Mapping Prairie Pothole Communities with Multitemporal Ikonos Satellite Imagery

Rick Lawrence, Rebecca Hurst, T. Weaver, and Richard Aspinall

Abstract

We evaluated the ability of Ikonos imagery from August and October 2000 to classify prairie pothole community types of the Missouri Coteau of North Dakota. Classification tree analyses were conducted to create land-cover maps at three levels of detail. The analyses successfully distinguished broad cover types (potholes including emergent vegetation versus upland vegetation) at 92 percent overall accuracy. Overall accuracy dropped to 80 percent when upland vegetation was segregated into woody and grassy communities and to 71 percent when we attempted to classify at the species or near-species levels. The use of two image dates was of importance in the classifications; the failure to acquire early season imagery, therefore, might have impaired our results.

Introduction

The advent of readily available high spatial resolution commercial satellite imagery (Petrie, 2001) presents important new opportunities for land managers and researchers needing classifications of landscapes that are heterogeneous at fine scales. Vegetation, for example, often varies at spatial resolutions finer than are detectable using widely available moderate resolution imagery, such as Landsat-based imagery. We examined plant communities of the Missouri Coteau, the terminal moraine of the Wisconsin Glacier, which reaches from north central Montana to Iowa. The Missouri Coteau's pothole and hilltop topography provides repeated examples of a moisture gradient occupied by vegetation reaching from aquatic through aspen, snowberry, tall grass prairie, and mixed grass prairie, to short grass prairie (Smith, 1998). The Missouri Coteau is valuable for range, agriculture, and wildlife, including migrating waterfowl (Murphy, 1993).

The ability to classify accurately both grassland communities and associated wetlands, such as the prairies of the Missouri Coteau and their potholes with emergent vegetation, is of vital importance. More than one-fourth of the Earth's land surface and over 60 percent of the United States is classified as grassland (Williams *et al.*, 1968; Holechek *et al.*, 1989; Laurenroth, 1979). Grasslands are critical for wildlife habitat, plant species diversity, hydrologic functions, ecosystem nutrient cycling, and grazing (Campbell and Lasley, 1969; Pearse, 1971). The importance of discriminating among grassland types with remote sensing has been noted as particularly important because of the vast extent of these ecosystems (Price *et al.*, 2001). Wetlands, such as are found with the potholes of the Missouri Coteau, are similarly critical habitat for species including migratory waterfowl, and mapping such features is critical to land-use decisions (Muller *et al.*, 1993; Semlitsch and Bodie, 1998).

Satellite imagery has been used extensively to map grassland vegetation. Moderate resolution imagery, however, has been almost the exclusive tool for such mapping, thereby limiting such efforts to either broad vegetation categories or areas of homogeneous cover types at the resolution of the imagery. Landsat imagery has been used to discriminate between cool- and warm-season grasses in eastern Kansas (Price *et al.*, 2002), four grassland habitat types in North Dakota (Jensen *et al.*, 2001), rough fescue grassland in western Canada (Thomson *et al.*, 1985), ten plant communities in southwestern Idaho (Clark *et al.*, 2001), and eight major grassland and shrubland groups in southwestern Idaho (Knick *et al.*, 1997). Classification accuracies ranged from 60 percent to over 90 percent, indicating that Landsat imagery has substantial potential for mapping grasslands where the vegetation communities occur in sufficiently homogeneous areas to be detectable at 30 m resolution.

Commercial high spatial resolution satellite-based sensors, including Ikonos and Quickbird, can provide classifications at resolutions of 4 m or less. Imagery from these sensors has been used for many applications, including monitoring prairie dog colonies (Sidle *et al.*, 2002), building extraction (Lee *et al.*, 2003), water monitoring and analysis (Huguenin *et al.*, 2004; JiQun *et al.*, 2004), site-specific agriculture (Metternicht, 2004; Vina *et al.*, 2003), documenting vegetation degradation in mountainous environments (Allard, 2003), measuring tree mortality (Clark *et al.*, 2004), estimating leaf area index (Colombo *et al.*, 2003; Johnson *et al.*, 2003), and assessing coral-reefs (Maeder *et al.*, 2002; Palandro *et al.*, 2003). Few reported studies, however, have used these sensors for classification of undeveloped land-cover (but see, e.g., Carleer and Wolff, 2004; Quinton *et al.*, 2003; Sawaya *et al.*, 2003), and the use of these data to examine grassland communities does not seem to be well explored. One possible reason for this lack of application might be that these sensors, having sensitivity in the visible and near-infrared portions of the spectrum (Goetz *et al.*, 2003; Thenkabail *et al.*, 2004), have less spectral resolution than Landsat, which also has sensitivity in the middle and thermal infrared (NASA, 2004),

Rick Lawrence is at the Department of Land Resources and Environmental Sciences, Montana State University, Bozeman, Montana 59717 (rickl@montana.edu).

Rebecca Hurst and T. Weaver are at the Ecology Department, Montana State University, Bozeman, Montana 59717 (rebecca@bnbriver.com, tweaver@gemini.oscs.montana.edu).

Richard Aspinall is at the Geography Department, Arizona State University, Tempe, Arizona 85287 (richard.aspinall@asu.edu).

Photogrammetric Engineering & Remote Sensing
Vol. 72, No. 2, February 2006, pp. 169–174.

0099-1112/06/7202–0169/$3.00/0

although many studies do not use the coarser spatial resolution thermal infrared.

One possible solution to the lack of spectral resolution in Ikonos and Quickbird imagery compared to Landsat is to incorporate temporal information through the use of multiple images across the growing season. Use of multi-date imagery has been shown to achieve higher classification accuracies (Guo *et al*., 2000) and has two potential advantages. First, certain cover types might be best distinguished on one date, while other cover types might be best distinguished on another date (e.g., Lawrence and Wright, 2001). Second, difference images (those created by subtracting spectral values of one date from spectral values on another date (Coppin *et al*., 2004)), certain components from multitemporal principal components analysis (Fung and LeDrew, 1987; Eastman and Fulk, 1993), or other techniques can represent differences in plant phenology among different cover types (Coppin *et al*., 2004). Use of high-resolution multi-temporal imagery can involve distinctive problems (Sugumaran *et al*., 2002). Precise georeferencing can be more difficult than with coarser resolution imagery and registration of images acquired at different look angles, for example, can be difficult. Shadows can be a greater problem with high-resolution imagery, and shadows appearing on one date might be absent on another, complicating classification efforts.

Our objective was to evaluate the ability of multi-temporal high spatial resolution satellite imagery to map vegetation communities in a spatially fine scale heterogeneous region. Classification success would suggest that such analysis could overcome the spatial resolution limitations of sensors such as Landsat imagery as well as the spectral resolution limitations of sensors such as Ikonos and Quickbird.

Figure 1. Location of study site, Lostwood National Wildlife Refuge, North Dakota, shown with an Ikonos panchromatic image.

Methods

Our study site was the northern half of the Lostwood National Wildlife Refuge (LNWR). LNWR is located in Burke and Montrail Counties of northwestern North Dakota, 37 km south of Canada and 113 km east of Montana (Figure 1) at an elevation of 675 m to 764 m. This terrain comprises non-integrated wetland drainages, filled by snowmelt and rainfall through surface runoff and subsurface seepage. The 10,888 ha refuge, thus, is dotted with 2,178 ha of prairie wetlands (Smith, 1998). The Prairie Pothole Region of the Missouri Coteau is useful for grazing and farming and, with its wetlands, is important for migratory waterfowl and upland bird species (Rolling and Dhuyvetter, 2003).

High spatial heterogeneity of vegetation types at LNWR is due primarily to diverse habitats (bottoms, slopes, and hilltops) in the rolling topography and, secondarily, to the clonal spread of grasses, shrubs, and trees. Vegetation includes native wetland communities; native prairie communities; native, but invasive, tree and shrub communities; and introduced cropland species. The pothole wetlands are diverse in size, depth, vegetation, and water quality. The primary woody communities are *Populus tremuloides* (aspen) and *Symphoricarpos occidentalis* (snowberry). The grassy prairie communities include northern phases of tall, mixed, and short grass prairie, dominated by *Stipa comata* (needle-and-thread), *Mulenbergia cuspidate* (plains muhly), *Bouteloua gracilis* (blue grama), *Agropyron smithii* (western wheatgrass), *Stipa viridula* (green needlegrass), *Festuca scabrella* (rough fescue), and *Mulenbergia richardsonis* (mat muhly). Dominant introduced grasses are *Bromus inermis* (smooth brome) and *Poa pratensis* (Kentucky blue grass). Both grasses are highly competitive, perennial, rhizomatous, and sod-formers.

LNWR's climate is semi-arid, with an annual mean precipitation of 43 cm and deviations of greater than 10 cm in four of ten years (Rolling and Dhuyvetter, 2003). The average annual temperatures at LNWR are between −40°C in winter (January maximum/minimum at 9°/–20°C) and 38°C in summer (July maximum/minimum at 28°/11°C). The growing season, therefore, is limited by winter storms that can occur as late as early June and frosts as early as August.

Ikonos multispectral imagery was acquired on 11 August 2000 and 10 October 2000. We attempted to obtain a spring and a fall image to capture maximum phenological variability, but were not able to obtain a clear image prior to August due to weather and acquisition difficulties. The imagery has a spatial resolution of 4 m and included four spectral bands (blue, 0.45–0.52 μm; green, 0.52–0.59 μm; red, 0.62–0.68 μm; and near-infrared, 0.77–0.86 μm). Pixel values represented 11-bit scaled radiance values. Imagery was georeferenced to a Universal Transverse Mercator (UTM WGS84) coordinate system and the images were registered to within one pixel. In addition to the raw Ikonos spectral bands, we used several derived components to represent potential changes in vegetation spectral responses between the two dates. These components included (a) difference images created for each of the four bands by subtracting the August spectral values from the October spectral values, and (b) seven principal components from a principal components analysis of the eight spectral bands from the two dates (the first principal component was determined to not include change data).

The reference data for classification and accuracy assessment were collected using on-ground surveys with differential GPS during summer months. A minimum of ten circular plots

Table 1. Classification Scheme for Ikonos Imagery of Lostwood National Wildlife Reserve

Level 1	Level 2	Level 3
Potholes, including emergent vegetation	Potholes, including emergent vegetation	Potholes, including emergent vegetation
Upland vegetation	Woody vegetation	Aspen
		Snowberry
	Grassy vegetation	Grasses with dwarf shrubs
		Grasses without dwarf shrubs

were collected for each of 21 vegetation cover types (later combined into five types for analysis), with each plot having a 6 m radius. Reference data for each cover type were randomly divided into equal training and accuracy assessment data sets.

Data used in the classification included eight original spectral bands, four difference image components, and seven principal components. Classification tree analysis (CTA) in S-Plus statistical software was used to create a set of decision trees and associated classification rules for the study area. CTA (sometimes referred to as classification and regression tree analysis, CART, decision trees, or recursive partitioning) is a non-parametric classification algorithm that has been demonstrated to be effective in classifying complex data sets with multi-temporal components (Lawrence and Wright, 2000).

Classification was conducted hierarchically, with each of three levels representing increasing discrimination among cover types (Table 1). Level 1, therefore, included only the broadest differentiation of potholes (including emergent vegetation) and upland vegetation. At Level 2, upland vegetation was segregated into two functional classes, woody vegetation (consisting of aspen and snowberry) and grassy vegetation (consisting of grasses with and without dwarf shrubs). Finally, at Level 3 woody vegetation was segregated into two species classes, aspen (both tree and shrub forms) and snowberry, and grassy vegetation was segregated into two functional classes, grasses with and without dwarf shrubs. Accuracy assessments followed traditional error matrix methods (Congalton and Green, 1999).

Results

Overall accuracy for the Level 1 classification was 92 percent (Kappa statistic 0.79). Individual class accuracies ranged from a low of 73 percent for producer's accuracy for potholes to 100 percent for producer's accuracy for upland species (Table 2). Most confusion was due to the classification of some pothole areas as upland vegetation. Areas of dense emergent vegetation, which had similar spectral

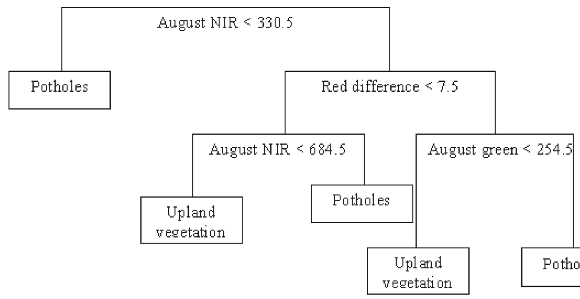

Figure 2. Decision tree for the Level 1 classification. Splitting rules at each node indicate the left branching at the nodes. Difference components were created by subtracting the August spectral values from the October spectral values.

characteristics to upland vegetation, were the primary cause of this error.

The decision tree for Level 1 was fairly simple, with five terminal nodes and the incorporation of 3 of the 19 potential explanatory variables (Figure 2). Explanatory variables used in the classification included the near-infrared and green bands from the August Ikonos image and the red band difference component. Potholes were identified primarily by lower radiance in the near-infrared portion of the spectrum for water-dominated areas, as would be expected due to the high absorption of infrared by water. Other pothole areas were distinguished by high green radiance, probably because ponded water kept emergent vegetation greener than upland vegetation in August. Finally, some pothole areas were distinguished by high near-infrared responses, possibly also indicating the presence of healthy vegetation in emergent vegetation zones.

For the Level 2 classification, which segregated upland vegetation into grassy and woody vegetation, overall classification was 80 percent (Kappa statistic 0.68). Individual class accuracies ranged from 68 percent for woody vegetation producer's accuracy to 99 percent for pothole user's accuracy (Table 3). The largest source of confusion was woody vegetation being classified as grassy vegetation, while the sum of grassy vegetation classified as woody vegetation and potholes classified as grassy vegetation accounted for an equivalent amount of error.

Table 2. Level 1 Classification Accuracy Assessment

	Potholes/ Emergent Vegetation	Upland Vegetation	Totals	User's Accuracy
Potholes/emergent vegetation	215	3	218	98.6%
Upland vegetation	78	759	837	90.7%
Totals	293	762	1055	
Producer's accuracy	73.4%	99.6%		
Overall accuracy	92.3%			
Kappa	0.79			

Table 3. Level 2 Classification Accuracy Assessment

	Potholes/ Emergent Vegetation	Woody Vegetation	Grassy Vegetation	Totals	User's Accuracy
Potholes/ emergent vegetation	215	3	0	218	98.6%
Woody vegetation	28	199	41	268	74.3%
Grassy vegetation	50	89	430	569	75.6%
Totals	293	291	471	1055	
Producer's accuracy	73.4%	68.4%	91.3%		
Overall accuracy	80.0%				
Kappa	0.68				

The decision tree for Level 2, which segregated upland vegetation into woody and grassy vegetation, was much more complex than the Level 1 decision tree, had nine terminal nodes, and incorporated six explanatory variables, the red band from the August image, the green, red, and near-infrared bands from the October image, and principal components 5 and 6 (Figure 3). We interpreted principal component 5 as representing changes in green spectral radiance from August to October and principal component 6 as primarily changes in blue radiance between the two images. Most grassy vegetation was distinguished by higher values in the October red band, possibly due to earlier senescence for grasses (i.e., less absorption by photosynthetically active vegetation). For those observations with lower red radiance, much of the woody vegetation was distinguished from grassy vegetation by lower radiance in the August red band, perhaps for the same reason.

For the Level 3 classification, which segregated woody vegetation into aspen and snowberry and distinguished grassy vegetation with and without dwarf shrubs, overall classification was 72 percent (Kappa statistic 0.62). Individual class accuracies ranged from 47 percent for snowberry producer's accuracy to 99 percent for pothole user's accuracy (Table 4). Grasses without dwarf shrubs were most often confused with snowberry and grasses with dwarf shrubs, while snowberry was the largest source of confusion for aspen. In addition, the grasses with dwarf shrubs were poorly distinguished and substantial confusion remained among aspen and other classes.

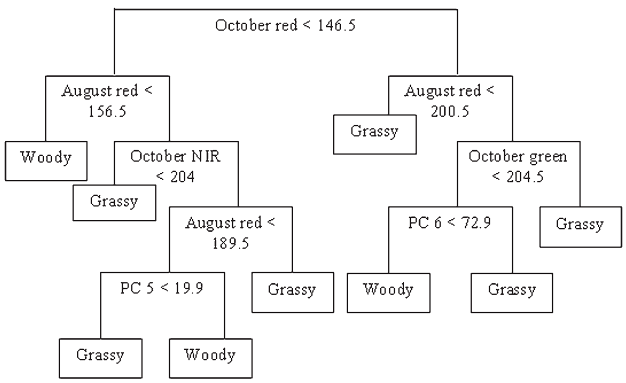

Figure 3. Decision tree for the Level 2 classification segregating upland vegetation into woody vegetation and grassy vegetation. Splitting rules at each node indicate the left branching at the nodes. PC refers to multi-temporal principal components created by principal components analysis of all eight bands from the two dates of imagery.

The decision tree segregating woody vegetation types for Level 3 had three terminal nodes and used two explanatory variables, the red band from the October image and the green band from the August image (Figure 4). Snowberry was distinguished by having higher responses in both bands, probably because the higher leaf area in aspen resulted in more absorption in the visible bands. The aspen present at the site, however, is mostly in the shrub stage, which would have leaf areas that overlap with those of snowberry, resulting in substantial residual confusion between these classes.

The decision tree segregating grasses with and without dwarf shrubs had five terminal nodes and used four explanatory variables, the near infrared band from the October image and principal components 2, 4, 7, and 8 (Figure 4). We interpreted principal component 2 as change in the visible bands, principal components 4 and 7 both as change in all bands except green, and principal component 8 as change in all bands. Grasses with dwarf shrubs were distinguished from grasses without dwarf shrubs primarily by having lower values in all principal components, indicating that the grasses with dwarf shrubs had less change in spectral values from August to October. One possible explanation for this might be that the dwarf shrubs senesced later than the grasses, resulting in less change between the two dates. An alternative might be that dwarf shrubs tend to appear on drier sites with less vegetation cover and more soil exposure. The exposed soil might result in a more constant spectral signature over time. The dwarf shrubs, however, are often topped by tall grasses, which could explain the substantial confusion between these two classes.

Discussion

Classification of multi-date Ikonos imagery for our prairie pothole site was fairly successful, with some notable exceptions. Classes at the broad first level, pothole versus upland vegetation, were well distinguished, as were most classes at the second level, grassy versus woody vegetation. At the third level, which included species and near species classes, however, accuracies dropped substantially. The snowberry and grass with dwarf shrub classes, in particular, were not well distinguished from grasses. Examination of the decision trees used to create these classifications suggests the probable reason for this confusion. We believe that the primary method of distinguishing dwarf shrubs and snowberry from grasses was differences in rates of spectral

TABLE 4. LEVEL 3 CLASSIFICATION ACCURACY ASSESSMENT

	Potholes/emergent Vegetation	Aspen	Snowberry	Grasses With Dwarf Shrubs	Grasses Without Dwarf Shrubs	Totals	User's Accuracy
Potholes/ emergent vegetation	215	3	0	0	0	218	98.6%
Aspen	0	88	5	0	3	96	91.7%
Snowberry	28	23	83	4	34	172	48.3%
Grasses with dwarf shrubs	0	0	19	54	14	87	62.1%
Grasses without dwarf shrubs	50	0	70	43	319	482	66.2%
Totals	293	114	177	101	370	1055	
Producer's accuracy	73.4%	77.2%	46.9%	53.5%	86.2%		
Overall accuracy	71.9%						
Kappa	0.62						

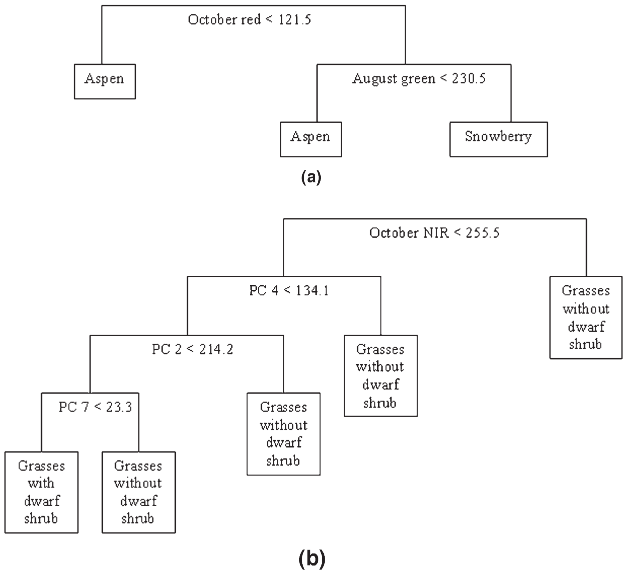

Figure 4. Decision trees for the Level 3 classifications: (a) segregating woody vegetation into aspen and snowberry and (b) segregating grassy vegetation into grasses with dwarf shrubs and grasses without dwarf shrubs. Splitting rules at each node indicate the left branching at the nodes. PC refers to multi-temporal principal components created by principal components analysis of all eight bands from the two dates of imagery.

change between August and October, due either to differences in rates of senescence, soil exposure, or both.

The decision trees used for our classifications support our concept that temporal information might be valuable for separating vegetation types. Raw spectral bands from both dates were used in the decision trees, although it is unknown whether this resulted from distinctions being evident only on certain dates or slight statistical advantages from a band on one date versus another. More compelling was the prominence of derived data representing changes from one date to the other. The difference in red radiance was important to the Level 1 classification. Several principal components that represented changes in radiance between the two dates were important at Levels 2 and 3. These principal component data were particularly important because late in the season, when our imagery was acquired, the rates of phenological change vary substantially among species. Our classifications, therefore, were able to exploit some of these differences among classes that most likely otherwise would not have been distinguishable because of the substantial overlap in spectral responses among classes on any single date.

The success of our classifications also might have been affected by the particular dates of imagery we obtained. Although we contracted for spring, summer, and fall images, Space Imaging, LCC was not able to obtain a spring Ikonos image during the study period. The failure primarily was due to unacceptable cloud conditions (one image was obtained but was returned as unacceptable for this reason, another was clear but followed a late season snow storm with substantial drifting snow still on the ground). The use of images from more phenologically varied periods might have been able to detect variations in vegetation that were not evident from two relatively late season images.

Conclusion

Our objectives were to determine whether multi-temporal Ikonos imagery could successfully map prairie pothole communities, both in terms of delineating potholes with their emergent vegetation and in distinguishing among upland vegetation communities. Our results indicate that these data can be highly successful for pothole and wetland determination. Results for upland communities were mixed. Broad categories were fairly well distinguished, and we found that the multi-temporal nature of the data was often important for making these distinctions. Several similar communities, however, remained confused. It is important for future research to determine whether obtaining imagery for more distinctive dates, such as spring and fall, can overcome these problems.

Acknowledgments

We gratefully acknowledge the following persons and organizations for their assistance with this research: (1) K. Smith, manager of LNWR, initiator of the research, energetic participant, and thoughtful consultant; and (2) The USDI Fire Coordination Committee (Research Initiative 1422-R220A8-0011) and NASA (ESES Data Purchase Project Task 1019), who provided funding, images, and encouragement for the research.

References

Allard, A., 2003. Detection of vegetation degradation on Swedish mountainous heaths at an early stage by image interpretation, *Ambio*, 32:510–519.

Campbell, J.R., and D. Lasley, 1969. *The Science of Animals that Serve Mankind*, McGraw-Hill, New York.

Carleer, A., and E. Wolff, 2004. Exploitation of very high resolution satellite data for tree species identification, *Photogrammetric Engineering & Remote Sensing*, 70:135–140.

Clark, D.B., C. Soto Castro, L.D. Alfaro Alvarado, and J.M. Read, 2004. Quantifying mortality of tropical rain forest trees using high-spatial-resolution satellite data, *Ecology Letters*, 7:52–59.

Clark, P.E., M.S. Seyfried, and B. Harris, 2001. Intermountain plant community classification using Landsat TM and SPOT HRV data, *Journal of Range Management*, 54:152–160.

Colombo, R., D. Bellingeri, D. Fasolini, and C.M. Marino, 2003. Retrieval of leaf area index in different vegetation types using high resolution satellite data, *Remote Sensing of Environment*, 86:120–131.

Congalton, R.G., and K. Green, 1999. *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices*, Lewis Publishers, New York.

Coppin, P., I. Jonckheere, K. Nackaerts, B. Muys, and E. Lambin, 2004. Digital change detection methods in ecosystem monitoring: A review, *International Journal of Remote Sensing*, 25: 1565–1596.

Eastman, J.R., and M. Fulk, 1993. Long sequence time series evaluation using standardized principal components, *Photogrammetric Engineering & Remote Sensing*, 59:1307–1312.

Fung, T., and E. LeDrew, 1987. Application of principal components analysis to change detection, *Photogrammetric Engineering & Remote Sensing*, 53:1649–1658.

Goetz, S.J., R.K. Wright, A.J. Smith, E. Zinecher, and E. Schaub, 2003. ikonos imagery for resource management: Tree cover, impervious surfaces, and riparian buffer analyses in the mid-Atlantic region, *Remote Sensing of Environment*, 88:195–208.

Guo, X., K.P. Price, and J.M. Stiles, 2000. Modeling biophysical factors for grasslands in Eastern Kansas using Landsat TM data, *Transactions of the Kansas Academy of Science*, 103:122–138.

Holecheck, J.L., R.D. Piper, and C.H. Herbel, 1989. *Range Management: Principles and Practices*, Prentice Hall, Englewood Cliffs, New Jersey.

Huguenin, R.L., M.H. Wang, R. Biehl, S. Stoodley, and J.N. Rogers, 2004. Automated subpixel photobathymetry and water quality mapping, *Photogrammetric Engineering & Remote Sensing*, 70:111–123.

Jensen, M.E., J.P. Dibenedetto, J.A. Barber, C. Montagne, and P.S. Bourgeron, 2001. Spatial modeling of rangeland potential vegetation environments, *Journal of Range Management*, 54:528–536.

JiQun, Z., X. KaiQin, M. Watanabe, Y. YongHui, and C. XiuWan, 2004. Estimation of river discharge from non-trapezoidal open channel using Quickbird-2 satellite imagery, *Hydrological Sciences Journal*, 49:247–260.

Johnson, L.F., D.E. Roczen, S.K. Youkhana, R.R. Nemani, and D.F. Bosch, 2003. Mapping vineyard leaf area with multispectral satellite imagery, *Computers and Electronics in Agriculture*, 38:33–44.

Knick, S.T., J.T. Rotenberry, and T.J. Zarriello, 1997. Supervised classification of Landsat Thematic Mapper imagery in a semi-arid rangeland by nonparametric discriminate analysis, *Photogrammetric Engineering & Remote Sensing*, 63:79–86.

Laurenroth, W.K., 1979. Grassland primary production: North American grasslands in perspective, *Perspectives in Grassland Ecology* (N. French, editor), Springer-Verlag, New York, pp. 3–24.

Lawrence, R.L., and A. Wright, 2001. Rule-based classification systems using classification and regression tree (CART) analysis, *Photogrammetric Engineering & Remote Sensing*, 67:1137–1142.

Lee, D.S., J. Shan, and J.S. Bethel, 2003. Class-guided building extraction from Ikonos imagery, *Photogrammetric Engineering & Remote Sensing*, 69:143–150.

Maeder, J, S. Narumalani, D.C. Rundquist, R.L. Perk, J. Schalles, K. Hutchins, and J. Keck, 2002. Classifying and mapping general coral-reef structure using Ikonos data, *Photogrammetric Engineering & Remote Sensing*, 68:1297–1305.

Metternicht, G., 2004. Role of high-resolution satellite sensors: Precision farming today, *GIM International*, 18:40–43.

Muller, E., H. Decamps, and K. D. Michael, 1993. Contribution of space remote sensing to river studies, *Freshwater Biology*, 29:301–312.

Murphy, R. K., 1993. *History, Nesting Biology, and Predation Ecology of Raptors in the Missouri Couteau of Northwestern North Dakota*. Ph. D. dissertation, Montana State University, Bozeman, Montana.

National Aeronautics and Space Administration, 2004. Landsat 7 Science Data Users Handbook, URL: *http://ltpwww.gsfc.nasa.gov/IAS/handbook/handbook_toc.html* (last date accessed: 14 November 2005).

Palandro, D., S. Andrefouet, P. Dustan, and F.E. Muller-Karger, 2003. Change detection in coral reef communities using Ikonos satellite sensor imagery and historical photographs, *International Journal of Remote Sensing*, 24:873–878.

Pearse, C.K., 1971. Grazing in the middle-east: Past, present and future, *Journal of Range Management*, 24:13–16.

Petrie, G., 2001. Commercial high resolution space imagery: A very long gestation and a troubled birth!!, *GeoInformatics*, 4: 12–17.

Price, K.P., T.J. Crooks, and E.A. Martinko, 2001. Grasslands across time and scale: A remote sensing perspective, *Photogrammetric Engineering & Remote Sensing*, 67:414–420.

Price, K.P., X. Guo, and J.M. Stiles, 2002. Comparison of Landsat TM and ERS-2 SAR data for discriminating among grassland types and treatments in eastern Kansas, *Computers and Electronics in Agriculture*, 37:157–171.

Quinton, W.L., M. Hayashi, and A. Pietroniro, 2003. Connectivity and storage functions of channel fens and flat bogs in northern basins, *Hydrological Processes*, 17:3665–3684.

Rolling, R., and T. Dhuyvetter, 2003. *Soil Survey of Burke County, ND*, USDA Natural Resources Conservation Service, Washington, D.C. 384 p.

Sawaya, K.E., L.G. Olmanson, N.J. Heinert, P.L. Brezonik, and M.E. Bauer, 2003. Extending satellite remote sensing to local scales: Land and water resource monitoring using high-resolution imagery, *Remote Sensing of Environment*, 88:144–156.

Semlitsch, R.D., and J.R. Bodie, 1998. Are small, isolated wetlands expendable?, *Conservation Biology*, 12:1129–1133.

Smith, K., 1998. *Lostwood National Wildlife Refuge Comprehensive Conservation Plan*, U. S. Fish and Wildlife Service, Region 6, Lostwood National Wildlife Refuge.

Sudkem J.G., D.H. Johnson, B.R. Euliss, and M. Tooze, 2002. Monitoring black-tailed prairie dog colonies with high-resolution satellite imagery, *Wildlife Society Bulletin*, 30:405–411.

Sugumaran, R., D. Zerr, and T. Prato, 2002. Improved urban land cover mapping using multi-temporal Ikonos images for local government planning, *Canadian Journal of Remote Sensing*, 28: 90–95.

Thenkabail, P.S., E.A. Enclona, M.S. Ashton, C. Legg, and M.J. de Dieu, 2004. Hyperion, Ikonos, ALI, and ETM+ sensors in the study of African rainforests, *Remote Sensing of Environment*, 90:23–43.

Thomson, K.P.B., C. Gosselin, B.W. Adams, and I. Sutherland, 1985. Thematic Mapper data used in rangeland management in rough fescue grasslands in western Canada, *Canadian Journal of Remote Sensing*, 11:162–176.

Vina, A., A.J. Peters, and L. Ji, 2003. Use of multispectral Ikonos imagery for discriminating between conventional and conservation agricultural tillage practices, *Photogrammetric Engineering & Remote Sensing*, 69(5):537–544.

Williams, R.E., B.E. Allred, R.M. DeNio, and H.E. Paulsen, 1968. Conservation development and use of the world's rangelands, *Journal of Range Management*, 21:355–360.

(Received 23 August 2004; accepted 11 January 2005; revised 14 February 2005)