

APPLICATION OF A GIS AS A MODELING TOOL FOR REMOTE SENSING IMAGE ANALYSIS OF AGRICULTURAL FIELDS

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ABSTRACT:

In the context of the analysis of remotely sensed data the question arises of how to analyse large volumes of data. In the specific case of agricultural fields in flat areas these fields can often be modelled in terms of geometric primitives such as triangles and rectangles. In this case the options are classical i.e. bottom-up, starting at the pixel level and resulting in a segmented, labelled image or top-down, starting with a model for image partitioning and resulting in a minimum cost estimation of shape hypotheses with corresponding parameters. Standard bottom-up classification methods usually concern the pixel as a main element and try to label the pixel individually. But various errors are involved in the image analysis with these methods. Mixed pixels, simplicity of the basic assumptions in the classification algorithms, sensor effects, atmospheric effects, and radiometric overlap of land cover objects lead to the wrong detection in image analysis. In this paper we propose a Model-Based Image Analysis (MBIA) approach to analyze the remotely sensed data. In this manner using the available knowledge about the remote sensing system we generate some hypothesis maps and then test them using the radiometric measurements (images). In order to test the method we used the boundaries of the agricultural fields stored in a GIS to model the objects in the scene. The results of the method have been compared with the result of a traditional Maximum-Likelihood classification and a standard Object-Based Classification using the boundaries. Using this approach we could reach to the 94% overall accuracy.

1. INTRODUCTION

Today remote sensing is a major source of data and information, which is used in various fields. Using the remotely sensed images we can obtain up-to-date, cheaper, and variety of data for different applications. Classification is a common and powerful information extraction method, which is used in remote sensing field. There are many classification methods that have their own advantages and drawbacks.

Standard classification methods usually concern the pixel as a main element and try to label the pixel individually. But various errors are involved in the image analysis with these methods. Mixed pixels, simplicity of the basic assumptions in the classification algorithms, sensor effects, atmospheric effects, and radiometric overlap of land cover objects lead to the wrong detection in image analysis.

To overcome these drawbacks and errors some new methods have been developed using the external knowledge about the objects. Object-based, knowledge-based classifications are some examples of these efforts. But these approaches usually are much complex to reach the more accurate results for a specific purpose. Then often they cannot be employed in the commercial systems simply.

This research concerns a powerful classification method, which is called Model-Based Image Analysis. A remote sensing system has two major components including RS data acquisition system and data analysis system [Abkar, 1999]. Data acquisition system part has four main parts including: atmosphere, the scene, sensor, and energy source.

Model-based classification is based on the modelling the data acquisition part of remote sensing system. With generating the geometric hypothesis about the existing objects on the basis of models, we can find the best values of the geometric hypothesis parameters. This is done by parameter estimation viz evaluating the cost of the set of parameters using the generated likelihood vectors (probability for radiometry given radiometric class) from multispectral remote sensing data. Finally we choose the best parameters based on the minimum cost estimation. For the modelling the remote sensing processes we can use any knowledge, which we have about them contained in a GIS such as air photos, existing maps, etc.

2. USING GIS AS A MODELING TOOL

As it was mentioned in the previous section, GIS is a powerful data and knowledge source for MBIA. GIS data, as ancillary data in image processing and analysis have been used in last decade [For example see Hutchinson (1982)]. Firstly, the use of GIS in image processing have been limited in providing prior knowledge for image processing and analysis, like control points for geocoding and prior probabilities for image classification. In fact, in this manner we have incorporated GIS data to aid the RS techniques but we don't perform any explicit integration of GIS and RS [Abkar, 1994].

In more advanced methods, GIS can be used to improve the image analysis results. The simplest usage of GIS data and/or knowledge is in the evaluation stage of the image analysis particularly image classification. The results of the image analysis are compared with the GIS information and the results are assessed. Then, we can decide to perform some improvements on the used algorithm. Rule based systems

(Richards, 1993) are one of the most popular multisource image analysis systems. They use the GIS data in cooperation with the image analysis outputs to extract the desired information [Richards, 1993].

Recently, another important issue of the interaction between GIS and RS is discussed, which is called GIS and RS integration. Integration deals with the higher level of the cooperation, which leads to the better result or a result that could not have been achieved. In this manner, GIS information is used to guide image analysis, which extracts more complete and accurate information, which is in turn used to update the GIS databases [Baltasavias et al. 2000].

Today GIS and RS integration not only is important but it is necessary in order to reach to the desired information. GIS databases are provided for many areas around the world. On the other hand remotely sensed images are taken from the various parts of the earth. These two kinds of the geo-spatial data can solve many of the problems of our life in combination to each other. Each of these powerful tools completes the other and the best results can be obtained by their cooperation. Baltasavias et al. [2000], have listed some major aspects of the GIS and RS integration. As a consequence we can say, "if we have information we should make use of them".

In this paper we make use of the available GIS data and/or knowledge in order to extract more accurate results by image analysis. We use the GIS and RS data to generate some hypothesis maps and our predefined cost function, is used to choose the best hypothesis for the objects. In our method we generate a likelihood map for each radiometric class and then overlay the existing boundaries of land cover objects on each likelihood map. After this, the average probability of each polygon is calculated and then using a threshold (variable parameter) we generate a hypothesis map for the class. Then for finding the best hypothesis map (the best threshold) for the class we compute the cost of it. Now we can choose the threshold with the minimum cost as the final estimated parameter. This procedure is done just for one class in each time (see Figure. 4).

2.1 Object Dynamics

During the existence of an object, it may be affected by various activations and things. This can affects its representation in GIS in three ways [Molenaar et al., 1992]:

Firstly, the thematic aspects of an object may change. In this simplest case the value of one or more attributes change, e.g. the cover type of an agricultural field changes or it may be that an object to be reclassified e.g. the landuse class of a field changes from farmland into build-up area. Secondly, the geometric aspects of an object may change. This might be a change of position, shape, size, orientation, or combinations of these. These changes may lead also to changes of topological object relationships (Figure 1(a)).

Thirdly, an object may change its aggregation structure. The aggregation structure indicates how a terrain object can be considered as a composite of smaller objects. Here too several possibilities exist for such a transition (Figure 1(b)). The fact that only the internal structure of the composite or aggregated object changes implies that its external relationships are not changed.

Here, we use GIS data (existing boundaries) to extract the first type of changes. Therefore, we assume that there are no changes of the reminder two types. But as it will be shown our method can detect a majority of the changes of the third type.

2.2 Biddinghuizen Study Area and Data

The area of interest for this study is located in Biddinghuizen region. This area represents a modern agricultural region in the Netherlands [Abkar, 1994]. The agricultural fields are large and usually rectangular. The main crops are grass, potatoes, cereals, sugar beets, beans, peas, and onion. The elevation differences in the Biddinghuizen region are very small. This region is a well known area that we have a good set of data and information about it. The RS data that we use for our experiment is a Landsat TM image that was acquired on 7 July 1987 (see Fig 2(b)). The image was of good quality and no atmospheric corrections were performed. The image was georeferenced to the national triangulation system using a first-degree affine transformation. The pixels were resampled to the original size of 30 m by 30 m. In this paper bands 3, 4, and 5 of TM were used for classification and to generate the likelihood maps. Additionally, various data at the Biddinghuizen test area were stored in a GIS. A land cover map of this area with information about crop types for 1987 was available. Then we have polygon boundaries for each agricultural field and its crop type in that specific date. Figure 2 shows the color composite image of the 3 used bands of the TM and land cover map of the study area.

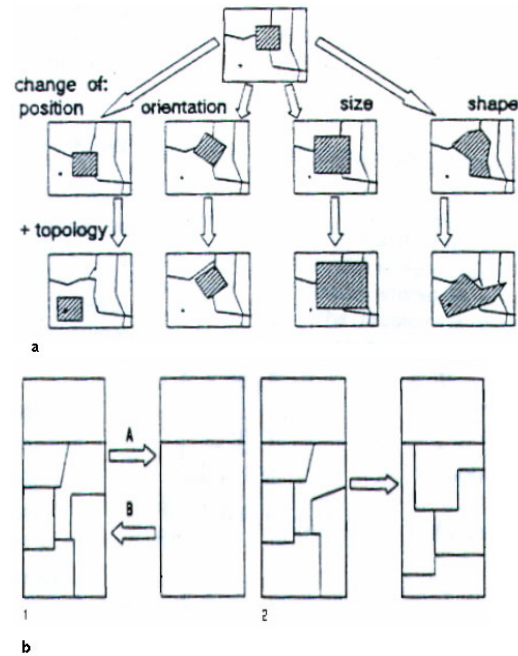


Figure 1. The second and third types of the changes for objects [Molenaar et al. 1992].

a) geometric changes b) aggregation structure changes; b1. a set of elementary objects dissolves into one larger object or an elementary (non-composite) objects fragmented into smaller objects. b2. a collection of small elementary objects building an aggregated object is replaced by a new set building the same aggregated object.

In this paper, the Land use/cover served three purposes:

- Training field selection for the classification of the satellite image
- To ensure the prior knowledge (fixed boundaries) for the MBIA
- Validation of the final results

- the object-based classification

A good description of these data can be found in Janssen (1994). However, we can use the boundaries as certain knowledge but some of the crop types have changed. Using the available knowledge we update the crop types on this basic assumption that the boundaries are fixed during the time. We are also aware of the existing errors in the data and they influence the final results, as it will be shown in the following sections.

3. GENERATION OF LIKELIHOOD MAPS

The first step of our method is generating the likelihood maps. This was done in Idrisi 3.2 for Windows using BAYCLASS soft classifier. For this purpose we considered 7 spectral classes including: Beans, Cereals, Grass, Onions, Peas, Potatoes, Sugar beets. Training samples of these classes were defined using the GIS data and a false color composite of the 3 Landsat TM bands (bands 3, 4, and 5). Training for some of the classes was very difficult due to the similarity in spectral properties. For example, Cereals and Sugar beets are very similar in the generated color composite or the Grass fields and Peas fields are also hardly distinguishable. Then, we generated 7 likelihood maps for the spectral classes. Figure 3 shows two likelihood maps for Beans and Potatoes.

In order to compare the results of the proposed method we performed a MLH classification on the TM data using the mentioned signatures. We exclude the area outside the GIS known boundaries from the classified image in order to have a better comparison of the results. Then all of the operations are only applied in the known regions and indeed the final results are also presented for this area. The MLH result can be seen in the Figure 2(c).

4. IMPLEMENTATION

In this method we use the agricultural fields stored in a GIS, for extracting more accurate results and finally using the obtained results we can update our GIS database. The proposed algorithm is on the basis of the generating the hypothesis maps and choosing the best hypothesis using the estimated costs. This leads to make use of the advantages of the top down approach in order to find the best results. Like the last example this procedure also works only for one class at a time and after the generation of the most accurate hypothesis or the hypothesis with the minimum cost the procedure is stopped. The procedure must be repeated for all the interested land cover classes. Figure 4 shows a schematic diagram of the algorithm.

In this experiment we use only the field boundaries from the GIS and ignore the other data stored in the GIS as crop rotation, crop calendar etc., which they can also be used in the method of MBIA. We assume that the agricultural fields have fixed boundaries and only the crop type of the polygons may change. This assumption in the modern agricultural areas such as Biddinghuizen region is usually correct and thus we can use it as a basic knowledge to extract the thematic information from the remotely sensed data.

As it was mentioned in the last section, we generated the likelihood maps and stored them to be used in the next steps. Here the approach to integrate the RS and GIS data is simple. For each polygon we compute the average of the probabilities that are laid in it. Several statistical factors for the polygon like

maximum or minimum value, average of values, sum of them and standard deviation of the grey values can be calculated. For our purpose we calculate the average probability for each polygon.

Therefore, we calculate 7 average maps. Each of these maps is for an individual class. After this stage we take an average map for a certain class, for example Beans, and using a simple thresholding we can divide the average map into two classes, class Beans and Not-beans. The pixel, which has an average value greater than the threshold t , is assigned to the class Beans. The other pixels are labelled as the other class viz Not-beans. In fact, in this manner we generate a binary map in which the pixels that have the value 1 belong to class Beans and the other pixels with values 0 implies the inexistence to class Beans.

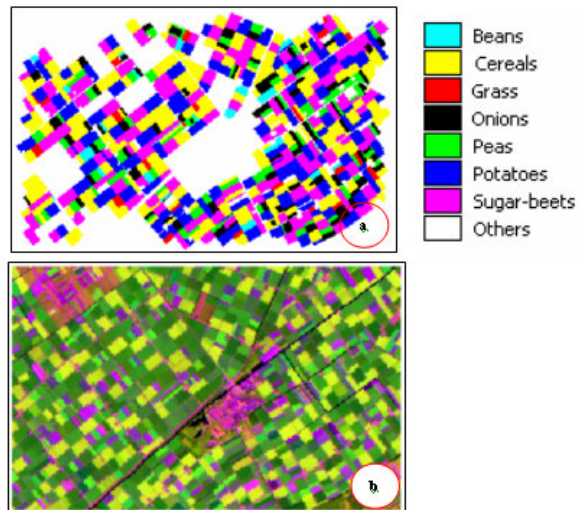
Now we must test the selected threshold t . For this purpose we use a cost function (Abkar 1999) as below. It is defined as

$$\text{Cost} = E1 H2 + E2 H1 \quad (1)$$

We write the cost function for two classes because by working in the level of one class in each iteration really we have two classes: class x and others. Thresholding the average map generates the hypothesis map for class x ($H1$). Thus we can calculate the hypothesis map for the others such as below

$$H2 = I - H1 \quad (2)$$

in which I is a matrix that all of the its elements are 1.



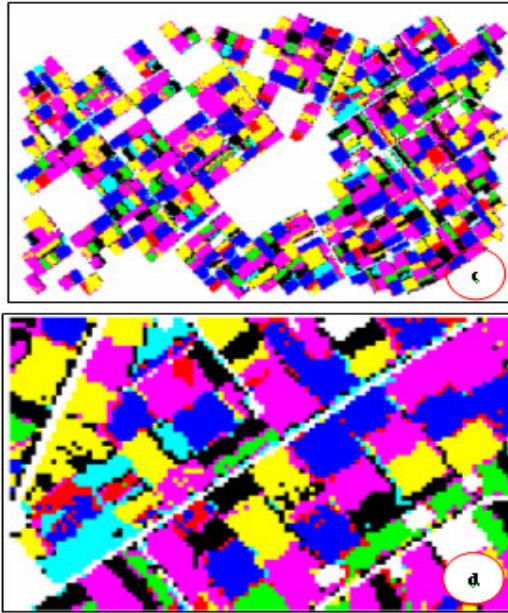


Figure 2. a) Landuse map in GIS b) Color composite of the bands 5, 4, 3 of TM (RGB 5, 4, 3) (size is 215 , 340 pixels) c) MLH classification result d) A zoomed part of the classified image shown in Figure. 2(c)

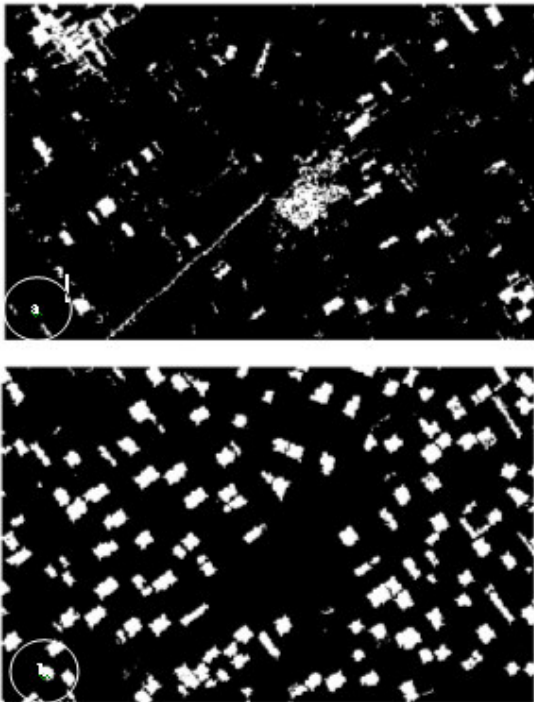


Figure 3 Two samples of the generated likelihood maps for the selected classes.

a) Likelihood map for class Beans b) Likelihood map for class Potatoes

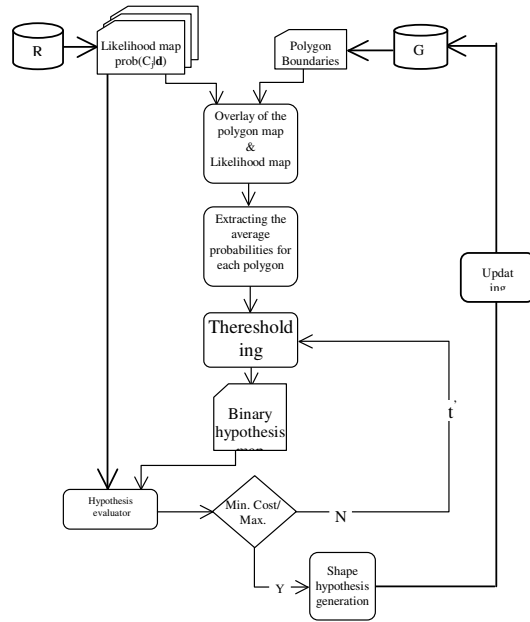


Figure 4. Schematic diagram of the proposed method for MBIA of the agricultural areas using the existing boundaries.

On the other hand we need the evidence maps to calculate the cost. In the first stage, we had generated the likelihood maps for each class individually. Then if we assume that we have just 7 classes in the image as we used for this data we can calculate the evidence map for others using a similar formula as it was for hypothesis maps namely:

$$E2 = I - E1 \quad (3)$$

In which $E1$ is the evidence map for that particular class which we are working on it. Performing these calculations now we have all of the components that we need to estimate the cost of the specific threshold t ; therefore using equation (1) we calculate the cost. After this we examine that this cost is minimum or not. If it is not, then we change the threshold value t to t' and repeat the whole procedure for the new hypothesis map. The cost graph of the various thresholds for class Onions have been shown in the Figure 5. Table 1 shows the corresponding minimum cost for each class. We store the final result for each class to merge them in the final map by assigning the relevant IDs to each resulted hypothesis map.

Integration of all of the final hypothesis maps can be seen in the Figure 6(b). In this map each polygon has a label defined by the procedure. As it has been shown some unlabeled polygons are in the final map. This implies that these polygons could not be categorized into any class. In other words, for all of the classes, the probabilities have not supported any of them. These polygons are shown in the Figure 6(c).

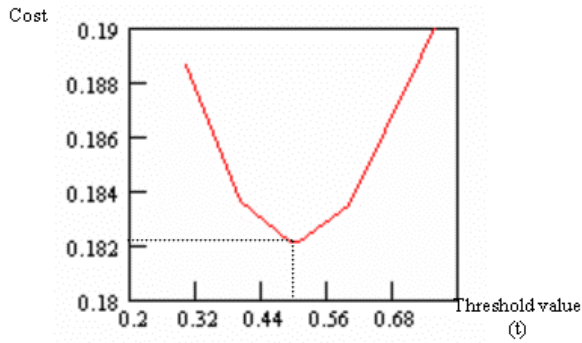


Figure 5. The cost function of the hypotheses maps for class Onions as a function of threshold t . t values have step of 0.1.

	Class	The best threshold	Minimum Cost
1	Beans	0.50	0.071903
2	Cereals	0.49	0.116372
3	Grass	0.50	0.088656
4	Onion	0.50	0.182127
5	Peas	0.5	0.0302247
6	Potatoes	0.51	0.085219
7	Sugar-beets	0.5	0.150371

Table 1. The best threshold value and corresponding minimum cost for each class

As it is clear most of these polygons are not consist of a single crop type (the basic assumption that we assumed). This shows that the proposed method is sensitive to some common errors that many of the usual methods ignore them. Therefore, we can be sure that if we assume the fixed boundaries, this is a true assumption and if this assumption violates for a specific polygon then this polygon will not be labelled. Thus, unlabeled polygons often are which within them some new internal boundaries have been produced and the polygon has been split into the new sub fields. Of course, some of these unclassified polygons have a single crop type and the other errors have caused the polygon not to be labelled. One of the major sources of these errors is the existing error in GIS data. These caused that the polygons are not matched at their place exactly and indeed some pixels which have high probability values are not fall into those polygons. Some examples of such polygons have been shown in the Figure 7.

5. OBJECT-BASED CLASSIFICATION

A common approach for classification of the remotely sensed images is Object-based classification (OBC) (boundary-based or parcel-based classification) using the boundaries in a GIS. In this method a traditional classification like MLH, is done and each pixel is assigned to the most probable class. After this, the existing boundary map is overlaid on the classified map. For each polygon the class, which is the more frequent or has the majority in that specific polygon is assigned to it. In such a

method usually all of the polygons or fields are allocated to a class because often there is a majority for one class in the polygons. We expect that this method should give the improved result relative to the traditional MLH approach. But as we will see in the next section, it dose not give the required information. This method is based on a simple logic that if one land cover class is in a field (in the real world) indeed it must have the majority for that (in the classified map). But this fails in the small fields relative to the sensor spatial resolution because of the radiometric overlaps between the classes and also errors, which are involved in the MLH classification. Consequently, we can see that this method cannot give results as good as the MBIA approach. The result of this method has been shown in Figure 6(a).

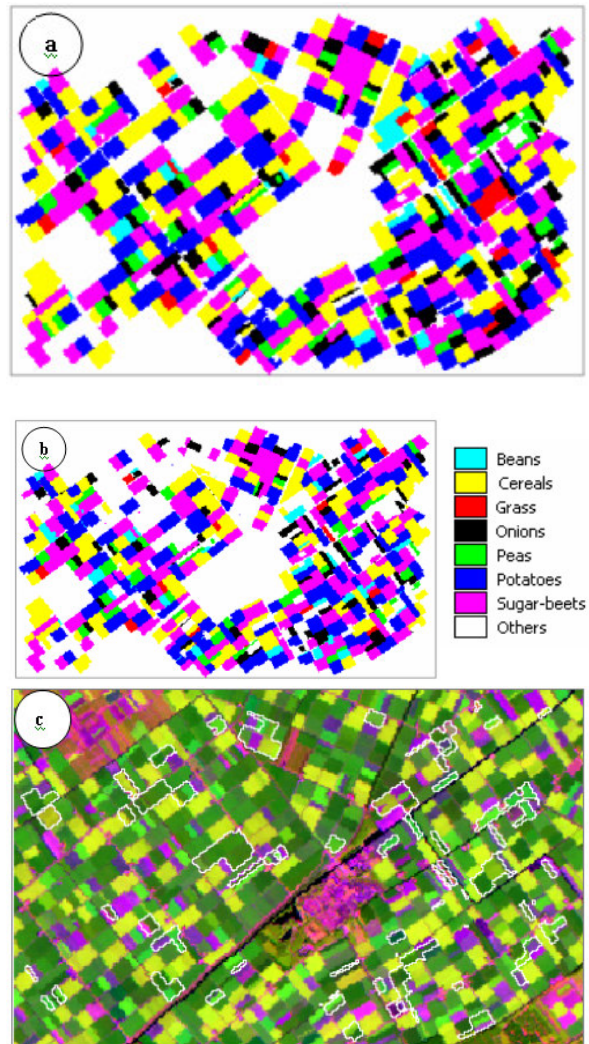


Figure 6 Result of the MBIA and OBC approaches (see the various crop types in the superimposed polygons).
a) final result of the OBC b) final result of the MBIA
c) undefined polygons by the MBIA superimposed on the color composite of the 3 TM bands

6. EVALUATION OF THE RESULTS

So far, we classified the Biddinghuizen RS data in three ways: Maximum Likelihood classification, Object-based classification

and Model-based image analysis. We compared the obtained result of each method with the existing landuse map. Table 2 shows the obtained overall accuracies for the 3 methods.

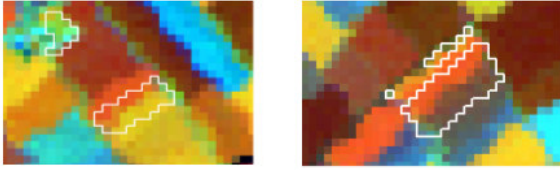


Figure 7. Existing GIS positional (georeferencing) errors

From the Table 2 it is clear that the highest overall accuracy is for MBIA, as it was expected. But some notes seem to be necessary. The calculated overall accuracies in this table have been obtained from the landuse-87, in which there may be some wrong data. In fact we have no ground truth data and therefore landuse map is considered as the reference data.

Method	Overall accuracy (%)	Kappa (%)
MLH	71.22	64.55
OBC	93.16	91.24
MBIA	94.22	92.45

Table 2. The overall accuracy of the classified images by 3 methods: Maximum likelihood (MLH), Object-based classification (OBC) and Model-based image analysis.

For the accuracy assessment, one way is to use some reliable data as reference data, however, some errors could be introduced in the accuracy assessment of the final results from the various sources like outdated reference data. In this case some polygons have a label in the landuse map that may be changed in the real world. Procedures may detect these changes and assign new label to the polygon but these are excluded from the correct pixels in error matrix and will not be involved in the calculation of the overall accuracies. However the main aim of this exercise is to compare the result of the mentioned methods and we think that the calculated overall accuracies are sufficient to imply the desired results.

However the overall accuracy of the OBC and MBIA are near to each other and they have a difference about 1.06 %. It may be said that this is a small difference and there is no improvement in the MBIA relative to the OBC. But as it is known, improvement of the classification accuracies in the high values (say greater than 90 %) is hardly obtainable and in this level we can improve the classification accuracy percent by percent! Additionally MBIA labelled about 740 fields from about 819 fields in the landuse map. Namely totally 79 polygons have not been labelled by MBIA but they have been labeled with OBC. As it was explained in the preceding section this occurrence has several reasons but the major reason is that instead of existing one cover type in the field, the polygon have been split into the several portions and each part has a different crop type. Considering this, OBC method has labelled these polygons and we know that these are not correct. Versus OBC, MBIA has sensitivity to this changes and then it dose not involve these polygons in the final map.

The results of OBC can be improved using a threshold to reject the weak majorities of the labels in the polygons, but the question will remain that what is the best threshold. Additionally OBC has less flexibility relative to the MBIA and

we expect that the MBIA can solve more complex and difficult problems in remote sensing. Therefore, MBIA gives hopefully more reliable results than OBC even if their overall accuracy were near to each other. Consequently, MBIA can also define the changes within the fields.

7. CONCLUSION

In this paper we investigated the effect of the using GIS data in the hypothesis generation and general MBIA performance. As this case study shows, the application of external knowledge in the classification can improve the results. But the manner in which knowledge used is very important, different from the existing bottom-up approaches, and effective as Table 2 Shows. MBIA can use the existing knowledge from GIS in an optimal and formular manner and it can also give some marginal information and data. A good example of this is the undefined polygons resulted from the MBIA method that almost many of them do not match with the basic assumption that each field has only one single crop type.

However, in this paper we show some aspects and abilities of the model-based image analysis method. For clarifying all of the major aspects of the proposed method it is still necessary to continue with experimenting on the method and development of the modelling tools.

8. REFERENCES

- Abkar, A.A. ,1994, Knowledge-Based Classification Method for Crop Inventory Using High Resolution Satellite Data. MSc. Thesis, ITC, Enschede, The Netherlands.
- Abkar A.A 1999, Likelihood-Based Segmentation and Classification of Remotely Sensed Images. PhD Thesis, University of Twente, ITC, Enschede, The Netherlands, ISBN 90-6164-169-1, ITC Publication 73.
- Baltsavias E., Hahn M. 2000, Integration Spatial Information And Image Analysis - One Plus One Makes Ten. ASPRS, Vol.XXXIII, Amsterdam, 2000.
- Hutchinson, C. 1982, Techniques for Combining Landsat and Ancillary Data for Digital Classification Improvement. Photogrammetry Engineering and Remote Sensing, Vol.48, No. 1, 123-130.
- Janssen, L. L. F. 1994, Methodology for Updating Terrain Object Data from Remote Sensing Data; The Application of Landsat TM Data with Respect to Agricultural Fields. Doctoral thesis, Wageningen Agricultural University, Wageningen, The Netherlands.
- Molenaar M., Janssen L.F 1992, Terrain Objects, Their Dynamics and Their Monitoring by the Integration of GIS and Remote Sensing. Proc IAPR.Tc7 workshop, Sept 7-9, 1992 Delft, The Netherlands, pp 113-134.
- Richards J.A 1993, Remote Sensing Digital Image Analysis: An Introduction. Second Edition, Springer, ISBN 0-387-5480-8.