Methodology for updating terrain object data from remote sensing data

The application of Landsat TM data with respect to agricultural fields

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Hoogleraar in de Theorie van de Geografische
Informatie Systemen en de Remote Sensing

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The application of Landsat TM data with respect to agricultural fields

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The cover shows a detail from
'Haupt- und Nebenwegen'
painted by Paul Klee in 1929.

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STELLINGEN

1 Beschikbaarheid van relevante geografische gegevens tezamen met kennis over de statische en dynamische kenmerken van terreinobjecten vergroot de bruikbaarheid van remote-sensing-gegevens voor actualisatie-doeleinden.
- Dit proefschrift

2 Geometrische context informatie biedt de grootste mogelijkheden voor het verbeteren van de informatie-extractie op basis van patroonherkennings-technieken.
- Dit proefschrift

3 Een pixelgewijze 'maximum likelihood' classificatie waarbij gebruik wordt gemaakt van conditionele a-priori kanswaarden kan niet worden toegepast voor pixels waarbinnen meerdere klassen van een nominale conditionele variabele voorkomen.
- Dit proefschrift

4 De mogelijkheden voor het gebruik van satelliet-remote-sensing voor controledoeleinden op perceelsniveau zijn beperkt door het beperkte aantal gewassen dat kan worden onderscheiden en de relatief onnauwkeurige bepaling van het areaal.
- Dit proefschrift

5 Dat het gebruik van satelliet-remote-sensing voor controle-doeleinden door de EG wordt gestimuleerd heeft meer te maken met de politiek-bestuurlijke context waarbinnen richtlijnen tot stand komen dan met de feitelijke mogelijkheden van deze techniek.
- Dit proefschrift
- Bekkers, V.J.J.M., Bonnes, J.J., De Moor-Van Vugt, A.J.C. en W.J.M. Voerman, 1993, Succes- en faalfactoren bij de uitvoering van EG-beleid. Bestuurskunde, Nr. 4, pp 192-200.

6 De resultaten van wetenschappelijk onderzoek zijn niet alleen voor de eigen kring interessant; de technisch-inhoudelijke resultaten zouden door beleidsmakers als directe aanknopingspunten moeten worden gebruikt.
- Vroon, P., Project. Column 'Signalement' d.d. 12-10-1991 in de Volkskrant.

7 De precisie waarmee in remote-sensing-studies de classificatie-nauwkeurigheid wordt aangeduid staat veelal in geen verhouding tot de precisie waarmee de klassen zijn omschreven of gedefinieerd.

8 Het gebruik van remote-sensing-gegevens in modelberekeningen vereist een afstemming van de bestaande modellen op de beschikbare waarnemingen; het is onjuist de gebruiksmogelijkheden van remote-sensing-gegevens te beoordelen op basis van de mate waarin deze direct geïntegreerd kunnen worden in bestaande modellen.

- Engman, E.T., 1991, Applications of microwave remote sensing of soil moisture for water resources and agriculture. Remote Sensing of Environment, Vol. 35, pp 213-226.

9 Fotografische afbeeldingen hebben een grote overtuigingskracht; het gebruik van remote-sensing-opnamen als achtergrond bij de visualisatie van 'kaart'bestanden heeft als groot voordeel dat de gebruiker zo'n bestand kritisch zal interpreteren.

- Sachs, W., 1992, Satellitenblick; die Visualisierung der Erde im Zuge der Weltraumfahrt. Kulturwissenschaftliches Institut, Essen, 44 pp.

10 Het gebruik van het aantal publikaties als beoordelingscriterium voor wetenschappelijk onderzoek heeft onder andere tot gevolg dat congresbundels voor een groot deel uit weinig vernieuwende artikelen bestaan.

11 Het gebruik van het woord 'centrum' ter aanduiding van geografisch verspreide organisaties wekt verwarring en dient te worden vermeden.

12 Een overeenkomst tussen het realiseren van een vanuit milieutechnisch oogpunt schoon milieu en medisch handelen is dat beide niet per definitie een groter menselijk welzijn tot gevolg hebben.

- Achterhuis. H., 1992, De illusie van groen; over milieucrisis en de fixatie op techniek. De Balie, Amsterdam, 52 pp.
- Dunning, A.J., 1982, Broeder Ezel; over het onvermogen in de geneeskunde. Meulenhoff, Amsterdam, 269 pp.

13 Het streven naar multi-culturele integratie moet gepaard gaan met het behoud van pluriformiteit; het zonder meer samenvoegen van ongerelateerde componenten betekent een verlies voor alle partijen, de 'shoarma-croquet' is daar een duidelijk voorbeeld van.

- J. van Dam, 1989, Alles warm. BZZTôH, 's-Gravenhage, pp 5-8.

Stellingen behorende bij het proefschrift van Lucas Janssen:
Methodology for updating terrain object data from remote sensing data; the application of Landsat TM data with respect to agricultural fields.
Wageningen, 19 Januari 1994

TO MY PARENTS

Abstract

Janssen, L.L.F., 1993, 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, (X) + 173 pp.

This thesis describes some methods for updating the thematic and geometrical data of terrain objects that are contained in a Geographic Information System (GIS). The updating is based on the application of digital interpretation techniques on high resolution satellite data. The potential for updating terrain object data from remote sensing (RS) data is largely determined by two factors:

(i) The thematic and geometrical characteristics of terrain objects that can be extracted from RS data depend on their relationship with the spectral and spatial information present in the RS data applied.

(ii) Furthermore, digital interpretation techniques cannot directly yield the information required due to the complexity of real world images.

The idea underlying this thesis is that information extraction from RS data (based on digital interpretation techniques) can be improved and optimized by using ancillary data and knowledge about the static and dynamic properties of the terrain objects of interest. Such an approach requires integrated processing of different types of data and knowledge. Important aspects of an integrated approach are the integration level (pixel-based versus object-based data integration), the spatial aspects (co-registration and vector/raster integration) and error propagation.

The terrain objects of interest in this thesis are agricultural fields. A data set was established consisting of a Landsat TM image and (multi-temporal) data on the crop type and field geometry of agricultural fields in a polder area in the Netherlands. Three updating methods by means of an integrated approach were developed and tested with the available data.

Knowledge about crop rotations was formalized by means of transition matrices which store transition probabilities. The transition probabilities, corresponding to the crop type grown in the preceding growing season, were used as (conditional) a-priori probabilities in a pixel-based maximum likelihood classification. For the test area, overall classification accuracy increased with 2 % to 17 % depending on the spectral separability and the set of a-priori probabilities applied.

Object-based classification was used to determine the crop type of agricultural fields

for which the geometry was already contained in a GIS. In the same process the field geometry is used to derive a reliable classification result by excluding boundary pixels which are most often mixed pixels. For 92 % of the fields in the test area a correct crop type was determined.

An integrated segmentation and classification method was applied to determine both the field geometry and crop type of agricultural fields. The results of an edge detection on the TM image were integrated with the fixed boundaries contained in the GIS by using knowledge about the aggregation structure and shape of the fields. The resulting field geometry corresponded for 87 % with field geometry derived from visual interpretation of the TM image.

Several aspects of data integration were identified. Object-based data integration, which means that knowledge is formulated in terms of terrain objects that have geometrical and thematic properties, is required for updating. A large number of representations are possible for formalizing knowledge; different methods for representation were used in this thesis: transition matrices, statistical functions and geometrical functions.

For the integration of the vector-structured terrain object data with the raster-structured RS data two approaches can be adopted: data conversion (vector-to-raster and vice versa) or 'direct integration'. The last approach was used to identify the raster elements that are located within a polygon in object-based classification.

The case studies showed that terrain object data can be updated based on digital interpretation of remote sensing data and that the ancillary data and knowledge are effective for improving and optimizing the information extraction. Nevertheless, the information (type and quality) that can be extracted still largely depends on the (spectral and spatial) relationship between the terrain objects of interest and the RS data applied.

Keywords: remote sensing, geographical information systems, pattern recognition, data integration, terrain object dynamics, monitoring, agricultural fields.

Preface

This thesis is the main result of the PhD project that started in 1988 under the title 'Integration of remote sensing and geographical data for land use classification'. This project was funded by the DLO Winand Staring Centre and supervised by Prof. Molenaar of the Department of Surveying and Remote Sensing of the Wageningen Agricultural University (WAU). In funded PhD projects the university is responsible for the scientific supervision while the application context, data and systems are provided by the funding body. For the duration of the project I was seconded to the Department of Remote Sensing at the DLO Winand Staring Centre.

In the Netherlands, PhD projects are funded for four years. Because of some additional research projects and parental leave, the total project has taken five years (July 1988 - August 1993). I have very good memories of this period in which not only data integration but also the integration of expertise from different parties was achieved. Although my desk and chair were at the DLO Winand Staring Centre, once every two weeks I spent one afternoon at the University. Because of additional projects that were being carried out I also had the opportunity to visit many other institutes, organizations and companies from which I learnt a great deal. I have experienced the combination of carrying out a PhD project with secondment as very stimulating and fruitful.

During the past years my wife Carla and I had two children, Camiel and Pepijn. The joys of our family have been a great source of energy to me and made me realize the relativity of the subject.

A large number of people have contributed one way or another to the realization of this thesis. I want to thank all of them for their efforts and in particular I would like to mention the following:

First of all I want to thank Martien Molenaar, my promotor, for many stimulating discussions, especially where more conceptual and formal problems were concerned. He was always able to formulate the essential questions clearly and concisely. An example of a highly motivating activity was e.g. the organization of the IAPR-TC7 Workshop in Delft (1992).

Since research groups are small these days, in 1989 Martien and I tried to set up a network for PhD students in the field of Geographic Information Systems (GIS) and Remote Sensing (RS). Unfortunately, these attempts failed. However, as a result of this initiative, contacts were made with Hans Middelkoop (from the International Institute for Aerospace Survey and Earth Sciences) and Ruud Verwaal (from the Technical University

Delft). Together with Hans the idea of crop rotations and conditional a-priori probabilities was worked out; with Ruud the integrated segmentation and classification strategy was realized. These joint projects were very successful and I was very sorry to see that both colleagues had to finish their PhD projects prematurely; more could have been achieved. However, much has been done and I have enjoyed our trip to Germany where we visited a large number of research groups and companies.

Some more people at the Department of Surveying and Remote Sensing (from WAU) should be mentioned. Henk Buiten's broad experience in remote sensing was an important source of knowledge for me; his precise corrections and comments on my manuscript are greatfully acknowledged. The philosophical and methodological discussions I had with René van der Schans have been of great value for putting things in perspective. The Msc projects of Hans van Amsterdam, Dennis Keeman and Kees Schotten were also of great help in gaining more insight into the subject. Apart from that, they were good company. The discussions with my PhD colleagues Jeroen Huising, Sylvia de Hoop and Hans van Leeuwen also contributed to this thesis.

The largest part of the PhD project was spent at the Remote Sensing Department of the DLO Winand Staring Centre. This is a very dynamic department: within those five years at least 20 people have come and gone (Msc students, conscientious objectors and those carrying temporary assignments). Gerard Nieuwenhuis' optimistic and joyful nature plays a big part in creating the good atmosphere in this department. Furthermore, Gerard allowed me the freedom to explore my own ideas with respect to the subject. Herman Thunnissen contributed by making valuable comments on the manuscript. Henk Kramer was of great help in producing the plates.

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Wageningen, 17 September 1993 Lucas Janssen

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1 Introduction

1 Introduction

1.1 Monitoring agricultural land use

Land inventories are carried out by national and supra-national organizations to acquire up-to-date information for a wide range of applications such as management, control, policy making and planning. In this thesis we concentrate on land inventories with respect to agriculture. The physical environment and landscape structure of the European Community (EC) is largely influenced by the agricultural sector. Of the 225 million ha of the 12 EC countries, 57 % was in agricultural use in 1988. In the same year 2 million ha (51 %) were used for agriculture in the Netherlands (Eurostat, 1990).

The basis for most inventories are data at the field or farm level which then are aggregated for larger (administrative) areas. In the Netherlands the agricultural statistics are based on aggregation of the data of individual farms; the municipality is the lowest level for which data are presented (CBS, 1992). The agricultural statistics of the EC are based on aggregation of the statistics that have been compiled by the statistical offices of the EC member states. In some applications, however, data at field-level are required, e.g.: in controlling the arable and forage subsidies of the EC, in controlling the cultivation of potatoes by the Dutch government and in the preparation and execution of land consolidation projects.

Because of the large amount of money spent on crop-specific subsidies, the EC is developing an integrated management and control system for EC regulations which will be based on the identification of individual agricultural fields (EC, 1992a). At present, the EC member states are obliged to check (a sample of) the farmer's declarations for area-based arable and forage subsidies (EC, 1992b). Therefore, the farmers have to provide a topographical map which indicates the position of the crops that are declared for subsidies. The control procedure anno 1993 is that the maps provided by the farmers are digitized and stored in a Geographical Information System (GIS) by a contractor. Of these declarations both the crop type and the field geometry must be checked. A pre-selection of the fields that should be visited may be made based on the interpretation of satellite images in order to limit the amount of field work. In general, the EC and also national statistical offices show great interest in the application of satellite remote sensing (RS) data for agricultural statistics, control, and forecasting (e.g. Kutch Lojenga and Meuldijk, 1992; Toselli and Meyer-Roux, 1992).

Another type of inventory at the field-level is carried out under the responsibility of the Netherlands Plant Protection Service (Van der Waal, 1993). If potatoes are grown too frequently on the same piece of land, the 'golden disease' can badly effect their quality and yield. For economic reasons farmers are therefore only allowed to grow potatoes once every few years. The number of years between two successive cultivations of potatoes depends on the potato variety, the soil type and the disinfection methods applied. To check if farmers comply with the regulation each year, approximately 100,000 ha of potatoes are surveyed in the field by authorized surveyors. The crop variety is determined in the field and the position of the boundaries is measured and drawn into a map (scale 1 : 5,000). The administrative data are stored in a field registration system while the spatial data are kept on analogue maps. Both types of data are linked by a unique parcel identification number. Until now, the data acquisition has been based solely on field surveys.

In the Netherlands, land consolidation projects are carried out by the Cadastre and the Government Service for Land and Water Use ('Landinrichtingsdienst'). The realization of a land consolidation project takes a large number of years (10 -15 years) and within that period land use may change and need to be updated (Van Kleef and Linthorst, 1986). One of the information requirements for land consolidation projects is the land use of the agricultural fields. Until now the updating has been based on field surveys and interviews. The Government Service for Land and Water Use (Droesen and Jaarsma, 1990) and the Cadastre (Cadastre *et al.*, 1993) are investigating the use of remote sensing data for updating their records.

The examples described above illustrate the need to monitor the changing land use or land cover of agricultural fields. In practice, monitoring is largely based on ground-based field surveys. Another approach is to apply RS data such as aerial photographs and satellite data.

1.2 Updating from remote sensing data

Data with respect to agricultural land cover are geographical data. At present, GIS is used to store, analyze and visualize geographical data. A GIS is a combination of hardware and software that is specially developed for these purposes. The data stored in a GIS can be considered as a representation of the 'real world'. This representation is an abstraction of reality within a certain application context. One of the approaches used to describe geographical phenomena is based on the identification of terrain objects. Within an agricultural or rural context, the elementary terrain objects are generally fields or parcels. Thematic data (crop type, soil type, owner) and geometrical data (position, size, shape) for these fields can be stored in a GIS.

An important characteristic of terrain objects is that they change in time. Changing field boundaries and changing crop type are examples of terrain object dynamics within the agricultural context. As a result of terrain object dynamics the data in a GIS have to be updated in order to maintain a valid representation of the 'real world'. Updating (data acquisition and interpretation) forms a substantial part of the efforts which are required for operational GIS application. Maguire (1991) estimates that the cost of getting data into a GIS exceeds the cost of hardware and software by a factor of two. Updating can be realized by land surveying, the application of RS data (e.g. aerial photographs, satellite RS data) and the application of global positioning systems (GPS).

In this thesis the possibilities of digital interpretation of RS data for updating purposes are investigated. Remote sensing can be defined as measurement of the electro-magnetic (EM) radiation coming from a surface or object. Instruments capable of measuring EM radiation are called sensors (Buiten, 1993a). Essential for the application of RS data is that the interpretation is based on an 'image' of the real world as defined by the sensor's characteristics. The oldest form of remote sensing is aerial photography which has been applied since the beginning of this century. In the last three decades an increasing number of satellites for earth observation have been launched which provide a wide range of different types of digital RS data (e.g. Ehlers, 1993a). Current and future RS programs will yield timely and repetitive data with considerable potential for monitoring purposes. An important condition, however, is that the required information can be extracted from the RS data.

The geometrical and thematic characteristics of terrain objects that can be extracted from RS data depend on the extent to which the spectral and spatial (EM) information present in the applied RS data can be translated into terrain object characteristics. The spectral information in a RS image can only be used to study terrain objects which have distinct spectral characteristics when compared to other types of objects. At the same time, the minimum size of the fields for which thematic or geometrical data can be extracted depends on the spatial resolution (pixel size) of the RS data applied.

The satellite RS data can be visualized on a screen or colour hardcopy for visual interpretation. Another approach is to apply digital interpretation techniques such as segmentation and classification. With digital interpretation of RS data large volumes of data can be dealt with at a repeatable and cost effective way. Until now, however, few results have been achieved by the extraction of geometrical information (e.g. delineation of a field) from satellite RS data using segmentation techniques. This can be explained by the spatial resolution of satellite data that is relatively coarse when compared with the size of e.g. agricultural fields. Furthermore, segmentation of 'real world images' is hampered by their complexity. Although e.g. agricultural fields in a Dutch polder area seem to be well-defined terrain objects, their geometry cannot be determined by the straightforward application of segmentation techniques due to e.g. the heterogeneity of the canopy and the presence of non-relevant features such as spots of bare soil. As a result of the limited possibilities for image segmentation a pixel-based classification is generally applied to extract thematic information (e.g. land cover) from the RS data. The results of a pixel-based classification have no direct link with terrain objects. A pixel-based approach limits the amount of spatial context information that can be taken into account in the classification. As a result, the types of classes that can be distinguished and also the classification accuracy are limited.

The potential of digital interpretation of RS data can be enhanced by using additional data and knowledge in the information extraction. In the last years a large number of studies have proposed a 'knowledge-based', 'GIS-based' or 'expert-based' approach for the interpretation of RS data. Most of these studies aim to enlarge the number of classes that can be distinguished from RS data and to improve the classification accuracy of pixel-based classifications. An important objective of this thesis is extract geometrical and thematic characteristics of terrain objects from RS data. In this process, the terrain object data (already) contained in the GIS will be used to improve and optimize the information extraction from the RS data.

1.3 Thesis objectives

The general objective of this thesis (Fig. 1) is to develop a methodology to:

(i) update terrain object data contained in a GIS;
(ii) from high resolution satellite data;
(iii) by applying digital interpretation techniques;
(iv) by using additional data and knowledge.

In this thesis, the terrain objects of interest are agricultural fields. It is assumed that the field boundaries and crop type present in a certain growing season are contained in a GIS. The next growing season the field boundaries and crop type may have changed. In that case, (part of) the data in the GIS have become outdated. Updating, then, will be based on the application of Landsat TM data which are digitally interpreted using segmentation and classification techniques.

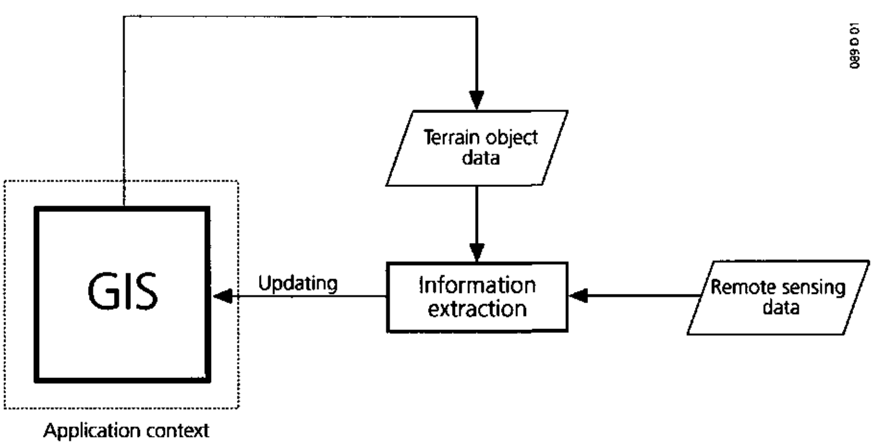

Figure 1 **Updating of terrain object data stored in a geographical information system (GIS) from remote sensing (RS) data.**

Knowledge about the changes that can or cannot be expected (crop rotation schemes, fixed and variable field boundaries) is used to improve and optimize information extraction. The information extraction should yield results which are directly linked with agricultural fields such as crop type and field boundaries of an agricultural field.

1.4 Thesis organization

In Part I, the relevant theory and concepts are described. Chapter 2 explains the relationship between terrain objects and remote sensing data. It also describes some of the problems encountered when applying digital interpretation techniques to information extraction from RS data. For updating an integrated approach is required in which RS data, terrain object data and knowledge are combined. Chapter 3 describes aspects involved in such an integrated approach such as: level of integration, spatial aspects and error propagation.

In Part II, three case studies are presented for the Biddinghuizen test area (Chapt. 4). The area chosen for the case studies depended on the availability of field geometry and crop type for a number of growing seasons preceding the growing season for the applied Landsat TM image (1987). The case studies can be summarized as:

- application of knowledge about crop rotation schemes to improve the overall accuracy of a pixel-based classification (Chapt. 5);
- updating crop type for agricultural fields which geometry is contained in a GIS (Chapt. 6);
- updating both the field geometry and crop type for agricultural fields for which the fixed boundaries are contained in a GIS (Chapt. 7).

Part III gives the concluding remarks with respect to the methods applied, aspects of data integration and some future perspectives of updating from RS data (Chapt. 8).

PART I THEORY AND CONCEPTS

2 Terrain objects and remote sensing data
3 Information extraction

2 Terrain objects and remote sensing data

In this chapter the link between terrain objects and remote sensing data is elaborated. In Section 2.1 the nature of geographical data and its representation in Geographical Information Systems (GIS) is introduced. The conceptual data model that is applied in this thesis is the so-called formal data structure (Sect. 2.2). In Section 2.3 different types of terrain object dynamics are distinguished. These are the different types of change that should be monitored by the application of RS data. In Section 2.4 a short description of the Landsat TM data which are applied for updating purposes in the case studies is given. The information that can be extracted depends on the extent to which the spectral and spatial information present in the applied RS data are related with terrain object characteristics (Sect. 2.5) in close relationship with the possibilities of digital interpretation techniques (Sect. 2.6). In Section 2.7 a selection of relevant methods reported in literature are discussed. The conclusions are given in Section 2.8.

2.1 Geographical data

Geographical data are a subclass of spatial data. The term 'spatial data' applies to any data concerning phenomena distributed in two, three, or N dimensions. Geographical data, more specifically, are spatial data which normally refer to data pertaining to the earth. These may be two-dimensional, modelling the earth surface as a plane, or three-dimensional to describe subsurface or atmospheric phenomena (Peuquet, 1984).

At present, geographical data are handled by geographical information systems (GIS). A GIS is a combination of computer hardware, computer software and data. The data in a GIS provide a representation (or model) of the real world. Due to human activities or natural processes the real world changes. As the real world changes the data in the GIS have to be updated to maintain a valid representation of the world. First some more information will be given about data modelling, the geometrical representations that are used for geographical data, and GIS architecture.

Data models

Geographical data models are abstractions of the real world made for a specific application context. In general, the design and implementation of a data model is described by three levels of models: conceptual, logical and physical (De Hoop, 1993). The conceptual model describes entities and relationships among them, which are considered relevant to the intended application. The conceptual model is system-independent, which means that it can be formulated without reference to an implementation in a database management system or GIS. Peuquet (1984) refers to the (conceptual) data model as "an abstraction of the real world which incorporates only those properties thought to be relevant to the application or applications at hand, usually a human conceptualization of reality". The logical data model describes the implementation of the conceptual data model. Usually the conceptual data model is mapped on a relational network or an object-oriented data model. The logical data model, therefore, depends on the type of database model which is chosen. Finally, the physical data model designates the actual implementation of the logical data model in the computer and the physical storage of the data (system dependent).

Concepts of space and geometrical data structures

Geographical information systems differ from other information systems because they deal with geographical data. Specific to geographical data is their spatial component for which two concepts are used: grid-based and object-based[1] (Ehlers *et al.*, 1989). In the grid-based concept, thematic data are stored for areas which have a predefined shape and size. A grid consisting of rectangular elements (raster) is the shape most frequently applied. A grid-based approach is often applied if an object-based approach is impossible, e.g.: to map natural vegetation or to model crop growth on a continental scale. Remote sensing data, which store the measured radiation, are another example of grid-based data. In the object-based concept the geometrical characteristics of a terrain object (size, shape, position) are related with the thematic attributes: it assumes a certain degree of homogeneity for one or more attributes. The geometry of an agricultural field, e.g., includes an area in which one

[1] In their article Ehlers *et al.* (1989) apply the terms 'field-based' and 'object-based'. In this thesis, to avoid confusion with agricultural fields, 'field-based' is referred to as 'grid-based'. In this context, grid-based does not refer to data structure (raster or vector) which is used to store the data.

type of crop is grown. Principally, the geometrical component of both representations (grid-based and object-based) can be stored by using a raster-structure or a vector-structure.

GIS architecture

Geographical data consist of a geometrical and thematic component. There are different ways to handle both components in an information system. According to Vijlbrief and Oosterom (1992) three types of GIS architecture can be distinguished in the commercial GIS's: dual architecture, layered architecture and integrated architecture.

The most common type is the dual architecture (Fig. 2a) which has a separate subsystem for storing and retrieving geometrical data while thematic data are stored in a relational database management system (DBMS). In the case studies that are presented in Part II, a dual architecture GIS (Arc/Info) is used to store and process

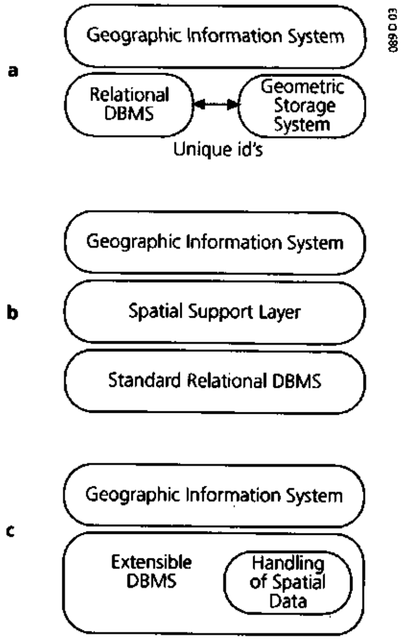

Figure 2 **Three types of GIS architecture (from Vijlbrief and Oosterom (1992)):**
a Dual architecture;
b Layered architecture;
c Integrated architecture.

terrain object data. In a dual architecture, terrain objects that have both a thematic and geometrical component have parts in both subsystems that are linked by a (unique) object identifier. An advantage of the dual architecture is that the geometrical data can be stored efficiently. One of the drawbacks of this type of architecture is that integrity constraints can be violated. In the layered architecture (Fig. 2b) both the thematic and geometrical data are stored in a relational data model. This requires that the coherent geometrical entities have to be broken into multiple parts, which are stored in separate tables. Retrieving, then, has to be done by relations, which make the system slower, and by using relatively difficult queries. In order to free the user from having to make the difficult queries some 'intelligent' translations are made by the layer on top of the standard relational database. The integrated architecture (Fig. 2c) is not based on a standard DBMS but on a extensible DBMS in which users can define their own basic abstract data types. Although definition of the basic abstract data types may be difficult for users, it enables easy implementation of a data model and extended possibilities for spatial query operations.

2.2 Formal data structure

The formal data structure (FDS) is a *terrain object*-oriented data model (Molenaar 1989). For clarity it should be noted that 'object-oriented' in this thesis refers to terrain objects and not to object-oriented database implementations (Aangeenbrug, 1991).

In object-oriented data models two semantic levels can be distinguished: a geometrical level comprising the metric and topology information of the geometrical primitives (arcs and nodes) and a thematic level on which the terrain objects are described by thematic information. The FDS has been developed for single-valued vector maps. The seven conventions to which vector maps should comply in order to be 'single-valued' are formulated in Molenaar (1989). A single-valued vector map may roughly be interpreted as a map layer or categorical coverage. The FDS (Fig. 3) is based on three main concepts:

- three types of terrain objects: point objects, line objects, area objects;
- terrain objects have thematic data;
- terrain objects have geometrical data.

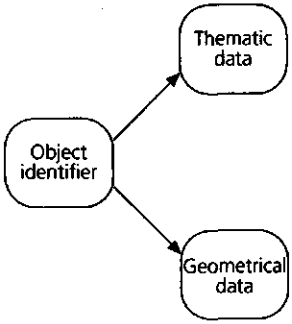

Figure 3 **Terrain objects, thematic and geometrical data.**

Figure 4 represents the FDS for a single-valued vector map. The sets of data are represented by rounded boxes. The link-types are represented by arrows and straight lines. Each arrow indicates a many-to-one relationship, e.g.: many arcs can have the same area object on their left side. A line without arrows represents a one-to-one relationship: a point object can only be represented by one node. In single-valued vector maps the primitives have one (indirect) connection with the (thematic) object classes. A map overlay of different single-valued map layers results in a multi-valued vector map, in which many connections between the primitives and the object classes may exist (De Hoop *et al.*, 1993).

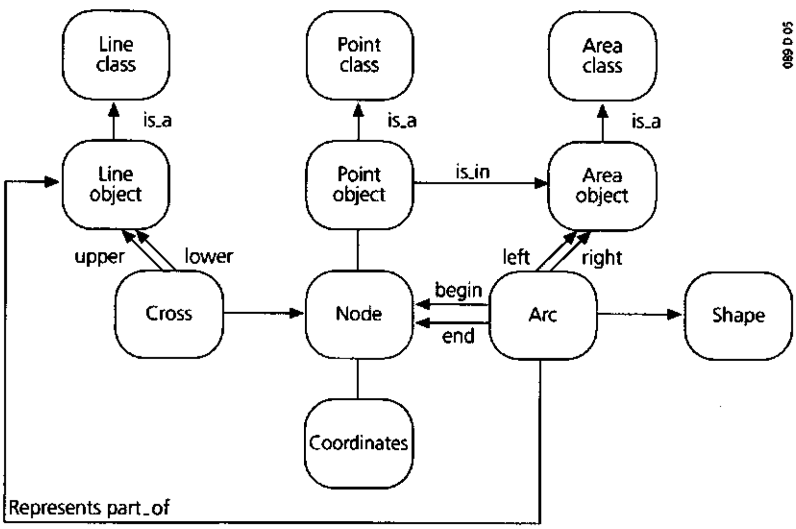

Figure 4 **Formal data structure for a single-valued vector map (from (Molenaar, 1989).**

In the FDS topology is stored explicitly. Topology is about how the different terrain objects are related to each other. Topological relationships are preserved under transformations such as translation, rotation and scaling. The purposes of topology in GIS are twofold: it avoids storage of redundant data and it enables efficient implementation of several types of spatial analysis. Three levels of topological relationships can be distinguished in single-valued vector maps (Molenaar, 1989):

- low-level topology: the relationships between the geometrical primitives as given by the graph-structure of the vector map;
- the linkage of the primitives of the vector map (arcs and nodes) with the terrain objects;
- high-level topology: the relationships between the terrain objects.

The first two levels of topological relationships give geometrical information about the terrain objects and are represented by the left/right, begin/end, upper/lower and is_in arrows in Figure 4. The high-level topology defines topology at the object level which is realized through the primitives. The high-level topology allows communication with the GIS at the level of the user, who deals with terrain objects, rather than at the system-level (Molenaar, 1991).

The FDS can be extended by classification and aggregation hierarchies which are described at the object-level (Molenaar, 1993).

Classification hierarchies

As they are based on common thematic attributes, the terrain objects can be grouped into object classes. The object classes that have partly common attributes can be grouped into superclasses, and so on (Fig. 5). The resulting classification hierarchy may comprise several levels. Note that the terrain objects form the lowest level of the classification hierarchy. These objects can be considered as the elementary objects within the classification hierarchy.

The scheme presented in Figure 5 refers to generalization and specialization operations on object classes. The upward-links in Figure 5 represent is_a-links and therefore denote generalization. E.g. the class 'potatoes' belongs to the class of 'root crops' which belong to the superclass of 'arable crops'. Therefore, 'potatoes' is_a 'arable crop'. It is important to stress that classification hierarchies are based solely on the thematic attribute structure of the terrain objects.

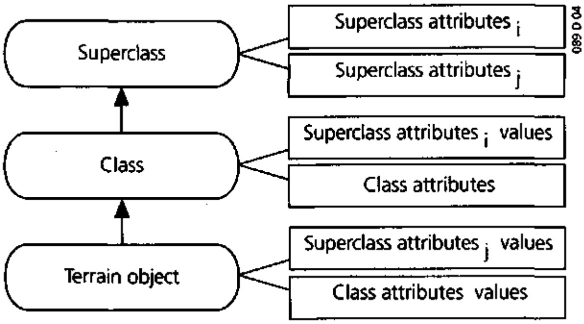

Figure 5 **Hierarchical (is_a) relationships between classes and superclasses.**

Aggregation hierarchies

The introduction of 'elementary objects' implies the existence of composite objects. Composite objects are defined by aggregation hierarchies which are based on both the thematic and geometrical data of the (elementary) objects. Aggregation into composite objects is based on two types of rules:

- Rules that define the (thematic) classes of objects that can be aggregated into a composite object. In Figure 6 the composite object 'farm' is aggregated from the elementary objects 'farmstead', 'farmyard', 'arable land' and 'grassland'. The arrows in Figure 6 represent part_of links and denote aggregation: 'arable land' and 'farmyard' are part_of the farm. Note that at this stage this aggregation can be applied to any set of (elementary) objects.

- Rules that define which individual objects should be aggregated into a particular composite object. These rules are mainly based on topological relationships between the objects. Composite objects may not be aggregated from objects which do not have any direct topological relationships (connected). Six specific objects are aggregated into composite object 'farm 1020' in Figure 7.

Furthermore, the composite objects should be defined in such way that composite objects of one type are disjoint which means that an elementary object can only belong to one particular composite objects of one type. E.g. an agricultural field can only belong to one farm. This restriction leads to the definition of many-to-one relationships between objects and composite objects at different levels in the hierarchy. It is important to note that, in general, aggregation into composite objects starts from elementary objects. The definition of elementary object and composite objects depends on the application context. An agricultural field may be the elementary object in a specific application context, while in another context the total area that belongs to one farm is an elementary object.

The relationship between aggregation and classification hierarchies is elaborated by Huising (1993). In Figure 8 it can be seen that composite objects are built from elementary objects. Different and independent classification systems, each with their own hierarchy, may be applied to both the elementary objects and the different composite objects (aggregations).

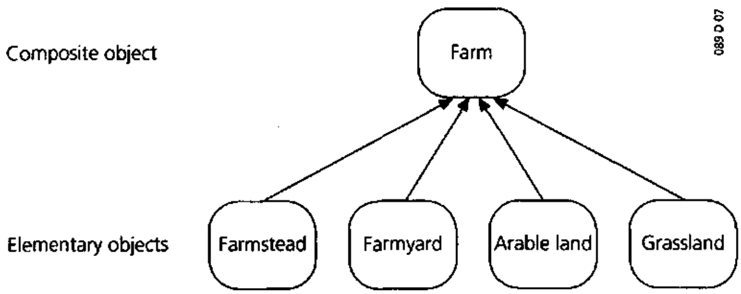

Figure 6 **Part_of relationships between elementary and composite objects.**

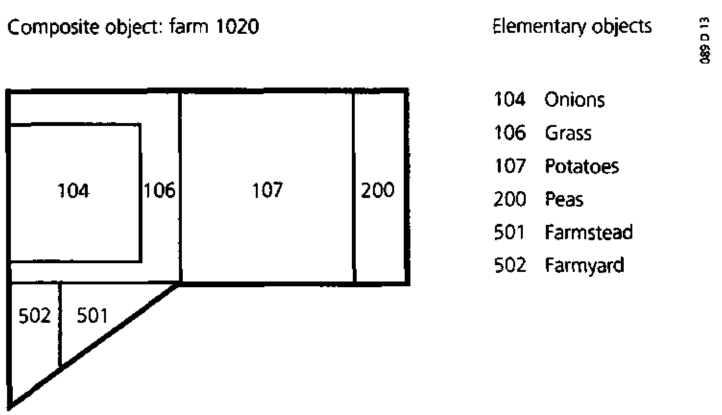

Figure 7 **Specific composite object composed of six elementary objects.**

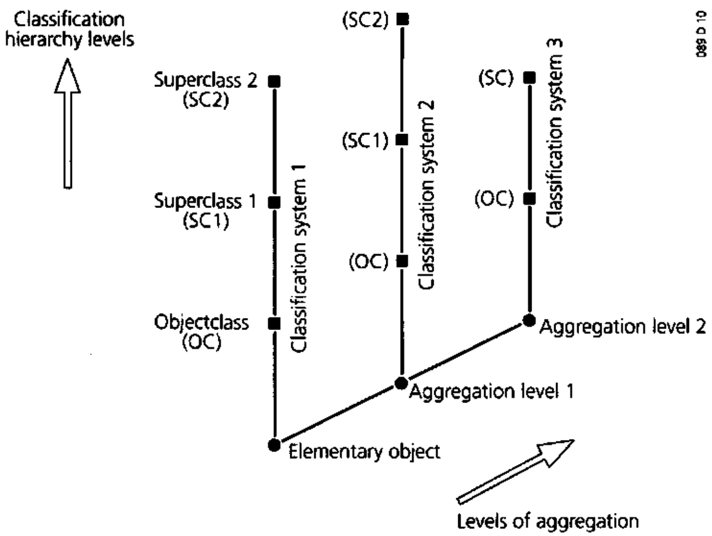

Figure 8 **Relationship between aggregation and classification hierarchies (from Huising (1993)).**

2.3 Terrain object dynamics

The terrain objects that are stored in a GIS refer to real-world phenomena. Due to human activities and natural processes the real world changes. This means that the data in a GIS should be updated to maintain a valid representation of the world. The application context of this thesis is agricultural land cover and it therefore deals with changes caused by man. The most obvious changes are that a new object comes into existence at the beginning of its lifetime (e.g. a clear cut in the forest) or that an old object ceases to exist at the end of it (e.g. a house that has been demolished). In general, more subtle changes will occur. For elementary objects this means that the geometrical and/or thematic data need to be updated; for composite objects this means that redefinition of the aggregation structure is required (Molenaar and Janssen, 1993).

Change in thematic characteristics

First of all the thematic characteristics of an object may change. In the simplest case the value of one or more attributes needs to be updated: e.g. the crop type present on an agricultural field changes from potatoes to sugar beets. In this case the object still remains an agricultural object and its attribute structure list does not change. Another possibility is that an object is reclassified, e.g.: the land cover type of a field changes from arable land into deciduous forest. This change may imply a change of the attribute list, in which case all the new attributes should be determined.

Change in geometrical characteristics

Secondly the geometrical characteristics of a terrain object may change. This might be a change in position, size or shape, or combinations of these (Fig. 9). These changes may also lead to change in topological relationships which can be derived (calculated) from the geometrical data.

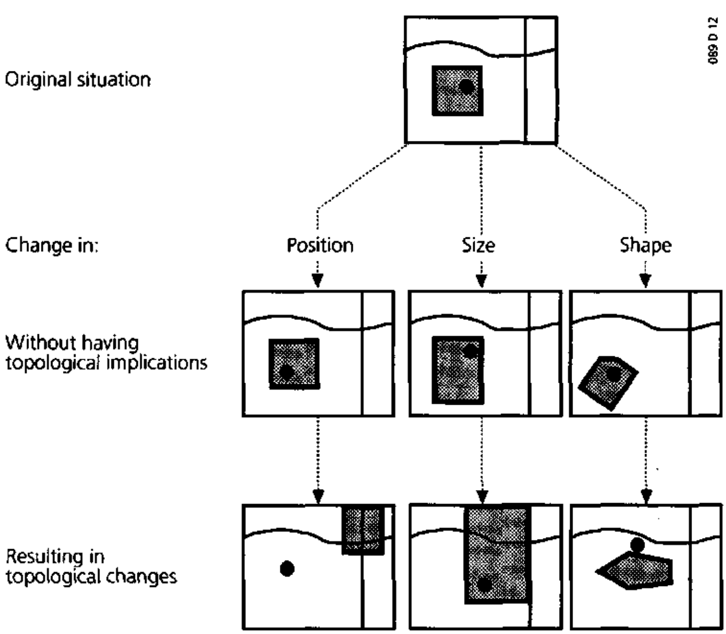

Figure 9 **Change in geometrical characteristics.**

Change in aggregation structure

Thirdly a composite object may change its aggregation structure. The changes that may occur are fragmentation (new boundaries are introduced), merging (old boundaries are dissolved) or replacement of the old set of elementary objects by a completely new set of elementary objects (Fig. 10). It is important to note that 'change in aggregation structure' depends on the way elementary objects are defined.

A village is a composite object if it consists of elementary objects such as streets and blocks. In another application context, the village as a whole can be defined as an elementary object; changes within the village then can only result in change of attribute values. A change of aggregation structure may also result in change in the geometrical and thematic attributes of the composite object. Once the relationship between the elementary and composite objects has been established, the geometrical and thematic attributes of the composite object can be derived from the attribute values of the elementary objects.

The types of terrain object dynamics which have been defined in this section can be considered as dynamic properties of terrain objects. Dynamic properties refer to the geometrical and thematic changes that may be expected. A distinction can e.g. be made between boundaries which are fixed and those which are not. This

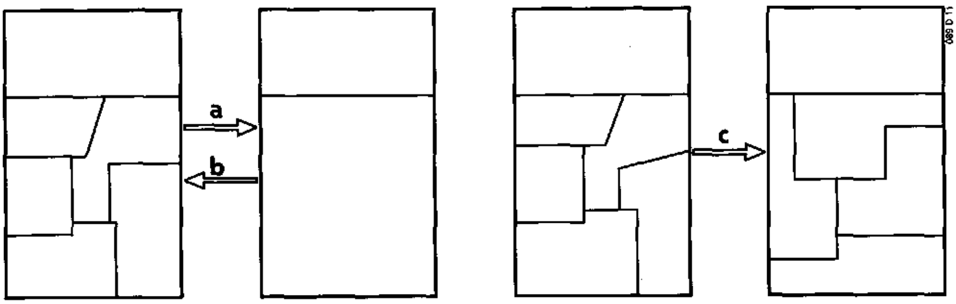

Figure 10 **Change in aggregation structure:**
a Fragmentation (boundaries are introduced)
b Merging (boundaries are dissolved)
c Replacement by a complete new set of terrain objects

knowledge enables an efficient updating strategy which does not have to bother with fixed boundaries. What is fixed and what is variable then is defined relative to the updating (monitoring) frequency.

2.4 Updating from Landsat TM data

In Section 2.2 elementary and composite objects are introduced for which different types of change have been identified (Sect. 2.3). The objective of this thesis is to update these changes from RS data. This means that geometrical and thematic terrain object characteristics need to be extracted from RS data. In the case studies that are presented in Part II of this thesis, Landsat Thematic Mapper (TM) data are applied for updating. Table 1 shows the spectral bands and ground resolution of the Landsat TM sensor. The ground resolution refers to the size of the picture elements ('pixels') after pre-processing. For each individual pixel the energy measured is quantified by an 8-bit code (values 0 to 255) which is also referred to as the Digital Number (DN). More information about the Landsat satellites and its TM sensor can be found in Massom (1991).

At present, two Landsat satellites are operational, which means that principally an image can be acquired once every eight days. However, it is noted that the operational application of Landsat TM data is restricted by the limited availability of cloud-free images acquired at the right moment in the growing season.

Table 1 Description of the spectral bands and ground resolution of Landsat TM

Band nr	Band width (nm)	Ground resolution (m)	Description of wavelength band
1	450-520	30	visible (blue)
2	520-600	30	visible (green)
3	630-690	30	visible (red)
4	760-900	30	near infra-red
5	1550-1750	30	middle infra-red
6	10400-12500	120	thermal infra-red
7	2080-2350	30	near infra-red

Experience of the Netherlands Land Cover Classification project ('LGN') shows that the availability of cloud-free satellite images during the growing season is a serious problem (Thunnissen *et al.*, 1992). In this project the aim was to establish a land cover database for 1986. For optimal classification results the date of acquisition should be between 1 July and the beginning of August. A complete cloud-free coverage of the Netherlands could only be realized by the application of images from 1984, 1986, 1987 and 1988.

Information about real-world phenomena may be determined from RS data on the basis of their spectral, spatial, temporal and polarization characteristics (Buiten, 1993a). The case studies presented in Part II of this thesis are based on a single date Landsat TM image and therefore concentrate on the spectral and spatial characteristics. The temporal characteristics have not been considered. Polarization characteristics are not relevant when dealing with the non-coherent radiation in the visible and reflective infra-red parts of the EM-spectrum.

Terrain objects are an abstraction from the real world in a specific application context (Sect. 2.1). RS data can only be used to determine thematic or geometrical characteristics of terrain objects if there is a relationship between the spectral and spatial (EM) information present in the applied RS data and the type of terrain objects (Sect. 2.5). At the same time, the terrain object characteristics that can be determined depend on the interpretation technique applied (Sect. 2.6).

2.5 Relationship between RS data and terrain objects

2.5.1 Spectral relationship

For a cadastre the terrain objects of interest are cadastral parcels which are defined by ownership and legal status. In general, ownership and legal status do not (directly) effect the EM radiation of the earth surface. It is therefore impossible to update ownership from RS data. The agricultural application context offers more opportunities for information extraction from RS data (e.g. Steven and Clark, 1990). Crop type, biomass and also some management practices such as irrigation and the application of fertilizer effect the EM characteristics of the vegetation or soil. In principle RS can be used to acquire information about these parameters. Within this context it is important to distinguish between 'land cover' and 'land use' (Rhind and Hudson, 1980). Land cover can be defined as the physical characteristics of the soil, vegetation and artificial constructions that cover the earth's surface (Burley, 1961). Land use can be defined as man's activities which are directly related to the land (Clawson and Steward, 1965). An extended definition of land use has been given by Stomph and Fresco (1991) who define land use as the sequence of operations and their timing, applied inputs of labour and capital and implements and traction sources used with the purpose of producing one or a number of specified commodities; land cover is thus considered as the result of land use at a certain moment in time. It will be apparent that the possibilities of RS for deriving such land use data are very limited.

The terrain objects of interest in this thesis are agricultural fields which are primarily characterized by the cultivation of one type of crop (monoculture). The ability to distinguish crops from satellite RS data depends on the crop reflectance in the recorded spectral bands. Crops which have a spectral reflectance that is distinct from other crops can be distinguished. Some crops have a spectral reflectance that is similar to other crops. In such cases (spectral confusion) it is impossible to determine either field boundaries or crop type from RS data. Spectral confusion between crops also depends on the moment in the growing season at which the RS data were acquired. Thunnissen *et al.* (1992) report spectral confusion between potatoes/grass and between maize/sugar beets. For the crops considered in this thesis spectral confusion is e.g. found between grass/sugar beets and between beans/onions (Sect. 4.3).

A pixel-based classification, e.g., assigns pixels to one of the classes that have been defined in the training stage. The classes defined in the training stage are principally spectral classes. This means that for the purpose of classification the required information classes are not classified as such but defined in terms of spectral classes (Lee *et al.*, 1987). Ideally, one-to-one or many-to-one relationships exist between the spectral and information classes. In a large number of cases one-to-many or many-to-many relationships will occur. In other words: information classes cannot be determined from the RS data alone. In addition to the RS data, other data and knowledge are required to make a distinction.

2.5.2 Spatial relationship

An implicit assumption that has already been made in the previous section is that the ground resolution of the sensor is several times smaller than the terrain objects (Strahler *et al.*, 1986). The optimal ratio between the size of a terrain object and the ground resolution of the sensor applied depends on the type of information that needs to be extracted. In general, the extraction of geometrical object characteristics requires a higher resolution than deriving thematic characteristics for objects with a known geometry. Buiten (1993b) observes that a few pixels may be sufficient to detect an object, but that multiple pixels (which can represent a certain structure or repetition pattern) are necessary for object recognition. Davis and Simonett (1992) distinguish between three types of tasks for which RS data are applied:

- Detection: determining the presence of an object;
- Identification or the labelling of an object;
- Analysis, where information is obtained about an object beyond its initial detection and identification.

Simonett *et al.* (1983) suggest that for low-contrast targets the effective ground resolution of the sensors required for analysis may be as much as 10 times less than that for identification and 30 times less than that for detection. Rengers *et al.* (1992) provide some tables that give an indication of the minimal size that objects should have (depending on the contrast) to enable detection, recognition and identification of a terrain object when applying visual interpretation. Their application context is mountain hazard mapping, which deals with a complex type of terrain object (landslides). Assuming high contrast the objects should measure at least 120 m, 210 m and 300 m for detection, recognition and identification respectively when applying Landsat TM data.

It is important to remember that terrain objects are (primarily) defined from an application context and not from their EM characteristics. Given the sensor's ground resolution, some classes of terrain objects will be represented by a homogeneous spatial distribution of EM radiation (e.g. 'lake') while other classes are characterized by a large spatial and spectral heterogeneity (e.g. 'village'). Spatial heterogeneity limits straightforward application of segmentation techniques to delineate terrain object boundaries (Sect. 2.6). On the one hand a relatively high ground resolution is required to determine more or less smooth edges. On the other hand this resolution may result in a large spatial heterogeneity which complicates the application of segmentation techniques.

A well known phenomenon in pixel-based image classification are 'mixed pixels'. Mixed pixels result from applying nominal classification schemes implicitly based on the definition of terrain objects. Agricultural fields, e.g., are characterized by one type of crop. Let's assume that the crop types can be distinguished according to their spectral characteristics. The measured EM radiation of pixels located at a boundary between two fields is contributed by two types of crops. Mixed pixels hamper digital image interpretation, especially in pixel-based classification (e.g. Mather, 1990). The problem of mixed pixels cannot simply be solved by applying a higher ground resolution. Markham and Townshend (1981) have carried out a comprehensive study on the accuracy of pixel-based classification as a function of ground resolution. In that context the spectral heterogeneity of the distinguished classes is referred to as 'scene noise' which was quantified by the standard deviation or coefficient of variation for a certain spectral class. In general, a reduction of scene noise (by applying a lower ground resolution; larger pixels) results in less spectral overlap between classes. As a result the classification results will be better. For their test data, Markham and Townshend (1981) concluded that the accuracy of pixel-based classification of land cover classes only marginally increased when applying a ground resolution of 5 m in stead of 30 m.

From the above it can be understood that the optimal ground resolution depends on (i) the size and characteristics of the considered terrain objects in relationship with (ii) the applied interpretation technique (segmentation or classification). In practice, both the ground resolution of a satellite sensor and the size/shape of the terrain objects of interest are given. This means that it is not always possible to extract the required information. Additional data and knowledge therefore should be used to improve information extraction from the RS data.

2.6 Image interpretation

RS data can be interpreted by visual interpretation. One of the objectives of this thesis is to apply digital interpretation (pattern recognition) techniques. Visual interpretation of images, whether from hardcopy or a computer monitor, is based on visual perception and processing of the perceived information by the human interpreter (e.g. Avery and Berlin, 1985; Lillesand and Kiefer, 1987). Visual interpretation is guided by nine interpretation elements that are implicitly or explicitly applied (Buiten, 1993c):

- tone : grey tone or relative brightness of an object;
- size : size or area of an object;
- texture : spatial grey tone distribution;
- shape : general form, configuration or outline of an object;
- resolution : ground resolution of the sensor applied in relation to the objects.
- pattern : noise pattern or structural pattern;
- shadow : presence of characteristic shadow;
- site : location of objects amidst other objects;
- association : interrelationships of objects.

Some of these interpretation elements such as tone, size and texture can be easily determined and quantified irrespective of the interpretation result. Other interpretation elements such as shadow, site and association are more complex and in fact already an interpretation themselves (e.g. 'the shadow of a house'). The combination of these interpretation elements and the experience of the interpreter, who uses both common sense and professional knowledge, enable different tasks (detection, labelling, delineation) to be carried out.

The digitally stored RS data enable digital interpretation which is based on the application of (statistical) pattern recognition techniques (see e.g. Duda and Hart, 1973; Castleman, 1979 and Schowengerdt, 1983). Castleman (1979) distinguishes three phases of pattern recognition:

1 <u>Object isolation</u>
   In this phase an object is spatially defined and its image data are isolated from the rest of the scene. In fact, this refers to the determination of the geometry (delineation) of the object which can be realized by segmentation techniques. The segmentation techniques applied for RS images can be categorized into edge detection methods and region growing techniques.

2 Feature extraction

Features are measurable properties. In this phase the features selected for classification are measured and stored as a feature vector. Both features based on the object's geometry (size, shape), as determined in the first phase, and features based on the spectral values of the RS image (tone, texture) can be used for discrimination. Typically only a limited number of features (interpretation elements) are used compared to visual interpretation: those which can be easily quantified (tone, texture, size, shape). Contextual features such as site and association are difficult to quantify and therefore hardly ever used.

3 Object classification

In the classification each object is assigned to a predefined class (labelling) based on the features selected by the use of a classifier, e.g. a maximum likelihood classifier.

In most applications of satellite RS data with respect to land cover, the first phase (object isolation) is skipped. In that case individual pixels are classified by their spectral characteristics (tone). The limited possibilities for the recognition of terrain objects from satellite RS data are due to a number of reasons:

- The relationship between the ground resolution and the size (and shape) of the terrain objects.

  Mostly, the ground resolution of satellite data is too low with respect to the size of terrain objects to enable the determination of a more or less smooth boundary. The delineation (segmentation) of objects requires a higher resolution than the resolution required for classification (Sect. 2.5.2). With respect to agricultural fields minimum field sizes of 32 pixels (Townshend and Justice, 1981) and 25 pixels (Grunblatt, 1987) have been mentioned for classification.

- The complexity of terrain objects.

  Segmentation techniques yield good results for relatively simple objects (e.g. the roof of a house). Geographical terrain objects are complex in the sense that large variations in spectral and spatial characteristics are accepted in one object class (Sect. 2.5.2). Visual interpretation is very flexible with regard to these variations: a field of grassland may consist of different qualities of canopy; spots of bare soil in a sugar beet field do not disturb the identification of its outer boundary. When e.g. applying edge detection, only part of the edges will correspond with object boundaries; the other edges are caused by texture or noise. Furthermore, segmentation techniques apply local or focal operations which lack the synoptic character of visual interpretation.

- The complexity of the segmentation procedure itself.
  Image segmentation, followed by vectorization, requires the application of several more or less complex algorithms (e.g. Gerbrands, 1988; Cheng, 1990). Furthermore, a very large number of algorithms have been proposed for e.g. edge detection. However, there is no clear theory that describes which algorithm yields the optimal results under particular circumstances.

The above mentioned reasons may also explain the limited possibilities for segmentation and vectorization in commercial image processing software for RS data.

The ground resolution of a specific satellite sensor is a given fact. It can be expected that the ground resolution for the next generation of multi-spectral scanners will remain within the range 10 m to 30 m. The only way to get data with a higher ground resolution is to apply other RS data, e.g.: multi-spectral aircraft data or scanned aerial photographs.

The complexity of the terrain objects hampers straightforward application of segmentation techniques. This problem can be solved by an approach in which additional data and knowledge are applied. An example of such an approach is given in Chapter 7 where the edge detection is applied to determine the geometry of agricultural fields from a Landsat TM image by such an integrated approach.

If an integrated approach is applied, the choice of an algorithm (and its parameters) may become less critical since its results are further processed with other data and knowledge (e.g. Ehlers, 1993b). This may also facilitate the choice of a segmentation algorithm and its parameters.

Visual and digital interpretation should be considered as two different approaches to image interpretation (Buiten, 1993c). Both have their advantages and disadvantages. The advantage of visual interpretation is that a large number of interpretation elements are applied in combination with specific (not formalized) professional knowledge. Some of the disadvantages of visual interpretation are the need of qualified interpreters, that the result changes from interpreter to interpreter (e.g. Middelkoop, 1990) and that the job may be very boring in an production environment. The disadvantage of applying digital interpretation techniques is that only a limited number of interpretation elements can be used and that all the relevant knowledge has to be explicated to the machine. Interaction of a human interpreter is required to define how and what is determined (e.g. selection of algorithms, setting of threshold parameters, definition of training data). Digital interpretation, therefore, is not objective. The advantage, however, is that the same interpretation method can be exactly repeated once the algorithms and parameters for digital interpretation have been defined. This offers great potential for batch processing of satellite data in a monitoring environment. Another advantage of digital interpretation is that it has larger discriminating possibilities than human interpreters for the interpretation elements that can be quantified. A person cannot compete with the computational strength of a machine e.g. to assign a pixel into one of 40 classes based on a six-dimensional feature vector.

2.7 Relevant experience from literature

The general objective of this thesis, as stated in the introduction (Sect. 1.3) is
(i) to update terrain object data contained in a GIS;
(ii) from high resolution satellite data;
(iii) by applying digital interpretation techniques;
(iv) by using additional data and knowledge.
The combination of these four elements make the approach that is pursued in this thesis almost unique. Some examples from RS literature which have almost the same objective are listed below.

A true updating approach is applied by the superimposition of vector-structured terrain object data on raster-structured RS data. Visual interpretation is then used to add or modify data by means of on-screen (heads-up) digitizing (e.g. Moore, 1989; Lynn-Usery and Welsh, 1991; Sanchez, 1991; Wilkinson *et al.* 1992). At present, visual integration of image data with vector-structured terrain object data can be realized in a large number of GIS's and image processing systems. The advantage of this approach is that optimal visualization of the image data can be realized (band combinations, stretching) while at the same time the geometry and thematic attributes of terrain objects can be interactively changed or added. As a result of the developments in scanning and digital photogrammetry this approach is applied on a large scale for aerial photographs.

Another approach aims to determine both the geometry and land cover type of terrain objects solely from the RS data (e.g. Stakenborg, 1986; Swann et al, 1988; Meyer, 1992). On the one hand such an approach is attractive: it can be applied to sample areas distributed over large areas (continent or globe) for which none or only limited standardized digital geographical data are available. On the other hand the growing amount of digital geographical data cannot be neglected and it is e.g. inefficient to determine terrain objects that are already digitally available (e.g. roads, built-up areas) and which may have been derived from more detailed sources (e.g. from aerial photographs).

A last approach that should be mentioned here is to improve the possibilities and quality of RS image classification by the application of additional terrain object data and knowledge in the digital interpretation of the RS data. However, it does not lead to feedback of the results to the GIS (e.g. Hutchinson, 1982, Kenk *et al.*, 1988; Bolstad and Lillesand, 1991; Thunnissen *et al.*, 1993). The main reason for the lack of feedback is that the applied terrain object data are from another application context, e.g. when using geomorphological, elevation or soil data for improving land cover classification. In some other cases the applied terrain object data (cadastral parcels, agricultural fields) are directly related to the land cover data extracted from the RS data (e.g. Pedley and Curran, 1991; Zhuang *et al.*, 1991). Feedback to the original terrain objects is then not considered relevant and the additional data are considered as 'just another' additional discriminating variable in a pixel-based classification (Sect. 6.1).

In this thesis the Landsat TM data applied should yield field boundaries and crop type of agricultural fields. Few studies have been found in which geometrical or thematic data are updated by digital interpretation from RS data. Lemmens and Han (1990) update boundaries and crop type of agricultural fields from the result of a pixel-based classification of Landsat TM data. Mason *et al.* (1988) apply a combination of segmentation and classification of airborne TM data to update an existing geographical map. Van Cleynenbreugel (1991) presents different strategies to update existing road data by a model-based interpretation of SPOT data. These studies are described and discussed in Chapter 7.

2.8 Conclusions

In Section 2.1 'terrain objects' were introduced. Terrain objects are abstractions of real-world phenomena for which thematic and geometrical data are stored in a GIS. Due to human activities and natural processes the real world changes. The data in the GIS should then be updated to maintain a valid representation of the world. In this thesis the updating of terrain object data is based on the application of satellite RS data which contain spectral and spatial information about the EM radiation that is reflected by the earth's surface; information extraction from the RS data is based on the application of digital interpretation techniques. The problems that are encountered when determining geometrical and thematic characteristics of terrain objects from RS data are twofold:

- The spectral and spatial information present in RS data allow the extraction of thematic and geometrical characteristics of certain types of terrain objects with only limited precision and reliability (Sect. 2.5.1);

- The complexity of real-world objects hampers the straightforward application of segmentation techniques for the delineation of terrain objects (Sect. 2.5.2). The results of pixel-based classifications are not directly related with terrain objects and are negatively effected by e.g. mixed pixels and spectral variability (Sect. 2.5.1).

As a result of these problems a very limited number of studies in literature have been applying digital interpretation of satellite RS data for updating purposes. The problems mentioned, however, can be solved (to a certain extent) by using additional data and knowledge about the terrain objects of interest. The idea underlying this thesis is an integrated approach in which RS data are used to update geometrical and thematic data of terrain objects, while at the same time the terrain object data contained in the GIS and additional knowledge about their (dynamic) properties are used to optimize and improve the information extraction from the RS data (Fig. 1).

Based on knowledge about terrain object dynamics, an updating strategy can be developed. Furthermore, knowledge about terrain objects properties should be exploited to improve the interpretation of the RS data. This means that different types of (spatial) data and knowledge[2] have to be 'integrated'. The propagation of errors, caused by data integration, should be minimized. These aspects are further elaborated in the next chapter: information extraction.

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2 In this thesis, the difference between data and knowledge is that data are stored on a medium while knowledge is contained in someone's mind. Knowledge needs to be formalized before it can be stored as data or used to guide data processing.

3 Information extraction

3.1 Introduction

In this chapter three aspects of an integrated approach to information extraction from RS data are set out. In the information extraction image, pixels or geometrical elements (edges, segments) need to be related to terrain objects. This can only be done by applying an object-based approach (Sect. 3.2). In the process of data integration, data with different data structures (vector and raster) and coordinate systems (map coordinates and image coordinates) need to be integrated (Sect. 3.3). Furthermore, the strategy applied to information extraction should minimize the propagation of errors (Sect. 3.4). Geometrical and thematic data are added/changed in a GIS as a result of updating. The last section (3.5) describes the methods used for the validation of the result.

The content of this chapter is largely based on the three strategies that are presented in the second part of this thesis. The terrain objects of interest are agricultural fields for which the field boundaries and crop type are updated from a Landsat TM image. A description of the test area and data is given in Chapter 4. The strategies applied to updating can be summarized as follows.

Application of conditional a-priori probabilities (Chapt. 5)
The crop type in the preceding growing season together with knowledge about crop rotation schemes is applied to improve the accuracy of pixel-based classification. For several reasons the available knowledge about crop rotations could only be integrated with a pixel-based approach (Sect. 5.1). As a result, this approach does not allow for updating of the terrain object data in the GIS.

Object-based classification (Chapt. 6)
The crop type of an agricultural field, of which the geometry is contained in the GIS, is determined from the Landsat TM image. Therefore, the pixels within the field are identified and the crop type of the field is determined from these pixels. Boundary pixels are excluded in the determination of the crop type to yield a reliable classification result.

Integrated segmentation and classification method (Chapt. 7)
The field boundaries and crop type of agricultural fields are updated from the Landsat TM image by an approach that is based on the application of edge detection and object-based classification. The strategy applied distinguishes between the fixed boundaries of the lots and the variable boundaries of the fields. The preliminary field geometry is derived by integrating the results of an edge detection with the fixed lot boundaries. In a further stage the crop type of the fields is determined by means of object-based classification. Finally, fields with similar crop types are merged to solve possible oversegmentation.

3.2 Level of integration

There is a large conceptual difference between terrain object data and RS data: terrain objects are the result of an interpretation while RS data should be considered as measurements of EM-radiation. In general, the approach is to apply (low level) pattern recognition techniques such as segmentation and classification on the RS data resulting in geometrical elements (edges, segments) or labelled pixels. These results, then, are integrated with terrain object data (e.g. Ehlers, 1989; Laurini and Thompson, 1993). Förstner (1993) distinguishes two semantical levels on which data integration takes place: pixel-based data integration and object-based data integration[3]. In pixel-based data integration the original (or derived) raster data are combined with local characteristics of terrain objects. This is the approach that is applied in Chapter 5 where temporal relationships between raster elements are used to improve the classification. In object-based data integration the semantics of the terrain objects (having both geometrical and thematic characteristics) is also explicitly used. Object-based data integration can therefore link the results of digital interpretation to terrain objects. This is the approach that is applied in Chapters 6 and 7.

[3] In his article, Förstner (1993) distinguishes between 'property-based' and 'object-based' information fusion. To avoid confusion with the terms 'dynamic' and 'static', used to describe the properties of terrain objects in this thesis, the terms 'pixel-based' and 'object-based' data integration are used.

3.2.1 Pixel-based data integration

In a large number of RS studies ancillary data are added to improve image classification. This is achieved by storing the ancillary data in the same grid geometry as the RS data. The data for corresponding grid elements (RS data and ancillary data) are thus combined in the classification of the pixels.

Different approaches are applied for pixel-based classification of multi-source data. A distinction can be made between (i) methods which apply the ancillary data in the classification itself and (ii) methods which combine the results of a pixel-based classification with ancillary data. The first method is based on a classifier operation which can combine different types of 'evidence'; examples are:

- a probabilistic approach using conditional a-priori probabilities in the maximum likelihood classification (e.g. Strahler, 1980; Kenk *et al.*, 1988; Skidmore, 1989; Bolstad and Lillesand, 1991; Chapt. 5 of this thesis);

- the application of non-probabilistic inference techniques such as Dempster-Shafer and fuzzy reasoning (e.g. Wilkinson and Mégier 1990; Desachy *et al.* 1992)

- the application of neural network classifiers (e.g. Benediktsson *et al.*, 1990; Hepner *et al.*, 1990; Zhuang *et al.*, 1991).

The second method combines the result of a pixel-based classification with other data by applying a look-up-table operation or If-Then rules (e.g. Van der Laan, 1988; Thunnissen *et al.*, 1993).

The potential of pixel-based classification can also be improved by using spatial context information. The simplest way is to apply a majority filter on the result of a pixel-based classification (e.g. Hutchinson, 1982; Thunnissen *et al.*, 1992; Kenk *et al.*, 1988). A filter-based method that takes spatial class interdependencies into account is e.g. presented by Gong and Howard (1992). Moler-Jensen (1990) applies an expert-system approach in which quantified knowledge about spectral, textural and context features is applied. A contextual classifier which applies both spatial and temporal context is presented by Jeon and Landgrebe (1992).

In general, the application of ancillary data and knowledge enables a better classification accuracy and the discrimination of other than spectral classes (e.g. land use classes) when compared with a pixel-based classification that is solely based on the spectral data. Characteristic of pixel-based data integration is that it does not result in terrain objects and that there is no direct link between the ancillary data applied and the data resulting after integration.

In this thesis, the objective is to extract information from RS data to update thematic or geometrical terrain object data. Updating cannot therefore be realized by pixel-based data integration. The results of pixel-based data integration, however, can be input for the object-based data integration with which updating is realized.

3.2.2 Object-based data integration

In Chapter 2 it is stated that the terrain objects in a GIS are described by geometrical and thematic data. In addition to this we have knowledge about the dynamic and static properties of the geometrical and thematic characteristics of the terrain objects. Dynamic properties refer to the changes that may be expected for specific terrain objects, e.g.: a distinction can be made between fixed and variable boundaries if a specific time span is considered (Sect. 2.3). Properties that refer to time-independent characteristics are called static properties, e.g: agricultural fields have a rectangular shape. A generic object model consists of formalized knowledge about general dynamic and static properties of terrain objects. These models play an important role in information extraction for updating purposes.

In this thesis, two generic object models are applied with respect to agricultural fields in the Biddinghuizen test area (Sect. 4.1). An agricultural field is defined as an area in which one type of crop is grown. The terrain object model applied in the object-based classification (Chapt. 6) related to the elementary object 'agricultural field' assumes that:

- the geometry of agricultural fields is fixed;
- the crop type may change from year to year.

This model is applied where the boundaries of agricultural fields are contained in a GIS. It implies that the RS data applied should be used to update the crop type (thematic data). At the same time the object model provides valuable spatial context information that can be exploited in the digital interpretation of the RS data: it is known beforehand that the interpretation of the pixels that are located within the object should yield one crop type. The results are directly related to specific terrain objects since the analysis is performed for terrain objects.

The other terrain object model that is applied in this thesis serves to update both field geometry and crop type from the RS data (Chapt. 7). This model links elementary objects (agricultural fields) with composite objects (lots):

- the geometry of a lot is fixed;
- each growing season a new set of fields is created within the lots (fragmentation);
- field boundaries and lot boundaries may have shared boundaries;
- in general, field boundaries have a perpendicular or parallel orientation within the lot geometry.

This model is applied in a situation in which the lot boundaries are contained in a GIS. The process of updating, therefore, should extract the field boundaries that are located within the lots and connect these with the fixed boundaries to derive (closed) field geometry. The crop type of these fields is then determined by means of object-based classification. The model also gives information that can be exploited in the information extraction from the RS data: edge characteristics can be compared with field boundary characteristics to select only those edges which are likely to correspond with field boundaries.

Object-based data integration can be realized in various ways and generally requires a (large) number of processing steps. Object-based classification (Chapt. 6) is achieved by the application of a statistical function (mode class) to the histogram of the labelled pixels that are located within an object. Geometrical relationships between edges and boundaries are determined while updating field geometry (Chapt. 7).

It is characteristic of object-based data integration that the data applied and knowledge relate to terrain objects characteristics. As a result information extraction yields results that have a direct relationship with the terrain objects contained in a GIS. An object-based integration approach is therefore required for updating. The generic object model, which consists of formalized knowledge about properties of terrain objects, defines what type of information should be extracted from the RS data (geometrical and/or thematic data) and gives information that can be used to reduce the errors associated with digital image interpretation.

3.3 Spatial aspects of data integration

In object-based data integration, pixels or geometrical elements (edges, segments) derived from the digital interpretation of the RS data need to be linked with terrain objects. This requires that the coordinate systems in which the terrain object data and RS data are linked (Sect. 3.3.1). Then, there are different possibilities to integrate vector-structured and raster-structured data (Sect. 3.3.2).

3.3.1 Co-registration

Terrain object data in a GIS are stored in a specific map coordinate system. RS data are generally stored in a row/column-based or image coordinate system. To link the pixels or geometrical elements with the terrain objects it is required that a position in one coordinate system can be expressed as a position in the other coordinate system. Principally, there are two approaches to dealing with different coordinate systems: geocoding of the image data or geometrical transformation of the terrain object data.

Geocoding means that the image (raster) data are transformed into the map coordinate system (image-to-map). The advantage of this method is that all the data are then in the required coordinate system. However, resampling is required when transforming raster structured data. Resampling can have a negative effect on the quality of the image data. The size of this effect depends on the type of data (continuous / nominal), the size of the pixels in the input and output coordinate system and the resampling method applied (nearest neighbour, bilinear interpolation or cubic convolution).

The other approach is to transform the vector-structured terrain object data which are stored in map coordinates into the image coordinate system (map-to-image). The advantage of this method is that the image data do not need to be resampled. When thematic data for terrain object are extracted, the result can be fed back to the GIS by means of object-identifiers. An inverse transformation (image-to-map) is required for feedback of geometrical data (e.g. field boundaries) to the GIS.

Both approaches have been applied in this thesis: geocoding of the image data in Chapter 5, in which pixel-based data integration is used and in the other two case studies (Chapts 6 and 7) the geometrical terrain object data (field and lot boundaries) are expressed in image coordinates to enable data integration. The transformation that is applied for co-registration of the Landsat TM image with the agricultural fields contained in the GIS is an affine transformation. The transformation parameters are calculated from sets of Ground Control Points (GCP) which are (visually) identified in both the image and geographical data. The transformation accuracy is calculated from the GCP-set and expressed as a planimetric Root of Mean Squared Error: $RMSE_{xy}$ (e.g. Veregin, 1989b).

Co-registration enables 'low-level' data integration by means of vector-on-raster superimposition. This enables, e.g., an interactive updating approach based on visual interpretation. The approach applied to updating in this thesis requires an additional step: integration of data structures.

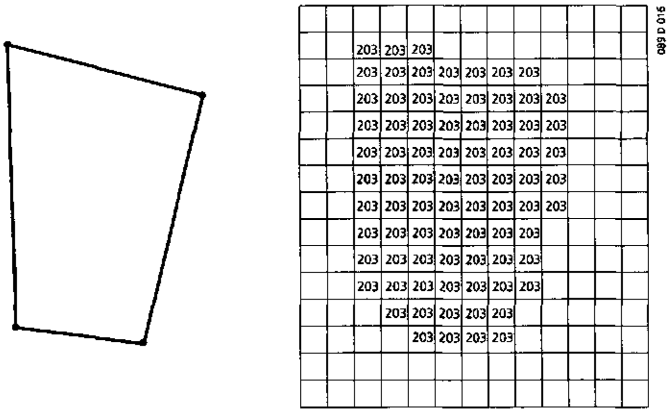
3.3.2 Integration of data structures

Molenaar and Fritsch (1991) present two approaches to linking raster and vector data: a position-oriented and an object-oriented approach. The object-oriented approach requires that the terrain objects represented in the vector-structured data are also present in the raster-structured data. This is not the case when dealing with raw RS data (spectral reflectance), nor when dealing with the results of a pixel-based classification. Therefore, terrain objects should first be derived from the RS raster data. Only a limited number of terrain object classes and the results of image segmentation (e.g. areas of open water) can be directly related to one another by means of e.g. relational matching (Vosselman, 1992).

When dealing with image pixels or geometrical elements (derived by low level segmentation techniques) a position-oriented approach is required to link these with terrain objects. A position-oriented approach requires that the data applied be co-registered. Subsequently, the data can be stored in a similar structure (raster or vector) by applying vector-to-raster or raster-to-vector conversions. Then, pixels or elements can be linked to terrain objects by means of overlay operations or by geometrical relationships. An alternative to data conversion (resulting in redundant and large volumes of data) is an approach that enables direct access of e.g. the values of the raster elements that are located in a polygon ('direct integration').

Object-based classification requires identification of the pixels that (spatially) correspond with an agricultural field (Chapt. 6). This can be achieved by a vector-to-raster conversion of the field geometry into the grid geometry of the RS data applied using the unique object-identifier as grid value. As a result the geometry of a field is represented in a raster-structure in which the value of the raster elements defines the field in which they are located (Fig. 11). A raster overlay operation is then used to identify the pixels of the RS data that correspond with a specific field. From these pixels the crop type of the field is determined. The result of the classification is directly related to a specific terrain object by the object-identifier.

In this thesis the direct approach is applied. Instead of converting, the values of the pixels that correspond with a terrain object are directly accessed and further processed (Sect. 6.2.2)



Terrain object 203
vector-structured

Terrain object 203
raster-structured

Figure 11 Vector and raster representation of the geometry of a terrain object.

In Chapter 7 the field geometry is derived from edges that are found by edge detection of the RS image. The edges that correspond with the fixed lot boundaries do not add any new information and are therefore discarded. This is realized by (i) a vector-to-raster conversion of the fixed boundaries followed by (ii) a raster overlay operation in which the edge pixels that correspond with a fixed boundary are assigned a background value. The remaining edges are vectorized by means of a least squares line fit to enable integration of edges with fixed boundaries. In an iterative procedure edges are selected by their geometrical relationships with other boundaries and subsequently connected with these boundaries.

3.4 Error reduction

Veregin (1989a) distinguishes between 'error propagation *per se*' and 'error production'. The former refers to the process in which errors present in spatial data (and knowledge) are passed through a GIS and accumulate in the output product. An important error source in this respect are the 'errors' caused in segmentation and pixel-based classification of RS data (Sects 2.5 and 2.6). The latter refers to a situation in which errors in the output product are attributable mainly to the operation itself, e.g.: the conversion of vector into raster data. Knowledge about error sources and uncertainty should be used to develop a strategy for information extraction which minimizes the amount of 'error' in the output product.

Lunetta *et al.* (1991) have described the accumulation of error in a remote sensing information processing flow that is based on pixel-based classification. It describes errors in data acquisition, data processing, data analysis and data conversion of RS data. In the following some examples are given with respect to error reduction in the (object-based) updating strategies applied.

Object-based classification (Chapt. 6) is based on the field boundaries contained in a GIS. The starting point for object-based classification is the geometry of agricultural fields in which only one crop type is grown. Let us assume a correct field geometry. Based on this field geometry the pixels of the RS data that correspond with the object are identified by co-registration which is followed by identification of the pixels within the field. If correct field geometry is assumed co-registration of field boundaries and the Landsat TM data can be realized at the sub-pixel level (e.g. Welch *et al.*, 1985; Buiten, 1988). This means that there is a high level of certainty that the pixels that are identified within an agricultural field actually are located within this field. For pixels located at the boundaries this is uncertain. Depending on the algorithm applied, boundary elements are assigned to either the left or right polygon (field) while actually being located in both polygons. Finally, boundary elements generally correspond with mixed pixels in the RS data. This means that (i) there is a large degree of uncertainty about the spatial link between boundary pixels and terrain objects and (ii) the spectral reflectance of the boundary pixels is mixed and therefore a potential source of error for classification. Based on this knowledge it can be expected that excluding boundary pixels in the classification of a field yields a more reliable result (crop type).

In Chapter 7 the field geometry is determined by combining the result of an edge detection on the Landsat TM image with the fixed geometry of the lots. Part of the edges that are found in the edge detection correspond with field boundaries (relevant edges). Another part of the edges are caused by different sowing dates or by in-field variation. The strategy applied should therefore distinguish between relevant and non-relevant edges. This is achieved in three stages:

1 Application of a relative low threshold value in the edge detection itself which results in a large number of relevant edges but also in a large number of non-relevant edges.

2 Edges that have a low degree of certainty to correspond with relevant edges are selected according to their length and discarded. This removes most edges that are caused by in-field variation. The remaining edges are connected with other boundaries to yield closed areas.

3 As a result of the low threshold value applied in (i) and the relative large number of edges that are assumed to be relevant in (ii) it is possible that boundaries separating areas with the same crops but with different sowing dates may be determined. These boundaries are not relevant for updating crop type and therefore removed (dissolved) by merging fields which have a similar crop type.

In the strategy applied the 'cost' of rejecting relevant edges is very high, since no additional geometric information is added afterwards. The 'cost' of accepting non-relevant edges is low, since these boundaries are removed in a later stage. Note that the strategy applied is analogous the approach in hypothesis testing in which the probability of a type I error (incorrectly rejecting hypothesis H_0 while true) is minimized.

It should be realized that error (and error reduction) is defined within a certain application context. This means that data which are optimal in its specific application context may be useless when applied in another context. In the above examples it has been shown that data integration reduces error in the information extraction. What is considered to be an 'error' depends on the application context. An example:

In Chapter 5 the crop type of the previous growing season together with knowledge about crop rotation schemes is used to improve pixel-based classification. According to the crop rotation schemes applied it is impossible for potatoes to be grown on a specific location (pixel) if potatoes were also grown on the same position in the previous growing season. This applied knowledge, or should we say assumption, is true in general. It therefore improves overall classification accuracy. However, due to this assumption, the approach applied (and its results) are useless for checking whether farmers comply the with national regulation that potatoes may not be planted on the same piece of land in two successive growing seasons.

This example illustrates the relationship between the derived data and its application context. What often occurs is that data, once generated, are distributed and applied by other users. Veregin (1989b, p24) states that "as data quality requirements are application-specific, it is the responsibility of the producer to document the data quality and the responsibility of the user to interpret this documentation and evaluate the fitness of the data for a particular application". Therefore, the quality of data that are distributed should not only be expressed in terms of positional or attribute error, but should be accompanied by the 'data lineage' which refers to the data (and knowledge) applied and the strategy (methods, operations, transformations) applied to derive the data.

3.5 Validation of results

The three case studies that are presented in Part II of this thesis result in geographical data. These data are compared with reference data (which are assumed to have a higher accuracy) in order to identify, to analyze and to quantify the errors. For each case study an 'error-analysis' is carried out.

Pixel-based classification result

The application of conditional a-priori probabilities (Chapt. 5) results in a raster file in which each element is coded with a certain crop type. The thematic accuracy of the classification is compared, pixel-by-pixel, with reference data. The comparison results in a confusion matrix from which errors of omission, errors of commission and overall accuracy are assessed. Methods for assessing errors using a confusion matrix are described in a large number of studies (e.g. Veregin, 1989b; Congalton, 1991; Janssen and Van der Wel, 1993) and therefore not further described here.

Field geometry and crop type

In Chapters 6 and 7 the geometry and crop type of agricultural fields is updated. A field is defined as an area that is characterized by the cultivation of one type of crop. This definition implies that the field geometry and thematic contents are interdependent, which complicates separate validation of thematic and geometrical accuracy. Two approaches for validation are applied in this thesis:

- Assessment of thematic accuracy (crop type)
  Based on the assumption that the field geometry is correct, the thematic accuracy can be determined by a straightforward comparison of the RS-derived crop type with the reference crop type. Class-based and overall accuracy can be expressed as a fraction of the total number of objects or as a fraction of the total area. This is the approach applied for the validation of the results of the object-based classification (Chapt. 6).

- Assessment of geometrical accuracy (field geometry)
  The RS-derived field geometry is compared with the reference field geometry. Two extremes can be distinguished when the geometry of two terrain objects is compared: objects which largely correspond, with some smaller differences

at the field boundaries ('positional error') and the fields which do not correspond at all, which can be considered as an 'interpretation error' (Chrisman, 1989). In practice, the problem is how the deal with the intermediate situations. In Section 7.2.4 a quantative approach is presented to distinguish between both types of errors.

PART II CASE STUDIES

4 Test area and data
5 Application of conditional a-priori probabilities
6 Object-based classification
7 Integrated segmentation and classification

4 Test area and data

In this Part of the thesis three case studies are presented. These case studies deal with agricultural fields located around the village of Biddinghuizen in Flevoland, the Netherlands, which is characterized by the cultivation of arable crops. There were three reasons for selecting this area:

- The field geometry and crop type for this area were available for a number of successive years. Until 1987, a yearly inventory of the fields and crops was made by a governmental organization. These data were needed as a starting point for updating and validating the results.
- The fields in the Biddinghuizen test area are relatively large when compared to the spatial resolution of high resolution satellite data (average field size 6.9 ha).
- Availability of a cloud-free Landsat TM image that was acquired during the growing season of 1987.

The following section (4.1) provides a general description of the test area and agricultural practice. Sections 4.2 and 4.3 describe the geographical and remote sensing data applied are described. The last section (4.4) describes the software used.

4.1 Description of the test area

The Biddinghuizen test area is located in East Flevoland, one of the polders reclaimed on the former Lake IJssel (Fig. 12). The land surface of the polder is flat with a mean altitude of 3 m below sea level. The soil in the test area is homogeneous and classified as a fine-textured Calcaric Fluvisol according to the World Soil Map (FAO, 1981). It is an agricultural area in which the land is mainly used for the cultivation of arable crops such as potatoes, sugar beets and cereals.

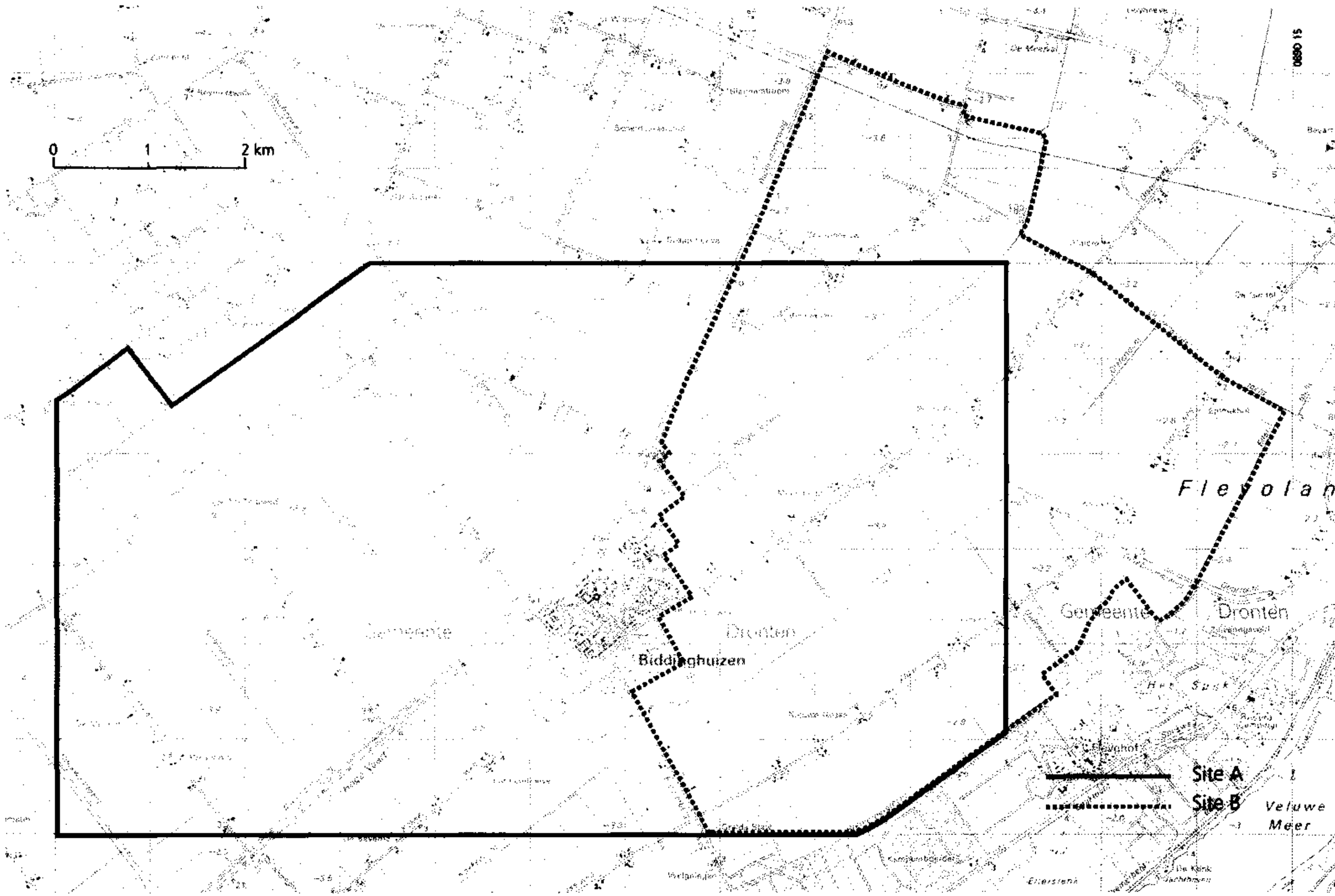


Figure 12 Outer boundaries of sites A and B at the Biddinghuizen test area overlaid on a copy of the topographical map 1 : 50,000.

Terrain objects

The landscape pattern in the Biddinghuizen test area is largely determined by the subdivision in lots. A lot is the basic unit that can be bought or rented by a farmer. The lots are generally separated from other lots by roads and ditches (topographical boundaries). A farm usually consists of one or two lots. Farm practice is to subdivide a lot into a number of fields for the cultivation of different crops. In other words: a farms is an aggregated object that consists of lots which in their turn are aggregated objects which consist of fields (Fig. 13). The agricultural fields are the elementary objects in this thesis. Agricultural fields are defined as areas that are characterized by the cultivation of one crop. Furthermore, an agricultural field is a functional unit which means that it is located within the fixed geometry of a lot. This means that although the geometry of an agricultural field is primarily determined by 'crop type' it is also determined by the lot boundaries which may not be visible in a RS image. Figure 14 shows the changing field geometry for three successive years. In general, the agricultural fields comprise segments of the (fixed) lot boundaries.

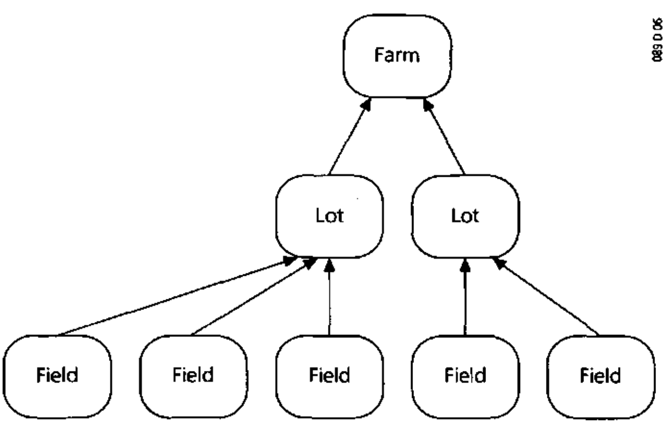


Figure 13 Aggregation hierarchy of farm, lots and fields.

Terrain object dynamics

The terrain object dynamics present in the Biddinghuizen test area concern the agricultural fields of which the crop type and boundaries change from growing season to growing season. From Figure 14 it can observed that an agricultural field only exists for one growing season. Each growing season the complete set of fields

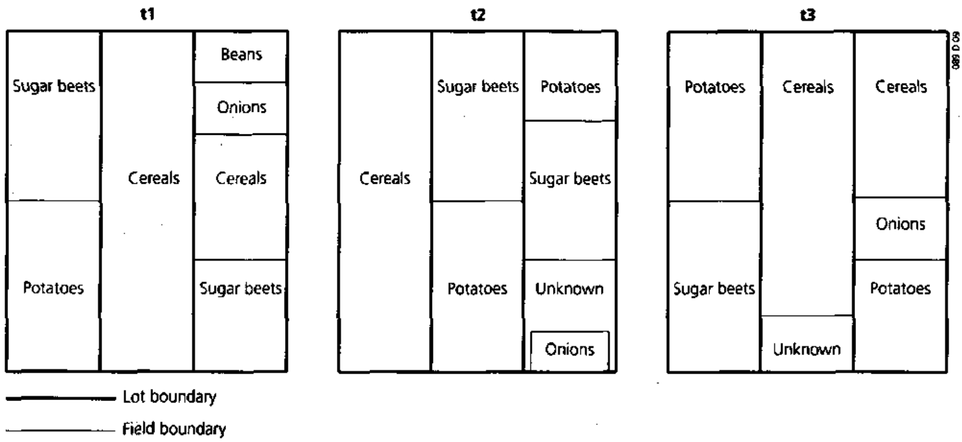


Figure 14 **Terrain object dynamics in three successive years in the Biddinghuizen test area. The agricultural fields (crop and geometry) change from year to year; the lot boundaries are fixed.**

within a lot is replaced by another set of fields. With respect to updating it is important to note the distinction between fixed and variable boundaries. Only the latter need to be extracted from the RS data when updating.

In the following it is explained why not only the crop type but also the field geometry changes from growing season to growing season.

Land use can be considered as the result of a large number of bio-physical and socio-economic boundary conditions (Mücher *et al.*, 1993). Also at the farm level the acreage and allocation of the crops are determined by these boundary conditions. In the Biddinghuizen test area a complex of crop succession, mechanization and national/EC regulations determines which crops are grown where.

In Figure 15 the risks of a number of crop successions are given. Good, moderate and bad successions with respect to yield can be distinguished. Mechanization also influences the cultivation pattern in the sense that (i) farmers aim at creating rectangular fields (straight boundaries) and (ii) the use of certain implements dictates special requirements, e.g. for harvesting onions large 'margins' are needed on the fringe of the field (Fig. 14).

National and EC regulations, which are socio-economic boundary conditions, also influence the cultivation pattern. An important national regulation is that potatoes, the most profitable crop, may only be cultivated once every three or four

Crop grown at t-1 \ Crop grown at t	Potatoes	Winter wheat	Sugar beets	Grass	Beans	Peas	Onions
Potatoes	G,C		G	G	G	G	G
Winter wheat		D					
Sugar beets	Sp	L	C	D	Sp	Sp	Sp
Grass	QDI	QI	I	D		Q	Q
Beans				L	D		
Peas	D		I			CD	SI
Onions				L			SD

$\boxed{}$ Good succession

$\boxed{Q}$ Moderate succession

$\boxed{G,C}$ Bad succession

S : Stem nematode
C : Cyst nematode
Q : Quality
L : Late harvest
G : Ground keeper
Sp: Soil structure problems
I : Insect damage
D : Diseases

Figure 15 Crops succession and its risks (after PAGV (1989)).

years, depending on the type of soil and disinfection methods applied. EC quotation regulations limit the acreage of e.g. sugar beets.

Crop rotation schemes describe the succession of specific crops and are the result of both bio-physical and socio-economic boundary conditions. From the literature (Van Langen, 1988) and interviews with agricultural consultants of the Agricultural Extension Service ('DLV') it was learned that at least five crop rotation schemes were applied in Eastern Flevoland in the period around 1987. The most important crop rotation schemes cover a period of three or four years: one three-year and two four-year crop rotation schemes which will be referred to as CR3, CR4.1 and CR4.2 (Fig. 16). The CR3 scheme, e.g., should be interpreted as follows. The scheme starts from potatoes, which is the most profitable crop. In the following growing season the field that was planted with potatoes is subdivided; the largest part is planted with sugar beets, the other part is planted with beans, peas or onions. The reason for introducing a new boundary is that it is not profitable to grow sugar beets on the total area that was planted with potatoes due to the quota regulations of the EC. Similar mechanisms are present for other crop successions. As a result the field geometry changes from growing season to growing season.

To get an idea of the extent of the dynamics, a dataset of South Flevoland, an area that is similar to East Flevoland and characterized by large scale cultivation of arable crops, was analyzed. For South Flevoland the geometry and crop type of

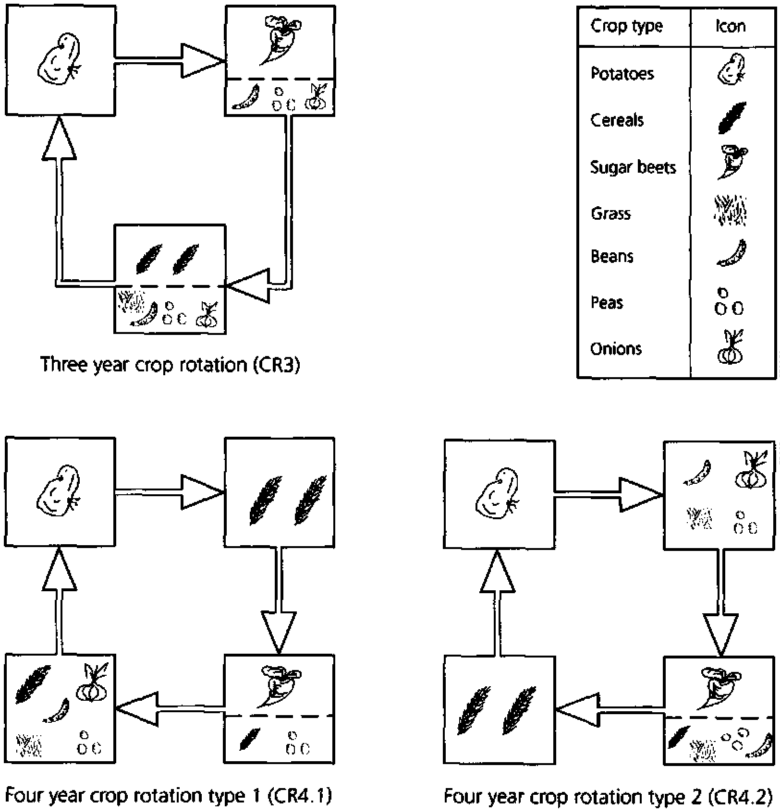


Figure 16 Dominant crop rotation schemes in the Biddinghuizen test area.

agricultural fields of an area of approximately 10,000 ha have been stored in a GIS in the framework of the ERS-1 SAR project (Nieuwenhuis and Schotten, 1992; Schotten *et al.*, in prep.). From this dataset it was derived that from 1991 to 1992 the crop type had changed for 88 % of the area. This large percentage can be explained by the fact that the area is almost completely used for arable crops. The areas in which the crop type did not change were covered by grass or orchard. Furthermore, from 1991 to 1992 the position of 32 % (expressed in length) of the boundaries had changed. The 68 % of the boundaries which did not change were mainly topographical boundaries (roads, ditches).

Summarizing, the terrain object dynamics in the Biddinghuizen test area is characterized by the fixed geometry of the lots; each growing season these lots are subdivided into a number of fields. In general, the lot and the fields have a rectangular shape. Temporal relationships between the cultivated crops exist in the form of a number of crop rotation schemes.

4.2 Geographical data

Various data at the Biddinghuizen test area were stored in a GIS. The Biddinghuizen test area is subdivided into two overlapping test sites (Fig. 12). For site A field geometry and crop type were stored for 1985, 1986 and 1987. For site B only the lot boundaries were stored. The data of site A were applied in the case studies described in Chapter 5 and 6; the data of site B were applied in the case study described in Chapter 7.

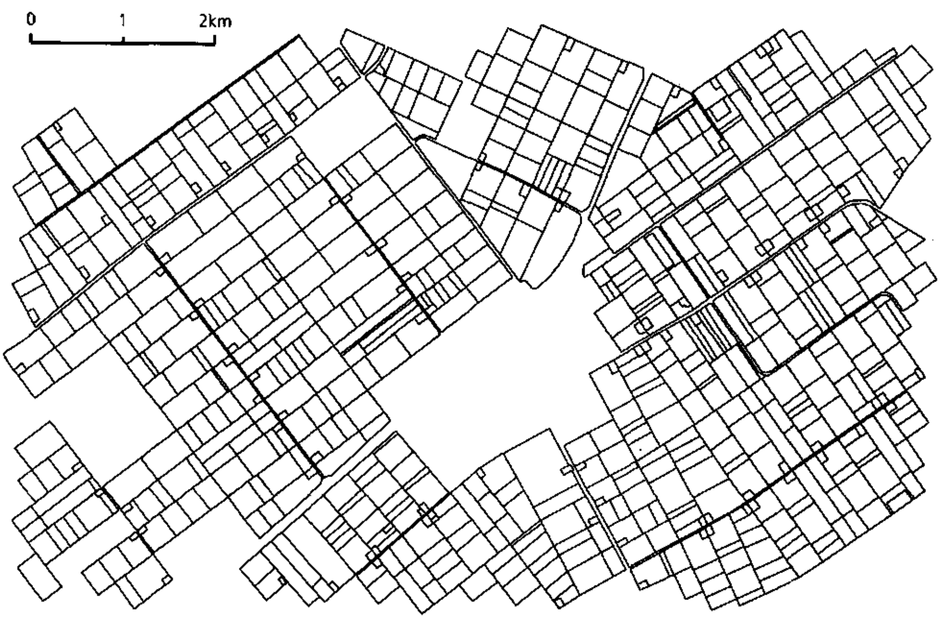


Figure 17 Field boundaries of site A at the Biddinghuizen test area (1987, 3754 ha).

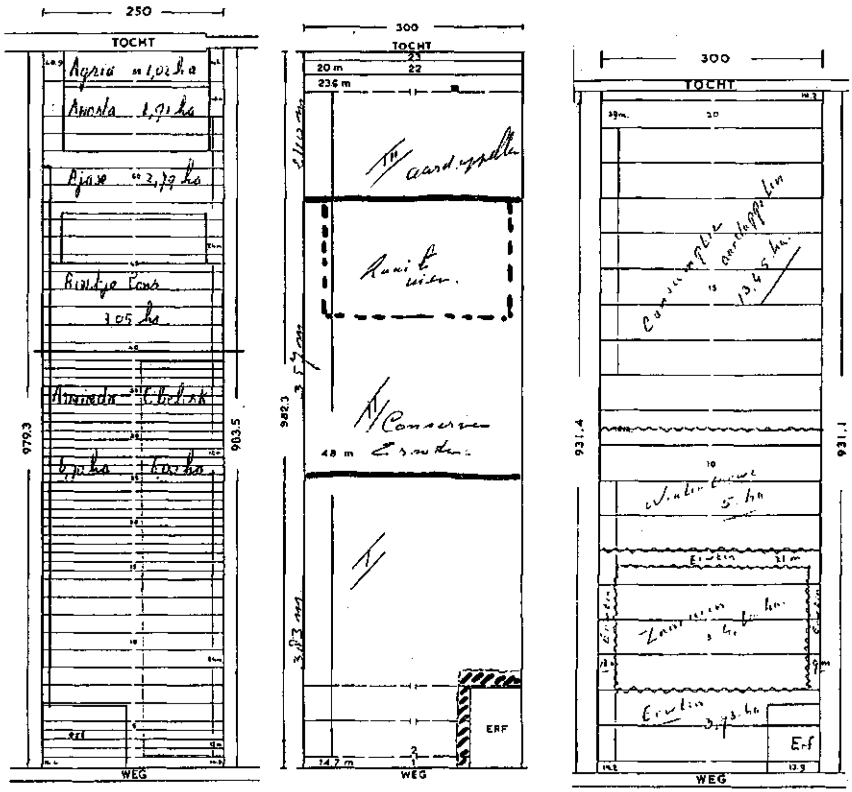


Figure 18 **Large-scale maps that were returned by the farmers indicating the position of the field boundaries and the cultivated crops.**

4.2.1 Site A

Field boundaries and crop type were stored for site A. These were derived from (paper) maps of the 'Rentambt Oostelijk Flevoland'. Until 1987 this government organization systematically gathered data about the agricultural crops grown in this area. For this purpose, large-scale maps (scale 1 : 5,000) were sent to the farmers in Spring. On these maps they had to indicate the position and acreage of their crops. The field boundaries that were present in the maps returned by the farmers were drawn into the topographical map to facilitate the digitizing. The lot boundaries at the Biddinghuizen test area can be found on the topographical map (scale 1 : 10,000). The field boundaries of 1985, 1986 and 1987 were digitized and stored in the map projection of the Dutch Triangulation System (Fig. 17). The crops that were considered (and stored in the GIS) are: potatoes, cereals, sugar beets, grass, beans, peas, onions and grass. The crops that were not taken into account because of their very small acreage were: maize, oilseeds, herbs and some horticultural crops.

The data for 1985 - 1987 are incomplete and not free of error. Not all of the farmers returned the maps since the inventory was on a voluntary basis. Some of the returned maps are shown in Figure 18. It can be seen that some of the field boundaries were not drawn very accurately into the maps. In some cases the annotated crop type could not be deciphered. As a result of the early inventory (March/April) it is possible that in some cases other crops than indicated on the map were actually grown. A last source of error is the approach applied to project (draw) the boundaries from the large-scale maps into the topographical map.

Table 2 Number and area of the digitized fields of site A at the Biddinghuizen test area.

Year	Number of fields	Area (ha)
1985	554	4072
1986	583	4024
1987	542	3754

The data of 1985 and 1986 serve as historical data. The 1987 data serve as reference data. In order to improve the quality of the reference data these were superimposed on the Landsat TM image of 1987 (Plate 2). By means of on-screen digitizing the position of some of the field boundaries was improved and fields for which the crop type was very doubtful were discarded. As a result, the area covered for 1987 is smaller than for the other years (Table 2). From Table 2 it can be calculated that the average field size in site A is 6.9 ha.

4.2.3 Site B

For site B the lot boundaries (fixed field boundaries) were digitized from the topographical map (scale 1 : 10,000) and stored in the map projection of the Dutch Triangulation system. Most lots measure 300 x 930 m^2 (28 ha). For site B 127 lots were stored in the GIS with a total area of 3082 ha (Fig. 19). In Chapter 7 the field geometry is updated from the Landsat TM image. The lot boundaries are applied to optimize the information extraction.

It had already been encountered that the positional accuracy of the field boundaries of site A was not 100 % accurate since it could be improved by visual interpretation of the satellite data. Therefore, it was decided that field boundaries for another site could just as well be derived directly from the satellite image. Based on superimposition of the lot boundaries on the satellite image the field boundaries were added by means of on-screen digitizing (Sect. 7.2.4).

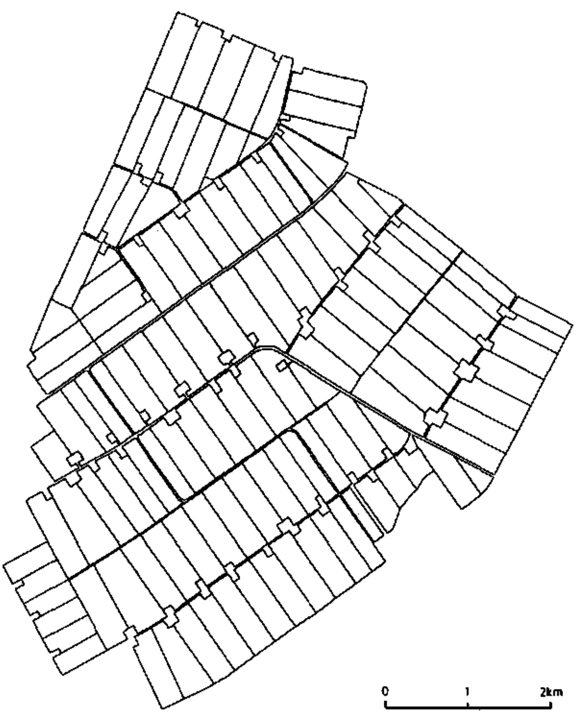


Figure 19 **Lot boundaries of site B at the Biddinghuizen test area (3082 ha).**

4.3 Remote sensing data

The high resolution RS data applied is a Landsat Thematic Mapper (TM) image that was acquired on 7 July 1987. The image is of good quality and although the date was captured rather early in the growing season the crops showed different spectral characteristics (Plates 4 and 6).

Some band combinations of Landsat TM are highly correlated when applied for vegetation. In this situation the application of a limited number of bands is more efficient. A large number of studies of agricultural and forested areas in England (Townshend, 1984), Germany (Kirchhof *et al.*, 1985), United States (DeGloria, 1984; Price, 1984), Brazil (Chen *et al.*, 1986) and the Netherlands (Epema, 1987) show that:

- the visible bands (1,2 and 3) are highly correlated;
- the middle infra-red bands (5 and 7) are also highly correlated;
- band 4 (middle-infrared) has a negative or slightly positive correlation with bands 1,2,3 and 7 and band 4 has a slightly positive correlation with band 5.

An optimal band combination to study agricultural areas, therefore, consists of a visible, a near infra-red and a middle infrared band. Anuta *et al.* (1984) define the combination of bands 3, 4 and 5 as optimal. Therefore, in this thesis bands 3, 4 and 5 were also used. Table 3 shows the dynamic range of these bands of the TM image applied.

In this thesis, information extraction from the RS data is based on the application of pattern recognition techniques. In the three case studies (Chapts 5, 6 and 7) the

Table 3 Dynamic range of the Landsat TM image (7-7-1987) at the Biddinghuizen test area.

Band no	Bandwidth (nm)	Mean (DN)	Standard deviation (DN)
3	630-690	27	8
4	760-900	113	30
5	1550-1750	67	18

same set of training data was applied for supervised classification. The training set comprises the following seven crops: potatoes, cereals, sugar beets, grass, beans, peas and onions. The mean vector and co-variance matrix of the seven crops were determined from a total of 125 to 460 pixels per class. Feature space plots of the seven classes are given in Figure 20.

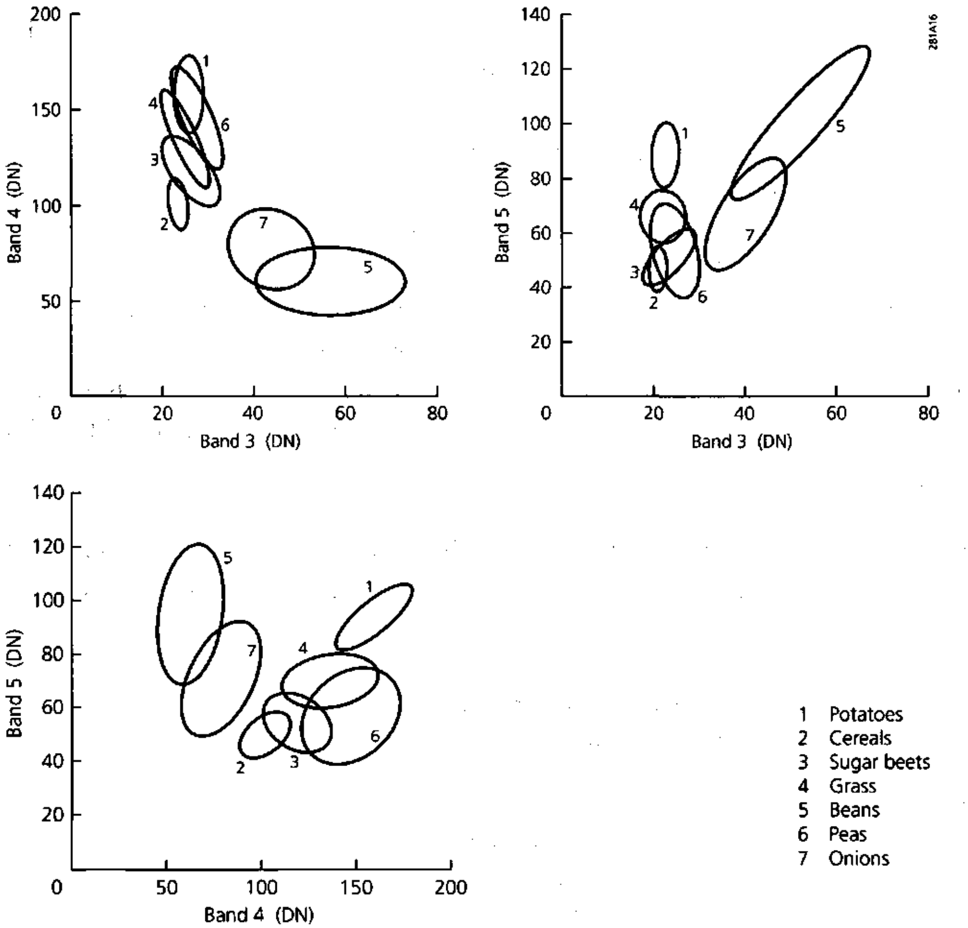


Figure 20 **Feature space plots of the classes under consideration. The ellipses represent the 95% confidence limits.**

From the training data the Jeffries-Matusita distance (Swain and Davis, 1978) was calculated (Table 4). This distance indicates the separability of each class-combination; the distance has a minimum value of 0 (inseparable) and a maximum value of 1414 (totally separable). From Table 4 it can be concluded that the crops in this study have a very high spectral separability. The lowest distance values are found for the combinations: sugar beets/grass, beans/onions, grass/peas and cereals/sugar beets.

Table 4 Jeffries-Matusita distance of the training data of the seven considered crops when applying bands 3, 4 and 5 of the TM image.

	Potatoes	Cereals	Sugar beets	Grass	Beans	Peas	Onions
Potatoes	-	1414	1414	1407	1414	1413	1414
Cereals	-	-	1391	1414	1414	1414	1414
Sugar beets	-	-	-	1385	1414	1401	1414
Grass	-	-	-	-	1414	1389	1414
Beans	-	-	-	-	-	1414	1387
Peas	-	-	-	-	-	-	1414
Onions	-	-	-	-	-	-	-

4.4 Software used

The data processing software used is Erdas 7.5 for image processing (Erdas, 1991) and Arc/Info 5.0 (Esri, 1989a) for the processing of vector-structured geographical data. Not all the required functionality and conversions were available in the standard software. Therefore, different computer programs have been developed by using the Erdas-toolkit (Erdas, 1990), the Arc/Info Macro Language AML (Esri, 1989b), and Fortran. Due to rapid developments in image processing software, the GIS software and the possibilities for integrating raster- with vector-structured data, some of the programs that were developed at the start of the research period had become obsolete by the end of it.

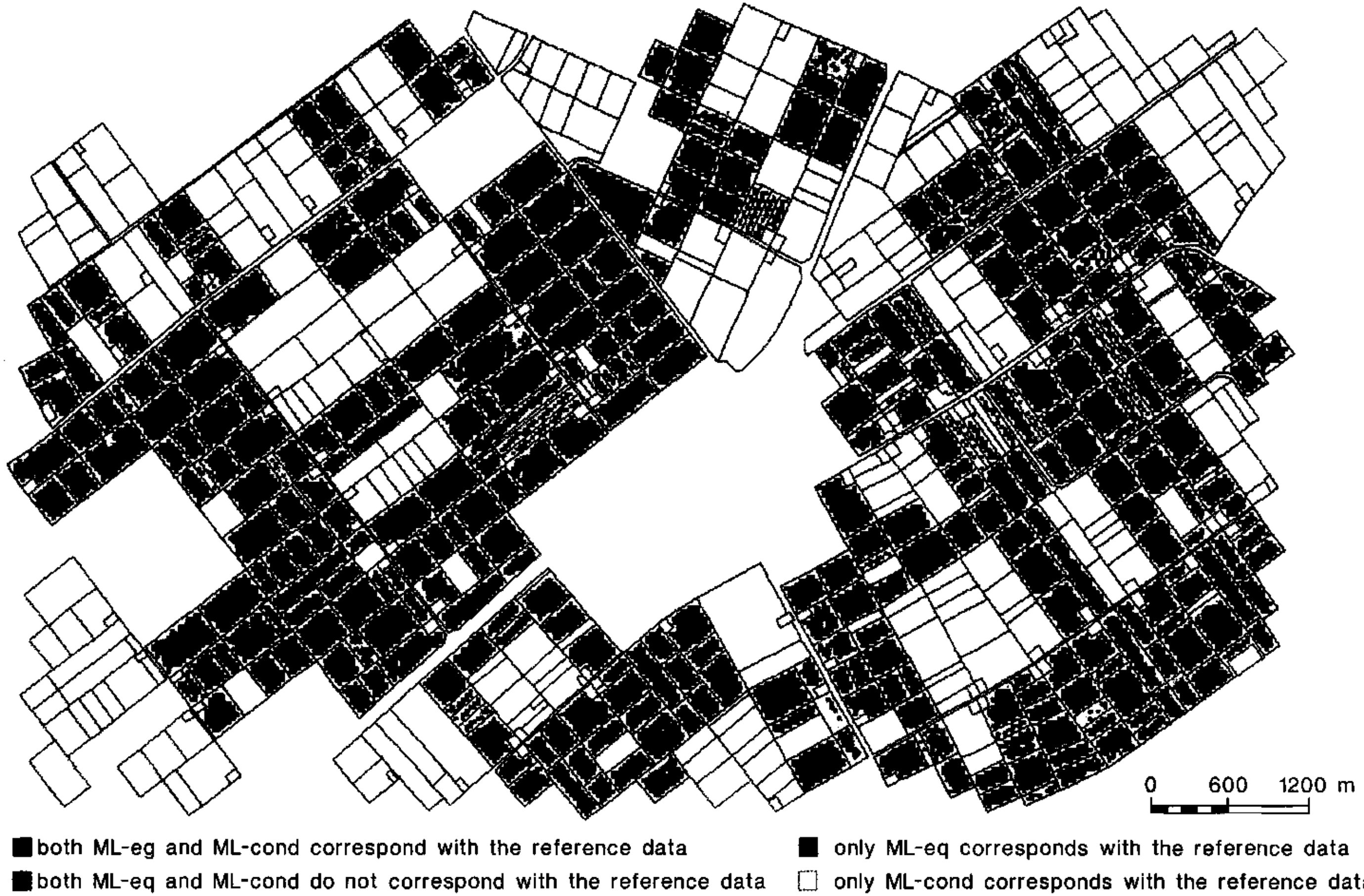


Plate 1 Comparison of the classification results of a ML classification with equal (ML-eq) and conditional (ML-cond) a-priori probabilities of TM image band 4 with the reference data. The reference field boundaries are superimposed.

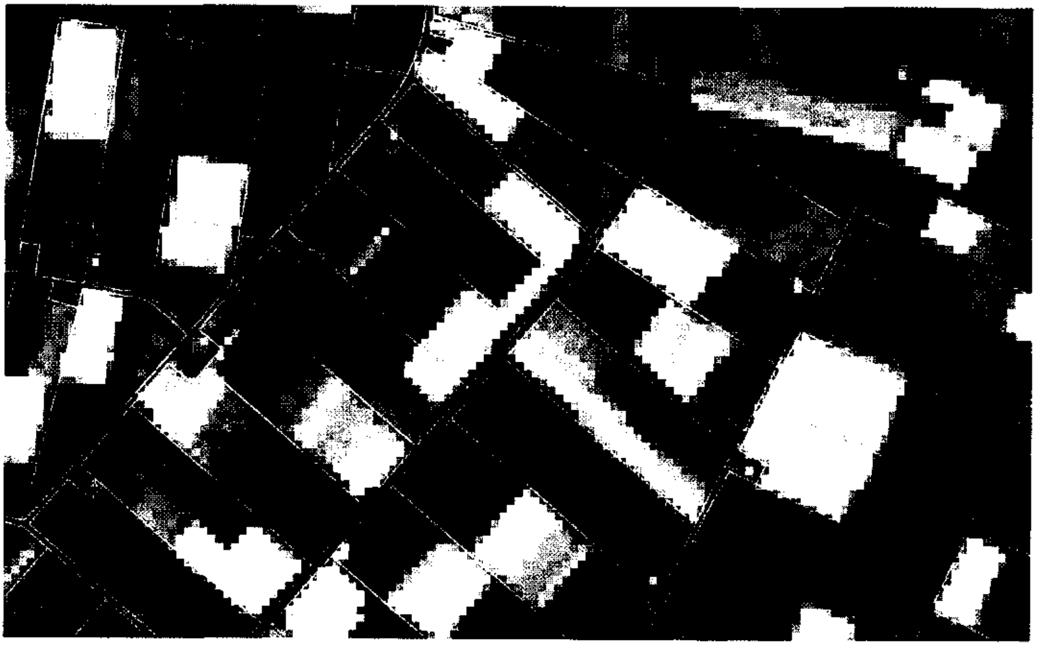


Plate 2 Lot boundaries superimposed on the Landsat TM intensity image.

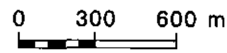


Plate 3 Preliminary field geometry derived from the Integrated Segmentation method superimposed on the Landsat TM intensity image.

Plate 4 Field geometry derived from the Integrated Segmentation and Classification method superimposed on a colour composite (RGB : 453) of the Landsat TM image.

Plate 5 Final result of the Integrated Segmentation and Classification method: field geometry and crop type.

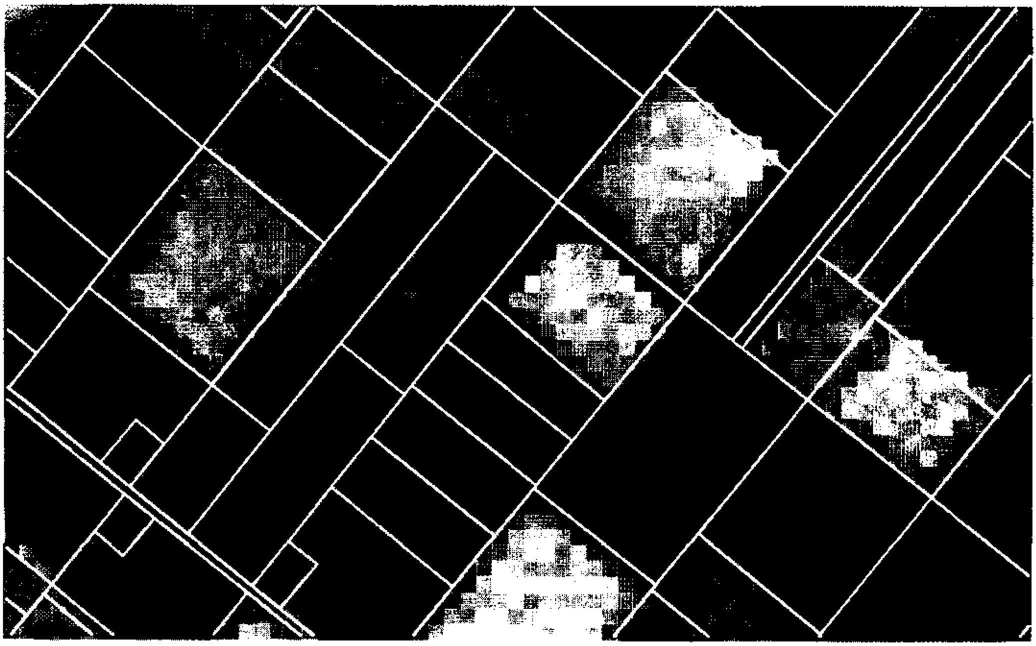
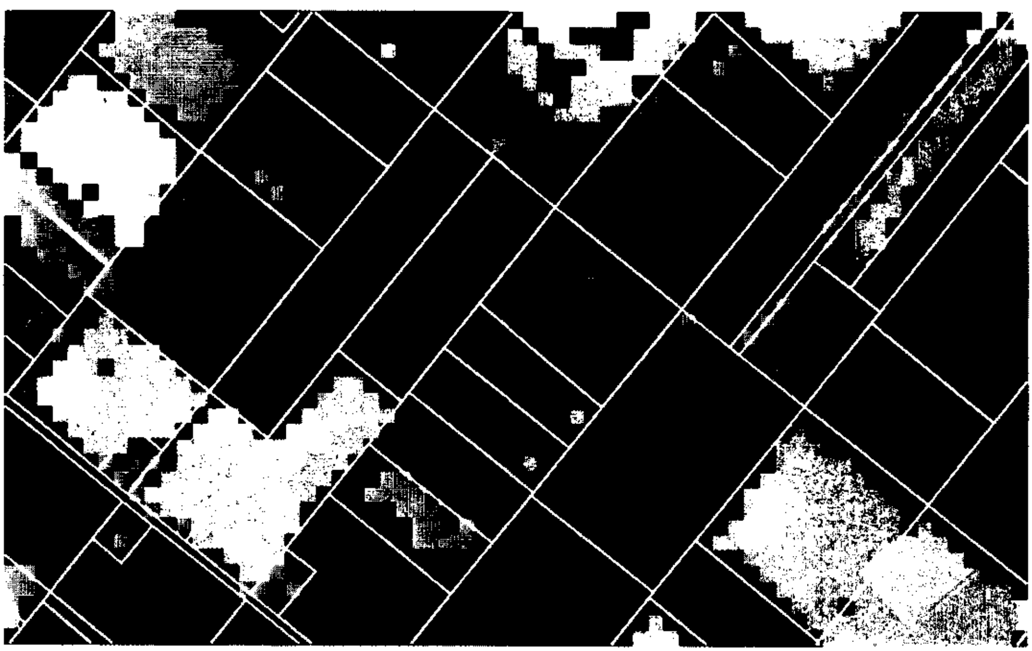


Plate 6 Reference field boundaries superimposed on a colour composite (RGB : 453) of the Landsat TM image.



■ potatoes ☐ cereals ■ sugar beets ■ grass ■ beans ■ peas ■ onions

Plate 7 Reference field boundaries superimposed on the pixel-based classification result of the Landsat TM image.

0 150 300 m

5 Application of conditional a-priori probabilities

5.1 Introduction

The initial objective of this case study was to apply the historical crop data and knowledge about the crop rotations (Sect. 4.1) in the updating. However, it was not possible to formalize the (expected) changes that take place between two successive growing seasons in terms of agricultural fields (and their crops). Let's assume that one crop rotation scheme is applied within the area that belongs to one farm (note that this assumption is a generalization since farmers exchange pieces of land and farmers also change crop rotation schemes). A key element, then, is that the land that belongs to one farm can be identified. Data were available at the field and the lot level but not at the farm level (Sect. 4.2). If it had been available, additional knowledge would have been required with respect to the spatial allocation (size, position) of the fields. In other words, we would need a land use model at the farm level with a spatial component (e.g. Sharifi, 1992). This model would probably require historical data that go back for a large number of growing seasons. In this study, crop data of (only) two preceding growing seasons were available. Since an object-based approach proved not to be possible the objective of the case study was modified in the sense that the historical crop data and knowledge about the crop rotations are used to improve the accuracy of a pixel-based classification.

The knowledge about temporal relationships between thematic classes (crop types) was implemented by means of conditional a-priori probabilities in the maximum likelihood (ML) classification. This means that the a-priori probability depends on the value of a conditioning variable. Strahler (1980) and Kenk *et al.* (1988) present studies in which slope, elevation or aspect are applied as conditioning variables in forest classification. The relationship between slope and the occurrence of a specific crop type is expressed in (a-priori) probabilities.

Strahler (1980) applies elevation and aspect data in a forest classification of a Landsat MSS image. Distributions of elevation/aspect and forest types were determined from 85 samples (points) and subsequently applied as a-priori probabilities in ML classification. The accuracy of the ML classification that applied equal a-priori probabilities was 58 %. Depending on the number of conditioning variables (elevation alone or the combination of elevation and aspect) a classification accuracy of 71 or 77 % was realized. Kenk *et al.* (1988) applied a-priori probabilities in image classification based on elevation and slope. The a-priori probabilities corresponding to the elevation and slope classes were estimated by an expert. In a forest classification of a Landsat TM image, classification accuracy improved 2 to 4 % when compared with a ML classification that applies equal a-priori probabilities. The modest increase was explained by the poor information contents of the conditioning data with respect to the discrimination of forest types.

The crop type grown in the previous growing season is applied as a conditioning variable in this case study. It is carried out for site A at the Biddinghuizen test area (Sect. 4.2.1). Much attention has been given to the modelling of (position-based) class dynamics. In the next section (5.2) the methods applied are described. In Section 5.3 the results are given and discussed. Section 5.4 gives the final conclusions.

5.2 Methods

5.2.1 Modelling of temporal relationships

The knowledge about crop rotations was formalized by treating crop rotations as a stochastic process. Stochastic processes can be described by Markov chains and transition matrices (Cox and Miller, 1965). This approach is applied by ecologists for describing vegetation successions (e.g. Van Hulst 1979; Lippe *et al.*, 1985). An application with respect to landscape changes is given by Turner (1987). Aerial photographs of 1942, 1955 and 1980 were interpreted by overlaying a grid of 1 x 1 ha and assigning each grid element one type of landscape (total of five types of landscape). Based on statistical census data two transition matrices were established for the landscape changes between 1942-1955 and 1955-1980. Then, the transition matrices were used to simulate the landscape for 1955 and 1980 based on the situation in 1942. Apart from the modelling that was based solely on the transition probabilities an approach was also applied in which the (spatial) neighbourhood relationships are taken into account. The latter enabled ‘patches’ to grow or to shrink. In the study of Turner (1987) there was a close agreement between the actual and simulated proportions. With respect to the simulated spatial distribution there was less agreement with the actual situation.

In this case study the temporal relationships between crops that are grown successively on a specific position are expressed solely in transition probabilities; spatial neighbourhood relationships were not taken into account. The latter are dealt with in the object-based approaches that are presented in Chapters 6 and 7.

A land cover class W_i of a specific position (raster-element) at a specific time t can be defined as the state of that element. The change from a certain class W_j at t-1 to another class W_i at t is a state transition. The transitions from the state $W_{j,t-1}$ to the state $W_{i,t}$ can be described by a transition matrix. In this context, t refers to a specific growing season and t-1 refers to the preceding growing season. Consider a three-year crop rotation scheme in which potatoes (PO), sugar beets (SB) and cereals (CE) are grown in succession (Fig. 21). The chain PO-SB-CE-PO-SB-CE-... is called a Markov chain; this chain is represented by transition matrix M (Fig. 22). The rows in the matrix are transition vectors, indicating the probability that a transition from state $W_{j,t-1}$ to state $W_{i,t}$ will occur in one unit of time.

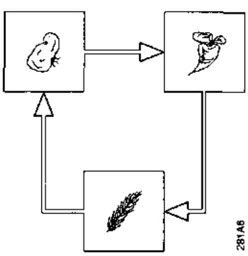


Figure 21 **Three-year crop rotation of potatoes, sugar beets and cereals.**

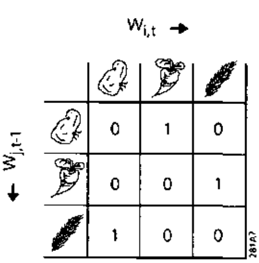


Figure 22 **Transition matrix M describing a three-year crop rotation of potatoes, sugar beets and cereals.**

In the Biddinghuizen area the situation is more complicated than in Figure 21: due to the changing field geometry, not one but different crops can be found at a certain position if the preceding crop type is given. In the three-year rotation scheme CR3 (Fig. 16) which is used in the test area, sugar beets, beans, peas or onions may be found in the area where potatoes were grown in the preceding growing season. In other words: given the crop W_j at t-1, it is not certain which crop type W_i will be grown at t. The three-year crop rotation scheme (CR3) is represented by matrix F (Fig. 23); another representation is given by the probabilistic state transition graph in Figure 24. Figures 23 and 24 are based on estimates that were made by (local) agricultural experts. The states in matrix F are defined by both the crop type (W_i, W_j) and a year index (Y_x, Y_y). The year index is needed because a number of crops (beans, peas and onions) are found in both the second or third year of the crop rotation for which the transition probabilities may be different: beans in the second year can be succeeded by different crops; beans in the third year are succeeded by potatoes.

$(W_i, Y_x)_t$ →

↓ $(W_j, Y_y)_{t-1}$

	1	2	2	2	2	3	3	3	3	3
1		0.80	0.07	0.07	0.06					
2						0.50	0.08	0.08	0.08	0.26
2						0.30	0.10			0.60
2						0.33	0.12			0.55
2						0.17	0.33	0.33	0.17	
3	1.0									
3	1.0									
3	1.0									
3	1.0									
3	1.0									

281A9

Figure 23 Transition matrix F describing the three-year rotation scheme CR3 (Fig. 16). Note that in this transition matrix a state is defined by the combination of crop type (W_i, W_j) and year index (Y_x, Y_y). The transition probabilities are based on expert judgement.

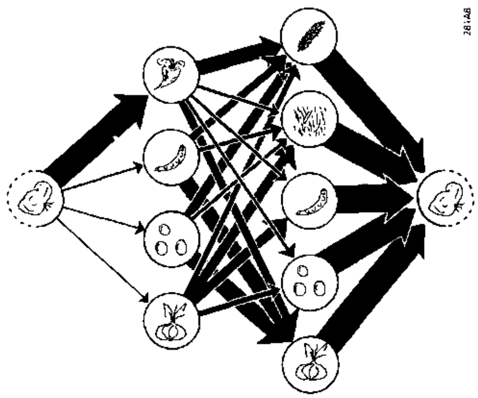


Figure 24 **Probabilistic state transition graph of the three-year crop rotation scheme CR3 (Fig. 16). The width of the arcs is proportional to the transition probabilities.**

The values of matrix F can be assessed if detailed knowledge is available on how the crop rotation schemes are applied. In this study we had spatial crop data for only two growing seasons (preceding the growing season in which the TM image was acquired), which means that year indices could not be used. By a weighted combination of the probabilities in matrix F the year indices can be removed, which results in matrix G (Fig. 25). The latter shows the state transition probabilities without regard to the year of the cycle. As a result some information is lost. However, a matrix such as G can be easily assessed by overlaying the crop data of two successive years.

$W_{i,t}$ →

$W_{j,t-1}$ ↓

		0.80			0.07	0.07	0.06
			0.50	0.08	0.08	0.08	0.26
	1.00						
	1.00						
	0.55		0.13	0.05			0.27
	0.52		0.16	0.06			0.26
	0.79		0.04	0.07	0.07	0.03	

Figure 25 **Transition matrix G describing the three-year rotation scheme CR3 (Fig. 16). Note that the year index has been removed when compared with matrix F (Fig. 23).**

Some characteristics of transition matrices

If the values of all entries of a transition matrix are non-negative and all its row sums are unity then the matrix is a 'stochastic matrix'. Matrices M and F are examples of a stochastic matrix. The rows in these matrices that store the probabilities that a transition from state $W_{j,t-1}$ to state $W_{i,t}$ will occur, $P(W_{i,t}|W_{j,t-1})$, are 'state transition probability vectors'.

The n[th] power of a transition matrix gives the probabilities of a transition taking place in n time lapses. M^2, M^3 and M^4 are the second, third, and fourth powers of matrix M, indicating the transitions over two, three and four years respectively (Fig. 26). If 'potatoes' are found at a certain position at a certain time, it can be concluded from M^2 that 'cereals' will be found at the same position two years later. The fourth power of M is the same as M, resulting from the fact that M represents a clear three-year rotation scheme.

A transition matrix is defined as 'regular' if all the entries in the matrix of some power n are positive. If so, the transition matrix describes 'ergodic chains' in which

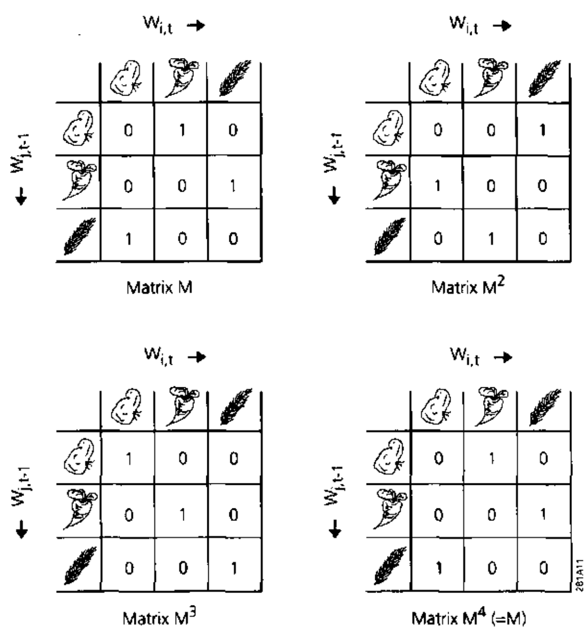


Figure 26 Powers 1 to 4 of transition matrix M.

the process can pass from any state to any other state (but not necessarily in one step). Matrix M, for example, is not a regular matrix. Matrix G is a regular stochastic matrix. An interesting property of a regular stochastic matrix is the following: the sequence of powers G^2, G^3, G^4,...G^n approaches a matrix in which each row stores an identical probability vector V^n that gives the relative areas of every class if the transition matrix is applied for n successive years. The 100th power of matrix G yields seven identical probability vectors V^{100} = (0.33, 0.27, 0.15, 0.03, 0.05, 0.05, 0.12). Identical probability vectors, furthermore, imply that the land cover type at a certain position is completely independent from the land cover at t-100 at the same position.

Transition matrices which store conditional probabilities $P(W_{i,t}|W_{j,t-1})$ can be used for position-based modelling of crop rotations. The next section describes how these probabilities are integrated in the image classification.

5.2.2 Bayes' rule and conditional a-priori probabilities

Supervised (pixel-based) image classification consists of a training stage and a classification stage. In the training stage representative samples of the classes of interest are defined. In the classification stage each pixel is assigned to one of the defined classes by a specific classifier. In this thesis a statistical classifier which is based on the statistical decision theory (e.g. Berger, 1980) is applied. The statistical decision theory departs from the conditional probability density functions (PDF) of the classes which are determined in the training stage. A distinction can be made between a parametric and nonparametric classifier. If the general form of the PDF is known and its specific form is determined by a few parameters, it is called a parametric classifier. In image classification it is usually assumed that the PDF's have a Gaussian distribution; the mean vector and covariance matrix of the class are then sufficient to describe the form of the PDF. This is also the approach pursued in this thesis. If the general form of the PDF's is unknown, the form of the PDF's should be completely determined from the training data. Therefore, nonparametric classifiers require considerably more training data (e.g. Castleman, 1979).

The conditional PDF $P(x|W_i)$ denotes the probability that (spectral) feature vector x will occur, given that the pixel belongs to class W_i. It therefore gives information about the class membership. Bayes' rule gives the so-called a-posteriori probability:

$$P(W_i|x) = P(x|W_i) \cdot P(W_i) / P(x)$$

where

$P(W_i)$	a-priori probability for the occurrence of class W_i
$P(x)$	$\Sigma_{i=1,m} P(x|W_i) \cdot P(W_i)$
m	number of classes

P(x) is a normalization factor required to make the set of a-posteriori probabilities sum to unity. Bayes's rule allows the combination of the a-priori probabilities of class membership $P(W_i)$, the conditional PDF and the given measurement (x) to compute, for each class (W_i), the probability that the pixel belongs to that class. Based on this information we can assign each pixel to its most likely class. Per feature vector x the P(x) denominator can be neglected for discrimination purposes and the resulting equation gives the maximum likelihood (ML) classifier:

$$P(x|W_i) \cdot P(W_i) \geq P(x|W_j) \cdot P(W_j)$$

where a pixel with feature vector x is assigned to the class i which has the largest value. If there is no information about the a-priori probabilities they can be replaced by equal a-priori probabilities. In this case the classification is solely based on the spectral data. Given the class's mean vector (M_i) and co-variance matrix (C_i), $P(x|W_i)$ can be calculated by:

$$P(x|W_i) = (2\pi)^{-N/2} \cdot |C_i|^{-0.5} \cdot \exp[\, -0.5 \ (x-M_i)^t \cdot C_i^{-1} \cdot (x-M_i)\,]$$

where:

N	number of spectral bands
x	feature vector of pixel under consideration
M_i	mean vector of class W_i
$(x-M_i)^t$	transposed difference vector of x and M_i
C_i	N * N symmetric co-variance matrix of class W_i
$|C_i|$	determinant of matrix C_i of class W_i

In this case study, the a-priori probabilities are substituted by conditional a-priori probabilities: $P(W_i)$ is substituted by $P(W_{i,t}|W_{j,t-1})$. The conditional a-priori probabilities can be found in the transition matrix (Sect. 5.2.1) if the crop type at t-1 is known. Note that the class-based a-priori probability, which is independent from the (conditioning) spatial data, is substituted by an a-priori probability whose value depends on the class that is found for a specific position. In Strahler (1980) an elaboration of the application of a-priori probabilities for single and multiple conditioning variables can be found.

In Figure 27 the flow-chart for the classification of a pixels with spectral observation x is given:

- $P(x|W_i)$ is calculated for each class W_i from the training data;
- $W_{j,t-1}$ is determined and the corresponding probability vector $P(W_{i,t}|W_{j,t-1})$ is read from the transition matrix;
- $P(x|W_i)$ and $P(W_{i,t}|W_{j,t-1})$ are multiplied for each crop W_i and the pixel is assigned to the crop W_i for which this product has the maximum value.

If $W_{j,t-1}$ is unknown, equal a-priori probabilities are applied, which means that classification then is based solely on the spectral observation.

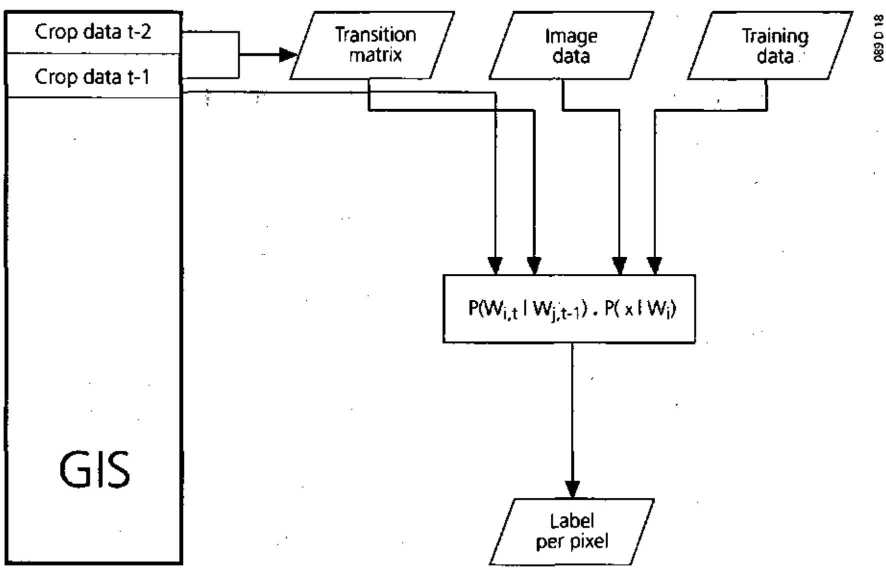


Figure 27 **Flow-chart showing the application of conditional a-priori probabilities.**

5.2.3 Spatial aspects of data integration

The application of conditional a-priori probabilities requires that the crop type of the previous growing season (1986) can be retrieved in the classification of the 1987 Landsat TM image (Fig. 27). Because of the pixel-based approach, both the RS data and crop data applied have to be stored in the same grid geometry. This is realized by geocoding the RS data and vector-to-raster conversion of the crop data.

The Landsat TM image was geocoded by means of an affine transformation of which the transformation parameters were calculated from ground control points (GCP). Nearest neighbour resampling was applied; the pixels after transformation have the same size as the input pixels (30 x 30 m^2).

The vector-structured crop data were rasterized into the grid geometry of the geocoded TM image. The vector-to-raster conversion yields a raster file in which each element is coded with the crop type that is found on that position. Boundary elements are assigned (only) one of the constituting crop types. When dealing with nominal classes the boundary elements should be neglected for their error (or incompleteness). Therefore, the boundary elements were set to the background value (0).

In addition, two other reasons can be mentioned for neglecting boundary elements. First, is has been described in Section 5.1 that the crop data have a limited positional accuracy. It was estimated that the positional accuracy for the field boundaries within the lots was in the order of 1 to 1.5 pixels. Second, although the accuracy of a geometrical transformation of satellite images can be realized at a sub-pixel level there is not an exact one-to-one match between Landsat pixels and the rasterized crop data. The latter is not a problem for the elements/pixels that are located within a field (in which one crop type is grown). For 'corresponding' boundary elements and pixels, however, there is a large degree of uncertainty. From the point of view of error reduction (Sect. 3.4) it is better not to apply the crop data of boundary pixels. As a result two types of pixels can now be distinguished:

- Pixels that are not located on a (1986) field boundary. The classification of these pixels is based on both spectral features and conditional a-priori probabilities.
- Pixels that are located on a (1986) field boundary. These pixels are classified

solely by their spectral features.

This implication of applying a nominal type of conditional data is not addressed in the studies of Strahler (1980) and Kenk *et al.* (1988), which can be explained by the fact that these studies apply data that are more or less continuous (elevation, slope, aspect) and that the 'terrain objects' are very large when compared with the ground resolution of the data applied.

5.2.4 Test and validation procedure

The objective of this case study is to improve classification accuracy by applying conditional a-priori probabilities. In order to assess the improvement in accuracy three types of ML classifications of the 1987 Landsat TM image were performed:

ML-eq — ML applying equal a-priori probabilities;

ML-pr — ML applying class-based a-priori probabilities $P(W_i)$. These are estimated by the relative areas of these classes in 1986;

ML-cond — ML applying conditional a-priori probabilities $P(W_{i,t}|W_{j,t-1})$ which are stored in transition matrices that are assessed from the 1985 and 1986 crop data. Two types of transition matrices were assessed: a general and a specific transition matrix. The general transition matrix represent the transitions caused by all the crop rotation schemes present in the area. The specific transition matrix represents the transitions caused by the CR4.1 crop rotation scheme.

In Section 4.4 it was shown that the crops under consideration are well-separated based on their spectral features in TM bands 3, 4, and 5. The ML classifications were also performed for TM band 4 alone to assess the effect of conditional a-priori probabilities in a situation with poor spectral discrimination.

The accuracy of the pixel-based classification was assessed by cross-tabulation with the reference data (1987). Therefore, the 1987 crop data were rasterized into the same grid geometry as the geocoded Landsat TM data. For the same reasons mentioned in Section 5.2.3 the boundary elements of the 1987 raster crop data were not taken into account in the cross-tabulation.

From the error matrices that resulted from the cross-tabulation, the errors of omission, errors of commission and the overall accuracy were calculated. In addition, the spatial distribution of the errors was visualized for further analysis.

5.3 Results and discussion

5.3.1 Spatial data integration

The co-registration was based on 10 GCP's for which an $RMSE_{xy}$ error of 0.7 pixel was found. The $RMSE_{xy}$ for the GCP's was 0.7 pixel. The geometrically corrected image consists of 220 rows x 345 columns (6,864 ha).

For further processing the vector-structured crop data of 1985, 1986 and 1987 were rasterized in to the grid geometry of the geocoded TM data. As explained in Section 5.2.3 the boundary elements should be neglected. This was realized by a vector-to-raster conversion of the boundaries. Subsequently the value (crop type) of the boundary elements in the rasterized crop data was set to the background value (0). Although the fields in the Biddinghuizen test area are relatively large, 31 % of the rasterized 1987 crop data was identified as boundary element. This large percentage can be explained by the vector-to-raster algorithm applied for lines (LINEGRID of Arc/Info) that identifies all the raster-elements that are located on a line. If the positional uncertainty is taken into account this approach is appropriate. In cases where a very precise co-registration is achieved a better approach would be to apply e.g. a shortest path algorithm (Van der Knaap, 1992).

One of the problems in pixel-based classification is mixed pixels (Sect. 2.5). The only way to solve this problem is by taking spatial context into consideration as e.g. in the object-based approach (Chapt. 6). The best classification result that can be achieved for these pixels is that they are assigned to one of the constituting classes. For the Biddinghuizen test area it can be stated that part of the boundaries present in 1986 are also present in 1987 (lot boundaries). It can already be concluded here that the approach presented in this case study cannot be used to improve classification accuracy of the (mixed) pixels located on the fixed boundaries.

5.3.2 Assessment of transition matrices

The rasterized crop data of 1985, 1986 and 1987 were used to assess transition matrices by cross-tabulation of crop data of two successive growing seasons. In the cross-tabulation the transition frequencies from class W_j at t-1 to W_i at t were counted and stored in a matrix in which the classes at t-1 are the row-index and the classes at t are the column index. The resulting frequencies were normalized over t-1 (row) to yield probabilities.

Table 5 General transition matrix representing the transitions found from 1985 to 1986 (TR8586) (- = 0.00).

1985\1986	Potatoes	Cereals	Sugar beets	Grass	Beans	Peas	Onions
Potatoes	0.02	0.71	0.15	0.06	-	0.04	0.02
Cereals	0.25	0.03	0.69	-	0.01	0.01	0.01
Sugar beets	0.12	0.28	0.02	-	0.04	0.26	0.28
Grass	0.35	-	0.50	0.10	-	-	0.05
Beans	0.93	0.04	0.03	-	-	-	-
Peas	0.95	-	0.01	-	-	-	0.04
Onions	0.89	0.03	0.07	0.01	-	-	-

Table 6 General transition matrix representing the transitions found from 1986 to 1987 (TR8687) (- = 0.00).

1985\1986	Potatoes	Cereals	Sugar beets	Grass	Beans	Peas	Onions
Potatoes	-	0.73	0.14	0.05	0.02	0.02	0.04
Cereals	0.23	0.01	0.74	-	-	0.01	0.01
Sugar beets	0.08	0.32	-	0.02	0.02	0.27	0.29
Grass	0.13	-	0.86	0.01	-	-	-
Beans	0.56	0.34	0.10	-	-	-	-
Peas	0.80	0.01	0.15	-	-	-	0.04
Onions	0.87	0.03	0.07	0.03	-	-	-

Transition matrices TR8586 and TR8687 were found for the transitions from 1985 to 1986 and 1986 to 1987 respectively (Tabs 5 and 6). These transition matrices are called 'general transition matrices', since they represent the transitions that result from the mixture of rotation schemes which are applied in the Biddinghuizen test area.

The 1985-1986 transitions are used in the classification to estimate the 1986-1987 transitions. Comparison of TR8586 and TR8687 shows that the probability vectors are quite similar for the crops with a large relative area (potatoes, cereals, sugar beets). Some differences can be found for the classes with a small relative area: grass, beans, peas. The highest transition probabilities in TR8586 and TR8687 clearly reflect the CR3 and CR4.1 crop rotation schemes (Sect. 5.2). This illustrates that the general transition matrices are a weighted combination of specific crop rotations. It can easily be verified that both matrices (TR8586 and TR8687) are regular.

As explained in Section 5.2.2 large powers of a stochastic transition matrix describe the relative areas of the classes that result if the transitions described take place for a large number of years. In Table 7 the probability vector of the 100th power of TR8687, V^{100}, is listed together with the relative areas of the crops in the Biddinghuizen test area. V^{100} largely agrees with the relative acreage of the crops. In a stable dynamic system the relative areas covered by each class do not change. It can be concluded that a stable dynamic system is present in the Biddinghuizen test area. Therefore, the transition probabilities can be considered as (more or less) constant, which allows us to apply the 1985-1986 probabilities to estimate the 1986-1987 probabilities.

Table 7 Relative areas of the seven crop types in the Biddinghuizen test area; V^{100} is the probability vector of the matrix that results when taking the 100th power of matrix TR8687 (Table 6).

Crop type	Relative area (%) in			V^{100}
	1985	1986	1987	
Potatoes	0.28	0.28	0.26	0.24
Cereals	0.30	0.27	0.27	0.27
Sugar beets	0.25	0.26	0.27	0.27
Grass	0.01	0.02	0.02	0.02
Beans	0.03	0.01	0.01	0.01
Peas	0.05	0.08	0.08	0.08
Onions	0.08	0.08	0.09	0.09

Transition matrices TR8586 and TR8687 describe the crop changes that result from the different crop rotation schemes. In addition to these matrices a transition matrix for a single rotation scheme was assessed. For that purpose the area in which the CR4.1 crop rotation scheme was applied was deduced from the multi-temporal crop data (1985 - 1987) and a land-ownership map. Based on the crop data for 1985 and 1986 transition matrix TR4.1 was determined for this sub-area (approx. 2,650 ha).

Comparison of the specific crop rotation scheme (Table 8) with the general crop rotation scheme (Tabs 5 and 6) shows that the former has many entries that are equal to 0. A zero entry means that the corresponding transition does not take place. When used as a-priori probabilities in the ML classification it means that a pixel will not be assigned to the crop(s) for which the a-priori probabilities are 0. It can be stated that the information content with respect to crop discrimination of a specific transition matrix is higher than that of a general transition matrix.

A last remark can be made on the accuracy of the transition matrices. Tabs 5 and 6 list a transition probability of 0.02 and 0.01 respectively for the cultivation of potatoes in two successive years. It is very unlikely that this occurred in the Biddinghuizen test area. These positive values, therefore, can be explained by positional or attribute errors in the crop data.

Table 8 Specific transition matrix representing the transitions found from 1985 to 1986 in the sub-area in which the CR4.1 crop rotation scheme is applied (TR4.1) (- = 0.00).

1985\1986	Potatoes	Cereals	Sugar beets	Grass	Beans	Peas	Onions
Potatoes	0.01	0.89	-	0.06	-	0.04	-
Cereals	0.20	-	0.80	-	-	-	-
Sugar beets	-	0.28	0.01	-	0.04	0.31	0.36
Grass	-	-	0.77	0.17	-	-	0.06
Beans	0.98	-	0.02	-	-	-	-
Peas	0.97	-	-	-	-	-	0.03
Onions	0.94	-	0.06	-	-	-	-

5.3.3 Classification results

The accuracy of the various classification results is listed in Table 9 from which a number of observations can be made. The classification accuracy of the ML classification of TM345 using equal a-priori probabilities is relatively high (88.4 %). In Section 4.4 it was already noted that the crops studied have a large separability value based on their spectral features. Furthermore, it should be realized that a limited number of crops have been distinguished and that the fields in the test area have a homogeneous canopy. Finally, the boundary elements (of 1987) were excluded in the validation (Sect. 5.4.3). Attention, however, should be given to the differences in classification accuracy found in Table 9.

It can be stated that in the sequence ML-eq, ML-pr, and ML-cond more and more information is added to the classifier for discrimination. This has the greatest effect on the classification accuracy of the TM4 image. If the class-based a-priori probabilities improve the classification accuracy by 4.4 %, then, classification

Table 9 Overall accuracy (areal percentage) of the classification results of a one-band (TM4) and three-band (TM345) Landsat TM image of site A when applying different types of a-priori probabilities.

Type of a-priori probability	Overall accuracy (%)	
	TM4	TM345
Equal (ML-eq)	70.9	88.4
Class-based (ML-pr) relative area 1986	75.3	89.1
Conditional (ML-cond) crop type 1986 and transition matrix TR8586	82.7	90.2
crop type 1986 and transition matrix TR4.1 (applied and validated for sub-area)	87.7	90.3

accuracy is improved by 11.8 % (TR8586) and 16.8 % (TR4.1) when applying conditional a-priori probabilities. As expected the specific transition matrix yields a higher classification accuracy than the general transition matrix. It is striking that the classification accuracy of TM4, using the specific transition matrix, approximates to the classification accuracy of TM345.

The application of a-priori probabilities for TM345 had a marginal effect on classification accuracy. Application of the conditional a-priori probabilities resulted in accuracies that were 1.8 to 1.9 % better when compared with the ML using equal a-priori probabilities. This improvement is very small if the amount of additional information (crop data at t-1 and transition matrix) is considered.

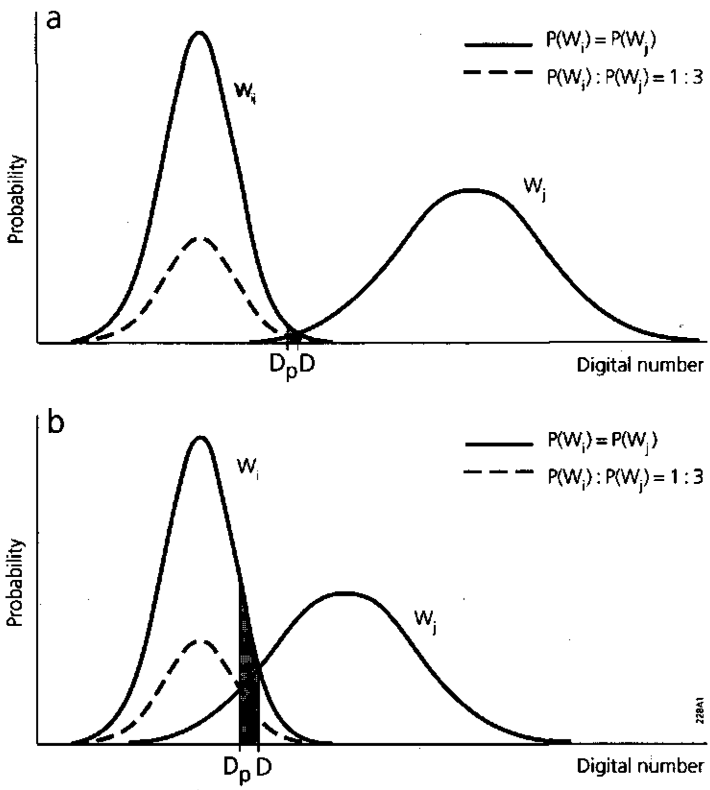


Figure 28 **Application of a-priori probabilities for one-dimensional classification of classes W_i and W_j. D and D_p are the digital numbers for which the probability of class W_i and W_j are equal. Two situations are illustrated:**

a Two classes with almost no spectral overlap;

b Two classes with clear spectral overlap.

Figure 28 explains (for a one dimensional situation) why a-priori probabilities are most effective when classes have (spectral) overlap. In Figure 28a there is almost no overlap between classes W_i and W_j. The application of a-priori probabilities for W_i and W_j of 0.25 and 0.75 respectively results in a small shift of the decision point (D to D_p). The pixels that have a spectral value which is between D and D_p are assigned a different class when applying a-priori probabilities. In Figure 28b there is clear spectral confusion between W_i and W_j. The application of a-priori probabilities now effects a larger number of pixels.

Another observation that can be made from Table 9 is that, as expected, application of the specific transition matrix results in a higher classification accuracy. A-priori probabilities are most effective when they are very high or very low. The specific transition matrix TR4.1 contains a large number of probabilities that are 0 or that approximate to 1. It therefore has a high information content within the context of crop classification. In general, it can be stated that the information content of a transition matrix with respect to class discrimination decreases if a complex of processes determines the changes that are present within one area. If the land cover change is fully deterministic, as e.g. in the simple three-year crop rotation (Fig. 22), there is no need for image classification: the statistical ML approach can then be substituted by If-Then rules (if $W_{j,t-1}$ then $W_{i,t}$).

In the framework of this case study transition matrices were also assessed by means of interviews with agricultural experts. It was found that the application of these matrices was only effective for the classification of the TM4 image. Application of this matrices in the classification of the TM345 even resulted in a worse classification accuracy when compared with a ML that applies equal a-priori probabilities (Janssen and Middelkoop, 1991).

The application of conditional a-priori probabilities was to improve the overall accuracy of the classification result. This implicitly results in larger errors of omission for the individual classes with a small relative area (Table 10).

Table 10 Error of omission and commission of the ML-cond classification compared with the ML-eq classification of the TM345 image. ML-cond is based on the application of TR8586.

Crop type	Relative area 1987 (%)	Relative error of omission (%)	Relative error of commission (%)
Potatoes	25.8	+ 1.7	- 0.6
Cereals	26.5	+ 1.7	+ 1.0
Sugar beets	26.6	+ 4.2	+ 0.5
Grass	2.2	- 15.1	+ 15.0
Beans	1.4	- 38.3	- 5.1
Peas	8.2	+ 3.8	- 1.7
Onions	9.3	+ 3.8	- 3.3

The spatial distribution of the errors in the classification results were visualized. Plate 1 shows the comparison of the ML-eq and ML-cond classification of the TM4 image with the reference crop type. From Plate 1 the following observations can be made.

First, the yellow coloured elements indicate where the conditional a-priori probabilities effected the classification in a positive way. It was most effective for pixels that are located near a field boundary. For different reasons the spectral reflectance of pixels near a boundary is less characteristic due to the declining canopy (spectral variability). From Table 9 and Plate 1 it can be concluded that conditional a-priori probabilities can be used to improve classification errors that are caused by spectral overlap and spectral variability.

Second, the red coloured elements indicate that both the result of ML-eq and ML-cond do not correspond to the reference data. These elements are mostly grouped as 'fields'. Some of these 'fields' were also found when the result of the TM345 classification was compared with the reference data. From Table 4 it can be derived that the crop type that resulted from classification could not be confused with the reference crop type, e.g.: potatoes/cereals and cereals/grass. Most likely the reference data are incorrect for a part of the red coloured areas. Another reason could be that the training data were not completely representative. For the other pixels the classification result is incorrect and can be explained by spectral overlap (e.g. confusion of beans and onions). Spectral confusion can only be partly solved by the application of conditional a-priori probabilities.

Third, the blue coloured raster-elements indicate that only ML-eq corresponds with the reference data. These elements are also clearly grouped as 'fields'. Since ML-eq is correct it should be concluded that the incorrect classification result of ML-cond is a direct result of incorrect crop data for 1986. Errors in the crop data of t-1 result in the application of an inappropriate probability vector. The inappropriate transition probabilities (applied as conditional a-priori probabilities) may then force an incorrect classification. From this it can also be concluded that the higher classification accuracy that is found when applying a-priori probabilities based on the 1986 crop data is a net result. An indirect effect of incorrect historical data is that the transition matrices that are calculated from these data are biased.

5.4 Conclusions

In this case study the temporal relationships between classes have been modelled by a Markovian approach and represented by means of transition matrices. Transition probabilities, describing the probability that class W_i is found at t if W_j is given at t-1, were assessed from multi-temporal data and applied as conditional a-priori probabilities in a maximum likelihood classification to improve the (overall) accuracy of pixel-based classification.

The transition matrices quantitatively describe the temporal relationships between classes (e.g. crop rotation schemes). Although a transition matrix can be assessed easily from a data set of two successive years it does not give insight in the processes underlying the dynamics. In general, different processes will be present within one area. Additional knowledge, then, is required to understand the values in the transition matrices.

Transition probabilities can be applied as conditional a-priori probabilities in a maximum likelihood classification. For that purpose the applied conditioning data and the RS data should be stored in the same grid geometry. The errors that origin from the vector-to-raster conversion of the conditioning data (especially when dealing with nominal data) and the co-registration of conditioning and RS data hinder the application of a-priori probabilities for the pixels that are located on the boundaries of the conditioning data.

The different results of the classification of a Landsat TM image show that the application of conditional a-priori probabilities results in a greater classification accuracy. The conditional a-priori probabilities can only partly force a correct classification for pixels that otherwise would have been incorrectly classified to spectral confusion or spectral variability. If the considered classes have a high spectral separability, the application of conditional a-priori probabilities at its best results in a marginal increase of the classification accuracy. A-priori probabilities close to 0 or 1 are most effective. When applying transition probabilities as a-priori probabilities these values only occur if a limited number of processes (e.g. crop rotation schemes) are present within a specific area.

The larger overall accuracy that was realized by applying conditional a-priori probabilities was found to be a net result; errors in the conditioning data also generated incorrect classifications (error propagation).

6 Object-based classification

6.1 Introduction

In Section 4.1 the terrain object dynamics of the agricultural fields in the Biddinghuizen area were described: both the field geometry and crop type change from growing season to growing season. For the purpose of testing it is assumed in this chapter that the field boundaries are fixed. This means that for each growing season the crop type of the fields has to be extracted from the RS data. In the next chapter (7) a method is described to update both field geometry and crop type by means of digital interpretation of the RS data. In addition to the updating context (fixed geometry), the object-based classification can also be applied in a context in which the field boundaries are determined from other sources (e.g. by visual interpretation of aerial photographs) and in which the crop type is determined by means of object-based classification. First some relevant literature is reviewed.

King-Liu (1986) proposes to use the centre-pixel of a field for the classification of the total field. This approach, however, requires an optimal relationship between the ground resolution and the spectral variability of the classes considered.

Baker and Drummond (1984) propose to update the land cover type of fields, which are digitally stored, by applying a 'parcel-to-parcel' classification of Landsat MSS data. The parcel's mean reflectance and its standard deviation are then input for the classifier. This approach, at the same time, makes it possible to exclude boundary (or mixed) pixels in the classification of the parcel.

Pedley and Curran (1991) report results on a per-field classification using SPOT data. In this study a field boundary map was derived from the combination of a topographical map with an up-to-date aerial photograph. The boundaries were digitized and subsequently stored in raster format. Then, the mean and the standard deviation of the DN in each of the three SPOT bands (excluding boundary pixels) is calculated per field; the resulting values are assigned to all the raster elements within a field. Training data of twelve land cover classes were established and both a pixel- and field-based classification were performed. The results of 455 fields were used for accuracy assessment by pixel-based comparison with reference data. The accuracy of the pixel- and field-based classification were 46 and 55 %

respectively. The field-based classification accuracy was further improved by 5 % by adding a simple measure of image texture to the classification. It should be noted here that the objective of Pedley and Curran (1991) is to improve classification accuracy by using the spatial context given by the field geometry. Although a more terrain object oriented approach seems obvious, the data processing and storage is realized by raster-structured data. The per-field classification is inefficiently achieved by classifying all the pixels within a field which have the same values.

Csornai *et al.* (1990) present a field-based approach for the classification of agricultural fields (average size: 60-80 ha) by means of Landsat MSS and TM data. First, the field boundaries were determined based on a combination of farm field maps and a TM image. Subsequently two methods were applied for classification:

- Method A, which is based on the result of a pixel-based classification. The pixels of a particular field are reassigned the most probable class; if the variation of the classes present within the field is high, no reassignment takes place.
- Method B, which computes second order statistics for the individual fields. The fields are checked for homogeneity. Homogeneous fields are classified per field, heterogeneous fields are classified by means of a pixel-based classification.

In both methods RS data are integrated at the object-level. The result, however, is a raster file; feed-back of the results to the terrain object data (in a GIS) is not addressed.

Zhuang *et al.* (1991) apply digital land ownership data to improve the classification of crop residues from Landsat TM data. In their study, land ownership (represented by unique object-identifier values) is added as the 8th band to the original TM image. Since the training statistics of the land ownership band are not meaningful it was impossible to apply a maximum-likelihood classification. Therefore, a three-layer neural network was applied for the classification of seven land cover types. The overall accuracy of the different classes varied from 82 to 90 % for a maximum likelihood classification (without ownership boundaries). When applying a neural network classifier of the 8-band image, the overall accuracy ranged from 78 to 96 %. In the study of Zhuang *et al.* (1991) pixel-based data integration is applied while data at the object-level were available: ownership data are considered as 'just another' discriminating variable. Therefore, the result of the classification is a raster file and no attention is given to feed-back of the results to the existing ownership data. Furthermore, it can be remarked that the information contents of the added ownership data for discrimination purposes cannot be assessed for the lack of a neural network classification from the TM data alone.

Pixels located at the boundary of the object are often mixed pixels. It can therefore be expected that a better classification result can be achieved if these pixels are not considered in the classification of an object. Grunblatt (1987) has studied the classification errors at field boundaries. Landsat MSS data were applied to discriminate five land cover types using a supervised pixel-based maximum likelihood classification. Field boundaries of large pivot irrigation systems were derived from aerial photographs. Initially, the modulation transfer function (MTF) of the MSS scanner was applied to predict the degradation of image quality (blur) at field boundaries. However, the MTF approach assumes ideal edges between very homogeneous fields. In practice, field boundaries are far from ideal: transitions are characterized by less homogeneous canopy and the presence of ditches, paths or dirt roads. Therefore, the MTF approach did not yield valuable results and the analysis was based on classification errors for boundary pixels. The classification errors for the boundary pixels was assessed by calculating the classification accuracy for the all the pixels located within the fields and for all the pixels located within a field exclusive the boundary pixels. It was found that the error for the first boundary pixel ranged from 40 to 60 % and that the error for the second boundary pixel ranged from 8 to 25 %. Based on the practical results Grunblatt (1987) expresses the opinion that fields sizes less than 5 by 5 pixels cannot be expected to be accurately classified.

The experience described above relates to the interpretation of optical RS data. Data resulting from active sensors in the microwave regions (e.g. SAR and SLAR) are characterized by speckle, which hampers the application of a pixel-based classification. The speckle problem can be solved by spatial averaging, which can be realized by means of filtering or segmentation. The other solution is to apply an object-based approach. Hoogeboom (1983), e.g., determines the crop type of agricultural fields by their (multi-temporal) mean backscatter value. The geometry of the fields was derived by visual interpretation of the applied SLAR images. The study of Hoogeboom (1983) was also performed for the Biddinghuizen test site

(182 agricultural fields) and the same crops that are considered in this case study were classified. The multi-temporal classification resulted in a correct crop type for 88 % of the fields, 10 % of the fields were not classified and 2 % were incorrectly classified.

The objective of this case study is to update the crop type of agricultural fields for which geometry is already contained in a GIS. Updating implies that feedback to the GIS is essential. This is achieved by means of an object-based classification in which the spatial context information (only one crop type is grown within an object) is applied to derive a reliable classification result.

This case study was carried out for site A at the Biddinghuizen test area (Chapt. 4.2.1). Section 6.2 describes the methods applied. In Section 6.3 the results are given and discussed. The general conclusions are given in Section 6.4.

6.2 Methods

6.2.1 Object-based classification

The aim of object-based classification is to determine the crop type present within an agricultural field. The ground resolution of the RS data applied must be smaller than the size of the terrain objects. If the objects are smaller than the applied pixels, there is not a direct relationship between the observed reflectance and the object's characteristics.

Two strategies were followed to arrive at object-based classification:

- 1-Stage object-based classification
  For each terrain object the mean Digital Number (DN) per band is calculated. The object's mean feature vector is then compared with the training data by applying a classifier (Fig. 29). As a result the object is assigned to a certain class and this result is fed back to the GIS by means of the object-identifier.

- 2-Stage object-based classification
  First a pixel-based classification is performed resulting in a label per pixel.

Subsequently, a histogram of the occurring labels per object is established and the object is assigned to the class with the highest frequency (mode class). The result is fed back to the GIS by means of the object-identifier. This strategy is called a 2-stage classification since decisions are made both at the pixel and object level (Fig. 30).

To reduce the amount of error related to boundary pixels (Sect. 3.4) the boundary pixels are excluded. This yields a more reliable result (Sect. 6.2.2). It has been considered to apply a measure of texture as an additional object feature in the 1-stage object-based classification. The causes for texture in arable fields are e.g. row-structures or the application of implements (mechanization). These phenomena, however, cannot be found in a TM image with a ground resolution of 30 m. Therefore, textural features were not applied in the classification.

It can already be noted here that spectral classes can only be discriminated in the object-based classification which is purely based on the spectral information that is present in the RS data.

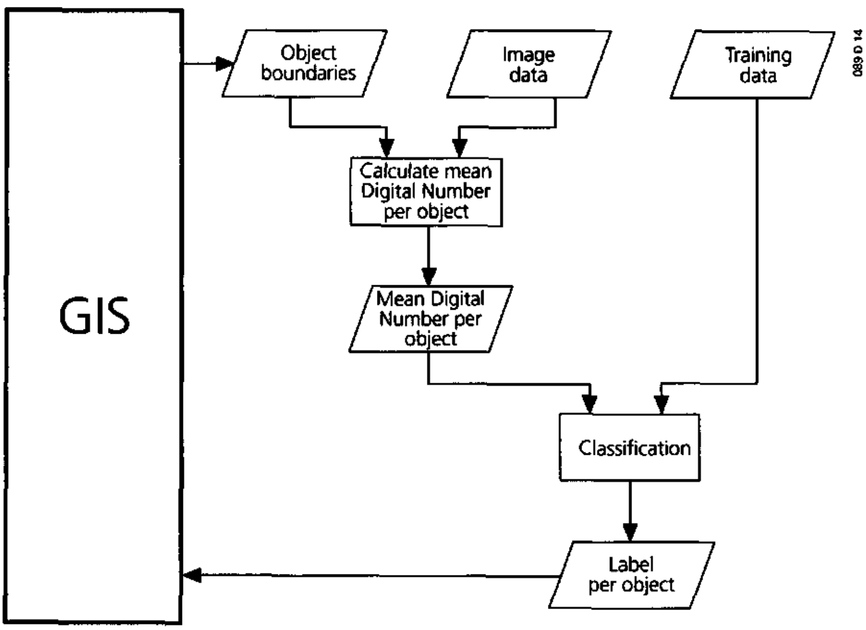


Figure 29 **Flow-chart of the 1-stage object-based classification.**

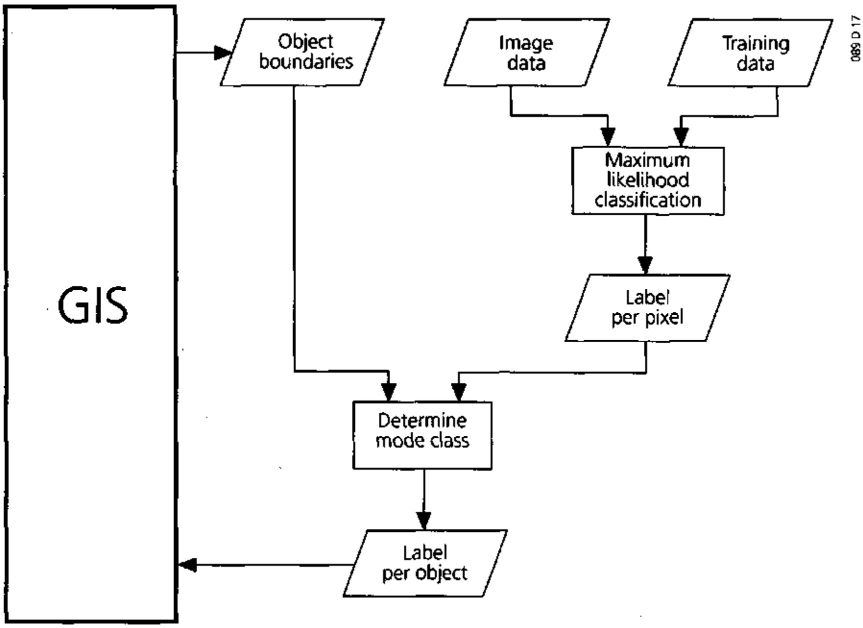


Figure 30 **Flow-chart of the 2-stage object-based classification.**

6.2.2 Aspects of spatial data integration

Object-based classification requires the identification of the pixels that are located within a terrain object. The following approach was used. The field boundaries of 1987 and the original Landsat TM image were co-registered by means of ground control points. A file was derived from the GIS in which each field is represented by a single polygon. The map coordinates in this file were then transformed into the image coordinate system. Subsequently, direct vector-raster integration was realized by a self-developed computer programme which uses the Erdas procedure POLY (Erdas, 1990). Based on the vector-structured description of a polygon (x,y coordinates) the procedure POLY calculates (row-wise) the pixels that are within this polygon; the first and the last pixel in a row are boundary pixels.

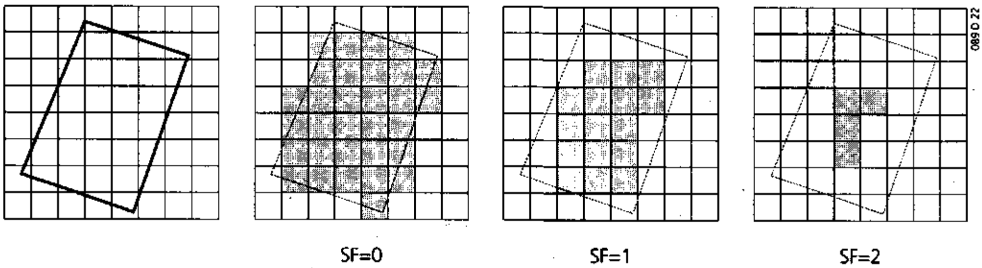


Figure 31 **Polygon-shrinking: the (number of) identified pixels depends on the Shrinkage Factor (SF).**

In the programme a technique called 'polygon-shrinking' (Catlow *et al.*, 1984) was applied to exclude boundary pixels (Fig. 31). The degree of shrinking is set by the shrinkage factor: a value of 0 means that boundary pixels are included; a larger shrinkage factor has the effect that a larger number of pixels (taken from the boundary towards the centre) are excluded.

The effect of a (very) large shrinkage factor may be that no pixels are found within an object. To avoid a situation where terrain objects remain unclassified due to the polygon-shrinking, the shrinking factor was automatically reduced (for shrinkage factors larger than 0) if no pixels were identified within the polygon.

6.2.3 Test and validation procedure

Input for the object-based classification of the 1987 Landsat TM image are the field boundaries from the 1987 crop data (Sect. 4.2). Based on these geometrical data and the training set described in Section 4.4 both the 1-stage and 2-stage object-based classifications were performed. Furthermore, different shrinkage factors were applied to assess the effect of excluding boundary pixels on classification accuracy.

The classification accuracy was assessed by comparing the output of the object-based classifications (crop type) with the reference crop type stored for 1987. The results of the comparison were expressed by the (relative) number of corresponding fields and its area.

6.3 Results and discussion

6.3.1 Spatial data integration

The co-registration of the Landsat TM image and the 1987 crop data was achieved by identifying nine GCP's. Based on these GCP's the parameters for an affine transformation were calculated. The $RMSE_{xy}$ of this transformation for the GCP's was 0.4 pixel.

It was found that the algorithm applied to identify raster elements within a polygon (procedure POLY of Erdas) is not consistent (Kramer and Janssen, 1993). The algorithm defines an element as a boundary element if the line that is projected through its centre (in row direction) intersects with the boundary of a polygon. These boundary elements are assigned to both the left and right polygon. As a result of this inconsistency, the area of a polygon (object) calculated from the rasterized data is always larger than the area when calculated from the vector-structured data. The size of the smallest field in the Biddinghuizen test area is 0.5 ha; for this particular field 10 TM pixels (0.9 ha) were identified by the approach used (shrinkage factor of 0).

A vector-to-raster conversion approach was applied in Janssen *et al.* (1990). In this study the object geometry was converted into the grid geometry of the applied Landsat data by using the vector-to-raster algorithm of Arc/Info (POLYGRID). With POLYGRID a boundary element is assigned to only one object: the object that has the largest area within this element ('dominant unit rasterizing'). Figure 32 shows

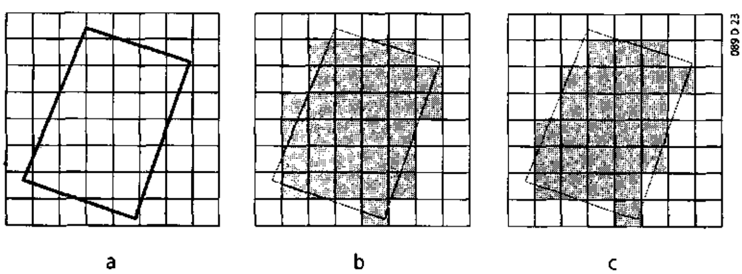


Figure 32 Vector-raster integration.

- **a Vector-structured polygon superimposed on a grid.**
- **b Raster elements (n=31) identified by Erdas when using the procedure POLY.**
- **c Raster elements (n=27) identified by Arc/Info when applying the conversion programme POLYGRID.**

the different number of pixels that are identified within an object depending on the applied Arc/Info or Erdas conversion algorithm. In the comparison of the results that were derived by using different approaches for combining the vector and raster data it was found that varying results were derived for smaller objects depending on the approach applied.

6.3.2 Object-based classification

The first aim of object-based classification is to extract the crop type of agricultural fields from the Landsat TM data (thematic updating). With the method applied it was possible to determine the crop type for all the 542 fields present in site A at the Biddinghuizen test area. This means that for all the fields at least one pixel was identified within its boundaries. This was no problem because of the relative large field size: the smallest field measures 0.5 ha and the average field measures 6.9 ha, which equals the area of 76 TM pixels.

The second aim of object-based classification is to derive a reliable crop type by using spatial context information that is given by the object geometry. Both 1-stage and 2-stage object-based classifications were performed and a varying number of boundary pixels were excluded (shrinkage factor ranging from 0 to 4). The results

Table 11 Correctly classified fields of site A (n=542; 3,754 ha) that result from the 1-stage and 2-stage object-based classification. The results are presented for a shrinkage factor, which determines the number of boundary pixels that are excluded, ranging from 0 to 4.

Shrinkage factor	1-stage		2-stage	
	No of correctly classified fields	Area (ha)	No of correctly classified fields	Area (ha)
0	411	3034	500	3591
1	483	3504	503	3601
2	495	3556	499	3585
3	499	3579	500	3588
4	499	3579	500	3589

Table 12 Numbers of incorrectly classified fields per area class of site A at the Biddinghuizen test area (n=542; 3,754 ha) that result from 1-stage and 2-stage object-based classification for shrinkage factors from 0 to 4.

Area class (ha)	Total number of objects	1-stage Shrinkage factor					2-stage Shrinkage factor				
		0	1	2	3	4	0	1	2	3	4
$0.0 < x \leq 1.0$	3	1	0	0	0	0	0	0	0	0	0
$1.0 < x \leq 2.0$	15	8	7	7	7	7	7	6	7	7	7
$2.0 < x \leq 3.0$	39	14	6	6	6	6	5	6	7	7	7
$3.0 < x \leq 4.0$	81	31	19	12	12	12	12	10	11	10	10
$4.0 < x \leq 5.0$	63	23	16	13	10	10	11	10	11	10	10
$5.0 < x \leq 6.0$	61	8	3	2	2	2	3	3	2	3	3
$6.0 < x \leq 7.0$	47	14	2	3	2	2	2	2	2	2	2
$7.0 < x \leq 8.0$	42	7	2	1	1	1	1	1	1	1	1
$8.0 < x \leq 9.0$	44	9	1	0	0	0	0	0	0	0	0
$9.0 < x \leq 10.0$	28	2	0	0	1	1	0	0	1	1	1
$10.0 < x$	119	14	3	3	2	2	1	1	1	1	1
Total	542	131	59	47	43	43	42	39	43	42	42

are listed in Tables 11 and 12. From Table 11 it can be observed that the classification accuracy for the 1-stage and 2-stage object-based classifications is almost the same if a shrinkage factor equal or greater than 2 is applied. In this case object-based classification resulted in a correct crop type for 92 % (500/542) fields of the Biddinghuizen test area. These fields comprise 95 % (3580/3754) of the test area.

The 1-stage object-based classification yields considerable worse results than the 2-stage classification for a shrinkage factor of 0 and similar result for a shrinkage factor larger than 2 (Tables 11 and 12). This can be explained by the following two reasons:

- Boundary pixels are mixed pixels or pixels that completely belong to another class (e.g. bare soil or water). In the 1-stage object-based classification a mean reflectance is calculated. The (deviating) reflectance of the boundary pixels may have the effect that the mean reflectance of the field is not representative for the present crop type. As a result, the field may be assigned to another crop type. The 2-stage classification is based on the result of a pixel-based classification in which some of the boundary pixels will be incorrectly classified. However, due to the large size of the fields, the fraction of incorrectly classified pixels within a field is less than the fraction of the mode class. This effect is greatest if no boundary pixels are excluded (shrinkage factor of 0). If these boundary pixels are excluded (shrinkage factor ≥ 2) it can be expected that in most situations the mean reflectance of a field is representative for a specific crop. This is especially the case since the fields in the test area have a homogeneous canopy.

- For smaller fields (area less than 5 ha) the larger number of errors of the 1-stage classification (shrinkage factor of 0) is also caused by the algorithm applied which assigns too many boundary elements (pixels) to a field (Sect. 6.3.1). Table 12 shows that this inconsistency did not negatively effect the classification result of the 2-stage object-based classification.

From these results it can be concluded that the 2-stage classification is less influenced by mixed pixels or incorrectly identified pixels than the 1-stage object-based classification. Furthermore, the 2-stage object-based classification yields better results than the 1-stage object-based classification for smaller objects. The 2-stage classification is therefore more robust than the 1-stage classification.

Plate 6 shows the original TM image and Plate 7 shows a pixel-based classification result for a part of the test area. The field boundaries (derived from the large-scale maps) are superimposed on both images. Two types of (pixel-based) classification errors can be distinguished in Plate 7: incorrectly classified pixels at the boundaries (mixed pixels) and incorrectly classified pixels within the fields. These are caused by the spectral variability of the crops or by phenomena such as spots of bare soil. From Plate 7 it can be understood that for most fields these classification errors form a minority and that they are therefore not propagated in the 2-stage object-based classification that assigns an object to the mode class.

A last observation from Table 12 is that there is no difference when the shrinkage factors 2, 3 or 4 are applied. On the one hand this can be explained by the large homogeneous fields. On the other hand, it should be remembered that the shrinkage factor is set back if less than one pixel is found within a field. This occurred for 79 of the 542 fields at a shrinkage factor of 3. This means that for these fields the same pixels were applied for both classifications with shrinkage factor 2 and 3. For 7 of these 79 fields the classification was based on a single pixel; for the other fields the number of pixels found within one fields ranged from 2 to 20.

In the pixel-based maximum likelihood classification, pixels might be assigned to a background class if they are classified with a likelihood that is below a certain threshold value (thresholding). It was tested if thresholding in the pixel-based classification resulted in better classification results of the 2-stage classification. Therefore, the pixels that were outside the 95 % confidence level were assigned to the background class (0). This result was then applied in the object-based classification using a shrinkage factor of 1. This classification resulted in a correct crop type for 499 fields while 4 fields remained unclassified. All the pixels within these 4 fields were classified as background class. It can be concluded that thresholding was not effective to improve the classification accuracy in the Biddinghuizen test area (due to the homogeneous canopy mainly boundary pixels were thresholded). These pixels are already excluded by polygon shrinking. For other areas, with a less homogeneous canopy, thresholding may be effective.

Error analysis

The optimal classification result, 2-stage object-based with a shrinkage factor of 1 (Table 11), was used to analyze the remaining differences between the reference crop type and the crop type as determined with the object-based classification. The result of an object-based classification depends on the following factors:

- <u>Spectral separability of the classes under consideration and the training data applied</u>

  The error matrix for the incorrectly classified fields is given in Table 13. Most errors can be explained by spectral confusion: beans/onions, grass/peas, sugar beets/cereals and beans/onions (Table 4). However, other error combinations cannot be explained by spectral confusion: e.g. onions/cereals and peas/onions.

Table 13 Error matrix of the crop type determined by the 2-stage object-based classification (shrinkage factor 1) and the reference crop type (n = 39 fields).

Classification result	Reference crop type						
	Potatoes	Cereals	Sugar beets	Grass	Beans	Peas	Onions
Potatoes	-	1	-	-	-	-	-
Cereals	-	-	-	-	-	-	-
Sugar beets	1	5	-	1	-	-	1
Grass	-	3	1	-	-	5	2
Beans	-	-	-	-	-	-	6
Peas	-	1	-	-	-	-	4
Onions	-	4	-	1	1	2	-

For each crop type considered one training class was established based on a number of fields (Sect. 4.4). Not all the fields with the same crop have a similar development (e.g. different sowing date). This may cause classification errors if the applied training data of a specific crop are not 100 % representative for all the fields in which this crop is grown.

Another explanation for an error combination in Table 13 it that the reference crop type instead of the classification result is incorrect. In Section 4.3 it has been noted that the reference data cannot be considered as 100 % correct.

- Co-registration and vector-raster integration

The co-registration of the image and map coordinate systems was clearly at the sub-pixel level ($RMSE_{xy}$ = 0.4). It can be stated that registration did not hamper identification of the pixels corresponding to a terrain object.

It was already noted that algorithm applied for identifying raster elements within a polygon is not consistent and assigns too many elements (pixels) to a field. Since the result of the 2-stage object-based classification for shrinkage factor 0 is similar to the results for higher shrinkage factors (Table 12) it can be concluded that this did not negatively influence the classification result.

- Accuracy of the field geometry and width of the fields

The incorrect classification results can be explained for 13 of the 39 fields by (i) positional errors in the field geometry and/or (ii) the narrow width of a field. The effect of a positional error in a field boundary is twofold. For one of the fields the classification is also based on the pixels that actually belong to another field in which another crop is grown; this effect is largely responsible for an incorrect classification result. For the other field the classification is based on a reduced number of pixels; in most situations this effect did not cause an incorrect classification.

Elongated fields (with a small area/perimeter ratio) are incorrectly classified because the pixels within these fields are often mixed pixels. The minimum acceptable width of a field depends, among other factors, on; the orientation of the fields in the RS image; the sensor's characteristics (e.g. point spread function) and the contrast between neighbouring fields. For this test site, the minimum field width that is required to enable a 100 % reliable classification result is estimated at 90 -120 m.

Summarizing it can be stated that the incorrectly classified fields of the Biddinghuizen test area can be largely explained by spectral confusion between the crops considered, incorrect field geometry and fields for which the ground resolution of the TM data applied is too low.

6.4 Conclusions

In this case study the crop type of agricultural fields is updated by means of an object-based classification. A prerequisite is that the field geometry is known (contained in a GIS) and it is based on the assumption that only one crop type is grown per field.

Two types of object-based classification are distinguished: 1-stage and 2-stage object-based classification. In the 1-stage classification a field is assigned to a certain class (crop) based on the mean spectral reflectance. The 2-stage classification is based on the result of pixel-based classification; a field is assigned to the mode class that occurs within the field. An advantage of object-based classification is that mixed pixels and spectral variability have no effect or a limited effect on the classification result.

The 2-stage object-based classification should be preferred for its robustness. It is less sensitive to co-registration errors and yields better results for smaller fields than the 1-stage object-based classification. Excluding the boundary pixels in a (2-stage) object-based classification did not yield a more reliable result. However, excluding boundary pixels may be effective for other areas in which the size of the fields is relatively small and in which the fields can have a more heterogeneous canopy.

It was found that algorithm applied to identify raster elements that are located within a polygon is not consistent: boundary pixels are assigned to both the left and right polygon (field). Although this did not negatively effect the classification result for this test area, it is better to apply a consistent algorithm.

The result of an object-based classification depends on the:
1 spectral separability of the considered classes;
2 co-registration of the field geometry and image data;
3 accuracy of the field geometry;
4 width (size) of the fields.

Factors 2, 3 and 4 are related to the ground resolution of the RS data applied. The accuracy of the field geometry and co-registration should be at the sub-pixel level. The ground resolution of the RS data applied determines the minimum size of a field in which pure pixels can be found. The latter is also related to the orientation of the fields in the image.

For the Biddinghuizen test area the object-based classification resulted in a correct crop type for approx. 90 % of the fields. The incorrect classifications can be largely explained by spectral confusion, incorrect field geometry, and fields for which the ground resolution of TM is too low (size/shape). The minimum width of a field for which a number of pure pixels can be found was estimated at 90 - 120 m.

7 Integrated segmentation and classification method

7.1 Introduction

Object-based classification was introduced in Chapter 6 to update the crop type of agricultural fields from RS data if the field geometry is known. Most often, however, not only the crop type but also the field geometry changes between growing seasons. In the Biddinghuizen test area, each growing season the set of fields within a lot are replaced by a completely new set of fields (Sect. 4.2). The aim of this case study is to extract both the field geometry and crop type from the available Landsat TM image. The lot boundaries (contained in the GIS) and knowledge about the aggregation structure of the fields is applied to optimize the information extraction. First some relevant experience from the literature is given.

One of the problems in segmenting real-world images is their complexity (Sect. 2.6). To overcome this problem additional information should be applied. Ton *et al.* (1991) present a knowledge-based approach for the segmentation of Landsat TM images. Their aim is to delineate terrain objects of 8 major land cover types in a forested area. Knowledge about spatial and spectral object characteristics is applied in a strategy that comprises clustering, seed detection and region growing, region interpretation and region adjustment. Although different types of knowledge are applied Ton *et al.* (1991) do no take advantage of any existing geographical data to optimize their strategy.

Bénié and Thompson (1992) present a method that is based on the application of a region growing technique. Initially some oversegmentation is accepted which is solved in a later stage by merging regions based on a similarity measure. Depending on the image data applied and the characteristics of the area of interest a specific similarity measure can be selected from a set of these measures. The segments that result after merging are classified. The results of this approach for an agricultural test area based on aircraft RS data with a ground resolution of 12.5 m are good. When compared with field boundaries derived from visual photogrammetric interpretation of aerial photographs the error percentage (areal percentage) varies from 2 to 6 % for most fields.

Lemmens and Han (1990) present an updating approach that starts from the terrain object boundaries which are contained in a GIS. First the image applied is classified by a pixel-based approach. Then, a histogram of the labels occurring within the object boundaries is established; if two or more classes occur within the object, their spatial coherence is checked. If the classes are spatially coherent, the boundary between these classes is determined and vectorized. Finally, the newly introduced boundary and class labels are fed back into the GIS. In this approach the geometry of the objects is based on the result of a pixel-based classification. The problems that are related to pixel-based classification (mixed pixels, spectral and spatial variability) can be expected to reduce the possibilities of boundary detection. Furthermore, knowledge about dynamic and static properties of the terrain objects of interest was not explained nor applied in the information extraction.

Mason *et al.* (1988) present an integrated method to update map data from RS images. A digitized topographical map was modified in such way that it gives the relevant area and line objects: objects that can possibly be distinguished if the ground resolution of the scanner used is taken into account. For the area objects some preliminary class or classes are added. This database is the starting point for updating. The basic system flow is based on the application of multi-temporal data in which the segmentation is updated for each image in the time sequence (this is described in more detail in Cross *et al.* (1988). Edge detection is performed separately for each band of the applied image by using a Sobel operator and an automatic thresholding stage. The results of the different bands are combined into one 'edge image'. The edges are thinned to a single pixel and texture edges are eliminated. The geometrical data contained in the GIS are then refined by using the knowledge that is contained in three sets of rules: domain consistency rules; split rules and merge rules. The result of the segmentation is then used as input for object-based classification. The prototype system was tested for two agricultural areas using the first four principal components of airborne scanner data with a ground resolution of 10 m. The knowledge-based (KB) segmentation results were compared with a segmentation result derived from a photo-interpreter. The classification results were validated by a pixel-based comparison with reference data. The result of the KB segmentation was more similar to the result of a photo-interpreter than the result of a traditional segmentation. The classification error for both test areas was 16 and 14 %, which is considerably better than the pixel-based classification with an error of 30 and 24 %.

An object-based approach with respect to the updating of road structures from RS data is given by Van Cleynenbreugel *et al.* (1990). It starts from a road network that is already contained in a GIS. Then a generic model for the type of road is formulated. The model for a forest path road, e.g. is the following: forest paths are normally straight and very often intersect perpendicularly; a forest is subdivided into repeating geometrical structures (rectangles) by the paths and there are usually chains of paths near the border of a forest region. This model was implemented in an object-based programming environment in which the result of edge detection is integrated with the roads that are already known. This approach was carried out for forest path and mountain roads; the information was extracted from SPOT data. Unfortunately, a quantitative validation of the updating result was not presented. The reasons for this were the lack of reference data and the lack of a methodology for error assessment (Van Cleynenbreugel, 1991).

In this case study a method is presented to update both the geometry and crop type of agricultural fields from Landsat TM data. The method is not based solely on the RS data, since other (relevant) data are already contained in the GIS and can be used to improve the information extraction. The segmentation part is based on spectral information to avoid the propagation of errors related to pixel-based classification. In the determination of the field geometry oversegmentation is initially accepted. This is solved later by merging 'fields' with a similar crop type. The method developed will be referred to as the Integrated Segmentation and Classification method: ISC method (Sect. 7.2). It is 'integrated' since the combination of segmentation and classification is applied to yield an optimal result. The ISC method was developed and tested for site B at the Biddinghuizen test area (Sect. 4.2.2) and the application of the available Landsat TM image (Sect. 4.3). The results are presented and discussed in Section 7.3. Section 7.4 gives the main conclusions with respect to the method presented in this case study.

7.2 Methods

7.2.1 Integrated segmentation and classification (ISC) method

Field geometry can be extracted from the TM data by the application of segmentation techniques. Principally, two techniques can be applied: region growing or edge detection. An edge detection approach was chosen for two reasons:

(i) most field boundaries are represented by a strong gradient in the TM image;

(ii) it seemed easier to link line objects (edges) than area objects (segments) with the available lot boundaries.

Straightforward application of an edge-detection algorithm on the Landsat TM image does not yield the required field boundaries. Although the fields in the Biddinghuizen test area have a homogeneous canopy, some in-field variation (spatial and spectral variability) can be observed (Plates 2 and 4). This means that apart from edges related to field boundaries edges related to in-field variation will also be found. Another problem is related to the definition applied: terrain objects are defined as areas in which one type of crop is present. This means that we are not interested in boundaries that separate areas of the same crop with different spectral characteristics (e.g. due to different sowing dates). A last problem is that of the definition of closed areas (fields) based on the results of the edge detection. Although the majority of the field boundaries are characterized by strong one-directional gradients, this is not true for boundary intersections. These problems can be solved to a large extent by using ancillary data (lot boundaries) and knowledge. The knowledge applied in this case study is the following.

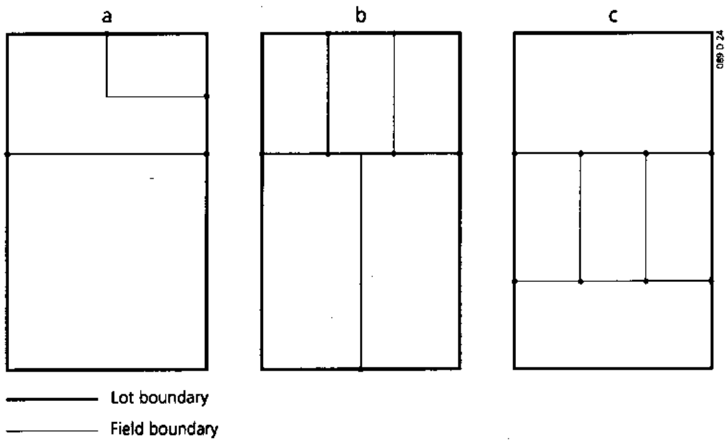


Figure 33 **Topological relationship between field boundaries and lot boundaries**
a Field boundaries of which both nodes meet a lot boundary.
b Field boundaries of which one node meets a lot boundary.
c Field boundaries which do not meet with lot boundaries.

In the context of yearly updating the lot boundaries in the Biddinghuizen area can be considered as fixed (Sect. 4.1). These boundaries are contained in a GIS. Within a lot, each growing season a new set of fields is introduced. In other words: the fields are a fragmentation of the lots. In general, the fields have a rectangular shape and the field boundaries share segments with the lot boundaries (Fig. 14).
For the field boundaries that do not share segments with the lot boundaries, three types of boundaries can be distinguished, depending on the number of nodes that meet with the lot boundaries (Fig. 33).

The following three-stage strategy (Fig. 34) was developed for updating both field geometry and crop type:

1 Segmentation of the image, combining its result with the fixed boundaries to yield preliminary field geometry. The segmentation is based on the application of edge detection. A characteristic of edge detection is that generally too many or too few edges, which coincide with field boundaries, are found (over- and undersegmentation). In this strategy the choice is to avoid undersegmentation at the cost of oversegmentation. Oversegmentation is solved in a later stage (stage 3).

2 For the preliminary fields that are derived in stage 1 the crop type is determined by means of object-based classification. Oversegmentation does not hamper object-based classification as long as pure pixels can be found within a field.

3 In the last stage oversegmentation is solved by merging neighbouring fields that (i) have a similar crop type and (ii) are located in the same lot.

The method for object-based classification method was explained in Chapter 6. In this case study the 2-stage object-based classification was applied; the training data applied are described in Section 4.4.

The next part of this section concentrates on the segmentation part of the strategy (stage 1). It is referred to as the Integrated Segmentation method (IS method). It is called 'integrated' since it is based on edges derived from the TM image, lot boundaries and knowledge about the aggregation structure of the fields.

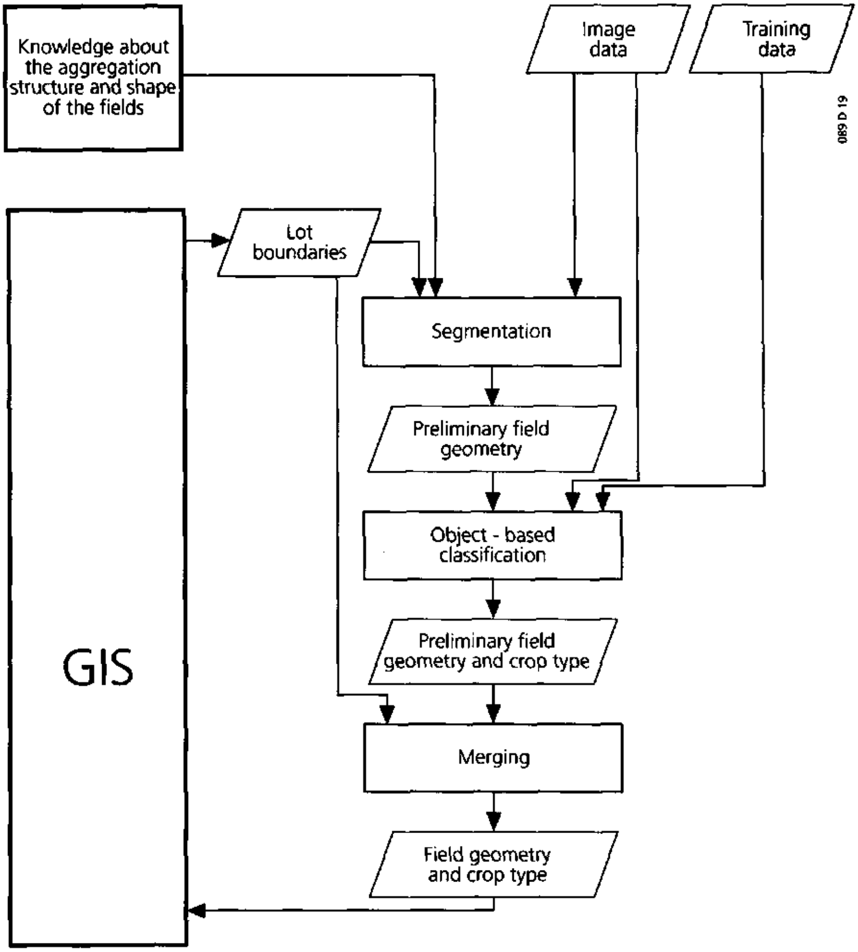


Figure 34 **Flow-chart of the integrated segmentation and classification (ISC) method.**

7.2.2 Integrated segmentation (IS) method

Figure 35 shows the flow-chart of the IS method, which consists of two modules: an edge detection module and an integration module. The edge detection module results in edges that are found within the lots. These edges are passed to the integration module in which they are connected with other boundaries in order to derive closed areas (fields). Non-relevant edges are discarded in both the edge detection module and integration module.

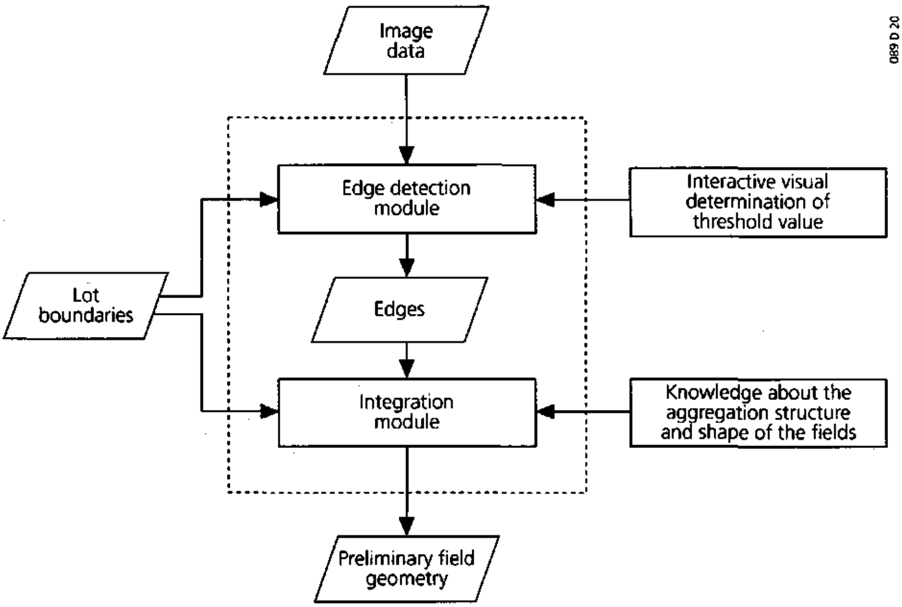


Figure 35 Flow-chart of the integrated segmentation (IS) method.

Edge detection module

The objective of the edge detection module is to produce a maximum number of edges that coincide with field boundaries. In the applied strategy the 'cost' of rejecting relevant edges is very high, since no additional geometric information is added afterwards. The 'cost' of accepting non-relevant edges related to different varieties or sowing dates of the same crop is low, since these boundaries are removed in a later stage. Note that this strategy is analogous to the approach in hypothesis testing in which the probability of a type I error (incorrectly rejecting hypothesis H_0 while true) is minimized. The following approach was applied:

Edge detection algorithms can only deal with a one-band image. To avoid the problem of having to combine the results of separate edge detections of TM bands 3, 4 and 5 these bands were combined into one 'intensity image'. Based on a covariance analysis of TM data and land cover data Tomppo (1987) found that the weights for the three bands were almost similar. Therefore, the intensity image was derived from an unweighed combination of the TM bands:

$$DN(\text{intensity image}) = 0.33 \cdot DN(\text{band3}) + 0.33 \cdot DN(\text{band4}) + 0.33 \cdot DN(\text{band5}).$$

The edge detection was based on the application of a Kirsch operator (e.g. Ballard and Brown, 1982). A Kirsch operator yields edge pixels; it cannot estimate the position of an edge at sub-pixel level. As a result it is impossible to detect a left- and right-boundary for agricultural fields that have a width of 1 or 2 TM pixels. In order to enable the detection of edges that are related to boundaries of these small fields (which occur in the Biddinghuizen test area) the TM image was (i) subsampled with a factor 3 and (ii) subsequently the values of the subsampled pixels were interpolated by a 3 x 3 moving average filter (Fig. 36a). To remove the random noise present in the resulting image a 3 x 3 Gaussian filter (Fig. 36b) was applied.

$$\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \cdot \frac{1}{9} \qquad \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix} \cdot \frac{1}{16}$$

a b

089 D 25

Figure 36 **a Moving average filter (3 x 3).**
b Gaussian filter (3 x 3).

For each (subsampled) pixel the magnitude and direction of the gradient were calculated using the four templates of the Kirsch operator; the size of the templates applied is 7 x 7 pixels (Fig. 37). After selection of the maximum gradient (and its associated direction) it is checked if it is a local maximum (non-maximum suppression). Pixels of which the maximum gradient is also a local maximum are 'edge pixels'. Next, edge following (e.g. Duda and Hart, 1973; Ballard and Brown, 1982) was applied to connect edge pixels. At this point, the edges are stored in a list by the coordinates of all constituting edge pixels. These edges were projected on the TM image and a threshold value with respect to the magnitude value of the edge pixels was defined interactively to distinguish between relevant and non-relevant edges. Note that at this moment the knowledge (experience) of a human operator is brought into the system. The choice of the threshold value is clearly an optimization process: a small threshold value results in a larger number of non-relevant edges being selected while a large threshold may exclude relevant edges

-1	-1	0	0	0	0	0
-1	-1	-1	0	0	0	0
0	-1	-1	-1	0	0	0
0	0	-1	0	1	0	0
0	0	0	1	1	1	0
0	0	0	0	1	1	1
0	0	0	0	0	1	1

0	0	-1	-1	-1	0	0
0	0	-1	-1	-1	0	0
0	0	-1	-1	-1	0	0
0	0	0	0	0	0	0
0	0	1	1	1	0	0
0	0	1	1	1	0	0
0	0	1	1	1	0	0

0	0	0	0	0	-1	-1
0	0	0	0	-1	-1	-1
0	0	0	-1	-1	-1	0
0	0	1	0	-1	0	0
0	1	1	1	0	0	0
1	1	1	0	0	0	0
1	1	0	0	0	0	0

0	0	0	0	0	0	0
0	0	0	0	0	0	0
1	1	1	0	-1	-1	-1
1	1	1	0	-1	-1	-1
1	1	1	0	-1	-1	-1
0	0	0	0	0	0	0
0	0	0	0	0	0	0

Figure 37 **Kirsch filter templates (7 x 7).**

(which coincide with field boundaries). At this point it should be remembered that the overall strategy makes it possible to discard non-relevant edges in the further process. Therefore, non-relevant edges were tolerated in favour of a maximum number of relevant edges.

The edges that were selected by the threshold value applied were then further processed. The chain length of these edges was calculated and very short edges (length $\leq$ 1 TM pixel) were discarded. Most of these very short edges were found as a result of in-field variation. A mask of the lot boundaries was created and all the edge pixels that are located within a distance of 1.5 TM pixels of the lot boundary were discarded. Finally, the remaining edges were vectorized and smoothed by a least squares line fit.

Integration module

The objective of the integration module is to determine field geometry (closed areas) based on the integration of the fixed lot boundaries and the edges that are passed by the edge detection module. In doing so, it should be possible to construct the different geometrical structures shown in Figure 33. Edges which have a large degree of uncertainty of coinciding with field boundaries should be discarded.

Integration was achieved by an iterative procedure in which two sets of vector-structured data are applied:

- Set of boundaries: B.

  When the process starts this set contains the lot boundaries; during the process accepted boundaries from E are added.
- Set of edges: E.

  When the process starts all the edges passed by the edge detection module are in this set; during the process edges are transferred from E to B.

The integration module consists of three components (I, II and III) in which boundaries and edges are combined according to the rules defined in a rule set. Each component has its own rule set (Table 14). After processing components I and II the content of E is modified by modification sets I and II respectively (Table 14). Because of the changing content of B the processing performed in each component is iterative; these changes may cause new edges of E to be selected. If no more changes occur in the sets, the process proceeds to the next stage (Fig. 38).

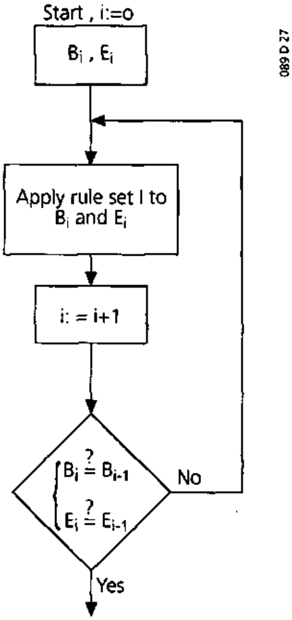


Figure 38 **Flow-chart of component I of the integration module.**

In the rules applied, different parameter values need to be set for the geometrical functions applied (distance, angle). In rule set I and II the maximum distance between an edge of E and boundaries of B is put at 3.33 TM pixel. The purpose of this condition is to exclude edges that end in the middle of a field with a large degree of uncertainty for representing field boundaries. The distance value used was determined by trial-and-error (it should be larger than 1.5 TM pixel, which is the distance applied in the edge detection module to select the relevant edges within a lot). Rule sets I and II require that the angle of intersection between and edge of E and a boundary of B should be within the range of 80 to 120 gon. This condition formalizes the knowledge about the perpendicularity of intersections. However, exact 100 gon intersections will seldomly occur as a result of the image resolution (30 m) in combination with the vectorization of the edges and of the geometrical transformation applied to link the lot boundaries of B with the edges of E. Therefore, 'perpendicular' was translated into 100 gon +/- 20 gon.

The knowledge about the field geometry is that: *in general*, fields have a rectangular shape. In fact, this largely depends on the shape of the lot. If a lot does

Table 14 Rule sets and modification sets applied in the Integration Module. Edges (set E) and boundaries (set B) are stored as line elements (arcs) consisting of a begin node and an end node; vertices are used to define the shape of a line. A line that is defined only by a begin node and an end node consists of one segment. The definition of topological relationships between line elements is according to De Hoop and Oosterom (1992). Angle is expressed in gon; distance in TM pixels.

Consider the following functions:

$d(l_1,l_2)$	distance between the nearest segments of l_1 and l_2
$d_n(l_1,l_2)$	distance between the two nearest nodes of l_1 and l_2
$\alpha(l_1,l_2)$	angle between the nearest segments of l_1 and l_2
$Cnts(l_1,l_2)$	all segments of l_1 are contained in l_2
$Meet(l_1,l_2)$	the begin or end node of l_1 meets l_2

RULE SET I

$\forall e \in E$ find two boundaries b_i and $b_j \in B$ so that:
$d(e,b_i)$ and $d(e,b_j) \leq 3.33$ and $\alpha(e,b_i)$ and $\alpha(e,b_j) \in [80, 120]$
then construct b so that:
$Cnts(e,b)$ and
$\alpha(b,b_i) = \alpha(e,b_i)$ and $\alpha(b,b_j) = \alpha(e,b_j)$ and
$Meet(b,b_i)$ and $Meet(b,b_j)$
and
$E := E - e$ and $B := B + b$

MODIFICATION SET I

$\forall e_i$ and $e_j \in E$ for which:
- $d_n(e_i,e_j) \leq 1$ construct e so that: $Cnts(e_i,e)$ and $Cnts(e_j,e)$
- $1 < d_n(e_i,e_j) \leq 3$ and $\alpha(e_i,e_j) \in [-10,+10]$ construct e so that $Cnts(e_i,e)$ and $Cnts(e_j,e)$

and
$E := E + e - e_i - e_j$

RULE SET II

$\forall e \in E$ find a boundary $b_i \in B$ so that:
$d(e,b_i) \leq 3.33$ and $\alpha(e,b_i) \in [80, 120]$
then construct b so that:

Cnts(e,b) and
$\alpha(b,b_i) = \alpha(e,b_i)$ and
Meet(b,b_i)
and
E:= E - e and B:= B + b

MODIFICATION SET II

$\forall e \in E$ for which:
length $e \leq 5$
E:= E - e

RULE SET III

$\forall e \in E$ find a boundary $b_i \in B$ so that:
$d(e,b_i) \leq 30$ and $\alpha(e,b_i) \in [0, 180]$
then construct b so that:
Cnts(e,b) and
$\alpha(b,b_i) = \alpha(e,b_i)$ and
Meet(b,b_i)
and
E:= E - e and B:= B + b

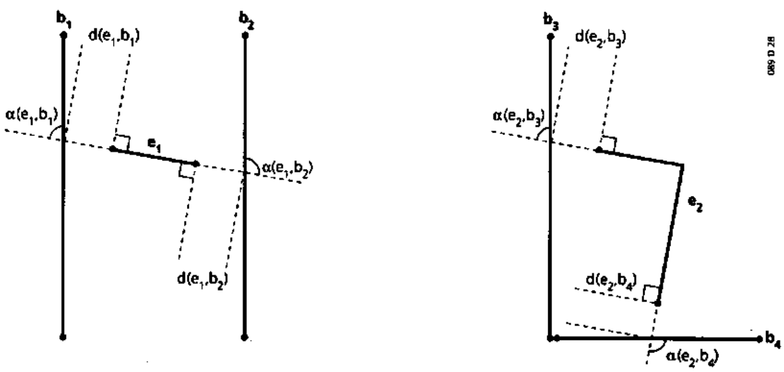


Figure 39 Distance and angle functions applied in the rule sets (Table 14).

not have a rectangular shape it is impossible to create rectangular fields within this lot. The shape variation of the fields was solved by applying strict rules in rule set I and less restrictive rules in rule sets II and III (Table 14). In component III of the integration module (which applies rule set III) the remaining edges of E (all with a length > 5 TM pixels) are connected with the boundaries of B irrespective of their intersection characteristics. As a result of the relaxation of the rules towards the end of the process there is a larger uncertainty related to the field boundaries that are then selected. For clarity: this procedural knowledge was not further applied in this case study.

Field geometry is derived by creating topology for the boundaries of B after integration of edges and boundaries. Finally, dangling arcs (which have the same field on both sides) are removed.
The IS method integrates geometrical data (lot boundaries; edges) by using knowledge about the aggregation structure and shape of the fields in the test area. For this area, the same method can be used for updating purposes in any growing seasons provided that TM data are available and the field/lot characteristics remain the same. The application of RS data with another ground resolution may require alterations of the edge detection module (pre-processing; edge operator; threshold values; vectorization) and of the integration module (geometrical functions and parameter settings).

7.2.3 Spatial aspects of the ISC method

The ISC method should result in field boundaries that are vector-structured and stored in map coordinates. A number of conversions and transformations were applied for the purpose of data integration.

In the edge detection module, edges that coincide with the fixed lot boundaries are discarded. Therefore, the lot boundaries were (i) transformed into image coordinates and (ii) converted into the grid geometry of the subsampled TM image. The edges that are not discarded in the edge detection module are converted from a coordinate list (expressed in centre coordinates of the subsampled pixels) into a vector-structured description by means of a least squares line fit. In this process the edges were smoothed by applying a tolerance of 1 TM pixel.

The processing in the integration module is based on vector-structured data since it enables easier determination of topological and geometrical relationships which are formulated in the rule sets and modification sets.

The preliminary field geometry that results after the segmentation phase is vector-structured and expressed in image coordinates. This geometry can be directly used as input for object-based classification.

After object-based classification the preliminary field boundaries were transformed into the map coordinate system to determine the fields that are located within the same lot.

The geometrical transformations applied (map-to-image and image-to-map) were based on a set of ground control points from which the parameters of an affine transformation were calculated. For the vector-to-raster conversion of the lot boundaries the program POLYGRID (Arc/Info) was applied; the raster-to-vector conversion in the edge-detection module (by means of least squares cure fit) has been programmed.

7.2.4 Test and validation procedure

In the ISC method both field geometry and crop type are updated. The updating of the crop type by object-based classification was dealt with in Chapter 6. This case study focuses on the quality of the field geometry that is derived from the TM image by means of the ISC method. The quality was assessed by:

(i) Visual comparison of the field geometry derived from the ISC method by overlaying it on the intensity image and a colour composite of the TM image.

(ii) Comparison with the field geometry derived by visual interpretation of the TM image applied. For this purpose reference data were established and a method was developed for the quantitative comparison of geometrical data (field geometry).

Comparison of object geometry

By overlaying two categorical 'maps' of the same scale two types of errors can be distinguished: positional errors and interpretation errors (Chrisman, 1989). Positional errors refer to errors in which it is certain that the delineated objects are intended to be the same but that small differences occur due e.g. to the limited ground resolution of the applied image data and the limited registration accuracy of the digitizing hardware used. An interpretation error refers to a situation in which (complete) terrain objects that belong to a different class are not distinguished. The biggest problem, however, lies in the fact that combinations of positional and interpretation errors may occur. In the following a method is presented in which threshold values are applied to categorize the continuum between positional and interpretation error.

Consider input data X and Y, both consisting of a number of terrain objects that have a different geometry. Differences in geometry can be determined by an overlay operation of the vector-structured descriptions. The overlay operation of X and Y results in XY (Fig. 40) in which the segments resulting from the overlay are characterized by unique combinations of the object identifiers of both input data (Table 15); the area of the segments can be calculated.

The areas of the terrain objects in the input data can be used to calculate a coefficient which quantifies 'correspondence' or 'match' between objects. The measure for the match between a terrain object from input data i and a terrain object from input data j, M_{ij}, is defined as:

$$M_{ij} = \sqrt{(M_i \cdot M_j)}$$

$$M_i = \text{Area}\ (j \mid i) = \text{Area}\ (i \cap j)\ /\ \text{Area}\ (i)$$

$$M_j = \text{Area}\ (i \mid j) = \text{Area}\ (i \cap j)\ /\ \text{Area}\ (j)$$

The measure for match, M_{ij}, is a geometrical mean of two conditional probabilities M_i and M_j and has a value that is between 0 and 1. If the geometry of two terrain objects completely match, M_{ij} equals 1. M_i quantifies the relative part of i present in the common area of i and j (if $M_i = 1$ then i is contained in j), M_j quantifies the relative part of j present in the common area of i and j (if $M_j = 1$ then j is contained in i).

The correspondence coeffients for the situation in Figure 40 are given in Table 15. It can be seen that the summed M_X and M_Y yield the total number of objects in input set X and Y respectively.

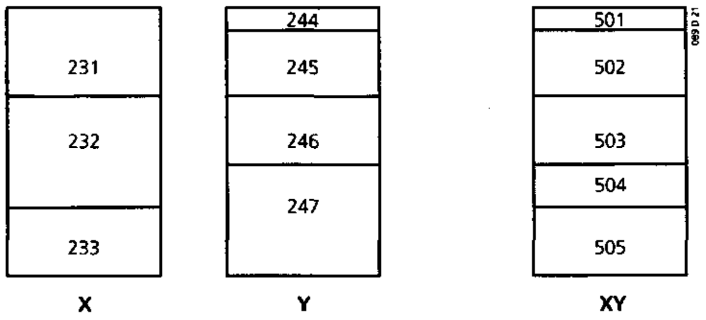


Figure 40 Geometry of X and Y and overlay XY (see Table 15).

Table 15 Relationship between the object geometry of X and Y expressed by correspondence coefficients M_{XY} (see Fig. 40).

XY	X	Y	Area	M_X	M_Y	M_{XY}
501	231	244	5	0.25	1.00	0.50
502	231	245	15	0.75	1.00	0.87
503	232	246	15	0.60	1.00	0.78
504	232	247	10	0.40	0.40	0.40
505	233	247	15	1.00	0.60	0.78
			Σ	3.00	4.00	3.33

$M_{ij} = 1$ means that the geometry of two terrain objects present in two sources have exactly the same geometry. This seldom occurs when different interpretation results are compared. Low values of M_{ij} indicate that the segment is related to two terrain objects which (spatially) do not have much in common. This is often caused by small differences at the boundaries ('slivers'). High values of M_{ij} indicate a large degree of match. Intermediate values of M_{ij} are caused by interpretation differences. Based on the value of M_{ij} three categories of segments can be distinguished:

- positional errors $M_{ij} \leq M_{pos}$
- interpretation errors $M_{pos} < M_{ij} < M_{int}$
- corresponding objects $M_{int} \leq M_{ij}$

For each category the relative area (percentage) of the total area can be calculated by summing the areas of all the segments that are in a specific category.

Application of this categorization requires evaluation of parameters M_{pos} and M_{int}. In this case study a pragmatic approach was applied by analyzing the Match values for objects that are considered to correspond. These objects were identified by visual interpretation of the two input data. E.g. if objects 231 and 245 can be considered as corresponding objects M_{int} can be set at 0.87. Likewise a value for M_{pos} can be set. M_{int} is not necessarily equal to (1 - M_{pos}) since M_{pos} will generally relate to one boundary and M_{int} to the geometry of a field as a whole. Once M_{pos} and M_{int} have been assessed, the relative area that belongs to the three distinguished categories can be calculated. The applied values for M_{pos} and M_{int} will depend on the type of terrain objects and the (RS) data applied. For man-made objects observed from aerial photographs other parameter values will be applied than for natural areas derived from satellite RS data.

In the categorization applied the differences between the input geometry are defined as 'error'; this is the case if one of the two input data can be considered as reference. If neither of the input data can be considered as a reference, the 'error' percentages should be understood as 'discrepancy' percentages.

Reference data

The results of visual interpretation of the field boundaries present on the TM image (of the Biddinghuizen area) can be considered to be accurate and reliable. But even then, the interpretations made by different persons will not be exactly the same. Three (skilled) persons were asked to digitize the field boundaries. Therefore, a colour composite of the TM image (RGB = 453) was put on the monitor with a magnification factor of three. The lot boundaries were overlaid on the TM image by means of vector-on-raster superimposition. The persons were then asked to add the field boundaries within the lots. From these results the degree of subjectivity was determined and the best result was selected for comparison with the result of the ISC method.

For site B at the Biddinghuizen test area persons A, B and C distinguished 507, 512 and 517 fields respectively. The differences in geometry between these results were assessed by the method described. Based on the visualization of different ranges of M_{ij}-values M_{pos} and M_{int} were determined. Differences of approx. 30 m (1 TM pixel) between two 'corresponding' field boundaries were considered as positional errors which resulted in a M_{pos} of 0.20. M_{int} was determined by considering segments that resulted from areas which were considered as one terrain object by a specific person while considered as two or more terrain objects by another person; M_{int} was assessed at 0.75.

Table 16 shows that the results of the three persons agree for 86 - 89 % of the area; for 3 - 4 % of the area this is caused by positional discrepancy and for 8 - 10 % of the area this is caused by interpretation discrepancy. The positional discrepancy can be explained by the degree of idealization: generalization of the boundary itself and its angle with the lot boundaries. The interpretation discrepancy is mainly found in situations where a slight difference in colour between neighbouring fields is found due to different sowing dates or different varieties of the same crop. Furthermore, the minimum size and width of a field to be distinguished had not been defined. This was also one of the causes for the interpretation errors.

The sensitivity of the error percentages for the values applied for M_{int} and M_{pos} was determined by evaluating other values. A more strict definition of 'match' and positional error can be realized by increasing the value of M_{int} and decreasing the value of M_{pos}. For M_{pos} and M_{int} values of 0.15 and 0.80 respectively were applied to calculate the match between the results of person A and C. As a result of the

Table 16 Comparison of field geometry of site B at the Biddinghuizen test area derived from on-screen digitizing by persons A, B and C, who distinguished 507, 512 and 517 fields respectively. The errors and correspondence are expressed in areal percentages.

Comparison of i - j	Positional error $M_{ij} \leq 0.20$	Interpretation error $0.20 < M_{ij} < 0.75$	Corresponding objects $0.75 \leq M_{ij}$
A - B	3.8	10.4	85.8
B - C	3.3	7.3	89.4
C - A	4.2	8.2	87.6

stricter definition the interpretation discrepancy increased from 8.2 % (Table 16) to 11.4 %. The positional discrepancy decreased from 4.2 to 3.6 %. It can be concluded that the measure applied is not disproportionally sensitive to changes in the parameter values.

From Table 16 it can be concluded that the result of person C has the largest correspondence with the two other results. This result, therefore, is the basis for the reference data. In the ISC method neighbouring fields with a similar crop (within the same lot) are merged. The interpretation differences between the visual interpretation can largely be explained by the vague definition of 'field' that was given to the persons. As a result neighbouring 'fields' with a similar crop type but with a (slight) different colour were distinguished. To enable comparison with the result of the ISC method the interpretation result of person C was further processed by object-based classification and the merging of neighbouring fields with a similar crop type. As a result the number of fields decreased from 517 to 472. Visual evaluation of the merged fields confirmed the result in most cases. In a limited number of cases fields with (apparently) different crop were merged. The result of the merging depends on the classification result and, therefore, on the applied training data. If the applied training set does not contain all crop types present in the area of interest, fields with different crop types may be merged into one field.

The result of person C after merging (472 fields) was applied as reference data for the evaluation of the result of the ISC method. It can be understood that these reference data are not free of error. Therefore, the error percentages calculated from these data should be interpreted with care.

7.3 Results and discussion

The ISC method, as described in Section 7.2.1, was applied for site B at the Biddinghuizen test area. The lot boundaries and TM image were co-registered based on a set of 13 GCP's. From this set the transformation parameters of an affine transformation were calculated. The $RMSE_{xy}$ of the GCP's was 0.9 TM pixel. When compared with the other two case studies the $RMSE_{xy}$ is relatively large. This can be explained by the fact that the lot boundaries were digitized from 4 different map sheets.

The intermediate and final results of the ISC method were the following:

- Segmentation (IS method). For the 127 lots of site B the edge detection module yielded 532 edges. These edges were put into the integration module which yielded the geometry of 540 (preliminary) fields.
- Object-based classification. For the 540 fields that resulted from the IS method the crop type was determined by means of object-based classification.
- Merging. In the last step of the ISC method neighbouring fields with a similar crop type were merged if they are located in the same lot. The merging decreased the number of fields from 540 to 457.

Plates 2 to 5 give an overview of the total process for a detail of the test area. Plate 2 shows the input data: intensity image and lot boundaries. Plate 3 shows the result of applying the IS method: preliminary field geometry. It can be observed that (i) most boundaries were detected with a positional accuracy at sub-pixel level and (ii) that also boundaries of small fields (width of approx. 2 TM pixels) were derived by the IS method. The delineation of these small fields was possible because of the high quality of the image, the large gradient in grey value at field boundaries and the approach applied in the edge detection module (subsampling in combination with Kirsch operator). Furthermore, the different types of field boundaries described in Figure 33 were realized by the integration module. Plate 4 shows the final field geometry of the ISC method (after the merging stage). When Plate 3 and 4 are compared it can be seen which boundaries were removed. Plate 5 shows the final field geometry and the crop types of the fields.

Table 17 Comparison of field geometry of site B at the Biddinghuizen test area derived from the ISC method with the reference data. The correspondence and errors are expressed in areal percentages.

Positional error $M_{ij} \leq 0.20$	Interpretation error $0.20 < M_{ij} < 0.75$	Corresponding objects $0.75 \leq M_{ij}$
3.1	10.3	86.6

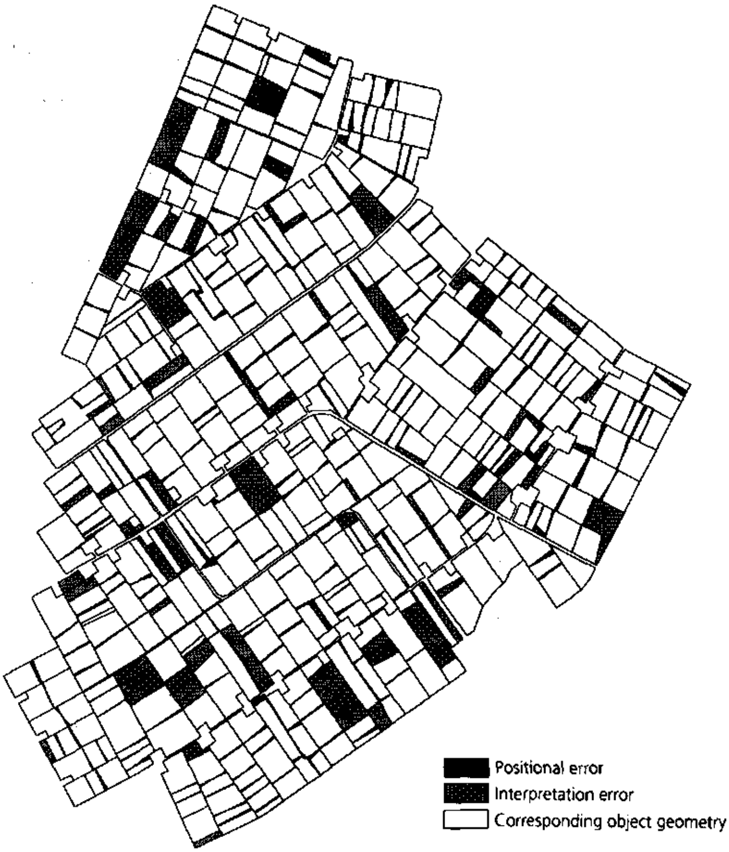


Figure 41 Comparison of the field geometry derived from the ISC method with the reference data (also compare with Plate 4).

The field geometry derived by the ISC method was compared with reference data (the result of a visual interpretation of person C, Sect. 7.2.2). The relative area for which fields were determined with a corresponding geometry is 87 % (Table 17). Interpretation errors (differences) were found for 10 % of the area; positional errors were found for 3 % of the area (Fig. 41).

In the following part of this section the interpretation errors and the error sources in the ISC method are discussed.

Co-registration

The lot boundaries and TM data were co-registered with an accuracy of approx. 1 TM pixel. Although a better co-registration can possibly be achieved, it did not hamper the segmentation part of the ISC method in which only the inside parts of the field (distance of 1.5 TM pixels) were taken into account.

The field geometry used for object-based classification consists of the combination of lot boundaries (which were co-registered) and the variable boundaries that were derived from the image by the IS method. This means that the accuracy of the co-registration refers only to a part of the field geometry (viz the fixed boundaries).

Edge detection module

For the 127 lots the ISC method finds 457 fields while the visual interpretation finds 472 fields. This means that the ISC method did not yield all the boundaries that were visually distinguished. The edge detection in the ISC method is based on a weighted average of TM bands 3, 4 and 5 (intensity image), while the visual interpretation is based on a colour composite of these three bands. When Plates 3 and 4 are compared it can be seen that some of the boundaries present in the colour composite cannot be found in the intensity image. In other words: some information was lost by combining the three bands into the intensity image.

The number of edges that result from the edge detection module depends on the threshold value applied to select edges based on their (gradient) magnitude value. In this case study a small threshold value was applied to select a maximum number of relevant edges. Decreasing the threshold value on the resulting edges, in this case, did not yield considerably more relevant edges.

A last source of error related to edge detection is the size of the Kirsch operator used which was 7 x 7 pixels in the subsampled image (approx. 2 TM pixels). This size was chosen to enable the detection of field boundaries of fields with a width of 1 - 2 TM pixels. Relatively few fuzzy boundaries were detected as a result of the small template size.

Integration module

The integration module started with 532 edges and ended with 518 variable field boundaries. In modification set I, edges are connected and in modification set II, edges with a length ≤ 5 TM pixels are discarded. Approx. 70 edges were discarded, most of which are related to in-field variation (colour differences, texture). Approx. 10 of these 70 edges were incorrectly discarded, as they did coincide with a field boundary.

Object-based classification and merging

The merging that takes place in the last stage of the ISC method is based on similar crop type. In a limited number of cases fields with (apparently) different crop types were merged. The merging is based on the classification result and therefore largely influenced by the training data applied. If the training set is not complete, fields with different crop types can be assigned to the same crop type and consequently merged into one 'field'. Some of the fields that were determined by the IS method are very small (width of approx. 2 TM pixels). In most cases the crop type that is determined for these fields by means of object-based classification is unreliable (Sect. 6.4).

In general, it is assumed that for segmentation purposes a (relatively) higher resolution is required than for classification purposes (Sect. 2.5.2). In this specific case study it proved to be the case that even field boundaries of very small fields, in fact consisting only of mixed pixels, could be determined (Plate 4).

To summarize: it can be stated that the most important type of error in the ISC method is that boundaries are not detected; oversegmentation (too many boundaries) is principally solved by (post-classification) merging. Therefore, the edge detection method and the training data applied for classification are the most critical parts of the ISC method.

7.4 Conclusions

In this case study both the field geometry and the crop type are updated from a TM image by means of a method that integrates segmentation and classification techniques (the ISC method). The result of an edge detection of the TM image is integrated with the lot boundaries (stored in a GIS) and knowledge about the aggregation structure and shape of the fields. The strategy applied is that a maximum number of edges are detected, which are then connected with the lot boundaries to derive the preliminary field geometry. For these fields the crop type is determined by means of object-based classification. Oversegmentation is then solved by merging neighbouring fields that (i) have a similar crop type and (ii) are located in the same lot.

For the Biddinghuizen test area the field geometry (field boundaries) derived by the ISC method corresponds for 87 % of the area with the result of a visual interpretation. The positional accuracy of most of the edges derived by the ISC method is at the sub-pixel level due to the subsampling of the image in combination with the Kirsch operator applied. Also boundaries of small fields (with a width of approx. 2 TM pixels) were detected. Furthermore, different types of field boundaries could be constructed by the ISC method.

The ISC method is based on a combination of segmentation and classification. Most critical is that at least all the edges that coincide with field boundaries are detected by the edge detector applied and that all the crops that are present within the area are represented in the training data used.

Although the ISC method was developed for the Biddinghuizen test area and data, it can be applied to other agricultural areas. Three factors, then, determine the extent to which this method will be successful:

- The relationship between fields/crops and the RS data applied.
  The most important condition is that the agricultural fields are represented as homogeneous areas with sharp boundaries in the RS data. This means that the ground resolution of the sensor used should result in little in-field variation. At the same time the ground resolution determines the positional accuracy of the boundaries determined. The different crops that are present in the specific area should have different spectral features in order to make both segmentation and classification possible.

- The presence of fixed field boundaries.
  If the fixed field boundaries are stored in a GIS, only the variable field boundaries need to be extracted from the RS data. In most areas there are a large number of (field) boundaries which can be considered as fixed, e.g. topographical boundaries.

- The shape of the fields.
  In this case study it was assumed that most fields have a rectangular shape. This knowledge was applied to construct field geometry and discard non-relevant edges. If knowledge about the field shape or other field characteristics can be formalized, it can be utilized in the ISC method.

PART III Concluding remarks

8 Concluding remarks

8 Concluding remarks

This chapter evaluates the methods applied for updating terrain object data and discusses further extensions and improvements (Sect. 8.1). Section 8.2 gives some results with respect to the aspects of data integration which were described in Chapter 3. This chapter concludes with some applications that could profit from the methods and results worked out in this thesis (Sect. 8.3).

8.1 Evaluation of the methods applied

The general objective of this thesis is to develop a methodology to:

(i) update terrain object data contained in a GIS;

(ii) from high resolution satellite data;

(iii) by applying digital interpretation techniques;

(iv) by applying additional data and knowledge.

The case studies were based on the use of a Landsat TM image, ancillary data on agricultural fields (contained in a GIS) and knowledge about the static and dynamic properties of the agricultural fields in the test area. The ancillary data applied were field boundaries and lot boundaries and the crop type grown in the preceding growing season. The knowledge applied concerned crop rotation schemes, the aggregation structure of fields and lots and the shape of the fields.
The general aims of the case studies was to extract thematic and geometrical information from the TM image to update the data contained in the GIS. The case studies were not defined from a specific application context; the results therefore give a general idea about the potential of the methods and data applied.

Sections 8.1.1-8.1.3 evaluate the results of the three case studies that are presented in Part II of this thesis. Section 8.1.4 provides a general discussion of the methodology applied.

8.1.1 Application of conditional a-priori probabilities

In this case study (see Chapt. 5) the crop type in the preceding growing season together with knowledge about crop rotation schemes was applied to improve the accuracy of pixel-based classification. This was done by treating crop rotation schemes as stochastic processes which can be formalized by transition matrices. The transition probabilities were then used as conditional a-priori probabilities in the maximum likelihood (ML) classifier. The application of conditional a-priori probabilities was expected to have a positive effect for pixels that would otherwise be classified incorrectly due to spectral confusion. The application of conditional probabilities improved the overall classification accuracy by only 2 % for the TM image consisting of bands 3, 4 and 5 when compared with a ML classification in which equal a-priori probabilities were applied: for the TM image consisting only of band 4 the overall classification accuracy was improved by 12 to 18 %. The classification improvement when applying conditional a-priori probabilities largely depends on two factors: (i) the spectral separability of the classes in the RS data applied and (ii) the information content of the a-priori probabilities.

In this case study the data and knowledge were combined by pixel-based integration which yields raster data. Therefore, it did not enable updating of the terrain object data in the GIS directly, but in an additional test, two pixel-based classification results (of TM bands 3, 4 and 5) were used as input for object-based classification:

- Input1: ML classification using equal a-priori probabilities resulting in an overall accuracy of 88 %, and
- Input2: ML classification using conditional a-priori probabilities resulting in an overall accuracy of 90 %.

Due to the errors introduced by incorrect conditional data (crop type 1986) the classification accuracy of the object-based classification using Input2 was even worse than the classification accuracy when using Input1. This can be explained by the fact that the pixels that were incorrectly classified due to the application of conditional a-priori probabilities can be found concentrated in 'fields' whereas the pixels that were correctly classified (when using conditional a-priori probabilities) can be found distributed throughout the image (see Sect. 5.3.3).

Despite the small positive effect of applying conditional a-priori probabilities such an approach should be considered if conditioning data are available. Therefore, it was investigated which type of conditioning data could possibly be used when classifying satellite images of the Netherlands.

In a large number of countries the relationship between topographical relief and the presence of natural vegetation or land use can be used. The macro-relief in the Netherlands has no significance in this respect. Alternative conditioning variables are e.g. soil type and 'ground water table class'. Keeman (1991) studied the relationship between these conditioning variables and land cover for different areas in the Netherlands. From this study it was concluded that the relationships are too vague to be used in image classification. The vague relationships can be largely explained by the effects of land consolidation projects and developments in farming as a result of which the production is more and more independent of its natural environment. Furthermore, for some areas the data contained in the soil database had been collected many years ago; this means that ground water table data were outdated for areas in which land consolidation projects have been carried out.

8.1.2 Object-based classification

In this case study (see Chapt. 6) the crop type of agricultural fields, of which the geometry is contained in a GIS, was determined from the TM image. The assumption underlying object-based classification is that one crop type is present within a field, and that this crop type can be distinguished from other crop types based on its spectral characteristics.

For object-based classification the pixels that are located within a field are identified and the crop type of the field is determined from these pixels. Boundary pixels can be excluded while processing to yield a (more) reliable classification result. Object-based classification yields a label (crop type) that is directly related to a specific agricultural field by means of the object-identifier. Object-based classification can be performed in two ways:

- 1-stage: classification of an object based on its mean DN, or
- 2-stage: determination of the mode class of the individually classified pixels.

It was shown that object-based classification provides a method to update the crop type of the agricultural fields in the test area. Furthermore, it results in a reliable classification result because it uses important spatial context information: by considering a field as a whole the classification result is only slightly affected by mixed pixels and spectral/spatial variability. For the Biddinghuizen dataset object-based classification did yield correct results for 92 % of the fields. The tests showed that the 2-stage object-based classification yielded slightly better results than the 1-stage classification.

The classification result of an object-based classification is much more reliable than the result of a pixel-based classification. A large problem in pixel-based classification are the mixed pixels (see Sect. 2.5). In a TM image of the Biddinghuizen test area 31 % of the pixels are located on a field boundary (Sect. 5.3.1). For other areas with smaller fields this figure will be even larger. When applying pixel-based classification most of these pixels will be incorrectly classified; when applying object-based classification these errors do not effect the classification result.

In general, it can be stated that the accuracy of object-based classification depends on the spectral separability of the classes considered, the accuracy of co-registration of the field geometry and image data, the accuracy of field geometry and the size and shape of the fields. If distinct spectral classes are considered, a reliable classification result is possible for fields which comprise at least one pure pixel. Depending on the orientation of the fields in the image grid this means that their minimum width should be 3 a 4 times the ground resolution. The average field size of the fields in the Biddinghuizen test area is relatively large (7 ha). For other areas with smaller (3 - 5 ha) and more irregularly shaped fields, object-based classification using one Landsat TM image acquired during the growing season did yield results with an overall classification accuracy between 75 and 85 % (Janssen *et al.*, 1990; Janssen and Van Amsterdam, 1991).

An advantage of object-based classification is that it enables the integration of multi-temporal and multi-sensor data by linking the data to the terrain objects and performing further processing at the object level. The advantage of this approach is that the pre-processing required for pixel-based data integration (resampling, filtering, IHS-transformation, etc.) is not needed.

Janssen and Keeman (1992) applied object-based classification using a SPOT XS image acquired in March and a Landsat TM image acquired in September. Per object a vegetation index class and a land cover class were determined from the

SPOT and TM image respectively. Then, per object, one final land cover class was determined from the combinations of both classes by means of a 2-dimensional look-up-table. In the same way, optical and microwave data can be integrated for classification and modelling purposes.

Another example can be found in Schotten *et al.* (in prep.) who applied 1-stage object-based classification to update crop type from an 8-date set of ERS-1 SAR images of South Flevoland. For the twelve crop types under consideration an overall classification accuracy of 80 % was achieved.

Object-based classification requires the availability of the geometry of terrain objects that are characterized by one land cover class (spectral class). Janssen and Keeman (1992) assessed the possibilities of applying object-based classification of satellite data to update the land use data of cadastral parcels stored by the Dutch Cadastre. The possibilities are very limited because of three reasons:

1 The geometry of a cadastral parcel is defined by ownership and legal status, not by land use. The land use classification scheme applied by the Cadastre therefore assumes more than one type of land use within a cadastral parcel. Separate land use codes are given for the built-up part and the other part of the cadastral parcel; if more land use types are present this is also indicated. This classification scheme does not fulfil the assumption made in the object-based classification, viz, that only one class is present within a terrain object.

2 The land use classification scheme applied by the Cadastre consists of approx. 90 classes most of which cannot be distinguished by their spectral features, e.g.: 'one-family housing' and 'multi-family housing'. Only a very limited number of classes such as 'forest', 'grassland' and 'arable land', can be distinguished using satellite RS data. But even then it should be realized that it can be very hard to distinguish between 'grassland' and 'park' on the basis of spectral features alone.

3 The size of a large part of the cadastral parcels (especially in the built-up areas) is too small to comprise even a small number of pixels from high resolution satellite data.

In some rural areas in the Netherlands, the land use of cadastral parcels could updated from remote sensing if spectral classes are considered. In that case, segmentation methods should be used first to determine if more than one class occurs within a parcel (see Chapt. 7).

The assumption underlying object-based classification is that one land cover type occurs within a terrain object. This assumption is generally valid when dealing with terrain objects (such as agricultural fields) that are defined at a low aggregation level. At a higher aggregation level more land cover types can be expected to occur within a terrain object. Huising (1993) applies an object-based approach for the classification of land use zones in the Atlantic Zone of Costa Rica. Land use zones are delineated based on visual interpretation of the spatial patterns present on aerial photographs. For each land use zone, then, the distribution of land cover classes within the zone is determined from the result of a pixel-based classification of a Landsat TM image. Based on geometrical and land cover characteristics each land use zone is assigned to a land use pattern class which is related to farming systems and land utilization. Similar to the approach applied in this thesis, Huising (1993) also departs from the terrain object geometry for which thematic data are extracted from RS data. Based on these thematic data the terrain objects are assigned to a specific class (classification).

8.1.3 Integrated segmentation and classification method

In the last case study (see Chapt. 7) both the field geometry and crop type of the agricultural fields were updated from the TM image. This was achieved by using edge detection techniques and object-based classification (ISC method). Fixed boundaries and knowledge about the aggregation structure of the lots and shape of the fields are applied to optimize information extraction. Preliminary field geometry is derived by integrating the results of an edge detection with the fixed lot boundaries. For these fields the crop type is determined by means of object-based classification. Finally, fields within a lot with similar crop types are merged to solve oversegmentation. For the Biddinghuizen test area the field geometry (field boundaries) derived by applying the ISC method corresponded for 87 % of the area with the result of a visual interpretation.

Most critical in the ISC method is that all the edges that coincide with field boundaries are detected and that all the crops that are present within the area are represented in the training data applied. Some boundaries that were clearly visible in the colour composite were not present in the (one-band) intensity image that was created for edge detection purposes. The result, therefore, could have been slightly better by combining the results of edge detection on the individual bands (see Mason *et al.*, 1988). An alternative approach for detecting boundaries is to apply both edge detection and region growing techniques (see Cheng, 1990; Schoenmakers, 1993). In that case, the fixed lot boundaries are used for an initial fragmentation of the image; subsequently within each fragment (lot) regions (fields) are determined. Knowledge about e.g. the expected number of fields per lot (based on historical data) can be used to optimize the result.

A small number of edges that coincided with field boundaries were incorrectly discarded in the integration module. This type of error can be minimized by e.g. checking the crop type on both sides of an edge with the result of a pixel-based classification. The integration of the fixed boundaries and boundaries derived from the TM image was programmed by selecting boundaries from the total sets of boundaries. This integration could have been realized more efficiently if it was programmed per lot by starting with the following topological query: 'select all edges within lot x'.

Although the ISC method has been developed on the basis of the characteristics of the Biddinghuizen test area and the TM data applied, it can be used for other agricultural areas. An important prerequisite is that the crop types under consideration can be distinguished on the basis of their spectral features and that the fields are large enough (relative to the ground resolution of the RS data applied) to enable application of segmentation techniques (see Sect. 2.6). The quality of the RS data applied may require alterations in the edge detection module (e.g. other edge detector). The rules applied in the integration module should be adapted to the landscape characteristics of the area under consideration.

Similar to object-based classification, the ISC method can be extended by a multi-temporal and multi-sensor approach in which the specific advantages of sensors are taken into account. In such an approach the field geometry can be based on SPOT data while the crop types are determined from Landsat TM and ERS SAR data.

8.1.4 General updating methodology

The object-based classification and ISC method were used to update thematic and geometrical data of terrain objects. The similarity between these methods is that they both depart from the geometrical data contained in a GIS. It is assumed that the geometrical data applied are up-to-date and accurate. Furthermore, both strategies apply knowledge about the static or dynamic properties of the terrain objects to improve and optimize information extraction.

The geometry of terrain objects makes it possible to derive a reliable thematic class from the RS data when it is known on forehand that only one (spectral) class is present within the terrain object. Thereby, the geometry provides valuable spatial context information that is used to determine the crop type of a field based on a number of pixels. In addition, boundary pixels, which are most often mixed pixels, can be neglected in the classification of the object.

The geometry of terrain objects is updated by using the terrain object boundaries that can be considered as fixed (e.g. topographical boundaries) as a starting point. Fixed, in this respect, means that it may be assumed that they do not change within the period between two updating operations. The advantages of using geometrical data as ancillary data are that:

- together with knowledge about the aggregation structure and shape of the terrain objects of interest they provide information that can be used to select relevant geometrical elements (e.g. edges), and

- they define areas which can be treated independently. This is e.g. very important when applying merging operations: merging of regions ultimately stops at the boundaries of these areas.

Both advantages are of great help in reducing error when extracting information from RS data based on the application of segmentation techniques.

8.2 Data integration

8.2.1 Level of integration

In Chapter 3 two levels of data integration were distinguished: pixel-based data integration and object-based data integration. The distinction refers to the level at which the knowledge is formalized and implemented. Object-based data integration is required for updating terrain object data contained in a GIS. In general, it is stated that object-based integration is realized by linking the results of (low level) pattern recognition to the terrain objects contained in a GIS. This is the approach in the 2-stage object-based classification (Chapt. 6) and the segmentation part of the ISC method (Chapt. 7). However, the available terrain object data can also be used at an earlier stage, as in the approach in the 1-stage object-based classification (Chapt. 6). It is, therefore, more correct to state that data integration can take place at any time during the information extraction.

Characteristic for object-based data integration is that the knowledge applied is expressed in terms of terrain objects (having geometrical and thematic characteristics). The knowledge applied in object-based classification is that only one crop type occurs within a terrain object; this knowledge was implemented by applying a statistical function (mode class). In the ISC method the knowledge about the aggregation structure and shape of the fields was formalized by rules which consider geometrical functions (distance, angle). Parameters values were set to allow small deviations in these functions. A wide variety of representations and techniques can be used to formalize knowledge. Kanal (1993, p252) states that ".... the integration of heterogeneous computational components, multiple sensors producing different types of data, and heterogeneous knowledge bases, is a significant systems design problem for which we currently have only ad-hoc techniques. Clearly more systematic methods and formalisms need to be developed for the design of complex multilevel systems consisting of heterogeneous modules performing specialized local computations while interacting with other modules at the same time and different levels of a hierarchical organization. Such interaction involves information and decisions flowing back and forth, with competition, and cooperation, all in the context of global constraint satisfaction." From the experience derived in this thesis it can also be concluded that various 'ad-hoc' methods were used for formalizing knowledge. Förstner (1993) identifies the lack of a theory for formalizing knowledge in object-based image interpretation as a key problem.

8.2.2 Spatial aspects of data integration

Co-registration

In this thesis, RS data and RS-derived results were linked with other data based on their position. This requires accurate co-registration of the RS data and the other data applied. Co-registration of the data was not an important topic because an affine transformation based on 5 to 10 GCP's was sufficient to link the geographical data with the RS data. This type of transformation was appropriate due to the flat character and relatively small size of the test area in combination with the regular geometrical characteristics of (optical) satellite data.

An alternative approach for linking geographical data is by means of relational matching (e.g. Vosselman, 1992). This technique requires a 'high level description' of the data to be matched. In other words: relational matching cannot be used to link pixels based on their grey values to agricultural fields. It has potentials, however, for linking geometrical elements (boundaries, regions) derived from RS data with other geometrical data contained in a GIS.

Vector-raster integration

Ehlers *et al.* (1989) categorize the possibilities for vector-raster integration into three levels. Most software packages can be categorized at the lowest level: separate databases for vector data and raster data, each with its own user interface; conversion programs enable the transfer of data from one system to the other. This is the level of integration of the Erdas and Arc/Info versions that were used in this thesis.

In the conversion programs available in Arc/Info (Esri, 1989a) one specific decision rule (for assigning values to raster elements) is applied. However, it can be stated that the optimal decision rule depends on the application; this means that one should be able to choose between e.g. central point or dominant unit griding for the conversion of area objects. Ideally, data conversion programs should enable a user to select a specific decision rule and allow the manipulation of decision parameters.

In 1988, we had to develop software to get area objects (polygons) stored in Arc/Info into the file format for vector data applied by Erdas. Since then, there have been significant technological developments. At present the possibilities of vector-raster integration of Erdas and Arc/Info have considerably increased. However, integrated processing using data from both databases as input is not possible with the standard software.

A very limited number of commercial software packages offer data-integration at the second level: a separate vector and raster database with full functionality, viz: *integrated spatial modelling using vector and raster data*. This means that, on the basis of co-registered raster and vector data, a function can be applied that calculates a value from the raster elements that corresponds with the vector-structured polygon; subsequently the result is stored as an attribute value for the polygon ('attribute function'). This functionality is reported to be available in the Intergraph MGE environment (Glenn *et al.*, 1993). We used routines from the Erdas-toolkit (Erdas, 1990) to write a program that enabled direct integration of vector and raster data without the need for data conversion. Still, additional programs had to be developed to link the result to the attribute table of the Arc/Info database (Kramer and Janssen, 1993).

The third and highest level of data integration consists of 'one database' comprising vector data, raster data and attribute data. The concepts for these systems still need to be developed.

8.3 Future perspectives

8.3.1 The Netherlands

In the future three 'terrain object'-oriented databases on topographical and land use data will be available for the Netherlands:

1 A land use database which has been established by the State Department for Physical Planning ('Rijks Planologische Dienst'), which mainly contains information on built-up areas.

2 A topographical database which is being established by the Topographical Survey Service (Vrijkotte, 1990); it contains all the topographical features present in the analogue map series 1:10,000 and 1:25,000.

3 A land use database which is being established by the Central Bureau of Statistics (Meuldijk, 1990) which concentrates on land use classes that are mainly found in urban areas.

The first database is derived by digitizing analogue maps whereas the other two are based on visual interpretation of aerial photographs (photo scale 1:18,000). The similarity between these three databases is that there is little differentiation between agricultural classes. In the database of the Department for Physical Planning most types of agricultural land use are in the class 'other land use'. The topographical database distinguishes between 'grassland' and 'arable land'; the land use database of the Central Bureau of Statistics has only one class 'agricultural land use' which comprises horticulture, grassland, arable land and orchards. As a result, these databases have only limited value for planning and control in agricultural regions. The usefulness of these databases can be enhanced by adding information from satellite RS data. Two approaches are possible:

- The first approach is to depart from the geometry of the terrain objects as contained in the database. In this case, the terrain objects are areas in which different types of crop or land cover can be expected. Based on the result of a pixel-based classification of RS data the land cover type(s) per terrain object can be determined and added to the database, e.g.: terrain object 807 comprises 45 % grass, 20 % forest and 35 % open water. The disadvantage of this approach is that it does not have the capability of reducing the effects of spatial and spectral variability (by determining mode class) and easy multi-temporal multi-sensor integration as in object-based classification.

- The second approach is to update the geometry, followed by object-based classification. In this way the advantages of object-based classification can be employed. The field geometry can be updated by visual interpretation (on-screen digitizing), digital interpretation (as in the ISC method) or by a hybrid approach. When compared with the first approach an additional advantage is that classification can also be based on other than spectral features, e.g. textural features.

The potential for updating is largely determined by the sensor(s) applied. The land cover types distinguished should have clear spectral (or textural) characteristics. The positional accuracy of field boundaries derived from RS data largely depends on the ground resolution of the sensors. The Netherlands Plant Protection Service requires that a minimal overlap of 3 m of potato fields in year t and year t + x is detected. This accuracy cannot be achieved using satellite RS data. In addition, the potato variety should be known: the latter can only be determined in the field. There is only a role for RS data here when aerial photographs are applied from which accurate geometrical data can be derived.

8.3.2 European Community

In the framework of the EC project Monitoring Agriculture by means of Remote Sensing (MARS) different methods are being developed. One of the methods developed provides early estimates of change from year to year in acreage and potential yield (Action 4, Rapid Estimates). The information for 53 sample sites spread throughout Europe is derived mainly from multi-temporal SPOT data. In each sample site, 16 segments (700 x 700 m^2) are selected which are visually interpreted to determine crop type and crop growth. Two problems related to this Action are (i) the spectral confusion between the crops and (ii) the costs. Spectral confusion can only be solved by adding other RS data such as Landsat TM and ERS SAR data. The integration of different sensor data can be realized by an object-based approach. From the ground documents (Perdigão, 1991) it can be concluded that the delineation of field boundaries based on segmentation techniques is difficult because of the sometimes small and heterogeneous fields. However, once the field boundaries are known, the other part of the interpretation (crop type, crop growth) can be largely dealt with by computer. As a result, the costs which incurred by the use of highly qualified personnel required to interpret the images may be reduced.

A last RS application discussed here is the control of surface-based arable and forage subsidies (EC, 1992b). As explained in the Introduction (Sect. 1.1) the Member States have to check a sample of the declarations provided by the farmers. Control of these declarations can, as an option, be assisted by using RS data. The idea is that according to the interpretation of the RS data the declarations are classified into three categories: accepted, refused or doubtful. The ground-based (on-the-spot) checks can then concentrate on the refused and doubtful declarations. In 1993 most Member States have opted to apply RS data.

The EC regulations are rather complex and comprise a large number of conditions and alternative utilizations for the areas declared for subsidy. In addition to the crop type grown in the declared area, historical land use and the destination of the yield (agricultural, industrial) are also relevant. Therefore, it can be stated that one of the elements of control is achieved by checking the crop type(s) present in the area declared on the maps. The presence and spatial distribution of the crop(s) within a field can be determined by the integration of the field boundaries and with the result of a pixel-based classification. If only one crop type occurs within the field and this crop type corresponds with the crop type indicated by the farmer, the declaration can be accepted; if more than one crop type occurs or if a crop type different from the one declared is found, the declaration is doubtful or refused depending on the extent of the discrepancy.

Although there are possibilities for applying an object-based approach it should be noted that the use of high resolution satellite RS limits the size of the fields and the types of crops which can be checked. A number of the crop types that should be distinguished have spectral overlap. Furthermore, the declared areas have a minimum size of 0.3 ha and a minimum width of 20 m; differences between actual and declared area in excess of 10 % should be detected for fields larger than 1 ha. But, even when based on visual interpretation, it will generally be impossible to determine the area of a (1 ha) field with this accuracy. Control is further complicated by the sometimes bad quality of the maps provided by the farmers. In a test carried out in 1992 it proved to be the case that inaccurate field geometry was responsible for a relatively large number of doubtful or refused declarations (SGS, 1991). In this application, accurate geometrical data (field boundaries) are a prerequisite.

Satellite RS data can be used to update thematic and geometrical data in a GIS. Although ancillary data and knowledge can effectively improve and optimize information extraction, the potential for updating largely depends on the spectral and spatial relationships between the terrain objects of interest and the RS data applied.

References

References

Aangeenbrug, R.T., 1991, A critique of GIS. *In:* Geographical Information Systems, Vol. 1, Maguire D.J., Goodchild M.F. and D.W. Rhind (eds), Longman Scientific & Technical: Harlow, England, pp 101-107.

Anuta, P.E., Bartolucci, L.A., Dean, M.E., Lozano, D.F., Maralet, E., McGillen, C.D., Valdez, J.A. and C.R. Valenzuela, 1984, Landsat-4 MSS and Thematic Mapper data quality and information content analysis. IEEE Transactions on Geoscience and Remote Sensing, Vol. 22, No. 3, pp 222-236.

Avery, T.E. and G.L. Berlin, 1985, Interpretation of arial photographs. Burgess publishing company: Minneapolis, Minnesota, 547 pp.

Baker, J.R. and J.E. Drummond, 1984, Environmental monitoring and map revision using integrated Landsat and digital cartographic data. ITC-Journal 1984, No. 1, pp 10-19.

Ballard, D.H. and C.M. Brown, 1982, Computer Vision. Prentice Hall, Englewood Cliffs, New York, 523 pp.

Benediktsson, J.A., Swain, P.H. and O.K. Ersoy, 1990, Neural network approaches versus statistical methods in classification of multisource remote sensing data. IEEE Transactions on Geoscience and Remote Sensing, Vol. 28, No. 4, pp 540-552.

Bénié, G.B. and K.P.B. Thomson, 1992, Hierarchical image segmentation using local and adaptive similarity rules. International Journal of Remote Sensing, Vol. 23, No. 8, pp 1559-1570.

Berger, J.O., 1980, Statistical decision theory; foundations, concepts and methods. Springer-Verlag, New York, 425 pp.

Bolstad, P.V. and T.M. Lillesand, 1991, Automatic GIS integration in land cover classification. Technical Papers ACSM/ASPRS Baltimore 1991, Vol. 3, pp 23-32.

Buiten, H.J., 1988, Matching and mapping of remote sensing images; aspects of methodology and quality. Proc. 16th ISPRS-Congress, Japan, 1988; Vol. 27-B10, Nr III, pp 321-330.

Buiten, H.J., 1993a, General view of remote sensing as a source of information. *In:* Land observations by remote sensing: Theory and applications. Buiten H.J. and J.G.P.W. Clevers (eds). Gordon and Breach Science Publishers, Amsterdam, the Netherlands, pp 9-26.

Buiten, H.J., 1993b, General aspects of imaging and recording of remote sensing data. *In:* land observations by remote sensing: Theory and applications. Buiten H.J. and J.G.P.W. Clevers (eds). Gordon and Breach Science Publishers, Amsterdam, the Netherlands, pp 63-88.

Buiten, H.J., 1993c, Image interpretation: visual or digital ? *In:* Land observations by remote sensing: Theory and applications. Buiten H.J. and J.G.P.W. Clevers (eds.). Gordon and Breach Science Publishers, Amsterdam, the Netherlands, pp 507- 513.

Burley, T.M., 1961, Land use or land utilization ? Professional Geographer, Vol. 13, No. 6, pp 18-20.

Castleman, K.R., 1979, Digital image processing. Prentice-Hall, Englewood Cliffs, New Jersey, 429 pp.

Catlow, D.R., Parsell, R.J. and Wyatt, B.K., 1984, The integrated use of digital cartographic data and remotely sensed imagery. Proc. Integrated approaches in remote sensing, ESA SP-214, pp 41-45.

CBS, 1992, Agricultural statistics in the Netherlands. Central Bureau of Statistics, Internal report, Voorburg, the Netherlands, 10 pp.

Chen, S.C., Bastia, G.T. and A.T. Tardin, 1986, Landsat TM combinations for crop discrimination. Proc. remote sensing for recources development and environmental management, Vol. I, pp 211-214.

Cheng, X.S., 1990, Design and implementation of an image understanding system: DADS. Technical University Delft, the Netherlands, PhD thesis, 226 pp.

Chrisman, N.R., 1989, Modeling error overlaid categorical maps. *In:* Accuracy of spatial databases, Goodchild, M.F. and S. Gopal (eds), Taylor and Francis, London, pp 21-34.

Clawson, M. and C.L. Stewart, 1965, Land use information, a critical survey of US statistics including possibilities for greater uniformity. John Hopkins press for resources for the future, Baltimore, USA.

Congalton, R.G., 1991, A review of assessing the accuracy of classification of remotely sensed data. Remote Sensing of Environment, Vol. 37, pp 35-46.

Cox, D.R. and H.D. Miller, 1965, The theory of stochastic processes. Chapman and Hall, Londen, 398 pp.

Cross, A.M., Mason, D.C. and S.J. Dury, 1988, Segmentation of remotely-sensed images by a split-and-merge process. International Journal

of Remote Sensing, Vol. 9, No. 8, pp 1329-1345.
Csornai, G., Dalia, O., Farakafalvy, F. and G. Nador, 1990, Crop inventory studies using landsat data on a large area in Hungary. *In:* Applications of remote sensing in agriculture, Stevens M.D. and J.A. Clark (eds), Butterworths, London, pp 159-166.
Davis F.W. and D.S. Simonett, 1991, GIS and remote sensing. *In:* Geographical Information Systems, Vol. 1, Maguire D.J., Goodchild M.F. and D.W. Rhind (eds), Longman Scientific & Technical: Harlow, England, pp 191-213.
DeGloria, S.D., 1984, Spectral variability of Landsat-4 Thematic Mapper and multispectral scanner data for select crop and forest cover types. IEEE transactions on Geoscience and Remote Sensing, Vol. 22, No. 3, pp 303-311.
De Hoop, S., 1993, Feature-oriented data models for GIS: concepts and potentials. Proc. 3rd Int. Users Forum, Geographical Information Systems - New Perspectives, Siemens Nixdorf Information Systems, Munich, 10 pp.
De Hoop, S. and P. Van Oosterom, 1992, Storage and manipulation in Postgres. Proc. EGIS'92, EGIS Foundation, Utrecht, the Netherlands, pp. 1324-1336.
De Hoop, S., Van Oosterom P. and M. Molenaar, 1993, Topological querying of multiple map layers. Lecture Notes in Computer Science, Springer-Verlag, Berlin, 18 pp.
Desachy, J. Zahzah, E.H. and M. Zehena, 1992, Images and geographical information systems for problem solving: a knowledge-based approach. Proc. IGARSS'92, IEEE Cat No. 92-CH3041-1, pp 1612-1624.
Droessen, W.J. and M.N. Jaarsma, 1990, Application of remote sensing in land consolidation projects. DLO-Winand Staring Centre, Rapport No. 48, Wageningen, the Netherlands, 82 pp. [in Dutch]
Duda, R.O. and P.E. Hart, 1973, Pattern classification and scene analysis. John Wiley and sons, New York, 465 pp.
EC, 1992a, Call for tender: Control of area based arable and forage subsidies using remote sensing. CEC, VI-G-4 19, Bruxelles, 19 pp.
EC, 1992b, Application of the integrated system. Publicatie-blad van de Europese Gemeenschap, Vol. 35, L3508/92. [in Dutch]
Cadastre, EFTAS and DLO-Winand Staring Centre, 1993, IRSELCAD project: Integration of remote sensing based data on environment and land use into cadastral land consolidation information. NRSP report 93-13, BCRS, Delft,

the Netherlands, 45 pp.

Ehlers, J., Edwards, G. and Y. Bédard, 1989, Integration of remote sensing with geographic information systems: a necessary evolution. Photogrammetric Engineering and Remote Sensing, Vol. 55, No. 11, pp 1619-1627.

Ehlers, J., Greenlee, D., Smith, T. and J. Star, 1991, Integration of remote sensing and GIS: data and data access. Photogrammetric Engineering and Remote Sensing, Vol. 57, No. 6, pp. 669-675.

Ehlers, J., 1993a, Developments in remote sensing: techniques and applications. Proc. IAPR TC7 workshop, Dept Land Surveying & Remote Sensing, Wageningen Agricultural University, Wageningen, the Netherlands, pp 55-64.

Ehlers, J., 1993b, Conclusive remarks to the workshop. Proc. IAPR TC7 workshop, Dept Land Surveying & Remote Sensing, Wageningen Agricultural University, Wageningen, the Netherlands, pp 243-245.

Epema, G.F., 1987, New information of second generation Landsat satellites for agricultural applications in the Netherlands. Netherlands Journal of Agricultural Sciences, No. 35, pp 497-504.

Erdas, 1991, Erdas Field Guide, Version 7.5, July 1991, Atlanta GA, USA, 394 pp.

Erdas, 1990, Software Toolkit Manual; Toolkit Routines, Volumes I & II, Version 7.4, Atlanta GA, USA, 412 pp.

Esri, 1989a, Arc/Info, Volumes I & II, Version 5.0, Redlands CA, USA.

Esri, 1989b, Arc/Info, ARC Macro Language and User Interface Tools, Version 5.0, Redlands CA, USA.

Eurostat, 1990, Agriculture statistical yearbook, European Communities, Luxembourg CA-57-89-637-5E-C, 262 pp.

FAO, 1981, Soil map of the world 1 : 5,000,000, Vol. V, Europe. Unesco, Paris, 199 pp.

Förstner, W., 1993, A future for photogrammetric research. NGT Geodesia, No 8, pp. 372-383.

Gerbrands, J.J., 1988, Segmentation of noisy images. Technical University Delft, the Netherlands, PhD thesis, 170 pp.

Glenn, D., Compton, B. and P. Crosbie, 1993, Dynamic integration of spatially referenced data independent of data source format. Intergraph, Huntsville, USA, Internal report, 10 pp.

Gong, P. and P.J. Howarth, 1992, Land-use classification of SPOT HRV data using a cover-frequency method. International Journal of Remote Sensing, Vol. 13, No. 8, pp 1459-1471.

Grunblatt, J., 1987, An MTF analysis of Landsat classification error at field boundaries. Photogrammetric Engineering and Remote Sensing, Vol. 53, No. 6, pp 639-643.

Hepner, G.F., Logan T., Ritter N. and N. Bryant, 1990, Artificial neural network classification using a minimal training set: comparison to a conventional supervised classification. Photogrammetric Engineering and Remote Sensing, Vol. 56, No. 4, pp 469-473.

Hoogeboom, P., 1983, Classification of agricultural crops in radar images. IEEE Transactions on Geoscience and Remote Sensing, Vol. 21, No. 3, pp 329-336.

Huising, E.J., 1993, Land use zones and land use patterns in the Atlantic Zone of Costa Rica, Wageningen Agricultural University, the Netherlands, PhD thesis, 222 pp.

Hutchinson, C.F., 1982, Techniques for combining Landsat and ancillary data for digital classification improvement. Photogrammetric Engineering and Remote Sensing, Vol. 48, No. 1, pp 123-130.

Janssen, L.L.F. and H. Middelkoop, 1991, Knowledge based image classification; the use of knowledge about crop rotations in a Thematic Mapper image classification procedure. DLO-Winand Staring Centre, Report 40, 71 pp.

Janssen, L.L.F. and H. Van Amsterdam, 1991, An object based approach to the classification of remotely sensed images. Proc. IGARSS'91, Vol. IV, IEEE Cat. Number 91CH2971-0, pp 2192-2195.

Janssen, L.L.F. and D.M. Keeman, 1992, Integrated use of cadastral ownership boundaries and remote sensing for land inventory purposes. NRSP report 92-16, BCRS, Delft, the Netherlands, 38 pp.

Janssen, L.L.F. and H. Middelkoop, 1992, Knowledge-based crop classification of a Landsat TM image. International Journal of Remote Sensing, Vol. 13, No. 15, pp 2827-2837.

Janssen, L.L.F. and F.J.M. Van der Wel, 1993, Accuracy assessment of satellite derived land cover data: a review. Photogrammetric Engineering and Remote Sensing, accepted for publication.

Janssen, L.L.F., Jaarsma. M.N. and E.T.M. Van der Linden. 1990, Integrating topographic data with remote sensing for land-cover classification. Photogrammetric Engineering and Remote Sensing, Vol. 56, No. 11, pp 1503-1506.

Jeon, B. and Landgrebe, D.A., 1992, Classification with spatio-temporal interpixel class dependency contexts. IEEE Transactions on Geoscience and Remote Sensing, Vol. 30, No. 4, pp 663-672.

Kanal, L.N., 1993, On pattern, categories and alternate realities. Pattern Recognition Letters, Vol. 14, No. 3, pp 241-255.

Keeman, D.M., 1991, Using ground water table classes for improving image classification. Dept of Land Surveying and Remote Sensing, Wageningen Agricultural University, the Netherlands, MSc-thesis, 39 pp. [in Dutch]

Kenk, E., Sondheim, M. and B. Yee, 1988, Methods for improving accuracy of Thematic Mapper ground cover classifications. Canadian Journal of Remote Sensing, Vol. 14, No. 1, pp 429-441.

King Liu, J.J., 1986, A GIS based image processing system for agricultural purposes. Proc. RS for Resources Development and Environmental Management, Enschede, August 1986, pp 27-29.

Kirchhof, W., Mauser, W. and H.J. Stiebig, 1985, Untersuchung des informations gehaltes von Landsat Thematic Mapper und SPOT Mulitiband-Bilddaten des Gebietes Freiburg, DFVLR Forschungsbericht DFVLR-FB 85-49, Koln, Germany.

Kramer, H. and L.L.F. Janssen, 1993, Updating a GIS from remote sensing data. Proc. Erdas User Group Meeting 1993, Erdas, Atlanta, USA, 10 pp.

Kutch Lojenga, F.J. and D. Meuldijk, 1992, Developments towards spatial statistics in Europe. Proc. 'The impact of remote sensing on the european statistical information system', CBS, Voorburg, the Netherlands, 15 pp.

Laurini, R. and D. Thompson, 1993, Fundamentals of spatial information systems. Academic Press, London, England, 672 pp.

Lee, T., Richards, J.A. and Swain, P.H., 1987, Probabilistic and evidential approaches for multisource data analysis. IEEE Transactions on Geoscience and Remote Sensing, Vol. 25, No. 3, pp 283-293.

Lemmens, M.J.P.M. and C.S.L.A. Han, 1990, Automized thematic interface of digital spatial imagery and geographical information systems. Int. Arch. of Photogrammetry and Remote Sensing, Vol. 28, 3/2, Comm. III, pp 395-404.

Lillesand, T.M. and R.W. Kiefer, 1987, Remote sensing and image interpretation. John Wiley & Sons, New York, 721 pp.
Lippe, E., De Smith, J.T. and D.C. Glenn-Lewin, 1985, Markov models and succession: a test from a heathland in the Netherlands. Journal of Ecology, No. 73, pp 775-791.
Lunetta, R.S., Congalton, R.G., Fenstermaker, L.K., Jensen, J.R., McGwire, K.C. and L.R. Tinney, 1991, Remote sensing and geographic information system data integration: error sources and research issues. Photogrammetric Engineering and Remote Sensing, Vol. 57, No. 6, pp 677-687.
Lynn-Usery, E.L. and R. Welch, 1991, A raster approach to topographic map revision. Photogrammetric Engineering and Remote Sensing, Vol. 55, No. 1, pp 55-59.
Maguire, D.J., 1991 An overview and definition of GIS. *In:* Geographical Information Systems, Vol. 1, Maguire D.J., Goodchild M.F. and D.W. Rhind (eds), 1991, Longman Scientific & Technical: Harlow, Engeland, pp 9-20.
Markham, B.L. and J.R.G. Townshend, 1981, Land cover classification accuracy as a function of sensor spatial resolution. Proc. 15th Int. Symp. on RS of Environment, Vol. 3, pp 1075-1090.
Mason, D.C., Orr, D.G., Cross, A., Hogg, D.C., Lawrence, D.H., Petrou, M. and A.M. Tailor, 1988, The use of digital map data in the segmentation and classification of remotely-sensed images. International Journal of Geographical Information Systems, Vol. 2, No. 3, pp 195-215.
Massom, R., 1991, Satellite remote sensing of polar regions; applications, limitations and data availability. Lewis Publishers, Boca Raton, Florida, 307 pp.
Mather, P.H., 1990, Theoretical problems in image classification. *In:* Application of RS in agriculture, Clark, J.A. and M.D. Steven (eds), 1990, Butterworths, London, UK, pp 127-135.
Meuldijk, D., 1990, Land use statistics in the Netherlands: a start with a GIS approach. Internal report CBS, Voorburg, the Netherlands, 4 pp.
Meyer, P., 1992, Segmentation and Symbolic description for a classification of agricultural areas with multispectral scanner data. IEEE Transactions on Geoscience and Remote Sensing, Vol. 30, No. 4, pp 673-679.
Middelkoop, H., 1990, Uncertainty in a GIS: a test for quantifying interpretation output. ITC Journal 1990, No. 3, pp 225-232.

Molenaar, M., 1989, Single valued vector maps - a concept in geographic information systems. Geo Information Systems, Vol. 1., No. 2, pp 18-26.

Molenaar, M., 1991, Terrain objects, data structures and query spaces. In Geo-informatik, Schilcher, M. (ed), Munich, Germany, pp 53-70.

Molenaar, M., 1993, Object-hierarchies, why is data standardisation so difficult. Geo Information Systems, Vol. 6, Nr 4, pp 22-28.

Molenaar, M. and D. Fritsch, 1991, Combined data structures for vector and raster representations in geographic information systems. Geo Information Systems, Vol. 4, No. 4 pp 26-32.

Molenaar, M. and L.L.F. Janssen, 1993, Terrain objects, their dynamics and their monitoring by the integration of GIS and remote sensing. Invited Paper Proc. IGARSS'93, in press.

Moller-Jensen, L., 1990, Knowledge-based classification of an urban area using texture and context information in Landsat-TM imagery. Photogrammetric Engineering and Remote Sensing, Vol. 56, No. 6, pp 899-904

Moore, H.D., 1989, SPOT versus Landsat TM for the maintenance of topographical databases. Journal of Photogrammetry and Remote Sensing, Vol. 44, pp 72-84.

Mücher, C.A., Stomph, T.J. and L.O. Fresco, 1992, A concept for a global land use classification. Dept. of Agronomy, Wageningen Agricultural University, Wageningen, The Netherlands, 20 pp.

Nieuwenhuis, G.J.A. and C.G.J. Schotten, 1993, Land cover monitoring with multi-temporal ERS-1 SAR observations in the Netherlands. Proc. First ERS-1 Symposium, ESA SP-359, pp 527-531.

Pedley, M.I. and P.J. Curran, 1991, Per-field classification: an example using SPOT HRV imagery. International Journal of Remote Sensing, Vol. 12, No. 11, pp 2181-2192.

Perdigão, V., 1991, Ground survey documents based on high resolution satellite imagery 1990 campaign. JRC, Ispra, SPI 91.29, 95 pp.

Peuquet, D.J. 1984, A conceptual framework and comparison of spatial data models. Cartographica, Vol. 21, No. 4, pp 66-113.

Price, J.C., 1984, Comparison of the information content of data from Landsat-4 Thematic Mapper (TM) and Multi-spectral Scanner (MSS). IEEE Transactions on Geoscience and Remote Sensing, Vol. 22, No. 3, pp 272-281.

Rengers, N., Soeters. R. and C.J. Van Westen, 1992, Remote sensing and GIS applied to mountain hazard mapping. Episodes, Vol. 15, No. 1. pp 36-45.

Rhind, D.W. and R. Hudson, 1980, Land use. Methuen, New York, 266 pp.

Sanchez, R.D., 1991, Personal computer assisted change detection for 1:50,000 scale map revision in Mexico using satellite data. Technical Papers ACSM/ASPRS, Baltimore 1991 Annual Convention, Vol. 3, pp 389-395.

Schoenmakers, 1993, Automatic field boundary extraction in optical remotely sensed imagery by a hybrid segmentation method. Proc. IAPR TC7 workshop, Dept Land Surveying & Remote Sensing, Wageningen Agricultural University, Wageningen, the Netherlands, pp 171-181.

Schotten, C.G.J., Van Rooy, W.W.L. and L.L.F. Janssen, in prep., Assessment of the capabilities to discriminate agricultural crops from multi-temporal ERS-1 SAR data. Submitted for publication in Photogrammetric Engineering and Remote Sensing.

Schowengerdt, R.A., 1983, Techniques for image processing and classification of remote sensing. Academic Press, London, 249 pp.

SGS, 1992, Remote sensing applied to oilseed control in the Netherlands; selection of declarations and provision of support documents for field inspections. Technical Report, SGS Geosys, Twello, the Netherlands, 80 pp.

Sharifi, M.A., 1992, Development of an appropriate resource information system to support agricultural management at farm enterprise level. Wageningen Agricultural University, the Netherlands, PhD thesis, 217 pp.

Simonett, D.S., Reeves, R.G., Estes, J.E., Bertke, S.E. and C.T. Sailer, 1983, The development and principles of remote sensing. *In:* Manual of remote sensing, Colwell (ed.), American society of Photogrammetry, Falls Church, Virginia, pp 1-32.

Skidmore, A.K., 1989, An expert system classifies eucalypt forest types using thematic mapper data and a digital terrain model. Photogrammetric Engineering and Remote Sensing, Vol. 55, No. 10, pp 1449-1464.

Stakenborg, J.H.T, 1986, Per-field classification of a segmented SPOT simulated image. Proc. Remote Sensing for Resources Development and Environmental Management, Enschede, pp 73-78.

Steven, M.D. and J.A. Clark, 1990, Applications of remote sensing in agriculture. Butterworths, London, 404 pp.

Stomph, T.J. and L.O. Fresco, 1991, Describing agricultural land use. Dept of

Tropical Crop science, Wageningen Agricultural University, the Netherlands, 30 pp.
Strahler, A. H., 1980, The use of prior probabilities in maximum likelihood classification of remotely sensed data. Remote Sensing of Environment, No. 10, pp 135-163.
Strahler, A.H., Woodcock, C.E. and J.A. Smith, 1986, On the nature of models in remote sensing. Remote Sensing of Environment, No. 20, pp 121-139.
Swain, P.H., Davis, S.M., 1978, Remote Sensing: the quantative approach. McGraw Hill, New York, 396 pp.
Swann, R., Hawkins, D., Westwell-Roper, A. and W. Johnstone, 1988, The potential for automated mapping from geocoded digital image data. Photogrammetric Engineering and Remote Sensing, Vol. 54, No. 2, pp 187-193.
Thunnissen, H.A.M., Olthof, R., Getz, P. and L. Vels, 1992, Land use database of the Netherlands based on Landsat TM data, DLO-Winand Staring Centre, Wageningen, the Netherlands, Rapport 168, 225 pp. [in Dutch]
Thunnissen, H.A.M., Van den Boogaard, P.J. and H.P.T Ullenbroeck, 1993, Operational land cover classification in the Netherlands using satellite images and other geographical information. Proc. Operationalization of remote sensing, Vol. 3, ITC, Enschede, the Netherlands, pp 9-20.
Tomppo, E., 1987, An application of a segmentation method to the forest stand delineation and estimation of stand variates from satellite images. Proc. 5th Scandinavian conference on image analysis, IAPR, Vol.1, pp 253-260.
Ton, J., Sticklen, J. and A.K. Jain, 1991, Knowledge-based segmentation of Landsat images. IEEE Transactions on Geoscience and Remote Sensing, Vol. 29, No. 2, pp 222-232.
Tosselli, F. and J. Meyer-Roux, 1992, Proc. Application of remote sensing to agricultural statistics. EC, Luxembourg, EUR 14262, 380 pp.
Townshend, J.R.G., 1984, Agricultural land cover discrimination using Thematic Mapper spectral bands. International Journal of Remote Sensing, Vol. 5, No. 4, pp 681-698.
Townshend, J.R.G. and C. Justice, 1981, Information extraction from remotely sensed data; a user view. International Journal of Remote Sensing, Vol. 2, No. 4, pp 313-329.
Turner, M.G., 1987, Spatial simulation of landscape changes in Georgia: a

comparison of 3 transition models. Landscape Ecology, Vol. 1, No. 1, pp 29-36.

Van Cleynenbreugel, J., Fierens, F., Suetens, P. and A. Oosterlinck, 1990, Delineating road structures on satellite imagery by a GIS-guided technique. Photogrammetric Engineering and Remote Sensing, Vol. 56, No. 6, pp 893-898.

Van Cleynenbreugel, J., 1991, Tapping multiple knowledge sources to delineate road networks on high resolution satellite images. Catholic University Leuven, Belgium, PhD thesis, 141 pp.

Van der Knaap, W.G.M., 1992, The vector to raster conversion: (mis)use in geographical information systems. International Journal Geographical Information Systems, Vol. 6, No. 2, pp 159-170.

Van der Laan, F.B., 1988, Improvement of classification results from a satellite image using context information from a topographic map. Proc. 16th ISPRS-congress, Vol. 27, B8, Cie 7, pp 98-108.

Van der Waal, P.A.M., 1993, personal communication.

Van Hulst, R., 1979, On the dynamics of vegetation: Markov chains as models of succession. Vegetatio, Vol. 40, No. 1, pp 3-14.

Van Kleef, H.A. and Th. J. Linthorst, 1986, Geographic information for land-use management. Netherlands Journal of Agricultural Science, No. 34, pp 329-338.

Van Langen, J., 1988, Summary of the crops planted by the farms in East Flevoland; time serie 1965-1985. RIJP report 1988-30cbw, Lelystad, 102 pp. [in Dutch]

Veregin, H., 1989a, Error modeling for the map overlay operation. *In:* Accuracy of spatial databases, Goodchild, M.F. and S. Gopal (eds), Taylor and Francis, London, pp 3-18.

Veregin, H., 1989b, Accuracy of spatial databases: annotated bibliography. Technical paper 89-9, NCGIA, University of California, Santa Barabara, USA, 108 pp.

Vijlbrief, T. and P. Van Oosterom, 1992, The GEO++ system: an extensible GIS. Proc. 5th International Symposium on spatial data handling, IGU Commission on GIS, Charleston, South Carolina, pp 40-50.

Vrijkotte, G.A.M., 1990, Production methods for topographical databases. NGT Geodesia, No. 9, pp 365-368. [in Dutch]

Welch, R., Jordan, T.R. and J. Ehlers, 1985, Comparative evaluations of the geodetic accuracy and cartographic potential of Landsat-4 and Landsat-5 Thematic Mapper image data. Photogrammetric Engineering and Remote Sensing, Vol. 51, No. 9, pp 1249-1262.

Wilkinson, G.G. and J. Mégier, 1990, A belief function approach for using GIS derived spatial context in satellite image understanding. Proc. EGIS'90, EGIS-foundation, Utrecht, the Netherlands, pp 1154-1163.

Wilkinson, G.G., Folving, S., Fullerton, K. and J. Mégier, 1992, A feasibility study on the automatic updating of the CORINE Land Cover database using satellite imagery in Portugal. Proc. EGIS'92, EGIS-foundation, Utrecht, the Netherlands, pp 1345-1354.

Zhuang, X., Engel, B.A., Baumgardner, M.F. and P.H. Swain, 1991, Improving classification of crop residues using digital land ownership data and Landsat TM imagery. Photogrammetric Engineering and Remote Sensing, Vol. 57, No. 11, pp 1487-1492.

Samenvatting

Samenvatting

Geografische Informatie Systemen (GIS) worden gebruikt voor het opslaan, analyseren en weergeven van ruimtelijke informatie. Meestal wordt gekozen voor een benadering waarbij geometrische (positie, vorm, oppervlak) en thematische (eigenaar, bodemtype, gebruik) kenmerken van terreinobjecten worden opgeslagen. Voorbeelden van terreinobjecten zijn: een perceel, een huis en een weg. Door menselijk handelen veranderen de geometrische en thematische kenmerken van de terreinobjecten in de loop van de tijd. De gegevens in het GIS moeten dan worden bijgewerkt (geactualiseerd). Afhankelijk van het type dynamiek van de terreinobjecten moeten de geometrische of thematische kenmerken of beide worden geactualiseerd. Verschillende technieken (landmeten, interpretatie van luchtfoto's en satellietopnamen) zijn te gebruiken de actualisatie.

Dit proefschrift behandelt de mogelijkheden voor gegevensactualisatie op basis van satelliet Remote Sensing (RS) gegevens met betrekking tot landbouwpercelen. Een steeds groter aantal satellieten voor aardobservatie levert gegevens die gebruikt kunnen worden voor actualisatiedoeleinden. De interpretatie van satellietgegevens kan plaatsvinden door middel van visuele interpretatie; er kan ook gebruik gemaakt worden van digitale interpretatietechnieken. Deze laatste zijn gebaseerd op een groot aantal classificatie- en segmentatie-rekenregels (algoritmen).

De mogelijkheden van digitale interpretatie van satelliet RS opnamen zijn beperkt door de complexiteit van beelden van het aardoppervlak. Voor ons is het veelal eenvoudig om de begrenzing van een agrarisch perceel aan te geven. De ruimtelijke variatie binnen een perceel en enkele onderbrekingen in de begrenzing zijn voor ons waarnemingssysteem niet storend. Bij digitale interpretatie ondervindt men hiervan wel hinder. Een ander probleem is dat de grondresolutie (pixelgrootte) van de toegepaste RS-gegevens vaak te grof is om een begrenzing nauwkeurig te bepalen. Meestal wordt daarom een pixelgewijze classificatie uitgevoerd wat resulteert in een rasterbestand waarvan elk element aan een bepaalde klasse (gewastype) is toegewezen. De pixelgewijze benadering resulteert niet in een expliciete beschrijving van terreinobjecten (in dit geval percelen) en heeft een beperkte classificatienauwkeurigheid.

Actualisatie impliceert dat relevante gegevens aanwezig zijn maar dat deze wellicht zijn achterhaald. Daarnaast is vaak bekend wat de aard van de te verwachten veranderingen is. Het idee dat ten grondslag ligt aan dit proefschrift is om reeds aanwezige gegevens en kennis te gebruiken om de informatie-extractie uit de RS-gegevens te optimaliseren waarbij gebruik wordt gemaakt van digitale interpretatietechnieken.

In dit proefschrift zijn drie interpretatiemethoden beschreven:

- kennisgebaseerde pixelgewijze classificatie;
- objectgewijze classificatie;
- objectgewijze segmentatie en classificatie.

De methoden getest met een gegevensset voor het landbouwgebied rondom Biddinghuizen (Oostelijk Flevoland). In een GIS zijn gegevens over de perceelsgrenzen en het gewastype van een aantal opeenvolgende jaren opgeslagen. Actualisatie van dit bestand vond plaats aan de hand van een Landsat Thematic Mapper (TM) opname.

Kennisgebaseerde pixelgewijze classificatie

In de eerste methode is het gewastype voorafgaand aan het jaar van de TM-opname tezamen met kennis over gewasrotaties gebruikt om de nauwkeurigheid van een pixelgewijze classificatie te verbeteren. De kennis over gewasrotaties houdt in dat er slechts een beperkt aantal mogelijke gewasopvolgingen zijn. Het bleek dat met deze methode de nauwkeurigheid in lichte mate verbeterde, afhankelijk onder andere van het aantal mogelijke gewasopvolgingen. Omdat deze methode de gegevens en kennis door middel van een pixelgewijze classificatie integreert, is het resultaat een rasterbestand waarin terreinobjecten niet expliciet zijn beschreven. Een direct verband met percelen (in het GIS) ontbreekt. Daarom heeft geen actualisatie van het gewastype plaatsgevonden. In de twee volgende behandelde methoden is dat wel het geval.

Objectgewijze classificatie

De objectgewijze classificatie bepaalt op basis van de perceelsgrenzen (aanwezig in een GIS) het gewastype uit de RS-gegevens en koppelt het resultaat ervan als thematisch gegeven aan het perceel in het gegevensbestand van het GIS. Daartoe worden per perceel de pixels bepaald die zich binnen de perceelsgrenzen bevinden.

Pixels die zich op de rand van een perceel bevinden hebben vaak een storend effect en worden daarom uitgesloten. Objectgewijze classificatie geeft betrouwbare resultaten indien meer pixels geheel binnen het perceel vallen en de te onderscheiden gewassen spectraal duidelijk zijn te onderscheiden.
Objectgewijze classificatie vereist wel dat perceelsgrenzen reeds in het GIS aanwezig zijn. In zijn algemeenheid kan een onderscheid gemaakt worden tussen vaste en variabele perceelsgrenzen. Vaste perceelsgrenzen vallen vaak samen met (reeds bekende) topografische grenzen. Actualisatie van de perceelsgeometrie moet zich dan met name richten op de variabele perceelsgrenzen.

Objectgewijze segmentatie en classificatie
Om de perceelsgeometrie te actualiseren is een methode ontwikkeld die is gebaseerd op een combinatie van segmentatie en classificatie. In de TM-opname wordt een maximaal aantal relevante grenzen bepaald via grensdetectie. De gevonden grenzen worden vervolgens op basis van geometrische relaties (hoek, afstand) met de reeds aanwezige vaste grenzen in het GIS gecombineerd tot percelen. De kennis over de vorm van de percelen wordt gebruikt om niet-relevante grenzen te verwerpen. Vervolgens wordt per perceel het gewas bepaald door een objectgewijze classificatie. Grenzen die geen gewasgrens zijn maar het gevolg zijn van bijvoorbeeld verschillen in zaaidatum zijn niet relevant en worden in de laatste fase verwijderd.
Deze methode voor het actualiseren van perceelsgrens en gewastype kan worden toegepast voor gebieden waarvoor (vaste) grenzen en kennis over de aard van de landschapsstructuur (verkaveling, vorm percelen) bekend zijn. De spectrale informatie die aanwezig is in de RS-opname bepaalt voor een groot gedeelte van welke gewassen perceelsgrenzen kunnen worden gedetecteerd; de grondresolutie bepaalt voor een groot gedeelte de minimale perceelsgrootte waarvoor grenzen kunnen worden gedetecteerd.

Een overeenkomst tussen beide objectgewijze methoden is dat de gegevensverwerking op objectniveau plaatsvindt: kennis wordt op objectniveau (perceel) geformuleerd en geformaliseerd. Interpretatie van de RS-opname resulteert dan in informatie die direct gekoppeld is aan terreinobjecten. Een bijkomend voordeel van een objectgewijze benadering is dat het relatief eenvoudig is om RS-opnamen van verschillende tijdstippen en sensoren te combineren. De methoden en ervaringen die zijn gepresenteerd in dit proefschrift kunnen bijvoorbeeld worden gebruikt reeds bestaande gegevensbestanden te actualiseren en aan te vullen.

Curriculum vitae

Lucas Lodewijk Franciscus Janssen was born in 's-Hertogenbosch, the Netherlands, at 20 september 1962. In 1980 he finished secondary education at the Peelland College in Deurne and started his study at the Wageningen Agricultural University (WAU). He graduated in 1987 majoring in land use and remote sensing. Part of this study was an internship at the Hydrology Laboratorium of the US Department of Agriculture in Beltsville, Maryland.

From 1987 to 1988 he worked as a research assistant at the Department of Surveying and Remote Sensing of WAU. This period was mainly spent on programming a PC-based image processing package and counselling students. In 1988 he started his PhD research at the WAU on the integrated use of remote sensing data and other geographical data. In this period he was seconded to the Remote Sensing Department of the DLO Winand Staring Centre that funded the research. Because of the interests and experience of the Winand Staring Centre the research was directed towards land inventory applications. An information analysis with respect to the use of remote sensing data for environmental research was carried out in 1992 for the National Institute for Public Health and Environmental Protection.

Presently he holds the position of 'Consultant RS & GIS' at the Survey Department of the Ministry of Transport, Public Works and Water Management in Delft, the Netherlands.