CHALLENGES OF INTEGRATING GEOSPATIAL TEHCNOLOGIES INTO RANGELAND RESEARCH AND MANAGEMENT

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Abstract

With the development and commercial availability of sub-meter spatial-resolution satellite imagery, geospatial tools can accommodate the needs of range professionals better 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 receivers. To produce reliable rangeland models it is important to collect field data which corresponds with what the satellite "sees". Further, it is frequently necessary to use high-resolution imagery which subsequently necessitates the use of high-accuracy global positioning system receivers to ensure field data is recorded in the correct pixel and properly co-registered. This paper describes the results of research and experimentation that have lead to the development of techniques to improve geo-spatial 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 global positioning system receiver with accuracy $\leq$50% of the size of satellite imagery pixels (e.g., if Landsat imagery is used –with 28.5m pixels—the GPS receiver must be able to achieve ±14m accuracy with 95% confidence). Finally, a series of best practices are suggested to help range managers and range scientists better understand and implement geo-spatial technologies.

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 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 (USGS 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 meters) and the small number of spectral bands (4) , 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 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 meters) are commercially available, so are sophisticated hyperspectral remote sensing platforms that record over 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 ($\geq$ 75% overall accuracy; Goodchild et al. 1994, Pettingill, J. pers. comm.2002), high-spatial resolution remote sensing imagery (pixel size < 2.5 meters) must be geo-registered very well (root mean square error (RMS) $\leq$ 1m) and field observation points must be accurately located ($\pm$ 1m). Generally, any single point can be geolocated only to within $\pm$ 0.5 pixel for raster and grid data. When using Landsat TM imagery, this means the horizontal positional accuracy of field locations could not exceed $\pm$ 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 $\pm$ 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 three 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 global positioning system receivers for image rectification and co-registration 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 two vegetation sampling techniques. The first followed more traditional vegetation sampling techniques and consisted of a 20 m base line directly north of each randomly located sample point. At 10 m increments (0, 10, and 20 m) along the base line, three 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 meter-stick placed perpendicular to the ground surface. All cover intersecting the meter-stick 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 one 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 two of those classifications. The first attempts a very detailed classification using seventeen cover classes (Table 1). The second uses simplified cover category data generalized into seven classes (Table 2). In both cases Landsat 5 thematic mapper data was used, which has a spatial resolution of 28.5 x 28.5 meter pixels. Following this, validation of each model was performed using traditional boot-strap estimation techniques (Efron 1979, McMahan and Weber 2003) and Kappa statistic (Titus et al. 1984; Congalton and Green 1999). Boot-strap estimation is a technique whereby a sub-set of hypothetical samples is drawn from an original larger sample set. These sub-sets are then iteratively analyzed and accuracy determined using the inverse or unused sub-set. 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 1500 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), 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 the summer of 2002. Validation was then performed using standard boot-strap techniques and calculated as an error matrix with Kappa statistic. The criteria used for evaluation were 1) cost-effectiveness and 2) classification accuracy, where an accurate and reliable classification is defined as having ≥ 75% accuracy with minimal omission error.

To consistently satisfy geo-registration and co-registration 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 three types of GPS receivers (Trimble ProXR, Trimble GeoXT, and Trimble GeoExplorer II). A primary differences 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 Wide-Area Augmentation System (WAAS) for real-time differential correction. In all experiments, 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 based on triangulation, PDOP masks are used to ensure optimal satellite geometry (i.e., the satellites used are not clustered close to one another). All locations were evaluated in raw format as well as post-processed differentially corrected format and evaluated for horizontal positional accuracy relative to the location of the City of Pocatello's ground control points established using traditional survey methods and survey-grade GPS with real-time differential correction from a US Geodetic CORS 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 four 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 1500 (Richards 1993, Lillesand and Kiefer 2000) (Table 4). Class 8 is separable from class 13 based upon an increase in shrub cover from 16-25% to 26-35%. Class 8 is also separable from class 15 based upon an increase in shrub cover from 16-25% to ≥36% and a loss of grass cover from 6-15% to 1-5%. Lastly, class 13 is separable from class 15 based upon 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 seven 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 > 1500 (Table 5).

These analyses show that even with high spatial resolution data, there is a limit to the amount of usable information 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 also on the soil background reflectance (Asner 2004). Reliable sub-species differentiation of plants has not been demonstrated nor has reliable differentiation of similar grasses and shrubs (e.g., differentiating crested wheatgrass from bluebunch wheatgrass) 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 (≥ 75% overall accuracy) of rangelands with models built from multispectral satellite imagery requires the use of categorical training site data. Applying training data that is 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, SPOT5, 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 towards 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 geo-rectification process easier since the imagery is "closer" to its correct location than if it were not terrain corrected.

An interrelated 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 where Landsat or MODIS 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 km^2 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 non-target features and helps explain improved detection accuracy during this time period.

Rectification and Registration

The Trimble ProXR GPS receiver consistently (95% CI) achieved sub-meter 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 sub-meter 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 (±1.2m) 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 resourcegrade GPS receivers is necessary to satisfy horizontal positional accuracy requirements (95% CI = ±1.2m).

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 two 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 WGS84 used as its horizontal datum. Any datum transformations and/or projections (i.e., converting geographic to UTM) 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 which 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 post-process 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 (3D mode). A twelve-channel receiver will provide higher location precision than a six-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 and/or map. For applications using high-spatial resolution imagery, reflective tarps will need to be staked in the field prior to image acquisition so rectification and co-registration is as accurate as possible.
9) Invest in geotechnical training and/or geotechnically trained personnel.

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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
1- rocks/ bare soil/ lichen crust	1-5%	1-5%	≥36%
2- low grass	1-5%	6-15%	≥36%
3- medium grass	1-5%	16-25%	≥36%
4- high grass	1-5%	26-35%	≥36%
5- low grass/shrub mix	6-15%	6-15%	≥36%
6- medium grass- low shrub mix	6-15%	16-25%	≥36%
7- high grass- low shrub mix	6-15%	≥36%	<36%
8- medium shrub- low grass mix	16-25%	6-15%	≥36%
9- medium grass/shrub mix	16-25%	16-25%	<36%
10- medium grass/shrub with rocks/bare soil/ lichen crust	16-25%	16-25%	≥36%
11- high shrub	26-35%	1-5%	≥36%
12- high shrub- low grass mix	26-35%	6-15%	<36%
13- high shrub – low grass mix with rocks/bare soil/ lichen crust	26-35%	6-15%	≥36%
14- high shrub- medium grass mix	26-35%	16-25%	≥36%
15- very high shrub	≥36%	1-5%	≥36%
16- very high shrub- low grass mix	≥36%	6-15%	<36%
17- very high shrub- low grass mix with rocks/ bare soil/ lichen crust	≥36%	6-15%	≥36%

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
1- grass with rocks/ bare soil/ lichen crust	<16%	≥16%	≥26%
2- grass	<16%	≥16%	<26%
3- shrubs with rocks/ bare soil/ lichen crust	≥16%	<16%	≥26%
4- shrubs	≥16%	<16%	<26%
5- grass and shrub mix with rocks/ bare soil/ lichen crust	≥16%	≥16%	≥26%
6- grass and shrub mix	≥16%	≥16%	<26%
7- rocks/ bare soil/ lichen crust	<16%	<16%	≥26%

Table 3. Accuracy and precision of global positioning system (GPS) receivers. Values are expressed in meters at the 95% confidence interval using a 120 position average per point (n = 70 points).

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

1. Using WAAS real-time differential correction along with post-processing.

Note: All results reported using post-process differential correction.

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

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17
C1	0																
C2	0	0															
C3	1999	0	0														
C4	2000	0	1999	0													
C5	1999	0	835	0	0												
C6	1999	0	1995	1829	1999	0											
C7	1761	0	1999	2000	1999	1999	0										
C8	1999	0	5.72	0	61	1999	1999	0									
C9	1999	0	1999	1999	1999	1623	1999	1999	0								
C10	1999	0	1170	0	968	1999	1999	1137	2000	0							
C11	1999	0	608	0	114	1998	1999	107	1999	995	0						
C12	2000	0	1999	0	1999	2000	2000	1999	2000	2000	1999	0					
C13	2000	0	1999	0	199	2000	2000	1999	2000	2000	1999	0	0				
C14	2000	0	2000	2000	1999	1999	1999	121	2000	2000	2000	2000	2000	0			
C15	2000	0	871	0	272	1999	1999	1999	2000	1442	308	1995	2000	2000	0		
C16	1999	0	2000	2000	1999	1999	1999	1999	1999	2000	1999	2000	2000	2000	2000	0	
C17	1426	0	1999	1999	1998	1999	1606	2000	1999	1999	1999	2000	2000	2000	1999	2000	0

Categories with a sufficient number of training sites (n ≥ 30) are shaded (C5, C8, C13, and C15). Of these, three were statistically separable based on a transformed divergence index ≥ 1500. The separable cover classes are those where shrub cover exceeds 16%, bare ground exceeds 36% and minimal grass cover is present.

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

	C1	C2	C3	C4	C5	C6	C7
C1	0						
C2	1973	0					
C3	1999	569	0				
C4	1090	1999	1999	0			
C5	1801	1733	1710	1732	0		
C6	1293	914	7.92	1608	518	0	
C7	2000	2000	2000	2000	2000	2000	0

All categories had a sufficient number of training sites (n>30); pairwise comparisons that are significant different are shaded. The cover class descriptions are give in Table 2.

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 32,400km^2
Landsat TM	30	32,400	$650	$0.02	$650
SPOT 5	10	3,600	$3,259[1]	$1.10	$35,640
Quickbird	2.4	64	$1,920	$30.00	$972,000