FIELD-ORIENTED ASSESSMENT OF AGRICULTURAL CROPS THROUGH TEMPORAL SEGMENTATION OF MODIS VI DATA

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ABSTRACT:

Monitoring agricultural crops constitutes a vital task for the general understanding of land use spatio-temporal dynamics. This paper presents an approach for the enhancement of current crop monitoring capabilities on a regional scale, in order to allow for the analysis of environmental and socio-economic drivers and impacts of agricultural land use. This work discusses the advantages and current limitations of using 250m VI data from the Moderate Resolution Imaging Spectroradiometer (MODIS) for this purpose, with emphasis in the difficulty of correctly analyzing pixels whose temporal responses are disturbed due to certain sources of interference such as mixed or heterogeneous land cover. It is shown that the influence of noisy or disturbed pixels can be minimized, and a much more consistent and useful result can be attained, if individual agricultural fields are identified and each field's pixels are analyzed in a collective manner. As such, a method is proposed that makes use of image segmentation techniques based on MODIS temporal information in order to identify portions of the study area that agree with actual agricultural field borders. The pixels of each portion or segment are then analyzed individually in order to estimate the reliability of the temporal signal observed and the consequent relevance of any estimation of land use from that data. The proposed method was applied in the state of Mato Grosso, in mid-western Brazil, where extensive ground truth data was available. Experiments were carried out using several supervised classification algorithms as well as different subsets of land cover classes, in order to test the methodology in a comprehensive way. Results show that the proposed method is capable of consistently improving classification results not only in terms of overall accuracy but also qualitatively by allowing a better understanding of the land use patterns detected. It thus provides a practical and straightforward procedure for enhancing crop-mapping capabilities using temporal series of moderate resolution remote sensing data.

1. INTRODUCTION

Proper monitoring of agricultural lands is extremely important for assessing land use changes and understanding their spatio-temporal dynamics. Indeed, the availability of good estimates of agricultural crop distributions on a regional scale is valuable for assessing agriculture impacts over the environment, including their consequences for issues such as carbon budget estimation, water and soil pollution and deforestation (Shimabukuro et al., 2004; Morton et al, 2006). In addition to that, such monitoring is also important for identifying and understanding the socio-economic factors and drivers involved in agriculture expansion and land use dynamics.

In this context, data from the Moderate Resolution Imaging Spectroradiometer (MODIS) have been proven to be useful for mapping land cover and land use at a regional scale (Huete et al., 1999; Strahler et al., 1999). In fact, MODIS provides a high quality, low cost source of surface reflectance satellite data whose moderate spatial resolution (250m) and very high temporal resolution (almost daily) are ideal for assessing vegetation phenological dynamics over extensive areas. More specifically, the sensor's MOD13Q1 VI (Vegetation Indices) product, with gridded and corrected 16-day composite data, has been found to be efficient in performing this task. In this sense, Anderson (2005) and Jonathan (2006) used this product in order to map vegetation covers in mid-western Brazil, covering areas in the Amazonian and Cerrado biomes.

Specifically in relation to agriculture, it has also been shown that multi-temporal MODIS imagery allows one to observe temporal VI profiles that present typical patterns or "signatures" that can be associated with distinct crop types. As such, Wardlow (2007) and Doraiswamy (2007) also employed MOD13Q1 data in order to differentiate between crops in the US Central Great Plains.

However, despite the success of these past experiences, some limitations can be pointed out when attempting to apply this kind of approach for large-scale classification and monitoring of agricultural crops. Indeed, general land use assessments with MODIS temporal data often display errors caused by pixels with noisy or atypical temporal profile patterns (Jonathan, 2005), which can be associated with mixed pixels (i.e., pixels containing non-homogeneous land cover) and eventual imperfections in MODIS lower-level detection and correction algorithms, along with other sources of signal interference.

In particular, Jonathan (2005) observed that MODIS temporal profiles are particularly affected by pixels close to a border between distinct land covers, especially when the transition between those covers is very abrupt. This is due to the fact that, at each date of observation, there is a slight variation in the portion of the gridded pixel effectively captured by the signal obtained by MODIS. As such, over the course of the time sequence there is also a corresponding variation in the amount of influence produced by the neighbouring land covers, leading to frequent and abrupt deviations in the observed temporal signal.

Within the context of agriculture assessments, it must thus be pointed out that the transitions observed between crops very often display such abrupt transitions. As such, proper monitoring of these crops is hindered by a significant amount of noise present at the limits of each agricultural field, leading to sub-optimal results even when the fields themselves are considerably larger than the MODIS pixel (250m x 250m, or 6.25 ha).

In a more general way, during the last years it has been widely stated in the literature that per-pixel classification procedures often lead to unrealistic land cover assessments, yielding the so-called "salt and pepper" effect due to a relatively high number of isolated misclassified pixels (Lillesand et Kiefer, 2000). As such, several authors have proposed to employ classification approaches based on the characteristics of segments or regions of the input image, as provided by image segmentation algorithms (Meinel and Neubert, 2004). These approaches, often called "object-oriented" classifications (Blaschke and Strobl, 2001; Meinel and Neubert, 2004), have been traditionally applied to high-resolution imagery, where image regions are computed based mainly on spectral similarities between neighbouring pixels.

In this work, it is thus proposed that a technique based on the same principles may be applied to MODIS temporal imagery in order to enhance classification results for agricultural areas with large fields, as is the case for the study region in mid-western Brazil. As such, it is suggested that the influence of noisy or disturbed pixels can be minimized, and a much more consistent and useful result can be attained, if individual agricultural fields are identified and each field's pixels are analyzed collectively. For that matter, a special methodology is presented here that is capable of taking advantage of the cleaner and more reliable samples within each segment, as opposed to those more affected by noise and thus more prone to lead to misclassification.

Figure 1. Location of the Brazilian State of Mato Grosso.

2. STUDY AREA

The study area used for this work corresponds to the Brazilian State of Mato Grosso (906 000 km²). It is located in mid-western Brazil, at the southern border of the Amazon Basin (Figure 1). In this region, high deforestation rates have been occurring for the last three decades, which can be related to colonization movements initiated in the 1970s and the consequential expansion of areas dedicated to crops and pasture use. The main planted crops are soybean (more than 6 millions of hectares according to IBGE, 2007), corn, rice and cotton.

3. MATERIALS

Ground truth data from an extensive field trip in the area was available. Data were acquired through interviews and comprise agricultural land use information for almost 50 farms and over 1300 parcels, covering the 2005-2006 and 2006-2007 harvest years. Harvest years considered in this study consist of periods between July (DOY 209) of a given year and July (DOY193) of the following year. In this way, a total of 93,424 hectares were mapped for the 2005-2006 year, whereas 151,627 hectares were mapped for the 2006-2007 year. The ground truth data quality was also tested and validated through a methodology based on outlier detection (Arvor *et al.*, 2008). Data were acquired at field scale, with parcels generally larger than 25 ha, being thus suitable for surveying procedures with 250m resolution MODIS data. Land cover classes charted by the survey consisted of single-crop (soybean and cotton separately) as well as double-crop production systems (soybean + millet, soybean + sorghum, soybean + corn and soybean + cotton), leading to a total of six classes considered in this study.

MODIS Data: MODIS/TERRA 250m resolution, 16-day composite VI data (product MOD13Q1) were acquired, processed and filtered for the 2005-2006 and 2006-2007 years, so as to build annual temporal sequences for both years, with 23 images each. The Enhanced Vegetation Index (EVI), proposed by Huete et al. (1999), was used in the analyses presented in this paper due to its ability to better avoid atmosphere and soil disturbances. In addition to that, it has been shown that EVI is more sensitive than NDVI in areas that present high vegetation activity (Huete *et al*., 1999), which is the case of the study area of Mato Grosso. The EVI is defined as:

$$EVI = \frac{2(NIR - R)}{(L + NIR + C1.R + C2.B)} \quad (1)$$

where *R*, *NIR* and *B* correspond respectively to red, near infra-red and blue bands. *L*, *C1* and *C2* are adjusting parameters to minimise aerosol effects (Huete *et al*., 1999).

The 16-day temporal resolution of the MOD13Q1 product is actually the result of the application of a Maximum Value Composition (MVC) algorithm on daily data, which is intended to eliminate noisy data caused by the presence of cloud cover. However, in some tropical areas such as Mato Grosso, this has been seen to be insufficient due to the extremely frequent cloud cover observed during the long 6-months rainy season. Thus, a smoothing algorithm based on the Savitzky-Golay filter (Savitsky and Golay, 1964) has been applied to that data.

4. METHODOLOGY

The proposal of this methodology is that, in order to enhance the assessment of agricultural land use with MODIS multi-temporal data, individual agricultural fields should be identified and each field's pixels should be analyzed in a collective manner. In this sense, it is reasoned that, within each agricultural field, more credit should be given to cleaner and more reliable samples, as opposed to those samples that are more affected by noise and thus more prone to misclassification.

In practice, this method proposes that two tasks need to be carried out. First of all, an image segmentation process should be performed in order to identify continuous and homogeneous patches of agricultural fields. This actually consists of a *multi-band* segmentation procedure, in which each band is associated with a date within the temporal sequence. This way, this process can be understood as a *temporal segmentation* of the area under study, meaning that homogeneous patches are identified based on similarities between the temporal signals observed for each point within the area. This way, it is intended that neighboring pixels that have suffered the same agricultural practices, and thus present similar temporal phenological behaviors, will be grouped together so as to form homogeneous segments or patches that agree with actual agricultural field borders. In this sense, it is argued that each of these segments will correspond to a region with uniform agricultural practices, and as such can confidently be assigned a single agricultural land use class. Finally, it is also suggested that a *region growing* segmentation algorithm (Bins *et al.*, 1996; Tilton and Lawrence, 2000) should be used for this task, since this kind of algorithm is more concerned with internal homogeneity of each segment rather than clear distinction between neighboring segments, which is the case of many other segmentation processes such as the *watershed* segmentation algorithm (Beucher and Meyer, 1993).

As a second step in the methodology, once the segments are identified, all of the pixels belonging to each segment can then be analyzed in order to identify the most probable class for the patch as a whole, thus providing a "field-wise" assessment of the area under study. For that matter, traditional approaches for segment or object-oriented image classification generally take into consideration two sets of data: overall segment measures (e.g., size, relation between the perimeter and the area) and mean values computed for all pixels within the segment, which in this situation corresponds to the mean temporal phenological behavior observed in each segment. However, it can be argued that taking these mean segment values into consideration can be inappropriate in this case, given that pixels with disturbed or noisy signals (such as those located close to the borders) end up influencing the overall segment measure as much as cleaner and more reliable pixels. In fact, as pointed out in the introduction, this (negative) influence can be particularly strong in agriculture areas, hindering the classification estimates for the area.

In this context, it is argued that a better approach consists of evaluating each of the segment's pixels *individually*, using posterior probabilities to estimate the chances by which each pixel may belong to each agricultural land use class. In fact, as observed in Jonathan (2005, 2006), higher posterior probabilities can actually be related to higher levels of classification confidence, in such a way that these pixels actually display higher accuracy rates than others. As such, it is argued that giving priority to evaluations with higher classification confidence should effectively lead to more accurate final mapping results. Thus, it is proposed that each segment as a whole should be evaluated as being covered by that land use class which displays the highest average posterior probability for all of its pixels, that is:

$$c_{seg} = \max_{C}\left(\frac{1}{n_{seg}}\sum_{i} P(c \mid x_i)\right) \tag{2}$$

where c_{seg} corresponds to the final class to be assigned to a segment, n_{seg} corresponds to the number of pixels within that segment and $P(c|x_i)$ corresponds to the posterior probability by which pixel *i* of the segment may belong to class *c*, according to the measures x_i of that pixel.

In this way, the influence of pixels with low posterior probabilities (usually associated with unrecognisable, atypical or disturbed temporal behaviors) is minimized in the final evaluation of each segment. It should be noted that this is also quite a different approach than individually classifying each pixel of a segment and then choosing the class associated with the most number of pixels. In this case, the presence of a high number of disturbed pixels could lead to misclassification (e.g., for "elongated" segments with a long borderline). Instead, the proposed method should manage to almost eliminate the influence of such disturbed pixels, mainly taking into account those points where high posterior probabilities were found for a class. As such, a more stable and reliable assessment of the area is achieved.

5. EXPERIMENT

A region-growing segmentation algorithm was employed based on the 23 bands available for the 2006-2007 year, so as to generate regions that displayed temporally homogeneous phenological behavior during the referred period. For that matter, the algorithm present in the freely available software SPRING (Câmara *et al.*, 1996) was employed. The parameters used were 100 for the similarity threshold and 4 for the area threshold. As such, resulting segments were computed with a minimum area of four MODIS pixels or 25 ha.

Several supervised classification approaches were then applied in order to test the methodology in a comprehensive way. The classification algorithms tested included the Maximum Likelihood approach (Duda and Hart, 2001), a C4.5 decision-tree (Quinlan, 1993), a Random Forest algorithm (Breiman, 2001), a Multilayer Perceptron (Neural Network) method using the backpropagation algorithm for training (Duda and Hart, 2001), and a Support Vector Machine (SVM) using a Sequential Minimization Optimization algorithm for training (Platt, 1998). The Maximum Likelihood approach was implemented as an independent program, whereas the implementations available in the WEKA data-mining package (Witten and Frank, 2005) were used for the remaining classifiers.

In all cases, training was performed during the 2005-2006 year, with the trained classifiers being applied to the 2006-2007 MODIS data. Experiments were carried out considering two different subsets of land cover classes, in order to assess different levels of classification complexity. Namely, the sets testes were the following:

- *6 class test case (more complex)*, comprising two single crop classes (soybean, cotton) and four double crop classes (soybean + millet, soybean + sorghum, soybean + corn and soybean + cotton)
- *3 class test case (less complex)*, comprising cotton, soybean + cotton, and soybean + other crops (i.e., areas occupied by soybean, soybean + millet, soybean + sorghum and soybean + corn). This test case

eliminates a relevant amount of ambiguity and confusion due to the similarity between the temporal responses given by soybean in double crop systems with millet, sorghum or corn.

As such, for each test case and each classifier, three classification predictions were computed:

- Regular per-pixel classification
- Application of the image segmentation procedure and per-segment classification based on traditional mean-value measures
- Application of the image segmentation procedure and per-segment classification based on the proposed method using posterior probabilities.

The classification accuracies and kappa coefficients of all results were then computed based on ground truth data available for the 2006-2007 year.

6. RESULTS AND DISCUSSION

Of the two test cases, the one with 6 classes corresponded to the most comprehensive and complex classification task. In this case, a significant amount of confusion can be expected between certain classes (notably soybean + sorghum, soybean + millet and soybean + corn), thus accuracies are not expected to be extraordinarily high. After running these experiments, the following results were reached (Table 1):

	Max Like	**C4.5 Tree**	**Neural Net**	**Random Forest**	**SVM**
Per-pixel	0.5157 61.78%	0.5104 63.21%	0.5605 66.90%	0.5125 63.03%	0.5749 68.21%
Segment. Normal	0.5670 65.66%	0.5352 65.91%	0.6397 73.09%	0.5534 66.72%	0.6027 70.43%
Segment. Method	0.6157 69.86%	0.6093 71.35%	0.6600 74.76%	0.6421 73.54%	0.6401 73.13%

Table 1. Kappa coefficients (above) and overall classification accuracies (below) computed for each classifier and each classification procedure, considering the 6 classes test case.

It can be readily seen in Table 1 that indeed the per-pixel classification approach consistently yielded the worst classification results for this test case, independently from the classifier algorithm being considered. In addition to that, it can be seen that performing image segmentation and attempting a "per-field" classification using the traditional method with mean segment values did increase classification accuracy in all cases studied. On average, the improvement observed for the kappa coefficient was 0.0448 with this approach. However, it can also be verified that even better results were obtained by applying the proposed method with posterior probabilities for estimating the most probable class for a segment. Indeed, improvements in accuracy relative to the traditional method were again consistently observed across al the classification algorithms. This way, an average increase of 0.0538 was observed for the kappa statistic when compared to the traditional method using mean segment values. Thus, when compared to the regular per-pixel classification approach, the application of the proposed field-oriented assessment of the area yielded results 0.0986 superior for the kappa statistic.

In a similar way, results were also computed for the test case with 3 classes (Table 2). Here, there is much less confusion between the land use classes and general classification accuracies are expected to be much higher.

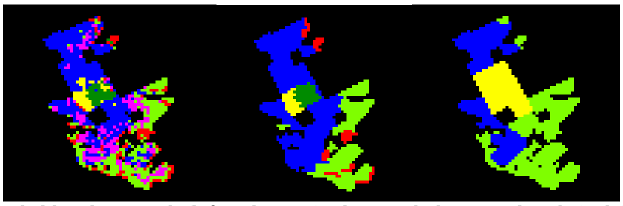
	Max Like	**C4.5 Tree**	**Neural Net**	**Random Forest**	**SVM**
Per-pixel	0.7762 88.54%	0.7202 85.58%	0.7554 87.11%	0.7242 85.95%	0.7608 87.60%
Segment. Normal	0.8412 91.77%	0.7084 85.21%	0.8223 90.55%	0.7519 87.27%	0.7898 89.05%
Segment. Method	0.8543 92.42%	0.7694 88.04%	0.8321 91.07%	0.7755 88.37%	0.7768 88.40%

Table 2. Kappa coefficients (above) and overall classification accuracies (below) computed for each classifier and each classification procedure, considering the 6 classes test case.

Once more, worst results were always obtained when using a per-pixel classification approach. This time, however, the improvements observed were not so significant. Again, using a per-segment classification approach always increased the classification accuracy, regardless of whether the proposed method or the traditional method with mean segment values was employed. Moreover, usage of the proposed method yielded better results on average than those obtained with the traditional per-segment approach (0.0189 for the kappa statistic). However, it should be pointed out that, for one case (classification with a Support Vector Machine), the traditional approach did reach a superior final classification accuracy rate (0.0130 better for kappa). Overall, comparison between the per-pixel approach and the proposed method showed an average improvement of 0.0543 for the kappa statistic when using the latter procedure.

Indeed, the less significant improvements observed for the 3-class test case can be related to the less complex nature of the classification task. In fact, it can reasoned that the lower amount of ambiguity between the classes enables the regular per-pixel approach to correctly estimate land use classes even when some amount of noise or disturbance is present. Another interesting issue to be discussed relative to the 3-class test case is the relatively worse performance observed for the method when using the SVM classifier. This may be related to the not so efficient procedure used by this classifier for obtaining proper posterior probability estimates, which is done by fitting a logistic regression model to the outputs of the support vector machine. As such, it is useful to note that the proposed method is more appropriate when using a classification algorithm that can properly estimate reliable probabilities for class assignment, rather than mostly concerning itself with identifying thresholds for proper class discrimination, as is the case of the SVM.

Finally, is should also be pointed out that a field-oriented approach such as the one proposed here can yield not only quantitative improvements in terms of accuracy but also qualitative improvements in terms of ease of interpretation and understanding of the land use patterns detected, as illustrated by Figure 2.



Likelihood approach (left and center), along with the ground truth (right) for a particular area in the study region. Red corresponds to soybean, dark green to cotton, yellow to soybean + cotton, blue to soybean + corn, light green to soybean + millet and magenta to soybean + sorghum.

Figure 2. Classification results obtained with the Maximum

Indeed, by observing this figure we can readily see not only the improvement in accuracy but especially the much better picture of the actual agriculture land use patterns in the area. This way, isolated errors and disturbances are eliminated and it becomes possible to compare the results obtained with the ground truth in a deeper and more comprehensive way. For example, the small field of class "cotton" (dark green) detected in the center of the area can be clearly seen to disagree with the large fields of class "soybean + cotton" (yellow) seen in the ground truth. However, when the MODIS EVI temporal signal for that area was analyzed, it could be seen that, indeed, there was virtually no sign of the characteristic soybean patterns in the area, meaning that either the soybean crop failed at that location or that there is an error in the ground truth collected. In any case, it becomes clear that, with this kind of approach, more practical and useful lessons can be learnt from the results, leading to the correction of errors in reference data, the identification of limitations in the possibilities of class discrimination, or the occurrence of specific situations in the field.

7. CONCLUSION

Results showed that the usage of temporal segmentation improves final classification accuracies in all cases. Improvements were more significant when using the new method proposed for evaluating each segment, particularly when similar classes were present and the classification task was harder. In this case, an increment of about 0.1 was attained for the kappa statistic, as opposed to a value of about 0.05 when using the traditional method based on mean segment characteristics. Moreover, using segment-oriented approaches enhanced results not only quantitatively but also qualitatively, since the resulting classification maps displayed much more realistic and visually understandable patterns, with actual agricultural fields and parcels being readily identified. Finally, the remaining classification errors could also be more easily interpreted, indicating that, with this approach, these errors become more related to specific field conditions or structural similarities between class responses, rather than caused by isolated noises and mixed pixels. As such, it is concluded that this methodology does provide a practical and straightforward way of enhancing crop-mapping capabilities using temporal series of moderate resolution remote sensing data.

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