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Tropical Agrarian Landscape Classification using high-resolution GeoEYE data and segmentationbased approach

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Abstract

We examine the use of high spatial resolution 'GeoEYE' imagery for land use classification in a tropical landscape. Image objects (I-Os) derived from features identification provide a basis for segmentation process and the Geographic Object Based Image Analysis (GEOBIA) framework. eCognition software with I-Os as classification unit and maximum likelihood algorithm facilitated the process. Supervised classification approaches (SCA) and rule set classification approach (RSCA) were used and performance and transferability of two approaches compared. Main conclusions: (a) high degree of details in GeoEYE data enables delineation of diverse land use zones, and (b) segmentation based analysis is more effective to tackle spatial intermixing.

Keywords: GeoEYE, segmentation, high-resolution, land use assessment, Image objects (I-Os), tropical.

Introduction

Information on landscape characteristics is significant for informed decision making on land-use systems, specifically agro-ecosystems [Nagabhatla et al., 2015]. Remote sensing and spatial analysis for natural resource management and decision making is an increasingly widespread approach used to capture the complexity of natural resource dynamics [Chauhan, 2004]. Up-to-date assessment is considered to be crucial for landscape-level management, particularly land use zoning at local or village level [Nagabhatla et al., 2012]. Widespread application of earth observation data is a promising approach to meeting this need [Roy, 2005]. Land use assessment methods that employ high resolution data, segmentation, and Image-Object (I-O) based classification approaches have been applied by scientific studies in different regions [Zhang, 1997; Burnett and Blaschke, 2003; Hay et al., 2005; Baatz et al., 2008]. However, while high spatial resolution should in theory capture vegetation (land use) details better, this is often not the case. This is

because intra-class or internal variability can limit accuracy and result in a conspicuous 'salt and pepper' effect when high resolution data is subjected to pixel based classification techniques [Myint et al., 2011]. Yu et al. [2006] explain how spatial complexity gives rise to the 'H-resolution' problem that inhibits vegetation inventory analysis particularly at a local level. I-O based classification techniques that take account of the spatial and spectral characteristics of high resolution data are periodically tested to overcome this problem [Yu et al., 2006; Byun et al., 2013].

Innovative data analysis methods are needed to enable more widespread environmental application of technological advancements in earth observation imaging systems [Bishop, 2007]. I-O based assessment demonstrates potential to overcome problems inherent to pixel based classification techniques [Jones and Reinke, 2009]. I-O based classification is a knowledge driven process that integrates ancillary data and ground based information into the process of delineating land use cover patterns [Rydeberg and Borgefors, 2002]. Most spatial analysis based assessments employ pixel based digital classification to study landscape structure and features, despite limitations arising from a peculiar problem of spatial intermixing that is commonly referred as the salt and pepper effect [Pinter et al., 2003]. The problem is accentuated when the area of interest is small but heterogeneous in composition, such as a field, village or a sample plot in a typical tropical setting [Li et al., 2011].

The present study applies Geographic Object Based Image Analysis (GEOBIA) as described by Hay and Castila [2008]. These authors describe GEOBIA as a sub-discipline of Geographic Information Science (GIS) devoted to developing automated methods for partitioning remote sensing imagery into meaningful image-objects (I-Os) and assessing their characteristics at spatial, spectral and temporal scales, so as to generate new geographic information in a GIS ready format. GEOBIA is emerging as a promising method for remote sensing image analysis, concentrating on pixel clusters. These clusters result from the segmentation process and form image-objects. In a classic segmentation based data classification process, the I-O layer serves as an intermediate output [Lang and Hay, 2008]. GEOBIA differs fundamentally from conventional remote sensing computing or pixel-based approaches [Yan et al., 2006] and is driving what may be a paradigm shift in digital image classification approaches, that is from pixels to objects. A principal advantage of GEOBIA is that it overcomes the problem of salt and pepper effects [Arvor et al., 2013]. This innovative approach is gradually evolving as a way to improve the accuracy of information extraction from high resolution remote sensing data [Cho et al., 2002; Johnson and Xie, 2011]. Blaschke [2010] reviews the adoption rate of GEOBIA, illustrating its application to various kinds of resource systems (forests, wetlands, agriculture). Spatial analysts report generally positive experiences of using GEOBIA to process earth observation data. For example, van der Sande et al. [2003] describe the application of segmentation based classification to high resolution IKONOS-2 data to derive a land cover map, and for assessing the risk of floods and flood damage in the Netherlands. More specifically for the agriculture sector, Rydberg and Borgefors [2002] describe an integrated method for delineating agricultural field boundaries in Sweden, employing a segmentation approach for analysis of multispectral satellite images.

Background, Rationale and Study area

This study was undertaken as part of an international project, whose overarching goal was to examine agriculture diversity of Wayanad, a district in the north of the state of Kerala in India. Wayanad harbours high ecological variability and provides a good test case for multiple segmentation based land use assessment techniques. Located between 11.27'-15.58' N latitude and 70.27' -75.47' E longitude, the district covers an area of nearly 2132 sq. km and has a predominantly agrarian economy. Referring to Koppen's classification, the region is a part of tropical monsoon zone with seasonally excessive rainfall and hot summer [Peel et al., 2007].

Other modules in the multi-disciplinary research project delineated land use transitions or land use cover change at sub-provincial level or district level using medium to coarse spatial resolution data that is- Aster and Landsat [Nagabhatla et al., 2015], this study employs GEOBIA as a multi-level classification approach using high resolution data to disaggregate the land use class 'agriculture'. Our study outlines an image classification approach for application to high resolution GeoEYE satellite data. The key objective was to create a detailed land cover map at the local level, in response to the demand for visually explicit policy support tools, a persisting requirement outlined by the Intergovernmental science-policy Platform on Biodiversity and Ecosystem Services. The study exploited the advantages of high spectral and spatial resolution of the earth observation data for assessment of agro-biodiversity in a tropical agrarian landscape.

The first step in the multi-level classification process is to select a representative case site for analysis, within the district of Wayanad. The administrative divisions in the district include three blocks or Taluks (Vythiri, Mananthavady and Sultan Bathery), which are subdivided into a total of 25 Grama Panchayaths (GPs). GPs are the smallest administrative unit of the Indian local governance system. Each GP is composed of a number of wards or villages (as shown in Fig. 1).The wards selected for the first phase of analysis, two from Panamaram GP and two from Vellamunda GP have a total area of 84.28 sq km and are part of the same digital image. A ground reconnaissance survey was conducted during October 2012 in order to validate that the selected sites were representative of the heterogeneous ecological diversity of the district, including a variety of agricultural land uses, and to collect training sets from each land use category.

Land-use in the tropical agrarian landscape of Wayanad is heterogeneous, mainly for the production of rice and other food and non-food crops. Prominent elements in the landscape include monoculture plantations of banana and areca nut, mixed plantations, and home gardens. Such variety of land use systems (landscape heterogeneity) is a feature that often limits accuracy in classifying earth observation data at the pixel level, especially in the case of a high resolution imagery [Lu and Weng, 2007]. Thus, Wayanad provide a good case study sites for testing the GEOBIA approach and its scaling potential. A global positioning system (GPS) and a stratified random sampling approach were used to establish ground control points (GCPs) during periodic field visits between 2012 and 2014. GCPs provide inputs for the software aided classification process and enable the accuracy of land use data outputs to be assessed. The GEOBIA framework was applied in a three-step process: (a) segmentation, (b) classification, and (c) evaluation.
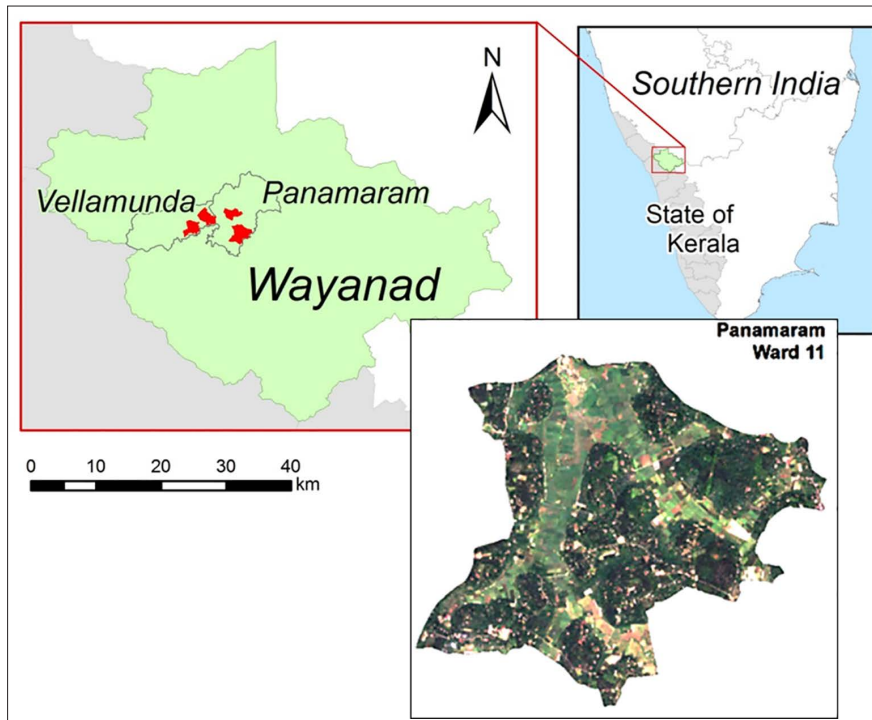
Figure 1 - Location of the Study Area (Wayanad) and selected sites or wards for analysis in Panamaram and Vellumunda regions (marked in red); also shown is the GeoEYE image for Panamaram Ward 11.

Segmentation is the initial phase that creates the I-Os. Segmentation can be single level or multi-level and is a prerequisite for I-O based classification. We adopted two different approaches for classifying I-Os, a supervised classification approach (SCA) and a rule set approach (RSCA). The segmentation level requirements for SCA and RSCA are different. Evaluation was carried out by means of a comparability analysis (CA) of the performances of SCA and RSCA; and a transferability analysis (TA), whereby we assessed the ability of the rule sets developed for application of the RSCA approach to one area (Ward 11 of the Panamaram Panchayat) to classify other area in the same data image. TA is an additional component that supplements the standard GEOBIA approach. Its purpose is to test the transferability and scalability of the RSCA approach.

The study area is shown in Figure 1. Ward 11 of the Panamaram Panchayat (with an area of 6.24 sq. km) was the principal study area or analysis window for land use classification. Data from three other wards (with areas ranging from 300 to 650 ha) were used for the TA. The selection of these three wards was made carefully so that land use structures corresponded to features of the main window. The GEOBIA framework is a method for making effective use of relevant information from high resolution imagery. In this case, information extracted via this process was intended to provide hard scientific evidence to feed into ongoing discussions in Wayanad on agro-ecosystem management and land use zoning processes at the sub-provincial level [Nagabhatla and Kumar, 2013]. In the present

study, the research questions were framed to provide substantive answers to technical queries, and practical guidelines for the adoption of the approach by the wider research community. In particular, we address the following research questions:

a) Does the more labour-intensive RSCA have significant advantages over the comparatively straightforward SCA?

b) Is a site-specific rule set developed for RSCA applicable only for land use classification of a particular area of interest, or can the rules also be successfully employed on other sites with a similar spatial organisation of land use classes? (In this case we asked: can the rule set designed for Ward 11 also be used for land use classification of adjacent wards.);

c) What are the pre-conditions for the wider applicability of a rule set (containing a proximity condition), for the transferability of a rule set designed for a single, specific spatial window to other regions in the landscape?

Data, Method and GEOBIA Approach

The principal data used for analysis was GᴇᴏEYE color Earth Imaging data, procured for 16th November 2011 with 0.5 m output resolution. The detail-rich multispectral and PAN-sharpened product of GeoEYE with spatial resolution of less than 1 m comprises four spectral bands: blue (450 to 510 nm), green (510 to 580 nm), red (655 to 690 nm) and NIR (780 to 920 nm). The data are projected on the Universal Transverse Mercator (UTM) zone 43North, WGS-84 datum and resampled using the nearest neighbour procedure. The in-built (segmentation and classification) algorithms in eCognition image processing software (Definiens®Developer 7) provided the software interface for data classification. This software offers features for executing all stages of the GEOBIA approach. Classification and Regression Tree Algorithm (CART), an operative feature in eCognition, was used for classification. In order to compliment the I-O segmentation and classification process, an NDVI (Normalized Difference Vegetation Index) layer was generated in ERDAS-2011 digital image processing software and referred to when necessary. The NDVI layer was generated according to formula: NDVI = (NIR-red)/(NIR+red) Rouse et al. [1974].

Ancillary data such as survey maps and secondary records of agriculture statistics from local agencies were consulted as required. Other data sets referred to during the classification process included: topographic data, and vector layer information on hydrology, elevation, and drainage and settlement density. The GCPs established using a GPS as described above provided ground truth information to assist the classification process. The Google Earth interface served as a supporting interface to validate discrepancies during the classification process. In the following, the application of the GEOBIA framework is discussed in two sections. Section "Segmentation and Image Object based Classification" describes the process of segmentation and application of SCA and the RSCA classification methods; Section "Comparability analysis (CA) and Transferability Analysis (TA)" describes the application of CA and TA for evaluation of the framework.

Segmentation and Image Object based Classification

The first step in the GEOBIA method is segmentation. This is followed by classification using SCA or RSCA. Figure 2 shows a schematic representation of the methodology. Segmentation refers to the process of clustering image pixels to create I-Os. Its purpose is to reduce the overall heterogeneity and, correspondingly, increase the degree of homogeneity

of the spatial data. The eCognition software uses heuristic algorithms and provides in-built segmentation options that include: chessboard, quad tree based, contrast split, multi-resolution, spectral difference, and contrast filter segmentation [Lathrop et al., 2006]. We used a patented segmentation method that takes account of four major attributes viz. scale, colour, compactness and smoothness [Navulur, 2007]. A combination of these attributes aids the user to create homogeneous I-Os at any specified resolution; alternative combinations can also be defined by assigning different weights to each of the attributes [Navulur, 2007].
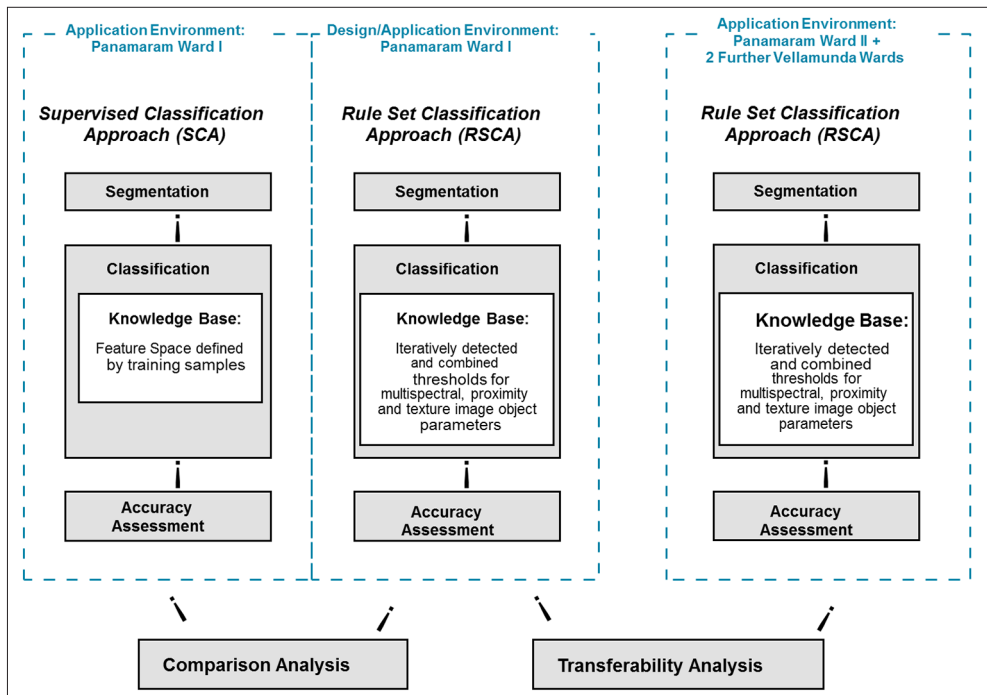

Figure 2 - Schematic representation of the GEOBIA methodological approach. RCA and RSCA are the two main components of the adopted spatial analysis framework.

A scale parameter is an abstract value to determine the maximum possible change of difference caused by combining different objects and dependent on the size of the I-O's. Small scale number and large scale number results in small objects and large objects respectively, referred mostly as multiresolution image segmentation [Varghese and Babu, 2016]. The multi-resolution segmentation algorithm then merges pixels or existing I-Os using a pairwise region merging technique [Yastikli and Uzar, 2013].

A single level segmentation process generates single I-Os of same pixel size, and is followed by the processing that merges several loops to form a larger unit. The cycle continues until a local threshold limit of homogeneity (user defined) is not exceeded. This 'homogeneity criterion' is defined as a combination of spectral and shape based uniformity.

By modifying the scale parameter [a user defined threshold to group and classify I-O's] the user can influence or customise the size of the I-Os. This function enables the analyst to set

a value that is suitable for a particular case study and associated landscape characteristics [Malik et al., 2001; Bishop, 2007]. The segmentation process is followed by knowledge base driven object-context based image classification (Step 2 of the GEOBIA method). In this study, seven land use categories were differentiated, such as- crop (mainly rice fields), banana stand, and fallow land, mixed plantation, palm stand (areca nut plantations), settlement and water body. The classification process involves delineation of main classes and auxiliary or supporting classes. The auxiliary class, for example 'AUX-drainage', is an intermediate product that requires further processing in order to generate a final output classification. For example, in the case of 'AUX- drainage', threshold settings for brightness and texture parameters were adjusted as per Gray-Level Difference Vector (GLDV) mean following Haralick et al. [1973]. The classification phase also includes an accuracy assessment analysis which provides inputs for evaluating the performance of both classification methods employed: SCA and RSCA.

For SCA and RSCA based classification, the segmentation process is a pre-requisite. Segmentation settings for both classification methods are calibrated using a similar format that is multi-resolution segmentation. However the iterative processes differs; specifically, the process design of RSCA requires two-level segmentation. The software interface in eCognition provides the opportunity for the segmentation process to be applied iteratively, thereby merging I-Os resulting from segmentation at a first level (Level 1) to generate a coarser level land use classification during a second stage of the process (Level 2).

SCA

The first step is to define the spectral features relevant for differentiating the land use classes. We employed mean and standard deviation for Bands 1 (Blue, 450-510 nm), 2 (Green, 510-580 nm) and 3 (Red, 655-690 nm) and NDVI (a total of 8 features), and brightness and maximum difference (an additional 2 features). In total, the supervised classification approach used this 10 feature portfolio as the default setting. Feature selection is a pre-process in SCA that helps to generate a knowledge base by providing training set I-Os. The next step, the sampling process, is initiated by defining the image features that represent the axes of statistical feature space. Spatial and spectral characteristics of each band include parameters such as standard deviation, brightness and Maximum Difference (Max.Diff) algorithms. These features are systematically integrated during the course of the classification procedure. The classification sampling of 20 units for each I-O based class category was derived from the raw GeoEYE data. The statistical algorithms of the classification software interface use a nearest-neighbourhood interpolation method to compute different class categories. We used this algorithm to assign I-Os or primitives to clusters in a feature space following Meinel et al. [2004].

RSCA

The RSCA classification process requires a two-level segmentation environment. First level segmentation is performed at a high resolution, small-scale parameter value of 30. This process mainly accounts for 'shape' and 'compactness' factors, set to the values of 0.1 and 0.9 respectively. The two-tiered segmentation process is particularly important to ensure sufficient accuracy to enable identification of thin linear features, like drainage ditches. A multi-level segmentation approach is applied when different threshold values are

required to differentiate multiple land use (target objects) categories that show overlap in a single threshold segmentation process [refer Dabboor et al., 2011]. Banana plantations of Wayanad are a land use where this is important, as they consist of lines of plants separated by drainage ditches; further transverse ditches give rise to a characteristic pattern of 'pits' in high resolution images (Fig. 3).
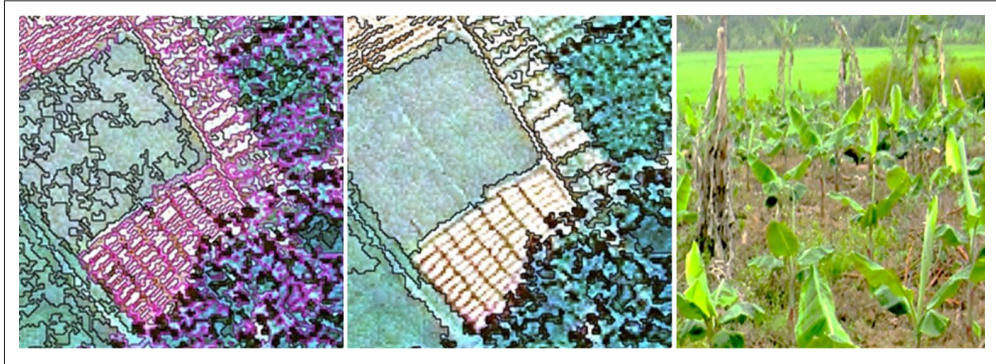

Figure 3 - Illustration of the RSCA segmentation process. (a) First level segmentation subdivided the image into fine units showing the pits typical in banana plantations (outlined in purple). (b) Second level segmentation performed at a coarse-level dissolved the boundary between banana strands and pits or drainage lines between two rows of strands. (c) Ground photo of banana plantation (foreground) and rice field (background) in Wayanad.

The first step in RSCA classification process is an analysis based on a coarse (I-O size) segmentation product, processed with a scale parameter of 100 and shape and compactness parameters as 0.5. During the process, the main land use category 'Crop', comprising of rice and other crop fields along with two auxiliary classes that is-'AUX-plantation' and 'AUX-no vegetation' are delineated. The function of auxiliary classes can be explained using the example of 'AUX-plantation', which represent a cluster of three plantation categories (mixed plantation, palm strands and banana plantations). Similarly, 'AUX-no vegetation' refers regions with little or no vegetation. In order to separate 'AUX-no vegetation' class from the other categories, an NDVI value threshold condition is consulted. Likewise, in order to differentiate 'Crop' and 'AUX-plantation', a rule setting threshold values for standard deviation of the green band and mean 90° texture parameter was employed [as per Haralick et al., 1973] is used. The degree value calculates the direction of the pixels within the shifting window and is a part of feature labelling process. The intermediate output layer from the first stage of the classification process is then subjected to correction application, a process for eliminating misclassified I-Os. This part of the analysis also includes sub-processing, for example the I-Os delineated as 'Crop' are subjected to a fusion process. After the I-O's are fused together, the process is subjected to reclassification (assigning the small or auxiliary I-Os to their respective land use class/category) as described below. The second stage of this classification process involves subdividing auxiliary classes. I-Os in the 'AUX- plantation' class are assigned to the main land use class categories 'Mixed plantation, 'Palm stand' and 'Banana'. To split 'Mixed plantation' and 'Palm stand', a rule

set based on a threshold of the texture parameter 'contrast' is used [Haralick and Shapiro, 1985]. I-Os of banana plantations are assumed to be interspersed with (in between or adjacent to) I-Os in 'AUX- plantation' or the other crop class 'banana-I'. In order to include the intermixed zones in the main land use class 'Banana', the CART spatial rule set based approach utilises a class description function as the basis for a classification algorithm. The rules are constructed by defining a threshold for the border ratio (relation) to the class share [Zhou and Troy, 2009]. Similarly, the auxiliary class 'AUX-no vegetation' is divided into the following categories: 'Settlement-I', Settlement-II', 'Water' and the auxiliary class 'AUX-potential banana'.

The final step in this classification process is I-O fusion. In order to finalise the categorisation of non-vegetation class such as class 'Settlement-I', the key feature parameter applied to define the rule-set is 'geometry' of land structures in settlement patters. The authors adopted a threshold combination of the geometric attribute 'asymmetry' and of the spectral attribute 'brightness'. Merged or fused 'AUX no vegetation' I-Os were assigned to the class 'Settlement-II' comprising the settlement area. The category 'Water' describes streams and standing water bodies along with the auxiliary class 'AUX-potential banana'. The division was achieved by applying thresholds for the NIR band and brightness. Thresholds that determine neighbourhood relations and area are embedded into class description. During the last stage of classification process, the auxiliary class 'AUX-potential banana' was tackled by defining the rule sets that either assigned it to the class categories of 'Banana II' or 'Fallow land'. It is important to note that this kind of allocation required identification of a distinct feature that is characteristic of that land use category. Ground reconnaissance data proved very useful in providing guidance for identification of appropriate features. For instance, drainage is a typical feature in Banana plantations that separates elevated rows of Banana plants from each other. To separate the drainage category, a spatial rule set indicator was adopted. This indicator could then guide the process of setting thresholds for the 'underlying' drainage component in 'AUX-potential banana', which could then be assigned either to the class 'Banana' or to 'Fallow land'.

SCA operates with training I-O samples that define a class specific area in a statistical feature space; RSCA is governed by multi-level rule set framework followed by a stepwise definition of land use types. Both SCA and RSCA classification methods visualise and analyse the spatial extension of land use categories, based on a skilful photo interpretation of elements in the landscape such as spectral characteristics, topographic and geometric features, texture and colour. The main difference between SCA and RSCA is the way knowledge base for the classification process is recruited.

Comparability analysis (CA) and Transferability Analysis (TA)

For CA, the first step is to assemble the observations from the standard supervised approach (SCA) and the rule set classification approach (RSCA) based on class-specific parameters. In short, the comparability analysis compares the accuracy assessments for RSCA and SCA. The purpose is to compare and evaluate the performance of the two classification methods. TA focuses on testing the transferability of rule sets defined in RSCA by using them to classify other GeoEYE data windows, in this case the three wards shown in Figure 1.

Results and Discussion

The results are discussed in two parts. The first part explains the segmentation common to both approaches and then summarises outputs from the two classification approaches; SCA and RSCA. The second part presents the results of the CA and TA. The discussion further considers technical issues involved in classifying high resolution data and provides some answers to usual queries (the questions listed above) arising from a standard I-O based classification experiment. The synthesized outputs, classified maps of three wards are also explained.

Segmentation

It is important to note that examining distinct spatial patterns of different land use units is fundamental for analysis of heterogeneity in the landscape [Nagabhatla and Kumar, 2013]; for an agrarian landscape this means delineation of different crop types. Multi-level segmentation is required when the area of interest, as in this case, is heterogeneous in composition, with various agricultural land use types interspersed in the landscape. For instance, at high resolution, banana plantations look like linear strands, a feature that prevents their differentiation from fallow land, a limitation fairly resolved during segmentation at Level 1.

The technical setting for this process is shown in Table 1 and the segmented output in Figure 3. The coarser Level 2 segmentation setting is used to address this problem. Specific features characteristic of the two categories of land use are identified for use during the Level 2 segmentation process. For example, the lands use category 'Banana' has characteristic 'pits' that are prominent especially during the juvenile stage of the crop. A specific function is defined to identify this feature. In the fine resolution Level 1 segmentation process. The feature is classified as a supplementary extra class, which is later integrated into the main class 'Banana' using rule based procedures, in this case relating to 'proximity'.

Table 1 - Parameter setting for two level multi-resolution segmentation processes.

Segmentation Step	Scale parameter	Shape	Compactness
1	30	0.1	0.9
2	100	0.5	0.5

Major land use types classified included: mixed plantation, areca nut plantation, banana plantation, fallow land, rice plantation, water body and settlement. The GeoEYE digital image subsets for seven major land use categories are shown in Figure 4. While both the classification methods were reasonably successful in delineating certain land use types, such as mixed plantation and areca nut plantations, overall RSCA worked better than SCA. For example, the land use class 'Fallow land' was not clearly distinguished from 'Banana' and 'Settlement' when the image was subjected to Maximum Likelihood Classifier based SCA classification, with low values for both producer and user accuracy. Producer accuracy measures the total of correctly delineated land use classes in the classified image, while user accuracy measures the chance or probability that land use

category in the classified image matches the details on the ground details [Carfagna and Gallego, 2005].

RSCA was better at identifying fallow land, with a user accuracy of more than 60%. SCA classification results in a significant over-representation of banana plantations. Rule based classification provides an analytical platform to address the limitation of the SCA approach by enabling the classifier to integrate the field knowledge base into the classification process. In simple words: spatial outputs (maps) derived from high spatial resolution data and segmentation based classification presents a detail overview of land use structure and associated agriculture diversity and provides an opportunity to examine patterns of land use and measure spatial extension of different land use types, and the biological diversity of agricultural landscapes (agro-biodiversity).
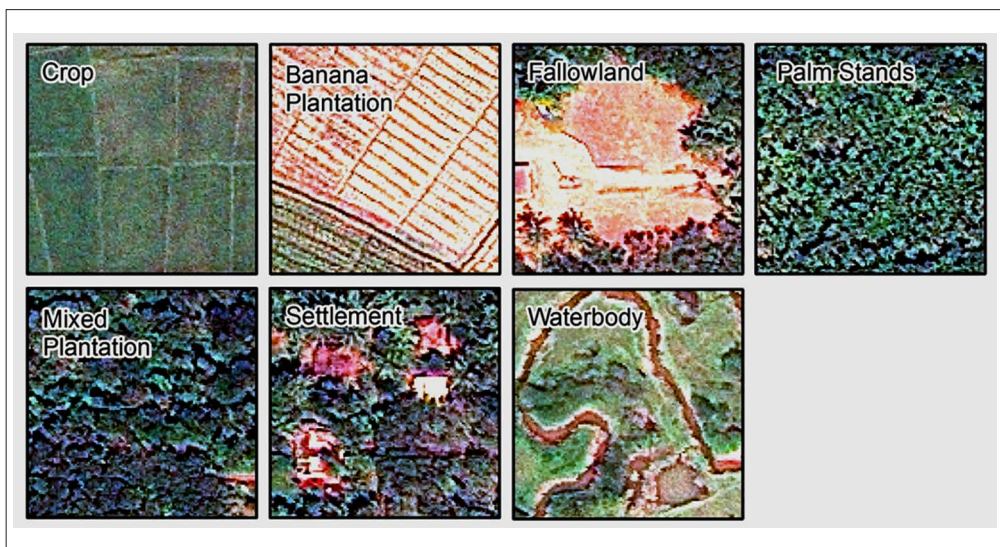

Figure 4 - GeoEye image subsets of land use/cover categories classified by adopting the GEOBIA framework.

Comparability analysis (CA) and Transferability Analysis (TA)

CA compares results from SCA and RSCA classification of GeoEYE data for Ward 11, as shown in Figure 5. This analysis highlighted the high degree of compactness of land use units delineated using the RSCA approach, compared with SCA. For example, rule set based feature identification provided a standardized process to identify the spatial distribution of banana stands. SCA performed reasonably well in delineating this land use class (banana plantations), although the classified output for Ward 11 shows evidence of over-representation and misclassification: The land use class 'banana' represents 12% of total area using SCA compared to 3.3% when using RSCA. Misclassifications are often attributed to variability of testing samples; for example more I-Os taken in by the classification algorithm setting. Overall producer accuracy for 'banana' class in our case was better using SCA and user accuracy was higher when using RSCA However, scientific

arguments favour user accuracy as a key parameter for judging classification performance [Jones and Vaughan, 2010].

In support of the above argument, Table 2 shows the results of accuracy assessment analysis for both methods and all land use classes. Spatial analysis of accuracy values indicates that low accuracy coincides with a high degree of misclassification in crop and fallow land areas. Accuracy values for mixed plantation and areca nut plantation were similar for the two approaches: using SCA, user and producer accuracy were 0.98 and 1.00, respectively, for mixed plantation and 0.91 and 0.90, respectively for areca nut plantation. PA value of 0.47 for banana plantations (RSCA) in Table 2 presents the accuracy of the classification approach, usually understood as a fraction of correctly classified IO's with regard to all IO's (test samples) employed for classifying that land use category.
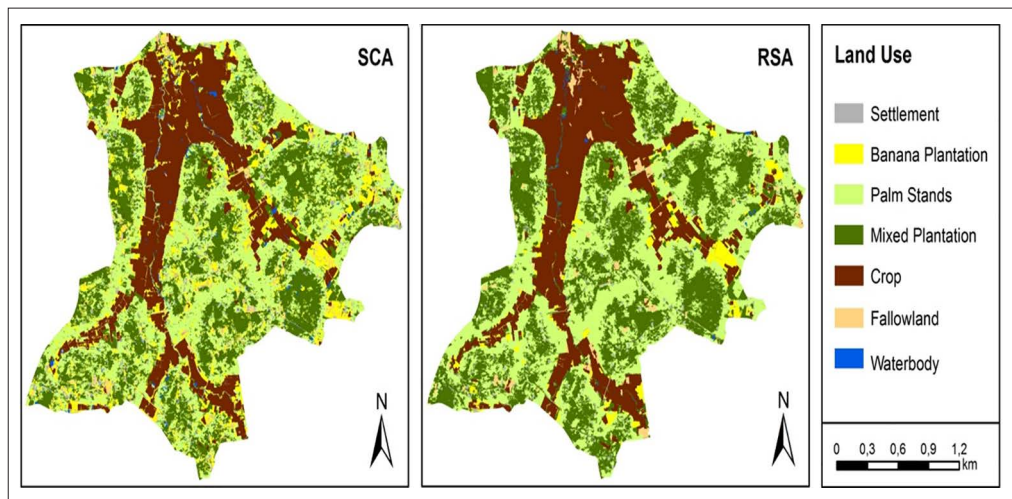

Figure 5 - The classified GeoEYE data for Panamaram (Ward 11) using two methods viz., SCA and RSCA.

Using RSCA, producer accuracy for mixed plantation is of the order of 0.98 and user accuracy has a slightly lower value of 0.92. Producer accuracy for areca nut plantation using RSCA was 0.94, higher than for SCA, whereas the user accuracy value is lower at 0.71. The user and producer accuracy of SCA for the land use category 'fallow land' are 0.51 and 0.71 respectively; while the corresponding value for RSCA for both user and producer accuracy is 0.61. In this case, the low accuracy values for RSCA might be attributable to misclassification of I-Os due to a failure to distinguish between the land use classes 'Settlement' and 'Crop' (for producers) and 'Settlement' and 'Banana' (for users). Crop fields (mainly rice) were detected satisfactorily by both approaches with producer accuracy of 0.8 and 1.00 for SCA and RSCA respectively.

Table 2 - Accuracy parameters of SCA and RSCA applied to Panamaram Ward 11 (Wayanad District, Kerala, India), for all land use categories. PA: Producer accuracy; UA: User accuracy; OA: Overall accuracy; KI: Kappa index. BAN-PL: Banana plantation; FALL: Fallow land; MIX-PL: Mixed plantation; PAL-PL: Palm plantation; SETT: Settlement; WAT-B: Waterbody).

Accuracy measure	BAN-PL	CROP	FALL.	MIX-PL	PAL-PL	SETT	WAT-B
SCA							
PA	0.75	0.80	0.51	0.98	0.91	0.57	0.99
UA	0.34	0.99	0.73	1.00	0.90	0.53	0.77
OA	0.80						
KI	0.73						
RSCA							
PA	0.47	1.00	0.61	0.98	0.94	0.66	0.71
UA	0.89	0.95	0.61	0.92	0.71	0.59	1
OA	0.86						
KI	0.81						
Diff. (SCA-RSCA)							
PA	0.28	-020	-0.10	0.01	-0.03	-0.09	0.28
UA	-0.55	0.04	0.12	0.08	0.19	-0.06	-0.23
OA	-0.06						
KI	-0.08						

User accuracy for rice was high at 0.99 and 0.95 for SCA and RSCA respectively. Overall accuracy was calculated to be 0.80 and 0.86 for SCA and RSCA respectively. CA analysis thus highlights the advantages of employing a rule set based approach. This conclusion was supported by the calculation of Kappa coefficient values (0.81 and 0.73 for SCA and RSCA respectively). In summary, SCA exemplifies feature supplied knowledge base concept where the training I-O samples are fundamental to outline a land use category; in a RSCA process, defining parameter thresholds is important. RSCA can be characterized as a user defined knowledge base approach where the iterative development of process design enables progressive improvement of the classification process.

The aim of TA was to assess the applicability and replicability of quality 'rule sets' outlined during the RSCA classification process. Specifically, we assessed the performance of rule sets developed for classification of Ward 11, when applied to other wards with similar landscape features. Since development of a rule based system (CART) for classifying high resolution data is a challenging task, it would clearly be an advantage if the knowledge base generated during the classification process could be successfully applied in different areas and at multiple scales. Thus we hoped to demonstrate scalability and replicative potential of CART. The rule sets developed during the RSCA process for Ward 11 were applied to classify three other wards in the image window, in a process that involves exchanging the subsets and running the rule sets. All four data subsets were extracted from the same GeoEYE and the spectral characteristics of the land use structure (detected reliably using proximity rules) were used to identify land use classes. Overall the TA analysis indicates that rule sets developed for one area can be readily applied with a reasonable degree of

accuracy to other areas (Tab. 3 and Fig. 6), at least in this case where the landscape features of the different areas analysed are more or less similar. The GEOBIA concept thus responds to the growing need to develop methods for wider application of high resolution imagery produced by remote sensing platforms. CA and TA processes are important modules in GEOBIA that evaluate the feature based threshold level approach adopted for image classification process and provide evidence of the potential and effectiveness of high resolution data for comprehensive agro-ecosystem assessment.

The paper presents site level application of a well-known processing technique (GEOBIA), the approach has received considerable attention in the last years. The innovative aspect of this exercise is testing the GeoEYE data analysis for a tropical region by employing GEO-BIA. To reflect the early works on GEOBIA, we referred the body of scientific literature, from early 2000's to examine how this approach is mainstreamed in the geospatial community, and if such geospatial exercises can serve as decision support tools for policy makers. It is noted that the cost and accessibility of high resolution satellite data and the processing software eCognition is a barrier along with the requirement of high level of technical skill to derive a final outcomes.
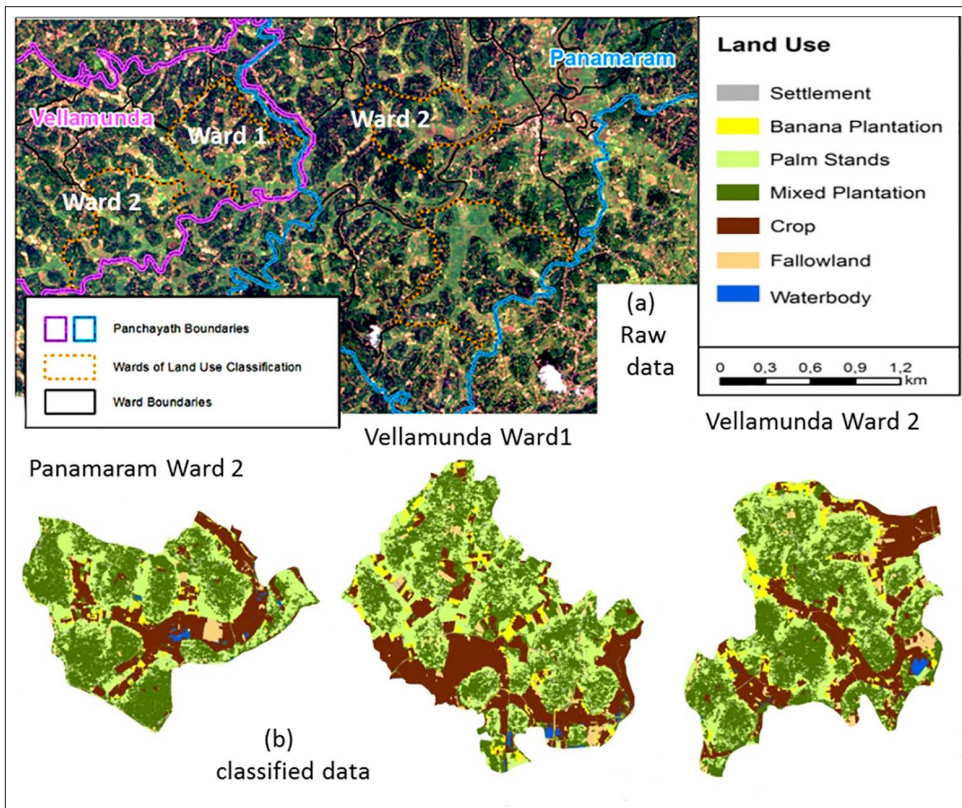

Figure 6 - (a) Location of selected wards in Panamaram and Vellamunda Grama Panchayats (b) Classified GeoEYE data image for Panamaram Ward 2 and Vellamunda Wards1 &2. The three maps shown are produced as the result of transferring rule sets (Transferability Analysis) outlined using Panamaram Ward 11 as the reference image.

Table 3 - Accuracy parameters and Kappa statistics for RSCA Transferability Analysis. Panamaram (PANA) Ward 11 served as the reference frame for application of the RSCA rule set to Panamaram Ward 2 and Vellamunda (VELLA) Wards 1 and 2. See Table 1 legend for key to abbreviations.

	BAN-PL	CROP	FALL.	MIX-PL	PAL-PL	SETT	WAT-B
PANA WARD 11 RSA							
PA	0.47	1.00	0.61	0.98	0.94	0.66	0.71
UA	0.89	0.95	0.61	0.92	0.71	0.59	1
OA	0.86						
KI	0.81						
PANA WARD 2 RSA							
PA	0.65	0.87	0.41	0.96	0.98	0.52	0.72
UA	0.91	0.94	0.33	0.77	0.83	0.48	0.77
OA	0.80						
KI	0.74						
VELLA WARD 1 RSA							
PA	0.56	0.84	0.86	0.91	1.00	0.76	0.08
UA	1.00	0.95	0.42	0.92	0.72	0.79	0.72
OA	0.81						
KI	0.73						
VELLA WARD 2 RSA							
PA	0.71	1.00	0.46	0.85	0.96	0.81	0.27
UA	0.94	0.97	0.74	0.72	0.71	0.45	1.0
OA	0.85						
KI	0.79						
Mean							
PA	0.60	0.93	0.59	0.93	0.97	0.69	0.88
UA	0.94	0.96	0.54	0.83	0.74	0.58	0.62
OA	0.83						
KI	0.77						

Conclusions

Agro-ecosystems are vital for provisioning ecosystem services to human society [IPBES, 2015]. Therefore, it is critically important to monitor and manage agriculture transitions in order to ensure long term ecological sustainability and human wellbeing. An up-to-date assessment of agrarian land use is fundamental towards this goal. Our study describes how an innovative methodological framework, GEOBIA, can be used for classification of high resolution earth observation data to enable assessment of the spatial distribution and patterns of agrarian land use. The spatial statistics provides a good input to evaluate the changes in ecosystems services profile of the landscape. The classified outputs show that GeoEYE data

can be used to identify crop diversity in an agrarian landscape with an impressive degree of spatial resolution. Use of in-built and customized (CART) classification algorithms in the eCognition software program enables definition of class parameters and construction of a decision tree for classifying spatial windows (in our case wards) with similar landscape features. The results underline the importance of examining spatial distribution of closely connected land use for land use zoning and planning, particularly at the local (village or ward) level. While comparability analysis reflects the highlights of image classification using RSCA and SCA, transferability analysis module take note of interoperability of the selected methodology (tested on an area of interest).

The results provide inputs for the development of sustainable land use management strategies for Wayanad, especially, in the context of a currently unregulated agricultural transition from food to non-food crops. Based on the above analysis, one could conveniently argue that comparative analysis (CA) is a good measure to evaluate the merit of rule based classification (RSCA) over the standard supervised classification (SCA) process. This argument also underlines that spectral properties representative of other land use categories show intermixing, as was the case with 'Banana' class misclassified in SCA and resulting in overrepresentation or exaggerated land cover portion for banana in different land use types, and the biological diversity of agricultural landscapes (agro-biodiversity).

The GEOBIA approach provides as effective way to generate a land use inventory process for a tropical landscape, specifically in this case for the evaluation of agro-biodiversity. Comparison of the two I-O classification methods, SCA and RSCA highlights the advantage of the CART approach (RSCA): The use of rule based decision algorithms enables more accurate differentiation of agricultural land use categories prone to spatial intermixing, for example, rice fields and banana plantations, mostly juvenile or the one planted interspersed with the crop. These differentiations is vital for an assessment of agro-biodiversity and in this case provide important scientific evidence to support the hypothesis that the Wayanad landscape is undergoing rapid change, in a process driven by changing agriculture practices, particularly the conversion of cost-intensive rice fields to more profitable banana plantations [Nagabhatla and Kumar, 2013]. In the context of concerns that these transitions in agricultural systems may ultimately threaten local food security, as well as loss of agro-biodiversity and disruption of beneficial ecological services in the region, stakeholders feel the need for hard evidence to inform policy discussions geared towards village level land use zoning and maintaining the food production capacity of local landscapes (see notes from meetings with stakeholders, accessible at http://www.uni-passau.de/fileadmin/dokumente/projekte/biodiva/BriefingNote6_Food_for_thought_final.pdf). Ground reconnaissance and data collected during periodic field visits from 2012-2014 proved to very useful for calibrating the remote sensing data and for validating the classified outputs (accuracy assessment).

Key points with regard to the analysis include: (a) Account needs to be taken of the cost implications of using high resolution data source such as GeoEYE. If the area of interest is large, one needs a dedicated budget for the data, which can be quite high compared to low to coarse resolution images. (b) The GEOBIA approach is highly dependent on specialised algorithms available in specific software packages like eCognition. This could restrict application of the approach by non-specialist researchers. The development of open source resources such as Spring-Freeware GIS and NASA's RHSEG image processing software

is opening up new opportunities for adoption of segmentation analysis by a wider range of researchers. (c) Basic technical knowledge of remote sensing based image classification is a pre-requisite for application of the GEOBIA approach for wider environmental problem-solving.

This study demonstrates the potential of remote sensing analysis towards quantifying and visually presentation agricultural systems pattern in a space-time continuum, as a powerful supplement to or even a substitute to survey-based field level assessments. The study responds to the call by Navalgund [2002] for a wide discourse on application of earth observation for sustainable development by filling some knowledge gaps regarding the potential of earth observation data for addressing real-world environmental problems, particularly at local (field) scale. The results of the study were presented to stakeholders in various discussion sessions and workshops in order to improve their understanding of agriculture transitions occurring in the area and their potential long term impact [Hindu, 2014].

Acknowledgements

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