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Spectral variability of coffee crop related to scene fractional components estimated through high resolution image

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Abstract. The structural complexity of coffee crop results in marked spatial variation in soil, vegetation and shadow fractions (scene components) inherent to remote sensing measurements. This paper describes how scene components in coffee crops vary in typical fields from Patrocinio, Minas Gerais State in Brazil. Scene components were acquired through high resolution image Quickbird which, after a fusion process, was available in 0.6 m spatial resolution. An inherent classification process was adopted to label pixel in scene components. The spatial variability in scene components was related to multispectral TM bands. Differences in agricultural practices resulted in spatial variability in scene components in both inside and between coffee crop fields. Regression models between TM bands and estimated shadow and vegetation fraction presented r^2 ranging from 0.73 to 0.94 and 0.64 to 0.86, respectively. Only near infrared (NIR) TM4 band response provided low r^2 values. The results showed that multispectral bands are very sensitive to spatial variability of scene components and this may be useful in remote sensing observations in other row crops.

Palavras-chave: remote sensing, quickbird, Landsat, mixture modeling, agriculture.

1. Introduction

Brazil has the largest area of coffee in the world. Therefore, the government agencies and farmers need to acquire spatial and temporal information about tree coffee fields. However, agricultural management and policies have been hampered by disagreements concerning information about coffee yield and acreage. Little efforts have been directed to the analysis of discontinuous crops such as coffee using remote sensing techniques. Most of the studies have been directed to the use of remote sensing data applied to row crops identification, acreage estimation, and vegetative vigor and health assessment. Some studies applied to row crop exploit the spectral features of the radiometric signal without paying attention to the spatial features.

Incomplete canopies, such as coffee, are complex targets for remote sensing interpretations because shaded and sunlit soil and vegetation components are included in the sensor field of view in different proportions (Jackson et al., 1979; Wassenaar et al., 2002). The extraction of information from a remote sensing scene composed by row crops has been attempted through models that allow the calculation of each scene components taking into account, for each picture resolution element, a set of conditions such as plant cover, plant height, plant width, row spacing, row orientation, time of the day and day of the year (Jackson et al., 1979). Although these authors have proposed the use models to describe row crop effects on reflectance, it is expected that these parameters cause a high spatial variability within-field that is position dependent. . Thus, it is interesting to quantify the actual spatial variation of canopy shadow, soil and vegetation fractions across coffee fields. The knowledge of this variability may be helpful to explain spectral variations in terms of these scene components when satellite multispectral images are used for local and regional monitoring.

Although more complex approaches taking into account the canopy tridimensionality by using radiative transfer models have been proposed to acquire information about sparse vegetation (Kimes and Kirchner, 1982; Myneni et al., 1995), linear mixture modeling has been proved to be more effectivefor extraction of information from multiespectral images (Shimabukuro and Smith, 1995). Linear mixture modeling does not require canopy architectural abstraction followed by mathematical modeling and this is an advantage in relation to radiative transfer models complexity.

In comparison to three vegetation index (NDVI, SAVI and MSAVI), McGwire et al. (2002) found that mixture modeling provided significantly better results to measure small differences in percent green vegetative cover for areas of sparse vegetation in arid environments. They pointed out that vegetation indexes have poor performance when the targets present shaded soil and vegetation in scene composition.

Although scene components fractioning effects are present in most of remote sensing observations, they have not been quantified. Their impact in spectral variability of sparse crops, such as coffee, is little understood; in general, field measurements are tedious and time consuming. However, high resolution images (~1m resolution) have provided an opportunity to observe details of plant canopies and to quantify spatial variation of canopy attributes such as forest shadow fraction (Asner and Warner, 2003) and individual crowns (Asner et al., 2002; Zarco-Tejada et al., 2004). Scalling up techniques have been used to demostrate the relation between field vegetation features and spectral variability in coarse resolution images.

A method using high resolution image is proposed to investigate the spatial variability of scene components in coffee tree fields. The estimated surface fractioning could then be related to TM/Landsat spectral variability.

2. Study area

The study site is located in Minas Gerais State within the Patrocinio municipality in southwest Brazil. This region accounts for the highest coffee production in Brazil and is important for region economic development (FAEMG, 1996). Coffee is a crop with a very complex spatial structure. Coffee fields are subject to different agricultural practices according to location, coffee species and varieties, site quality and social and economic factors. This variety of practices results in scene components heterogeneity: coffee can be placed in various row spacings, which can vary from 1.5 to 4.5 m depending on the agricultural practices adopted, topographic site condition, water availability and coffee plant variety morphology (Tomazzielo, 2000). This leads to variability in vegetation cover density.

Agricultural practices used by farmers vary in relation to soil cover between rows; in the wet season, farmers allow the grasses to grow in between rows to avoid erosional processess. On the other hand, in the dry season the grasses are removed to avoid competition for water and nutrients between coffee plants and grasses. Thus, the substrate composition that covers the soil between coffee rows varies in reflectance and spatial structure. An additional variability is caused by missing plants in stands poorly managed coffee fields.

3. Estimetion of scene components by high resolution images

The availability of a 0.61 m panchromatic Quickbird image, in combination with 2.44 m visible (green, blue and red) and infrared bands, offered the opportunity to create an effective 0.6 m VIR pan-sharpened image by fusing these images (Zhang, 2002). This allowed the use of all spectral bands in 0.6 m resolution to spatially distinguish the soil, shadow and vegetation in coffee plantation.

The next step is the choice of spatial resolution to label scene components. Obviously, the scene components could not be fully accommodated in both spectral and spatial resolution available for this study; thus, a proper classification process was necessary. Actually, scene components are accommodated into shaded and sunlit soil, substrate and vegetation.

However, because of high variability and not enough spectral and spatial resolution, only soil, shadow and vegetation fractions were labeled by the classification method used in this study **(Figure 1)**.

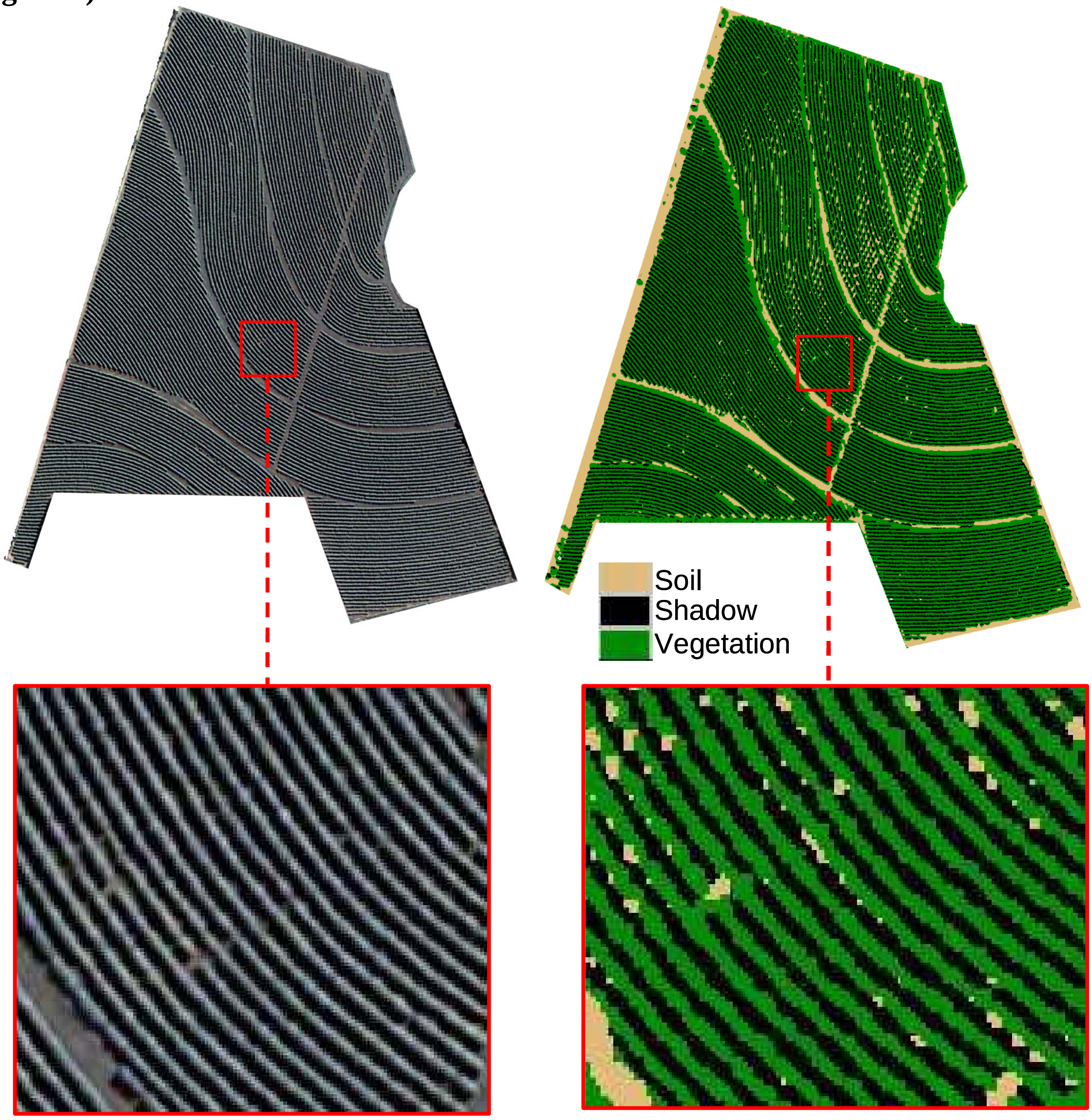

Figure 1. Sampled plot placed in a coffee field located in the fused Quickbird image (left side). Spatial variability of scene components acquired by the classification method (right side).

According to **Asner and Warner (2003)**, we used the red band histograms to determine a threshold DN (digital number) value between shadows and sunlit features. Depending on the coffee field, this process was successful to label these components. When the fields were poorly managed, the substrate was quite spectrally variable, thus a post supervised classification process was adopted to accommodate the pixel into its actual fraction. Soil fraction was the most difficult case because of high substrate variability (organic matter, dry and wet grasses and coffee crop residuals), which turned this fraction spectrally very heterogeneous.

Five days after Quickbird image acquisition (july 9th, 2002) a TM-Landsat-5 image was acquired and both images were registered to assure spatial compatibility. The proximity between the dates of both image acquisitions assured a fair relation between sun position and angle observation, avoiding changes in shadow patterns. The same sun-sincronous orbit (Quickbird and Landsat) and cloud free days assured almost the same illumination conditions at the time of image acquisitions, eliminating the shadowing daily variations due to the sun elevation.

Scene component fractions were acquired for different coffee fields **(Figure 1)**. Twenty seven field plots were located in specific positions with different row direction, management practices and vegetation cover density. Each plot accounts for vector polygons representing four TM pixels (4 x 30 m x 30 m) placed in coffee fields. The borders of the fields were not used for plot locations in order to minimize uncertainties about missregistration and sensor modulated transfer function.

Regression statistics were generated to outline the relationships between soil, shadow and vegetation fractions and TM spectral bands 1, 2 3, 4 and 5 for each plot corresponding to the average of the four pixels.

4. Results

As expected, the scene components showed high spatial variability among coffee plots (**Figure 2**). Variations in agricultural management systems caused differences in vegetation cover fraction mainly because of the row spacing variability and plant health state. Even for high row density, poorly managed fields showed an increase in soil fraction and a decrease in shadow fraction. However, in specific sites, vegetation cover increases mainly due to grass cover between coffee trees and rows (gaps) when the crop is poorly managed.. In general, the Quickbird spectral resolution did not allow to separate vegetation fraction into grass and coffee trees. This is possible only when the row spacing is very large.

A reasonable estimate about coffee tree density in a specific field could be made using the number of plants by row distance relation. This is clearly available in the true color composition for high resolution image (**Figure 2**). When row density increases the soil and shadow fractions drop; however this is not straight in all conditions. Even in lower row density (4.0 m row spacing) some plots did not output large shadow fraction. This was observed for those fields with broken rows caused by missing plants in poorly managed coffee fields.

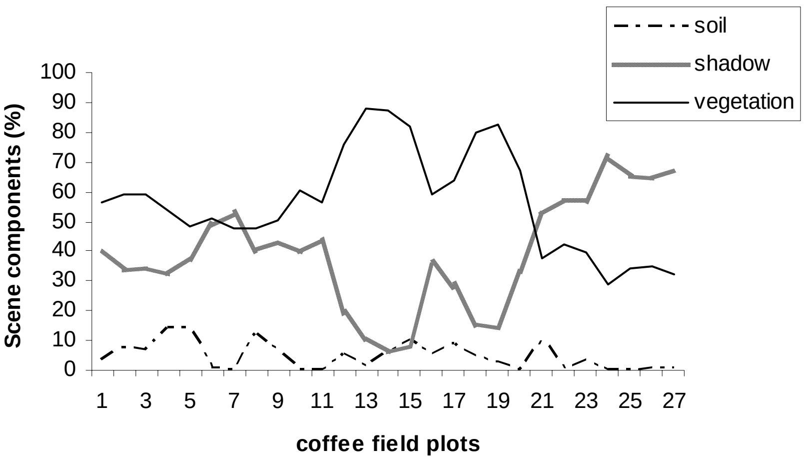

Figure 2. Scene components variability along the coffee plots.

The high correlations between shadow and vegetation fractions correspond to tall coffee cultivars in plots in well managed fields. On the other hand, the correlation drops in some sites probably caused by short cultivars or fields of low leaf area index (LAI) due to harvest methods that remove the leaves, and management techniques that remove the stems.

There was substantial variation in the observed scene fractions within “Landsat” 2 x 2 pixels (each individual plot) derived from the Quickbird spectral imagery (**Figures 1,2**) scattered on the coffee fields.

The soil fraction was poorly correlated to TM band responses (**Figure 3**). A possible reason is that the soil fraction was the most confused fraction estimated for high resolution classification method applied here. Pixels located out of vegetation and shadow fraction showed a high spectral variability, probably due to the effect of heterogeneous substrate on coffee fields. However, to label the soil pixels taking into account all the substrate variation it would be necessary to derive the substrate endmembers directly from field spectra. The aggregation of all substrate variation into a single soil fraction may explain the bad fit to the regression models between soil fraction and NIR TM band. However, the substrate effect did not seriously disturb the relationship between vegetation and shadow fractions and TM bands (**Figure 3**).

TM bands were highly sensitive to shadow and vegetation fractions (**Figure 3**). Vegetation fraction was positively correlated with almost all TM bands response. This was confirmed by positive gain value of the regression models (**Figure 3**). In general, the sensor response substantially increased as shadow fraction decreased. This suggests that coffee crop and other crops with similar structure (e.g. orchards) are a particular *agricultural biome*, in which the shadow fraction strongly drives the sensor response, and can be considered one of the main attributes related to the observed spectral response differences between different kinds of vegetation. The actual biome maps (Myneni et al., 2002) should consider the changes in shadow pattern for each day of the year in order to avoid erroneous interpretation in remote sensing of row crops.

The effects of scene components on sensor response depend upon both the scene components fractioning in the coffee field and the waveband. Thus, for the range of fractional scene component values occurred in the coffee fields observed here, spectral responses of visible and NIR were different. Visible radiation has a simple interaction with live vegetation in comparison to the NIR radiation. In the red spectral region occurs high photon absorption by pigments, thus reducing directional effects (Curran, 1989) and multiple interactions. The results indicated the low response for visible bands; however, the response is even lower as shadow fraction increased (**Figure 3**). The impact of shadowing is less complex at visible wavelengths because the multiple scattering of radiation is minimal. As a consequence there was a better agreement between scene component fractions and sensor response in this spectral region.

On the other hand, NIR spectral region was more dramatically affected. A bad fit was observed for all three scene components and it was confusing to interpret the relationship between coffee crop structural factors and NIR responses. In addition to the soil labeling dificulty, the interaction between NIR radiation and coffee crop spatial structure is much more complex, as stated by some authors for other crops (Epiphanio and Huete, 1985;).

5. Conclusions

Usually high resolution images are not available for crop temporal monitoring in large areas. However, the use of these products to validate the remote sensing interpretation of products of intermediate spatial resolution, such as Landsat images, is very important. This paper presents an example in which a tedious and laborious field work could be replaced for method using a highly detailed image to estimate attributes which are generally measured in the field.

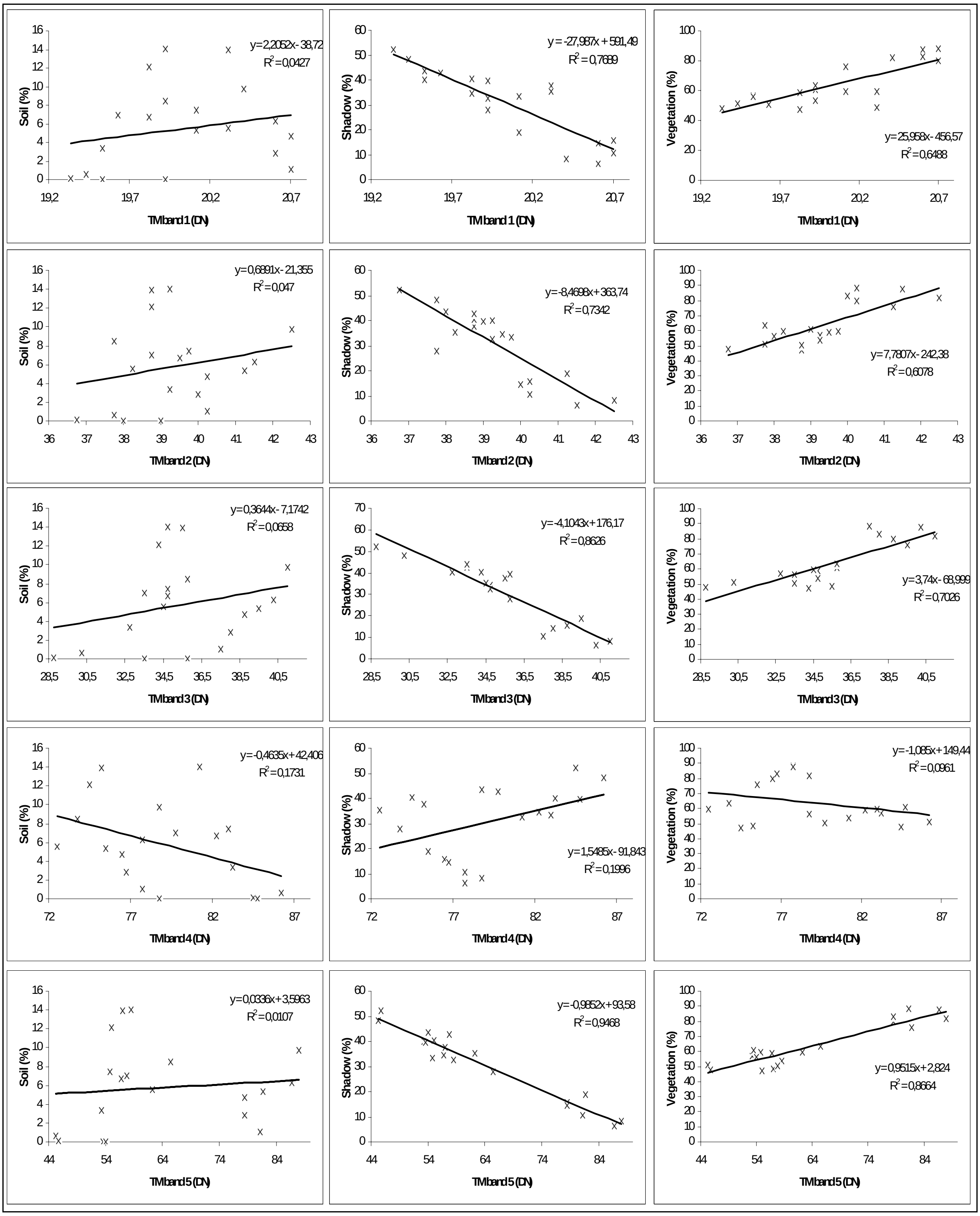

Figure 3. Regressions between TM multispectral bands (DN average of four pixels) and percent of scene components for each plot.

Spatial patterns of scene fractions (e.g. shadow and vegetation fractions) in coffee row crop were derived by scene component classification method using fused Quickbird images. Independent of wavelength, it was possible to conclude that changes in the proportion of scene component fraction have substantial impact over the pixel response in multispectral TM data in coffee fields. The spectral variation within coffee fields can also lead to misclassification if the training data set is not representative of the full range of spectral variations found in the remote sensing data employed in local and regional monitoring.

The results showed that more studies are needed for the extraction of useful information about perennial crops, such as coffee. The effects of age and agricultural practices and their relations to remote sensing data should be studied in more detail. The scene components: shadow, vegetation and soil have significant impact on the scene radiometry.

We suggest the effects mentioned above be studied in relation to their impact on the CBERS-2 data, as it is now easily available. In addition, as CBERS-2B is planned to be launched with a 2.5 m spatial resolution, the use of this kind of data together with medium resolution data should be encouraged.

Some degree of caution is required in using the NIR waveband and derivative indexes. The relationship between this wavelength and coffee crop spatial structure was not clear, therefore more studies must be done. Moreover, these results are derived from a small area and there are a lot of coffee crop features not addressed in this work. Therefore, these relationships should be understood over a higher geographical and temporal variability.

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