CHALLENGES OF INTEGRATING GEOSPATIAL TECHNOLOGIES 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. This paper discusses the opportunities and challenges offered by today's state-of-the-art geotechnologies. In addition, a series of best practices are provided to help range managers and range scientists better understand this technology.

Introduction

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. While this satellite represented an enormous advance in geotechnical capabilities, it fell far short of the needs and demands of the range community, because of the sensor’s spatial resolution (pixel size of 80 meters) and the small number of spectral bands (4) available, both of which severely limited its applicability. In addition, the heterogeneity and complexity of rangeland ecosystems and the fact that rangeland plants/stands are quite small (in contrast to forested ecosystems where Landsat imagery has yielded more satisfactory results) relatively low classification accuracies resulted (<75% overall accuracy ((McMahan et al 2000, Johnson et al 2001)). Today, high-spatial resolution multispectral satellite imagery (pixel size of <5 meters) is commercially available, so are sophisticated hyperspectral remote sensing platforms that record over 100 spectral bands of data across the electromagnetic spectrum (approximately 450nm-2500nm wavelengths). 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.

Whereas 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 (e.g., >75% overall accuracy), high-spatial resolution remote sensing imagery (e.g., pixel size of 2.5 meters) must be geo-registered very well (RMS ≤1m) and field observation points must be accurately located (+/-1m). In addition, these data must be accurately co-registered with the imagery. When using Landsat TM imagery, this means the horizontal positional accuracy of field locations could not exceed +/- 15.0m (+/-0.5 pixel) (i.e., field training sites had to register within the correct pixel of the imagery). Such generous error margins are easily satisfied today with even fairly simple GPS receivers. This same "rule of thumb" (+/-0.5 pixel) applies to all imagery, however, so when using high-spatial resolution imagery, acceptable horizontal positional accuracy is reduced to +/- 1.2 m as in the case of Digital Globe's Quickbird imagery (pixel size of 2.4 meters). To satisfy the latter accuracy requirement involves the use of more sophisticated GPS receivers and more stringent data collection protocols.

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, Williams and Hunt 2002, and Mundt 2003). To satisfy these criteria requires the use of state-of-the-art instrumentation, powerful computers, and highly skilled analysts.

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

Methods

Sampling vegetation in the field that results in an accurate description of rangelands is an age-old problem (Pechanec and Pickford 1937, Daubenmire 1958). 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 fails to yield highly accurate and reliable classifications (<75% overall accuracy)(Witt and Weber 2000). 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).

Numerous classifications and models were generated using both types of field data. 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). 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 separable each category or class of data is, based on the spectral signatures extracted from available imagery.

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 meters), SPOT 5 (pixel size of 10 meters), and Quickbird (pixel size of 2.4 meters) 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 $\geq$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 WAAS for real-time differential correction. In all experiments, estimations were acquired only under 3D GPS conditions (i.e., a minimum of 4 concurrent GPS signals were processed), 120 positions were averaged per point, and the PDOP mask was set at 6.0. All locations were evaluated in raw format as well as post-process differentially corrected format and evaluated for horizontal positional accuracy relative to a known location (e.g., typically a level 1 geodetic marker).

Results

Field Sampling for Rangeland Remote Sensing

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 is more detailed (i.e., cover data collected at species levels) frequently results in unacceptably poor accuracy. Tables 1 and 2 provide a comparison of percent cover classifications for rangelands in southeastern Idaho. Table 1 describes separability of 253 training sites into 17 cover categories (eight sagebrush cover categories with varying amounts of grass and bare ground understories). Note that 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 2 describes separability of the same training sites generalized into eight cover categories. Seventy-one percent (15 of 21) of these categories were statistically separable.

Selection of Appropriate Spatial Resolution

Improved spatial resolution has allowed researchers to improve classification accuracy relative to platforms such as Landsat TM. Figure 1 illustrates mean classification accuracies using maximum likelihood, minimum distance to means, and spectral angle mapper classification techniques for leafy spurge infestation detection in southeastern Idaho. An inverse relationship exists between spatial resolution and overall classification accuracy for leafy spurge detection.

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 (+/-0.96 m @ 95% CI). In contrast, the Trimble GeoExplorer II GPS receiver achieve horizontal positional accuracy of +/-3.25 m @ 95 CI), which failed to consistently achieve the accuracy needed (+/-1.2m) to collect field sample points for use with high-spatial resolution imagery even when differentially corrected.

Discussion

Field Sampling for Rangeland Remote Sensing

Collecting detailed vegetation data --like that described above-- is typically unnecessary for use with current multispectral remote sensing satellites. 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 the desired mapping or modeling result. In other words, field personnel must collect measurements and observations that will correspond with what the satellite "sees". As a rule of thumb, land cover estimates and measurements must never exceed 100% since multispectral imagery cannot be expected to sensor anything beneath the upper-most canopy.

Selection of Appropriate Spatial Resolution

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. 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 meters) 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 (e.g., land cover change, rangeland trend analysis, etc.).

SPOT 5 imagery (pixel size of 10 meters) was able to achieve reasonable accuracy (figure 1) at a much reduced cost (table 3). 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. Yet, the overall accuracy (51%) of SPOT imagery for detection of leafy spurge may be adequate for weed management. Further, because of larger pixel size (pixel size of 10 meters) the use of SPOT imagery makes co-registration (i.e., positioning a field sample within the correct pixel) easier.

In addition to these considerations, the user should also consider the temporal aspects of image acquisition, specifically as it relates to the phenology of targeted plant species. Figure 1 illustrates the variation in overall accuracy when using imagery acquired in early summer (78%) versus late summer (67%).

Rectification and Registration

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 (e.g., +/-1.2m @ 95% CI).

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 geographic with WGS84 used as its horizontal datum. Any datum transformations and/or projections (i.e., converting geographic to UTM) are usually handled “on-the-fly” through receiver specific software. Ordering imagery in a specific coordinate system is usually acceptable.

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 will corroborate well with "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". Using this statement, select the most cost-effective imagery platform.

3) Understand that cost-effectiveness means the least expensive platform that satisfies your accuracy requirements. Choosing the platform that is simply the least expensive can result in 100% waste of financial resources.
4) Invest in research grade GPS receivers.
5) Collect all GPS points using the native latitude-longitude and WGS84.
6) Establish a good "baseline" 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).
   b. Use WAAS real-time differential correction whenever available.
   c. Work in 3D mode at all times (where 4 or more GPS satellite signals are always available to the receiver).
   d. Establish and follow PDOP and elevation mask protocols.
7) Collect geo-registration control points in the field. Use these to test and correct imagery as needed. 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.
8) If real-time differential correction (producing acceptable horizontal positional accuracy (e.g., +/-1.2 m 95% CI) is not available, use post-process differential correction for all GPS acquisitions.
9) Invest in geotechnical training and/or geotechnically trained personnel.

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Table 1. Separability of training sites using 17 cover categories (C1-C17)(separability calculated using transformed divergence).

	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 ($n \geq 30$) are highlighted (C5, C8, C13, and C15). Of these, three are statistically separable (C8 is separable from C13, C8 is separable from C15, and C13 is separable from C15).

Table 2. Separability of training sites using 8 cover categories (C1-C8)(separability calculated using transformed divergence).

	C1	C2	C3	C4	C5	C6	C8
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	
C8	2000	2000	2000	2000	2000	2000	0

All categories had a sufficient number of training sites. Fifteen of 21 were statistically separable.

Table 3. 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

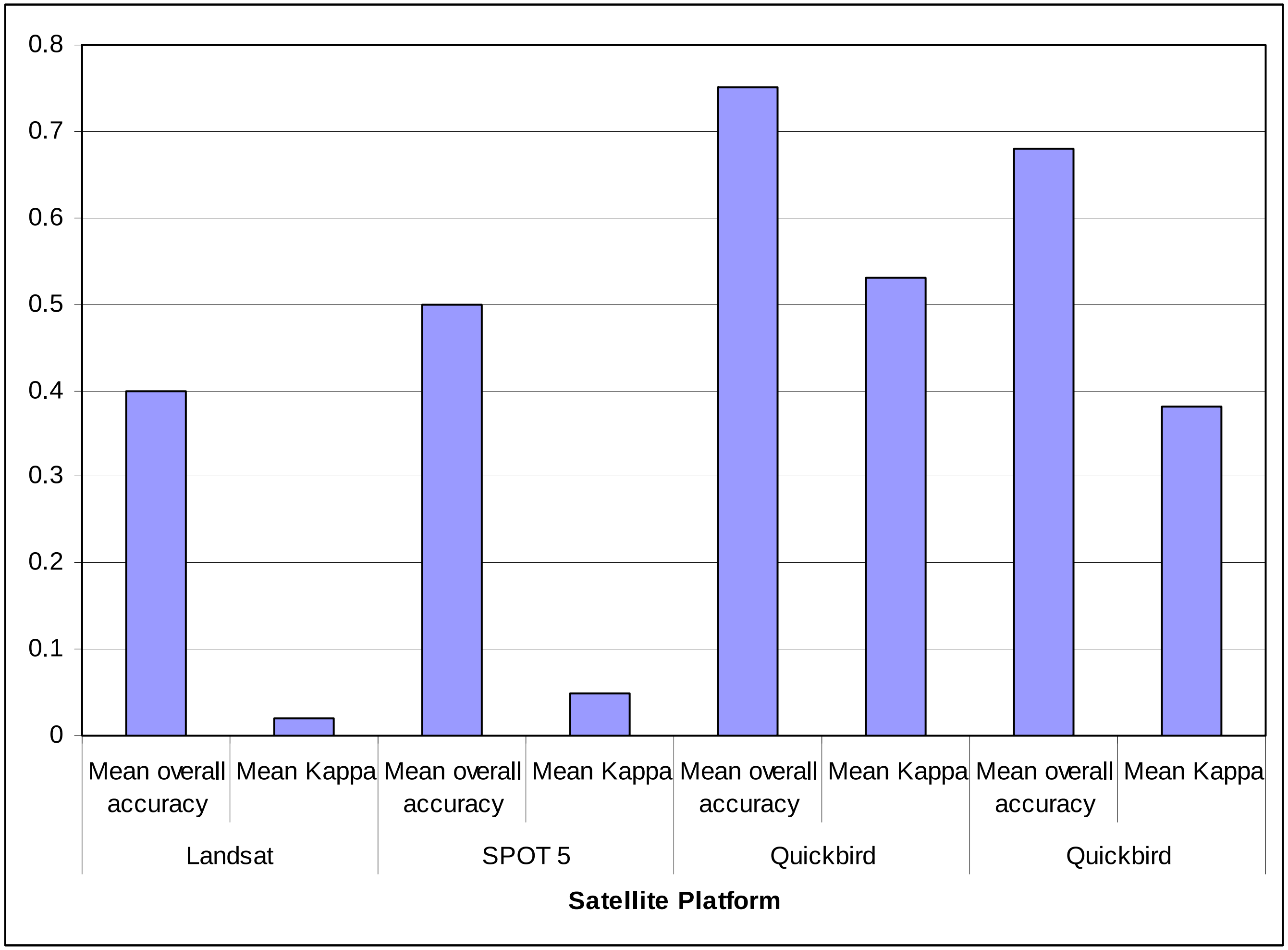

Figure 1. Mean accuracy of leafy spurge classifications (maximum likelihood, minimum distance to means, spectral angle mapper) derived from various satellite platforms. Quickbird 1-Satellite imagery acquired in early summer, Quickbird 2- imagery acquired in late summer.