SPATIAL AND TEMPORAL DYNAMICS OF VEGETATION IN THE SAN PEDRO RIVER BASIN AREA

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ABSTRACT

Changes in climate and land management practices in the San Pedro River basin have altered the vegetation patterns and dynamics. Therefore, there is a need to map the spatial and temporal distribution of the vegetation community in order to understand how climate and human activities affect the ecosystem in the arid and semi-arid region. Remote sensing provides a means to derive vegetation properties such as fractional green vegetation cover (*fc*) and green leaf area index (*GLAI*). However, to map such vegetation properties using multitemporal remote sensing imagery requires ancillary data for atmospheric corrections that are often not available. In this study, we developed a new approach to circumvent atmospheric effects in deriving spatial and temporal distributions of *fc* and *GLAI*. The proposed approach employed a concept, analogous to the pseudo invariant object method that uses objects void of vegetation as a baseline to adjust multitemporal images. Imagery acquired with Landsat TM, SPOT 4 VEGETATION, and aircraft based sensors was used in this study to map the spatial and temporal distribution of fractional green vegetation cover and green leaf area index of the San Pedro River riparian corridor and southwest United States. The results suggest that remote sensing imagery can provide a reasonable estimate of vegetation dynamics using multitemporal remote sensing imagery without atmospheric corrections.

INTRODUCTION

Climate change and increasing human activities have resulted in a substantial change in the vegetation type and distribution in the southwest United States. Chihuahuan Desert shrubs and mesquite trees increasingly have become dominant and replaced native grasses over large areas (Kepner et al., 1998, and Watts et al., 1998). The change in vegetation pattern has a feedback influence on the local and regional climate by reducing evaporative water losses from surface to atmosphere. Therefore, the spatial and temporal distribution of vegetation characteristics is important in understanding how climate and human activities affect the ecosystem in the semi-arid environment.

Estimation of vegetation properties with remotely sensed imagery has been quite successful. However, when applied to satellite imagery, tremendous processing efforts related to atmospheric and bidirectional corrections are needed. Although procedures to correct these effects are available, ancillary data about atmospheric conditions and bidirectional properties of the surface types are limited in both space and time. This has prevented satellite data from being used to quantify vegetation dynamics for practical applications. A common practical technique to correct atmospheric effect is dark-object subtraction (Chavez, 1988, Caselles and Garcia, 1989), which subtracts the minimum pixel values of a dark object found in a scene with an assumption that no energy is reflected from that dark object. However, in many cases, it is impossible to find a dark object within a scene that is large enough to occupy more than one single pixel, especially when coarse spatial resolution satellites are used. An alternative is to use pseudo invariant objects (PIO) within a scene to convert digital numbers to radiance or reflectance values (Schott et al., 1988, Moran et al., 1996 and 1997). Pseudo invariant objects are those objects whose reflectances are known and remain approximately constant throughout time and therefore can be used to "calibrate" multitemporal images.

Reflectance properties of most PIOs, however, vary with many factors such as surface conditions. When bare soil fields are used as PIOs, for example, their reflectances vary with soil moisture content and surface roughness, which changes throughout the season because of the impact of rainfall events. Use of either a dark object or a pseudo invariant object for atmospheric corrections will not correct for bidirectional effects. When an image is acquired at an oblique view, the reflectance properties of most objects including pseudo invariant objects may vary substantially. Therefore, oblique viewing will introduce a constant bias when PIOs are used for atmospheric corrections. Noise associated with atmospheric and bidirectional effects will be magnified when calculating derivative products such as vegetation cover and biomass, especially over sparsely vegetated surfaces. Thus, it is critical that methods be developed to circumvent atmospheric and bidirectional effects. The objective of this study is to develop an alternative technique to derive remote sensing products such as fractional green vegetation cover (*fc*) and leaf area index (LAI) that are less sensitive to atmospheric effect. Although viewing angles may introduce errors in estimated *fc* and LAI, no attempt was made to correct bidirectional effects in this study.

METHODOLOGY

By definition, a pseudo invariant object is an object whose reflectance properties are invariant throughout time. Examples of such objects are bare soil fields, airstrips, and highways. Therefore, multitemporal remote sensing images can be converted to surface reflectances by using a linear relationship between raw digital numbers on the image and the known reflectances of the pseudo invariant objects found within the scene. The key assumption is that the object is invariant in terms of surface reflectance. This assumption, however, is not valid for most natural land surfaces because their reflectance properties are known to vary with many external factors such as surface conditions and sensor's viewing angles. Therefore, the fundamental assumption of invariance in reflectance fails in most cases, resulting in uncertainties in surface reflectance and its derived products.

There are other physical properties besides reflectances that are indeed invariant with time and surface conditions. Such physical properties include the presence of vegetation or green biomass. For example, a bare soil field, which is often used as a PIO, changes in surface reflectance with surface moisture condition, roughness, and sensor/sun viewing angles. However, the fractional green vegetation cover (*fc*) or green leaf area index (*GLAI*) does not vary with these factors. Therefore, the bare soil field is variant in surface reflectances but invariant in green vegetation cover or green biomass, allowing one to use this truly invariant property to calibrate the green cover product rather than to calibrate reflectance.

We thus designed an adjustment approach (Figure 1), using true invariant properties of most land surfaces, to circumvent the atmospheric effect in the derivation of biophysical properties of land surfaces. The adjustment approach (Figure 1) consists of three steps. The first step is to identify surface targets void of vegetation, analogous to pseudo invariant objects, whose physical sizes are at least twice larger than the spatial resolution of the remotely sensed imagery used. Such objects may be areas of bare soil fields, airport runways, and highways. To differentiate these objects from traditional pseudo reflectance-invariant objects, these objects are termed here as objects void of vegetation (OVV). By definition, the fractional green cover and green leaf area index values of OVVs should be zero. However, due to atmospheric effect, the derived *fc* and *GLAI* values of OVVs may not be zero and need to be adjusted. The second step is to compute this non-zero adjustment factor in terms of fractional cover and green leaf area index (algorithms for computing these two variables are described below). The third and final step is to compute the *fc* and *GLAI* spatial distribution by subtracting the adjustment factor from the entire image.

In this study, we focused on the derivation of temporal dynamics of vegetation in the San Pedro River basin where the SALSA (Semi-Arid Land-Surface-Atmosphere) program is currently focusing its effort (Goodrich et al., 1999, this issue). In particular, we used the proposed adjustment approach to derive spatial and temporal distributions of the fractional green vegetation cover (fc) and green leaf area index ($GLAI$) of the study area. The selected OVVs in this study included the Wilcox playa, Arizona for all TM images and White Sands, New Mexico for the VEGETATION images. These OVVs can also be used as pseudo invariant objects. The fc and $GLAI$ values of the Wilcox playa and White Sands were computed and subtracted from the entire fc and $GLAI$ images. The fc and $GLAI$ values of these OVVs provided baselines for each image to allow an automatic adjustment of the fc and $GLAI$ values from multitemporal remote sensing imagery.

Green Vegetation Cover Estimate

Fractional green vegetation cover (fc) in arid and semi-arid regions is an important variable in hydrological and ecological modeling studies. Their temporal dynamics and spatial distributions are often needed in global circulation models (GCMs) in order to compute the energy or water fluxes. Estimation of fractional green vegetation cover, fc, from remotely sensed data is often associated with computation of spectral vegetation indices and their empirical relationships with fractional green vegetation cover. In this study, we used a linear mixing model to relate fc with spectral vegetation indices.

Assume that a pixel signal consists of the contribution from two components: soil and vegetation. Let the fractional green vegetation cover be fc and, therefore, the fractional soil cover would be $1 - fc$. The resulting signal, S, as observed by a remote sensor can be expressed as

$$S = fc \times Sv + (1 - fc) \times Ss\,, \tag{1}$$

where Sv is the signal contribution from the green vegetation component and Ss from the soil component. For pixels consisting of more than two components, equation (1) needs to be modified. This analysis assumed that a pixel consisted of only vegetation and soils. Equation (1) can be applied to remotely sensed data in the reflectance domain (Maas, 1998) and in the spectral vegetation index domain (Zeng et al., 1999). When applied with a spectral vegetation index such as the normalized difference vegetation index (NDVI), equation (1) may be approximated by

$$NDVI = fc \times NDVIveg + (1 - fc) \times NDVIsoil \ , \tag{2}$$

which can be re-written as

$$fc = \frac{NDVI - NDVIsoil}{NDVIveg - NDVIsoil} \ , \tag{3}$$

where *NDVIsoil* is the NDVI value of an area of bare soil or objects void of vegetation, and *NDVIveg* is the NDVI value of a pure vegetation pixel.

Although many vegetation indices are available, we selected NDVI because of its traditional use in deriving vegetation variables. The *NDVIsoil* values should be constant throughout time and close to zero in theory for most type of bare soil surfaces. However, due to atmospheric effect, and changes in surface moisture conditions, *NDVIsoil* values vary substantially with time. In addition, they also vary from location to location because of difference in soil types and colors. Therefore, using a single value of *NDVIsoil* as a baseline for the entire image may not be valid unless the area of interest consists of uniform soil types. For this reason, we selected surfaces near the center of an image to minimize errors associated with variations in NDVI values of OVVs. To use the proposed adjustment approach, it is not necessary to know the exact values of *NDVIsoil* because this value will be computed from each image. The *NDVIsoil* values from each image were used to compute the associated *fc* and *GLAI* adjustment factors.

As previously stated, the spatial variation of bare soil surfaces may also be related to the sensor's observation angles. Therefore, depending on the sun-viewing geometry of each pixel, the selected *NDVIsoil* may be different and thus result in uncertainties in *fc* and *GLAI* estimation. To minimize the bidirectional effect, it is suggested to avoid large view angle data when nadir-looking images are available. In this study, the nadir-viewing TM images were used in the analysis. The proposed adjustment approach was designed to circumvent primarily the atmospheric effect, aiming at analyzing vegetation dynamics from multitemporal images. Uncertainties were expected when using images acquired with large viewing angle sensors.

The value for *NDVIveg* represents the maximum value of a fully vegetated pixel. Because of the temporally dynamic nature of green vegetation cover, this value needs to be empirically determined. In selecting such a value, we examined all images and selected an image acquired during the peak-growing season within the area of interest. The *NDVIveg* was determined in this study to be 0.8 from high spatial resolution data. During the selection process, surfaces of known to be 100% green cover were identified and the corresponding NDVI values were computed from multitemporal images, and then the highest value (0.8) was used for all image. This empirically determined value may also vary with atmospheric conditions (Kaufman 1992 and Qi et al., 1994), which may cause some errors in the fractional cover computation in equation (3).

Because the NDVI is a ratio vegetation index, it can be directly computed with digital numbers, or with top of atmosphere radiance or reflectance, or surface reflectance. In this analysis, *NDVIveg* of 0.8 was determined using surface reflectances derived from TM images. When used with radiance, or digital numbers, or top-of-atmosphere reflectance or radiance, the *NDVIveg* may be different. However, once the data type (radiance, raw digital numbers, or top-of-atmosphere reflectance or radiance) is determined, the *NDVIveg* should be constant.

Green Leaf Area Index Estimate

Another important vegetation characteristic is the green leaf area index (*GLAI*). Unlike the fractional green vegetation cover, which is a two-dimensional horizontal variable, the *GLAI* is a variable describing the density of green vegetation. It is defined here as the total single-side area of green leaves per unit ground area. Therefore, its values can theoretically range from 0 to infinity, whereas *fc* ranges from 0 to 1.

Approaches to deriving *GLAI* exist using either empirical relationships with spectral vegetation indices or model inversion techniques. For arid and semi-arid regions such as the San

Pedro River basin, we adapted the approach by Qi et al. (1999), which was derived using a combination of modeling and empirical approaches:

$$GLAI = aNDVI^3 + bNDVI^2 + cNDVI + d \qquad (4)$$

where a, b, c, and d are empirical coefficients and were found to be a = 18.99, b= -15.24, c = 6.124, and d = -0.352 for arid and semi-arid regions. The *GLAI* values derived from these coefficients were validated using TM imagery data over a desert grassland, and therefore, the use of them over a large area of diverse vegetation remains to be further validated. Since the TM imagery used in this study covered the same geographic areas, it is expected that uncertainty in *GLAI* estimation from these coefficients would not be significantly from the original study. Furthermore, if adjusted NDVI was used in equation (4), the coefficient d should be adjusted to zero to ensure that the *GLAI* values of objects void of vegetation were zeros for all seasonal images.

DATA DESCRIPTION

Remote Sensing Data

Multitemporal images were acquired with Landsat TM, French SPOT 4 VEGETATION, and airborne sensors over the study area. They were geometrically registered to UTM coordinates. A total of fifteen Landsat TM images were acquired in 1992 and 1997 over the San Pedro basin area (Table 1). Thematic Mapper Simulator (TMS) was deployed on an aircraft during the SALSA intensive field campaign in August 1997 (Goodrich et al., this issue) to acquire images at a three-meter spatial resolution. Daily SPOT 4 VEGETATION images were acquired over this study area at a spatial resolution of 1000 meters. Therefore, the remotely sensed images had a range of spatial resolution from three meters to one kilometer. In addition to these satellite- and aircraft-based remote sensing data, surface reflectances were also measured at the Audubon ranch near Elgin, Arizona, in 1998, using a MMR radiometer in the same spectral bands as Landsat TM sensor.

Vegetation Data

Ground vegetation properties were recorded in 1992, 1997 and 1998 using both destructive sampling technique and Li-Cor's LAI-2000 instrument. Vegetation samples were collected at three study sites. The first site was located in the center of Walnut Gulch Experimental Watershed and the site was dominated by tobosa grasses (*Hilaria mutica*) with some desert shrubs. The second site was near the Lewis Springs within the San Pedro River basin and the dominant grass was sacaton (*Sporobolus wrightii*). The third site was at the Audubon research ranch near Elgin, Arizona, and the dominant vegetation types were native upland grasses, Lehmann's lovegrass, and sacaton grasses.

Both destructive and non-destructive methods were used to measure the green leaf area index. For the destructive method, vegetation samples were collected in the field and brought back to the lab and separated into green vegetation, senescent vegetation, and litter. The single side leaf areas were measured by passing them through a LAI-3000 area meter for each component and green leaf area index was then computed. For the non-destructive method, LAI-2000 instrument was used to measure total LAI, and the lab-based ratio of green to total leaf areas was used to compute the green leaf area index. Measurements of the total fractional vegetation cover were made by visual estimate on site during each field visit. Detailed descriptions of this data set can be found in Moran et al. (1998). The ground *in-situ* measurements were then used in this study to examine the effectiveness of the proposed approach.

RESULTS

Spatial Dynamics of Green Vegetation

The spatial distribution of the estimated green vegetation cover and green leaf area index was derived from the 3-meter resolution TMS data (Figure 2). The spatial extent covered the riparian corridor of the San Pedro River from Hereford to Fairbanks (see Figure 2 in Goodrich et al., this issue). Dense green vegetation cover was distributed along the river where the cottonwood-willow riparian forest gallery was located. Away from the riverbanks toward the upland areas, the green vegetation cover diminished. There was also a vegetation cover gradient from Fairbanks to Hereford or from north to south of the study area. This gradient was most likely due to water availability from the river and weather pattern variation due to elevation changes. Along the river were cottonwood and willow trees, which require easy access to water. They were the major vegetation community of this riparian corridor that caused evapotranspirative water loss to the atmosphere (Schaeffer and Williams, this issue, Scott et al., this issue, and Qi et al., this issue). Away from the river were sacaton grasses and mesquite trees. Although the sacaton grasses were denser than mesquite trees, they did not appear as green as the mesquite trees. This was due to the fact that the senescent sacaton grasses limited the new growth by blocking solar radiation from reaching to the lower layers of the clumps. Therefore, even in the rainy wet season, the sacaton grasses did not appear as green as the cottonwood-willow community and mesquite trees. The fractional green vegetation cover of the sacaton was thus less than the cottonwood-willow community and mesquite trees.

Temporal Dynamics

To examine the temporal dynamics of vegetation in the San Pedro River basin, a portion of the basin was extracted from two Landsat TM images acquired on 21 April (DOY 111) in the dry season and on 12 September (DOY 255) in the wet season of 1997. The spatial distribution of green vegetation cover (Figures 3) and green leaf area index (Figure 4) of the two seasons covered a portion of the San Pedro River basin. Note the scale difference between Figure 3 and Figure 4. The Huachuca mountains are located at the lower left corner of the images. The spotty areas with yellow color on the left side of Figures 3b and 4b were clouds. The dry season was characterized with little green vegetation while the wet season, due to increased precipitation, produced more green vegetation cover. In the dry season, only the river and mountainous areas had green vegetation. In the wet season, cottonwood, willows and mesquite trees were green. The sacaton, in spite of possible new growth underneath the canopy, did not appear green. Due to increased precipitation during the monsoon season, the wet season (Figures 3b and 4b) had more green vegetation than the dry season (Figures 3a and 4a).

Large Scale Vegetation Cover and GLAI

The proposed adjustment approach was applied with SPOT 4 VEGETATION data over a large area that encompassed the San Pedro River basin to demonstrate the application of the approach at different spatial scales. The imagery covered southwest United States and the northern part of Mexico. Equations (3) and (4) were applied to the VEGETATION images acquired in both the dry (April) and wet (September) seasons of 1998, and the results are presented in Figures 5 and 6. Figure 5 is a map of green vegetation cover derived from SPOT 4 VEGETATION sensor on 21 April and on 12 September 1998 whereas Figure 6 is the green leaf area index maps of the two dates. These two maps (Figures 5 and 6) showed the vegetation patterns of large scales. The coarse spatial resolution fc maps showed little detailed structures (Figures 5 and 6) in comparison with those derived from TM images (Figures 3 and 4). Clearly, the San Pedro River can be seen with TM derived maps (Figures 3 and 4), but can barely be seen on VEGETATION derived maps in Figures 5 and 6.

VALIDATION

Because of only limited ground-based data available for this study, it was difficult to fully validate the proposed adjustment approach. However, intercomparison of results from different data sets was made in three ways to verify the adjustment approach: 1) intercomparison across atmospheric corrections, 2) intercomparison across spatial scales, and 3) comparison against ground *in-situ* data.

Across-Atmosphere Comparison

For this analysis, we selected 1992 TM images because of availability of ancillary data for atmospheric corrections. A window of 9 x 9 pixels, a size of approximately 270 by 270 meter area near Tombstone within the Walnut Gulch Experimental Watershed, was extracted from all 1992 TM images. The mean values of reflectance at the surface (with atmospheric correction) and at the top of atmosphere (without atmospheric correction) were used to compute multitemporal NDVI values. These values were then used in equations (3) and (4) to compute temporal dynamics of *fc* and *GLAI* values without any adjustment. The data without atmospheric correction was then applied to the adjustment approach to investigate its effectiveness on reducing atmospheric effects. The results were plotted as a function of day of year (DOY) in Figure 7. Without atmospheric correction and OVV adjustment, the temporal dynamics of fractional green cover varied substantially with time and showed little seasonal patterns of vegetation dynamics of the region. After atmospheric corrections, the temporal pattern showed two seasonal variations, with peak growing season being around DOY of 226 and dry season for the rest of the year. The results obtained with the adjustment approach were similar to the results derived from the atmospherically corrected data and represented the vegetation dynamics of the study area more realistically. The results suggested that the use of OVV approach could reduce the atmosphere-induced noise in the temporal vegetation dynamics estimated from TM images even though no atmospheric correction was made.

Across-Scale Comparison

The remotely sensed data used in this analysis had a range of spatial scales from 3 to 1000 meters (Table 1). To compare results across spatial resolutions, a common area (5 x 1 km) found in both TMS (3m) and TM (30m) images was extracted and the statistical means were computed. This could not be done with VEGETATION images because the TMS coverage was not enough to cover even a single pixel of the VEGETATION data. To compare spatial scales between TM and VEGETATION, a separate common area (5 x 5 km) was extracted and statistical means were used for intercomparison. Due to limited TMS data, we could only compare TMS with TM for the wet season, while comparison between TM and VEGETATION was made for both dry and wet season. The results were plotted in Figure 8. Although the spatial scales were different, the mean values of the fractional green cover estimated at three spatial scales agreed well. Because the TMS image was acquired over the intensive study site at the Lewis Springs site of SALSA program and had a spatial resolution of 3 meters, we felt quite confident about the *fc* estimate with this image. Therefore, the estimated *fc* from the fine resolution TMS image could be used to assess the accuracy of *fc* estimates by the coarser resolution TM and VEGETATION images. The good agreement among all three scales (Figure 8) suggest that the estimated *fc* with TM and VEGETATION images had approximately the same accuracy of that estimated by TMS image.

Comparison With In-Situ Measurements

In this analysis, we selected 1997 TM images because of availability of ground *in-situ* measurements of fractional cover and green leaf area index from the SALSA program and other research projects at the three study sites described previously. The estimated *fc* and *GLAI* values for this analysis were all derived from 1997 TM images without atmospheric corrections to demonstrate the effectiveness of the adjustment approach for reducing atmospheric perturbation.

Because of rigid Landsat satellite overpass schedules over the study sites, the ground *in-situ* measurements were not always coincident with the satellite overpass dates.

The results from the Lewis Springs (sacaton grasses) in the San Pedro River basin and the Walnut Gulch Experimental Watershed (tobosa grasses) were presented in Figure 9. The *in-situ fc* values agreed reasonably well with those derived from TM images. The seasonal trends of the estimated *fc* were reasonably well in agreement with those observed on the ground. In spite of the fact that there was a good agreement between estimated *fc* values and *in-situ* measurements, no conclusive statements could be made, due to limited number of data available for this analysis.

For the Audubon study site, both fractional green cover (*fc*) and green leaf area index (*GLAI*) values were derived using ground-based reflectance measurements with the adjustment approach. The computed *fc* and *GLAI* values were compared with *in-situ* measurements in Figure 10. The estimated fractional green cover agreed reasonably well with ground measurements in the early growing season. On day of year (DOY) 216, the fractional green vegetation cover, *fc*, was underestimated by approximately 50%. This unexpected discrepancy on this date could be due to several factors. One was the heterogeneous nature of the study areas. Since ground sampling was made within several 2m x 2m blocks, the averaged values may not represent what a sensor would 'see' with a footprint of 30m by 30m area. The estimated green leaf area index, *GLAI*, agreed reasonably well with *in-situ* measurements. It should be pointed out that there were uncertainties associated with ground *GLAI* measurements. The uncertainty in the *in-situ GLAI* measurements could result from spatial variation of the vegetation density, random errors of the equipment used, and measurement condition variations when using LAI-2000 instrument, resulting in discrepancies between *in-situ* measurements and remote estimates.

DISCUSSION

The results presented here are preliminary. The remotely estimated *fc* and *GLAI* were compared with ground-based measurements using a limited data set. Further validation of the results from this study is needed in order to assess the accuracy of the adjustment approach. This would require carrying out extensive ground measurements at varying spatial and temporal scales with coincident satellite overpasses. Furthermore, a scaling up scheme for *fc* and *GLAI* variables needs to be developed in order to conduct a thorough validation of the proposed approach.

The use of the $NDVIveg = 0.8$ in equation (3) was specific to the research area and was independent of vegetation types. This upper boundary may vary with vegetation types within the area of interest. Use of this approach for other vegetation types may require knowledge of this boundary condition. Furthermore, the equation used to compute *GLAI* was developed for desert grasslands in arid and semi-arid regions. The use of this equation for other vegetation types such as dense agricultural crops needs further investigation.

The objects void of vegetation (OVVs) selected for this study were the bare soils of Wilcox playa in southern Arizona and White Sands, New Mexico, which resulted in a valid assumption that no vegetation was present all year round. When working with other data sets of different spatial resolution, one may find other invariant objects to be more suitable. However, it should be pointed out that the OVVs should be large enough to encompass at least a few pixels. For remotely sensed imagery such as Landsat TM, a field of bare soil may prove to be sufficient for this purpose.

Although a dynamic baseline adjustment factor, derived from objects void of vegetation, was used to circumvent atmospheric effects found in most remotely sensed, no consideration was given to the effect of atmosphere on the dynamic range of NDVI values. As shown in other studies, the atmosphere could reduce NDVI dynamics by as much as 10 percent (Qi et al., 1994), which would result in errors in *fc* and *GLAI* estimation. Quantitative assessment of atmospheric and bidirectional effects on the dynamics of vegetation indices, and on the *fc* and *GLAI* estimation need to be further investigated.

Finally, equations (3) and (4) did not specify the vegetation types. Because different types of vegetation tend to result in variable NDVI dynamics, use of these equations for remotely sensed imagery of multi-vegetation types may result in a constant bias towards some vegetation types. Therefore, uncertainties in estimated *fc* and *GLAI* associated with multiple vegetation types needs to be quantified. When applying these two equations for large-scale remote sensing images, it may be a good exercise to classify the imagery first and then use variable upper boundaries for different classes.

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Table 1. Remote sensing images acquired in 1992, 1997, and 1998 over the study area in the Southwest United States on different dates and day of year (DOY).

Airborne TMS		**Landsat TM**		**SPOT 4 VEGETATION**
Date	DOY	Date	DOY	
		Feb. 16, 97	46	
		Mar. 20, 97	79	
		Apr. 21, 97	111	
		Apr. 24, 92	114	
		Jun. 8, 97	159	
		Jun. 11, 92	162	
Aug. 12, 97	224	Jun. 27, 92	178	Daily from April 30 to December 30 1998
		July 13, 92	194	
		Jul. 10, 97	222	
		Jul. 14, 92	226	
		Sep. 12, 97	255	
		Oct. 1, 92	274	
		Oct. 14, 97	287	
		Nov. 2, 92	306	
		Nov. 18, 92	322	
Spatial Resolution: 3 meters		Spatial Resolution: 30 meters		Spatial Resolution: 1000 meters

Figure captions

Figure 1. Flow chart of the approach to computing green vegetation cover (*fc*) and green leaf area index (*GLAI*) using objects void of vegetation (OVVs).

Figure 2. Spatial distribution of green vegetation cover (a) and green leaf area index (b) derived from TMS images (3m resolution) over a portion of the San Pedro basin near the Lewis Springs, Arizona.

Figure 3. Green vegetation cover maps derived from TM imagery of 21 April, DOY 111 (a) and 12 September, DOY 255 (b) 1997.

Figure 4. Green leaf area index maps derived from TM imagery of 21 April, DOY 111 (a) and 12 September, DOY 255 (b) 1997.

Figure 5. Green vegetation cover maps derived from SPOT 4 VEGETATION imagery of 21 April, DOY 111 (a) and 12 September, DOY 255 (b) 1998.

Figure 6. Green leaf area index maps derived from SPOT 4 VEGETATION imagery of 21 April, DOY 111 (a) and 12 September, DOY 255 (b) 1998.

Figure 7. Comparison of fractional cover values derived with data before and after atmospheric correction, and with the proposed approach using the data without atmospheric correction.

Figure 8. Comparison of fractional green cover estimated using the proposed approach at different spatial scales: 3m (TMS), 30m (TM) and 1000m (VEGETATION).

Figure 9. Comparison of ground-based green vegetation covers (as indicated with a suffix g) with those estimated using satellite imagery (as indicated with suffix s) for tobosa and sacaton grasses using the proposed approach.

Figure 10. Comparison of *in-situ* fractional green cover (a) and green leaf area index (*b*) measurement with those derived using the proposed approach and ground-based reflectance measurements at Audubon site, where native grasses and Lehmann lovegrass were dominant species.