.F., Ritchie, J.T., and Cassel, D.K. 1983. Field-Measured Limits of Soil Water Availability as Related to Laboratory-Measured Properties. *Soil Science Society of America Journal* 47:770-775.

Rawls, W.J., and Brakensiek, D.L. 1989. Estimation of Soil Water Retention and Hydraulic Properties. In *Unsaturated Flow in Hydrologic Modeling: Theory and Practice*, ed. H.J. Morel-Seytoux, pp. 275-300. Amsterdam: Kluwer Academic Publishing.

Ripple, W.J. 1985. Asymptotic Reflectance Characteristics of Grass Vegetation. *Photogrammetric Engineering and Remote Sensing* 51:1915.

Rudd, V.E. 1951. Geographical Affinities of the Flora of North Dakota. *American Midland Naturalist* 45:722-39.

Simpson, J.J., Gobat, J.I., and Frouin, R. 1995. Improved Destriping of GOES Images Using Finite Impulse Response Filters. *Remote Sensing of Environment* 52:15-35.

Skidmore, A.K., and Turner, B.J. 1988. Forest Mapping Accuracies are Improved Using a Supervised Nonparametric Classifier with SPOT Data. *Photogrammetric Engineering and Remote Sensing* 54(10):1415-1421.

Spangrud, D.J., Wilson, J.P., Nielsen, G.A., Jacobsen, J.S., and Tyler, D.A. 1995. Sensitivity of Computed Terrain Attributes to the Number and Pattern of GPS-Derived Elevation Data. In *Site-Specific Management for Agricultural Systems*, ed. P.C. Robert, R.H. Rust, and W.E. Larson, pp. 285-301. Madison, Wisconsin: American Society of Agronomy.

Tansley, A.G., and Chipp, T.F. 1926. *Aims and Methods in the Study of Vegetation*. London: British Empire Vegetation Committee.

Thomas, R.W., and Ustin, S.L. 1987. Discriminating Semiarid Vegetation Using Airborne Imaging Spectrometer Data: A Preliminary Assessment. *Remote Sensing of Environment* 23(2):273-290.

Thompson, K.W. 1978. *Soil Survey of Slope County, North Dakota*. Washington, D.C.: Soil Conservation Service.

U.S. Geological Survey. 1993. *Digital Elevation Models, Data Users Guide*. Reston, Virginia: United States Geological Survey.

U.S. Soil Conservation Service. 1993. *State Soil Geographic Database User's Guide*. Washington, D.C.: Soil Conservation Service.

Wilson, J.P., and Gallant, J.C. 1996a. Terrain-Based Approaches to Environmental Resource Surveys. In *Landform Monitoring, Modelling and Analysis*, Ed. S.N. Lane, K.S. Richards and J.H. Chandler, in press. New York: John Wiley.

Wilson, J.P., and Gallant, J.C. 1996b. SRAD, A Grid-Based Program for Estimating

Radiation and Temperature in Complex Terrain. *Computers and Geosciences* (submitted).

Wilson, J.P., Spangrud, D.J., Landon, M.A., Jacobsen, J.S., Nielsen, G.A. 1994. Mapping Soil Attributes for Site-Specific Management of a Montana Field. In *Optics in Agriculture, Forestry and Biological Processing*, ed. G.E. Meyer and J.A. DeShazer, pp. 324-335. Bellingham, WA: International Society for Optical Engineering.

Wolock, D.M., and McCabe, G.J. 1995. Comparison of Single and Multiple Flow Direction Algorithms for Computing Topographic Parameters in TOPMODEL. *Water Resources Research* 31(5):1315-24.

Zhuang, X., Engel, B.A., Xiong, X., and Johannsen, C.J. 1995. Analysis of Classification Results of Remotely Sensed Data and Evaluation of Classification Algorithms. *Photogrammetric Engineering and Remote Sensing* 61(4):427-433.

APPENDICES

APPENDIX A

DESCRIPTION OF FOREST SERVICE LANDCOVER TYPES
(by Jeff Dibenedetto, Custer National Forest ecologist)

FOREST SERVICE LANDCOVER TYPES

Code

2100 Cropland, cultivated pasture, and hay.

3110 Low grass/low cover

This type is typically found on ridge tops and clay outwash areas below buttes. Vegetation found within this class is blue grama (*Bouteloua gracilis*), needle and thread (*Stipa comata*), threadleaf sedge (*Carex filifolia*). The type is characterized by low biomass productivity (less than 700 lbs/acre) and low ground cover and bare ground.

3111 Low grass/moderate cover

This type is typically found on hillslopes. Vegetation found with this cover class are needle and thread, western wheatgrass (*Agropyron smithii*), blue grama. This type is characterized by medium biomass productivity, moderate ground cover values and less bare ground than cover class 3110.

3201 Mesic upland shrub

This type is found on northerly aspect slopes, depressions and draws. Vegetation found with this cover class include snowberry (*Symphoricarpos occidentalis*), buffalo berry (*Sheperdia argentea*), chokecherry (*Prunus virginiana*), creeping juniper (*Juniporus horizontalis*). Occasional young green ash (*Fraxinus pennsylvanica*) trees may also be found within this type.

3309 Silver sage

This type is found mainly within valley bottoms on terraces adjacent to stream channels. Vegetation is dominated by silver sagebrush (*Artemisia americana*) with and understory of grass species western wheatgrass and blue grama. Snowberry may also be found within this type as in some situations as a co-dominant shrub.

4102 Upland broadleaf forest

This type is associated with upland settings, mainly on steep northerly aspect slopes associated with badlands or deeply incised drainageways or draws.

4206 Ponderosa pine forest

This type is associated with shallow soils associated with ridges and hillslopes. Vegetation include with this type is dominated by ponderosa pine (*Pinus ponderosa*). Other vegetation that may be found with this type include rocky mountain juniper, green ash, snowberry and chokecherry.

4214 Rocky Mountain juniper forest

This type is typically found on very steep north aspect badland slopes. Vegetation is dominated by rocky mountain juniper (*Juniperus scopulorum*). Associated species may include green ash as an occasional tree or patch within the stand.

5000 Water

6102 Riparian broadleaf forest

This type is found along river bottoms, drainage bottoms, valley bottoms and narrow draws. Included within this type are woody draws often dominated by green ash.

6201 Riparian grass and forb

This type is found along drainage bottoms and draws. Vegetation found within this type include western wheatgrass, baltic rush (*Juncus balticus*) and a mixture of forbs.

6202 Riparian shrub

This type is found along drainage bottoms, valley bottoms and narrow draws. Vegetation found within this class includes snowberry, buffaloberry, chokecherry, with occasional young ash trees.

7601 Badland

This type is associated with steep badland slopes, often very steep south aspect slopes and outwash areas at the base of buttes and slopes. Vegetation associated with this type are scattered patches of grass and big sagebrush (*Artemisia tridentata wyomingensis*) shadscale (*Atriplex confertifolia*, green rabbitbrush (*Chrysothamnus visidiflorus*) and greasewood (*Sarcobatus vermiculatus*).

APPENDIX B

TERRAIN ATTRIBUTE VALUES AT GROUND-TRUTH LOCATIONS

VEGCODE	LONG (deg)	LAT (deg)	ELEV (m)	SLOPE (%)	ASPECT (deg)	UPSLOPE log(m^2)	WET	DYNWET	SRAD W/m^2
2100	103.251	46.587	846	2.2	45	4.01	9.66	2.67	161
2100	103.274	46.581	865	3.3	243	3.26	7.25	2.64	153
2100	103.277	46.597	870	5.7	236	3.37	7.38	2.54	148
2100	103.307	46.608	837	9.1	117	3.49	7.08	2.58	162
2100	103.307	46.608	837	9.1	117	3.49	7.08	2.58	162
2100	103.315	46.582	882	2.8	297	3.74	7.16	2.52	150
2100	103.385	46.525	836	7.4	27	3.35	6.92	2.34	128
2100	103.390	46.529	842	8.4	31	3.78	7.66	2.57	156
2100	103.462	46.628	743	2.4	180	2.95	7.47	2.42	146
2100	103.480	46.653	734	1.7	0	4.24	10.49	2.67	150
2100	103.487	46.649	736	1.7	0	3.25	8.40	2.67	158
2100	103.490	46.647	738	2.6	225	3.28	7.43	2.39	155
2100	103.392	46.767	796	4.4	315	5.31	11.46	2.65	154
2100	103.457	46.770	807	5.0	0	4.21	9.37	2.67	151
2100	103.488	46.701	797	4.9	194	4.91	9.17	2.66	152
2100	103.402	46.558	790	2.2	45	5.15	8.67	2.67	165
2100	103.405	46.559	790	6.0	0	4.87	10.62	2.66	160
2100	103.409	46.562	786	3.0	117	4.02	9.40	2.67	149
3110	103.295	46.589	878	7.4	166	3.88	7.87	2.45	154
3110	103.308	46.585	874	2.9	90	4.60	10.39	2.66	149
3110	103.317	46.585	899	7.4	59	2.99	6.65	2.37	180
3110	103.319	46.589	882	16.4	276	3.15	5.93	2.64	143
3110	103.328	46.578	885	12.0	236	3.30	6.56	2.35	151
3110	103.336	46.583	877	7.3	225	3.83	8.02	2.39	154
3110	103.338	46.585	884	2.2	27	2.95	8.33	2.32	173
3110	103.338	46.593	844	6.3	104	3.10	6.94	2.32	154
3110	103.341	46.591	846	3.9	270	4.49	8.34	2.45	156
3110	103.348	46.598	851	4.5	315	3.23	7.43	2.34	159
3110	103.368	46.599	834	2.9	45	3.00	7.26	2.55	170
3110	103.369	46.610	831	5.3	18	3.27	7.18	2.65	154
3110	103.386	46.663	846	5.6	90	3.19	7.06	2.36	156
3110	103.387	46.787	778	0.7	0	3.79	11.22	2.67	139
3110	103.389	46.604	844	6.5	146	3.66	7.91	2.66	164
3110	103.390	46.791	780	4.0	72	4.05	9.25	2.44	148
3110	103.398	46.656	817	4.5	27	3.16	7.14	2.32	149
3110	103.400	46.644	814	35.5	227	3.38	5.45	2.21	143
3110	103.400	46.750	819	7.4	281	5.28	7.88	2.62	168
3110	103.403	46.649	834	2.0	90	2.95	7.64	2.41	161
3110	103.406	46.745	810	3.5	243	4.05	9.29	2.33	151
3110	103.409	46.742	798	10.2	304	4.69	7.21	2.63	151
3110	103.488	46.768	886	8.9	101	3.21	6.76	2.44	157
3110	103.491	46.767	888	3.9	45	2.99	7.12	2.57	139
3111	103.288	46.589	874	4.7	162	4.11	9.14	2.67	153
3111	103.294	46.589	883	1.4	0	3.19	8.79	2.67	158
3111	103.296	46.587	873	4.8	135	4.15	9.09	2.38	152
3111	103.296	46.592	882	5.2	0	3.51	7.75	2.66	139
3111	103.303	46.586	879	2.7	270	3.05	7.56	2.50	148
3111	103.309	46.586	885	8.1	169	3.14	6.63	2.50	156
3111	103.361	46.597	831	6.1	346	2.95	6.58	2.32	155

VEGCODE	LONG (deg)	LAT (deg)	ELEV (m)	SLOPE (%)	ASPECT (deg)	UPSLOPE log(m^2)	WET	DYNWET	SRAD W/m^2
3111	103.381	46.790	789	5.2	0	3.07	6.75	2.66	155
3111	103.385	46.683	889	14.9	186	3.45	6.64	2.58	172
3111	103.388	46.790	778	3.3	90	4.00	9.13	2.63	155
3111	103.398	46.643	794	16.1	243	4.23	7.88	2.34	135
3111	103.398	46.744	825	10.1	207	3.39	6.89	2.61	157
3111	103.398	46.756	821	0.1	0	2.95	10.18	2.67	151
3111	103.401	46.748	819	4.7	252	3.44	7.86	2.52	142
3111	103.402	46.637	778	20.8	35	3.30	5.93	2.36	136
3111	103.402	46.643	798	16.2	66	3.59	6.78	2.47	155
3111	103.408	46.748	808	1.3	0	3.96	10.31	2.56	139
3111	103.410	46.749	806	3.2	297	6.12	13.12	2.67	157
3111	103.413	46.784	888	5.9	153	2.95	6.73	2.54	141
3111	103.541	46.551	803	9.0	129	4.56	8.81	2.64	157
3111	103.546	46.551	812	4.1	153	3.24	7.43	2.48	146
3201	103.378	46.606	829	15.7	252	4.28	7.53	2.48	149
3201	103.403	46.638	773	10.1	141	4.45	8.51	2.50	155
3201	103.427	46.805	779	10.9	281	2.97	5.78	2.37	136
3201	103.433	46.803	785	6.2	0	4.27	9.29	2.66	141
3201	103.435	46.798	781	6.7	14	4.04	8.57	2.66	143
3201	103.440	46.794	794	5.5	236	5.95	11.71	2.52	148
3201	103.442	46.797	795	6.2	180	4.86	8.50	2.66	146
3201	103.449	46.788	818	19.6	5	3.38	6.17	2.63	156
3201	103.454	46.780	805	2.1	225	6.02	12.32	2.62	158
3201	103.479	46.775	822	29.5	43	4.66	8.60	2.59	160
3309	103.384	46.788	780	2.3	180	2.95	7.29	2.66	132
3309	103.386	46.789	775	2.2	180	7.36	12.34	2.67	135
3309	103.387	46.793	774	0.3	0	4.58	13.79	2.67	141
3309	103.387	46.797	770	7.1	194	7.58	14.02	2.66	153
3309	103.431	46.631	741	6.3	236	4.82	10.23	2.64	145
4102	103.316	46.587	872	14.9	21	4.24	8.30	2.46	134
4102	103.316	46.588	857	14.8	58	4.69	9.37	2.64	145
4102	103.361	46.589	826	4.8	315	4.46	9.81	2.46	155
4102	103.370	46.588	805	14.7	229	5.39	6.73	2.63	147
4102	103.397	46.727	840	17.9	73	4.10	7.80	2.52	163
4102	103.405	46.738	797	12.2	186	6.88	14.11	2.50	148
4102	103.413	46.677	863	22.3	299	3.82	6.85	2.27	141
4102	103.438	46.698	858	27.4	11	4.07	6.91	2.39	163
4102	103.440	46.699	854	20.9	24	4.54	8.42	2.29	153
4102	103.449	46.695	816	18.7	297	5.05	9.55	2.62	164
4102	103.479	46.775	851	35.1	51	3.85	6.61	2.20	160
4102	103.535	46.574	785	17.8	229	3.93	7.24	2.46	146
4206	103.468	46.599	794	6.3	45	2.95	6.35	2.33	158
4206	103.479	46.566	792	12.2	14	3.06	6.10	2.48	136
4206	103.506	46.569	778	13.5	7	3.50	6.73	2.64	129
4206	103.531	46.579	790	13.7	249	3.59	6.48	2.65	144
4206	103.538	46.551	810	5.6	252	2.95	7.30	2.57	147
4206	103.542	46.567	801	9.1	349	3.69	7.50	2.43	135
4206	103.547	46.553	804	11.1	8	3.54	6.78	2.65	168
4206	103.547	46.556	803	16.5	326	3.40	6.38	2.58	168

VEGCODE	LONG (deg)	LAT (deg)	ELEV (m)	SLOPE (%)	ASPECT (deg)	UPSLOPE log(m^2)	WET	DYNWET	SRAD W/m^2
4214	103.415	46.786	852	20.1	350	4.05	7.59	2.46	129
4214	103.416	46.787	833	27.7	333	4.24	7.69	2.54	125
4214	103.421	46.772	835	31.6	286	4.10	6.83	2.23	141
4214	103.428	46.781	838	44.0	301	3.24	5.22	2.17	164
4214	103.431	46.776	872	47.7	274	3.24	5.02	2.28	163
6102	103.501	46.602	731	4.7	326	8.29	16.96	2.67	185
6102	103.279	46.615	878	6.1	194	4.52	7.88	2.64	162
6102	103.282	46.611	858	8.1	18	5.29	10.77	2.66	159
6102	103.283	46.619	851	11.3	201	5.43	10.52	2.56	131
6102	103.283	46.621	858	6.9	180	4.74	9.84	2.34	165
6102	103.289	46.623	846	7.8	233	5.24	9.07	2.60	147
6102	103.305	46.605	830	8.7	270	3.47	7.14	2.44	154
6102	103.382	46.534	821	13.1	256	4.85	6.76	2.64	153
6102	103.383	46.531	828	12.5	270	3.43	6.71	2.65	148
6102	103.391	46.619	809	9.1	261	4.47	7.85	2.59	156
6102	103.393	46.670	838	17.1	216	4.46	6.57	2.44	154
6102	103.394	46.616	797	10.7	225	4.40	8.72	2.64	167
6102	103.397	46.621	782	6.9	217	5.99	10.38	2.66	160
6102	103.399	46.766	798	7.2	243	4.00	8.40	2.66	153
6102	103.401	46.540	840	12.8	120	3.45	6.72	2.65	165
6102	103.403	46.537	835	7.0	104	4.71	10.03	2.34	145
6102	103.404	46.536	843	11.3	279	3.78	7.42	2.59	170
6102	103.404	46.546	831	13.5	249	3.64	6.82	2.65	145
6102	103.408	46.541	840	11.0	261	4.56	7.77	2.50	140
6102	103.411	46.535	840	6.0	214	3.66	7.84	2.39	161
6102	103.417	46.543	835	11.8	217	3.57	7.07	2.53	167
6102	103.420	46.543	829	7.6	333	4.75	8.94	2.66	132
6102	103.441	46.651	790	19.1	225	3.43	6.24	2.63	177
6102	103.442	46.650	782	12.8	166	4.74	7.20	2.64	155
6102	103.443	46.640	751	6.5	117	6.07	9.96	2.55	148
6102	103.445	46.638	748	6.9	153	3.29	7.18	2.42	153
6102	103.445	46.694	864	25.8	247	3.25	5.53	2.56	153
6102	103.446	46.653	792	5.5	194	5.31	11.08	2.62	150
6102	103.446	46.701	857	11.5	0	4.93	9.63	2.61	147
6102	103.452	46.685	798	17.0	84	4.23	8.10	2.43	132
6102	103.452	46.702	873	11.5	56	4.38	8.91	2.59	145
6102	103.454	46.688	799	11.2	63	4.59	9.38	2.38	149
6102	103.456	46.702	860	25.2	48	4.66	8.71	2.60	169
6102	103.456	46.795	810	6.2	34	5.65	11.84	2.66	130
6102	103.461	46.642	735	13.3	231	8.16	9.42	2.58	150
6102	103.461	46.794	825	4.3	34	4.76	11.00	2.67	161
6102	103.468	46.682	770	14.7	261	5.98	10.05	2.44	150
6102	103.473	46.640	736	1.1	270	3.84	10.07	2.67	152
6102	103.481	46.644	735	1.8	270	3.94	9.67	2.37	156
6102	103.494	46.633	787	6.9	288	5.31	11.51	2.66	154
6201	103.255	46.594	845	1.3	0	3.36	8.89	2.48	160
6201	103.268	46.589	851	1.7	180	3.69	8.90	2.67	152
6201	103.271	46.588	851	2.7	0	6.62	13.06	2.58	154
6201	103.274	46.590	854	2.5	0	6.19	13.60	2.67	140
6201	103.275	46.587	856	6.8	194	3.30	6.98	2.66	168
6201	103.287	46.581	860	1.7	90	6.51	14.46	2.61	145

VEGCODE	LONG (deg)	LAT (deg)	ELEV (m)	SLOPE (%)	ASPECT (deg)	UPSLOPE log(m^2)	WET	DYNWET	SRAD W/m^2
6201	103.302	46.622	822	19.4	250	3.22	5.83	2.60	158
6201	103.304	46.622	814	7.2	127	6.18	10.19	2.63	156
6201	103.312	46.617	806	6.2	342	6.51	11.64	2.49	156
6202	103.312	46.620	807	19.2	207	5.54	6.51	2.63	165
6202	103.377	46.782	782	4.6	270	6.61	8.71	2.66	161
6202	103.546	46.579	750	0.0	0	4.85	14.37	2.67	153
6202	103.567	46.546	769	1.7	270	5.18	8.40	2.66	154
6202	103.568	46.544	769	2.6	135	4.07	9.61	2.67	153
7601	103.379	46.798	787	2.1	0	3.27	7.81	2.67	160
7601	103.387	46.759	819	17.0	110	3.26	6.22	2.64	154
7601	103.406	46.792	803	3.0	45	2.95	7.25	2.48	153
7601	103.406	46.793	800	4.0	0	3.89	8.82	2.63	155
7601	103.407	46.784	817	7.2	45	3.42	7.28	2.31	154
7601	103.432	46.696	869	42.7	218	3.42	5.45	2.31	148
7601	103.436	46.692	859	25.8	68	2.95	5.08	2.25	147
7601	103.440	46.785	824	6.7	180	2.95	6.33	2.64	154
7601	103.463	46.693	886	34.4	207	3.28	5.49	2.21	163
7601	103.466	46.697	877	34.3	227	3.01	5.14	2.23	142
7601	103.467	46.692	835	37.6	185	3.16	5.09	2.22	162
7601	103.470	46.691	824	15.4	63	2.95	5.67	2.30	160
7601	103.482	46.691	832	26.4	198	3.26	5.62	2.49	158

APPENDIX C

METADATA AND PARAMETER FILES FOR TAPES-G PROGRAMS

DATA IDENTIFICATION TAPES-G Ascii
CREATED TAPES-G version 6.0
DATA TYPE grid
GRID CELL SIZE 30.00000
NODATA VALUE -999.0000
OPTION No-Data cells included in output file
OPTION Traditional output file
INPUTFILE t_alb.asc DEM
PARAMETER DEM Input File Type = 6
NUMFIELDS 14
FIELD 1 X
FIELD 2 Y
FIELD 3 Flow direction
FIELDRANGE 3 1.0 256.0
FIELD 4 Elevation
FIELD 5 Drainage area (cells)
FIELD 6 Flow width (grid spacing)
FIELD 7 Slope (%)
FIELD 8 Aspect (degrees)
FIELDRANGE 8 0.0 360.0
OPTION Convex curvatures are negative
FIELD 9 Profile curvature * 100 (convex -ve)
FIELD 10 Tangent curvature * 100 (convex -ve)
FIELD 11 Plan curvature * 100 (convex -ve)
FIELD 12 Elevation residual (m)
FIELD 13 Flow path length (m)
FIELD 14 $d(As)/ds$
XMIN 1044863.
XMAX 1081133.
YMIN 260031.0
YMAX 306471.0
OPTION Depressionless DEM created
OPTION Flow direction Rho8
OPTION Flow accumulation FRho8
PARAMETER Maximum cross-grading area 200000.0
OPTION Flow accumulation Rho8
OPTION First record is in northwest corner
OPTION Slope computed with finite differences
END METADATA

DATA IDENTIFICATION SRAD Binary
CREATED SRAD version 3.0
DATA TYPE grid
INPUTFILE study.asc DEM
GRID CELL SIZE 30.00000
PARAMETER DEM input file type = 4 ascii
XMIN 1044863.
XMAX 1081133.
YMIN 260031.0
YMAX 306471.0
PARAMETER Number of horizon directions = 16
PARAMETER Solar constant = 1354 W/m2
OPTION Results output in W/m2
OPTION Summary temperatures included
INPUTFILE bismarck radiation parameter file
OPTION Lumped transmittance
PARAMETER Start month = 1
PARAMETER Start day = 1
PARAMETER Finish month = 12
PARAMETER Finish day = 31
PARAMETER Time step = 4
NUMFIELDS 14
FIELD 1 X
FIELD 2 Y
FIELD 3 Elevation
FIELD 4 Short wave radiation ratio
FIELD 5 Short wave radiation on sloping surface
FIELD 6 Short wave radiation on horizontal surface
FIELD 7 Incoming atmospheric longwave radiation
FIELD 8 Outgoing surface long-wave radiation
FIELD 9 Net long-wave radiation
FIELD 10 Net radiation
FIELD 11 Max air temperature
FIELD 12 Min air temperature
FIELD 13 Average air temperature
FIELD 14 Surface temperature
END METADATA

SRAD PARAMETER FILE

```

46.766
.083 .099 .123 .145 .167 .188 .208 .188 .153 .121 .080 .071
.66 .66 .66 .47 .29 .18 .18 .18 .21 .40 .63 .66
.303 .303 .292 .292 .285 .279 .236 .247 .276 .295 .319 .315
.54 .54 .59 .59 .62 .64 .74 .72 .65 .58 .44 .47
-18.72 -14.94 -7.89 -0.56 5.67 10.89 13.56 12.17 6.17 0.28
-7.89 -15.94
-6.56 -3.11 3.61 12.72 19.89 25.06 29.11 28.17 21.56 14.83
4.06 -4.17
-12.64 -9.03 -2.14 6.08 12.78 17.97 21.33 20.17 13.86 7.56
-1.92 -10.06
6.50 6.50 6.50 6.50 6.50 6.50 6.50 6.50 6.50 6.50 6.50 6.50
7.30 7.30 7.30 7.30 7.30 7.30 7.30 7.30 7.30 7.30 7.30 7.30
6.00 6.00 6.00 6.00 6.00 6.00 6.00 6.00 6.00 6.00 6.00 6.00
1.00
0.2 0.2 0.2 0.5 1.5 2.5 2.5 1.5 1.0 0.5 0.2 0.2
5.0 0.97 0.00008 504
0.716 0.746 0.713 0.689 0.686 0.701 0.684 0.677 0.664 0.671
0.704 0.711

```

DATA IDENTIFICATION DYNWETG Ascii

CREATED DYNWETG version 2.0

DATA TYPE grid

GRID CELL SIZE 30.0000

INPUTFILE starfill.asc TAPESG

NUMFIELDS 5

FIELD 1 X

FIELD 2 Y

FIELD 3 Elevation

FIELD 4 Dynamic wetness index

FIELD 5 Steady state wetness index

XMIN 1.04486E+06

XMAX 1.08113E+06

YMIN 260031.

YMAX 306471.

OPTION Uniform soil properties

PARAMETER Soil depth = 0.500000 m

PARAMETER Saturated conductivity = 15.0000 mm/h

PARAMETER Porosity = 0.250000 m³/m³

PARAMETER Drainage time = 240.000 hours

END METADATA

MONTANA STATE UNIVERSITY LIBRARIES



3 1762 10309049 2