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A comparison of single date and multitemporal satellite image classifications in a semi-arid grassland

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Landsat Thematic Mapper (TM) satellite data were used to produce maps depicting ranges of major vegetation types at the Jornada Experimental Range, New Mexico, U.S.A. Single date and multitemporal classification accuracies were compared using vegetation ground data as references. Single date image classifications were more accurate than multitemporal images for mapping land cover types in this region. Use of single date imagery generally involves less expenditure of time and costs related to data acquisition and processing. Multitemporal images have improved classification accuracies in some landscapes; however, single date images may provide a reliable method for mapping vegetation cover in semi-arid environments.

Keywords: Jornada; remote sensing; semi-arid grassland; multitemporal; vegetation classification

Introduction

Land cover and land use classifications from remotely sensed data are often used for mapping and inventory of natural resources over relatively large areas. Satellite image data can be used with field data to map existing vegetation or changes in land cover over time. Earth-observing satellite imagery and data, like the U.S. Landsat satellites, have been used by plant ecologists to aid in land cover assessment (Petersen *et al.*, 1987; Quattrochi & Pelletier 1991), changes in land cover (Pickup & Foran, 1987; Fiorella & Ripple, 1993), and in mapping vegetation types and seasonal changes (Briggs & Nellis, 1991; Loveland *et al.*, 1995). Image data may also be used to examine large-scale spatial patterns, to assess damage after a disturbance like a fire or a hurricane, and to study the vegetation response to a disturbance.

Combining and classifying bands from more than one date, season, or year, is known as multitemporal classification. Multitemporal classifications have been used to map vegetation in a variety of environments including wetlands (Lunetta & Balogh, 1999), forests (Mickelson *et al.*, 1998), and semi-arid mountain regions (Storms *et al.*, 1998). The Kansas GAP project used a multi-seasonal approach to map grasslands from Landsat Thematic Mapper (TM) imagery (Egbert *et al.*, 1995, 1997). Multitemporal classifications proved successful at discriminating land cover types in these studies. Multiple date analyses involve acquiring two or more images, co-registering multiple images, and handling of larger data sets. These factors may lead to increased costs and handling time for a project.

Various types of ecological experiments utilizing remotely sensed data have been conducted at, or have focused on, the Jornada del Muerto Basin. Included in these studies were an assessment of spectral vegetation indices (Duncan *et al.*, 1993), a study that used principal components analysis (PCA) with multitemporal data (Yool *et al.*, 1997), and one that used a normalized difference vegetation index (NDVI) and time-series analysis over a growing season (Peters *et al.*, 1997). Eve *et al.* (1999) used remotely sensed data to determine if irreversibly degraded areas remained spectrally consistent over time. These studies used sensors other than Landsat TM and focussed on spectral relationships and change detection rather than on vegetation mapping.

In a practicum conducted by University of Wisconsin, graduate students used supervised and unsupervised classification of principal components derived from Landsat TM scenes from five different dates to map vegetation over Jornada. The focus of this practicum was to learn fundamentals of image processing and no final products were generated. However, using a small number of field references, the students demonstrated that unsupervised methods were more appropriate for the data and information available (Scarpace *et al.*, 1995). The overall accuracy of the various products ranged from 60–70%, depending on which field data points were included.

The use of multitemporal data has not yet been fully explored in semi-arid environments. We hypothesized that a multitemporal image classification would yield a more accurate classification than that of a single date. Information from more than one season may help the producer to discriminate between vegetation types and species based on information available at different times of the year. Onset of greenness and senescence occur in different species at different times. The primary objective of this study was to compare single date and multitemporal image classifications using vegetation ground data as references. Landsat TM data from three dates, and four combinations of these dates, were used to classify vegetation on the Jornada Experimental Range. Accuracy of each of the resulting seven classification files was assessed and a final vegetation classification map was produced.

Study site: the Jornada Experimental Range and the long-term ecological research (LTER) program

The United States Department of Agriculture (USDA) established the Jornada Experimental Range in 1912. It is now part of the Agricultural Research Service (ARS) (Jornada Staff, 1980) and the Long-Term Ecological Research (LTER) Program, administered by the National Science Foundation. The Jornada LTER site is located in the Jornada del Muerto (Journey of Death) plain of southern New Mexico (Fig. 1). One of the primary goals of the research carried out at the range is to examine the mechanisms leading to the desertification of semi-arid grasslands. The Jornada LTER site, primarily a semi-arid grassland, is located in the Chihuahuan Desert. This site consists of approximately 78,266 hectares (194,000 acres). Mean annual temperature is approximately 15·6°C (60·1°F) and mean annual rainfall is approximately 21 cm (about 8 inches) (Schlesinger *et al.*, 1990). More than 50% of the precipitation occurs from July to September. One aspect of the current research involves the investigation of cattle grazing as a long-term disturbance in this ecosystem (Schlesinger & Reynolds, 1994). This area was not historically grazed by bison or other large herbivores and has a very short evolutionary history of cattle grazing (Schlesinger & Reynolds, 1994). Consumers such as lizards, birds, rabbits, and insects historically harvested less than 10% of the net primary production (NPP) (Schlesinger & Reynolds, 1994). In the 100 years or so since the introduction of cattle to this region, large stretches of black grama (*Bouteloua eriopoda*) grassland have been succeeded by communities dominated by shrubs, most

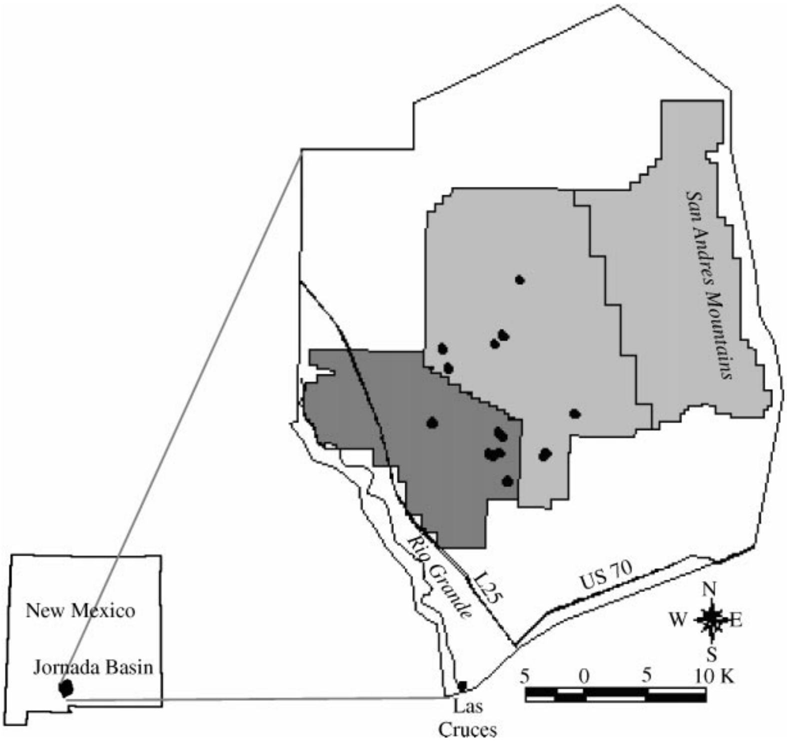

Figure 1. The Jornada Experimental Range, Las Cruces, New Mexico. The Range is located 23 miles (37 km) north of Las Cruces. Most of the Range is on the Jornada del Muerto Plain, which lies between the Rio Grande Valley on the west and the San Andres Mountains on the east. The crest of the San Andres Mountains roughly coincides with the eastern boundary of the Range (after http://jornada.nmsu.edu/gis-rs/gis/gis_frm.htm). LTER permanent plots (●), basin boundary (▢), Jornada Experimental Range ; Chihuahuan Desert Rangeland Research Center (▣).

prominently creosote (*Larrea tridentata*) and mesquite (*Prosopis glandulosa*) (Buffington & Herbel, 1965). Today, the resultant landscape is a mosaic of grasslands and expanses of relatively bare ground dotted with ‘shrub islands’. In the proposal for Phase II of the LTER work, Schlesinger and Reynolds (1994) hypothesized that ‘during desertification the distribution of soil resources changes from spatially homogeneous, as seen in semi-arid grasslands, to heterogeneous, as seen in shrublands’ (Schlesinger *et al.*, 1990). Grazing in semi-arid grasslands may effect changes in ecosystem properties leading to changes in the vegetation cover. The interactions between grazing and ecosystem properties, including net primary productivity, water use, and nitrogen cycling, may result in a fairly homogenous grassland community changing to a spatially heterogeneous shrub land community. These changes may be detectable and perhaps could be identified or predicted with the use of remotely sensed data. Satellite data are among the tools being utilized to better understand and map change at this site. Remote sensing may be useful in identifying and defining the spatial distribution of grasslands and shrub islands at all hierarchical levels being investigated in this semi-arid region.

Methods

All Landsat Thematic Mapper (TM) data used in this project were acquired in the USDA/ARS JORNEX project (Rango *et al.*, 1998). The resolution of the six Landsat bands corresponding to visible and reflected infrared (IR) is 30 × 30 m and 120 × 120 m for the thermal band. A standard Landsat TM image covers 185 × 170 km. Landsat 5 scenes for World Reference System, Path 33, Row 37, were acquired for the study area for three different dates: 5 June 1995, 25 September 1995, and 16 February 1996. The three scenes were registered to a Transverse Mercator projection and geocoded with Universal Transverse Mercator (UTM) coordinates at the Agricultural Research Service (ARS) in Beltsville, Maryland, using control points established with Global Positioning System (GPS) units on site. The three scenes were also co-registered to each other. All pre-processing steps were performed using the software package PCI. The PCI files were then imported into the Erdas IMAGINE software package. The scenes were subset using UTM coordinates located outside of the range boundaries for the four corner points to clip out identical areas of interest from each scene. The resulting subsets were 1220 pixels high by 821 pixels wide, resulting in an image covering approximately 90,146 hectares (220,356 acres).

Landsat TM bands 3 (red), 4 (near infrared), and 5 (mid-infrared) were used in analyses for consistency between dates and to reduce the redundancy inherent in the spectral information. In general, there is a high degree of correlation between bands 1, 2, and 3 (the visible bands) (Jensen, 1996). Bands 4, 5, and 7 are also usually highly correlated. Band 3 (0·63–0·69 μm) is an important band for vegetation discrimination and, unlike bands 1 and 2, has fewer effects due to atmospheric attenuation (Jensen, 1996). Reflectance in this band, known as the red chlorophyll absorption band, is largely controlled by chlorophyll *a*, chlorophyll *b*, and leaf pigments such as carotenoids, xanthophylls, and anthocyanins (Jensen, 1996). Band 4 (0·76 to 0·90 μm) is sensitive to canopy cover or vegetation biomass (Jensen, 1996). Leaf structure, the internal air spaces and water filled cells in the spongy mesophyll of the leaf, largely controls reflectance in this band (Campbell, 1987). Leaves at the top of the canopy may transmit as much as 50–60% of the near infrared (NIR) radiation. Lower leaves may then reflect some of it upward again, transmitting it back through the upper canopy leaves as bright infrared reflectance (Campbell, 1987). Band 5 (1·55–1·75 μm) is responsive to vegetation stress or disease. Reflectance in this band is controlled by leaf cell turgor, which is directly related to the amount of water in the cell (Campbell, 1987). When a leaf wilts, less light is scattered and there is an increase in the reflectance of red (band 3) and a decrease in the mid-infrared (band 5) because of decrease in chlorophyll and water content (Campbell, 1987; Jensen, 1996).

The single date subset images were combined using all possible one, two, and three date combinations. This produced seven multitemporal image files of TM bands 3, 4, and 5 for each of the three dates: February, June and September. Six target vegetation classes (grass, mesquite, creosote, tarbush, yucca, and unvegetated) were selected for these analyses based on existing vegetation maps (Jornada Staff, 1980; Duncan *et al.*, 1993) and knowledge of the area. These six vegetation classes were chosen because they closely corresponded to classes selected in previous analyses at the Jornada Range (Scarpace *et al.*, 1995; Duncan *et al.*, 1993; Jornada Staff, 1980) and their distribution is important for management decisions. A seventh class was created to account for areas obscured by shadows.

To maintain consistency, an unsupervised approach was used for all image classifications. This approach is often used in thematic mapping from imagery, is easy to apply, and widely available in image processing and statistical software packages. Test images were classified using different numbers of clusters to determine the number needed to discriminate the six vegetation classes. After preliminary assessment to establish the methodology, unsupervised classifications were performed on each of the image subsets from the three different dates using 25 clusters. Each of the 25 spectral clusters was then assigned to one of the seven target classes using existing vegetation maps (Duncan *et al.*, 1993; Jornada Staff, 1980), knowledge of the area, and phenological discrimination between vegetation types. Study plots outlined on a September 1989 SPOT XS false colour composite image of the Jornada basin (Duncan *et al.*, 1993) were the primary means of deciding which class a cluster was in or if it was a member of a confusion, or mixed, class. Knowledge of the area was helpful in making assignment decisions. A 1963 land cover map of brush species classes was also used as a reference (Jornada Staff, 1980). In addition, the single-date three band false colour composite images were referred to in order to distinguish phenological differences in the vegetation types for cluster class assignments. In some cases the assignment was ambiguous or mixed, because of confusion between two or more target classes. The ambiguous or confusion classes were noted, along with the probable classes to which the member pixels belonged.

A single masking operation was performed to extract the confusion classes from each of the seven data sets. Areas corresponding to confusion classes were again classified into 25 clusters, further separating these clusters. The resultant 25 clusters were then assigned to one of the seven target classes using the same references and criteria used previously. The masking operation and subsequent classification of confusion clusters proved adequate for classifying the six vegetation types.

Due to time and cost constraints two sets of vegetation data acquired in a previous study (Scarpace *et al.*, 1995) were used for accuracy assessment. The first data set consisted of nineteen sites with three co-dominant plant species recorded for each nine metre circular plot. UTM coordinates for the centre point of each plot were recorded using Differential GPS. The second data set was a survey conducted along roads of one to three dominant species, or bare ground. UTM coordinates were determined from map measurements at 29 points using road intersections and other landmarks. A total of 48 sites and 15 plant species were listed in the two reference files, including bare ground at two sites. Mormon tea (*Ephedra trifurca*) and snakeweed (*Gutierrezia sarothrae*) were present in the study area but are found in association with both grasses and shrubs and do not form distinct communities. Consequently, these two species were not considered to be dominant and were eliminated from the analyses. Nine species of grass were also listed as present and were combined into one image category. Point files were created from the ground reference data using UTM coordinates for each sample site.

Classification accuracies for the seven different image data sets were assessed individually by overlaying each output with the ground reference points. Individual points were determined to be correctly classified if, on the image, the image category occurred within five pixels of the estimated position of the field data. A buffer was allowed to account for geometric registration errors in the image, GPS errors, and errors in the estimated positions of points acquired along roads without GPS. In addition, small scale patchiness, such as that exhibited at the Jornada Range, may make it difficult to relate point data acquired in the field to pixel-based classifications. In the type of discrete classification that was used, mixed pixels are identified as members of one particular group and assigned to it accordingly. Pixels may be only partial members of the class to which they are assigned. General patterns of patchiness can be seen in the image while specific patch locations may be too small to be resolved.

Error matrices were established comparing reference classes to target classes for each of the seven assessments. Row entries represent the number of samples classified in a particular category; column entries represent reference or actual sites in the error matrix. One site that fell in shadow in the February image was dropped from analysis.

Three important statistics are generally reported when assessing accuracy. The diagonal values in the matrix (the number of pixels that are correctly identified) may be summed and divided by the total number of points as a measure of the overall accuracy (Jensen, 1996). User accuracy and producer's accuracy are the flip side of commission and omission errors, respectively. User accuracy is a percentage measure indicating the probability that a pixel included in a class actually represents that category on the ground (Jensen, 1996). This measure is generated by dividing the number of correctly identified points (diagonal value) by the total number of points classified in that row. Producer's accuracy is a percentage measure of the omission error. It indicates how accurate the class is compared to the reference data or how well the area was classified (Jensen, 1996). This statistic is calculated by dividing the number of correctly identified points (diagonal value) by the total number of reference points in that column.

A discrete multivariate technique called KAPPA analysis yields an estimate called the K_{hat} statistic that measures the agreement or accuracy of the classification (Congalton & Mead, 1983). The K_{hat} statistic is calculated from a normalized error matrix and generally accounts for unequal class sizes. The K_{hat} statistic may be more representative of the overall accuracy because it contains information about the off-diagonal cell values, or the errors of omission and commission (Jensen, 1996), and measures the accuracy of the classification versus chance alone. This statistic also facilitates comparisons between interpreters and classification techniques. User's accuracy, producer's accuracy, overall accuracy, and the KAPPA statistic, K_{hat} (Congalton & Mead, 1983; Jensen, 1996) were calculated for each data set. Each of these statistics is useful for comparisons of accuracy between different interpreters and different methods.

Results

Results of the single date and multitemporal image classifications were compared by generating error matrices for each of the seven output maps (Table 1). Overall classification accuracies for the seven single date and multitemporal image classifications ranged from 81% in the February/June combination to 94% in the September image classification (Table 2). The highest K_{hat} was 92% (Table 2). This value may be more indicative of the overall classification accuracy because it contains information about the off-diagonal cell values. It indicates whether the results from the error matrix are significantly better than random. Both the highest overall accuracy and highest K_{hat} were for the single date September image classification (Fig. 2).

The lowest classification accuracy was a 53% user's accuracy for creosote in the February/June multitemporal classification. In this multitemporal image, areas classified as creosote had only a 53% probability of actually being creosote when compared to the reference data. All of the areas misclassified as creosote were, in fact, grass. For most of the single date and multitemporal classifications, the lowest accuracies for any individual class were associated with confusion between the categories 'creosote' and 'grass'. This categorical confusion accounted for relatively high omission errors for the grass category; areas omitted from grass tended to be misclassified as creosote. Omission and commission errors associated with the categories creosote and grass were lowest in the September image classification.

The two-date February/June combination and the three-date combination files had the lowest overall accuracies (Table 2). These image classifications also had a wide variation in both producer and user accuracies.

Discussion

The hypothesis that a multitemporal image classification would yield a more accurate classification than that of a single date was not supported by this study. While multitemporal classifications have been widely used to discriminate vegetation types, the use of multiple dates does not appear to enhance classification accuracies in the study area. Use of single date imagery generally involves less expenditure of time and costs related to data acquisition and processing and appears to generate satisfactory results.

The seasonality or phenological variation in vegetation types, at this time of year and in this region, may result in a more accurate classification map using a single image date.

Table 1. *Example of error matrix for February single date image classification*

Class	Grass	Mesquite	Creosote	Tarbush	Yucca	Unvegetated	Total interpreted	Commission error
Grass	14	0	0	0	0	0	14	0
Mesquite	1	10	0	0	1	0	12	2
Creosote	6	0	8	0	0	0	14	6
Tarbush	0	0	0	2	0	0	2	0
Yucca	0	0	0	0	3	0	3	0
Unvegetated	0	0	0	0	0	2	2	0
Total interpreted	21	10	8	2	4	2	47	
Omission error	7	0	0	0	1	0		

Overall accuracy is determined by dividing the sum of the diagonal elements by the total number of points sampled. A higher value for Producer Accuracy indicates how well the pixels were classified when compared to the reference data. A higher valuer for User Accuracy indicates that more image class pixels were correctly identified.

Table 2. *Results of accuracy assessments for the seven image classifications*

		Feb	June	Sept	Feb/Jun	Feb/Sept	Jun/Sept	Feb/June /Sept
Overall	Accuracy	83	90	94	81	85	88	83
K_{hat}		77	86	92	75	81	83	77
Producer	Max.	100	100	100	100	100	100	100
accuracy	Min.	67	81	88	60	63	73	53
User	Max.	100	100	100	100	100	100	100
accuracy	Min.	57	62	67	53	62	67	57

The K_{hat} statistic measures the accuracy of the class *vs.* chance alone. A higher value indicates a more accurate classification.

Multitemporal images which included the February data had the poorest results. The combination of senescence and winter shadowing in the February image may account for the low accuracies and low K_{hat} statistic for the single date and multitemporal image classifications. As a result, this image alone or in combination with any other image particularly lowered classification accuracies.

In general, classification accuracies for the June image were high, with the exception of confusion between the grass and creosote categories. While variations in the onset of greenness may help to differentiate between dominant vegetation types, the dominant vegetation types identified in this project were fully leafed out by June. The 'leaf on' conditions and high sun angles in the June image may help to account for the higher statistical accuracies when compared to the February image, but the relatively uniform phenological stage of the vegetation and dry conditions may have reduced spectral variability in the categories of interest. In addition, most of the grass species do not achieve peak tissue greenness until after the late summer/early fall rainy season. This image in combination with other image dates may have reduced overall classification accuracies by reducing spectral differences among the vegetation classes. The combination of shadows present in the February image and reduced phenological variation in the June image may account for the combination image (February/June) having the lowest overall accuracy (81%) as well as the lowest reported accuracy for any single category (53% user accuracy for creosote).

The September image classification had the highest statistical accuracies among all single date and multitemporal image classifications (Table 2 and Fig. 2). The rainy season occurs in the late summer/early fall in this region. Some of the grasses, such as black grama, do not truly 'green up' until after the rainy season begins. Onset of greenness in this species, and others that respond dramatically to the increased moisture, may alter the spectral responses in the chlorophyll sensitive band, band 3. Changes in plant colours due to the onset of senescence in some species may also help to discriminate between vegetation types in band 3 in the fall. Mesquite and tarbush are mainly deciduous which would help distinguish these from the grasses; creosote is primarily marcescent, with leaves withering in autumn. The autumn rains may also alter the spectral responses of the predominately xerophytic plant communities in band 5. Band 5 is highly responsive to leaf cell turgor, which is directly related to the moisture regime and plant stress. Plant biomass, especially for the grasses, may also be highest here in the fall. Band 4 is responsive to the amount of vegetation present.

The combination of the two best single date images (June/September) actually lowered overall accuracy below either single date values. Grass is confused, in the combined image, with multiple categories, not just creosote. Combining individual images in which classes are spectrally distinct may offset the spectral distinctions. In addition, the effects of leaf litter on the soil surface may aid in discriminating

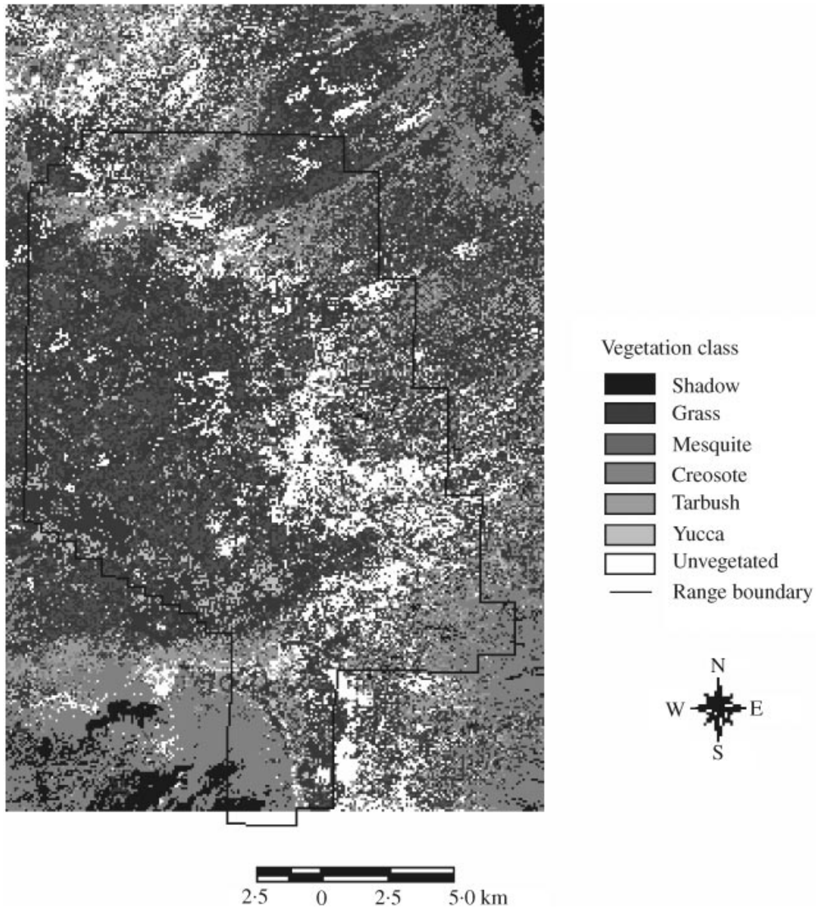

Figure 2. Classification map for September Landsat image bands 3, 4, and 5 at the Jornada Experimental Range. Image data were classified into one of seven dominant vegetation classes in this semi-arid grassland.

between grass dominated and shrub dominated areas throughout the year. The amount of leaf litter, especially in the grass dominated areas, may influence the pixel brightness values. Senescent black grama is a fairly dark, gray colour and the senescent material may remain on, or in close proximity to the base of the upright plant. Other herbaceous vegetation in the area also contributes to the amount of litter on the soil surface. The leaf litter obscuring the soil surface may be a factor in aiding in the discrimination between the spectral responses of shrub and grass areas later in the year. Mesquite, on the other hand, tends to trap litter at the trunk(s) of the stem(s). Bare branches radiate outward many feet above the soil surface and may obscure the spectral response of the trapped litter in the summer.

Summary

Single date Landsat TM data provided a reliable method for mapping vegetation cover in this semi-arid region. The September single image classification may be more accurate than the others because of more distinct spectral responses for the target vegetation classes and fewer shadows in this geographic region at this time of year. Reliable maps can thus be produced rapidly and inexpensively if the selected image is acquired at the time of maximum phenological variation.

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