Rangeland Ecol Manage 59:38–43 | January 2006

Special Feature: Applications of Geospatial Techniques

Challenges of Integrating Geospatial Technologies Into Rangeland Research and Management

Keith T. Weber

Author is Geographic Information Systems Director, Idaho State University, Pocatello, ID.

Abstract

With the development and commercial availability of submeter spatial resolution satellite imagery, geospatial tools can better accommodate the needs of range professionals than ever before. However, with these new tools comes a new set of challenges. Range managers and range scientists must now 1) better understand and take advantage of the geotechnical tools at their disposal, 2) collect field observations/measurements in ways that act synergistically with these tools, and 3) utilize high-accuracy global positioning system (GPS) receivers. To produce reliable rangeland models it is important to collect field data that correspond with what the satellite "sees." Further, it is frequently necessary to use high-resolution imagery, which subsequently necessitates the use of high-accuracy GPS receivers to ensure field data are recorded in the correct pixel and properly coregistered. This paper describes the results of research and experimentation that have led to the development of techniques to improve geospatial rangeland applications. For optimal classification accuracy, field data collected for use in remote sensing applications should estimate/measure ground cover using general vegetation community types and must never exceed 100%. Further, the field sample sites used for classification must be located using a GPS receiver with accuracy $\leq$ 50% of the size of satellite imagery pixels (e.g., if Landsat imagery is used—with 28.5-m pixels—the GPS receiver must be able to achieve $\pm$ 14 m accuracy with 95% confidence). Finally, a series of best practices are suggested to help range managers and range scientists better understand and implement geospatial technologies.

Resumen

Con el desarrollo y disponibilidad comercial de imágenes de satélite de resolución espacial de menos de un metro, las herramientas geoespaciales pueden satisfacer, mejor que antes, las necesidades de los profesionales del manejo de pastizales. Sin embargo, con estas nuevas herramientas viene un nuevo grupo de retos. Los manejadores de pastizales y científicos de esta disciplina ahora deben: 1) entender mejor y tomar ventaja de las herramientas geotécnicas a su disposición, 2) colectar observaciones/mediciones de campo en formas de que actúen sinérgicamente con estas herramientas y 3) utilizar recibidores de sistemas de posicionamiento global de mayor exactitud. Nuestros resultados indican que para producir modelos de pastizales confiables es importante colectar datos de campo que correspondan con lo que los satélites "ven." Más aun, frecuentemente es necesario usar imágenes de alta resolución las cuales subsecuentemente necesitan el uso de recibidores de sistemas de posicionamiento global de alta precisión para asegurar que los datos de campo están registrados en el píxel correcto y co-registrados adecuadamente. Se discuten varias técnicas y se sugieren una serie de mejores prácticas para ayudar a los manejadores y científicos de pastizales a entender mejor e implementar esta tecnología.

Key Words: GIS, remote sensing, global positioning system, range science

INTRODUCTION

Sampling vegetation in the field that results in an accurate description of rangelands is an age-old problem (Pechanec and Pickford 1937; Daubenmire 1958), and collecting field or ground-truth data is critical to the success of any remote sensing or geographic information system (GIS) project. However, applying traditional ecological vegetation sampling techniques directly to geotechnical studies frequently fails to yield highly accurate and reliable classifications (Witt and Weber 2001).

In July 1972, Landsat Multi-Spectral Scanner was launched into orbit (US Geological Survey 2003). This remote sensing satellite offered natural resource scientists the first significant platform on which to analyze the earth's surface for landscape-level vegetation characteristics. Whereas this satellite represented an enormous advance in geotechnical capabilities, it fell far short of the needs and demands of the range community, due to the sensor's spatial resolution (pixel size of 80 m) and the small number (i.e., 4) of spectral bands; detailed (and reliable) models of shrub cover or bare earth exposure was not possible. In addition, the heterogeneity and complexity of rangeland plant communities and the fact that

Much of the research described in this paper was funded by grants from the National Aeronautics and Space Administration Goddard Space Flight Center. Idaho State University acknowledges the Idaho US Congressional delegation for their assistance in obtaining this grant.

Correspondence: Keith T. Weber, GIS Training and Research Center, Campus Box 8130, Pocatello, ID 83209-8130.

Manuscript received 6 July 2004; manuscript accepted 15 July 2005.

Table 1. Cover classes used for detailed classification of sagebrush-steppe rangelands (total cover could not exceed 100%).

Class	Shrub cover	Grass cover	Rocks/bare soil/lichen crust
Rocks/bare soil/lichen crust	1%–5%	1%–5%	≥ 36%
Low grass	1%–5%	6%–15%	≥ 36%
Medium grass	1%–5%	16%–25%	≥ 36%
High grass	1%–5%	26%–35%	≥ 36%
Low grass/shrub mix	6%–15%	6%–15%	≥ 36%
Medium grass–low shrub mix	6%–15%	16%–25%	≥ 36%
High grass–low shrub mix	6%–15%	≥ 36%	< 36%
Medium shrub–low grass mix	16%–25%	6%–15%	≥ 36%
Medium grass/shrub mix	16%–25%	16%–25%	< 36%
Medium grass/shrub with rocks/bare soil/lichen crust	16%–25%	16%–25%	≥ 36%
High shrub	26%–35%	1%–5%	≥ 36%
High shrub–low grass mix	26%–35%	6%–15%	< 36%
High shrub–low grass mix with rocks/bare soil/lichen crust	26%–35%	6%–15%	≥ 36%
High shrub–medium grass mix	26%–35%	16%–25%	≥ 36%
Very high shrub	≥ 36%	1%–5%	≥ 36%
Very high shrub–low grass mix	≥ 36%	6%–15%	< 36%
Very high shrub–low grass mix with rocks/bare soil/lichen crust	≥ 36%	6%–15%	≥ 36%

individual plant cover and leaf area index are low compared with forested ecosystems resulted in relatively low classification accuracies; < 75% overall accuracy (McMahan et al. 2000, Johnson et al. 2001). Today, high spatial resolution multispectral satellite imagery (pixel size of < 5 m) are commercially available, and so are sophisticated hyperspectral remote sensing platforms that record more than 100 spectral bands of data across the electromagnetic spectrum. Coupled with thousands of global positioning system (GPS) base stations and state-of-the-art GPS receivers, the range community has the ability to analyze the earth's surface with unprecedented resolution and reliability.

While these readily available technologies have the potential to accurately and reliably monitor rangelands, they also bring with them a new set of challenges. To obtain successful analyses and classifications (≥ 75% overall accuracy; Goodchild et al. 1994; J. Pettingill, personal communication 2002), high spatial resolution remote sensing imagery (pixel size < 2.5 m) must be georegistered very well (root mean square error ≤ 1 m), and field observation points must be accurately located (± 1 m). Generally, any single point can be geolocated only to within ± 0.5 pixel for raster and grid data. When using Landsat Thematic Mapper (TM) imagery, this means the horizontal positional accuracy of field locations could not exceed ± 14 m. Such generous error margins are easily satisfied today with even fairly simple GPS receivers (Serr et al. 2005). However, when using high spatial resolution imagery, acceptable horizontal positional accuracy is concomitantly reduced. For example, the horizontal positional accuracy required of data used with Digital Globe's Quickbird imagery (pixel size of 2.4 m) is ± 1.2 m. To satisfy the latter accuracy requirement involves the use of more sophisticated GPS receivers and more stringent data collection protocols. Classification accuracy is substantially decreased with poor geolocation accuracy (Peleg and Anderson 2002).

In addition to these considerations and challenges, to extract reliable information from hyperspectral remote sensing data requires the application of advanced classification tools such as fuzzy classification (McMahan et al. 2003), spectral angle mapper (Kruse et al. 1993), or mixture-tuned match filtering (Boardman 1998; Parker-Williams and Hunt 2002, 2004; Mundt 2003).

This paper will present 3 challenges confronting range managers and range scientists using the geotechnologies in their decision-making process. These challenges are: 1) to better understand and take advantage of geotechnical tools, 2) to collect field observations/measurements in ways that act synergistically with these tools, and 3) to utilize high-accuracy GPS receivers for image rectification and coregistration with field observation sites. These challenges and potential solutions will be described. Following this, a series of best practices will be suggested.

METHODS

To determine optimal field sampling design for sagebrush-steppe rangeland remote sensing studies in southeastern Idaho, we compared 2 vegetation sampling techniques. The first followed traditional vegetation sampling techniques and consisted of a 20-m baseline directly north of each randomly located sample point. At 10-m increments (0, 10, and 20 m) along the base line, 3 25-m transects were read east of the base line. Ground cover was recorded along each transect at 1-cm resolution using a steel tape measure and meterstick placed perpendicular to the ground surface. All cover intersecting the meterstick was classified as bare soil, rock, litter, herbaceous, graminoid, or woody plants. Percent cover for each class of vegetation was then calculated. While an accurate record of the vegetation found at each site was collected, total ground cover frequently exceeded 100%, making application of these data very difficult for remote sensing classification unless they were generalized. The second vegetation sampling technique consisted of simple ocular estimates of ground cover (using the same cover type categories listed above) found within the area occupied by 1 pixel, which was presumed to be centered over each randomly located sample point. This method was designed to estimate the percent cover "seen" by a satellite. Percent cover was estimated using categorical breaks of 0%, 1%–5%, 6%–15%, 16%–25%, 26%–35%, 36%–50%, 51%–75%, 76%–95%, and 96%–100% (Weber and McMahan 2003).

We experimented with numerous classifications using both types of field data and report here the result of 2 of those classifications. The first attempts a very detailed classification using 17 cover classes (Table 1). The second uses simplified cover category data generalized into 7 classes (Table 2). In both cases, Landsat 5 TM data were used, which have a spatial resolution of 28.5 × 28.5 m pixels. Following this, validation of each model was performed using traditional bootstrap estimation techniques (Efron 1979; McMahan and Weber 2003) and

Table 2. Cover classes used for general sagebrush–steppe rangeland classification (total cover could not exceed 100%).

Class	Shrub cover	Grass cover	Rocks/bare soil/lichen crust
Grass with rocks/bare soil/lichen crust	$< 16\%$	$\geq 16\%$	$\geq 26\%$
Grass	$< 16\%$	$\geq 16\%$	$< 26\%$
Shrubs with rocks/bare soil/lichen crust	$\geq 16\%$	$< 16\%$	$\geq 26\%$
Shrubs	$\geq 16\%$	$< 16\%$	$< 26\%$
Grass and shrub mix with rocks/ bare soil/lichen crust	$\geq 16\%$	$\geq 16\%$	$\geq 26\%$
Grass and shrub mix	$\geq 16\%$	$\geq 16\%$	$< 26\%$
Rocks/bare soil/lichen crust	$< 16\%$	$< 16\%$	$\geq 26\%$

kappa statistic (Titus et al. 1984; Congalton and Green 1999). Bootstrap estimation is a technique whereby a subset of hypothetical samples is drawn from an original larger sample set. These subsets are then iteratively analyzed and accuracy determined using the inverse or unused subset. To readily compare both types of field data for this paper, separability was calculated using the Transformed Divergence Index (Richards 1993; Lillesand and Kiefer 2000). Separability statistics calculate the statistical "distance" between classification categories. The separability value of the spectral signatures derived for each class of training site provides a measure of classification accuracy. In essence, this statistic determines how discrete each category or class of data is, based on the spectral signatures extracted from available imagery. While no minimum number of sites per class was imposed to calculate separability, only those classes containing at least 30 training sites were evaluated in this part of the study. The significant separability threshold was set at 1 500 in accordance with values suggested by other authors (Richards 1993).

To explore the potential advantage of using high spatial resolution imagery, we compared classifications of leafy spurge infestations in southeastern Idaho using Landsat (pixel size of 28.5 m), Systèm pour d'Observation de la Terre 5 (SPOT 5) (pixel size of 10 m), and Quickbird (pixel size of 2.4 m) satellite imagery. Classifications were made using 253 stratified-random field observation points collected during summer 2002. Validation was then performed using standard bootstrap techniques and calculated as an error matrix with kappa statistic. The criteria used for evaluation were cost-effectiveness and classification accuracy, for which an accurate and reliable classification is defined as having $\geq 75\%$ accuracy with minimal omission error.

To consistently satisfy georegistration and coregistration requirements and effectively use available high spatial resolution imagery requires the use of sophisticated GPS receivers and the implementation of more stringent data collection protocols. To establish these protocols we experimented with 3 types of GPS receivers (Trimble ProXR, Trimble GeoXT, and Trimble GeoExplorer II). A primary difference between these receivers is that the ProXR and GeoXT are 12-channel receivers (i.e., 12 satellites can be connected simultaneously allowing the receiver to select the optimal geometric configuration), whereas the GeoExplorer II is a 6-channel receiver. In addition, the GeoXT can utilize the Wide-Area Augmentation System (WAAS) for real-time differential correction. In all experiments,

Table 3. Accuracy and precision of global positioning system (GPS) receivers.[1]

GPS receiver	Accuracy	Precision	Applicable image resolution	Effective map scale
Trimble ProXR	$\pm$ 0.78	$\pm$ 0.46	$>$ 1.6 m	1:925
Trimble GeoXT[2]	$\pm$ 0.96	$\pm$ 0.66	$>$ 2.0 m	1:1 100
Trimble Geoexplorer II	$\pm$ 3.25	$\pm$ 2.90	$>$ 6.5 m	1:3 800

[1]Values are expressed in meters at the 95% CI using a 120-position average per point ($n = 70$ points). All results are reported using postprocess differential correction.
[2]Using Wide-Area Augmentation System real-time differential correction along with postprocessing.

estimations were acquired only when a minimum of 4 concurrent GPS signals were processed, 120 positions were averaged per point with a 95% confidence interval (CI) to indicate location error, and the mask for Position Dilution of Precision (PDOP) was set at 5.0. Because GPS estimates location on the basis of triangulation, PDOP masks are used to ensure optimal satellite geometry (i.e., the satellites used are not clustered close to each other). All locations were evaluated in raw format and were processed after differentially correcting the format, and evaluated for horizontal positional accuracy relative to the location of the ground control points of Pocatello, Idaho, which were established using traditional survey methods and survey-grade GPS with real-time differential correction from a US Geodetic continuously operating reference station (Table 3).

RESULTS AND DISCUSSION

Field Sampling for Rangeland Remote Sensing

Table 4 describes the separability of 253 training sites into 17 cover categories. Only 4 categories contained a sufficient number of training sites (> 30) to develop reliable spectral signatures. Of these, 3 of the classification categories were found to be statistically separable with Transformed Divergence Index scores exceeding 1 500 (Richards 1993; Lillesand and Kiefer 2000) (Table 4). Class 8 is separable from class 13 on the basis of an increase in shrub cover from 16%–25%, to 26%–35%. Class 8 is also separable from class 15 on the basis of an increase in shrub cover from 16%–25% to $\geq 36\%$ and a loss of grass cover from 6%–15% to 1%–5%. Finally, class 13 is separable from class 15 on the basis of an increase in shrub cover from 26%–35% to $> 36\%$ and a loss of grass cover from 6%–15% to 1%–5%. The data were then combined into 7 general cover categories (Table 2) and re-evaluated for separability. Seventy-one percent (15 of 21) of these categories were statistically separable with Transformed Divergence Index scores $> 1\ 500$ (Table 5).

These analyses show that even with high spatial resolution data, there is a limit to the amount of usable information that can be obtained by remote sensing. Even with a sufficient number of training sites, many of the classes in Table 1 would still not be separable because the signatures also depend on the soil background reflectance (Asner 2004). Reliable subspecies differentiation of plants has not been demonstrated, nor has reliable differentiation of similar grasses and shrubs (e.g., differentiating crested wheatgrass from bluebunch wheatgrass)

Table 4. Separability of training sites using 17 detailed cover categories calculated using the transformed divergence index.[1]

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17
C1	0																
C2	0	0															
C3	1 999	0	0														
C4	2 000	0	1 999	0													
C5	1 999	0	835	0	0												
C6	1 999	0	1 995	1 829	1 999	0											
C7	1 761	0	1 999	2 000	1 999	1 999	0										
C8	1 999	0	5.72	0	61	1 999	1 999	0									
C9	1 999	0	1 999	1 999	1 999	1 623	1 999	1 999	0								
C10	1 999	0	1 170	0	968	1 999	1 999	1 137	2 000	0							
C11	1 999	0	608	0	114	1 998	1 999	107	1 999	995	0						
C12	2 000	0	1 999	0	1 999	2 000	2 000	1 999	2 000	2 000	1 999	0					
C13	2 000	0	1 999	0	199	2 000	2 000	1 999	2 000	2 000	1 999	0	0				
C14	2 000	0	2 000	2 000	1 999	1 999	1 999	121	2 000	2 000	2 000	2 000	2 000	0			
C15	2 000	0	871	0	272	1 999	1 999	1 999	2 000	1 442	308	1 995	2 000	2 000	0		
C16	1 999	0	2 000	2 000	1 999	1 999	1 999	1 999	1 999	2 000	1 999	2 000	2 000	2 000	2 000	0	
C17	1 426	0	1 999	1 999	1 998	1 999	1 606	2 000	1 999	1 999	1 999	2 000	2 000	2 000	1 999	2 000	0

[1]Categories C5, C8, C13, and C15 had a sufficient number of training sites ($n \geq 30$). Of these, 3 were statistically separable based on a transformed divergence index $\geq$ 1 500. The separable cover classes are those where shrub cover exceeds 16%, bare ground exceeds 36%, and minimal grass cover is present.

with multispectral imagery. Field observation sites must be collected appropriately for image processing regardless of the desired mapping or modeling result. In other words, field personnel must collect measurements and observations that will correspond with what the satellite "sees" (i.e., collecting data describing functional group and vegetation structure is typically more useful than species-level differentiations with multispectral imagery unless the target species has a very distinctive spectral signature [e.g., blooming leafy spurge] present when the imagery was acquired, and at high enough abundance within the imagery to allow for easy detection).

Achieving accurate and reliable classification ($\geq$ 75% overall accuracy) of rangelands with models built from multispectral satellite imagery requires the use of categorical training site data. Applying training data that are more detailed (i.e., cover data collected at species levels) frequently results in unacceptably poor accuracy.

Selection of Appropriate Spatial Resolution

Using imagery with better spatial resolution has allowed researchers to improve classification accuracy relative to platforms such as Landsat TM. Figure 1 illustrates mean classification accuracies using Landsat, SPOT 5, and Quickbird for leafy spurge infestation detection in southeastern Idaho. An inverse relationship exists between spatial resolution and overall classification accuracy for leafy spurge detection.

Training sites must be accurately located relative to the imagery. In other words, the field training site must be placed inside the correct pixel. The first step toward that end is to acquire terrain-corrected imagery from the vendor whenever possible (it is noted that this is typically the most expensive package from vendors). Doing this does not preclude the need to collect good control points and further rectify the imagery. Rather, it makes the georectification process easier because the

Table 5. Separability of training sites using 8 cover categories calculated using the transformed divergence index.[1]

	C1	C2	C3	C4	C5	C6	C7
C1	0						
C2	**1 973**	0					
C3	**1 999**	569	0				
C4	1 090	**1 999**	**1 999**	0			
C5	**1 801**	**1 733**	**1 710**	**1 732**	0		
C6	1 293	914	7.92	**1 608**	518	0	
C7	**2 000**	**2 000**	**2 000**	**2 000**	**2 000**	**2 000**	0

[1]All categories had a sufficient number of training sites ($n > 30$); pairwise comparisons that are significantly different are boldface. The cover class descriptions are given in Table 2.

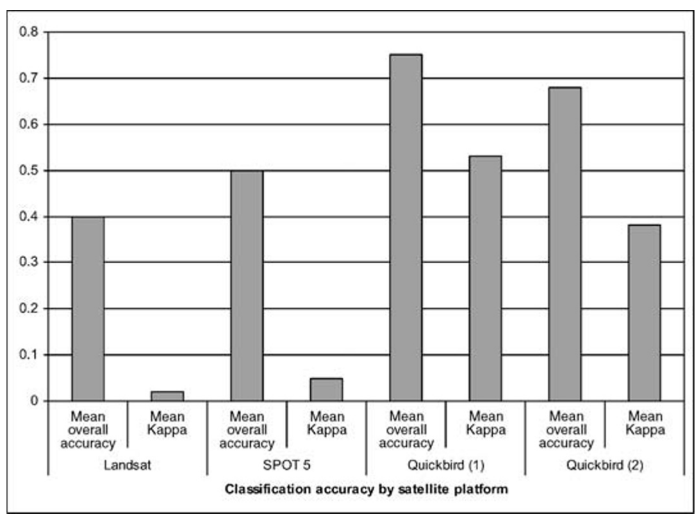

Figure 1. Mean overall accuracy and kappa analysis results for classification of leafy spurge derived from various satellite platforms. Kappa $\geq$0.35 is significant (maximum likelihood, minimum distance to means, and spectral angle mapper classification techniques were used). Quickbird (1), satellite imagery acquired in early summer. Quickbird (2), satellite imagery acquired in late summer.

imagery is "closer" to its correct location than if it were not terrain-corrected.

An inter-related consideration is the spatial resolution required to address specific problems. In the case study presented above, detection of patchy invasive plant infestations required the use of high spatial resolution imagery (pixel size of < 5 m) to achieve 75% overall classification accuracy. In this case, we observed an inverse relationship between accuracy and spatial resolution. Other rangeland applications may not follow this trend. In fact, there are many applications for which Landsat or Moderate Resolution Imaging Spectroradiometer imagery is perfectly well suited (Reeves et al. 2001).

SPOT 5 satellite imagery was able to achieve reasonable accuracy (Fig. 1) at a much reduced cost (Table 6). For this reason, SPOT imagery is very attractive and it may be the most cost-effective imagery for the detection of leafy spurge. The cost per square kilometer is higher than that of Landsat but substantially lower than that of Quickbird. The overall accuracy (51%) of SPOT imagery for detection of leafy spurge was below the given accuracy requirements; but the 75% overall accuracy requirement was arbitrary. It is important to note, however, that because of a fairly low mean kappa value, additional research will be required before a firm conclusion can be made regarding applicability of SPOT imagery for rangeland classification.

In addition to these considerations, the user should also consider temporal aspects of image acquisition, specifically as it relates to the phenology of targeted plant species (Everitt et al. 1995). Figure 1 illustrates the variation in overall accuracy when using imagery acquired in early summer (78%) versus late summer (67%). The phenology of leafy spurge has bright, conspicuous flowers in the early summer, which increases its separability from nontarget features and helps explain improved detection accuracy during this time period.

Table 6. Comparison of spatial resolution and cost of various satellite platforms.

	Spatial resolution (meters per pixel)	Minimum scene size (km^2)	Cost per scene	Cost per km^2	Cost for 32 400 km^2
Landsat TM	30	32 400	$650	$0.02	$650
SPOT 5	10	3 600[1]	$3 259	$1.10	$35 640
Quickbird	2.4	64	$1 920	$30.00	$972 000

[1]Minimum scene size requirements have changed since this case study was completed. For details see http://www.terraimageusa.com.

Rectification and Registration

The Trimble ProXR GPS receiver consistently (95% CI) achieved submeter horizontal positional accuracy (± 0.78 m) when a clear view of the sky was available (Bays 2003) and differential correction was used. Likewise, the Trimble GeoXT also achieved submeter horizontal positional accuracy (95% CI = ± 0.96 m). In contrast, the Trimble GeoExplorer II GPS receiver achieved horizontal positional accuracy of only 95% CI = ± 3.25 m, which failed to consistently achieve the required accuracy for the Quickbird imagery (± 1.2 m) even when differentially corrected.

GPS is quickly becoming the most needed yet most misused technology available. This is perhaps because many users are already familiar with recreational-grade GPS receivers. The result is that these users approach GPS research applications with basic familiarity but without a full appreciation of the differences in receiver-specific accuracy and error propagation. When using high spatial resolution imagery, the use of resource-grade GPS receivers is necessary to satisfy horizontal positional accuracy requirements (95% CI = ± 1.2 m).

At the core of this problem is the fact that users are not simply trying to navigate to a point in the field, but rather are trying to match observations from 2 independent systems (i.e., imagery and field). To succeed, both systems must use the same datum and projection. The native coordinate system for the GPS is latitude-longitude with World Geodetic System 1984 (WGS84) used as its horizontal datum. Any datum transformations or projections (i.e., converting geographic to universal transverse mercator), or both, can be handled with receiver-specific software. Ordering imagery in a specific coordinate system is usually acceptable.

MANAGEMENT IMPLICATIONS

As a result of experiences in the field, a set of best practices has been assembled to guide rangeland scientists in their efforts to integrate geospatial technologies into their profession.

1) Design and collect field observations that match what the satellite "sees."
2) Develop a problem statement that clearly defines the questions you want the geotechnologies to address. As part of this statement, decide upon an acceptable level of error.
3) Understand that cost-effectiveness means the least expensive sensor that satisfies the accuracy requirements. Choosing a sensor that is the least expensive can result in 100% waste of financial resources.
4) Invest in high-quality GPS receivers, particularly when using high spatial resolution imagery.
5) If real-time differential correction (producing acceptable horizontal positional accuracy [e.g., ± 1.2 m]) is not available, use postprocess differential correction for all GPS acquisitions from nearby base stations.
6) Collect all GPS points using native latitude-longitude and the WGS84 datum. Conversion can be made at a later time using receiver-specific software.
7) Establish as accurate a location as possible while in the field. To do this:

    a. Collect a sufficient number of positions per point to account for instantaneous environmental errors (typically 120 positions per point) and ephemeris errors arising from differences between the anticipated location of a satellite and its true location.
    b. Use signals from 4 or more GPS satellites available to the receiver (3-dimensional mode). A 12-channel receiver will provide higher location precision than a 6-channel receiver.
    c. Establish and follow PDOP and elevation mask protocols.

8) Collect ground control points in the field using clearly identifiable points on the imagery, or map, or both. For applications using high spatial resolution imagery, reflective tarps will need to be staked in the field prior to image acquisition so that rectification and coregistration are as accurate as possible.
9) Invest in geotechnical training or geotechnically trained personnel, or both.

LITERATURE CITED

Asner, G. P. 2004. Biophysical remote sensing signatures of arid and semiarid ecosystems. *In:* S. L. Ustin [ed.]. Remote sensing for natural resource management and environmental monitoring. Manual of remote sensing, Volume 4. 3rd ed. Hoboken, NJ: John Wiley & Sons. p 53–109.

Bays, K. 2003. Draft GPS data accuracy standard. US Department of the Interior Bureau of Land Management. Available at: http://giscenter.isu.edu/gps_cbs/cached_blmstd_04_22_03.pdf. Accessed 1 August 2005.

Boardman, J. W. 1998. Leveraging the high dimensionality of AVIRIS data for improved subpixel target unmixing and rejection of false positives: mixture tuned matched filtering. Summaries of the seventh annual JPL airborne geoscience workshop; October 1998; Pasadena, CA. p 581–583.

Congalton, R. G., and K. Green. 1999. Assessing the accuracy of remotely sensed data: Principles and practices. Boca Raton, FL: Lewis Publishers. 160 p.

Daubenmire, R. F. 1958. A canopy-coverage method for vegetation analysis. *Northwest Science* 53:43–64.

Efron, B. 1979. Bootstrap methods: another look at the jackknife. *Annals of Statistics* 7:1–26.

Everitt, J. H., G. L. Anderson, D. E. Escobar, M. R. Davis, N. R. Spencer, and R. J. Andrascik. 1995. Use of remote sensing for detecting and mapping leafy spurge (Euphorbia esula). *Weed Technology* 9:599–609.

Goodchild, M. F., G. S. Biging, R. G. Congalton, P. G. Langley, N. R. Chrisman, and F. W. Davis. 1994. Final report of the Accuracy Assessment Task Force. California Assembly bill AB1580. Santa Barbara: University of California, National Center for Geographic Information and Analysis.

Johnson, T., G. Russel, and K. T. Weber. 2001. GAP analysis agreements of rangeland vegetative communities of southeast Idaho. Available at: http://giscenter.isu.edu/research/techpg/nasa_wildfire/abstracts/GAP_2002_abstract.pdf. Accessed 20 January 2004.

Kruse, F. A., A. B. Lefkoff, J. W. Boardman, K. B. Heidebrecht, A. T. Shapiro, P. J. Barloon, and A. F. H. Goetz. 1993. The Spectral Image Processing System (SIPS)—interactive visualization and analysis of imaging spectrometer data. *Remote Sensing of Environment* 44:145–163.

Lillesand, T. M., and R. W. Kiefer. 2000. Remote sensing and image interpretation. 4th ed. New York: John Wiley and Sons. 724 p.

McMahan, J. B., and K. T. Weber. 2003. Validation alternatives for classified imagery. *In:* K. T. Weber [ed.]. Final report: Wildfire effects on rangeland ecosystems and livestock grazing in Idaho. 209 p. Available at: http://giscenter.isu.edu/research/techpg/nasa_wildfire/Final_Report/Documents/Chapter10.pdf. Accessed 1 August 2005.

McMahan, J. B., K. T. Weber, and J. Sauder. 2003. Fuzzy classification of heterogeneous vegetation in a complex arid ecosystem. *In:* K. T. Weber [ed.]. Final report: Wildfire effects on rangeland ecosystems and livestock grazing in Idaho. 209 p. Available at http://giscenter.isu.edu/research/techpg/nasa_wildfire/Final_Report/Documents/Chapter7.pdf. Accessed 1 August 2005.

McMahan, J. B., W. C. Witt, and K. T. Weber. 2000. GAP analysis ground-truthing in southeastern Idaho. Available at: http://giscenter.isu.edu/research/techpg/lcc/documents/GAP_ABfinal.pdf. Accessed 20 January 2004.

Mundt, J. T. 2003. Detection of leafy spurge (Euphorbia esula) in Swan Valley, Idaho, using hyperspectral remote sensing with limited training data [master's thesis]. Pocatello: Idaho State University, Department of Geosciences. 107 p.

Parker-Williams, A., and E. R. Hunt, Jr. 2002. Estimation of leafy spurge cover from hyperspectral imagery using mixture tuned matched filtering. *Remote Sensing of Environment* 82:446–456.

Parker-Williams, A., and E. R. Hunt, Jr. 2004. Accuracy assessment for detection of leafy spurge with hyperspectral imagery. *Journal of Range Management* 57:106–112.

Pechanec, J. F., and G. D. Pickford. 1937. A weight estimate method for determination of range or pasture production. *Journal of the American Society of Agronomy* 29:894–904.

Peleg, K., and G. L. Anderson. 2002. FFT regression and cross-noise reduction for comparing images in remote sensing. *International Journal of Remote Sensing* 23:2097–2124.

Reeves, M. C., J. C. Winslow, and S. W. Running. 2001. Mapping weekly rangeland vegetation productivity using MODIS algorithms. *Journal of Range Management* 54:A90–A105.

Richards, J. A. 1993. Remote sensing digital image analysis. New York, NY: Springer-Verlag. 363 p.

Serr, K., T. K. Windholz, and K. T. Weber. 2005. Comparing GPS receivers: A field study. Available at: http://giscenter.isu.edu/research/techpg/nasa_weeds/to_pdf/gps_accuracy_precision.pdf. Accessed 11 May 2005.

Titus, K., J. A. Mosher, and B. K. Williams. 1984. Chance-corrected classification for use in discriminant analysis: ecological applications. *American Midland Naturalist* 111:1–7.

US Geological Survey. 2003. USGS Landsat project. Available at: http://landsat.usgs.gov/history.html. Accessed 21 October 2003.

Weber, K. T., and J. B. McMahan. 2003. Field collection of fuel load and vegetation characteristics for wildfire risk assessment modeling: 2002 field sampling report. *In:* K. T. Weber [ed.]. Final report: Wildfire effects on rangeland ecosystems and livestock grazing in Idaho. 209 p. Available at: http://giscenter.isu.edu/research/techpg/nasa_wildfire/Final_Report/Documents/Chapter2.pdf. Accessed 1 August 2005.

Witt, W. C., and K. T. Weber. 2001. Project report: Land cover change detection error assessment. Available at: http://giscenter.isu.edu/research/techpg/lcc/documents/2000_report.pdf. Accessed 14 January 2004.