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# Remote sensing for soil map unit boundary detection

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## ABSTRACT

Creating accurate soil maps at small scales using traditional methods is a time-consuming and expensive process. However, remote-sensing techniques can provide spatially and spectrally contiguous data in a timely manner. For this study, 20 root zone soil moisture maps derived from Landsat images during the growing season were used for the detection of soil boundaries. A split moving-window analysis along two demonstration transects in, respectively, a semi-arid desert and riparian area located in the Middle Rio Grande Valley of New Mexico showed that remotely sensed root zone soil moisture can reveal subsurface trends that can be used to identify soil boundaries that do not have a strong surface expression. Overall, the use of multiple remotely sensed root zone soil moisture and Landsat images for soil boundary delineation shows great promise of becoming a valuable tool in the field of digital soil mapping.

## INTRODUCTION

Soil conditions have an impact upon virtually all aspects of Army activities and are increasingly affecting its systems and operations. One critical soil condition is soil moisture because it affects operational mobility (Lessem et al., 1996), detection of landmines and unexploded ordnance **[[OK?]]** (Borchers et al., 2000; Das et al., 2001; Hong et al., 2001, 2002; **[[Please note: Citations changed to chronological order for consistency with other chapters.]]** Hendrickx et al., 2003; Van Dam et al., 2003, 2005; Miller et al., 2004), military engineering activities, blowing dust and sand, watershed responses (Senarath et al., 2000; Downer et al., 2002; Downer and Ogden, 2003, 2004; Niedzialek and Ogden, 2004), and flooding (Ogden et al., 2000; Dingman, 2002). Soil moisture also determines near-surface atmospheric conditions and the partition of incoming solar and long-wave radiation between sensible and latent heat fluxes (Shukla and Mintz, 1982; Milly, 1994). Atmospheric turbulence can hamper the performance of optical and infrared sensors as well as acoustic detection systems. The lack of reliable soil moisture maps for weather prediction models can result in significant over- or under-estimation of surface evaporation, which results in great **[["considerable"?]]** uncertainty for the predictions of cloud cover, precipitation, air and soil temperature, and humidity (van den Hurk et al., 1997).

Soil moisture is a very dynamic variable subject to rapid changes in time as well as with depth and space. Soil moisture fields are not continuous but are full of discontinuities caused by many factors, including: strong precipitation gradients, snowfall redistribution, topographical divides, slope-aspect, land use, differences in soil hydraulic properties, fluvial and/or aeolian deposition, human intervention (irrigation, drainage, and flooding), and vegetation cover. The existence of discontinuities in soil moisture fields and their temporal variability make it difficult to use statistical interpolation techniques based on a limited number of point measurements for the generation of high-resolution soil moisture maps. Predictions of regional soil moisture distributions with distributed hydrological models will be greatly improved when accurate soil maps are available that capture soil heterogeneities on a scale of tens of meters.

Soil maps of non-agricultural areas of the United States are usually Level Three surveys at a scale of 1:24,000, due to the logistical and cost constraints. However, there is an increasing demand for more accurate soil information of such areas for monitoring the impacts of climate change, environmental modeling, trafficability, land mine detection, etc. The traditional method of developing Level Three soil maps is through extensive use of aerial photographs, expert local knowledge of soil patterns, and limited validation through soil pit descriptions (Soil Survey

Staff, 1975). The technical limitations associated with producing larger-scale soil maps mean that remote sensing of soil properties is the only option for producing larger-scale soil maps of non-agricultural areas. **[[Sentence is a bit unclear. Would the following work: "Due to technical limitations associated with developing Level Three soil maps, remote sensing is the only option for producing larger-scale soil maps of non-agricultural areas."?]]**

The goal of mapping soils is to identify parts of the landscape that are relatively homogeneous with respect to the soil properties of interest. A key element of soil mapping is to identify and accurately locate the boundaries between units containing different soil properties. Soil boundaries are located where the rate of change of soil properties between two different units is the greatest. Identification of this point in the landscape is not always easy. Numerous studies have identified some of the difficulties of demarcating places where soil properties are changing significantly (Gile, 1975a; Burrough et al., 1997; Greve and Greve, 2004).

The traditional approach for soil map unit boundary detection is based on qualitative evaluation of soil morphological characteristics with emphasis on texture. Because texture strongly affects soil moisture properties (Taylor and Ashcroft, 1972), it can be expected that boundaries based on soil moisture conditions would show good agreement with those detected using soil morphological characteristics. Analysis of several soil moisture data sets along transects in southern New Mexico using the moving split window **[["split moving-window"?]]** technique (Webster, 1973; Webster, 1978) found good agreement between boundaries located qualitatively based on soil morphological characteristics and those located quantitatively based on soil water content measurements with depth (Hendrickx et al., 1986, 1990; Wierenga et al., 1987). An important observation of these studies was that using multiple days of soil moisture observations over longer periods yields more information than a single data set for one day only.

Therefore, these studies firmly established that a series of soil water content measurements with depth provide sufficient information for soil boundary detection in semi-arid New Mexico.

Unfortunately, taking soil water content measurements along transects on the km-scale is logistically impractical for mapping soils. Even when non-invasive electromagnetic induction is used for soil water content measurements (Kachanoski et al., 1988, 1990, 2002; Sheets and Hendrickx, 1995), the effort is too large to obtain data sets that can cover an entire watershed. ~~Only by~~ Using operational remote-sensing satellite imagery ~~one can~~ is the only method to prepare regional root zone soil moisture maps at an acceptable cost **[[OK?]]** (Scott et al., 2003; Fleming et al., 2005).

Geographic information systems (GIS) and remote sensing are the basis of digital soil mapping (Lagacherie et al., 2007). For example, the Landsat Multispectral Scanner (MSS) and Thematic Mapper (TM) have been successfully used to map land cover, soils, terrains, and man-made features such as dams and urban areas (Baban and Yusof, 2001). The use of the India Remote Sensing satellite Linear Imaging Self-scanning Sensor (IRS-1B LISS-II) can provide details about soil classes that are often not found on existing soil maps produced by more traditional means (Karale et al., 1991). While these are only two examples of the types of surveys and methods using remotely sensed data, they have one facet in common with most other studies: all use digital values from a single image that only provide information about the land surface, i.e., reflectance of the visible, near-infrared and mid-infrared bands and long-wave emission of the thermal infrared band. In general, such data represent the top few cm of the soil surface at best; or under full vegetative cover, the data represent the characteristics of the vegetation that may or may not be related to soil type. Since in semi-arid New Mexico some soil boundaries have surface expressions while others do not (Gile, 1975a, 1975b), it is expected that the use of digital data of the reflectances from Landsat images only will be insufficient to detect all soil boundaries in the landscape. In addition, we will use the values of relative soil moisture as determined by the Surface Energy Balance Algorithm for Land (SEBAL) code as a second method for determining soil map unit boundaries.

Soil map unit boundaries on traditional soil maps are all shown to be sharp boundaries, indicating the soil properties change significantly over a short distance. However, it has been recognized that soil properties can change abruptly or gradually; so not all soil map unit boundaries are the same. Identification of the nature of soil map unit boundaries has been one of the areas of focus for the Digital Soil Mapping Community (McBratney et al., 2003). Sharp or crisp boundaries are usually associated with landform boundaries, whereas gradual changes in soil properties are termed fuzzy or gradual boundaries (Burrough et al., 1997; Greve and Greve, 2004). A more refined boundary definition has been proposed by Lagacherie et al. (1996) **[[Not in reference list?]]** where boundaries were defined on the basis of the abruptness of the change in soil properties (fuzziness) and on the certainty (uncertainty) of the location of the boundary. Four situations were defined: (1) high fuzziness, low uncertainty; (2) high fuzziness, high uncertainty; (3) low fuzziness, low uncertainty; and (4) low fuzziness, high uncertainty. Traditionally in large-scale soil mapping, boundaries are identified using proxy data such as landform or vegetation boundaries and slope properties. Gile (1975a, 1975b) described a number of geomorphic and pedogenic processes that result in boundaries between different soil map units and showed that in many instances there is no surficial expression of the boundary. Shallow subsurface geophysical techniques such as electromagnetic induction methods are increasingly being used to provide information on soil properties; they have the advantage of being quick and easy to apply but are still logistically difficult to apply over large areas. The only logistically viable method of obtaining landscape-scale data on soil properties is through analysis of remote-sensing images. Furthermore, in traditional chloropeth maps, all boundaries are represented as being the same, so gradational and intergrade boundaries that may occur over several hundred meters cannot be separated from sharp boundaries. Analyzing a series of remote-sensing images allows identification of boundary movement due to changing environmental conditions. The objective of this study is to determine whether remotely sensed root zone soil moisture can be used to detect soil map unit boundaries—in particular,**[[OK?]]** whether the use of multiple images from several years provides a more robust data set for the identification of soil map units.

## STUDY AREA

Two field areas in central New Mexico, USA, were used in this study: the Sevilleta National Wildlife Refuge (NWR) and the Hilton Ranch (Fig. 1). These areas were chosen in part because the soils had been recently mapped by the Natural Resources Conservation Service (NRCS). A landform map was produced from analysis of aerial photographs and field validation at a scale of 1:24,000 (Rinehart (unpublished map)**[[Please incorporate data in paper, convert to personal communication, or delete.]]**, 2009). These soil and landform maps were used to evaluate how well remotely sensed satellite imagery detects soil map unit boundaries.

The Sevilleta National Wildlife Refuge is located in central New Mexico and covers an area of ~1000 $km^2$. This area contains four major ecosystems: the Chihuahuan desert, Great Plains grasslands, Colorado Plateau shrub-steppe, and conifer woodlands (Sevilleta Long Term Ecological Research Site; http://sev.lternet.edu). Landforms include alluvial fans, pediments, and terraces of various ages and active channels. The NRCS map includes 17 soil associations and complexes (Johnson, 1984).

The Hilton Ranch is located on the east side of the Rio Grande opposite the town of Socorro, New Mexico. The range of landforms is similar to those of the Sevilleta. However, due to its proximity to the Rio Grande, more riparian vegetation is present along the floodplains. There are six soil complexes and associations in this area (Johnson, 1984).

## METHODS

Just as in our previous studies (Hendrickx et al., 1986; Wierenga et al., 1987), we used the split moving-window technique (Webster, 1973, 1978) for soil boundary detection. However, instead of ground-measured soil water contents, we employed a relatively new technique for determination of root zone soil moisture content from Landsat images (Scott et al., 2003; Fleming et al., 2005). Twenty Landsat 5 TM and Landsat 7 ETM+ images captured during the growing season from April to October (Table 1) were used to map root zone soil moisture using SEBAL. Fourteen of the images were used for the Sevilleta, due to lack of full coverage of the study area, and all 20 were used for the Hilton Ranch. The pixel size of the Landsat 5 TM and Landsat 7 ETM+ images is 30 m for bands 1, 2, 3, 4, 5, and 7 with visible, near-infrared and mid-infrared light reflectances and, respectively, 120 and 60 m, for the band 6 with thermal emissions. The root zone soil moisture maps that are used for soil boundary detection have a pixel size of 30 m.

### Surface Energy Balance Algorithm for Land (SEBAL)

Each image was processed through SEBAL, which is a remote-sensing flux algorithm that solves the surface energy balance on an instantaneous time scale for every pixel of a satellite image (Bastiaanssen et al., 1998a, 1998b, 2002; Allen et al., 2007a, 2007b). The method computes evapotranspiration and root zone soil moisture. It considers a user-defined wet and dry pixel to assume the sensible heat flux is zero and the latent heat flux is zero, respectively. The radiation balance can then be solved for each pixel in the entire image relative to those two points (Bastiaanssen et al., 1998a, 2000). Surface Energy Balance Algorithm for Land is a physically based analytical method that evaluates the components of the energy balance and determines the ET rate as the residual

$$R_n - G - H = \lambda E, \quad (1)$$

where $R_n$ is the net incoming radiation flux density (W m$^{-2}$), $G$ is the ground heat flux density (W m$^{-2}$), $H$ is the sensible heat flux density (W m$^{-2}$), and $\lambda E$ is the latent heat flux density (W m$^{-2}$), which is converted to the ET rate. The parameter $\lambda$ is the latent heat of vaporization of water (J kg$^{-1}$), and $E$ is the vapor flux density (kg m$^{-2}$ s$^{-1}$). Evaporation $E$ includes both bare soil evaporation and canopy transpiration. The SEBAL method uses an internal auto-calibration process that greatly eliminates the need for atmospheric corrections, and it does not require actual measurements on the ground. The method computes the surface albedo, surface temperature, and vegetation index from multispectral satellite data. The surface albedo is used to calculate net short-wave radiation and surface temperature for the calculation of net long-wave radiation, soil heat flux, and sensible heat flux. The vegetation index governs the soil heat flux by incorporating light interception by canopies and is used to express the aerodynamic roughness of the landscape. The latent heat flux is computed as the residue of the surface energy balance. Air humidity measurements are not needed because evaporation is computed from the latent heat flux. The SEBAL method has been applied for water balance estimations (Pelgrum and Bastiaanssen, 1996), irrigation performance assessment studies (Roerink et al., 1997), and for weather prediction studies (Van den Hurk et al., 1997).

Co-author Hendrickx and his research group have applied SEBAL within the United States in New Mexico, Arizona, California, Wyoming, Illinois, and Texas as well as in Panama, Morocco, and the Volta Basin in West Africa (Hendrickx and Hong, 2005; Hendrickx et al., 2005, 2006; Alkov, 2008; Compaoré et al., 2008; Hong et al., 2008, 2009). Soil moisture conditions in the root zone can be determined from the evaporative fraction using the empirical relationship (Ahmad and Bastiaanssen, 2003):

$$S = \frac{\theta}{\theta_{sat}} = e^{\frac{\Lambda-1}{0.42}}, \quad (2)$$

where *S* is relative degree of saturation, θ is volumetric water content, $\theta_{sat}$ is volumetric water content at saturation, and Λ is the evaporative fraction defined as the ratio $\lambda E/(R_n - G$**[[OK?]]**). The validity of Equation 2 has been tested in several studies (Ahmad and Bastiaanssen, 2003; Scott et al., 2003) including one in New Mexico (Fleming et al., 2005).

Where Equation 2 is used over homogeneous soils with known porosity or saturated volumetric water content, it can yield the volumetric water content in the root zone after $\theta_{sat}$ is moved toward the right-hand side of the second equal sign in the equation. However, in semi-arid terrain with heterogeneous soils that still need to be mapped, porosity is not known, and we can use Equation 2 only to estimate the relative degree of saturation in the root zone. The disadvantage of *S* is that no direct relationship exists for determination of the amount of water in the soil, but it has been our experience that the wetness index *S* performs quite well for boundary detection.

**Split Moving-Window Analysis**

We selected split moving-window analysis for the detection of soil boundaries for several reasons: (1) the method had been successfully used for boundary detection of soil series on the basis of soil water content measurements in a semi-arid landscape (Hendrickx et al., 1986; Wierenga et al., 1987); (2) the method is very simple to implement; and (3) successful applications by other researchers (Webster, 1973, 1978; Ludwig and Tongway, 1995; Panis and Verheyen, 1995; Nash et al., 1999). An alternative method is the maximum level-variance analysis (Hawkins and Merriam, 1973, 1974), but it was not considered for this exploratory study since its effectiveness for boundary detection is similar to split moving-window analysis (Webster, 1978).

The split moving-window analysis was applied**[[“is applied”?]]** as follows: (1) starting at one end of the transect, select an even number of pixels that occupy the “window”; (2) split this window with spatially contiguous soil moisture or digital values into two equal groups; (3) compute a dissimilarity index between these two groups; (4) move the window one position further along the transect and compute another dissimilarity index; and (5) make a plot of the dissimilarity indices (on the vertical axis) versus distance along the transect (on the horizontal axis) (Webster, 1973, 1978; Hendrickx et al., 1986; Ludwig and Tongway, 1995). In this study, Student’s *t*-statistic is used as the dissimilarity index to compare whether the two groups within one window are different, since the *t*-statistic is an effective measure for dissimilarity between two small groups (McClave and Dietrich, 1979). First, a *t*-value is calculated for each window; then, these values are plotted on the horizontal axis at each window mid-point. Boundary locations are identified by peaks in the plot of *t*-values versus distance. Sampling at equal distances along a transect is quite different from the random and independent sampling required for hypothesis testing using the *t*-statistic. Therefore, we cannot put a true significance level on the *t*-values, but instead we have used our field knowledge for the approximation of *t*-values that are sufficiently large as to detect a boundary.

Sixteen transects were randomly selected in our field areas for analysis (Engle, 2009), but for this “method paper,” we will only present data from transects 3 and 10. For the split moving-window technique (Webster, 1973, 1978), a window size of five pixels was selected because it is sufficiently narrow to capture boundaries that occur over short distances but also adequate to minimize noise. A *t*-test was used to determine the statistical difference between the windows; boundaries should coincide with maximum *t*-values. We used four *t*-values (6, 8, 10, and 12) to identify soil boundaries. More boundaries are identified at lower *t*-values, and the higher the *t*-value, the more robust the boundary.

While we can determine the soil moisture status of an individual pixel, for mapping purposes, the smallest area that can be clearly defined is ~1 $cm^2$. At a scale of 1:15,000, a 1 $cm^2$ area on a map would equal 150 $m^2$ on the ground or five pixels (Vink, 1963). In general, sharp boundaries such as landscape boundaries are distinct. However, gradational boundaries are harder to detect because they do not exhibit the sudden change in properties that generates a large *t*-value in the split moving-window analysis. Transitional boundaries (boundaries that shift locations due to antecedent conditions) are also hard to detect because they may occur in slightly different locations on different days. All boundaries detected were classified based on two properties: the percentage of image days over which each boundary is present (the boundary strength) and the spatial range over which they occur (Table 2).

The split moving-window technique was applied to four different sets of variables: (1) the first principal component of the digital values of the seven Landsat bands for each day (daily**[[“digital”?]]** values**[[OK?]]** [DV] principal component analysis [PCA], Fig. 2A); (2) the first principal component of the digital values of the seven Landsat bands for all days (overall DV PCA, Fig. 2B); (3) the root zone soil moisture values of each day (daily RZSM, Fig. 2A); and (4) the first principal component of the root zone soil moisture (RZSM) values for all days (overall RZSM, Fig. 2B). The principal components were calculated using ERDAS IMAGINE and captured ~70% of the variability in the data.

## RESULTS AND DISCUSSION

Figures 2 and 3 show the results of the split moving-window technique along transects 3 and 10. Transect 3 (Fig. 2) crosses a number of landform and soil map boundaries including the ephemeral stream channel of the Rio Salado. In the daily data (Fig. 2A), the northern boundary of the Rio Salado is clearly seen in all data sets, while the southern boundary is not readily apparent. Some of the boundaries correspond with landform and soil map boundaries; others do not and could either be false detections or boundaries that were not identified in the previous soil mapping. The overall PCA data show similar results (Fig. 2B), but use of the daily data yields more boundary information (Fig. 2A). The northern boundary of the Rio Salado appears in only one data set (overall digital value PCA). The third and fourth boundaries seen at 2280 and 2500 m in the daily data appear in the overall PCA data also. There are boundaries, mostly in the northern section of the transect, that do not correspond to previously identified boundaries. However, they are also identified in the daily data, which is further evidence that they are real boundaries that have not previously been mapped.

Transect 10 (Fig. 3) is an example of a transect crossing agricultural fields and the Rio Grande floodplain representing the most complex soil landscape in both study areas. As a result, many boundaries were detected in both the root zone soil moisture and the digital value PCA. Because the fields are often irrigated separately, the moisture content in each field will be different so that the boundaries detected are the edges of the field. Most of the boundaries detected have high *t*-values, which attest to their strength. The start of the fields can be detected easily with this method due to the difference between the fields and the surrounding desert. The overall PCA data show similar results (Fig. 3B), but use of the daily data yields more boundary information (Fig. 3A).

In these two examples along a one-dimensional transect, both the daily root zone soil moisture and daily digital value PCA (Figs. 2A and 3A) were successful at detecting boundaries, while the overall data sets (Figs. 2B and 3B) were not as efficient. There are cases where daily root zone soil moisture detects soil boundaries better than the daily digital value PCA. For example, inspect for *t*-values of 12 in Figures 2A and 3A the two lowest lines: in Figure 2A, the daily DV PCA 12 detects one boundary versus four with the daily RZSM 12; while in Figure 3A, it is three boundaries versus eight. This suggests that the root zone soil moisture is detecting changes at depth that did not have a surficial expression detectable by Landsat digital values. Because most of these images were taken during the growing season, the root zone moisture conditions vary temporally and spatially across the study areas. By combining multiple images, we can reduce this effect while still incorporating a sequence of varying levels of soil moisture. Thus, we are able to enhance the spatial trends while minimizing the temporal effects of localized wetting due to precipitation or irrigation.

Valuable information can be gained from the SEBAL-derived root zone soil moisture; but under certain environmental conditions, valuable information can also be taken from the daily DV PCA. When all data sets were combined, the efficiency of the methodology at detecting confirmed boundaries decreased as the *t*-value increased (Figs. 2B and 3B). This was expected because as the *t*-value increases, the boundaries with lower differences across the windows will be filtered out leaving only the strongest boundaries.

The overall digital value PCA performs better than the overall root zone soil moisture data in transect 3 (Fig. 2B) but not in transect 10 where the overall root zone soil moisture detects more boundaries. This suggests that root zone soil moisture images might be more useful in areas of high soil moisture such as close to the rivers and streams or agricultural areas. On the other hand, the daily digital value PCA can convey a great deal of information in areas where there is little change in the soil moisture because the digital values will be detecting surficial properties such as color when there are few other physical changes.

**CONCLUSIONS**

Analysis of multiple images collected over several years revealed consistent response patterns in all data sets. The boundaries of these response patterns as determined by a split moving-window technique frequently coincided with soil map unit and/or landform boundaries. In such instances, these boundaries are termed hard or sharp boundaries, and they represent a significant change in soil properties over short distances. In other instances, the boundary location ranged over several pixels in the different images, suggesting that these were gradational or fuzzy boundaries representing a gradual spatial change in soil properties. It is only through a temporal analysis of the remote-sensing images that such boundaries can be identified. Root zone soil moisture identifies boundaries best under conditions when the moisture content is higher. The daily PCA data tend to identify landform boundaries and are more efficient when the soil moisture content is low, indicating that in conditions where soil moisture variability is low, the calculation using the SEBAL model may be unnecessary.

The advantage to this method is that it is not expert knowledge-based, unlike traditional soil mapping methods. At a low *t*-value, over 70% of previously detected boundaries can be identified; however, the data suggest that there are previously undetected boundaries that may be also identified by this approach. Furthermore, this method allows identification of different types of boundaries and the temporal strength of those boundaries, which is impossible under traditional mapping techniques.

With a pixel size of 30 m and a split moving-window size of 5, the area being examined is ~150 m. If multiple boundaries occur in this distance, they will not be detected very accurately. Georeferencing is another source of error in our methodology. Because all Landsat images were individually georeferenced, there can be significant differences from one image to another. It is impossible that multiple georeferenced images lie exactly on top of each other. Five locations near the study areas were selected to analyze the georeferencing error. The first date for each location is used as a reference point, and each subsequent date is measured to that reference point. The resulting average georeferencing error is 74 m with a standard deviation of 30. ~~There are~~ Two dates of images—7 April 2000 and 3 August 2005—contribute the most to this error.

The images used were randomly chosen from images taken during the growing season May to September. We believe that ~~with~~ images chosen for the moisture status (for example, close to a significant rainfall) would result in greater resolution of difference in soil properties. Future work will also focus on validating these boundaries and identifying the physical processes that produced changes in the satellite images. Overall, the use of multiple remotely sensed root zone soil moisture for soil boundary delineation shows great promise of becoming a valuable tool in the field of digital soil mapping,

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**FIGURE CAPTIONS**

Figure 1. Location of Sevilleta National Wildlife Refuge and Hilton Ranch in central New Mexico, USA. The lines depict the soil boundaries as they are currently mapped by the Natural Resources Conservation Service (NRCS).**[[On map, please add North arrow.]]**

Figure 2. (A) Graphical representation of the boundaries generated using daily digital value**[[“(DV)”?]]** principal component analysis (PCA) and daily root zone soil moisture at critical t-values of 6, 8, 10, and 12, respectively, compared to landform and soil boundaries mapped along transect 3 (vertical lines). The dot size represents the percentage of days the boundary occurs, and the line length represents the spatial range over which it occurs. (B)

Graphical representation of overall root zone soil moisture and overall digital value PCA data at critical *t*-values of 6, 8, 10, and 12 along transect 3. The size of the dot represents the *t*-value of each boundary. The vertical lines represent landform and soil boundaries mapped along the transect.

Figure 3. (A) Graphical representation of the boundaries generated using daily digital value**[[“(DV)”?]]** principal component analysis (PCA) and daily root zone soil moisture at critical *t*-values of 6, 8, 10, and 12, respectively, compared to landform and soil boundaries mapped along transect 10 (vertical lines). The dot size represents the percentage of days the boundary occurs, and the line length represents the spatial range over which it occurs. (B) Graphical representation of overall root zone soil moisture and overall digital value PCA data at critical *t*-values of 6, 8, 10, and 12 along transect 10. The size of the dot represents the *t*-value of each boundary. The vertical lines represent landform and soil boundaries mapped along the transect.

TABLE 1. DATE, PATH, AND ROW NUMBERS OF LANDSAT 5 AND ~~LANDSAT~~ 7 IMAGES

| Date | Path number | Row number | Landsat satellite | Study area(s) |
|---|---|---|---|---|
| 04/07/2000 | 33 | 36 | 7 | Sevilleta, Hilton |
| 05/06/2002 | 34 | 36 | 7 | Sevilleta, Hilton |
| 05/09/2000 | 33 | 36 | 7 | Sevilleta, Hilton |
| 05/12/2004 | 33 | 36 | 5 | Hilton |
| 05/22/2005 | 34 | 36 | 7 | Sevilleta, Hilton |
| 05/28/2004 | 33 | 36 | 5 | Hilton |
| 05/31/2002 | 33 | 37 | 7 | Sevilleta, Hilton |
| 06/04/2001 | 34 | 36 | 7 | Sevilleta, Hilton |
| 06/13/2004 | 33 | 36 | 5 | Hilton |
| 06/16/2002 | 33 | 36 | 7 | Sevilleta, Hilton |
| 07/02/2005 | 33 | 36 | 5 | Hilton |
| 07/06/2004 | 34 | 36 | 5 | Sevilleta, Hilton |
| 07/28/2000 | 33 | 36 | 7 | Sevilleta, Hilton |
| 07/31/2004 | 33 | 36 | 5 | Hilton |
| 08/03/2005 | 33 | 36 | 5 | Sevilleta, Hilton |
| 08/19/2002 | 33 | 36 | 7 | Sevilleta, Hilton |
| 09/14/2000 | 33 | 36 | 7 | Sevilleta, Hilton |
| 09/17/2004 | 33 | 36 | 5 | Hilton |
| 09/30/2000 | 33 | 36 | 7 | Sevilleta, Hilton |
| 10/14/1999 | 33 | 36 | 7 | Sevilleta, Hilton |

*Note:* Sevilleta—Sevilleta National Wildlife Refuge; Hilton—Hilton Ranch.

TABLE 2. CLASSIFICATION SCHEME FOR DETECTED BOUNDARIES

| Days (%) | Boundary strength | Range (m) | Boundary type |
|---|---|---|---|
| 0–30 | Strong | 0–100 | Stable |
| 30–60 | Intermediate | 100–200 | Intermediate/stable |
| 60–100 | Weak | 200–300 | Intermediate/transitional |
| | | 300–400 | Transitional |

**[[Should forward slashes between “Intermediate” and “stable” and “Intermediate” and “transitional” be replaced with “and/or” or en dashes?]]**