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Using remote sensing as a tool for conservation : detecting change in the Sheyenne National Grassland

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USING REMOTE SENSING AS A TOOL FOR CONSERVATION: DETECTING CHANGE IN THE SHEYENNE NATIONAL GRASSLAND

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A post-classification comparison change detection was performed using satellite imagery and a geographic information system. Land cover type was classified from three image dates (July 22, 1985; August 10, 1992; July 6, 1998) for a portion of one Landsat Thematic Mapper (TM) scene (path 30, row 27). Comparisons were then drawn between the areal extents for 12 cover types from each image date. Flooded Vegetation exhibited the largest percentage increase of all the cover types mapped (2000% between 1985 and 1998). Water increased from 447 acres in 1985 to 8,168 acres in 1998, a change of 1700%. In contrast, the Xeric Grass cover type declined from 60,526 acres in 1985 to 55,421 acres in 1998, an 8% loss over the 13-year study period. Areal coverage of all remaining types fluctuated between increases and decreases, showing no consistency of change. Thematic accuracy, averaged across the three classifications, ranged from a high of 100% for Water to a low of 52% for Mesic Shrub. Relatively high accuracy levels for Water and Flooded Vegetation confirm the ability of the method to measure change in the spatial extent of wetlands. Discussion of the results depict how a change detection analysis based on remote sensing can address the information needs of land mangers, ecologists, and conservationists working on the SNG. Finally, the results suggest that if conservation actions are not taken, especially to control livestock grazing, the integrity of this relict patch of tallgrass prairie will almost certainly decline.

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INTRODUCTION

Human-induced land cover change has long been a problem in the West. Competing land uses, destruction of wildlife habitat, and loss of forest cover are all cause for concern in a landscape increasingly lacking in biological diversity. The need to quantify and track this type of activity, along with natural fluctuations in ecological systems, has led many scientists and conservation professionals to turn to remote sensing. Remote sensing provides a reliable and non-intrusive method for monitoring change in land cover and land use, while affording the capability to do so on a broad scale. Cost, availability, platform stability, and frequency of data capture are also attractive attributes characteristic of most satellite-derived information. The interaction between electromagnetic radiation (EMR) and Earth features is such that sophisticated sensors on board satellite platforms can detect relatively small changes in the energy flux. Recording these fluctuations allows scientists to track and even predict landscape changes in a particular region or to determine the health and distribution of vegetation types at a landscape scale.

Defries and Belward (2000) have stated that one of the most significant contributions to be gained from satellite data is the identification of land cover change. Change detection studies can be useful in determining what type of land cover change has occurred, and more importantly, how this change affects the composition of natural vegetation communities and the species they support. These are just a few of the questions that can be addressed, at least in part, by performing a change detection analysis. In any case, the analysis of remotely sensed data can pave the way for the predictive modeling of the forces that shape future landscape changes.

Statement of the Problem

The Sheyenne National Grasslands (SNG) in southeastern North Dakota comprise a fraction of the area in North America that was once occupied by the tall and mixed-grass prairie ecosystems (Brown, 1985). The tallgrass prairie found on the SNG is one of the last and best representations of its type and is considered to be the rarest ecosystem under management by the U.S. Forest Service in the Northern Region (C. McCarthy, U.S. Forest Service, pers. comm.). The SNG is home to two federally listed species; the western prairie fringed orchid (*Platanthera praeclara*), listed as threatened by the U.S. Fish and Wildlife Service (Seig et al. 1999), and the Greater Prairie Chicken (*Tympanucus cupido*) listed as sensitive by the U.S. Forest Service (C. McCarthy, U.S. Forest Service, pers. comm.). This is a fragile ecosystem made more so by intensive management activities such as cattle grazing and fire suppression. In addition, the SNG has experienced severe flooding since 1993, causing concern for the continued viability of the western prairie fringed orchid (Seig et al. 1999). Grazing and fencing, along with a network of roads and flooding, have caused biotic impoverishment and fragmentation of habitat within the SNG, further endangering this already imperiled area and setting the stage for an irretrievable loss of biological diversity.

The Objective

The objective of this study is to identify and articulate the potential applications of remote sensing technology for addressing the information needs of ecologists, land managers, and conservation professionals. To illustrate this potential, I will provide evidence, in the form of a digital database and hard-copy maps, of quantifiable land cover change in the Sheyenne National Grasslands in southeastern North Dakota. This study is a multi-temporal, image-based monitoring project, focusing on whether change detection techniques are capable of detecting temporal and spatial change in the extent of wetlands across the SNG landscape. The result of this analysis should reveal the practicality of using such data in other real world monitoring situations.

THE STUDY AREA

The study was conducted in the Sheyenne National Grasslands (SNG), in southeastern North Dakota, 60 miles southwest of Fargo (Figure 1). The study area encompasses the 70,100 acres under management of the U.S. Forest Service and approximately 66,746 acres of intermixed private land, all occurring within the administrative boundary of the SNG.

Barker and others have described the vegetation of the SNG as consisting of tallgrass prairie, mixed grass prairie, and forest and woodland communities interspersed with agricultural cropland (1974, in Svedarsky et al. 1996). The sandhills that comprise the underlying geology of this unique area are the remnants of a massive sand delta left over from the last glaciation. Retreating ice sheets produced large amounts of glacial meltwater that in turn deposited vast amounts of sand, silt, and debris at the mouth of what was once Glacial Lake Agazziz (Shephard 1996). The lake has long since gone, but the high sand delta remains. It is here that tallgrass prairie mingles with oak savanna and sedge meadow while deciduous woodlands occupy the lowlands alongside the Sheyenne River. Major tree species include bur oak (Quercus macrocarpa), aspen (Populus tremuloides), green ash (Fraxinus pennsylvanica), basswood (Tilia americana), and plains cottonwood (Populus deltoides). Big bluestem (*Andropogon gerardii*), little bluestem (*Andropogon scoparius*), and blue grama (*Bouteloua gracilus*) are but a few of the grasses that occur within the study area. This is a biologically rich environment with many habitat types supporting several animal species and over 800 species of plants (Shephard 1996).

METHODS

Source Data

Three image dates for one Landsat Thematic Mapper (TM) scene (path 30, row 27) were used in the analysis. Of the three images, one (August 10, 1992) was already part of the WSAL archive. A July 6, 1998 image was acquired from the U.S. Geological Survey's Earth Resources Observation Systems (EROS) data center through the Multi-Resolution Land Characteristics Consortium (MRLC), and a July 22, 1985 image was also purchased from EROS. The 1985 and 1992 images were both comprised of the full seven bands, while the 1998 image was absent band six (thermal). Although not precise anniversary dates, which could not be obtained due to cloud cover, all of the images fall within the same general growing season of mid-to-late summer. U.S. Geological Survey (USGS) 7.5' digital elevation models (DEMs) were used as general reference data and to provide elevation, slope, and aspect information for the supervised classifications. Ground reference data were obtained from the U.S. Forest Service in the form of plot data for an earlier land cover classification (Redmond et al., 1997) and as aerial photographs that were scanned and registered by the U.S. Forest Service.

Pre-Processing

Satellite imagery often contains significant distortion that must be rectified before processing. Terrain correction removes geometric distortion that results from the image acquisition process, thus allowing for multiple images to be co-registered to a common projection. The 1992 image was terrain corrected by the Hughes/STX Corporation using proprietary techniques. The 1985 image was terrain corrected by the EROS data center, as was the 1998 image. All scenes were projected into a Universal Transverse Mercator (UTM) projection, Zone 14, NAD27 datum, and co-registered in ERDAS Imagine version 8.0. Following projection and registration, all scenes were clipped to the study area boundary using a masking operation available in ERDAS Imagine. Original $30m^2$ pixels then were resampled to $15m^2$ using the cubic convolution resampling algorithm. Prior to classification, the spectral bands for all three images were combined into a single 20-band image using a layer stacking procedure available in ERDAS Imagine.

Unsupervised Classification

For the purposes of this study, three separate steps were employed in the overall classification process. The first step was to perform an unsupervised classification of pixels on the combined 20-band image using an algorithm known as the Iterative Self-Organizing Data Analysis Technique (ISODATA; Tou and Gonzales 1974). This method clusters pixels into classes according to the natural groupings of spectral values that are inherent in the imagery. The user specifies the maximum number of spectral classes allowed and the number of iterations or passes to be made over the image. The algorithm then measures the Euclidean distance between cluster sets starting with an arbitrarily chosen seed pixel. This process is repeated until the natural groupings or clusters of pixel values in the image reach a point where their divergence from their initially determined cluster set is at a minimum (ERDAS 1997).

The unsupervised (ISODATA) classification initially produced 119 spectral classes, but several of these were quite large in terms of numbers of pixels. To more accurately reflect the heterogeneity that existed in the multi-date image, classes containing more than 250,000 pixels were split in two and re-classified, thus producing a final set of 130 spectral classes.

In the output of the unsupervised classification, spectral values were assigned to each pixel in each image. Once every pixel had been classified, the images were then subjected to a merging process designed to aggregate pixels of similar spectral values into regions representative of the natural features and patterns found on the ground (Ford et al., 1997 and Ma et al., 2001). In the merging process, a group of pixels smaller than the user-specified minimum mapping unit (MMU), in this case varying between 5 pixels (0.28 acres) and 22 pixels (1.2 acres), were aggregated with their most similar neighbor. Ultimately, the objective was to segment the classified image into raster polygons or regions that represented patterns on the ground. Once the merging process was completed, the resulting raster image was imported into ARC/INFO (GRID module) and ancillary attribute fields were added to each region in the database. At this point, the raw imagery was used to calculate mean TM values for each region in the database, while 7.5-minute DEM's were the basis for calculating mean elevation, mean slope, and majority aspect.

Ground-truth Data

From the WSAL archive, 359 data points were retrieved, reviewed, and evaluated for use in the new classification. An intensive review of the training set was necessary due to the fact that all of the points were acquired for use in the earlier classification of p30r27 (1992). To insure that these points accurately reflected conditions present in 1985 and 1998, they were displayed over these two image dates. Ultimately, the goal was to determine the feasibility of using the 1992 training set for all three classifications. The entire data set was screened for positional accuracy, data attribute accuracy, and agreement with all three image dates. The results of the review process revealed that many of the points were not suitable. The majority of the points deemed to be unusable were duplicates, that is, more than one plot fell within the same region. Also, as land cover could be assumed to have changed between image dates, attribute accuracy for some of the points was called into question. This was most evident on the 1998 image, as many of the 1992 vegetation points were now located in water. Likewise, the ground data did not always fit the 1985 image, apparently because vegetation cover had changed in the intervening years. In light of these problems, an attempt was made to obtain additional training data to better reflect land cover as it existed in 1985 and 1998. Additional points were selected and labeled by interpreting $1m^2$-resolution scanned aerial photographs provided by the U.S. Forest Service. Subsequent to review, some of the points were moved through participation in a conference "net-meeting" with SNG biologists. Here again, further examination revealed that many of the new plots were duplicates, and thus had to be eliminated from the training set. Due to the relative similarity between the 1992 and 1985 images, all of the remaining plots were deemed appropriate for use in the classification of both images. This was not the case with the 1998 image due to intensive flooding. The final training sets consisted of 292 points for the supervised classification of the 1985 and 1992 images, and 229 points for the 1998 image (Figures 2 and 3).

Supervised Classification

The second step in the classification process was the assignment of land cover type labels to each region based on a supervised classification. Supervised classifications were carried out separately for each image date using a posterior spatial probability (PSP) classifier which first measured the Euclidean distance between known and unknown regions in the data set, then adjusted the posterior probability estimates based on spatially derived information (Steele and Redmond, 2000).

Manual Modifications

The third and final step was the manual classification of special features. Special features included agricultural classes, Urban, Water, and Flooded Vegetation. Manual classification of agriculture was necessary because of the spectral similarity that can exist between land use and land cover. Commercially grown crops and natural vegetation often times have similar spectral values, thus leading to a confusion that can only be adjusted through the use of a modified classification. Similarly, urban areas are characterized by a spectral heterogeneity that is sufficient to cause confusion with other non-urban classes. Finally, preliminary results from the supervised classification revealed that a great deal of confusion existed between Water and Flooded Vegetation, thus requiring the use of an alternate classification method.

Agriculture

For the purposes of this study, agricultural lands were designated as either wet or dry. This can be taken to mean that the fields are either under irrigation or not. The manual classification is a 6-step process developed at WSAL, and is based on the following observations and assumptions:

1. Agricultural lands tend to be associated with particular spectral classes;
2. They tend to occur in larger patches (> 25 pixels) than other types;
3. These patches tended to be more homogenous in terms of their spectral composition than did other types; and
4. They tended to be spatially clumped across the TM scene.

First, all spectral classes representing probable agricultural classes were identified from the merged image. This was accomplished by manually selecting, in Imagine, the spectral classes associated with agricultural fields. All classes thought to be associated with lush, green growing crops (irrigated agriculture) were coded with the color blue, whereas all classes associated with fallow fields or dry pasture land (dry agriculture), were coded with the color yellow. Once all possible classes were chosen, the next step was to separate the "wet" and "dry" classes into three sub-classes. Sub-class labels were used to identify how strongly correlated a particular spectral class was with agriculture. The sub-classifications are as follows:

(0) Never agriculture

(1) Occasionally dry agriculture

(2) Sometimes dry agriculture

(3) Usually dry agriculture

(4) Occasionally irrigated agriculture

(5) Sometimes irrigated agriculture

(6) Usually irrigated agriculture

Once all of the previously identified spectral classes had been assigned to one of the above sub-classes, a database file containing those values was exported from Imagine. This export database file was used in conjunction with the unsupervised classification (u-grid), the merged image file (m-grid), and the full database zone grid (z-grid) in the production of an output grid. This process is known as the outperc and was developed at WSAL using ARC Macro Language (AML). The output, or outperc grid was a new grid, resulting from the AML assigning output class values to all raster polygons in the m-grid. The output class values are based on three attributes: the seven possible agricultural class values (0-6, listed above), the number of pixels in each raster polygon, and a homogeneity class value based on the spectral similarity of pixels in the "u" versus "m" grids. This process yields 130 possible output codes that are assigned one per region, by the AML, to each region in the grid. Once this is done, each region in the output grid is color coded according to its output code.

The next step was to visually determine, by comparing the outperc grid with the raw TM imagery, the final class, wet or dry, for all of the regions in the oupterc. It is possible and advantageous to limit this manual classification to areas specific to agriculture. This is done to avoid mis-classifying non-agricultural regions. To accomplish this, agricultural areas were broadly digitized on the raw imagery, thus limiting the classification to these predominately agricultural regions.

Urban Areas

Urban areas were delineated simply by digitizing their perimeter and creating a separate "hard-coded" class. An AML was written to merge the manual classification with the full database grid. The AML stipulates that the manual classification takes precedence over the supervised in any instances where the two classifications intersect.

Water and Flooded Vegetation

Regions from the zone grid (z-grid) were recoded to Water and Flooded Vegetation using a rule-based approach in ARC/INFO. Decision rules were developed by visually determining the spectral classes and TM band signatures most closely related to these cover types. For each cover type, an AML was written to perform the rule-based classification particular to the spectral values in a given scene. The AML classified each scene and then created a new grid from the results of the classification. Once this was done, the AML converted the grid to a polygon coverage. Invariably, some confusion existed between spectral classes sufficient to cause an over-classification, i.e., regions that shared spectral characteristics with Water or Flooded Vegetation were inadvertently included in the classification. This necessitated a manual editing process designed to remove the confused regions from each polygon coverage. Once this was done, the edited coverages were converted to grids and merged with the manually classified images prior to being merged with the full database grid. In addition, Water was classified with the use of training data. This allowed not only for a comparison of methods, but provided, by combining the manual and supervised procedures, the strongest classification possible.

Change Analysis

A post-classification change analysis technique (Jensen, 1996) was used to determine change, over time, of the 12 land cover types mapped (Table 1). Typically, post-classification change detection studies involve the use of independently produced classifications for each of the image dates (Mucher et al. 2000). This study differed in that a single unsupervised classification was performed on a combined 20-band image. The effect was to produce the equivalent of three individual unsupervised classifications, but in a much shorter time frame. Once the supervised and manual classifications were complete and all of the regions in the database grid were assigned one of the 12 cover type labels (Figures 4, 5, and 6), a comparison was made among dates for each region, thus allowing the development of a "from-to" change matrix (Jensen 1996). In essence, change was found to have occurred if land cover in a region differed from one date to another. For example, a region that was classified as Xeric Grass (3192) in 1985 and Water (5300) in 1998 would have a "from- to" classification of Xeric Grass to Water. The areal extent of this change could then be calculated by determining the sum of the changed pixels.

Accuracy Assessment

Thematic (users') accuracy of the supervised classifications was measured using a leave-one-out, cross-validation method (McLachlan 1992). With this method, one training point was removed from the training set and classified using the remainder of the points. The predicted code resulting from the classification of the single point is then compared to the actual code, thus arriving at an estimation of accuracy through cross-validation. This process was repeated until all training points were "left out" once.

RESULTS OF THE ANALYSIS

Changing Trends in the Project Area

As a class, Flooded Vegetation exhibited the largest percentage increase of all the cover types mapped. From 1985 to 1992 it increased 30% from 91 acres to 118 acres. This would pale in comparison to the 1500% increase (1,823 acres) that occurred between 1992 and 1998 and the total change between 1985 and 1998 (2000%), (Table 2). Similarly, Water coverage increased from 447 acres in 1985 to 8,168 acres in 1998, a change of 1700%. None of the other classes came close to the percentage increase seen in Water and Flooded Vegetation. Unlike the increase in Water and Flooded Vegetation, Xeric Grass experienced a consistent loss of cover over time, declining from 60,526 acres in 1985 to 55,421 acres in 1998, an 8% loss in cover over the 14 year time period (Table 2). Areal coverage of all remaining classes fluctuated between increases and decreases, showing no consistency of change. Like Xeric Grass, six of the remaining classes experienced a loss in cover between 1985 and 1998. Percentage-wise, the combined agricultural classes experienced the largest cover loss for a total of 38%. Urban was close behind, losing 28%. Riparian Broadleaf lost 21%, Mesic Shrub lost 20%, and finally, Mesic Grass declined by 13% over the course of the 14-year study period. Three classes, excluding Water and Flooded Vegetation, experienced positive change over the duration of the study period. Mixed Broadleaf expanded by 60% since 1985, while Sumac/Xeric Shrub increased by 28%. Finally, Willow increased by 26% between 1985 and 1998.

The Nature of Change

Changes between 1998 and each of the earlier years are shown in Tables 3 and 4 for each cover type. For example, of the 60,525 acres that were classified as Xeric Grass (3192) in 1985 (Table 3), only 42,103 of these acres were still classified as Xeric Grass in 1998; 8,142 acres became Mesic Grass and 1,859 acres became water, while the remainder was distributed among all other cover types, excluding Urban and Riparian Broadleaf.

Results from the analysis indicate that over 7,200 acres of potential habitat were lost to water and flooded vegetation during the period under study. In other words, 7,200 acres that were not Water or Flooded Vegetation in 1985 or 1992 were classified as such in 1998. The entirety of this inundation occurred after 1992 and peaked in 1998.

Accuracy

As mentioned previously, the accuracies of the manually classified types (e.g., Water and Flooded Vegetation) could not be addressed by the cross-validation procedure. Nevertheless, because the study area was small relative to the size of a full TM scene, it was possible to perform a subjective visual analysis of the results from the spectral classification of these two cover types. Through a careful process of comparing the spectral classification with aerial photographs, my subjective impression was that accuracy levels for Water and Flooded Vegetation exceeded 80%. Manual classes such as dry agriculture, irrigated agriculture, and urban were evaluated in much the same fashion and as such should be accorded similar accuracy.

For all other classes, accuracy was assessed using the leave-one-out cross-validation method (McLachlan 1992) described previously. Error matrices (Tables 5, 6, and 7) detail resulting map accuracy by depicting the confusion that exists between classes while also providing an overall percentage of accuracy. Accuracy, averaged across the three classifications, ranged from a high of 100% for Water to a low of 52% for Mesic Shrub (Table 8).

DISCUSSION

Despite some classification errors, the results from the change detection analysis appear to be a reliable measure of long-term change on the Sheyenne National Grassland. The objective was to ascertain the amount of change that occurred in the spatial extent of wetlands, and high accuracy levels among Water (5300) and Flooded Vegetation (6600) illustrate the successful realization of this goal.

Over 85% of the federally administered portion of the SNG is divided into range allotments for cattle grazing, and the majority of these allotments are grazed with an intensity sufficient to cause lasting changes in the composition of vegetation communities on the SNG (McCarthy et al. 1998). An illustration of this can be found, as depicted in the study, by examining the decline in Xeric Grass levels. Xeric Grass (3192) declined by 1% from 1985 to 1992, followed by a 7% decrease between 1992 and 1998. These findings reinforce the suggestion that the decline in upland grass species is getting progressively worse, perhaps as a result of overgrazing. Couple this with the fact that the remnant prairie habitats on surrounding private lands have largely been converted to cropland (McCarthy et al. 1998), and the long-term viability of this last vestige of tallgrass prairie is left in doubt.

To lose any more of the habitat on the SNG is to further endanger resident TES species; the western prairie fringed orchid and the greater prairie chicken. The orchid depends upon the moist or wet conditions that predominate in the lowland swales or sedge meadows that occur across the SNG (Bjugstad and Fortune, 1989). But in times of flooding, such as the mid-1990's, many of these areas are no doubt under water

(Newell1987, in McCarthy et al. 1998). Seig and Wolken (1999) found that protracted flooding on the SNG is negatively correlated with the persistence of the western prairie fringed orchid, but they also discovered that limited numbers of orchids do manage to survive by growing on higher ground. Unfortunately, this shift out of the flooded swales serves only to relocate to areas where there is an increased danger of grazing or trampling by livestock.

Due to heavy livestock grazing in upland areas, nesting availability for the greater prairie chicken has become severely limited. In times of drought, these animals can seek refuge in the lowland depressions or swales that occur on the SNG, but again, in times of flood many of these swales are under water. A dramatic increase in woody vegetation (Willow increased by 26% over the duration of the study period) has also functioned to further fragment habitat and reduce suitable nesting sites for the prairie chicken (McCarthy et al. 1998).

Catastrophic flooding, heavy livestock grazing, intensive agriculture, and poor land management practices have led to the fragmentation and ultimate decline of habitat on the SNG. The end result is an increased stress on the remaining populations of orchids and prairie chickens. And as Ruggiero and others found (1994), habitat changes that result in a decrease of population size increase the likelihood of extinction.

CONCLUSION

The results from the analysis demonstrate the capability of Landsat TM imagery to detect change in land cover on the Sheyenne National Grassland. The previous discussion depicts how this type of technology can address the information needs of land mangers, ecologists, and conservationists working on the SNG. Monitoring the spatial distribution of habitat on the SNG is integral to promoting the biodiversity potential of this landscape, and doing so at large scales and regular intervals will require the use of remote sensing. The changes detected by this analysis suggest that, if conservation actions are not taken, ecological conditions on the SNG will almost certainly decline. And continued flooding, such as appears to be occurring again in 2001, will only hasten the process. In light of this, it is my recommendation that future conservation strategies place greater emphasis on the protection of the unique tallgrass prairie ecosystem on the SNG. Traditionally, land management plans have not taken into account the dynamic nature of natural systems, and as this study has shown, heavy flooding can function to remove much of the habitat base set aside for TES species. In short, once the inherent variability of natural systems is taken into account, there is simply not enough available habitat to support heavy livestock use and simultaneously to provide for the protection of native species. If sound conservation strategies are developed and adhered to, the tallgrass prairie ecosystem may again flourish on the SNG. The results from this analysis should provide insight into which areas are in need of greater protection.

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CROSS WALK TABLE FOR VEGETATION CODES	
CODE	COVER TYPE
1100	Urban
2010	Dry Agriculture
2020	Wet Agriculture
3191	Mesic Grass
3192	Xeric Grass
3610	Mesic Shrub
3613	Willow
3630	Xeric Shrub / Sumac
4740	Mixed Broadleaf
4760	Riparian Broadleaf
5300	Water
6600	Flooded Vegetation

Table 1. Cross walk between code and cover type name.

COVER TYPE	1984 ACRES	1992 ACRES	% CHANGE 1984-1992	1998 ACRES	% CHANGE 1992-1998	% CHANGE 1984-1998
Urban	128	128	0	92	-28.1	-28.1
Dry Ag	16,773	9,966	-40.5	15,132	+51.8	-9.7
Wet Ag	20,081	24,711	+23.0	14,447	-41.5	-28.0
Mesic Grass	19,228	22,754	+18.3	16,667	-26.7	-13.3
Xeric Grass	60,526	59,913	- 1.0	55,421	-7.4	-8.4
Mesic Shrub	4,129	2,748	-33.4	3,322	+20.8	-19.5
Xeric Shrub	3,681	5,064	+37.5	4,656	-8.0	+26.4
Sumac/Xeric Shrub	1,739	1,374	-20.9	2,233	+62.5	+28.4
Mixed Broadleaf	8,354	7,539	-9.7	13,444	+78.3	+60.9
Riparian Broadleaf	1,668	1,901	+13.9	1,322	-30.4	-20.7
Water	447	630	+40.9	8,168	+1196.5	+1727.2
Flooded Vegetation	91	118	+29.6	1,941	+1544.9	+2032.9
TOTAL	136,845	136,846		136,846		

Table 2. Acres and percent change for 12 land cover types on the Sheyenne National Grassland (1985-1998).

	ACRES BY COVER TYPE AS THEY EXISTED IN 1985												
1998 Cover Type	1100	2010	2020	3191	3192	3610	3613	3630	4740	4760	5300	6600	Totals (1998)
1100	92												92
2010		5,425	8,855	163	387	72	52	1	164	6		7	15,132
2020		5,619	7,551	334	287	145	88	11	361	16		34	14,447
3191		815	968	5,874	8,142	279	408	38	129	12	3		16,667
3192		3,546	298	5,963	42,103	1,540	604	541	819	6	2		55,421
3610		97	1	161	1,028	1,407	39	461	129				3,322
3613		176	210	981	1,833	15	968	4	391	77	1		4,656
3630		200	25	66	743	13	33	500	653				2,233
4740		337	179	2,031	3,496	542	1,045	154	5,118	494	24	23	13,444
4760							10		273	1,030	9		1,322
5300	34	463	1,474	3,106	1,859	100	365	26	288	28	406	19	8168
6600	3	95	520	548	647	16	69	5	28		3	8	1,941
Totals (1985)	129	16,773	20,081	19,227	60,525	4,129	3,681	1,741	8,353	1,669	448	91	136,847

Table 3. Change detection matrix of acres by cover type by year (1985-1998).

	ACRES BY COVER TYPE AS THEY EXISTED IN 1992												
1998 Cover Type	1100	2010	2020	3191	3192	3610	3613	3630	4740	4760	5300	6600	Total (1998)
1100	92												92
2010		3,256	10,774	393	528	47	107	8	20				15,132
2020		3,292	10,095	325	465	38	170	2	57			3	14,447
3191		632	1,027	6,158	7,534	321	720	39	179	2	35	20	16,667
3192		1,729	629	9,436	41,146	738	567	432	740			2	55,421
3610		73	22	379	1,156	1,101	48	412	131				3,322
3613		94	109	1,282	1,499	19	1,188	2	382	62	4	14	4,656
3630		72	88	91	886	25	37	428	607				2,233
4740		287	339	2,056	3,336	392	1,262	45	4,944	729	13	40	13,444
4760							1		227	1,092		1	1,322
5300	33	415	1,163	2,126	2,761	55	792	6	200	15	570	31	8,168
6600	3	114	467	508	603	12	171		52		7	5	1,941
Totals (1992)	128	9,966	24,711	22,754	59,913	2,748	5,064	1,374	7,539	1,901	630	118	136,847

Table 4. Change detection matrix of acres by cover type by year (1992-1998).

OUTPUT MATRIX FOR:									
Resampling Distance Weighted with Nearest Member Group Spatial Classifier									
K Value: 10									
	3191	3192	3610	3613	3630	4740	4760	5300	Total
3191	21	11	0	0	0	2	0	0	34
3192	5	77	3	1	0	0	0	0	86
3610	3	1	9	0	2	1	0	0	16
3613	0	0	0	15	0	8	0	0	23
3630	0	3	2	0	5	0	0	0	10
4740	3	2	1	0	0	52	2	0	60
4760	0	0	0	0	0	2	7	0	9
5300	0	0	0	0	0	0	0	54	54
Total	32	94	15	16	7	65	9	54	292
Total Correct / Total Points: 240 / 292									
Cross Validation Accuracy: 82.19									

Table 5. Cross validation error matrix for supervised classification (1985).

OUTPUT MATRIX FOR:									
Resampling Distance Weighted with Nearest Member Group Spatial Classifier									
K Value: 10									
	3191	3192	3610	3613	3630	4740	4760	5300	Total
3191	19	13	1	0	0	1	0	0	34
3192	5	78	2	1	0	0	0	0	86
3610	2	4	5	2	0	3	0	0	16
3613	0	0	0	18	0	5	0	0	23
3630	0	0	1	0	8	1	0	0	10
4740	1	1	2	3	0	51	2	0	60
4760	0	0	0	0	0	2	7	0	9
5300	0	0	0	0	0	0	0	54	54
Total	27	96	11	24	8	63	9	54	292
Total Correct / Total Points: 240 / 292									
Cross Validation Accuracy: 82.19									

Table 6. Cross validation error matrix for supervised classification (1992).

OUTPUT MATRIX FOR:									
Resampling Distance Weighted with Nearest Member Group Spatial Classifier									
K Value: 10									
	3191	3192	3610	3613	3630	4740	4760	5300	Total
3191	7	1	0	0	0	2	0	0	10
3192	1	48	3	0	0	1	0	0	53
3610	0	4	14	0	0	2	0	0	20
3613	0	0	0	5	0	11	0	0	16
3630	0	5	1	0	5	0	0	0	11
4740	0	1	1	0	0	52	1	0	55
4760	0	0	0	0	0	3	7	0	10
5300	0	0	0	0	0	0	0	54	54
Total	8	59	19	5	5	71	8	54	229
Total Correct / Total Points: 192 / 229									
Cross Validation Accuracy: 83.84									

Table 7. Cross validation error matrix for supervised classification (1998).

USER'S ACCURACIES			
	1985	1992	1998
Urban	n/a	n/a	n/a
Dry Ag	n/a	n/a	n/a
Wet Ag	n/a	n/a	n/a
Mesic Grass	68.5%	70.0%	85.7%
Xeric Grass	87.5%	82.7%	81.6%
Mesic Shrub	52.6%	50.0%	71.4%
Willow	94.1%	75.0%	100.0%
Sumac/Xeric Shrub	75.0%	100.0%	77.7%
Mixed Broadleaf	82.2%	88.1%	79.1%
Riparian Broadleaf	80.0%	80.0%	88.8%
Water	100.0%	100.0%	100.0%
Flooded Vegetation	n/a	n/a	n/a

Table 8. Thematic (users') accuracy for supervised classifications by cover type by year.

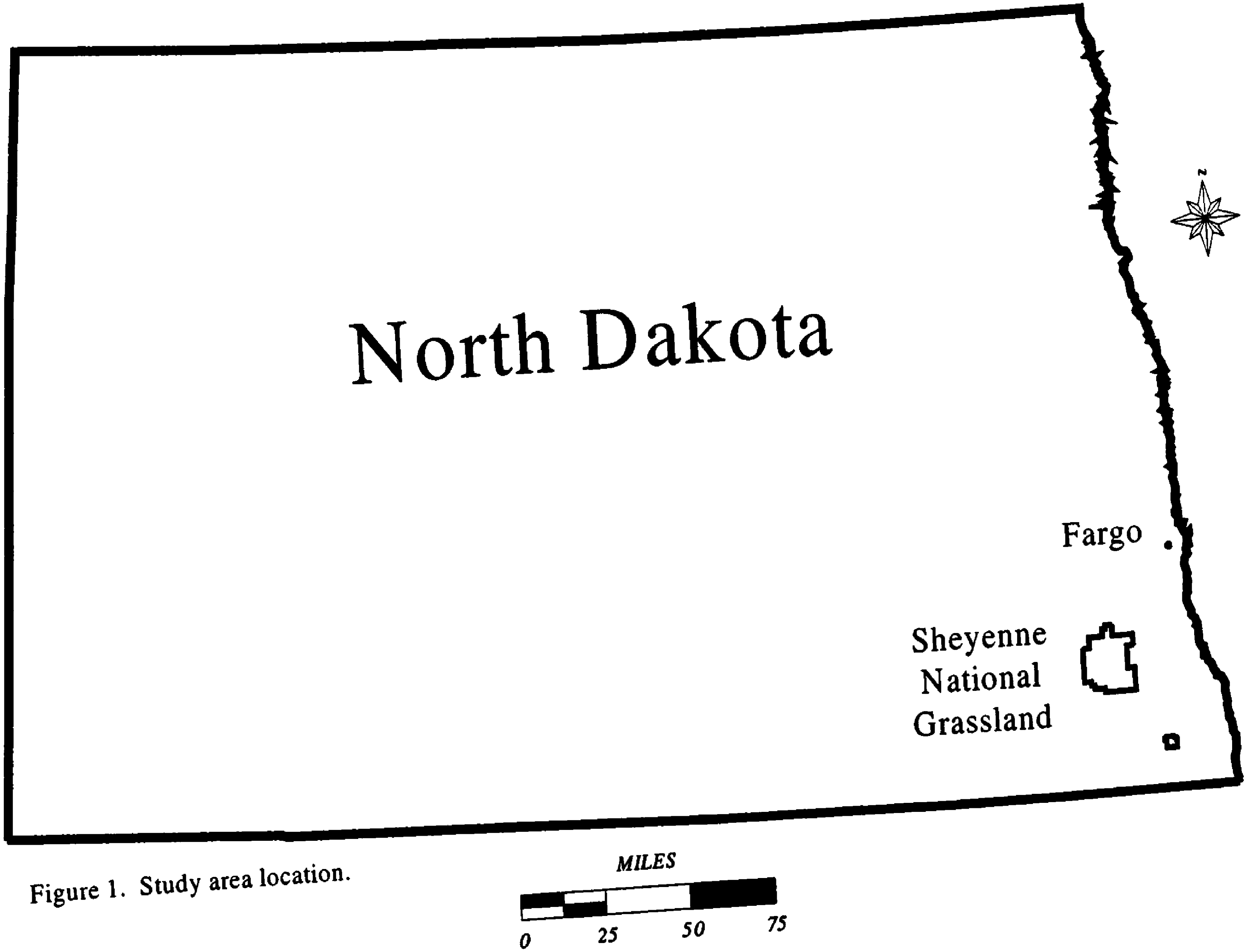

Figure 1. Study area location.

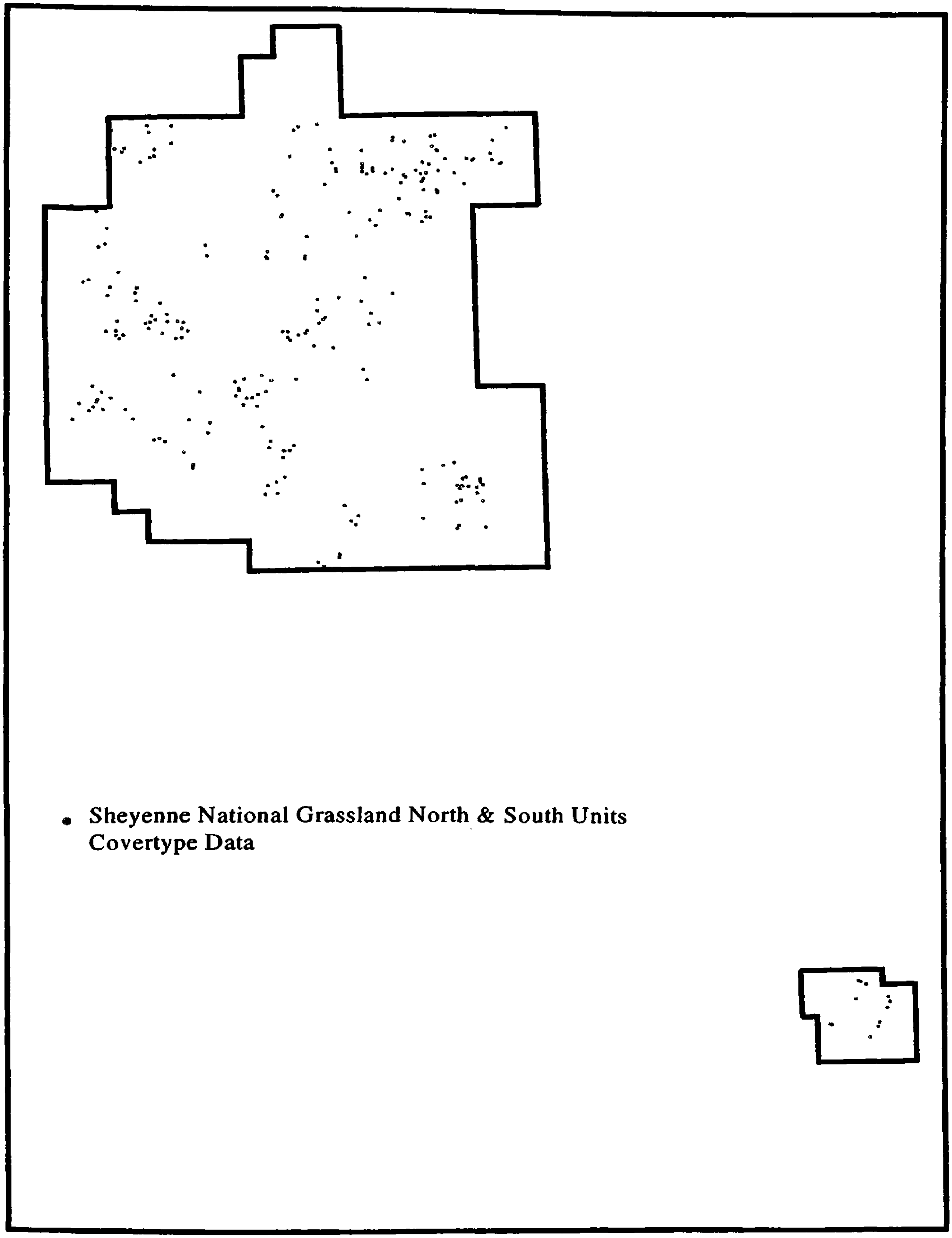

Figure 2. Spatial distribution of 292 ground-truth points on the northern and southern portions of the Sheyenne National Grassland (1985 and 1992).

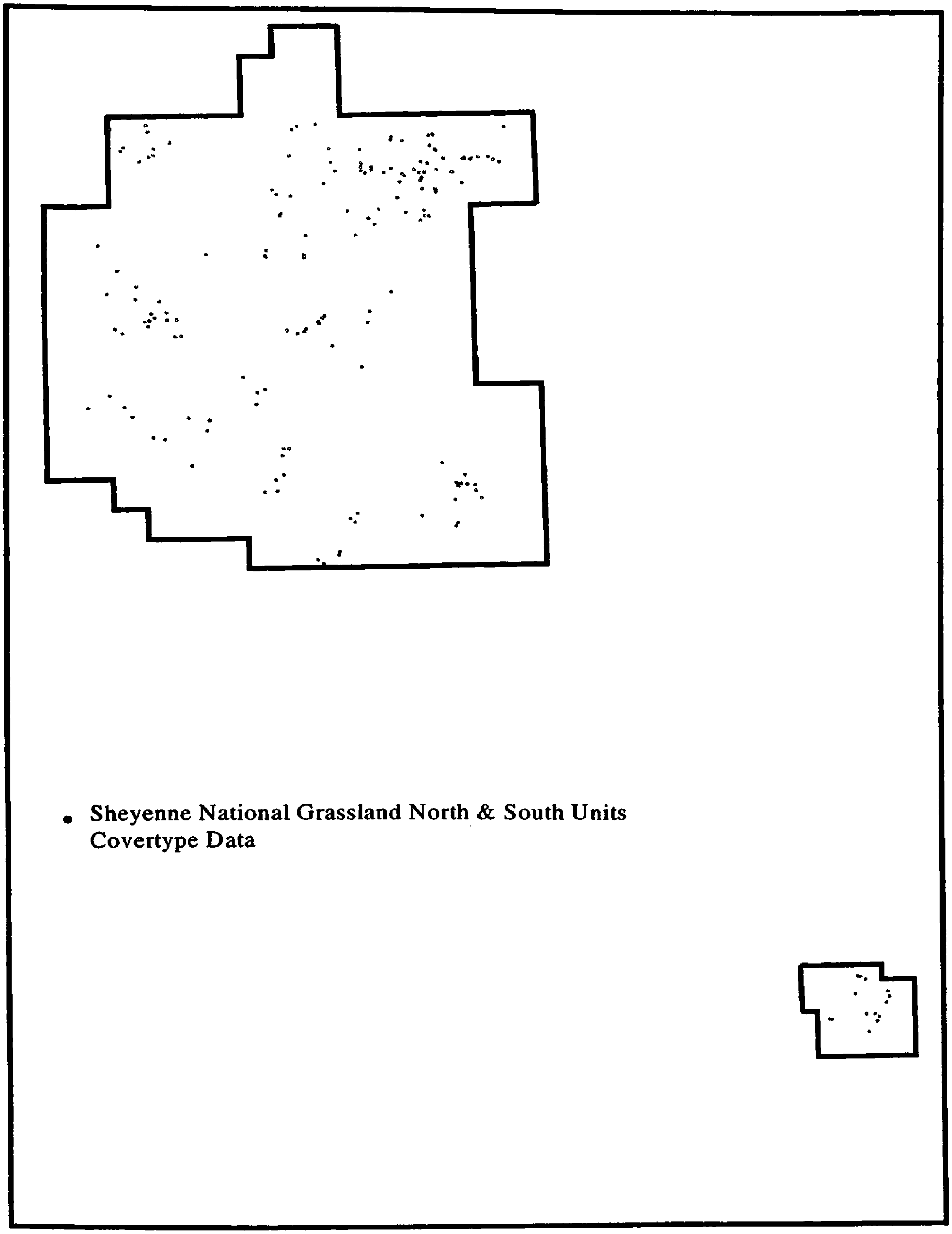

Figure 3. Spatial distribution of 229 ground-truth points on the northern and southern portions of the Sheyenne National Grassland (1998).

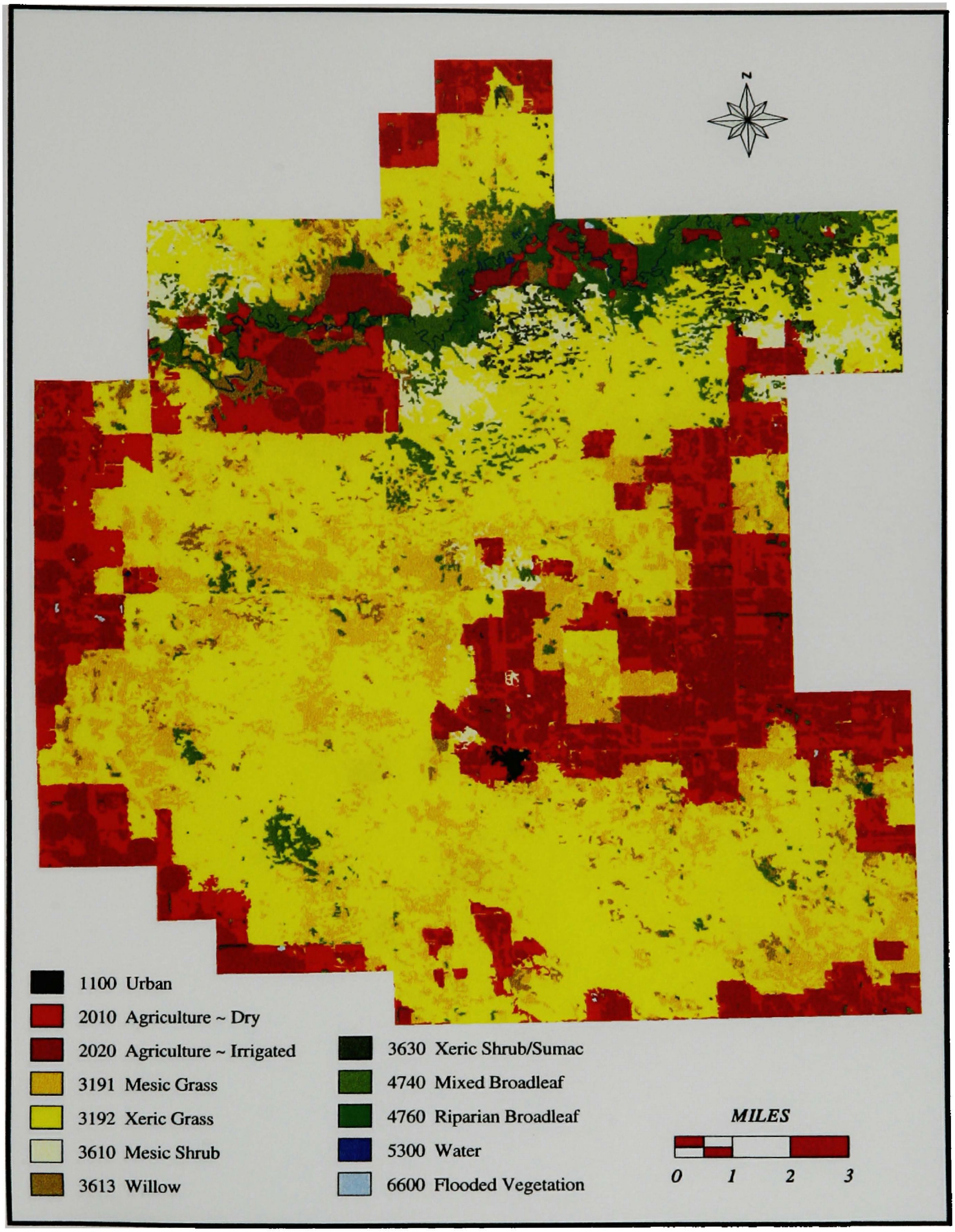

Figure 4. Spatial distribution of 12 land cover classes on the northern portion of the Sheyenne National Grassland in 1985.

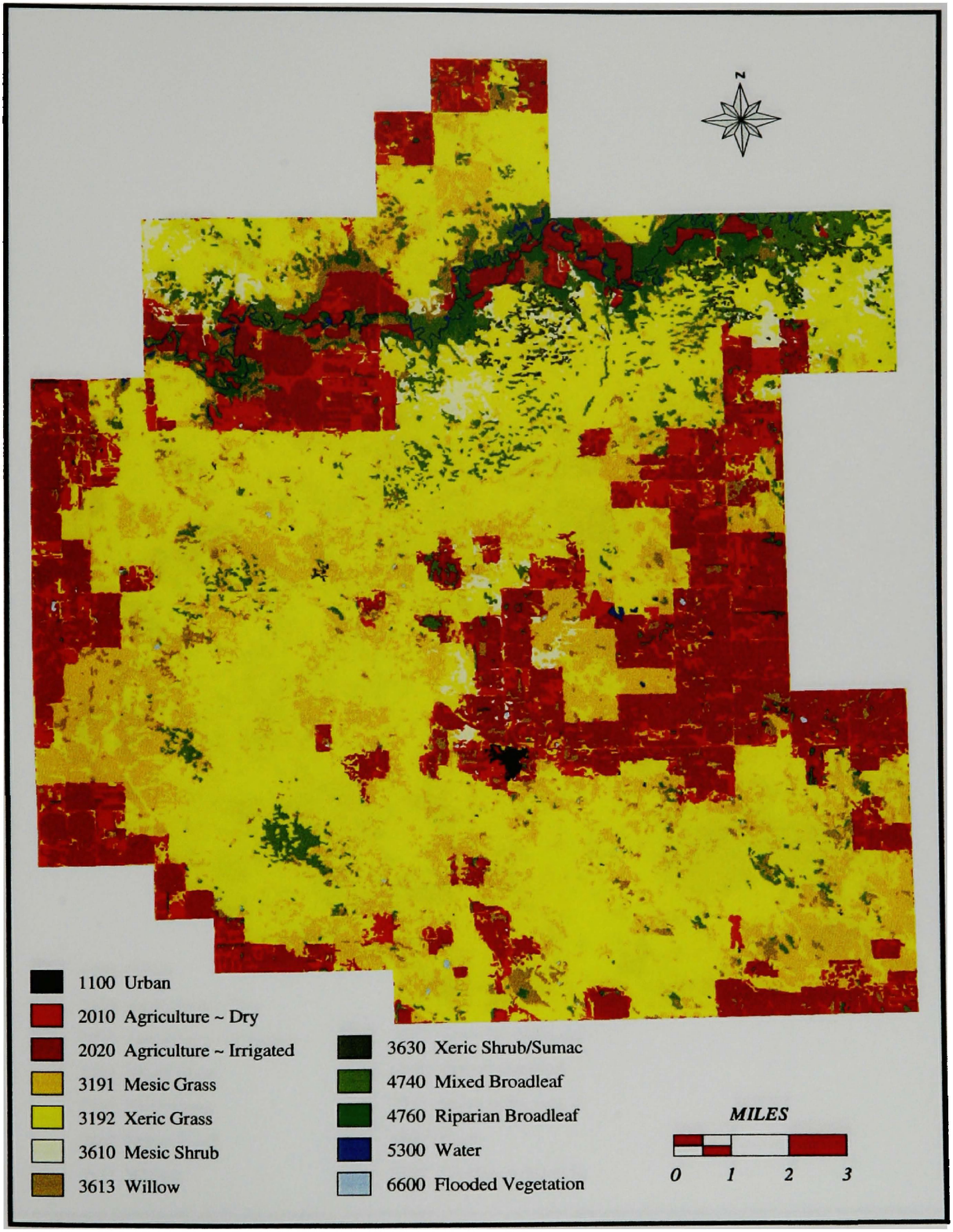

Figure 5. Spatial distribution of 12 land cover classes on the northern portion of the Sheyenne National Grassland in 1992.

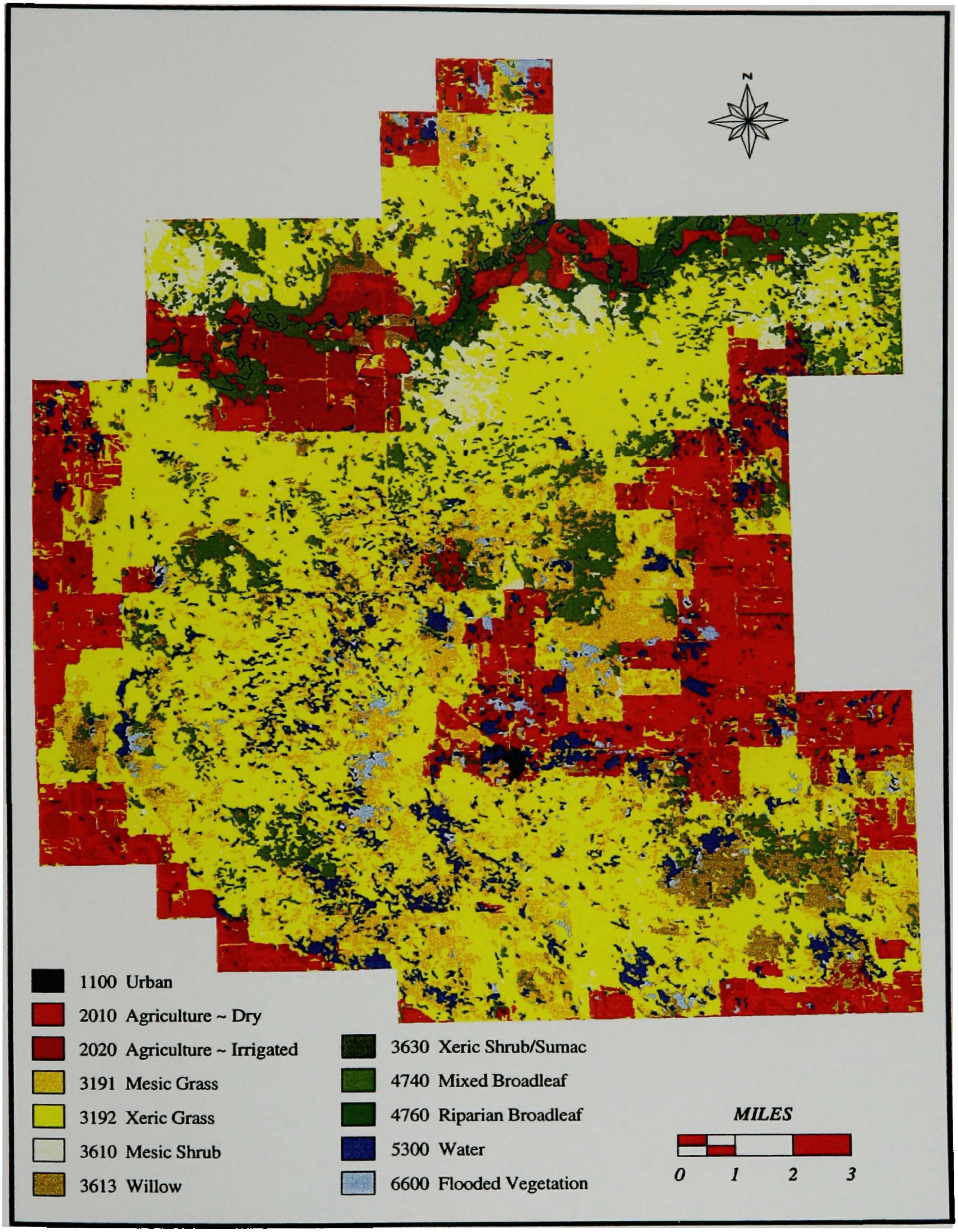

Figure 6. Spatial distribution of 12 land cover classes on the northern portion of the Sheyenne National Grassland in 1998.