TROPICAL FOREST CHANGE ASSESSMENT: THE USE OF AGGREGATES, A SEMANTIC APPROACH

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ABSTRACT

Assessing land cover changes in tropical rain forest areas is an issue of worldwide importance. Multi-spectral, higher spatial resolution satellite data are often the only data source for generating the necessary change information. Applying conventional remote sensing processing methods, however, induce uncertainties for both the spatial and thematic components of land cover changes in tropical rain forest areas. The induced uncertainties are not a problem of mixed-pixels, but concern: (a) the relation between the aggregation level of change processes in tropical rain forests and the measurement resolution of the remote sensing data used to observe these change processes, and (b) the problem of handling heterogeneous object classes with fuzzy extents at supra-pixel level.

To model the object-related induced uncertainties the concept of a process-driven semantic approach is described in this article. It is based on the use of *aggregate sets* occurring at supra-pixel level to model changes of heterogeneous spatial objects with fuzzy extents. A conceptual framework on aggregate sets, aggregate classification and aggregate change assessment is defined and related classification and change assessment models are described. The methodical development to process remote sensing imagery at supra-pixel level for different aggregation levels of land cover changes, is a further step to model real-world phenomena.

1. INTRODUCTION

Assessing land cover changes in tropical rain forest areas is an issue of worldwide importance. The alarming rate of tropical rain forest depletion and the potentially disastrous effects of deforestation on soil, water, climate, genetic richness and the future supply of economic products are growing concerns among scientists, politicians and the public community (van der Sanden, 1997). The anthropogenic and natural processes causing the on-going decline and spatial fragmentation of tropical rain forests have their own spatial pattern and dynamics. The recognition and description of these patterns and dynamics is essential geo-information to support sustainable management of tropical rain forest resources.

Multi-spectral, higher spatial resolution satellite data are often the only data source for generating the necessary change information, especially in vast and inaccessible areas. Conventional change assessment methods using remote sensing imagery, however, have proven to be ineffective to map land cover changes in tropical rain forest areas at a defined high level of confidence (Sader and Joyce, 1985; Malingreau, 1991; Lambin and Ehrlich, 1997). This is due to two interrelated facts. First, the data-driven measurement resolution of the satellite data used to observe land cover changes do not coincide with the aggregation level of change processes in tropical rain forests. On-going anthropogenic land use processes, like logging of commercial tree species, cultivation of forestland for agricultural practices, collection of forest products, and natural processes, like forest fires and regrowth are scale dependent (resolution and extent). Resulting land cover patterns are spatially heterogeneous and distinguishable at supra-pixel level on higher spatial resolution satellite data. Second, land cover in tropical rain forests exhibits many transition zones due to the anthropogenic and natural processes. Describing the transition zones by discrete categories causes thematic inaccuracies in defining change processes. Applying conventional remote sensing processing methods to assess land cover changes in tropical rain forest areas induces uncertainties for both the spatial and thematic components of change information. The induced uncertainties are not a problem of mixed-pixels, but are related to the problem of measuring heterogeneous object classes with fuzzy extents at supra-pixel level.

The spatial and thematic behavior of the above mentioned land cover patterns is related by semantics. Semantics are described by two hierarchies: classification hierarchies to define the thematic hierarchy among object classes, and aggregation hierarchies to define the spatial complexity within object classes (land cover composites). In tropical rain forest areas, aggregation hierarchies are process-driven, since changes in land cover patterns are derivatives of anthropogenic land use processes and natural processes.

To model the object-related induced uncertainties the concept of a process-driven semantic approach is described in this article. It is based on the use of *aggregate sets* occurring at supra-pixel level to model changes of heterogeneous spatial objects with fuzzy extents and ultimately, to assess land cover changes in tropical rain forest areas.

2. CHANGE ASSESSMENT METHODS

Methods of assessing change using digital remote sensing data can be broadly divided into two categories: pre-classification comparison and post-classification comparison. Image differencing, image rationing, selective principal component analysis, on-screen digitizing (mono-ortho-compilation) are commonly used pre-classification methods (Metternicht, 1999). These methods detect changes due to variations in the brightness values of the remote sensing images being compared. It is a qualitative change assessment; areas of changes are identified, but the kind of change can not be straightforward (categorically) labeled.
For quantitative change analysis, post-classification comparison is the most commonly used method (Jensen, 1997). It requires a complete classification of the individual dates of the remote sensing images and a change matrix that identifies 'from-to' change classes. Classification errors of individual images are propagated.

Both categorical change assessment methods are data-driven and rely on a 'one-pixel-one-class' strategy (Wang, 1990a). In tropical rain forest areas, classes of interest (information classes / object classes) are spatially heterogeneous, thematically fuzzy and occur on supra-pixel level. Under these conditions applying the above mentioned digital 'one-pixel-one-class' processing strategies induce uncertainties, both spatially and thematically. These object-related induced uncertainties cause problems to separate areas of change / no change at required confidence levels.
In literature, numerous methods and techniques are described in order to overcome either the spatial or the thematic induced uncertainties. Contextual classifiers were introduced based on spatial features derived from spectral imagery: co-occurrencies (Roan and Aggarwal, 1987; Peddle and Franklin, 1991), cover-frequencies (Wharton, 1982; Zhang et al. 1988; Gong and Howard, 1992; Bandibas et al. 1995), Markov random fields (Cortijo and Perez de la Blanca, 1998), semi-variograms (Oliver and Webster, 1986), fractals (De Jong and Burrough, 1995), wavelets (Dale, 1998). These contextual classifiers were applied in the classification stage of the individual images. Generally, the overall classification accuracy improved. Two major problems were addressed: the blurring effect of the moving windows, especially by increasing windows (to calculate spatial measures) and the impossibility to distinguish land cover classes which differ only in terms of the pattern of cover composites. In a window, land cover classes having similar spectral classes, can be different in the spatial arrangement of their cover composites.
To overcome the thematic induced uncertainties, fuzzy set theory (Zadeh, 1965; Bezdek et al., 1984) was incorporated in the image classification process. Measures of class membership were calculated in order to overcome the so-called mixed-pixel problem (Fisher and Pathirana, 1990; Foody, 1994 and 1996) and to address indistinct spectral classes (Key et al., 1989; Wang, 1990a and 1990b; Wang et al., 1990; Lowell, 1994; Foody and Trodd, 1994; Palubinskas et al., 1995). Applying fuzzy reasoning in single classification processes improved the overall accuracy compared to conventional "hard" (maximum likelihood) classifications. The impact of fuzzy reasoning at supra-pixel level is hardly recognized in literature (Verburg et al., 1999).

Current contextual and fuzzy techniques are per-pixel (or sub-pixel) oriented and hence data-driven. Change assessment methods, however, should be able to model object-related induced uncertainties. There is a need for a process-driven semantic approach that incorporates both the spatial heterogeneity and the thematic fuzzy components of change information at supra-pixel level. Such a change assessment method should rely on a *'many-pixels-many-classes'* strategy.

3. AGGREGATES, A CONCEPTUAL FRAMEWORK

3.1 The Aggregate Concept

To process remote sensing imagery at supra-pixel level, groups of individual image pixels have to be aggregated (from 'one-pixel-' to 'many-pixels-'). Aggregation in its broadest sense is a syntactic pattern recognition approach. In the syntactic approach, pattern primitives (or cover composites) of an object are selected by their structure (Mantas, 1987).

The pattern primitives constitute the basis symbols of the pattern language. The description of each primitive can be either deterministic or statistical and the recognition of primitives is often based on the decision-theoretic (statistical) approach (Haralick and King-Sun Fu, 1983).
The structural description of spatial objects can be regarded from different viewpoints. Three viewpoints are given: as a sampling procedure, as a segmentation procedure and as a generalization procedure. The entire remote sensing image can be seen as a sample of size *N*, with the pixels being the sampling units *n*. Such an image is further systematically stratified into equally sized spatial blocks called aggregates. An aggregate is then defined as a spatial *n x n* pixel block at supra-pixel level containing n^2 clustered sampling units, where $n \in \{1,2,3,4,5,\ldots$ *image size*$\}$ pixels.
Aggregating remote sensing imagery into spatial blocks can also be seen as a kind of a segmentation technique. This aggregate 'segmentation' is not driven by physical aspects of the remote sensing data, but by semantic aspects of the object classes. The region of the aggregate 'segmentation' is not defined by pure data values, but restricted to an *a-priori* defined aggregate.
Aggregation of individual image pixels is a kind of a raster generalization process. According to McMaster and Monmonier (1989), it is a categorical raster generalization. Generalization for analytical purposes is an important tool to study scale-dependent phenomena, like land cover changes in tropical rain forest areas. João (1989) mentioned that the use of a larger scale (or higher resolution) does not necessarily lead to a more appropriate analysis. Sometimes, land cover patterns emerge only after generalization, and only then they can be analyzed.
In this study, an aggregate is the measurement resolution to process remote sensing imagery to be differentiated from the data resolution of satellite sensors.

3.2 Aggregate Sets

The structure, function and change of spatially heterogeneous areas are scale-dependent (Verburg et al., 1999). Although various methods have been described to determine the scale of measurement, Cullinan and Thomas (1992) concluded that "no one method provides consistently good estimates of scale … and no one method is correct because each method addresses a different statistical question and each has a different sensitivity over changes in scale". The latter was confirmed by Marceau et al. (1994) who stated that "there is no unique spatial resolution appropriate for the detection and discrimination of all geographical entities composing a complex natural scene such as a forested environment". Verburg et al. (1999) applied two artificial aggregation levels to allow for a systematic analysis of spatial scale effects. In addition, Turner et al. (1989) stated that the spatial scale of ecological data encompasses both the data resolution and the extent of the data set.

A set of varying aggregate sizes or '*aggregate set'* overcomes the problem of selecting the non-existing 'one-and-only' measurement resolution. An aggregate set is a true bottom-up multi-scale approach. Having defined an aggregate as a spatial *n x n* pixel block, where $n \in \{1,2,3,4,5,\ldots$ *image size*$\}$ pixels, an aggregate set can be defined as a spatial pixel block series *s*, where $s = \{n \times n + n \times n + n \times n + \ldots + n \times n\}$ spatial blocks (Figure 1). Such an aggregate set is defined for each object class in particular. The selection of the elements of the aggregate set (number and size) is semantically driven by each object class, with two limits: the lower limit and the upper limit. The lower limit is the pixel size (data resolution) of the remote sensing data applied since this study does not focus on sub-pixel data extraction. The upper limit is defined by the remote sensing image scene size (extent of the data set). For a true 'many-pixels-' strategy, however, $s \notin \{1x1\}$ spatial block, and hence $n \notin \{1\}$ pixel.

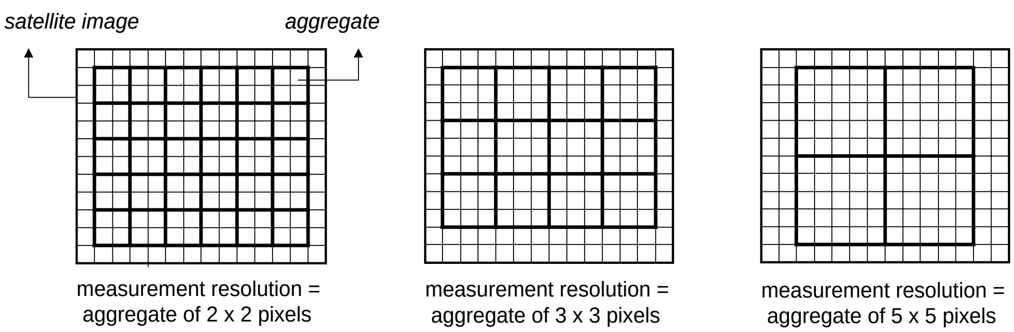

Figure 1: Example of an aggregate set, where s = {2 x 2, 3 x 3, 5 x 5} spatial pixel blocks

There are two other advantages of using aggregate sets. First, they overcome the problem of defining the extent of fuzzy spatial objects. An aggregate set provides a 'virtually infinite set' of representations instead of merely one version of

reality as Lowell argued for (1994). The other advantage is that land cover patterns, which only differ in geometric arrangement, can be separated by this true bottom-up multi-scale approach. Each object class has its own (statistical) signature, if plotted against the elements of the aggregate set.
The disadvantage of the aggregate concept is the (visual) disappearance of line objects, especially with increasing block sizes. For study of linear features, specific interpretation and classification techniques are available in literature (Smith, 1986; Wang and Howarth, 1991). It could be possible, however, that line objects are important pattern primitives. Though their spatial existence becomes invisible with increasing block sizes, thematically they are ‘visible’ in the structural measures.

3.3 Measuring in Aggregates

For a true ‘-many-classes’ strategy the outcome of any operator per aggregate should be multi-dimensional, depending on the number of pattern primitives. The multi-dimensionality can be regarded as a fuzzy partition of the aggregate universe. This can be derived by mapping measures of the strength of pattern primitives memberships.
In literature, (multi-dimensional) operators acting within neighborhoods (or windows), are called focal operators (Tomlin, 1990). There are two types of focal operators: pixel-moving windows and block-moving windows. With a small adjustment to the definition of Molenaar (1998), a pixel-moving window is defined as a neighborhood of a predefined window size about a particular raster element. Similarly, a block-moving window is then defined as a neighborhood of a predefined window size about a particular aggregate. Pixel-moving windows are pixel-oriented (overlapping neighborhoods) while block-moving windows are aggregate-oriented (neighborhoods do not overlap). In Figure 2, an illustration is given of the two types of focal operators. Examples of pixel-moving windows are spatial filters, which are well known in image processing (Lillesand and Kiefer, 1987). Less known, but described in software packages like ESRI (1996) and PCI-ILWIS (1997), are block-moving windows and available as ‘block functions’ respectively ‘aggregate map’ raster operations.

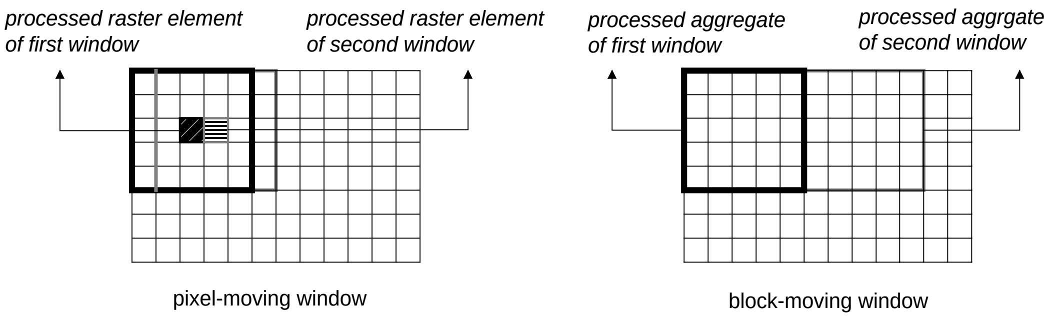

Figure 2: Two types of focal operators (for a window size of 5 x 5 pixels)

The advantage of a block-moving window above a pixel-moving window is the absence of blurring effect due to increasing window sizes. A block-moving window can be regarded as a thematic operator, since it is independent of neighbouring aggregates. The disadvantage of a block-moving window can be its crisp approximation of spatial objects with fuzzy extents. This is the mathematical issue of discrete approximation of continuous values. However, spatial objects are not measured by only one predefined block-moving window but by a set of focal operators (per aggregate set), and hence the fuzzy extent of spatial objects are measured by a set of measures providing a ‘virtually infinite set’ of representations (section 4.2).
Any statistical or deterministic function like the spatial measures used in contextual classifiers (section 3), can be performed per aggregate. Unlike most aggregate studies, the output of a block-moving operator is stored for all pixels that fall within the neighborhood instead of generating a reduced resolution of the image. The advantage of maintaining the cell structure size (raster size) of the original image is that the output results of block-moving operators with different defined neighborhoods can be compared (except for the united boundary pixels. Boundary pixels are a result of the size of the window and the extent of the data set; each window should be completely inside the raster image).

3.4 The Aggregate Classification Model

For processing satellite imagery following the ‘many-pixels-many-classes’ strategy, the aggregate concept has to be implemented in the classification routine. A model is used to describe such an aggregate classification. The concept of the so-called State Space Model (SSM) is used because the structure of the model is very suitable to describe the classification components of satellite remote sensing data (Figure 3). The structure of SSM consists of four subsystems:

an input (u), a state (x), a process (f) and an output (y) (van Straten, 1999). For a conventional remote sensing image classification, the satellite data can be regarded as the input (u), spatial objects are the state (x), the classification algorithm applied is the process (f) and the resulting state map is the output (y).

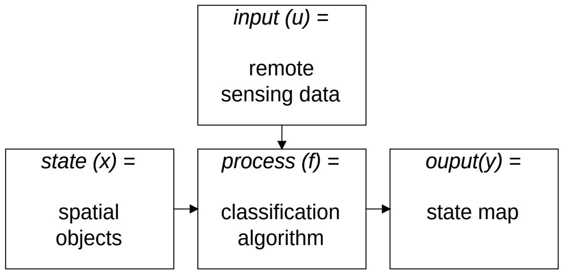

Figure 3: Classification model of remote sensing imagery (in State Space Form)

Using this basic form to describe *aggregate classification*, results in a model consisting of five basic units, where the output of one unit is used as input for another unit. The five components of aggregate classification are: (a) defining pattern primitives, (b) classifying pattern primitives, (c) defining object classes and aggregate sets, (d) partitioning classified pattern primitives by the elements of the aggregate sets, and (e) classifying object classes (Figure 4).

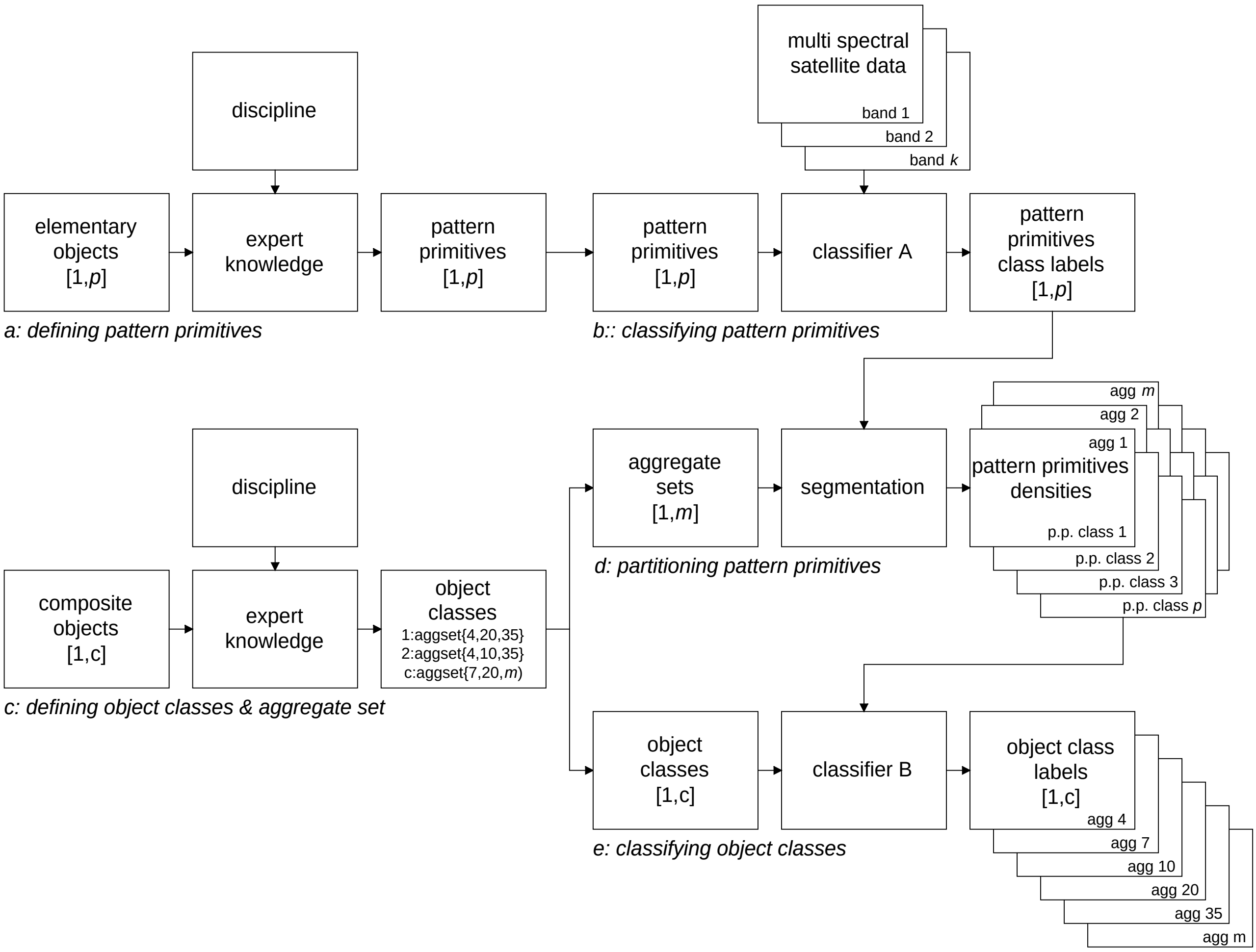

Figure 4: The aggregate classification model (in State Space Form)

The first two components, (a) and (b), are conventional image classification components. The contextual classifiers or fuzzy sets discussed previously were incorporated in classifier A. The classified pattern primitives is the input subsystem in the partitioning stage of aggregate classification. Classified pattern primitives, in stead of multi-spectral remote sensing data, is used as input to reduce the dimensionality of the data to be processed. Alternately, pattern primitive densities are the input for the classification of the object classes. Object classes are classified in order to reduce the dimensionality of the data to be processed. In this respect pattern primitives densities are congruent with radiometric densities of remote sensing images, and classified object classes are congruent with classified pattern primitives. However, they act on a different level of scale. Pattern primitives act on a per-pixel resolution and object classes on a supra-pixel resolution using higher spatial resolution satellite data.

3.5 Aggregate Change Assessment Methods

Referring to the aggregate classification model as given in section 4.4, Figure 3 and Figure 4, there are four stages in the classification model where change can be assessed if two temporal data sets are available. The first stage is at the second input subsystem (u/b); this is the conventional pre-classification comparison method. The second stage is at the second output subsystem (y/b), this is the conventional post-classification comparison method. The third stage is at the fourth output subsystem (y/d), which is in this article defined as the *pre-aggregate* classification comparison method. Finally, the fourth stage is at the fifth output subsystem (y/e) and defined in this article as the *post-aggregate* classification comparison method.
Both the pre-aggregate classification comparison and the post-aggregate classification comparison are of prime interest for further research.

3.6 Accuracy Assessment

Scale, accuracy and purpose are fully interrelated (Zonneveld, 1979). The purpose of assessing land cover changes determines the accuracy. The level of detail (measurement resolution, aggregate) in the classification is related to scale. In this respect, accuracy is not absolute but relative. Relative to the purpose and the hierarchical level of object classes. This has to be considered when producing a confusion matrix to compare the aggregate change assessment results with reference data based on ground truth data (Congalton, 1991). The change assessment results obtained by aggregate classification will also be compared with change assessment results obtained by a standard Maximum Likelihood classification, a conventional contextual classification and a conventional fuzzy reasoning classification. Statistics, Kappa coefficient and its estimated variance will be used to determine the significance level of the differences between applied methods. These statistics have been recommended as a suitable accuracy measure in thematic classification for representing the whole confusion matrix (Congalton et al., 1983).

4. CASE STUDY

The aggregate change assessment method is currently being tested using optical (Landsat TM) and radar (ERS SAR) data for a study site in Indonesia (South Kalimantan). Preliminary results show that geo-information on land cover and land cover changes in tropical rain forest areas varies for different aggregate sizes. Since aggregate sets are defined by the semantic aspects of object classes, relevant geo-information can be generated.

5. CONCLUSIONS

Conventional change assessment methods using remote sensing imagery are ineffective to map land cover changes in tropical rain forest areas at a defined high level of confidence. A new image processing strategy is defined and described in this article to relate semantic aspects of spatial objects via *aggregate sets* in order to model heterogeneous spatial objects with fuzzy extents. The methodical development to process remote sensing imagery at supra-pixel level for different aggregation levels of land cover changes, is a further step to model real-world phenomena. The conceptual framework on aggregate sets, aggregate classification model and aggregate change assessment model as defined and described has to be tested and validated in case studies.

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