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Object-Oriented Image Processing in an Integrated GIS/Remote Sensing Environment and Perspectives for Environmental Applications

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Abstract

While remote sensing has made enormous progress over recent years and a variety of sensors now deliver medium and high resolution data on an operational basis, a vast majority of applications still rely on basic image processing concepts developed in the early 70s: classification of single pixels in a multi-dimensional feature space. Although the techniques are well developed and sophisticated variations include soft classifiers, subpixel classifiers and spectral un-mixing techniques, it is argued that they do not make use of spatial concepts. Looking at high-resolution images it is very likely that a neighbouring pixel belongs to the same land cover class as the pixel under consideration. Algorithms in physics or mechanical engineering developed over the last twenty years successfully delineate objects based on context-information in an image on the basis of texture or fractal dimension. With the advent of high-resolution satellite imagery, the increasing use of airborne digital data and radar data the need for context-based algorithms and object-oriented image processing is increasing. Recently available commercial products reflect this demand. In a case study, ‘traditional’ pixel based classification methods and context-based methods are compared. Experiences are encouraging and it is hypothesised that object-based image analysis will trigger new developments towards a full integration of GIS and remote sensing functions. If the resulting objects prove to be ‘meaningful’, subsequent application specific analysis can take the attributes of these objects into account. The meaning of object dimension is discussed with a special focus on applications for environmental monitoring.

1. Introduction

The world in its complexity and manifold relationships cannot be grasped in full depth. Creating models of the world or computer-based representations of its surface poses a series of problems. In landscape ecology, there is growing awareness about continuity of phenomena and discontinuities of scales. Forman (1995) described this

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ambiguity through the image of a person gradually sinking with a spaceship or balloon. The human perception starts to discover pattern and mosaics abruptly. Many mosaics are quasi-stable for a while, separated by rapid changes that represent the "domain of scales". Each domain exhibits a certain spatial pattern, which in turn is produced by a certain causative mechanism or group of processes. This article does not deal with landscape ecology but takes it as a starting point to look into different image processing strategies. It will be argued that the suggested approach coincides well with the human perception and the way we extract information from visual impression. Our perception of an image's content is mainly based on objects. Once having perceived objects, we link them together by means of a complicated network made up by experience and knowledge. This very step was hardly implemented in image interpretation software. The image analysis presented here implies dealing with and handling image semantics. In most cases, information important for the understanding of an image is not represented in single pixels but in meaningful image objects and their mutual relations. Procedures for image object extraction which are able to dissect images into sets of useful image objects are therefore a prerequisite for the successful automation of image interpretation. Although segmentation is not new (see Haralick et al. 1973), it rarely featured so far in image processing of remotely sensed data. Only a few of the existing approaches lead to qualitatively convincing results while being robust and operational. One reason is that the segmentation of an image into a given number of regions is a problem with a huge number of possible solutions. The high degrees of freedom must be reduced to a few which satisfy the given requirements. A new approach is presented. Called "fractal net evolution approach" (Baatz/Schäpe 2000), it could actually revolutionize image processing of remotely sensed data.

2. Advances in Image Processing

With the advent of higher resolution image data the need for more efficient, more accurate methods has grown more than ever. Despite increased resolutions the problem of so-called *mixed pixels* still remains. Sensor systems have a specific instantaneous field of view (IFOV) or ground-projected instantaneous field of view (GIFOV) – to put it simply: a certain spatial resolution. Several targets of interest are often found within one unit of GIFOV. Only a single category is assigned to each pixel. But in fact one pixel could represent more than one target. To overcome this problem certain methods have been developed as alternatives to the conventional 'hard' classification techniques. In general they aim at the classification within one pixel, thus termed *sub-pixel classification*.

Early attempts at sub-pixel analyses started when the first MSS data were available back in the early seventies (Napelka & Hyde 1972).

One method is the *linear mixing model (LMM)*. Here we start from idealized, pure signatures for a class, so-called *end-members*. The spectral reflectance of each pixel is then assumed to be a linear combination of the spectra of these end-members weighted by their respective areal proportions within the pixel (Ichoku & Karnielli 1996):

$$r_i = \sum_{j=1}^{n} \left(a_{ij} x_j \right) + e_i$$

r_i is the reflectance of the pixel in the i^{th} band. a_{ij} is the reflectance of the j^{th} component of the pixel in the i^{th} spectral band and x_j denotes the proportion of the j^{th} component in the pixel. e_i is the error term in the i^{th} spectral band. The linear equation above can be used to compute the proportion of x_j. Spectra for the end-members are taken from libraries or from the image itself. As a result, class fraction and residual maps are created. This process of linear un-mixing shows some limitations (Ashton & Schaum 1998):

- End-member spectra should be as accurate as possible.
- The surface component is assumed to be opaque so that photons interact with only one component, otherwise non-linear modelling would be required and the LMM would be rendered invalid.

Another family of methods that strive to improve accuracy of classification are those using *fuzzy sets*. With this concept each pixel may have fuzzy membership with more than one class expressed as the degree of its membership to each class (values range between 0 and 1). Training data for fuzzy classification need not be homogeneous as is desirable for conventional hard classifiers. Throughout the classification procedure one needs to assign known portions of mixing categories. Popular fuzzy set based approaches are the *fuzzy c-means clustering (FCM,* v.a. Bezdek et al. 1984*)*, the *possibilistic c-means clustering (PCM,* v. a. Krihnapuram & Keller 1996*)* as well as the *fuzzy supervised classification* introduced by Wang (1990). The fuzzy classifiers produce images showing the degree of membership of pixels to stated categories. One caveat of the fuzzy set based methods might be:

- The accuracy of fuzzy classification depends to a high degree on the complete definition of training data sets. Foody (2000) remarks that untrained classes will only display membership to trained classes, which can introduce a significant bias to classification accuracy.

A third advanced method is the use of *neural network classifiers* borrowed from artificial intelligence research. Training data together with a known land-cover class (the input layer) are fed into the neural network system (the hidden layer). The algorithms inside the network try to match training data with the known class spectra patterns and produce an output layer together with errors of non-matching neural nodes. The procedure restarts trying to minimize errors. The process can be repeated several times. For the classification of specific objects neural networks have proven to be more accurate than conventional methods (Civico 1993; Foschi & Smith 1997; Skidmore et al. 1997). Especially Skidmore et al critically discussed the use of neural network classification:

- Accurate meaningful results require good training data sets; otherwise outputs will not be very reliable.
- The classification procedure needs the adjustment of various parameters, which highly increases complexity of the whole system and seems to limit its usefulness.
- Computational demands of neural network classification are strikingly high. Efficient computing could be realized on expensive, specialized parallel processing machines.

None of the various pixel-based classification methods seems to really satisfy all the needs for the production of reliable, robust and accurate results.

3. From Segmentation Algorithms to Operational Image Analysis

Segmentation

As stated above, the strong motivation to develop techniques for the extraction of image objects stems from the fact that most image data exhibit a characteristic texture which is neglected in common classifications. The texture of an image can be defined in terms of its smoothness or its coarseness. One field of image processing in which the quantification of texture plays a crucial role is that of industrial vision. These systems are used to assess the quality of products by measuring the texture of their surface. Most methods are based on the statistical properties of an image as well as the spectral or Fourier characteristics of airborne data, radar or VHR-satellite data which are playing an increasing role in remote sensing. But how can neighbourhood information across several spectral bands be included for a pixel-based analysis? Several research groups tried to do this by using pre-defined boundaries (‘per-parcel classification’ or ‘per-field classification’, see Janssen 1993, Aplin et al. 1999). Besides methodological questions one also has to ask what to do in case there are no boundaries readily available or exactly those boundaries should be updated. One solution is image segmentation. In many cases, image analysis leads to meaningful objects only when the image is segmented in ‘homogenous’ areas (Gorte 1998, Molenaar 1998, Baatz & Schaepe 2000).

From most studies following a segmentation approach it is argued that image segmentation is intuitively appealing. Human vision generally tends to divide images into homogeneous areas first, and characterises those areas more carefully later (Gorte 1998). Following this hypothesis, it can be argued that by successfully dividing an image into meaningful objects of the land surface, more intuitive features will result. The problem is to define the term 'meaningful objects'. As stated earlier, nature hardly consists of hard boundaries but it is also not a true continuum. There are clear, but sometimes soft, transitions in land cover. These transitions are also subject to specific definitions and subsequently dependent on scale. Therefore, segments in an image will never represent meaningful objects at all scales, for any application and, as will be argued later, for multi-resolution segmentation.

Edge-based segmentation

Edges are regarded as boundaries between image objects and they are located where changes in values occur. There are various ways to delineate boundaries. A specific approach is presented by Hoffman and Boehner (1999). They calculate a representativeness of each pixel for its neighbours. The image segmentation is based on the representativeness values of each pixel. At first these values are calculated by a harmonic analysis of the values for each spectral channel. The minima in the matrix of representativeness – typically arranged in pixel-lineaments – represent spatial unsteadiness in the digital numbers. For the image segmentation, the vectorized minima of the representativeness delimit areas consisting of pixels with similar spectral properties (spatial segments). A convergence index is combined with a single-flow algorithm for the vectorization of the representativeness minima. A standardisation is performed through the calculation of a convergence index for every pixel in a 3 x 3 window.

Region-based segmentation

Region growing algorithms cluster pixels starting with seed points and growing into regions until a certain threshold is reached. This threshold is normally a homogeneity criterion or a combination of size and homogeneity. A region grows until no more pixels can be attributed to any of the segments and new seeds are placed and the process is repeated. This continues until the whole image is segmented. These algorithms depend on a set of given seed points, but sometimes suffering from lacking control over the break-off criterion for the growth of a region. Common to operational applications are different types of texture segmentation algorithms. They typically obey a two-stage scheme (Jain/Farrokhnia 1991, Mao/Jain 1992, Gorte 1998, Molenaar 1998, Hoffman et al. 1998):

1. In the modelling stage characteristic features are extracted from the textured input image, including spatial frequencies (Jain/Farrokhnia 1991, Hoffman et al. 1998), Markov Random Field models (Mao & Jain 1992, Panfwani/Healey 1995), co-occurrence matrices (Haralick et al. 1973), wavelet coefficients (Salari/Zing 1995), wave packets (Laine/Fan 1996) and fractal indices (Chaudhuri/Sarkar 1995).

2. In the optimisation stage features are grouped into homogeneous segments by minimising an appropriate quality measure. This is most often achieved by a few types of clustering cost functions (Jain/Farrokhnia 1991, Mao/Jain 1992, Hoffman et al. 1998). A further possibility is the watershed transformation.

Also listed among the two-step approaches, the Markov Random Field (MRF) method is worth mentioning in more detail. They classify a particular image into a number of regions or classes. The image is modelled as a MRF and a *Maximum a posteriori* (MAP) probability approach is used or classification. The problem is posed as an objective function optimisation, which in this case is the *a posteriori* probability of the classified image given the raw data which constitutes the likelihood term, and the prior probability term, which due to the MRF assumption is given by the Gibb's distribution.

Sometimes seen separately is the group of ‘split-and-merge’ algorithms. They start by subdividing the image into squares of a fixed size, usually corresponding to the resolution of a certain level in a quad tree. These leaves are then tested for homogeneity and heterogeneous leaves are subdivided into four levels while homogeneous leaves may be combined with three neighbours into one leaf on a higher level etc.

Per-field or per-parcel classification

The per-field classification approach has shown improved results in some studies (e.g. Lobo et al. 1996). The results are often easier to interpret than those of a per-pixel classification. The results of the latter often appear speckled even if post-classification smoothing is applied. ‘Field’ or ‘parcel’ refers to homogenous patches of land (agricultural fields, gardens, urban structures or roads) which already exist and are superimposed on the image. Some studies (e.g. Janssen 1993, Aplin et al. 1999) indicate that the methodology is positively contributing to the classification of remote sensing imagery of high to medium geometric resolution. This classification technique is especially applicable to agricultural fields. Distinct boundaries between adjacent agricultural fields help to improve the classification due to the fact that boundaries in an agricultural landscape are relatively stable while the cropping pattern (also within the lots) changes often.

Multi-resolution segmentation and object-based classification

Because an 'ideal' object scale does not exist, objects from different levels of segmentation (spatially) and of different meanings (ecologically) have to be combined for many applications. The human eye recognises large and small objects simultaneously but not across totally different dimensions. From a balloon for instance, the impression of a landscape is dominated by the land use pattern such as the composition of fields, roads, ponds and built up areas. Closer to the ground, one starts to recognise small patterns such as single plants while simultaneously small scale pattern loses importance or cannot be perceived anymore. In remote sensing, a single sensor correlates highly with a specific range of scales. The detectability of an object can be treated relative to the sensor's resolution. A rough rule of thumb is that the scale of image objects to be detected must be significantly bigger than the scale of image noise relative to texture. This ensures that subsequent object oriented image processing is based on meaningful image objects. Therefore, among the most important characteristics of a segmentation procedure is the homogeneity of the objects. Good results are expected only if contrasts are treated consistently (Baatz/Schäpe 2000). Furthermore, the resulting segmentation should be reproducible and universal to permit application to a large variety of data. Baatz and Schäpe argue that multiresolution image processing based on texture and utilisation of fractal algorithms can alone fulfil all main requirements at once. Their 'fractal net evolution approach' uses local mutual best-fit heuristics to find the least heterogeneous merge in a local vicinity following the gradient of the best-fit. Furthermore, their algorithm can be applied with pure spectral heterogeneity or with a mix of spectral and form heterogeneity.

Uncertainties in segmentation and classification

Uncertainty includes any known or unknown error, ambiguity or variations caused by inherent properties or the interaction of various aspects constituting the system. Thus, uncertainty may arise from such elements as measurement error, inherent variability, instability, conceptual ambiguity, over-abstraction etc. Uncertainty is virtually inevitable in the decision making process in GIS and has been extensively studied since the late 80s (Goodchild/Gopal 1989). In the context of this paper, we focus on the aspect of a system which is either certain due to its variability or cannot be objectively quantified for likely occurring errors. Several elements lead to uncertainty in images: Firstly, the accuracy of satellite data itself and atmospheric conditions; secondly, the inherent inaccuracy of ground data elements and categories due to complexity, soft transitions and semantic differences between different rules in the classification process of the surface's characteristics.

Inherent uncertainties in the categories imply that there is uncertainty in the description of the objects. Cheng (1999) distinguishes four aspects which cause uncertainty in the image definition according to Plewe (1997), namely fuzziness, multiple criteria, spatially incomplete definitions and time incoherence. Gahegan and Ehlers (1999) discussed the uncertainties in the procedure of image classification. They used four models to represent data in four different forms: field model, image model, thematic model, object model. A data set in each model may be described by a number of abstract properties, i.e. data value, spatial extent, temporal extent and lineage information, and uncertainties can be associated with these aspects. The uncertainty associated with the mapping result is the uncertainty that already resides in one data form plus the uncertainty associated with the data transformation. For example, through image capture a data value may be affected by measurement error or quantification; grid processes or relief distortion may force a change in spatial location. Therefore, uncertainty of objects comprises uncertainty in the image plus uncertainty associated with the segmentation and classification. The work of Gahegan and Ehlers (1999) provides a general conceptual framework to understand and trace uncertainty in the object generation process, where it originates from and what effects it has. However, as Cheng (1999) points out, the actual effects of transformation have not been analytically measured. There is a strong need to investigate uncertainties in object generation. As we are – from a 'pure mathematical' point of view – not even able to define the 'ideal' objects to extract, we strongly recommend the use of multi-resolution segmentation: the meaningfulness and interpretability of several layers of objects in different dimensions is analysed later within an object-oriented classification process utilising semantic knowledge.

4. Per-Pixel Classification vs. Context-Based Classification

To compare 'traditional' per-pixel classifications and context-based classifications, a study area in the German-Austrian border region close to the city of Salzburg was selected, including parts of Berchtesgaden National Park (Germany). Data included Landsat TM imagery, SPOT pan and various GIS data layers. The software used for pixel-based classification is Erdas Imagine^{TM} 8.4 and multiresolution segmentation is carried out with *eCognition*^{TM} for object oriented image analysis (Delphi2 Creative Technologies, Munich). *eCognition*^{TM} is a new integrated software environment for multiresolution segmentation and object-oriented fuzzy-rule classification. Using a beta version of the programme, multiresolution segmentation was successfully applied to several different problems in the fields of remote sensing, image analysis in medicine and structure analysis (Baatz/Schäpe 2000, Buck et al. 1999, de Kok et al. 1999). A visual impression of the resulting differences is given in Fig. 1. The object-based approach delineates "naturally looking" configurations rather than pixel-dominated pattern. To test the results, an accuracy assessment was performed utilising detailed land cover data derived from interpretation of aerial photographs at 1:10,000 scale. Per-pixel classification results in the well-known salt and pepper effect. Single pixels are classified differently than the surrounding area and homogenous regions cannot be generated. The only way to smooth the image is to use filters, which however work without considering the original information. Classification based on segmented images won’t show any salt and pepper effect and does not need any filter operations. Homogeneous regions (image objects) are built up first, and then the classification is applied to these objects.

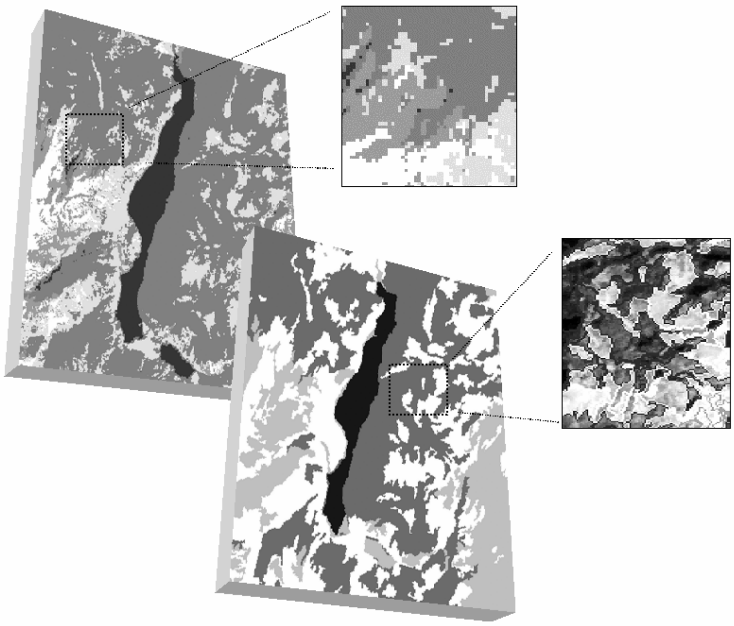


Figure 1
Results obtained from ‘traditional’ pixel-based classification (top) vs. segmentation-based objects (bottom). See text for explanation.

5. Integration of GIS and Remote Sensing

GIS and Remote Sensing have a rather long history as unequal siblings in the geoinformation family and never really managed to move onto common platforms. Commercially available software systems clearly show their respective backgrounds in vector vs. raster/image technologies, and usually attempt to integrate some basic functionality from the 'other' world. The main difference is in the core data models, but beyond that remote sensing analyses spatial information by starting from the complete picture and trying to dissect the image into homogeneous 'objects', while (vector) GIS builds a representation of spatial reality from bottom up.

Remote sensing was always seen as an attractive means to overcome the spatial data bottleneck of GIS, delivering continuous data coverage over large areas. Mostly, the crossing over from (multi-)spectral to thematic data was handled as a one-way route using remote sensing as a data generation technology before applying the analytical capabilities of raster or vector GIS. On a conceptual level, two distinct theories were employed as foundations: (quasi-)continuous spatial observation of radiometric characteristics, e.g. looked upon as "fields", has been contrasted with the dual geo-relational and more recently the object-relational models of representing entities by vector objects.

The issue of closer integration of these two different strands of geo-spatial technologies has been around for quite a while. This mostly meant that data as well as functionality from both backgrounds were to be available in single hybrid software systems, often with a strong emphasis on back-and-forth data conversion routines. It was thus acknowledged that for many application domains, the holistic image view and the analytical object view would complement each other. Integration was limited though: even simple tasks like the delineation of samples or training areas in images with objects from a vector dataset, or the spectral description of a parcel by aggregating corresponding image values often required and still requires tedious conversion routines. Most success has probably been achieved through loose coupling of dedicated systems, as can be observed from the mutual integration of key routines in the ESRI and ERDAS software families.

Now, we are set to carry the integration one or more significant steps further: software technology has evolved to a point where tighter integration of components has become feasible on a large scale, and the standardization and open systems movements have provided us with an application-oriented integrated conceptual foundation for geo-spatial information processing (see www.opengis.org). New technologies are emerging now which, instead of combining functions from both ends, directly straddle the (former) borderline between remote sensing / image processing and object-relational GIS. This is probably not as special from a technology point of view but much more from a conceptual perspective: radiometric responses and traditional image processing tools are being used side by side with GI functions describing spatial distance, topological characteristics and thematic values. With all of these observations being available in a seamless environment, the 'integration' debate is no more about 'easily going back and forth', but clearly about bringing these two geoinformation heritage lines together.

The benefits of these developments are only beginning to show and it will take some time to modify our somewhat entrenched frames of mind to adjust: remote sensing and GIS integration is no longer just about vectors-on-top-of-images or easy mutual conversion, but about integrated views from spectral as well as thematic perspectives. These different domains and scales of empirical measurement are joined to provide a better picture of reality, thus opening up entirely new ways of generating spatial knowledge. Examples in this paper provide but a small glimpse of novel insights!

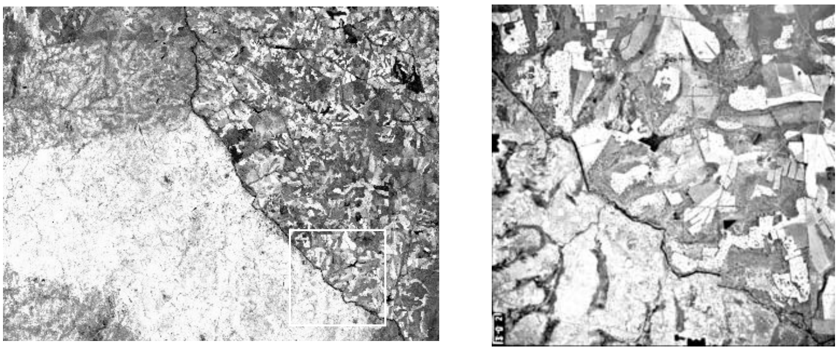
6. New Perspectives for Environmental Applications

Remote sensing is however not as widely used for natural resource management as predicted 20 years ago or as often claimed by the field's experts and data providers. One of the frequently stated reasons for this is the lack of expertise among the users to extract information available in remotely sensed imagery in support of their endeavours (Skidmore 1999). This stumbling block causes headaches for space agencies and industry when considering the emerging markets for image data as predicted for fields such as agriculture, insurance, intergovernmental agencies and international treaties (DGLR, BMBF 2000; Skidmore 1999). At a time when GIS concepts and software penetrate the workplace to the level of common office software packages, remote sensing sales and revenues do not follow at the same pace.

Looking at environmental monitoring, the major tasks are either to update existing geo-information (observing changes at t_1 in regard to conditions recorded at t_0) or to delineate land cover features in areas which haven't been mapped before (baseline data at t_0). In both cases knowledge about the nature of boundaries between adjacent objects (sharp or fuzzy) and their specific properties (texture, neighbourhood, relationship) exists, though at various degrees of certainty. The methodology of multi-resolution image segmentation as described above offers the possibility to reproduce the boundaries across different data sets (e.g. medium and high resolution imagery, regional to local) and allow for a transparent inspection of results. To translate spectral characteristics of image objects to real-world features, the object-oriented classification approach uses semantics based on descriptive assessment and knowledge, in other words it incorporates the wisdom of the user.

How the implementation of the methodology could benefit remote sensing and GIS users will be shown for two applications. Where agricultural monitoring focuses on controlling compliance with regulations governing subsidies, the shift of field boundaries (area estimates) and the nature of the crops are of main concern. For example, the European Community initiated a project to develop an objective methodology which could be applied in all member states and be uniformly credible. One of the main aims was to obtain estimates of crop yields per unit area so that the total production could be estimated (Taylor et al. 1997). Even though the combination of ground surveys and remote sensing improves the overall accuracy of agricultural statistics, the authors conclude that area estimates based on pixel-based classification methods fail to deal satisfactorily with field boundaries. That the delineation of boundaries inside fixed parcels and resulting crop area estimates can be successfully improved by rule-based object-oriented classification was already demonstrated by Janssen (1993) for agricultural land use in the Netherlands.

In regions such as the southern part of Africa where reliable statistics on yearly crop yields are missing (Fig. 2), the primary task is to carry out segmentation of agricultural land across different farming schemes, e.g. large-scale commercial, small-scale commercial and communal farms (Gomez & Gallego 2000). Applying the above-mentioned methodology while using new high-resolution imagery data could certainly reduce the relatively high standard errors per unit area obtained during the first survey.



a b

Figure 2: Crop area estimation in Zimbabwe. a. Landsat TM, upper right: large scale commercial farms, upper-left: small-scale commercial farms, lower left: communal farmland. b. aerial photograph (white box in a.). Courtesy of S. Gomez, ERSI, Harare

The second example concerns the role of data in environmental conflict resolution. At the root of conflicts such as access to natural resources we often find that the relevance of the available data or their interpretation is debated among the conflicting parties (Moore 1996). An important factor for successful mediation is the ability of the parties to agree on a common data model from where information is derived in a transparent way to allow the development of options and the assessment of impacts from possible decisions/solutions. In this process, the image could serve as the unbiased base; the conflicting parties jointly develop the rules for the translation into information and explore options for sustainable solutions by simulations based on well-defined meaningful objects.

7. Conclusions

Satellite remote sensing has made tremendous progress over the last three decades. However, the applicability of image processing is often limited by spatial resolution. While some users still argue for steadily increasing resolutions it becomes more obvious that progress in environmental applications is hampered by the quality of spectral information that can be reliably extracted from remotely sensed data. In this paper, it was argued that the whole conceptual framework based on a pixel as the smallest unit of consideration is limited as long as spatial neighbourhood and proximity are not considered. Enormous efforts are invested to classify pixels accurately, including soft or fuzzy classification methods, sub-pixel approaches and spectral unmixing. These methods focus mostly on the well-known phenomenon of the 'mixed pixel'. This term implies that the scale of observation is inappropriate and does not match the scale of variation in the landscape. By increasing spatial resolution this phenomenon does not disappear. One can observe that the percentage of pixels regarded as 'real mixed pixels', e.g. falling between two adjacent fields, is actually decreasing. At the same time, a new problem appears: Areas which are relatively homogeneous at a 30 m resolution (Landsat TM) exhibit variation at 4 m resolution (multi-spectral IKONOS). Suddenly gaps within a natural forest appear because small islands in the coverage are now represented by several pixels.

Therefore it is argued that while the importance of the mixed pixel problem is declining, the consistency of groups of pixels is becoming more important. Concepts of adjacency and context of information are becoming more important. It is expected that the software industry will react to these demands, and first operational products in 'standard computing environments' are becoming available today. It is further expected that these developments will trigger the development of integrated GIS/remote sensing environments leading to a new dimension of joint interpretation. These tools will facilitate all levels of processing remotely sensed raster data, from pixel-based to per-parcel approaches and context-based approaches in an object-oriented environment. This could subsequently lead to a full implementation of spatial operators ('GIS-operators') in remote sensing software.

Multi-resolution segmentation produces highly homogeneous segments at arbitrary resolution and from arbitrary image data. This allows application of this segmentation technique to different types of image data and problems. Object-based classification enables the user to define complex rules based on spectral characteristics and on inherent spatial relationships. With the object-oriented approach, complex semantics can be developed based on physical parameters and knowledge about relationships. Objects can be defined and classified by the structure and behaviour of similar objects. Inheritance provides natural classification strategies for different kinds of objects and classes and allows for the communality of objects to the full advantage in modelling and constructing object systems.

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