Assessment and visualisation of uncertainty in remote sensing land cover classifications

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Assessment and visualisation of uncertainty in remote sensing land cover classifications

Afleiding en visualisatie van onzekerheden in remote sensing landbedekkingsclassificaties

(met een samenvatting in het Nederlands)

PROEFSCHRIFT

TER VERKRIJGING VAN DE GRAAD VAN DOCTOR
AAN DE UNIVERSITEIT UTRECHT,
OP GEZAG VAN DE RECTOR MAGNIFICUS PROF.DR. H.O.VOORMA,
INGEVOLGE HET BESLUIT VAN HET COLLEGE VOOR PROMOTIES
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Promotores: Prof. Dr. F.J. Ormeling
Faculteit Ruimtelijke Wetenschappen, Universiteit Utrecht

Prof. Ir. N.J. Mulder
Faculteit Elektrotechniek, Universiteit Twente

Het onderzoek dat verricht werd voor de totstandkoming van dit proefschrift is mede gefinancieerd door de Beleidscommissie Remote Sensing (BCRS), Delft

In memory of Els van der Wel-Veerkamp,
my mother,
who learned me not to give up easily

We're starting up a brand new day - Sting

Voorwoord

Met het beëindigen van het proefschrift is mijn interesse in het thema, de kwaliteit van ruimtelijke gegevens, nog even groot als bij aanvang van het onderzoek. Dat begin werd gekenmerkt door mijn afstudeerstage in 1990 bij de Rijksplanologische Dienst, afdeling Informatievoorziening, destijds gevestigd in een statig gebouw in hartje Zwolle. Vooral op basis van literatuurstudie en gesprekken met medewerkers probeerde ik een vinger te krijgen achter het fenomeen "onzekerheid". Achteraf zou blijken dat hier de basis werd gelegd van mijn wetenschappelijke carrière. Veel mensen hebben *de onderzoeker in mij* aangemoedigd en dit is de juiste plaats om hiervoor mijn dank te betuigen.

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Table of contents

List of figures

List of tables

List of appendices

1 Introduction

"...Like the Sorcerer's Apprentice, we are awash in information.
And all the Sorcerer has left us is a broom..."

Neil Postman (1992) - "Technopoly"

1.1 Technology changes cartography

Since its very beginning, mankind has tried to fathom the *why* and *wherefore* of its surroundings. Over time, the physical appearance of planet Earth has been unveiled bit by bit, while the processes that affect its dynamic nature have been subjected to complex spatio-temporal modelling. Maps have always played an important role in the ongoing search for more spatial understanding: *"maps serve as a visual shorthand for how we conceptualise and integrate the unknown"* (Hall, 1993). From the oldest map of an inhabited site - the Bedolina map assumed to be between 3500 and 4000 years old (Thrower, 1996) - to the satellite image mosaics of our modern times, these representations all express the *status quo* of techniques that help to spatially summarise and visually communicate data about specific earthbound themes. Chrisman (1982b) states it more poetically: *"... any map is a fossil, reflecting the technology used in its production..."* Techniques have changed the art and science of mapmaking or, as Stephen Hall (1993) puts it, *"...instrumentation has been the silent partner of all cartographic revolutions..."*

The very first developments in map printing marked the beginning of the *"democratisation of access to maps"* (Kraak & Ormeling, 1996) because of the ability to reach a wider audience by producing multiple copies in a short period of time. Likewise, the first aerial photograph shot by Gaspard-Félix Tournachon ("Nadar") in 1858 ushered in a new era of data acquisition for topographic mapping (Strain & Engle, 1992). Reconnaissance from space was preceded by the first flight ever of a satellite, the Russian Sputnik in 1957, and followed by the beginning of systematic earth observation by the American Tiros-1 weather satellite in 1960. These technological milestones in the history of remote sensing have left their mark on cartographic practice, not the least because of the dramatic impact of the bird's-eye views providing so much data at a glance. Also, the relevance of the large-scale introduction of computers since the 1970s is beyond all doubt. The impact of these technological and inherent organisational developments on the collection, storage, processing and presentation of spatial data has given rise to a computer-assisted cartography that is still evolving.

Primarily, these technological issues alone are of minor importance as far as the determination of new directions in cartography is concerned (Taylor, 1991), but it would be unwise to deny their catalytic effect on the development of the discipline. It is true that a disproportionate emphasis on technique could disturb the conceptual basis for cartography as presented and revised by Taylor (1996) and depicted in figure 1.1. Understanding the consequences of this "technology-shift" requires knowledge of the advancements in areas that have an undeniable impact on cartography - remote sensing, GIS and computer science.

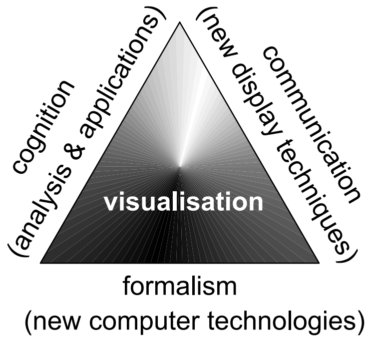


Figure 1.1: A conceptual basis for cartography (after Taylor, 1991)

1.2 The information revolution and the digital decade

Cartography concerns the conveyance of spatial information by means of maps (Kraak & Ormeling, 1996) or as Taylor (1991) defines it more elaborately: "*...the organisation, presentation, communication and utilisation of geo-information in graphic, digital or tactile form. It can include all stages from data preparation to end use in the creation of maps and related spatial information products...*"

Although this definition leaves room for some confusion concerning the concepts of map and related products (Vasiliev *et al.* (1990) deal with the question *"what is a map?"*), it touches upon an important issue that could lead to misunderstanding. Geo-information covers a subset of spatial information, and strictly spoken its cartography can be pin-pointed as terrestrial cartography as opposed to the much wider definition used by Hall (1993) in his essay "*Mapping the next Millennium"*. To avoid any ambiguity, the use of the term cartography in this thesis is "restricted" to the geographic domain.

Geo-information relates to meaningful data about earthbound objects, that therefore include a reference to position and topological connections in addition to attributes (Burrough & McDonnell, 1998). In other words, it describes the place of an object in the geographical space by means of some coordinate system, its qualitative and quantitative appearances and the way in which it is linked with other objects in terms of adjacency, proximity and connectivity. Grimshaw (1994) expresses himself in concrete terms by defining the questions *"where is it?"*, *"what is it?"* and *"what is its relationship to other spatial features?"* respectively.

Geo-information occupies a key-position in the cartographic discipline and constitutes the core of many decision-making strategies. Grimshaw (1994) quotes a study by Moloney *et al.* (1993) who states that 90% of business data is geographical. In the Netherlands, such numbers seem to hold only for utility companies as pointed out by Van der Beek *et al.* (1995). The availability of geo-information is undoubtedly improving increasingly, and the dimensions of the accompanying data flow are so impressive that the notion of an information revolution is by no means exaggerated. Advancements in computer development have created the preconditions for the introduction of Geographical Information Systems (GIS), which have made both new and existing data sets accessible in a systematic way. Remote sensing techniques have really caused a flood of data that is likely to swell even more in the near future. Hall (1993) foresees a huge amount of data stemming from NASA's Earth Observing System (EOS) whose first satellite, Terra, was successfully launched on December 18, 1999. According to NASA, the constellation of satellites within the EOS program will eventually generate 1 to 2 Terabytes of data per day!

Computers as part of cartographic practice not only allow us to control such data volumes, they facilitate tasks that used to be labour-intensive, practically unfeasible or even impossible before their advent. As an example of the latter, think of the nearly continuous flow of digital remotely sensed data that require some computer processing before being represented as a map. Taylor (1991) calls the 1990s the Digital Decade because of the impact that automation exerts on several geo-disciplines, including cartography. As this automation proceeds, different cognate disciplines and techniques influence each other as well and their interrelations have been the subject of many discussions. Maguire (1991) for example elucidates the relationships between computer cartography, remote sensing, GIS, database management and computer-aided design (CAD). Although being discussed thoroughly in chapter 2, these positioning schemes of disciplines and techniques seem to be a reflection of clashing interests and conflicting claims. It is far more interesting (and probably more productive as well) to consider **if** and **to what extent** spatial concepts need to be redefined as a result of the amalgamation of digital techniques and the availability of a nearly infinite amount of volatile data. It appears to be unlikely that automation and more data are synonymous with an unconditional progression. Integrating different map layers may become an easy job to do by using a GIS, but is it always sensible? Remote sensing seems to offer an alternative for a lot of traditional mapping tasks, but how do we decide whether or not to use the data? And if a visual representation exhibits a more or less ephemeral character that fails to reflect its integrity - like traditional maps used to bear the quality stamp of its maker (Morrison, 1995) - how can we judge its usefulness? The answers to these questions require an emphasis on concepts, not techniques.

1.3 Technological possibilities and conceptual impediments

As a starting point for further discussion it could be stated that technological achievements in geographical information processing have overcome the impediments raised by the nature of the data. But appearances are deceiving, more likely this technological progression obscures the incompatibilities between different data types, especially these inconsistencies that refer to contents (Hootsmans & Van der Wel, 1992). There is a considerable danger lurking in the ease with which data are processed and integrated with other data that bear no comparison with each other. As a consequence, unpredictable and often useless *data*, not *information* (data with a meaning) results, whose true character is not seldom hidden behind an aesthetically appealing cartographic mask.

As an example, consider the integration of a satellite image and a topographic map digitised at a certain scale. Space images are often used to produce or help revise topographic maps to keep up with changes in large, inaccessible and dynamic regions (see for example the study of Petrie & Liwa (1995) who investigated the usefulness of small-scale aerial photographs and SPOT satellite images for topographic mapping of Southeast Africa). Digitisation of a topographic map, which has already been subjected to cartographic generalisation, brings forward two major potential problems. First, some people assume the digital map to be scaleless because of the ability of information systems to scale its contents in a gradual way (in both directions!), thus enabling a perfect physical match with other data whose original scale or resolution deviates considerably from the “slave” representation. In the second place, as Muehrcke (1990) argues, digitised maps could be mistaken for absolute, geographical information instead of abstracted, cartographic information. In other words, a representation is normally in accordance with the level of information that it contains and the objectives it pursues, but this balance can be disturbed if there fails to be an explicit notice of the degree of “elasticity” of the data manipulation. For example, problems could arise if a small-scale topographic map is enlarged in order to fit a high-resolution satellite image for updating purposes. The advantage of scaling the digital map is that “missing” topographic objects are more easily identified on the image; the geometric accuracy of the map is, however, seriously decreased because of the generalisations that it has undergone.

During the entire *information process* the harmony between data and manipulations must be considered. This process, describing the life cycle of geographical data from acquisition to presentation and on (see chapter 2), is characterised by a decrease of professionalism in the ongoing digital era. Cartographers, for example, lost control over part of the process as more people were involved in producing and using the data by means of computer information systems (Morrison, 1995). Geographic information systems exemplify an automated version of this process, and although they are not primarily designed for mapping tasks, their output is often some cartographic product realised by an average non-expert user. This does not mean that the processing quality is suddenly worse than during the traditional cartographic process with an expert in charge of the preparatory and ultimate visualisation tasks. But these developments require the availability of explicit information from which a user can derive guidelines concerning the appropriateness of data and methods for the application pursued. As maps resulting from computer processing are not any longer necessarily reflecting the *truth-value* of the underlying data, users must be guarded against improper use. And the fact that for a particular region several digital data sets are readily available whereas their mutual differences and similarities are not always clearly distinguishable hampers a sensible choice. The critical question this thesis intends to answer therefore is:

Can one prevent a user from using inappropriate data or maps for making decisions or for further processing? And if not, how can a user make the best decision based on inappropriate data or maps?

1.4 A problem arises: how to keep upright in the information revolution?

The question that concluded the preceding section refers to a general problem in information communication: the ability to meet the "information-hunger" of some users, to provide them with sufficient and appropriate information to extend their intellectual substance, to answer their questions. Data obtain meaning if they appear to be helpful in solving or handling a problem, and this requires not only the data themselves, but clues about them as well. Abler (1987) stresses the relevance of knowledge about the accuracy of data and the propagation of the errors attached to them in order to perform a well-considered information extraction. Blakemore (1984) is even more firmly of the opinion that something is missing if only data are transmitted and he substantiates his statement by citing Poiker: *"...the absence of any notion of precision and accuracy is like a person with the body of an athlete in his prime time and the mind of a child..."* All information is imperfect, according to Stephanou & Sage (1987), because it is *"...incomplete, uncertain, inconsistent, or otherwise not totally suited to the judgemental task at hand..."*.

The problem that is identified above can be summarised as a quest for information about the *quality* of data. Chrisman (1984) has defined it as "fitness for use" and this meaning of quality is now generally accepted in the geographical information society: *"...the process of converting a particular fact into information must comprehend the fitness of that fact for some particular purpose..."* (Chrisman, 1991)

The need for information on the fitness for use of a geographical data set has increased considerably since the introduction of information systems and the availability of a huge amount of digital data (especially remotely sensed data!). However, quality aspects have always played an important but more implicit role in geographical data handling. Cartographers, for instance, traditionally maintain a balance between the form and content of a graphic representation. In order to achieve this, they sometimes even have *"to lie a little in order to tell the truth"* (Muller, 1987), thus introducing error in the data to improve interpretation by a user. Goodchild & Gopal (1989) give a number of reasons why digital data handling requires a more explicit emphasis on quality issues than conventional mapping. They all more or less relate to the fact that information systems pursue a high precision, which fails to correspond to the accuracy of the data considered. This is extremely dangerous when one realises that this incompatibility could give rise to an impression of *pseudo*-accurate data that are to be used by a widely differing audience.

The discussion can be structured by defining a number of questions that relate to the information value of geographical data.

Question 1: What is quality and what are its components?
The general consensus with respect to the need for quality statements notwithstanding, research in the field of geographical data quality is characterised by widely divergent and careless definitions. Unambiguous terminology is obviously a prerequisite for understanding the crux of the matter. Quality, error, uncertainty, reliability, accuracy and precision all have a distinct meaning that will be elucidated in chapter 4. Moreover, quality seems to contain both direct and indirect indications of the fitness for use; as an example of the latter, think of statements concerning the source and acquisition date of data ("based on Landsat Thematic Mapper data of July 5, 1994").

From this, a second more broadly defined question arises:
Question 2.1: How can quality be assessed and what quality measures are available?
This question touches upon the quintessence of the quality problem. There is no such thing as an ultimate quality toolbox that enables a systematic and comprehensive derivation of quality statements in an information system, although partial success has been achieved (e.g. Heuvelink, 1993). Nor can quality be captured in one measure because of the different components of geographical data (position, attribute, time, and topology) and the divergent nature of the data itself. Remote sensing data are dealing with a different view of the world as compared with digitised map data in a GIS, based on image samples instead of objects (Goodchild & Wang, 1989) as a result of the underlying *pattern model* (Abkar, 1999). This model describes the interaction of energy with the atmosphere and with the configuration of *real world* objects in addition to the characteristics of the sensor system. Furthermore, apart from being a relative characteristic dependent on context and purpose (Couclelis, 1992), quality is also a dynamic characteristic of data as these data can be processed and integrated with other data in an information system during different stages of the information process. This means that data sets that are not sufficiently appropriate for a particular application can be improved by adding or removing parts of them so that the result meets the requirements. It also means that quality can be affected adversely as a consequence of the introduction of uncertainties during the information process (e.g. Lunetta *et al.*, 1991).

From this, it becomes clear that the problem defined above is much too general to handle in a thesis; it is necessary to focus the issue on a specific type of data and a specific application, thereby concentrating on a subset of the quality problem. The revolutionary impact of remotely sensed data on geographical information processing in general and cartography in particular has already been pointed out. Trotter (1991) stresses the potential for using digital remotely sensed data as input to a GIS while making a reservation as far as the triviality of this integration is concerned (see chapter 2). A rewording of the second question therefore is:

Question 2.2: How can quality of digital, remotely sensed data be assessed and what quality measures are available?
The point is to guide users in order to derive information from a remotely sensed data set without getting entangled in an infinite trial-and-error process. In this thesis, the emphasis will be on the *cartographic use of optical remotely sensed data* which, in turn, can be further specified according to the type of sensor and the steps involved in their processing. The extraction of information from remotely sensed data requires a number of these steps, but *classification* of the digital data is one of the most straightforward manipulations as far as cartographic output is concerned. Robinove (1981) considers this process a statistical manipulation of (multi) spectral reflectance data as "surrogates" for earthbound attributes in order to categorise information classes in an area (see chapter 3). Without having a clue at one's disposal that reveals the fitness for use of the classification, information extraction - and decision-making - becomes a random procedure dominated by mere practical considerations like accessibility and availability, or relying heavily on conventional routine. Can the introduction of additional knowledge in the classification process improve the subsequent decisions by reducing or weighting the amount of uncertainty that results from an inadequate pattern model (see above)? And what exactly is the role of a GIS in this process?

An additional question arises when considering the nature of quality:

Question 3: Is it sensible to improve the value of the quality components, or more specifically, is error reduction preferable to mere error assessment in remote sensing classification?
Instead of assessing the quality of a particular data set, the reduction of errors and uncertainties could actually improve its fitness for use. If a user knows how to achieve this, it means that he really understands the information process and the nature of the geographical data under consideration, and this knowledge would enable him to model the errors and uncertainties to a satisfactory level. This assumes also that there would be sufficient time and money available to pursue this reduction. When would these latter drawbacks surpass the former prospects? Is it too simple to state that the investments in favour of an optimisation of errors and uncertainties to a predefined tolerance level are to be rendered by a limited number of proper applications? GIS practice learns that it is difficult, if not impossible, to anticipate all possible future applications of a data set, which makes the definition of a useful tolerance level not an easy job to do - except if maximum accuracy is pursued. Chrisman (1991) argues that *"...as GIS develops, databases will become more and more pivotal to a diverse range of users, and the ability to determine a blanket tolerance will become less certain..."* The point is, according to Openshaw (1989), *"...how to live with error and uncertainty in the spatial databases being manipulated by GIS..."*

A last question concerns the conveyance of data quality to users in order to make them aware of the value of the considered data set:

Question 4: How can quality information be summarised and conveyed to a user? As quality is such an important issue in geographical data handling users have to be conscious of its full extent. As a starting point for an optimisation process in which the "best" decisions are pursued, assessment of the amount of uncertainty present in a data set is required. Here, "best" refers to a situation in which either the risk of taking a wrong decision is minimised by increasing the accuracy of the data, or the selection of the most appropriate decision is achieved by weighting the uncertainty with some user-defined criterion, for example costs attached to a wrong class assignment. From cartography it is evident what impact a graphic representation of spatially varying attributes can have on understanding the information value of a data set. Goodchild *et al.* (1994a) state that *"...the measurable aspects of data uncertainty will probably have a spatial component, since quality will be higher in some areas than others, or higher for certain features..."*, thus providing a clue for the visualisation of data quality (Van der Wel *et al.*, 1994). In this thesis the emphasis is on the assessment of uncertainty and its subsequent communication to a decision-maker. Can a straightforward application of cartographic principles meet the requirements of these "new" visualisations? And in which stage of the information process are they needed most?

1.5 The definition of objectives

The above problem description has resulted in the derivation of a number of research objectives that need to be achieved in order to tackle the questions that arise from the uncertainty issue. The ultimate goal should be defined as the development of a "tool" with which the value of specific remotely sensed data and additional data can be assessed, conveyed and weighted with respect to the application under consideration. Ideally, an information system extended with a "quality module" enables a decision-maker to monitor the usefulness of the data before, during and after classification. Less utopian and more feasible given the limited sphere of action of a dissertation, the main goal can be narrowed to:

...the development of a methodological framework offering classification and other decision rules to detect and identify objects or parts of objects in a remotely sensed data set whose information value can be assessed and graphically conveyed by adopting quality measures...

As far as the classification of remotely sensed data is concerned, this objective corresponds with the statements made by Berry (1987). He proposes an approach that takes into account both the nature of image data and the classification process to create an "error image" that could complement the thematic information from the classification (in a GIS).

In order to be manageable, the above objective can be split into the following five aims (between brackets a reference to the above defined questions):

- **Aim 1: Stimulate user's awareness (1).** Uncertainty is inextricably bound up with the nature of geographical data and has to be taken into account when seriously considering the usefulness of these data for a particular application. Awareness alone, however, is not sufficient as Veregin & Hargitai (1995) point out; it is a prerequisite to a more advanced pursuit of determining and conveying the quality of a data set. A demonstrable reduction of costs or gain of other benefits may persuade users to explicitly consider uncertainty in their decision-making process. Hunter & Goodchild (1996) put this aptly by stating that *"...investigating product uncertainty may not be a 'money-making' issue, failure to cope adequately with it may well make it a 'money-losing' one..."*

- **Aim 2: Improve insight into the information process (1, 2).** The introduction of uncertainty and the propagation of errors during the life cycle of remotely sensed data urge for an understanding of the separate processing steps. As pointed out before, the emphasis in this thesis is laid on classification as a transformation of reflected energy (or *scaled photon counts*) into thematic information classes. It is deemed necessary to give the relevant algorithms a moment's thought and consider their ability to deal with uncertainty. All classification approaches that are described in chapter 3 do have a statistical backbone and particular attention is given to the appropriateness of probability theory as a framework for coping with different kinds of uncertainty. Without tending to step in the discussion concerning the ability of probability theory to deal with all aspects of data uncertainty, it is felt fair to point out to the reader that there are some other concepts that attract considerable attention in the literature. Advocates of *fuzzy set theory* heap criticism on the statisticians who emphasise the fact that probability theory is a mathematically well-founded and extensively tested theory (Van der Gaag, 1990). The mutual distrust is best addressed by Zadeh (1986) and Cheeseman (1985) who cast doubt on the usefulness of probability theory and more or less mathematical "alternatives" respectively (see also chapter 3). Stephanou & Sage (1987) provide an overview of alternative methods to represent imperfect knowledge.
- **Aim 3: Build a methodological framework to handle data uncertainty (3).** The systematic and mathematically correct assessment of data uncertainty requires a thorough understanding of the spatial nature of the data, their non-spatial features and their interrelations. Assessment methods have to deal with different types of uncertainty, for example uncertainty relating to the position or geometry of an object, or to its attributes. Veregin (1989a) contends that *"...no single error model is applicable in all instances..."* while Heuvelink (1993) adds that *"...there are many different aspects of the problem of error and error propagation in* GIS*..."* Both observations support the idea that the development of a more generally defined uncertainty framework is far from trivial. The approach adopted in this thesis is to investigate the appropriateness of a series of methods that link up with the characteristics of the sampled remotely sensed data and their subsequent processing in a GIS environment. More specifically, the aim is to define a methodological approach and develop an appropriate conceptual model as a basis for handling uncertainty in classified optical remotely sensed data that are applied in decision-making strategies. "Handling" in the first place refers to the determination of data quality such that the restrictions implied by the imperfections can be considered. Besides the proper application of statistical methods to derive uncertainty information, quality assessment will be dealt with in the wider context of standardisation efforts directed at data storage and exchange. Next, a reduction of the amount of uncertainty is pursued, particularly by means of

the integration of remotely sensed data with other geographical data using GIS approaches (Davis & Simonett, 1991; Strahler, 1980; Wilkinson, 1996). Finally, efforts can be made to minimise the amount of uncertainty by adopting an optimisation procedure which, in turn, requires considerable knowledge about the objects that have to be identified (Abkar, 1999; Fang Luo & Mulder, 1993).

- **Aim 4: Develop visualisation tools to both explore and explain uncertainty patterns (4).** With the availability of uncertainty information the need for effective representations is becoming urgent. Visualisation has gained considerable attention from experts in cartography and beyond, who consider a graphic representation of uncertainty valuable to support exploratory visual thinking as well as explanatory visual communication (DiBiase *et al.*, 1992; MacEachren *et al.*, 1992; Van der Wel *et al.*, 1994). Visualisations can reveal the potential information value of a data set by throwing light on its different aspects in a preparatory stage of the information process. As far as classification is considered, a graphic representation of a *feature space* can be quoted as an example. At the far end of processing, a reliability diagram attached to a map product revealing the source of the underlying data can exemplify visualisation of uncertainty. The different roles of visualisation before, during and after classification will be dealt with extensively in this thesis (chapter 7).
- **Aim 5: Demonstrate the usefulness of the conceptual framework (1, 2, 3, 4).** Burrough's (1991) proposed *intelligent geographical information system* pursues a predefined quality level by evaluating meta-information about data, methods and models that are applied during a particular information process. The realisation of such an ideal system probably remains one of the most important driving forces behind research efforts in the near future. Within the framework of this thesis a demonstration tool has been designed which is, up to now, only a faint reflection of its abstract example. Its immaturity notwithstanding, such a tool exemplifies concepts dealing with uncertainty in remotely sensed data and makes a user acquainted with a well-considered decision-making strategy. To achieve this goal, a research project named CAMOTIUS was initiated (see section 1.6), in which a pragmatic position is taken as regards the introduction of uncertainty measures.

The scope of the research is "restricted" to so-called *pixel-based* classifications instead of *object-based* approaches (see e.g. Abkar 1999; Mulder, 1991; Mulder & Abkar, 1999: Schutte, 1994). Although the derivation of objects links up better with the way in which users tend to handle spatial data, it is not always possible to have the disposal of a model that describes spectral, spatial as well as temporal characteristics of an object. The aim of the adopted approach here is mainly to improve the handling of uncertainty during present classification practices as a first step to better decision-making. The distinction of separate objects can be considered a further refinement that lies beyond the scope of this thesis.

The above challenges serve as a guideline for an exploratory expedition to the disciplines that contribute to the turbulent field of geographic data handling. The programme for this voyage will be presented in section 1.7, after a brief introduction of the above-mentioned CAMOTIUS project.

1.6 The CAMOTIUS research project

When the idea of starting a project solely dedicated to the issue of data uncertainty came into existence in the autumn of 1991, some international initiatives were developed that created favourable conditions for the acceptance of a research proposal. The US National Center for Geographic Information and Analysis (NCGIA) had prepared a number of papers concerning the accuracy of spatial databases as the result of its first research initiative focused on problem areas in GIS (Goodchild & Gopal, 1989). The same *think tank* started research efforts in the field of the visualisation of spatial data quality in June 1991 (Beard *et al.*, 1991). The cartographic community did not stay behind when the International Cartographic Association (ICA) granted its permission to the establishment of the Commission on Spatial Data Quality in September 1991. Besides these influential developments, a considerable number of studies stressed the issue of errors and uncertainties in the context of GIS. From a personal point of view, the dissertation of Nick Chrisman (1982a) aroused the curiosity that is required to scrutinise this apparently elusive issue.

When the Cartography Section of the Faculty of Geographical Sciences in Utrecht University submitted its CAMOTIUS proposal to the Netherlands Remote Sensing Board (BCRS), the need for more methodological research in the field of remote sensing and GIS was getting urgent. As Molenaar (1991) recalls, remote sensing was a promising field in the seventies but its sound application in the geo-disciplines stagnated when the user community concluded that the information extraction was still too cumbersome. The increased interaction between GIS and image processing systems as foreseen by Marble & Peuquet (1983) has certainly strengthened the confidence in the potential of remote sensing for spatial data analyses.

One of the most important and challenging prerequisites for approving a feasible remote sensing project is the expectation of an operational and possibly commercial continuation, which will guarantee that the techniques are starting to pay off at last. In fact, this can be considered the ultimate goal of this research project: instead of illustrating the umpteenth application of digital imagery, it attempts to assess its extra value for a number of predefined case studies. This ambitious endeavour accounts for the composition of the research group, in which, next to the Cartography Section, the International Institute for Aerospace Survey and Earth Sciences (ITC), Eurosense BV and the Dutch National Physical Planning Agency (RPD) participated as well until the completion of the project in 1996.

Eventually, CAMOTIUS has grown into a three-stage project, consisting of a preliminary examination, a main phase and an end phase respectively. The project has focussed on the handling of uncertainty related to land cover classifications based on Landsat Thematic Mapper data. As such, CAMOTIUS has served as a “playground” in which several methodological approaches to uncertainty have been reviewed in order to create a sound and pragmatic case study illustrating some aspects of the many-branched issue of data uncertainty.

1.7 Structure of this thesis

Figure 1.2 gives an overview of the contents of this thesis by arranging the chapters and their interrelations in an evolutionary model. Firstly, it is felt desirable to dedicate a separate chapter to the main relationships between cartography, remote sensing and GIS. Therefore, **chapter 2** creates a clear atmosphere allowing for a multidisciplinary approach to the data uncertainty problem. The classification of remotely sensed data is subjected to an elaborate study in **chapter 3** in order to gain an in-depth insight into all aspects of the process that is at the centre of the research. Some of the more common classification methods are reviewed and by discussing their shortcomings, a course is plotted towards an extended and hopefully better approach.

Having prepared this breeding ground, the seeds of uncertainty can be put in. This marks the beginning of the second part of the thesis, in which the components of the methodological framework are discussed sequentially. First of all, it is necessary to create some order in the terminology used because especially GIS literature is caught at employing confusing and not seldom erroneous language when approaching the imperfections in geographical data. Unfortunately, the jumble of definitions hasn't been an incentive to create some clarity, at least as far as the recent publication of an International GIS Dictionary is concerned (McDonnell & Kemp, 1995). The booklet fails to mention any relevant terminology as regards the data uncertainty issue! In **chapter 4**, the discussion on uncertainty in remotely sensed data will give occasion to an elaboration on the meaning and extent of quality and other apparently alternative but conceptually different notions of uncertainty.

Error sources are listed and their impact on the information process is discussed. Furthermore, embroidering further on the statistical classification approaches, probability theory is introduced as a framework to describe and quantify the errors and uncertainties in a classified remotely sensed data set.

Proceeding with the growth metaphor, **chapter 5** represents the germination of errors and uncertainties in receptive classification grounds and the attempts that are made to nip this development in the bud. Attention is paid to the fact that classification results can be improved considerably by introducing additional knowledge before, during and after the process. The extra value of *a priori* knowledge is stressed and its derivation is placed at the centre of the discussion. But before a serious reduction can be realised, uncertainty has to be assessed - in a quantitative or - more descriptive - qualitative way. The recognition of probability theory as a valuable instrument to describe imperfect spatial data helps to derive a number of measures that make up the basis of a framework for handling uncertainty in remote sensing classifications.

After chapter 5 has touched upon the assessment and reduction of errors and uncertainties, **chapter 6** presents concepts from the mathematical theory of decision analysis that are aimed at the control of uncertainties. In fact, the proposed ideas serve as a means to prevent the seeds of uncertainty from growing into a many-branched and impenetrable wilderness that seriously threatens a sound information extraction. Accepting a particular level of uncertainty in the data and dealing with it in

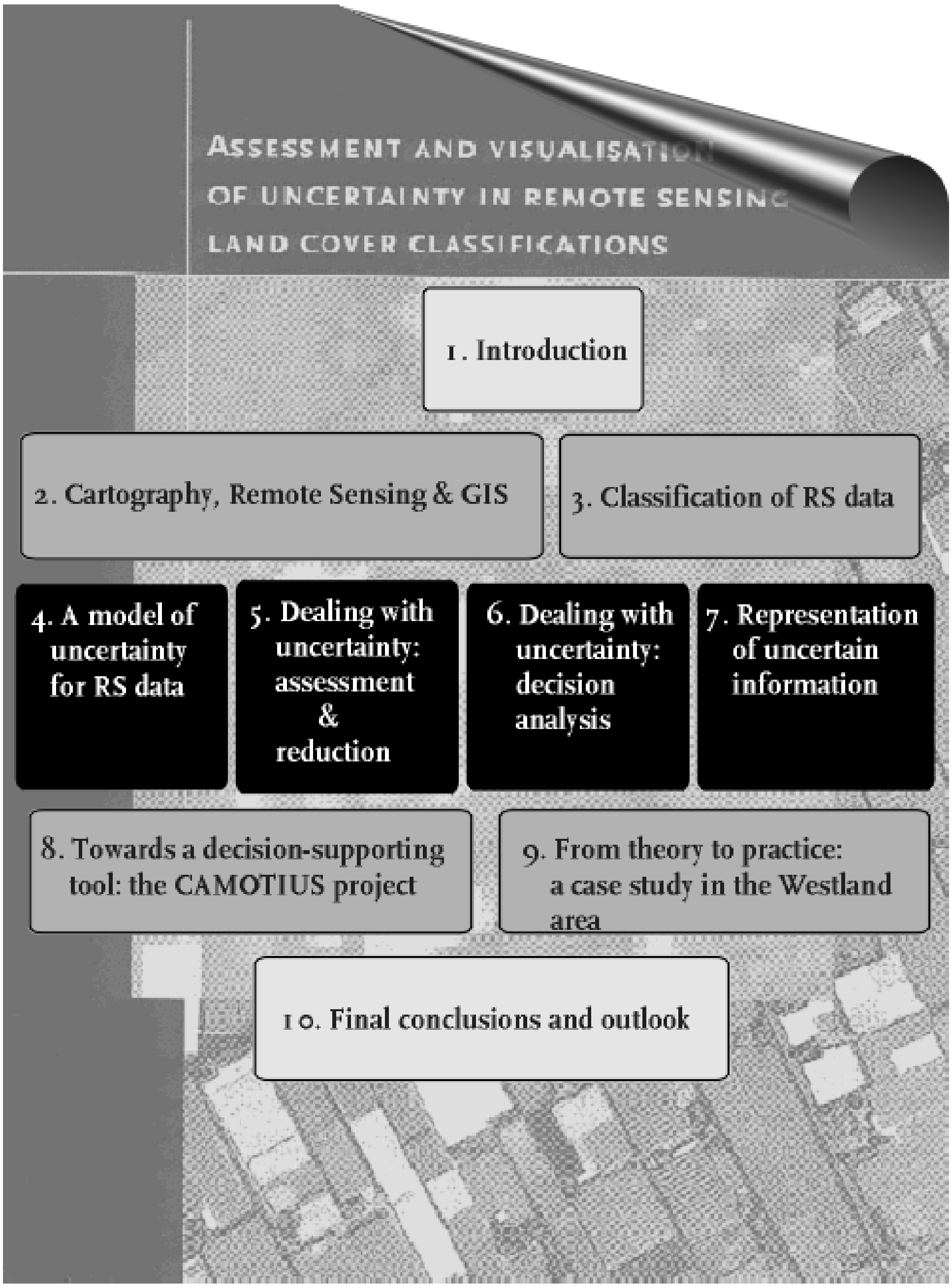


Figure 1.2: Schematical representation of the structure of this thesis

a way that links up best with the nature of decision-making is thought to offer more prospects.

To conclude the methodological part of the thesis, emphasis is laid on the issue of visualisation of uncertainties; proceeding with the figurative language for a last time, the objective is to leave visual marks that enable a user to find his way in the uncertainty-grown data set. Based on the ongoing scientific discussion concerning the role of visualisation during different stages of the information process, a cartographic framework is introduced, summarising the usefulness of conventional as well as newly proposed graphic variables and techniques as regards the representation of uncertainties. This **chapter 7** aims at a better understanding of the data under consideration and their information potential.

The third part of the thesis concentrates fully on the CAMOTIUS project and the tool that has been developed in the course of the project. The preceding chapters have established the components of a methodological framework, and **chapter 8** presents the blueprint of the construction scheme that brings all these building blocks together. In fact, this chapter deals with the design of a CAMOTIUS tool and considers the questions that are raised when shifting to the development of a (semi-) operational tool. The "why" and "how" of choices that have been made with respect to the functionality of the proposed CAMOTIUS tool are further elaborated. Furthermore, it provides a discussion on the effectiveness of such a tool in view of the defined objectives (section 1.5). The potential user group is identified and ordered in a number of profiles, partly based on feedback provided by a small evaluation group.

Chapter 9 reflects the results of two extended case studies in which the validity of the proposed concepts has been tested and the development of a demonstration tool has been pursued. One of the appendices (2) is dedicated to a systematic description of the functions of this CAMOTIUS Demonstration Program and the interactive and user-friendly way in which it can be applied (cartographic interface).

Finally, the thesis is completed by discussing the main achievements of the research in a concluding **chapter 10**. Here, all initially defined objectives are considered critically as viewed in the light of the final results. In a look to the future, the role of error and uncertainty information in a "GIS-based decision-making environment" will be held to the light.

2 Cartography, remote sensing and GIS

"...The results of remote sensing processes are seen more and more as single steps in the greater context of GIS. The appropriate means of making the various streams of information provided by GIS visible, still remains cartography. But the cartographic representations of the various relationships need not be maps in the convential sense at all..."

H.J. Vogel (1991)

2.1 On defining cartography, remote sensing and GIS

2.1.1 Introduction

In order to understand the full extent of the process that transforms remotely sensed data into meaningful information, one has to define the meaning of remote sensing and its position amidst other but related disciplines. Remote sensing, GIS and cartography are interacting mapping fields in the sense that they - at least partly - exhibit mutual dependencies as far as sound information extraction is concerned. They tend to grow closer to one another under the influence of technology (see previous chapter). A remarkable number of papers dating from the late 1980s is exclusively dedicated to the distinctions and relations among these three areas of interest and their separate definitions (e.g. Blakemore, 1988; Cowen, 1988; Fisher & Lindenberg, 1989; Fussel *et al.*, 1986; Maguire, 1991).

From the positions taken in these publications, one could not escape the impression that some of them are dictated by a "survival instinct". Exemplary for this observation is the critical attitude of cartographers with respect to the restricted presentational tasks in a GIS environment assigned to them. The "de-skilling crisis" (Rhind, 1988) expressing the depreciation to which some exclusively cartographic knowledge is subjected in the GIS era is put into its perspective by Muehrcke (1990) who states that *"...currently, information systems supported by electronic technology are forcing a creative transformation of cartography as we know it...fortunately, this promises life, not death...."*. This seems to link up very well with the idea of a "new cartography" as proposed by Taylor (1985) in response to technological and socio-economic changes caused by the information revolution. As an exponent of the latter, remote sensing techniques offer promising opportunities for a challenging cartography (Denègre, 1994; Monmonier, 1987).

The danger that is lurking in the above-mentioned discussions, however, is that of losing oneself in the goo concerning the dominance of one of the disciplines. Instead, a more practical approach is advocated, namely that of exploring the actual possibilities for interchanging concepts among the disciplines, for example in higher education (Dahlberg & Luman, 1991). It would be interesting to consider the core concepts in cartographic communication as discussed by Ormeling (1992) in view of developments in GIS and remote sensing. Therefore, as a brief introduction, attention is paid to the relevant relationships between remote sensing, GIS and cartography. But first, the three areas of interest will be subjected to a critical review that clearly demarcates their extent. Remote sensing will receive somewhat more attention in order to link up better with the contents of the chapters to follow.

2.1.2 Cartography

When reviewing the cartographic literature of the past 30 years, the predominant role of theories of cartographic communication in the 1960s and 1970s catches the eye. The communication models proposed by e.g. Koeman (1971), Kolacny (1969) and Ratajski (1973) are well known in the cartographic community but their initial illuminating views on the cartographic process are now considered too restricted to do justice to the subject. Among the objections raised against the communication paradigm are its failure to deal with *"the extraction of cartographic information (map reading) and the cognitive processes involved in interpreting the map image"* (Wood & Keller, 1996) and its intolerance to the art component in cartography (MacEachren, 1995). Due to the interest in computer assisted cartography in the 1980s, the communication theories have lost some of their influence as well.

In accordance with MacEachren (1995), cartography is defined here as a discipline dealing with "representation". Instead of considering maps merely graphic messages to convey relevant geographic information, based on information theory (Shannon, 1948) and semiotics (Bertin, 1983), maps are viewed as spatial representations, thereby stressing cartography's function as *"...creating interpretable graphic summaries of spatial information (i.e., representations)..."* (MacEachren, 1995). Such a representation is just one out of many possibilities to depict the complex environment, for example for decision-making purposes, without claiming to be an objective and all-embracing "messenger". Ormeling (1995) states that *"...no one map can be considered as the only true map based on specific data, as subjective decisions regarding data thresholds, classification systems, class boundaries, or numbers of classes have been made..."* (Monmonier (1991a) even dares to claim that providing a single view is unethical!). It is interesting to note that these opinions are deviating from the "traditional" communication paradigm in which, according to MacEachren & Ganter (1990) *"...there is an optimal map for each (known) message..."* In fact, this doesn't affect the definition proposed by Taylor (1991) that has been given at the beginning of section 1.2, at least if one keeps one's mind on this "flexible" map concept. As will be learnt from chapter 7, the *"multiple map view"* is referring to a field known as cartographic visualisation.

In order to create interpretable graphic summaries, metadata have to be provided, preferably graphically as well. This presupposes understanding of the data gathering and processing stages of the information process.

2.1.3 Geographical Information Systems (GIS)

Defining GIS is not an easy task to do as is apparent from the large number of divergent views spouted in literature. Chrisman (1984) refers to it as a complicated type of software covering the whole life cycle of geographical data, from data collection to interpretation and on. A better and more widely accepted definition of GIS is given by Burrough & McDonnell (1998) who consider GIS a complex of computer hardware and software embedded in a proper organisational context. The latter refers to such issues as training of staff and appropriate implementation of the system in the present workflow.

As far as the software is concerned, Burrough & McDonnell (1998) distinguish the following five technical tasks (see figure 2.1):

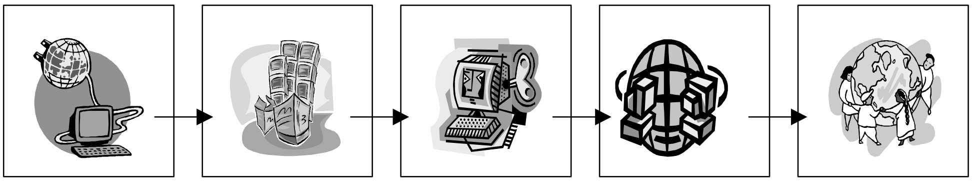


Figure 2.1: Five main tasks of GIS software, schematically represented

- Data input and data verification. The conversion of collected data into a suitable, digital format, for example by means of digitizers, scanners or keyboard. Moreover, it involves some kind of pre-processing, as data can be subjected to generalisation or simple classification procedures.
- Data storage and database management. Once passed the input stage, data are stored in a database according to a particular data structure and database structure.
- Data manipulation. This involves all transformations being applied to the data. Berry (1987) uses the term "operations" whereas Abel (1989) prefers "transactions". In general, a distinction can be made between analyses (spatial or not) and more trivial processing tasks like updating and simple error removal.
- Data output and presentation. The data, processed or not, can be presented in a graphic or alphanumeric way, as hardcopy (e.g. a paper map) or softcopy (e.g. so-called ephemeral output on a computer screen).
- Interaction with a user. A user is able to communicate with the information system ("query input") in order to extract information from the stored data.

Marble & Peuquet (1983) give a well-chosen description of the functionality of a GIS, that summarises the above-mentioned tasks: *"... a GIS is designed to accept large volumes of spatial data, derived from a variety of sources, including remote sensors, and to efficiently store, retrieve, manipulate, analyse and display these data according to user-defined specifications..."*

2.1.4 Remote sensing

In general, remote sensing is considered primarily a data acquisition technique that includes traditional aerial photography as well as more advanced air- and spaceborne sensor technology. Its extent is, however, dependent on the various disciplines that make use of the technology; here, remote sensing refers to the use of electromagnetic energy sensors that derive information about the features at the Earth's surface by measuring and analysing the type and amount of energy that they emit or reflect. The type of energy is referring to different parts of the electromagnetic spectrum ("wavelengths"), e.g. visible, near-infrared, thermal infrared or microwave bands (with increasing wavelengths). Figure 2.2 presents a schematic representation of the principle of electromagnetic remote sensing of the

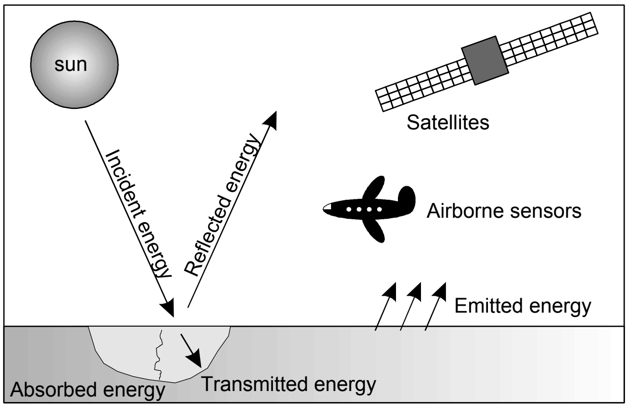


Figure 2.2: The principle of remote sensing (after Lillesand & Kiefer, 1994)

Earth (after Lillesand & Kiefer, 1994). Based on the observations made by Rees (1990), it encompasses the collection of information about a *scene object* (Abkar, 1999) located on or near the earth's surface without coming into physical contact with it, by using an airborne or spaceborne sensor that is more or less above and at a "substantial" distance from this object. Moreover, the information is carried by electromagnetic radiation, as stated before. Note that the above definition does exclude other remote sensing techniques such as sonar that uses acoustic waves and medical imaging that does indeed apply electromagnetic energy, yet not in the sense that is meant by environmental remote sensing with a sensor at a "substantial distance" from an earthbound object.

In order to understand the unique character of remotely sensed data, some attention will be paid to the principles of remote sensing. A more extended discussion on remote sensing techniques can be found in e.g. Richards (1999), Mather (1987) and Lillesand & Kiefer (1994). Gonzalez & Woods (1992) provide an introduction to the concepts and methodologies to process the image data that are acquired by remote sensing techniques.

The term remote sensing dates back to the early 1960s when new data acquisition techniques failed to conform to the narrow definition of aerial photography (Fussell *et al.*, 1986). Since then, satellite platforms have enabled observations from high altitude with sensors operating in the visible, infrared and thermal section of the electromagnetic spectrum as well as in the microwave region as exemplified by active radar systems. Fussell *et al.* (1986) state that there exists no single definition of the field because of the different viewpoints that could be taken by a differing audience and the lack of a widely accepted academic home base. The latter contention is easily tackled by the fact that the process does have a sound physical basis, e.g. quantum mechanics describes the behaviour of electromagnetic radiation in terms of waves as well as quanta (photons). Concentrating on *passive*, *imaging* remote sensing systems such as represented by the Landsat Thematic Mapper (TM) whose data are dealt with in this thesis, the following observations can be made. The TM sensor onboard the Landsat satellite behaves like a line scanner - a "whiskbroom" scanner (Rees, 1990) - carrying a number of detectors (100) that can be characterised as *photon counters* (figure 2.3). Physical models describe the interactions between objects and the atmosphere on the one hand, and electromagnetic energy - emitted or reflected - on the other. The amount of energy measured by the detectors provides some clues concerning the nature of the objects. The system that measures the so-called photon flux (amount of energy per second) can be described by physical models as well.

The data acquisition process can be roughly subdivided in the following stages (see also figure 2.2):

- The flow of incident solar energy and its interactions with the atmosphere such as scattering and absorption as well as the atmospheric interactions of the reflected and emitted portion of that energy.
- The interaction with earth-bound objects and the subsequent reflection, absorption and transmission of energy.
- The recording of energy values by scanner optics, over an area on the ground that is observed by the sensor at a certain point in time - the Instantaneous Field of View (IFOV).
- The transformation of the photon or radiant flux into an electrical current and the subsequent sampling during which analogue photon counts are converted into digital integer numbers or DN's (quantization).

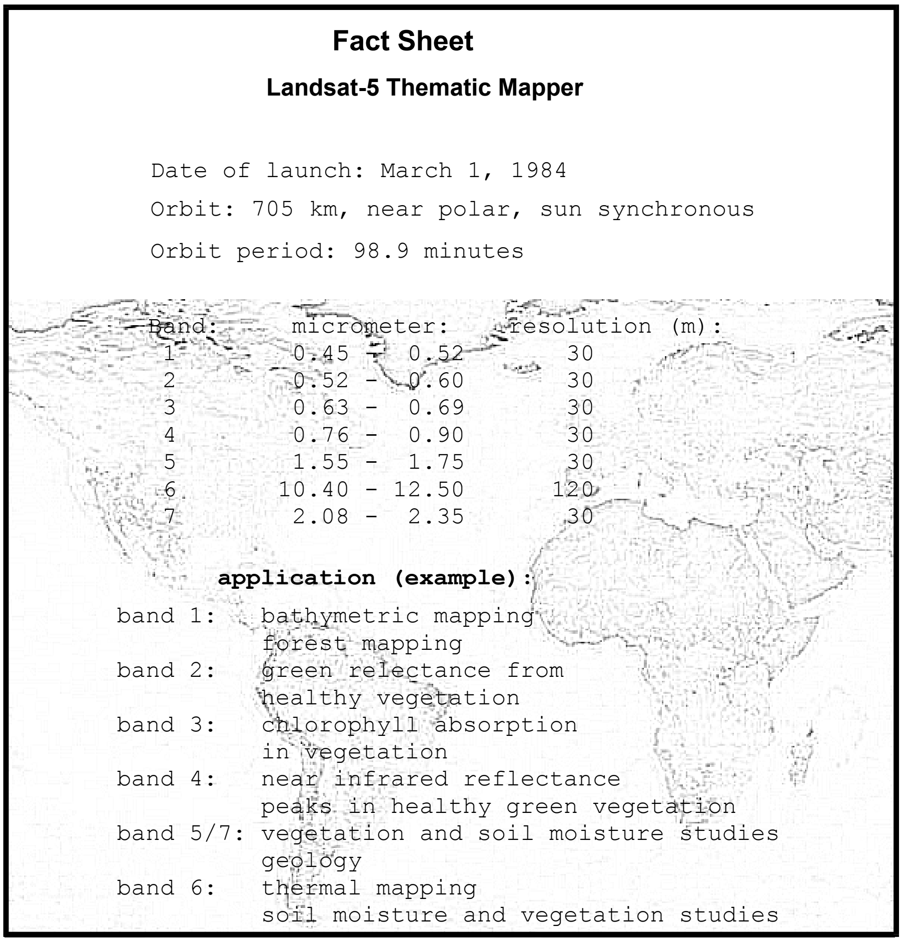


Figure 2.3: Characteristics of the Thematic Mapper onboard Landsat-5

Actually, the system records a value that corresponds with a weighted average of radiance values over a particular field of view. The *point spread function* of a sensor (the "weighting function"), determined by the characteristics of the optical system and the extent to which features are in contrast with their environment (as far as radiance values are concerned), can be held responsible for the fact that this recorded radiance is affected by the surroundings of the actual measurement area. In areas where the radiance values exhibit a high spatial variability, such as in urban areas, this phenomenon can cause serious problems with respect to classification (Curran, 1985). Estimation of the point spread function of the sensor could contribute to a reduction of this confusion as Abkar (1999, page 40 and on) demonstrates.

Pixels can be considered the representations of samples in the eventual image ("image samples"). They correspond e.g. with a *scene element* of 30 by 30 meters; talking about pixels of this size is utter nonsense (!), and it is depressing to observe that literature still fuels this confusion (e.g. Moss *et al.*, 1989).

2.2 A closer look at some relevant relationships

2.2.1 Introduction

As indicated in section 2.1, the interrelationships between the above-mentioned areas of interest have been the subject of a number of - only by spurts captivating - discussions since the late 1980s, attempting to model the mutual interactions. The simple "model of three-way interaction" presented by Fisher & Lindenberg (1989) offers the best way to depict the equivalent positions of cartography, remote sensing and GIS (see figure 2.4). From this, it becomes clear that - next to overlaps - each field exhibits its own scientific area of interest, remote sensing for example is strongly rooted in physics. This observation has consequences for the individual domain expert. A cartographer for example, is unable to gain a comprehensive view of all aspects of GIS (e.g. modelling) and remote sensing (e.g. non-imaging techniques) and his innovating role must be played in the overall overlap area (represented in black in figure 2.4). It is stated that remote sensing and GIS are primarily data acquisition and data processing techniques whereas cartography can only partly be regarded as such because it encompasses more than mere tools. The establishment of a *Spatial Information Science* as proposed by Goodchild (1990) could, however, offer a framework for a functional coexistence of science and technology with respect to the above-mentioned overlap.

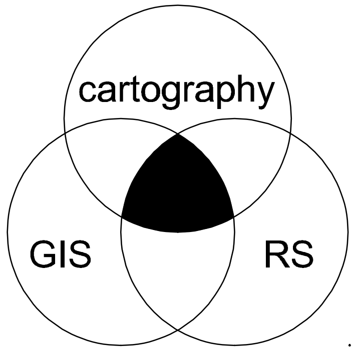


Figure 2.4: The positions of cartography, remote sensing and GIS *(after Fisher & Lindenberg, 1989)*

The elements of such a framework can be crystallised from the separate interactions among cartography, remote sensing and GIS. Here, the main issues will be touched upon before being discussed more thoroughly in one of the following chapters. It must be mentioned in advance, that a more or less isolated view on the mutual relationships is not always a realistic option. As an example consider the updating of topographic maps in a GIS environment, a cartographic application in which e.g. satellite imagery is subjected to a change detection process.

2.2.2 Remote sensing - GIS

As the relationship between remote sensing and GIS is brought up for discussion, the keyword is *integration*. Efforts are directed at the development of a workable synergy of both technologies on system as well as data level. Referring to the latter, Archibald (1987) makes a further distinction between display integration (visual overlay of digital images and maps in a GIS) and integrated data analysis that requires a higher level of data integration. Wilkinson (1996) summarises the relationships in terms of complementarity:

- Remote sensing can be considered a data acquisition and processing technology whose (digital) data sets serve as input to a GIS. As such, "raw" images as well as classified images can add a substantial information potential to the cartographic GIS data. Trotter (1991) attributes this extra value to possible reduced costs of data acquisition as compared to more traditional collection methods, while still meeting minimal requirements regarding such aspects as accuracy and topicality. Hellyer *et al.* (1990) present an interesting study demonstrating the value of land use/land cover information derived from Landsat Thematic Mapper data for further processing in a GIS during an environmental investigation of a wetland area.
- GIS data can be used as ancillary information to increase the quality of products derived from remotely sensed data. With reference to the classification process, these data can be applied during all stages of the information extraction: before, during as well as after classification. As an example of the first stage, the stratification of a remotely sensed image in preparation to classification comes into mind, while the second stage refers to the use of GIS data as *a priori* knowledge (Strahler, 1980). Janssen (1993) gives an example of using cartographic GIS data during a post-classification editing procedure in order to improve the accuracy of the classification. In his 2-stage object-based classification, a pixel-based classification is integrated with object boundaries (agricultural fields) that are contained in a GIS, and the objects are labelled in accordance with the membership of the majority class of the pixels within the object's boundaries.
- A third relationship concerns the use of both remotely sensed and GIS data in environmental modelling and analysis. Davis (1991) provides an overview of some of the research issues concerning the processing of remotely sensed and GIS data for environmental analyses. Probably, some of the more interesting research initiatives are to be expected in the area of scale (with respect to information contents) and time (in view of dynamic modelling).

The processing of digital imagery from satellites is still bound to specific image analysis systems and the discussions on integration are therefore not only concentrated on data exchange from one system (image processing) to another (GIS) and vice versa, but on actual system integration as well. Ehlers *et al.* (1989) argue that the integration of GIS with remotely sensed data and with image analysis *"...can be considered an evolutionary extension of the capabilities of existing geographic information* *systems technologies..."* They describe the developments in integration as "separate but equal" (based on data exchange formats), "seamless integration" (common user interface) and "total integration" (based on a complete, comprehensive model of the real world) respectively. The latter is still a blueprint for a total information system that can achieve maturity on the breeding ground of Goodchild's (1990) Spatial Information Science.

These perspectives notwithstanding, data integration is seriously hampered by the different levels of generalisation of remotely sensed image data and GIS data. This issue touches upon the concepts of space on which both technologies are based, most obviously expressed in terms of object-based models versus models based on image elements (Ehlers *et al.*, 1991). This difference is primarily a conceptual discord as Goodchild & Wang (1989) argue, but it can be regarded as a technical problem if it is projected on the issue of data structure, so on the raster-vector dichotomy. Note that image elements are not necessarily represented by a raster data structure (e.g. a Digital Elevation Model composed of a *Triangulated Irregular Network* or TIN (Ehlers *et al.*, 1989)) whereas objects are not the exclusive domains of vector data structures. Ehlers *et al.* (1991) provide an extended discussion on the topic of data structures with respect to the integration of remote sensing and GIS. As far as the conversion of geographical data is concerned (raster-vector formats), Piwowar *et al.* (1990) present an interesting benchmark study in which they included not only the speed of the operation, but also the quality, accuracy and efficiency of the conversion methods.

Besides the conceptual and technical impediments to integration, Lauer *et al.* (1991) distinguish some more institutional issues relating to e.g. costs of data, availability of processing equipment, education and training, and organisational infrastructures. It is indeed of the utmost importance to prepare the user community for the integrated use of remote sensing and GIS as this may prove to be decisive for the acceptance and widespread application of remotely sensed data.

2.2.3 Cartography - Remote Sensing

Mason (1990) states that *"...the close relationship that presently exists between cartography and remote sensing is one which is founded upon the importance of remote sensing as a basic data source in map compilation..."* The data that are acquired by earth observation satellites can prove their value for cartographic applications in one of the following three ways (Albertz, 1991):

- to produce and subsequently update topographic maps;
- to derive satellite image maps;
- to generate thematic maps.

The creation of a *topographic map* solely on the basis of satellite imagery places stiff requirements on the data, especially with respect to the geometric accuracy. With the advent of the French SPOT series of satellites, started in 1986 and already spanning years to come with the expected launch of SPOT-5B in 2004 (Gomarasca, 1996), high spatial resolutions and stereoscopic capabilities have opened up new perspectives for cartography. The HRG instrument onboard SPOT-5 will allow for spatial resolutions of

5 and 10 meters in the panchromatic and multispectral range respectively! But the Russian Resours series, carrying photographic instruments (e.g. KFA-1000) already succeeds in providing images with a very high resolution (up to about 6 meters). In the near future, digital data exhibiting still higher spatial resolutions are to be expected from the United States with the launch of commercially exploited but military inspired satellites. The Ikonos series of satellites will provide incredible high spatial resolutions of 1 meter and 4 meters in panchromatic and multispectral mode respectively (after the unfortunate launch of Ikonos-1 at April 27, 1999 Ikonos-2 has been placed into orbit successfully at September 24, 1999). These performances notwithstanding, it is still too early to consider the production of topographic maps with large scales (larger than 1 : 25000) without the introduction of serious positional errors.

Image maps still exhibit the characteristics of a satellite image but they have been subjected to extensive radiometric as well as geometric corrections before being completed with cartographic signatures representing topographic information such as road hierarchies and rivers (Galtier & Baudoin, 1992; Ruas, 1992). As an example, the ortho-images of the cartographic institute of Catalunya can be put on the scene. This autonomous Spanish region is covered by colour composites derived from Landsat-5 Thematic Mapper images and eventually presented as a series of 8 map sheets at a scale of 1:100 000. They differ completely from the attractive, exciting and eye-catching images that spark off enthusiasm without conveying spatial information, such as in advertising (note the use of colour composites as background in telecommunication ads!).

The third application, the generation of *thematic maps*, is closely (but not exclusively) related to the classification process that transforms remotely sensed data into land cover / land use information classes. Denègre (1994) presents a number of studies that each demonstrate the exclusive, supplementary or substitute use (Ciolkosz & Kesik, 1994) of remotely sensed data for thematic mapping purposes.

Focussing on the visualisation tools that could improve the interpretation of remote sensing information further expands the relationship between cartography and remote sensing. The adequate representation of dynamic information can for example support the identification of relevant change patterns (Van der Wel, 1995) whereas terrain visualisations provide for a “fly-through” reconnaissance as a preparation to military operations, e.g. in the Kosovo region.

2.2.4 Cartography - GIS

The relationship between cartography and GIS is an interesting issue for discussion. Tomlin (1990) pays attention to the role of GIS for cartographic modelling, thereby emphasising the way in which cartographic data (map layers) are used during the derivation of information instead of focussing merely on the presentational tasks of cartography. The latter view is, however, prevalent in the GIS literature and a thorn in the flesh of the cartographer who is right to cast doubt on the *“...wonderful, almost* *magical powers...”* (Muehrcke, 1990) that GIS offers. Instead of considering GIS a threat to traditional cartographic skills, it seems more sensible to concentrate on the new role of the cartographer in the GIS era, e.g. as a “geographical data broker”, a visualisation expert or a contributor to knowledge based information systems. Or the cartographer can help to tag data sets with a quality statement as he is well versed in dealing with meta-information as a consequence of handling and combining divergent geographical data (Kraak & Ormeling, 1996).

This “quality task” is becoming increasingly relevant as GIS has evolved into a multidisciplinary technology lacking a clearly circumscribed conceptual basis (there has been a vivid discussion on the question “GIS: tool or science?” summarised by Wright *et al.*, 1997). In other words, who can be held responsible for the sound application of geographical data given the methodologies present in the GIS repository? Certainly, the user has to rely on his own knowledge in the first place, but is the level of userfriendliness offered by the current generation of information systems not providing opportunities to an inexperienced, unsuspecting and therefore vulnerable group? And given this observation, is it not sensible that the cartographer fills this knowledge gap? It is stated that the cartographer can indeed contribute to a better information extraction and decision-making process, not on his own, but as the integrator that brings together all relevant meta-information in such a format that a user will be inclined to really consider it during processing. In essence, this role doesn’t differ substantially from the traditional one as the cartographer has always taken care of an, as appropriate as possible, conveyance of geographical information, mostly by means of taking advantage of the distinguishing abilities of human visual perception.

Without joining in the discussion concerning the extent to which GIS has evolved from efforts in computer cartography or other disciplines (e.g. Coppock & Rhind, 1991), it is undoubtedly true that digital mapping and GIS have approached each other very closely as far as the production of map end-products is concerned. Mapping agencies have changed over to information system technology or are still working on it, although they won’t use all integrated analysis capabilities of such systems. Rhind (1988) considers this development an indication of the acceptance of GIS, as he brings forward the introduction of such technology at Bartholomew’s, an example of a solid, formerly traditionally operating cartographic firm in the United Kingdom.

2.3 Beyond parochialism: the multidisciplinary nature of geographical data management

The above discussion on three major fields of interest within the realm of geographical data management emphasises the obvious need for co-operation. While computer technology progresses with maturing internet technology, the way in which data are accessed and used will change substantially. Maps will be produced on demand on specially equipped map servers, in large numbers and according to an astonishing variety, and distributed along the internet without intervention of a cartographer. As this thesis is written from the viewpoint of a cartographer, his role is recognised. Instead of looking sadly on the ongoing developments, it is stated that cartographic knowledge must be made available to the field of geo-informatics by joining forces. The extraction of information from remotely sensed data crosses several interdisciplinary borders, and in the remainder of the thesis the contribution of cartography will be assigned some more attention. Managing huge amounts of geographical data doesn't necessarily require the physical presence of a cartographer, but it sure suffers from his intellectual absence!

3 Classification of remotely sensed data

"...Viewed from outer space, our planet presents a beautiful sight with its rich palette of colours, the familiar contours of continents, ramified mountain ranges, and picturesque cloud formations..."

Pavel Popovich, former space pilot of the USSR, in Koval & Desinov (1987)

3.1 Introduction

Computer-assisted spectral classification can be considered an expression of statistical pattern recognition aiming at the extraction of thematic information from remotely sensed data. *"...Classification is the process of assigning individual pixels of a multispectral image to categories, generally on the basis of spectral reflectance characteristics..."* (Simonett & Ulaby (1983) in the Manual of Remote Sensing). Mostly, and certainly as far as this thesis is concerned, this information relates to land cover and, indirectly, land use. Campbell (1987) defines the difference between these two as follows: *"...land cover designates the visible evidence of land use, to include both vegetative and nonvegetative features..."* The result of a classification is mostly a thematic map, a cartographic product, at least if it conforms to a sound geometric framework (projection and co-ordinate system).

Basically, classification can be viewed as a decision-making process; classifiers have "decision rules" that are designed to assign spectral measurement values to a finite set of application-dependent classes. In case of an ideal remote sensing system, classification would be an easy task to perform as each earthbound feature would possess its own, characteristic spectral response that could be stored in a consultative "universal signature bank" (Estes *et al.*, 1983). But reality is much more complicated and there is no such thing as a unique spectral signature for a particular feature over time and space. Classification thus becomes a decision- making process that is attended by an amount of uncertainty as far as the correct assignment of a measurement vector to an information class is concerned. In accordance with statements made in section 1.5, a statistical approach is advocated in order to cluster the multispectral data into meaningful classes and to estimate the associated probability of error. Before elaborating on the meaning of some classifiers, a number of more general observations can be made with respect to the use of statistical approaches. In the following discussion remember that a pixel-based classification is assumed as opposed to an object-based approach ("bottom-up" and "top-down" respectively – Abkar, 1999). Chapter 4 will elaborate on the relationship between pixels and objects.

3.2 The statistical foundation of classification rules

A remote sensing data set consisting of just one band is hard to classify automatically because it possibly fails to sufficiently distinguish the "hidden" information classes by their spectral characteristics alone (figure 3.1). The multispectral character of data

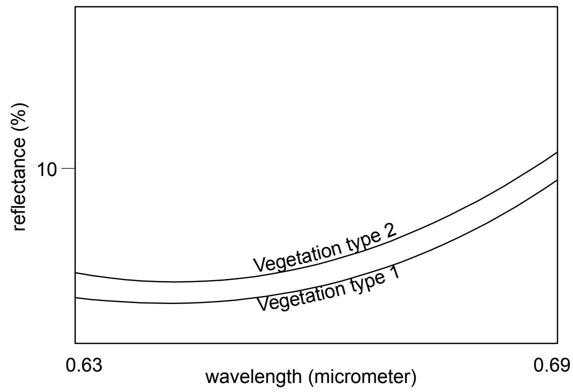


Figure 3.1: One spectral band provides little information to distinguish between different land cover classes

such as acquired by Landsat's Thematic Mapper can be held responsible for the ability of a classification rule to detect and subsequently identify information classes. As can be seen from figure 3.2, representing a so-called *feature space* consisting of three bands, the multidimensionality of a data set reveals clusters that are clearly distinct from each other. Note that more features (here: spectral bands) do not necessarily improve this distinction; in fact, highly correlated bands cause data redundancy that

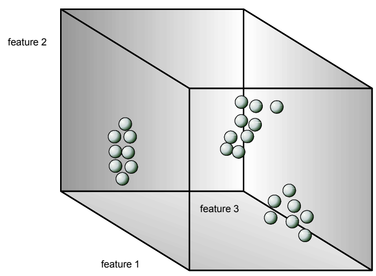


Figure 3.2: Example of a 3-dimensional feature space, clearly revealing data clusters

seriously affects processing time!

The basic idea underlying statistical, spectral classifiers is the concept of imaginary "decision boundaries" that can be drawn in the feature space according to different assumptions concerning the distribution of the data values in a particular class. Starting point is a set of representative samples for each class to be distinguished. This is not as easy as it may seem, because the construction of a classification scheme requires a certain level of knowledge about the occurrences of particular classes in the - unknown - area under consideration.

Normally, classification has been preceded by a more or less extensive fieldwork during which the presence and absence of land cover classes has been assessed as part of a sampling strategy. Moreover, an indication of the number of spectrally distinguishable classes can be achieved by means of an unsupervised classification or clustering procedure being performed on the remote sensing data set. The clusters are not necessarily equivalent to information classes as the latter usually show some spectral diversity that is covered by more than one cluster. Clustering is no classification, also because the meaning of a cluster remains unknown until some sample data are introduced.

These samples are derived from a training stage in which known land cover is isolated from the data set and used as a steppingstone to structure the whole data set. Samples must be representative, thus encompassing the total spectral range of an information class; in addition, the sample size must be large enough in order to allow for the valid application of statistical methods. Estes *et al.* (1983) state that at least $10 \cdot m$ to $100 \cdot m$ samples are required for each training class (where m is the number of spectral bands or channels used in the classification procedure). They continue by stating that *"...within reason, the more pixels that can be used in training, the more accurate the results..."* This can be understood from the point of view that a higher data density contributes to a better estimate of the statistical descriptors of each class.

Parametric approaches assume a Gaussian distribution as an approximation to a continuous *probability density function* (pdf) that describes the probability of a pixel with a measurement value x for a particular feature ("band") while being a member of class C_i:

$$p(x \mid C_i)$$

with $i = 1,...,n$ where n represents the number of classes.

The parameters of the assumed Gaussian distribution, mean and variance in case of a single band, are estimated from the training data set. Figure 3.3 shows the pdf's for two classes and one feature.

It is worth giving the assumption of a Gaussian distribution a moment's thought. In practice, it appears that many training data sets fail to conform to the requirement

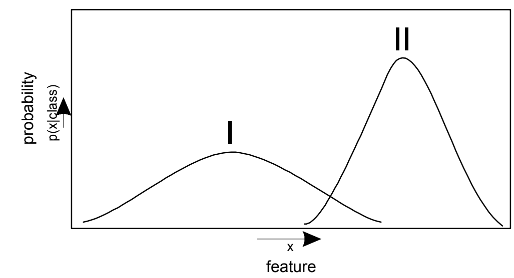


Figure 3.3: The probability density function (pdf) for 2 classes (I and II) and 1 feature (band)

of a normal distribution. The view taken in literature is, however, pragmatic as the assumption of a Gaussian pdf is considered an acceptable simplification of reality that seems to perform well (Swain & davis, 1978). In case of multispectral classification, with unknown distributions $p(X \mid C_i)$ where X represents the measurement *vector* (see figure 3.4), an appeal has to be made to methods from multivariate probability theory which, as Gonzalez & Woods (1992) recall, are met with difficulties if *"...the number of representative patterns from each class is not large or if the underlying form of the probability density functions is not well behaved..."* Mather (1987) makes a reservation as far as the unimodality of the distribution is concerned (just one "peak" is allowed). Abkar (1999) adds that if multimodality violates the normality assumption, the particular class has to be divided in a number of sub-classes that meet the unimodal requirement of a normal distribution (improving the class definition scheme - Gorte, 1998).

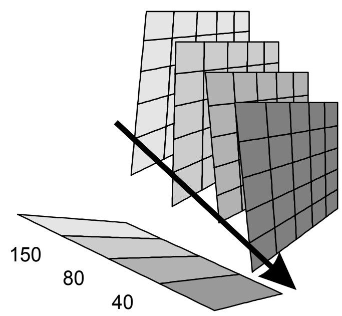


Figure 3.4: Measurement vector summarising the digital numbers per pixel, for each band

If no parameters are derived concerning the shape of the sample distribution, as in **non-parametric** classification approaches, $p(x \mid C_i)$ is estimated per class. In fact, these methods do require some parameter to initiate the decision process and they are better described as "less-parametric" classification approaches. The next sections will deal with often used parametric and "less-parametric" approaches in some more detail, in order to lay the foundation of the methodological framework being discussed as a sequel to this chapter. Again, only statistical, spectral classifiers are considered here thus excluding methods that are primarily based on for example texture or expert rules.

3.3 Maximum Likelihood Classification

The eventual decision whether a pixel belongs to class C_i, so the calculation of the *posterior probability* $p(C_i \mid X)$, is not only based on the pdf for each sampled class. *A priori probabilities* $p(C_i)$ can be introduced to "scale" the pdf's; *"...prior probabilities are probabilities of occurrence of classes which are based on separate, independent knowledge concerning the area to be classified..."* (Strahler, 1980). Chapter 5 will elaborate further on the way in which these priors can be derived and applied. A simple decision rule, involving only two classes and one single band, can be summarised as follows (x represents a single measurement, **not** a vector):

[3.1]

if
$$p(x \mid C_1)\, p(C_1) > p(x \mid C_2)\, p(C_2)$$
then the pixel belongs to class C_1

This simple statement illustrates one version of what is called the "Maximum Likelihood Decision Rule".

Maximum Likelihood classification is an example of a *supervised* procedure. This means that the assessment of data dimensionality ("feature selection"), the selection of representative training samples and the construction of a sound classification scheme are all based on an interaction between computer system and operator. The mathematical basis of this method is provided by Bayes' Theorem which relates the unknown conditional *posterior* probabilities $p(C_i \mid X)$ - which are pivotal with regard to the decision of the most likely class - to the conditional class probabilities $p(X \mid C_i)$ that are derived from the training data as outlined in the previous section. This relationship involves the prior probabilities of the classes $p(C_i)$ and measurements $p(X)$ as well. In formula, Bayes' Rule looks like:

[3.2]
$$p(C_i \mid X) = p(X \mid C_i)\, p(C_i) \;/\; p(X)$$

in which:

$p(C_i \mid X)$	the *posterior* probability that a pixel with measurement vector X belongs to class C_i;
$p(X \mid C_i)$	the conditional class probability that for a given class C_i the measurement vector X occurs;
$p(C_i)$	the *a priori* probability that an arbitrary pixel belongs to class C_i independent of its measurement vector;
$p(X)$	the feature probability defining the probability of occurrence of measurement vector X independent of a particular class.

As $p(X)$ has a constant value for each C_i that has been distinguished, its height is not of crucial importance as far as comparison of *posterior* probabilities is concerned. In other words, it can be ignored if only the Maximum Likelihood class is required (see also formula [3.1]). Nevertheless, the determination of *posterior* probability **values** asks for knowledge about $p(X)$. Given the prerequisite that the classification concerns an "all-inclusive number of classes C_i that are conditionally related to X" (Davis, 1986) then, using conditioning and marginalisation, $p(X)$ can be rewritten as:

$$\Sigma_i \, p(X \mid C_i) \, p(C_i) \qquad [3.3]$$

Therefore, substituting [3.3] for $p(X)$ in [3.2] results in:

$$p(C_i \mid X) = p(X \mid C_i) \, p(C_i) \; / \; \Sigma_i \, (\, p(X \mid C_i) \, p(C_i) \,) \qquad [3.4]$$

As a consequence of this "normalisation" it is possible to calculate the *posterior* probabilities for each class that make up the *probability vector* for each pixel. Bayes' Maximum Likelihood Rule is based on the selection of class C_i with the highest value for $p(C_i \mid X)$, given a particular pixel. Now remember that the definition of the probability density function from which $p(X \mid C_i)$ is derived, is bound by assumptions regarding its Gaussian character (this discussion assumes a Gaussian model although it allows for the prediction of negative photon counts - Mulder & Abkar, 1999). Gonzalez & Woods (1992) prove extensively that the more realistically this assumption holds, *"...the closer the Bayes classifier approaches the minimum average loss in classification..."* thus minimising the average probability of error.

Extending Bayes' Maximum Likelihood Rule to a multidimensional classification problem, i.e. concerning more than one feature or band, the pdf for a particular trained class becomes a multivariate normal probability distribution. Such a distribution can be fully described by its mean vector and covariance matrix parameters (variance and correlation). In a mathematical way, the pdf can be characterised by the following formula:

$$p(X \mid C_i) = 2\pi^{-0.5\,m} \, |S_i|^{-0.5} \, e^{[-0.5 (X-m_i)^t \, S_i^{-1} \, (X-m_i)]} \qquad [3.5]$$

where:

m	the number of features or bands used in the classification;
$\lvert S_i \rvert$	the determinant of the covariance matrix for sample class C_i;
S_i^{-1}	the inverse of the covariance matrix for sample class C_i;
X-m_i	the difference vector, achieved by substracting the mean vector of class C_i from measurement vector X;
$(X$-$m_i)^t$	the transpose of the difference vector.

See e.g. Mather (1987) and Gonzalez & Woods (1992) for more details on the derivation of this formula. Anton (1987) gives a useful introduction into the linear algebra involved in the calculation of the above terms.

The term $[(X\text{-}m_i)^t \; S_i^{-1} \; (X\text{-}m_i)]$ represents a squared distance function, also known as the Mahalanobis Distance. It can be thought of as a measure of correspondence between a measurement vector X and a mean vector m_i in a multidimensional feature space, and as Mather (1987) states *"...corrected for the variance and covariance of class C_i..."*

A simplification of [3.5] is often advocated for reasons of operational efficiency, thereby avoiding the exponential expression. Instead, a natural logarithm is adopted that maintains the "rank order" (Mather, 1987) of the values of $p(X \mid C_i)$; stated in another way, one is often only interested in the relative values of the probabilities. As Strahler (1980) notes, the logarithm of these probabilities is *"...a monotonic increasing function of the probability..."* so the performance of the decision function remains unaffected. If no exact *posterior* probability vector values are required, but merely the identification of the most likely class is at stake, this approach can seriously speed up classification performance. The absence of any prior knowledge concerning the occurrence of a particular class, i.e. all *a priori* probabilities are equal, reduces the classification decision to the ranking of conditional class probabilities.

Formula [3.5] still represents just one part of Bayes' Rule as defined by formula [3.2] and if the above restrictions are not valid, a more complete decision rule is needed. Substituting [3.5] for $p(X \mid C_i)$ in [3.2] therefore results in the following adaptation of Bayes' Rule:

$$p(C_i \mid X) = 2\pi^{-0.5\,m} \, |S_i|^{-0.5} \, e^{[-0.5(X-m_i)^t \, S_i^{-1} \, (X-m_i)]} \, p(C_i) \, / \, p(X) \qquad [3.6]$$

Here, for reasons of convenience the denominator at the right hand side of equation [3.6] is simply written as $p(X)$. In fact, it summarises the sum of the product of the conditional class probabilities $p(X \mid C_i)$ and the *a priori* probabilities that class C_i actually occurs (see [3.3]). As stated before, simplifications can be applied on formula [3.5] in order to reduce computation time and hence improve classification performance. In commercial image processing packages it is not unlikely that the Maximum Likelihood Decision Rule consists of a comparison of the product of conditional class probabilities and *a priori* probabilities, as given in its most straightforward form by formula [3.1]. For computational purposes, consider the numerator of the right hand side of equation [3.6]; the introduction of the natural logarithm results in the following:

$$-0.5\; m \ln(2\pi) - 0.5 \ln|S_i| - 0.5[(X\text{-}m_i)^t \; S_i^{-1} \; (X\text{-}m_i)] + \ln(p(C_i)) \qquad [3.7]$$

The elimination of constants and the multiplication by a factor of -2 gives the following result:

$$\ln|S_i| + [(X\text{-}m_i)^t \; S_i^{-1} \; (X\text{-}m_i)] - 2 \ln(p(C_i)) \qquad [3.8]$$

Now classification is reduced to finding the class C_i for which [3.8] is **minimised**. The role of *a priori* probabilities will be further elucidated in chapter 5, but it is nevertheless interesting to give it a moment's thought from a mathematical point of view.

- The natural logarithm of a small *a priori* probability value (< 1) results in a large negative number which, in turn, hampers the achievement of a minimum because of the multiplication by -2 (resulting in a considerable positive number!). A small *a priori* probability for class C_i indeed fails to contribute to the assignment of that class to a particular pixel.
- Strahler (1980) makes an interesting remark concerning the directive, almost compelling influence of *a priori* probabilities. A very small value (close to 0) can make a class assignment prospectless, the possible resemblance between mean and measurement vector notwithstanding ("small value for the Mahalanobis Distance"). On the other side, high priors for a particular class (close to 1) result in an almost inevitable assignment of a pixel to that class, as can be understood from the structure of [3.8] and the fact that probabilities, so *a priori* probabilities as well, must sum to 1. And the remaining, small priors are not able to change this assignment as can be learned from the previous point. In conclusion, extreme priors tend to ignore the actual measurement values in a per pixel classification.

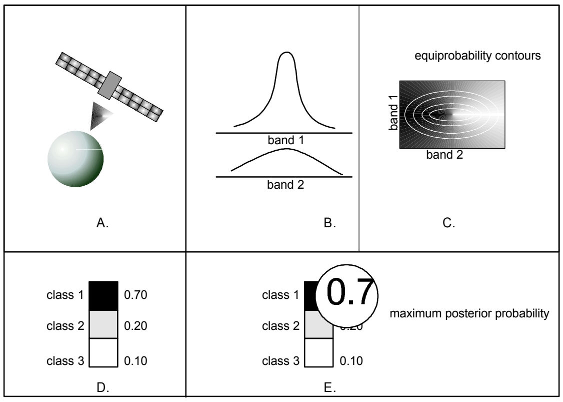


Figure 3.5: The principle of Bayes' Maximum Likelihood classifier:
a. sampling b. probability density function c. signature matching d. posterior probability vector e. selection of maximum value

- In an object- or model-based approach, *a priori* probabilities express the initial strength of hypotheses concerning the geometric and temporal properties of an object: $p(C_i \mid x, y, t)$ where x and y are related to geometry and t to time. The spatio-temporal parameters are adapted to optimise the combined probability of radiometric evidence (the remote sensing image) and geometric/temporal hypotheses (Abkar, 1999; Mulder & Abkar, 1999).

Figure 3.5 provides a graphic summary of the principle of Bayes' Maximum Likelihood Classifier. Of course, the above method has certain shortcomings that can affect the accuracy of the classification results. The last section of this chapter is dedicated to a critical review of both this particular parametric approach and the "less-parametric" approach being dealt with in the next section.

3.4 K-Nearest Neighbour Classification

In a non-parametric classification approach no assumptions are made with respect to the way in which the measurement values of training class C_i are distributed. As such, the identification of spectrally heterogeneous and complex land cover could potentially benefit from the absence of a rigid "statistical corset" and the presence of some statistical discriminant function on which the grouping and labelling - classification - of data is founded. Therefore, the most obvious advantage of non-parametric approaches as compared to parametric methods, is its insensitivity to deviations from the assumptions of (multi)normality. Because of this, improvements in classification accuracy can be easily achieved in case the Gaussian assumption is far from being appropriate. It is remarkable that most textbooks on remote sensing and digital image processing neglect the wide range of non-parametric supervised classification algorithms. This could be caused by the fact that these methods require considerable training sets in the absence of an assumed probability density function.

A rather well known non-parametric approach is based on the *Nearest Neighbour* rule, whose first formulation is attributed to Fix & Hodges (1951) according to Hardin (1994). The idea is simple but well thought-out. A useful starting point is provided by considering the training data for all n classes in the m-dimensional feature space (m representing the number of features or bands). A particular measurement vector X is subjected to an evaluation process that involves the comparison of X with its k nearest neighbouring sample vectors. In fact, k is a parameter that needs to be assessed before the actual classification can take place (this explains why the term "non-parametric" is so deceiving).

The selection of the k nearest neighbours is such that X is at the centre of the smallest spheroid V_X that encloses all k sample vectors in the feature space. It is appropriate to assume an Euclidean distance function to judge the adjacency of k neighbours and thus to determine the size of the spheroid (Hardin, 1994). As the feature space is discrete, as a consequence of the non-continuous character of the features that constitute its frame, the number of *measurement vectors* present in V_X can be counted. This number, s_X, represents the actual size of the spheroid. From the k (*sample*) points that are captured by V_X, k_i belong to class C_i, such that:

$$k = \sum_{i=1,\ldots n} k_i \qquad [3.9]$$

The conditional probability that a measurement vector X is contained in V_X, given the corresponding pixel is a member of class C_i can be described as:

$$p(X \in V_X \mid C_i) \quad [3.10]$$

This probability can be estimated from the total numbers of samples collected for class C_i, n_i, during the training stage:

$$p(X \in V_X \mid C_i) = k_i / n_i \quad [3.11]$$

The conversion of these conditional probabilities to the feature probability densities $p(X \mid C_i)$ can be achieved by assuming that a small spheroid - i.e. data vectors do not deviate too much from each other - contains a constant probability density. Or, stated in another way, $p(X \mid C_i)$ is equal for all s_X measurement vectors present in V_X, the original measurement vector X included. From this, it can be stated that (see also Gorte, 1998 and Van der Wel & Gorte, 1995):

$$p(X \mid C_i) = p(X \in V_X \mid C_i) / s_X = k_i / (n_i\, s_X) \quad [3.12]$$

This interpretation of the *k*-Nearest Neighbour classifier can be implemented in a Bayesian approach, meaning that known *a priori* probabilities are utilised. Such a "Bayesian Nearest Neighbour Rule" (Hardin, 1994) results in the calculation and subsequent comparison of *posterior* probabilities $p(C_i \mid X)$, much like being discussed in the previous section (it can be named therefore a *maximum posterior probability* classification, a more general designation that includes the Bayes' Maximum Likelihood classifier as well).

Literature often gives examples of other decision rules that are derived from the *k*-Nearest Neighbour concept. They assign a pixel with measurement vector X to the class that is most frequently encountered in the spheroid as defined by the k neighbours in the feature space:

if $k_i > k_j$ for all $j = 1,...n$ and $j \neq i$, then the corresponding pixel is assigned to class C_i

This "majority rule" can be demonstrated to be a special case of Bayes' Maximum Likelihood classifier when the number of training samples for each class C_i is in proportion to the size of these classes in the whole population, thus if $n_i = n \times p(C_i)$ - see also James (1985). Besides a rank order, this rule doesn't necessarily result in a complete *posterior* probability vector for the pixel under consideration.

3.5 A critical review - grips for an elaborated study on uncertainty

Both parametric and non-parametric classification approaches are attended by serious drawbacks. Maselli *et al.* (1992) state that these minus points *"...have often prevented the full exploitation of remotely sensed data for applicative purposes..."* What exactly are the impediments that are encountered when applying a Bayes' Maximum Likelihood or *k*-Nearest Neighbour classifier? Do these drawbacks urge for the introduction of "new" algorithms or do adjustments to the existing decision rules suffice for most applications? In order to find answers to these pressing questions, it is important to consider the following point by point discussion.

- One of the most quoted disadvantages of a parametric classifier in general relates to the validity of the statistical assumptions that have to be made regarding the distribution of the training data (see also section 3.2). Small deviations from the assumed unimodal, Gaussian distribution are indeed not unusual. Serious differences between the real and modelled distribution of training data are responsible for unreliable *posterior* probability vectors and hence incorrect class assignments. The statistical model underlying the classification thus may be a too general representation of a spectrally complicated land cover class.
- The malfunction could be just as well traced back to an incomplete training data set from which the statistical parameters of the distribution are derived. Besides Estes *et al.* (1983), Mather (1987) puts emphasis on the considerable size of a training sample for a particular class C_i, namely at least $30 \cdot m$ (with m the number of features or bands) and the requirement of representative but independent (not spatially autocorrelated) samples. Diverging from these basic guidelines while holding on to a strict statistical model introduces biased results and seriously hampers the validity of the classifier. The relevance of the training stage is underlined by Estes *et al.* (1983): *"...the success of the classification process, and therefore the value of the information generated from the interpretation, relies directly on the quality of the training procedure..."* Lillesand & Kiefer (1994) provide an extensive and above all clear discussion on the training stage of a supervised classification.
- Nevertheless, Bayes' Maximum Likelihood classifier requires not as many training data as a *k*-Nearest Neighbour classifier. In the latter case, considerable sample sizes are needed in the absence of a distribution model that summarises (and generalises, think about data loss!) the spectral characteristics of that particular sample. A small and biased training data set can affect the performance of these classifiers and undo the advantages of a more flexible training class representation. All samples (again, they are numerous) remain in computer memory for evaluation purposes during classification, which is not efficient from a computational point of view. Hardin (1994) suggests that this is one of the causes of the fact that non-parametric approaches have found little application so far, but it is evident that Bayes' Maximum Likelihood classifier puts a considerable load on CPU time as well.
- The accuracy of classification results achieved by means of a Bayes' Maximum Likelihood classification is often disappointing or even unacceptable for many applications (Bolstad & Lillesand, 1992). Partly, this relates to the invalidity of the statistical assumptions being made. Hardin (1994) provides an interesting study in which he compares a number of parametric and non-parametric (Nearest Neighbour inspired) classifiers. From the results, it appears that the latter are performing far better than the former, given large training data sets. If no notice is taken of this condition, accuracy loss is more dramatic than would be the case for its parametric opponents.

- Another, interesting cause of bad performance is the limitation of all image classification techniques to make sound distinctions solely on the basis of spectral information; temporal as well as spatial information could be considered beneficial. Structural pattern recognition (e.g. Mulder, 1990) involving spatial relationships can improve classification accuracy in case of heterogeneous, spectrally overlapping land cover. In such a situation unanimous class assignment to a particular pixel turns out to be difficult; instead, an appeal is made to random "tie-breaking" procedures, neglecting the idea of a pixel as - part of - a real world object. Swain (1978) illustrates the successful incorporation of temporal information in a multistage "cascade classifier" that enables an unremitting updating of the discriminant function from which a classification can be derived.
- The question arises how to assess the number of samples k that needs to be evaluated during a k-Nearest Neighbour classification. What is the sensitivity of the classification as far as the value of k is concerned? A large value for k means an increased spheroid in the feature space, possibly violating the assumption of constant probability densities $p(X \mid C_i)$ for all measurement vectors present in the imaginary spheroid. On the other hand could a larger k better deal with the variation within a paricular class. The value of k should certainly not surpass the size of the smallest training class because in that case *"...a pure pixel of that class can never be found..."* (Gorte, 1998). There can be argued about the necessity of anything more complicated than a first Nearest Neighbour classifier; advocates stress the unambiguous class assignment that never requires a "tie-breaking" procedure. Furthermore, it is stated that the error rate of the 1-Nearest Neighbour is far from dramatic when the available sample sets are large, as Gorte (1998) demonstrates for his "Twente data set". The discussion about the assessment of the most optimal value for k is, however, beyond the scope of this thesis; it is nevertheless interesting to touch slightly upon the parametric "hot potato" of a non-parametric classifier!

Of course, the approaches discussed in the above are not the only representatives of a parametric or not classifier. They are, however, commonly used in practice and accepted as an advanced classifier, as in the case of a Maximum Likelihood classifier, including the Bayesian variant with specified *a priori* probabilities. Or they are proposed as a better performing alternative, not suffering from the somewhat contrived statistical assumptions - justifying research into Nearest Neighbour classifiers. By understanding the limitations of these classifiers, it becomes possible to improve their performance by adapting (parts of) the algorithms and deal with their inherent uncertainties. To exclude any possible confusion beforehand, it is stressed that this thesis won't pursue new classification algorithms, but rather improve some of the more useful approaches in an attempt to tackle the impediments that invited Maselli *et al.* (1992) to pronounce upon the too unpretentious status of remote sensing (see the beginning of this section). This could be considered a pragmatic way of acting, but it is thought preferable to the almost exaggerated and apparently unconditional embrace of e.g. "non-parametric" Artificial Neural Network classifiers whose assumed benefits are increasingly propagated with respect to multispectral classification (e.g. Foody, 1996; Foody *et al.*, 1995; Paola & Schowengerdt, 1995a; Paola & Schowengerdt, 1997).

This distant attitude is partly caused by the impression that the disadvantages of the earlier mentioned approaches are subjected to an evaluation that is too superficial (*"...probabilistic methods are slow and computationally demanding..."* according to Foody (1996)). Moreover, it is often too incomplete to remove the appearance that the need for alternative, "black box" classifiers seems to be fuelled by innovative whims that outshine ambitions aimed at improvement. It is believed to be more sensible to "wring out" the potential of basically well defined classification approaches. Artificial Neural Network classifiers, like other improved non-parametric spectral classifiers such as the Skidmore/Turner (S/T) method (Skidmore & Turner, 1988) or the improved Skidmore/Turner classifier (Dymond, 1993 compares three types of S/T classifiers and a maximum likelihood classifier) have already proved to be useful in comparative studies when **the assumption of normally distributed training data sets is far from feasible** (Paola & Schowengerdt, 1995b).

The result of a classification will always contain uncertainty and the recognition of its presence and the subsequent assessment of its extent must gain further attention. If the focus of the present research isn't on the improvement of the decision rules themselves, how is this uncertainty managed? To answer this question, the nature of errors and uncertainty must be subjected to a closer acquaintance.

4 Uncertainty in remote sensing classifications

"...Variation seems inevitable in nature (...) It follows that it is necessary to have some simple methods of describing patterns of variation. Statisticians have developed such methods..."

Grant & Leavenworth (1988) - "Statistical Quality Control"

4.1 Introduction

The classification of remotely sensed data by means of digital automated feature extraction is attended by an often undefined amount of uncertainty concerning the properties of the extracted features (Kretsch & Mikhail, 1990). This uncertainty causes spatial and non-spatial variability in the processing outcomes that, in turn, could hamper a sound decision-making procedure. Here, decision-making refers to the eventual use of the processed (classified or not) remotely sensed data – not to the classification rule itself. Smith *et al.* (1991) provide examples that illustrate the relevance of knowledge about this variability, which allows for more well balanced decisions including cost-benefit considerations. With respect to remote sensing classifications, Middelkoop *et al.* (1989) state that *"...the maximum likelihood rule (...) can include weight factors for the cost of incorrect decisions and the benefit of correct ones..."* Within this context, the issue of data quality has been put on the scene in section 1.4. But what exactly does this quality involve and what is its relationship, if any, with uncertainty, error and accuracy?

The aim of this chapter is to remove possible confusion as far as intermixed terminology is concerned. This is not achieved by simply providing definitions only. By retrieving the sources from which the imperfections in remotely sensed data originate and by revealing the mechanisms by which they are propagated during processing, the distinctions between different concepts are best elucidated.

Furthermore, the concept of uncertainty is considered in view of the two maximum posterior classification rules that have been discussed in the previous chapter. From this, strategies are designed to deal with this inherent characteristic of the considered geographical data.

4.2 On defining some relevant concepts

For a start, a number of definitions is presented in an attempt to produce order out of chaos.

- **Error.** According to Heuvelink (1993) error can be described as *"...the difference between reality and our representation of reality; it includes not only 'mistakes' or 'faults' but also the statistical concept of 'variation'..."*, thereby linking up with Burrough (1986). Errors evoke negative, unfavourable associations; *"...error is a bad thing..."* as Chrisman (1991) notices. But, on the other hand, in everyday language the use of the term error suggests that they can be corrected and hence don't need to be too disastrous after all. As Chrisman (1989) points out, this may be the case for *blunders* (the easy-to-detect-and-remove mistakes in Heuvelink's (1993) definition) but it certainly fails to account for the more subtle, random errors that are being dealt with in a statistical way. In the literature, a number of error taxonomies have been proposed whose aim is to improve understanding of the way in which errors are introduced and propagated (see next section).
- **Accuracy.** Accuracy is often described as *"...the closeness of results of observations, computations or estimates to the true values or the values accepted as being true..."* (AGI, 1991). In a statistical sense, this can be interpreted as the degree with which an estimated mean differs from the true mean (Burrough, 1986). In order to assess accuracy, a source of higher accuracy is needed as a representation of the true or real world, *"...but the 'truth' can never be known..."* (Drummond, 1995). Consider for example the comparison of a remote sensing classification with a ground truth map during an accuracy assessment procedure. The accuracy of the classification can be affected by errors, but the reference - ground truth - data itself (the "modelled" truth) could be error-prone as well. Their obvious relationship notwithstanding, error and accuracy are clearly not the same thing, as Unwin (1995) contends correctly. *"...Accuracy differs conceptually from error in measuring discrepancy from a model; error measures discrepancy from the truth..."* (Buttenfield & Beard, 1994). Accuracy can be distinguished in a positional and attribute component, in accordance with the respective errors that could arise in geographical data.
- **Precision.** Precision is *"...the exactness with which a value is expressed, whether the value be right or wrong..."* (AGI, 1991). Unwin (1995) expresses himself in more concrete terms by defining it as *"...the number of decimal places or significant digits in a measurement..."* High precision doesn't necessarily relate to high accuracy; instead, it is even possible to characterise data in a very precise, but completely erroneous way!
- **Quality.** Quality is defined as *"...fitness for use..."* by Chrisman (1984). Its relevance is discerned by a number of digital spatial data standards, e.g. the American Spatial Data Transfer Standard (SDTS) issued by the United States Geological Survey (USGS) in 1992. In order to enable a self-contained exchange of spatial data between heterogeneous computer systems it is required that - among others - data sets be described according to a metadata structure, involving quality issues as well. Its aim is to provide users with sufficient information in order to evaluate the fitness for a particular application. Moellering (1987), in his well-known report in preparation to the completion of the SDTS, advocates a "truth in labelling"

approach, meaning that information about uncertainty is made available without assigning a predefined, *a priori* value judgement. Quality, therefore, is a relative concept dependent on the pursued aims and the considered context. It is this lack of an absolute meaning that makes quality a difficult concept to work with directly. Instead, a number of quality components has been proposed that clearly reveal the extensiveness of the concept. Guptill & Morrison (1995) offer an excellent collection of papers on each of these components. Later on in this chapter more attention will be paid to these quality components because of the prominent position that they occupy in spatial data standards.

- **Uncertainty.** Increasingly, the concept of uncertainty is introduced when discussing the imperfections inherent to geographical data handling. Quality may be a good starting point for summarising and describing a lot of - different - data characteristics affecting the appropriateness of that data for a particular purpose, but it is also a very general and comprehensive concept. Goodchild (1995) argues that uncertainty is *"...generic and reasonably value-free, and implies nothing about sources or whether they can be corrected..."* This is in flat contradiction to the observation made by Heuvelink (1993) that uncertainty is *"...synonymous to error..."* In this thesis, uncertainty is used as a useful concept to express the inability to be confident of, and knowledgeable about the *truth value* of a particular data characteristic; uncertainty indicates a *"...lack of knowledge..."* (Stephanou & Sage, 1987). The argument that MacEachren (1995) brings forward to support his move to abandon the idea of uncertainty, namely that it bears a negative load, is rather weak; instead of adopting certainty as a complementary (and more positive) concept, he advocates the use of *reliability*. This concept, however, is commonly used in a more narrow statistical sense, referring to the repeatability and verifiability of measurement and processing results. In an earlier paper, MacEachren (1992) elucidates the distinction between quality and uncertainty as he emphasises the issue of variability over both space and time, and within categories. In case of a remote sensing classification, the aggregation of thematic land cover classes causes uncertainty, the possible high quality of the separate classes notwithstanding. To make it even more complicated it is stated that the impact of this uncertainty is dependent on the user's perception of the real world. A simple, almost "binary" worldview (urban versus non-urban area) allows for more general categories whose validity is not disturbed by within-class variability.

4.3 Sources of uncertainty in remotely sensed data

During the life cycle of remotely sensed data, uncertainties are introduced and propagated in an often unknown way. In this respect, these data are not any different from other spatial data except for the fact that the acquisition and processing techniques used can be held responsible for specific types of uncertainty. A reconstruction of the information process of remotely sensed data allows for the creation of an inventory, listing all possible sources from which imperfections could originate. As a starting point, consider table 4.1 summarising a number of error and uncertainty taxonomies distinguished in literature. Although mostly relating to GIS data, the general subdivisions can seriously help to structure the divergent uncertainty sources underlying the remote sensing information extraction process. Here, the division in three categories proposed by Goodchild & Wang (1988) and Beard (1989) will be further discussed.

Table 4.1: Examples of error and uncertainty taxonomies from literature

	Main Distinction		
Geographical Approach			
Bédard (1987)	locational error		descriptive error
Chrisman (1987)	positional error		attribute error
Veregin (1989)	cartographic error		thematic error
Mathematical Approach			
general	random/accidental error		systematic error
Bédard (1987)	categoric/qualitative error		numeric/quantitative error
Veregin (1989)	measurement error		conceptual error ("fuzziness" according to Chrisman, 1987)
Process Approach			
Walsh et al. (1987)	inherent error		operational error
Goodchild & Wang (1988)	source error	processing error	product error
Beard (1989)	source error	process error	use error

Uncertainty relating to source

As briefly pointed out in section 2.1.4 remote sensing is considered here primarily a data acquisition technique based on the interaction of electromagnetic radiation and earthbound objects. Basically it involves a sampling process by which information about our environment is collected; objects are "reshaped" in spectral values only to re-create a more abstract but understandable image of reality. As a result, uncertainty is introduced but its extent is dependent on a number of factors that are briefly addressed in the following discussion.

- **The sensor system.** Without dwelling too much upon the technical characteristics of the Thematic Mapper instrument onboard Landsat 4 and 5, it can be stated that the velocity of its scanning mirror, the number of detectors for each spectral band and the height at which the satellite is operating are among the parameters that determine the signal-to-noise ratio and thus the "goodness" of the measurement. Furthermore, the characteristics of the orbiting satellite system can be translated in terms of resolution: *spatial* (density of samples in space, extent of the scene element), *spectral* (range of the spectral channels in which radiation is measured), *radiometric* (measurable difference in radiant flux) and *temporal* (periodicity of coverage) resolution. The values for the Thematic Mapper are summarised in table 4.2. All data resulting from this sensor are affected by these properties, although not always to the same extent. As a consequence of the - temporary - malfunction of individual detectors, biased or even incomplete data sets are acquired, for example as the result of "bright target overshoot" (Helder *et al.*, 1992). This phenomenon originates from the occurrence of highly reflective objects, spectrally

Table 4.2: Figures for the reolutions of the Thematic Mapper instrument

Resolutions Landsat-tm	
spatial	30 m
	120 m (thermal band)
spectral	7 bands
radiometric	8 bits quantisation (256 DN)
temporal	16 day repeat cycle

standing out as a result of which the detectors overshoot. Examples of such objects are greenhouses and fields covered by snow. Here, it is not possible to speak about "errors" because a correction is impossible - the data are simply missing ("dropped lines") and only cosmetic operations are able to create a complete image. Finally, clouds can seriously decrease the usefulness of a series of images collected over time thereby reducing the temporal resolution. But these internal differences notwithstanding, the resolutions roughly indicate the boundaries within which a successful classification can be performed. However, the situation is far more complicated as high resolutions are not always required or even desired as will be pointed out in the following.

- **The complexity of the area that is covered by the remote sensing image** (figure 4.1). Consider a highly complicated area as far as land cover is concerned, such as

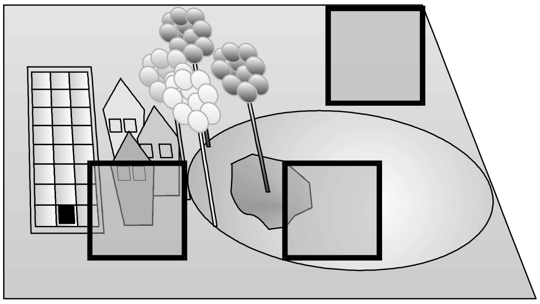


Figure 4.1: The limited ability of a sensor to correctly capture areas with high complexity

represented by the outskirts of an urban area, and a uniformly arranged area covered by only one type of land cover, such as grass-land. In the former case, the detection of small objects by spectral information alone is only achieved if the spatial resolution of the imaging system is sufficiently high or if the earthbound objects exhibit a spectrally strongly divergent pattern that can be sensed within the range of the instruments. The latter case doesn't provoke impure spectral responses and thus the occurrence of so-called mixed pixels in the resulting image (e.g. Fisher & Pathirana (1990), figure 4.2). Mixed pixels are also introduced if objects are separated by transition zones rather than sharp boundaries. These "fuzzy boundaries" (Goodchild & Wang, 1988) could induce uncertainty if they fail to comply with the predefined classification scheme and instead represent a varying spectral mixture of two or more land cover classes. Knowledge of the sensor system, particularly the point spread function, can help to unravel this mixture (e.g. Abkar, 1999).

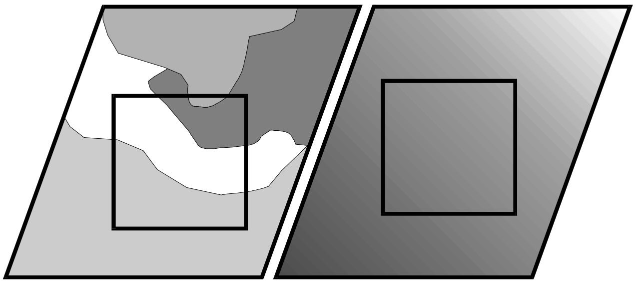


Figure 4.2: The concept of mixed pixels or "mixels"

- **The extent of geometric and atmospheric distortions.** Variations in the operational parameters of the sensor (e.g. height and velocity) can be held responsible for geometric errors in the raw data set but the curvature of the earth surface and the presence of relief are important as well when considering the sources of geometric imperfections. Partly, these can be corrected but of course some uncertainty remains as a consequence of the inability to correctly capture the world in a flat representation. The interaction of electromagnetic radiation with the atmosphere can seriously reduce the information potential of the signal being detected by the sensor system. When travelling through the atmosphere, the radiation is subjected to both absorption and scattering, sometimes collectively referred to as "attenuation" (Rees, 1990). Without going into details, it is evident that these processes affect the quality of the measured radiation in an adverse way. It is even possible that the energy radiated by the sun doesn't reach the earth's surface because of the occurrence of thick clouds that can only be penetrated by microwaves (radar!).
- **The image space.** As a result of the above mentioned sampling process, the earth surface is subdivided in scene elements that are represented in the image space as picture elements or pixels (see also section 2.1.4). These pixels generally fail to relate directly to real world objects, in which we are truly interested.

Uncertainty relating to processing

The processing of remotely sensed data encompasses a wide range of steps and is dependent on the ultimate purpose as defined by a user. Here, the goal is to achieve a land cover classification and this involves usually a pre-processing stage preceding the classification itself. The amount of uncertainty "allowed" in the data is related to the success of the radiometric and geometric corrections and the information loss during data conversions. The latter could refer to a resampling process in order to fit different pixel sizes during synergism of Landsat-TM, SPOT-P and aerial photo data aimed at an improved information extraction (e.g. Patrono, 1996). Pellemans *et al.* (1993) merge SPOT-panchromatic with SPOT-multispectral information, thereby stressing the relevance of methods that preserve absolute pixel values such that post-processing algorithms remain meaningful.

Geometric correction is mostly executed according to the selection of ground control points (GCP's) in both the image itself (with image co-ordinates [i,j]) and a reference image (with reference co-ordinates [x,y]). The definition of a polynomial equation helps to link both co-ordinate systems (see e.g. Janssen & Van der Wel (1994) for more details). Usually, a root-mean-square (RMS) error is calculated as an estimate of the positional accuracy of the referenced pixels. Paulsson (1992) assumes that a positional accuracy of about 15 meters is feasible for Landat Thematic Mapper data. The correctness of GCP's is decisive for the success of the registration process; the identification of these points from cartographic documents is somewhat ambiguous because maps are generalised and idealised for a particular purpose, such that the true position of road intersections and landmarks (popular GCP's) can be biased. GPS techniques (Global Positioning System) could help to accurately determine the position of identified control points (Clavet *et al.*, 1993) but the limiting factor remains the spatial resolution of the satellite image and the identification of reference points instead of objects (the latter allow for a more accurate match).

The geometric correction is completed when the image is transformed into a new grid that corresponds to the *"...x- and y-axis of the chosen reference co-ordinate system..."* (Janssen & Van der Wel, 1994). This *resampling* can be performed before or after classification; the former is required if more than one image is considered, such as in multi-temporal classification or during synergism while the latter can be justified when expecting adverse effects on classification performance. Some resampling procedures calculate "new" image values out of existing ones, thereby possibly impairing the relation with land cover classes. Smith & Kovalick (1985) have compared the effects of different resampling techniques on classification accuracy and from this it is clear that neither “pre- nor post-classification” nearest neighbour resampling (not involving the calculation of "new" measurement values) has an adverse effect on the classification results.

Radiometric corrections are aimed at the removal of errors introduced by e.g. atmospheric interactions, different illumination conditions or instrument malfunction. As these imperfections have a systematic nature they can be modelled by some mathematical relationship (e.g. Thapa & Bossler, 1992). In fact, they arise during the acquisition stage and as such they have been touched upon in the previous section. As far as processing is concerned, it is worth mentioning a phenomenon known as "banding", introduced by differences between the forward and reverse sweeps of the TM scan mirror. In an image, the regular pattern of stripes is easily recognised over large water bodies or snowfields. The deviating responses of individual detectors per band have to be corrected or at least these differences have to be reduced during pre-processing, otherwise it will seriously disturb quantitative processing. Helder *et al.* (1992) provide a technique to reduce banding in TM images.

In the above, a number of factors has been discussed that can be held responsible for the introduction of uncertainties. The classification process further introduces and propagates uncertainty while translating spectral information into information classes. Before elaborating on this issue it is necessary to give the following consideration a moment's thought. When capturing our environment in an image by remote sensing techniques, an irreversible abstraction of reality takes place. No matter how carefully pre-processed and classified, the most attainable is a **reconstruction** of this real world situation. However, we need to abstract in order to understand - and optimise the differences that exist between our view of the world and reality by embodying the uncertainties in our decisions and actions.

At different stages, uncertainties can enter the classification process. Lunetta *et al.* (1991) recognise problems that relate to the classification scheme being used (the classes that are distinguished during classification). As a consequence, they distinguish uncertainty caused by:

- the occurrence of transition zones, mixed classes and rapidly changing land cover that is not foreseen by the predefined classes;
- an incomplete or ambiguous definition of classes;
- the subjectivity of the human interpreter;
- the incompatibility of different classification schemes when integrated - consider the distinction of the land cover class "built-up area" and the land use class "residential area" in two separate classifications that are used in a change detection analysis during a particular time span.

Furthermore, the number and correctness of samples used during classification (see section 3.2) affects the performance of the classifier and the accuracy of its output. Samples could be non-representative (only partly covering the general characteristics of a particular land cover class), insufficient, incomplete (overlooked classes) or even outdated and thus lay an unstable foundation for a classification. Realise that the collection of these data is often a time-consuming and money-swallowing activity that is easily replaced by a visual inspection of some cartographic document or the image itself. But maps are not always up-to-date, comparable or even available and a visual interpretation rarely excludes uncertainty. Again, the observation made by Estes *et al.* (1983) comes into mind, namely that the quality of the training stage encompassing the collection of sample data is of the utmost importance as far as the success of the classification is concerned (see also section 3.5).

The classification algorithm itself is an important source of uncertainty as well, as is demonstrated by a study performed by Hardin (1994). He compares a number of parametric and nearest-neighbour methods and concludes that the latter give a better result ("higher accuracy") if the training data sets are large and in proportion to the assumed class populations (see also section 3.5). It must be noticed, however, that the selection of a classifier is often attended by a casualness that often indicates a lack of understanding of these mutual differences. In practice, a user applies the classifier that is readily available in the image-processing package without bothering too much about the validity of statistical assumptions in case of a parametric approach. Moreover, the performance of the classifier remains very often unknown because accuracy assessment procedures are omitted.

Uncertainty relating to products and their use

Once a classification has been applied, the uncertainty related to the distinguished classes can be estimated according to an error assessment procedure. In practice this means that the classification is subjected to a comparison with some reference data set - a map, another classified image or ground truth data - resulting in an error matrix or confusion matrix (Story & Congalton, 1986), see table 4.3. Although

Table 4.3: The error or confusion matrix

		Reference data				
		X	Y	Z	row total	correct (%)
Classified data	X	24	2	4	30	80
	Y	6	45	9	60	75
	Z	3	5	52	60	87
	column total	33	52	65	150	

apparently contradictory, here again uncertainty can be introduced as a consequence of sloppy procedures. Take the collection of ground truth as an example. Curran & Williamson (1985) demonstrate that these data can be more erroneous than the remote sensing data set itself although they are assumed to be suitable for checking its accuracy! There are different reasons for these imperfections, e.g. the spatial variability of the study area considered or differences in the results of ground truth surveyors who inaccurately locate samples or visit an insufficient number of samples. They can all contribute *"...to the erroneous conclusion that it is the remote sensing map which is in error..."* (Smedes, 1975). With respect to the location of field samples or - better stated - the recognition of pin-pointed spots during fieldwork, the study of August *et al.* (1994) is worth mentioning as they report on the use of GPS for accurate and precise positioning measurements. And as far as the number of samples is concerned, Hay (1979) provides a guideline by considering at least 50 samples (!) per class.

The usefulness of many accuracy assessment procedures is questionable as they fail to proceed beyond the derivation of a simple overall accuracy statement like "85% of pixels correctly classified". The meaning of such figures partly depends on the representative samples that have been checked. But as accuracy has a spatial extent here, it would be more promising to locate accurate spots on the classified image or at least to give an impression of the correctness of separate classes. Janssen & Van der Wel (1994) present a review of accuracy assessment procedures, emphasising the possibilities of the error matrix to derive additional and more informative accuracy statements.

Another important source of uncertainty during the "post-classification stage" relates to the presentation of the classification results. Usually a thematic map is derived, depicting the distribution of land cover types over a particular region. Not seldom, not the classification itself but a post-processed image is presented in order to provide a visually attractive as well as informative compromise. Such products have been subjected to a "noise removal procedure", e.g. by the application of a majority filter that helps to re-label thematically isolated pixels in the classified image (see also chapter 5). The problem, however, is that this definition of noise is inappropriate when dealing with an area that is characterised by the scattered occurrence of relatively small objects. Furthermore, such a smoothing operation "de-fuzzifies" boundaries to such a degree that the possibly transitory nature of the concerned changes in land cover types is obscured. Obviously, this results in a loss of information! In case the land cover map is nothing more than a "nice picture" approximately illustrating the contents of tabular data (*"...10 ha of arable land, 20 ha of built-up area..."*) and used accordingly, this point could be considered to be of minor importance.

Generalised or not, a standard cartographic representation always "hardens" the probabilistic results of the classifications discussed in the previous chapter. They only show the maximum posterior probability class which is indeed assumed the most likely although its meaning may be affected by the height of the probability of assignment. According to Goodchild & Wang (1989) such an approach *"...deletes all potentially useful information on uncertainty..."* and they support the idea to store the entire posterior probability vector in a GIS. But before elaborating further on the role of the probability vector as an indication of uncertainty, it is interesting to consider the cartographic consequences of this observation.

- Traditional thematic mapping aimed at the creation of static - paper or electronic - maps appears to be failing as far as the conveyance of probabilistic classification results is concerned. The compliance with cartographic rules will lead to *"...valid representations..."* without *"...representing the validity..."* of the underlying data (after Goodchild *et al.*, 1994a, see also chapter 7).
- The use of these classifications in decision-making is therefore attended by risks, especially if the probability information is taken for granted and considered not worth storing.
- A map that somehow communicates the full extent of the information that has been derived during classification is clearly desirable. Such an image could reveal both the distribution of land cover while providing a measure of the classification uncertainty at the same time.

There are more sources of uncertainty that can be distinguished during the post-classification stage, such as those related to the interpretation of the results. Different users can draw strongly deviating conclusions from the same map depending on their map reading skills, motives, and acquaintance with raster information and the subsequent ability to translate this information into meaningful objects. As a special case of product-related uncertainty, consider the result of a temporal analysis or *monitoring* operation.

The detection and identification of changes in land cover by means of the comparison of two or more classifications is called *post-classification comparison* (see chapter 8). The representation of the same area at different points in time provides information about the dynamics of processes or phenomena in that particular region. However, the monitoring method is sensitive to errors and uncertainties which is understandable from the possible sources of imperfections for separate classifications as given in the above. According to Lindgren (1985) it is necessary to make a distinction between on the one hand *ideal* and on the other *realistic* change information. The former assumes a situation in which the precise location, character and possible quantitative nature of changes are known. A more likely situation is illustrated by a monitoring image (*change map*) characterised by a combination of the following:

- large, contiguous areas revealing changes as a result of unambiguous spectral distinction of land cover in the separate classifications;
- large, contiguous areas characterised by change that is not revealed in the monitoring map as a consequence of unambiguous spectral distinction;
- small, scattered patches that are wrongly identified as areas of change, e.g. as a result of inaccurate geometrical registration of the original classifications;
- small areas in which indeed a change has occurred that is not detected as a consequence of careless registration, insufficient spectral discrimination and a limited spatial resolution of the underlying images.

The result of a multi-temporal comparison of two or more images can be disturbed by the introduction and possible propagation of errors and uncertainties. Among other things, their gravity is dependent on the source data, the (pre-)processing steps undergone and the pursued application.

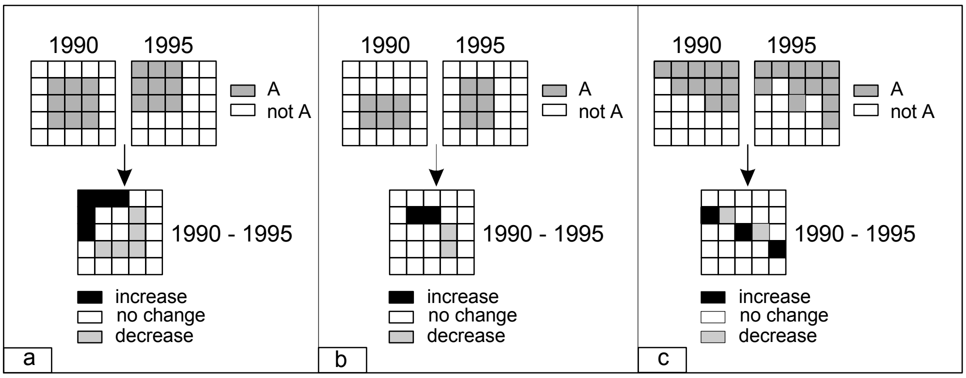


Figure 4.3: a. Edge effect as a result of a careless registration b.Edge effect as a consequence of mixels c. Confetti effect

The fact that the classifications have to possess the same geometrical basis in order to enable a comparison, implies the probability of wrong registration. In change maps, linear artefacts can turn up due to a minimal shift in the mutual alignment of the original data layers (figure 4.3a). This causes an interfering pattern that can be described as an *edge effect*. Not only a careless registration, but also the occurrence of mixed pixels can be held responsible for such an effect (figure 4.3b). Mixed pixels or *mixels* can arise at the edges of (spectrally) homogeneous objects and provide a substantial contribution to wrong class assignments. If the mixels are assigned different class labels in the separate classifications (although concerning the same class), the observed “change” can be recognised as false and subsequently ignored as long as its manifestation and context reveal sufficient clues (for example, linear change patterns along roads). A heterogeneous area, on the contrary, such as an urban fringe characterised by a mixture of buildings and vegetation causes a considerable amount of mixels. The interpretation of the resulting change map can be somewhat treacherous: is there a change or is it just an expression of the *confetti effect* (figure 4.3c)?

It is evident that a *change map* can benefit from comparative classifications, meaning based on compatible and representative training strategies. If not, the effect will be noticeable in the reliability of the monitoring results unless, of course, the separate classifications reveal an extreme level of accuracy (Jensen, 1985).

Table 4.4: The monitoring error chart, t_1 and t_2 represent different points in time, m refers to the monitoring result

Description		
error		**effect**
t_1	**t_2**	**m**
none	none	no change
none	commission	increase
none	omission	decrease
commission	none	decrease
commission	commission	no change
commission	commission	decrease
commission	commission	increase
commission	omission	decrease
omission	none	increase
omission	omission	no change
omission	omission	decrease
omission	omission	increase
omission	commission	increase

Recognition of wrong class assignments is an unfeasible task to accomplish without the availability of some sort of reference data. In such a case, only the change pattern that is exposed after the combination of two or more classifications can give a clue as far as the correctness of (one or more) classifications is concerned. The interpretation of the results, then, requires that the original classifications are at the disposal of the user as table 4.4 clearly points out. The "error chart" stresses the ease with which changes are implied when different error combinations are at stake.

4.4 Probability information as an indication of uncertainty?

In the previous section it has been stated that *"...the uncertainty associated with a classified scene is represented by the probability vectors..."* (Goodchild *et al.*, 1992). However, the average user who has to content himself with the highest probability value (or rather the accompanying class labels) is often ignorant of the composition of these vectors. It is true that the consideration of all these vectors requires considerable computer storage capacity, although this point lost relevance since disk space seems almost unlimited - surely as far as costs are concerned. A far more valid reason for this deficiency is the doubt that is harboured with respect to the ability of an average, non-expert user to deal with all this information. After all, such a user is not particularly well educated in statistics and therefore the risk of abuse is seriously lurking. Therefore, the key issue is whether or not the evaluation of posterior probabilities bears an extra value for the decision-making process.

Before accepting the posterior probability vector as an instrument that could improve the interpretation of remotely sensed data, one has to understand their relative meaning. These values reveal the probability that a case actually belongs to one of *n* distinguished classes. An inappropriate classification scheme and inaccurate training samples can therefore result in meaningless class assignments, which are not easily detected from the underlying posterior probabilities. A comparison of these values over time, e.g. in a change detection procedure, is therefore very controversial. Furthermore, it is evident that in order to prevent so-called *outliers* from being involved in the classification (cases that are not easily classified in one of the defined categories) a class "unknown" has to be established.

Keeping these limitations in mind, the idea of storing posterior probability vector information is strongly advocated here. Its potential has to be exploited carefully and considered appropriately - it must be made accessible through unambiguous and understandable communication media. At the moment, most commercial image processing packages fail to provide a user with the entire probability vector - which is almost calculated, though (see section 3.3) - and thus *"...it is wasteful of information generated within the classification..."* (Trodd *et al.*, 1989).

The main argument for storing and possibly considering all probabilities during subsequent decision-making, is based on the assumption that they are **indicative of the uncertainty in the classification**. The composition of the probability vector not only reveals uncertain class assignments, but heterogeneous classes and mixed pixels as well, according to Goodchild *et al.* (1992). As an example of the latter, figure 4.4 illustrates a situation in which a transition zone separates two land cover types. The highlighted pixel contains the spectral response of both, and the probability vector resulting from the classification expresses this.

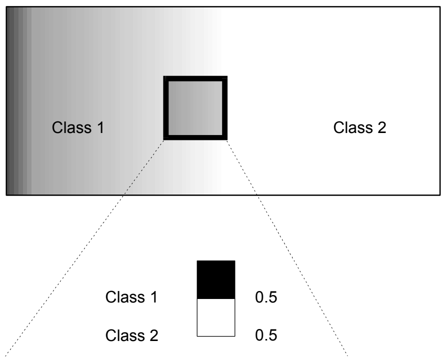


Figure 4.4: A posterior probability vector revealing a mixed pixel

Probability vectors are the *by-product* of some classification procedure and it is interesting to know whether they are sufficiently indicative of all uncertainty. In order to provide some clues consider the following point-by-point discussion.

Firstly, what part of the uncertainty is represented by the probabilities? Or, stated in another way, how are geometric, thematic and temporal components reflected in the figures - if they are at all? In fact, the question arises to what extent these components can be truly separated (note that in a model-based approach radiometric, geometric and temporal properties are dealt with at an object level). For example, an incorrect shift in pixels resulting from a geometric correction procedure (or rather, the resampling of pixels involved) could affect the subsequent classification result. This effect can be even more intensified when the original digital numbers are altered by bilinear interpolation and cubic convolution resampling methods (e.g. Lillesand & Kiefer, 1994).

Apart from the difficulty to distinguish between thematic and geometric uncertainties it appears hard if not undesirable to track down and **quantify** all uncertainty sources for a particular end product. It is, however, important to know these sources in view of getting an understanding of the value of the present results and achieving an improvement of future classification results.

Interpretative uncertainties are beyond the scope of the probability vector, but on the other hand its posterior probabilities could contribute to a reduction of the occurrence of interpretation errors. They can give an in depth insight in the strength of class assignments and the credibility of the selected class. As such, the interpretation of change information revealed by a *post-classification comparison* can benefit from their availability as well.

There exists another collection of uncertainties that are not represented by the *posterior* probability vector. They relate to the validity and the appropriateness of the data set. In fact, a classification result that is attended by high posterior probabilities doesn't always exclude uncertainties in the decision-making process that follows. The underlying remote sensing data set needs to link up with the information need of a user. The selected area, the date of acquisition (see example and figures 4.5 and 4.6), the classification scheme used - all may appear inappropriate in view of the intended use. Also, the pixel-based classification may eventually be questioned because users are more interested in "real world" objects as has been noted in chapter 1 (e.g. to update their GIS, see e.g. Abkar, 1999)

It seems that a posterior probability value only tells part of the uncertainty story, to wit that part that directly relates to the classification process. As such, its indicative meaning can be justified from a statistical point of view, at least as far as the maximum posterior probability values are concerned. Especially a parametric classification approach could model the class distributions in too simplified a way (unimodal, normal) and this can affect the probabilities in the vector in an adverse way.

Without trivialising the relevance of these uncertainties, it is evident that they "only" partly support a user who needs to judge the value of the classification results for a particular application. They provide clues about the (un)certainty of a class assignment, not necessarily related to the correctness of such an assignment! Even a good observer can be tempted to cast doubt on the sense of deriving, storing and

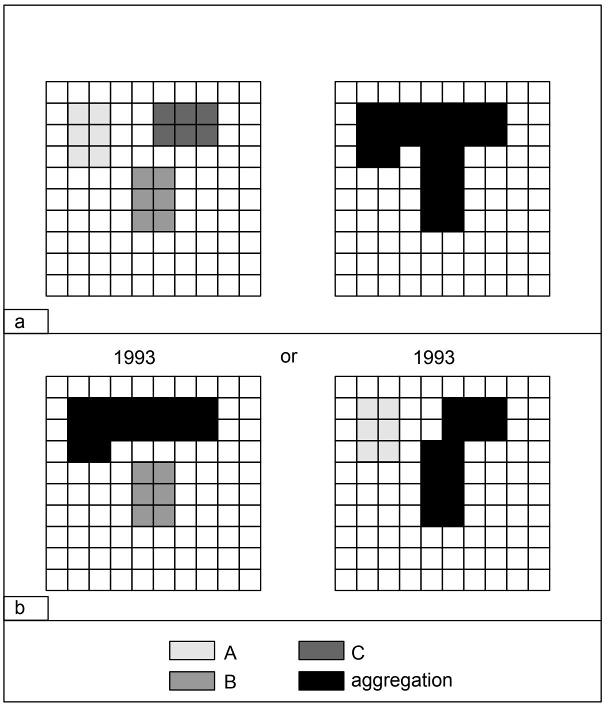


Figure 4.5: a. Start and end of a development characterised by the aggregation of three objects
b. The temporal uncertainty is related to the order of aggregation

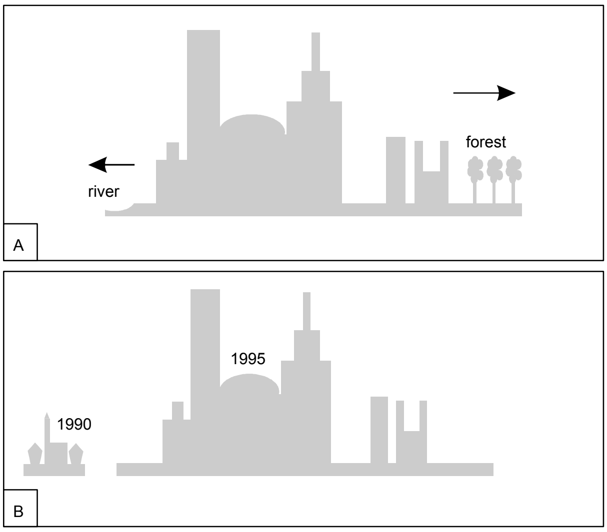


Figure 4.6 a and b: Knowledge about the possibility and probability of an extension can simplify the interpretation of a monitoring result

interpreting probability vectors. But such a person needs to bear in mind that the availability of this information offers grips for improving the classification process that has become far more transparent in this way.

In order to cover all aspects of uncertainty, additional **quality** information is required to complement the probability vector information. The next section will briefly introduce some of these metadata, but this issue will be further elaborated in chapter 7.

4.5 Quality and quality standards

In section 4.2 the issue of metadata standards has been mentioned. Moellering (1997) defines spatial metadata in accordance with the ICA as *"...data that describe the content, data definition and structural representation, extent (both geographic and temporal), spatial reference, quality, availability, status, and administration of a geographic dataset..."* He mentions five major uses of metadata, namely:

- documentation of a database **- what data is in it?**
- availability of a database **- where is the data?**
- quality and fitness for use **- how appropriate is the data?**
- access to a database **- how can the data be obtained?**
- spatial database transfer **- how are datasets exchanged between computer systems without information loss?**

Currently, there are several initiatives to structure spatial data and their accompanying meta-data according to international standards. A main distinction can be made between *transfer standards*, directed at the self-contained exchange of spatial data sets, and *content standards*, prescribing what data and organisational characteristics should be described. As an example of the former and in addition to the Spatial DataTransfer Standard (SDTS), NATO's DIGEST transfer standard can be mentioned (Digital Geographic Information Exchange Standard, Beaulieu & Dohmann, 1997). The latter includes CEN TC-287, the metadata standard of the European standards organisation (CEN) which is considered by most of the cartographic organisations that are interested in adopting a spatial data standard (CEN, 1996; Ostman, 1997).

Especially the part that deals with quality is worth mentioning, because it provides extended guidelines to describe several quality components. At the same time, the International Standards Organisation (ISO) prepares a set of standards relating to spatial data. Within the framework of its Technical Committee 211 the issue of quality is being scrutinised and although this work is still under construction, it is clear that its contents are deviating from the CEN norm - some adjustments notwithstanding (Godwin, 1997). Fortunately, CEN and ISO have recently harmonised their efforts, known as the "Vienna Agreement"(it remains to be seen whether ISO 15046, or at least parts of it, will be adopted by CEN in the future).

The Content Standards for Digital Geospatial Metadata from the Federal Geographic Data Committee (FGDC) has been developed in the framework of the National Spatial Data Infrastructure (NSDI). Its quality "group" relies on the recommendations provided by the SDTS. This content standard is mandatory by presidential order since 1994, meaning that federal agencies have to implement the standard for the description and unlocking of - new - geospatial data as from that moment.

4.6 Towards a strategy for dealing with uncertainty in classified remotely sensed data

From the provided overview of errors and uncertainties with which remotely sensed data are attended, it appears that it is by far unfeasible to assess the extent of separate contributions. In addition to simple interpretation rules, as in the case of change detection, probability theory offers a framework for dealing with uncertain information. The statistical decision rule on which Bayes' Maximum Likelihood Classification is based enables the derivation of posterior probability vectors that reveal indications of possible class confusion. Obviously, it covers only part of the total range of imperfections in the data set but nonetheless it offers a grip to users who are eagerly willing to pursue "better" results and refuse to reconcile themselves to the fact that time and money for extensive fieldwork is often lacking. Fieldwork is required to obtain absolute reference data for the assessment of the accuracy of a data set.

True, probability and other quality information don't always directly allow for a distinction between "wrong" and "correct" because of their relative meanings. However, quantitative probability information and descriptive meta-information are often readily available and the problem that needs to be resolved in the following chapters relates to ways in which this information can be dealt with (see also figure 4.7, that will be extended during the following chapters).

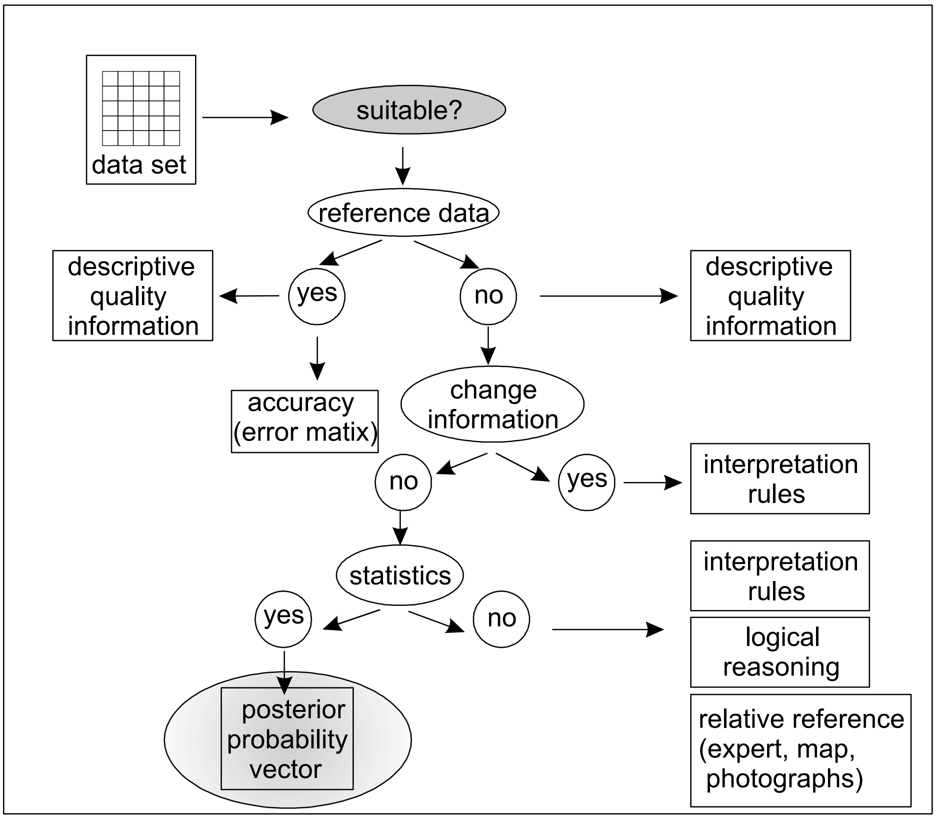


Figure 4.7: The role of quality information in information extraction

5 Dealing with uncertainty: assessment and reduction

"... The Landsat satellite is capable of taking a complete photograph of the entire planet every two weeks, and it's been collecting data for more than 20 years. In spite of the great need for that information, the vast majority of those images have never fired a single neuron in a single human brain ..."

Al Gore - "The Digital Earth: Understanding our planet in the 21st Century, speech given at the California Science Center, Los Angeles, January 31 - 1998

5.1 Introduction

From the previous chapters it has become clear that the derivation of a posterior probability vector could provide clues about the uncertainties in a classification result. Although the exact nature of these imperfections remains to be clarified, it is beyond doubt that probability theory allows for a well-considered interpretation of the results of statistical classification rules. Before embroidering further on the value of these vectors, it is worth recalling the incentive of deriving uncertainty information. This has been defined in chapter 1 as:

...preventing a user from using inappropriate data or maps for making decisions or for further processing...
or
...helping a user to make the best decision based on inappropriate data or maps...

Obviously, the questions arises what "inappropriate" really implies, besides a reference to the concept of quality (section 4.2). How could such a qualitative label be translated to the quantitative realm of a probability vector? What uncertainty measures can be derived from the posterior probabilities without coming into conflict with statistical rules? Are these vectors always required in order to assess the appropriateness of spatial data for a particular usage? And, finally, is it possible to distinguish between situations in which one uncertainty measure is preferred to the other?

This chapter will shed some light on these matters and goes even further by zeroing in on different approaches aimed at the reduction of uncertainty in classified remotely sensed data.

5.2 Approaches to uncertainty: from ignorance to awareness

The most easily adopted approach to dealing with uncertainty is ignoring or even neglecting its existence. Hunter & Goodchild (1995) call this the "do nothing" option, and they are - unfortunately - right by stating that this *"...tends to be the rule rather than the exception..."* On the one hand, such an attitude is encouraged by the often scanty presence or even lack of tools to handle uncertainty in geo-information software packages. On the other hand, source data are not attended by serious uncertainty information, or users simply disregard this information. Imagine a situation in which a cartographic office has to process large amounts of spatial data, for example to produce regional land cover maps. With strict deadlines, tough competition and a client desiring high quality graphic output, what are the odds that results will overrule methodology? Users being confronted with this "failing", judge the assessment of uncertainty indeed scientifically justifiable, yet from a practical point of view infeasible.

This is not to blame the ignorant user but to incite the scientific community to bridge the gap between theory and practice! Users need to become more conscious of the relevance of uncertainty information, e.g. to select "the best from the rest" (see the above quotation of Al Gore!). They will, however, only accept the assumed extra value if they have the disposal of easy-to-use tools and methodologies to derive and handle this particular meta-information. The registration of meta-information (including quality related topics) according to content standards such as prescribed by the Federal Geographic Data Committee (FGDC) in the USA and the European Standards Organisation (CEN) could be a fruitful step forward (see chapter 7).

Thinking about a more active and conscious manner of handling uncertainty doesn't really stretch the imagination, quite the contrary! The fact that remotely sensed data are used, acquired at a certain moment in time, can be considered indicative of the expected amount of uncertainty. Reliability diagrams that are often displayed on

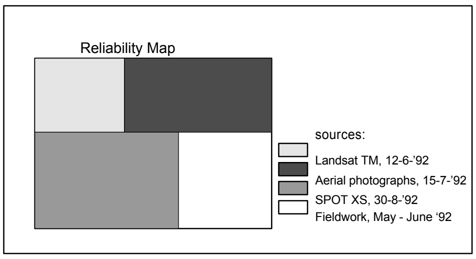


Figure 5.1: Example of a reliability diagram

map sheets that are created from multiple data sources anticipate this by revealing indirect uncertainty information (figure 5.1). Or take as an example the deforestation of the Amazon rain forest. The progressive tree felling can only be conveyed properly by a series of images, including a recently acquired data set. Here, obsolete data equals uncertain information because the phenomenon considered is highly dynamic.

These approaches do possess a strong qualitative nature and their usefulness as a starting point for uncertainty reduction - thus improving the data set - is only limited. Focussing on the classification of remotely sensed data, accuracy assessment procedures are probably the most common quantitative approach to uncertainty handling. Already mentioned in section 4.3, it will be dealt with here in some more detail (section 5.3). One of the main drawbacks of such procedures, however, is the prerequisite that sufficient and representative reference data have to be available. Although accuracy measures have a more absolute meaning (class assignments are right or wrong after being compared to a model of the "real" world), section 5.4 will elucidate uncertainty measures that are based on the posterior probability vector per image sample. The derivation of uncertainty information directly from the classification result doesn't require additional reference data. The posterior probabilities do not, though, relate to terms of correctness directly but rather to the conformity with the applied classification model. Here again, emphasis is laid on the statistical validity of classification methods in order to interpret the resulting posterior probabilities as indications of uncertainty.

5.3 Accuracy assessment: the versatility of error matrices

When consulting remote sensing journals of the 1980's, the number of papers dedicated to accuracy assessment is striking. One possible explanation for this "boom" is believed to have its origins in the "computerisation" of that particular decade. With the availability of computer systems, the digital processing of remotely sensed data came within the reach of an increasing group of users. They evoked research efforts directed at the extraction of information from these large data sets. In order to be accepted, statements about the "truth value" of derived products - such as classifications - were considered indispensable, hence the emphasis on accuracy assessment procedures.

This approach considers thematic, attribute, or simply classification accuracy which is not always easy to distinguish from its geometric counterpart. The general idea is based on the composition of an *error matrix*, sometimes also referred to as *confusion matrix* or *contingency table* (Story & Congalton, 1986). Such a matrix (table 5.1) summarises the results of a sample survey in which a reference data set is compared to corresponding spots on the classified image. As a consequence, hits on the diagonal of the matrix represent correctly classified image elements from which a Proportion of pixels Correctly Classified or PCC (Veregin, 1989b) can be calculated (see the example in table 5.1). Assuming the samples are representative and their number statistically significant, a PCC surely provides valuable information.

Table 5.1: The error matrix (after Janssen & Van der Wel, 1994)

		Reference data				
		X	Y	Z	row total	correct (%)
Classified data	X	24	2	4	30	80
	Y	6	45	9	60	75
	Z	3	5	52	60	87
	column total	33	52	65	150	
PCC = (24 + 45 + 52) / 150 = 81 %						

Off-diagonal scores indicate erroneous assignments also known as errors of *commission* and *omission*. The former relates to unjust assignments, so classified data actually belong to other real world classes (too much classified as X, see table 5.2). The latter is a measure of lacking assignments, meaning that spots actually covered by class X are not identified as such by the classification (table 5.2).

Table 5.2: Errors of omission and commission
(after Janssen & Van der Wel, 1994)

		Reference data				
		X	Y	Z	row total	commission (%)
Classified data	X		a	b	c	
	Y	d				
	Z	e				
	column total	f				
	omission (%)					
class x	error of commission: (a + b) / c					
	error of omission: (d + e) / f					

Some more simple accuracy statements can be found in the complements of these error types. *User's accuracy* and *producer's accuracy* (Story & Congalton, 1986) are interpretations of the correctness of separate classes. While user's accuracy provides a clue about the accuracy of the classified land cover class, producer's accuracy reveals information about the number of reference samples that correspond with correct counterparts in the classification. The interpretation of these figures is as follows. A map user reading land cover data from a classified image could state that 80% of the pixels labelled as deciduous forest is correct (user's accuracy). If that person takes the map to that forest he could exclaim that eventually only 40% of these trees has been represented correctly by the classification! It is obvious that both figures are of interest for a user and therefore it is better to express classification accuracy in terms of errors of omission and commission instead of maintaining the deceiving distinction between user and producer (Janssen & Van der Wel, 1994). The relation between both approaches is defined as:

user's accuracy (%)	=	100(%) - error of commission (%)
producer's accuracy (%)	=	100(%) - error of omission (%)

The relevance of such measures of uncertainty (they are, indeed!) has been discerned by many authors (e.g. Prisley & Smith, 1987; Felix & Binney, 1989). It is important to note that adverse error rates should be considered an incentive to improve the classification, for example by selecting more representative training samples. But the high error rates could also have been caused by the classification method adopted. A maximum likelihood classification allows for a better consideration of the covariance with which clusters of samples are characterised in the feature space than, say, a simple box classifier (based on a far too simple model that the representation of classes in the feature space can be decribed by minimum and maximum values defining a rectangle or box)! Therefore, one needs to compare the results from different classification approaches, applied on the same data set. Simply comparing PCC values is too straightforward because this fails to account for the contribution of chance agreement. For this reason, Congalton *et al.* (1983) introduced the *Kappa Coefficient of Agreement* as an indication of accuracy that lends itself for a comparative study of classification performance: *"...Kappa adjusts the percentage correct measure by subtracting the estimated contribution of chance agreement..."* (Campbell, 1987)

The error matrix of table 5.1 reveals for example a Kappa coefficient of 0.70, meaning that the classification accuracy is 70% better than the accuracy that would result from a random assignment (the derivation of this value is not considered within the scope of this thesis). The main advantage of this measure is its relation to the complete error matrix, instead of considering just diagonal (PCC) or off-diagonal values (errors of omission and commission). More details are given by Hudson & Ramm (1987) and Rosenfield & Fitzpatrick-Lins (1986), who proposed to use the Kappa coefficient as a standard measure of accuracy for classifications.

All the above approaches require a well-balanced sampling survey as a basis for the construction of an error matrix. Having derived such a matrix, even more procedures can be considered, reflecting the usefulness of statistical knowledge. Confidence limits for the PCC can be read from binomial nomograms for example, given sample size, number of correct classifications and significance level (Janssen & Van der Wel, 1994). To reduce sample sizes and hence keep fieldwork to a minimum, a strategy of *acceptance sampling* can be introduced. The idea originates from the practice of statistical quality control (Grant & Leavenworth, 1988) in which products are sampled and tested on their conformity to certain specifications. Translated to remote sensing applications, a classification can be tested on its acceptance by defining hypotheses, for example:

H_0: classification accuracy (PCC) >= 75%
H_1: classification accuracy (PCC) < 75%

while retrieving the number of reference samples and the maximum allowable number of misclassifications. Elaborating on the details of this strategy goes beyond the scope of this thesis. The interested reader is referred to the paper of Ginevan (1979) who presents a sound study on acceptance sampling in view of land cover classification.

The above approaches assume that sample data are always readily available to assess classification accuracy. The usefulness of accuracy assessment procedures notwithstanding, these often come at the bottom of the list of actions of the user of remotely sensed data. **Why?** Not because strategies are too complicated or require a disproportionate amount of statistical knowledge - as can be concluded from the above examples. It is more likely a question of priorities, arranged according to a limited quantity of time and money. Although extensive field work is not always necessary (aerial photographs of the same data as the imagery will often do just as well for selecting reference samples), its "time-consuming and money-spending" character is still brought forward as an excuse for the lack of an accuracy assessment. Maybe its is the *blinding effect of visualisation*; once a classification has been obtained, it is presented on a computer screen and considered "done" because it looks quite good...This hampers a critical and possibly more informative consideration of the mapped data, for which there is no "true map" (remember the statements made by Ormeling (1995) and Monmonier (1991a) from section 2.1.2). Here, the professional user needs to x-ray the picture and concentrate on the data, unless - of course - the derivation of a nice map is the only pursued goal.

Without reference data modelling the real world situation, it is not possible to assess the accuracy (e.g. is a spot labelled **correctly** as corn, is it **right** or **wrong**). It is, however, feasible to comprehend the uncertainty in the classified data (e.g. is a spot **more likely** to be labelled as corn than as wheat, is it **probably** corn).

5.4 Uncertainty measures and probability theory

In chapter 3, Bayes' Maximum Likelihood Rule has been discussed while chapter 4 has stressed the meaning of the derived posterior probability vectors as a measure of uncertainty (Goodchild & Wang, 1989; Goodchild *et al*, 1992; Marsh *et al*, 1980). Such vectors provide for each pixel in the image *n* posterior probabilities that define the probability of membership to all *n* distinguished classes. The value of the maximum posterior probability is responsible for the thematic label in the eventual classification and is clearly indicative of uncertain assignments. Consider therefore figure 5.2, showing a simple example based on a two-class, one-feature situation. Point x_b belongs more to class I than class II, while point x_a is clearly a member of class II although its assignment is far more weaker than that of x_b to class I. The position of a data value - or measurement or *pattern vector* (Gonzalez & Woods, 1992) if more features are considered - in the probability landscape as defined by the probability density functions, is reflected by the height of the maximum posterior probability.

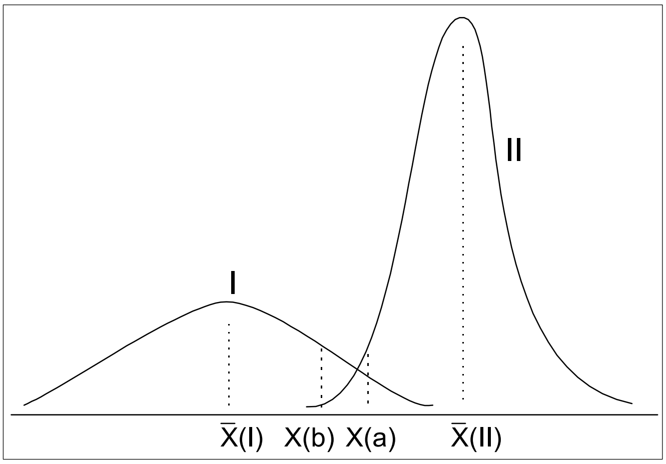


Figure 5.2: The strength with which points can be assigned to a class can differ substantially (after Foody et al., 1992)

The validity of maximum posterior probabilities notwithstanding, it seems that the above observation calls for a few comments. In the first place, remember that commercial image processing software packages often apply a simplified version of Bayes' Maximum Likelihood algorithm. The avoidance of exponential expressions for reasons of computational efficiency (section 3.3) has as its result that the rank order of the probability vector is maintained, but at the expense of reliable absolute values. Normalisation procedures further weaken the statistical grounds for mutually comparing posterior probabilities. Moreover, when the *unknown class* (Abkar, 1999; Gorte, 1998) is fully ignored, all image data are subjected to a more or less forced assignment to one of the *n* distinguished classes. If, however, the *n* classes fail to sufficiently describe the spectral variance present in the considered image, a serious problem arises. It can be seen from formula 3.6 (section 3.3) that normalisation by the denominator term could result in improbable vector values. This term is the sum of the product of the conditional class probabilities $P(X|C_i)$ and the prior probabilities $P(C_i)$, with i = 1 to n. Figure 5.3 gives an example of such a situation; the dashed line represents the "ignored" class.

Foody *et al* (1992) deal with this problem in an interesting way. They define so-called *a-typical* points in the feature space (pattern vectors that actually belong to none of the *n* distinguished classes) on the basis of the Mahalanobis Distance (section 3.3). The relation between this typicality value and posterior probability is as follows (Foody *et al.*, 1992): *"...the a posteriori probabilities give the relative probabilities of a case belonging to each class in turn, on the assumption that the case belongs to one or the other of the classes, while the typicality probabilities indicate whether it is reasonable to assume that a case actually belongs to a class..."*

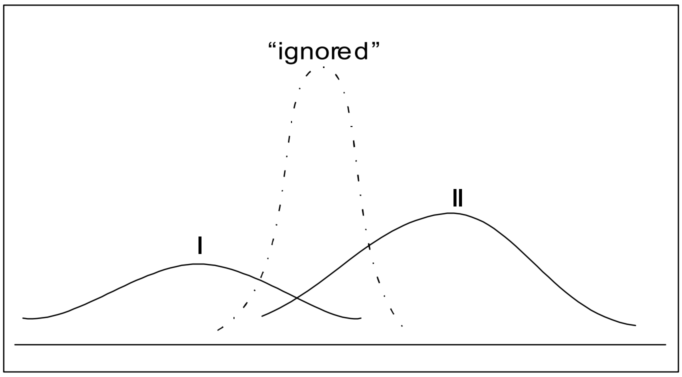
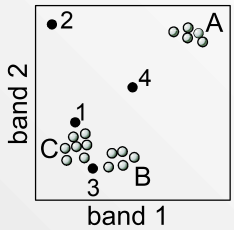


Figure 5.3: Two distinguished classes fail to cover all spectral variance and a third class should be sampled (dashed line)

Both measures, posterior probability and typicality (or, *eccentricity*), should be interpreted in conjunction with each other in order to detect the pitfalls in the probability landscape. As opposed to Mather's (1987) suggestion, namely to establish



posterior probability	typicality	description	#
high	high	sound classification	1
high	low	- badly trained classes (non-representative) - mixed pixel - changed characteristic (e.g. due to crop disease) - effect a priori knowledge	2
low	high	- badly trained classes (overlap in feature space) - effect a priori knowledge	3
low	low	bad training (lack of significant class)	4

Figure 5.4: Example of an interpretation table

a "reject class" to which a-typical values can be assigned ("Mahalanobis Distance exceeds a certain threshold value"), Foody *et al.* (1992) stress the relevance of storing all information in a GIS for further processing. An interpretation table such as exemplified by figure 5.4 could then contribute to a sound evaluation of classification results, thereby possibly excluding points from further consideration.

To recapitulate the above, it can be stated that in order to correctly judge maximum posterior probability values, either of the following approaches is recommended:

- accept additional measures of uncertainty (e.g. typicality);
- pursue completeness as far as the distinction of meaningful classes is concerned, such that each case could be assigned to one of them.

Even then, caution is still required with respect to the interpretation of the posterior probability vector. Because of the objections already mentioned in this section, all values ranking after the highest one should be dealt with in a sensible way. What is the meaning of the second, third or even fourth posterior probability? It would be wrong to interpret them as *partial membership* values for the classes under consideration, from which the corresponding proportions of land cover on the ground can be derived. Canters (1997) states that: *"...it remains questionable if reliable conclusions on fuzzy membership can be drawn from the output of a supervised classification procedure which generates spectral signatures from training pixels that are* entirely *assigned to a priori defined cover types through a* hard *classification procedure..."* and subsequently adopts a more fuzzy set approach to image classification. Also, Fisher & Pathirana (1990) suggest that a more fuzzy set based approach helps to estimate the proportions of land cover types occurring within a single pixel, although their interpretation of fuzzy membership values is unfortunately related to probability theory! Fisher (1996) provides a clear treatise on the distinction between fuzzy sets and probability theory. Unfortunately, he concludes that the posterior probabilities that result from a maximum likelihood classifier could be considered fuzzy membership values as well. In both studies, however, a well-defined model that describes the mixing of reflected energy per object class is lacking.

Does the probability vector fail to reveal information about mixed pixels, as stated earlier? No, the relationship between first and second ranking values can indeed hold some information, as appears from the following example. The decision boundary between two equally likely occurring classes I and II (identical prior probabilities) is defined by:

$$p(x|\mathrm{I}) = p(x|\mathrm{II})$$

and hence the posterior probability vector would reveal equivalent first and second values, or - stated otherwise - zero difference between maximum and second posterior probabilities. Transition zones between soil type classes could be represented in this way, but signature mixing at the subpixel level can be fully identified by these difference values as well if a sound sensor model is adopted.

It is felt that "fuzzification" of approaches based on "classical sets" (as opposed to fuzzy sets) is the result of conceptual misunderstandings, it is admitted that the posterior probability vector as a whole holds potentially valuable information. A maximum posterior probability of $p(\textit{class A} \mid X) = 0.80$ should therefore be interpreted as: with a probability of 80% the considered case belongs to *class A*, given measurement vector X. The probability $P(\textit{class B} \mid X) = 0.20$ on the other hand can not simply be considered a partial membership of this case to *class B*. This is a direct consequence of the assumption that each case can only be unambiguously assigned to one particular class, as emphasised by the aim to collect "pure" training samples. Researchers have found a new challenge in applying fuzzy set theory on image classification (e.g. Gopal & Woodcock, 1994). This approach (as opposed to the "fuzzification" approaches referred to in the above) is not the subject of this thesis. Hootsmans (1996) dedicated his thesis to the role of fuzzy set theory in spatial data handling.

5.5 Uncertainty measures based on the whole probability vector: weighted uncertainty

The vectors of probabilities computed by a classification procedure for a set of remotely sensed data provide useful information about the quality of the resulting classification in terms of the uncertainty involved. In the previous section, some simple quality measures that are in use for extracting this type of information have been reviewed. Unfortunately, as these measures do not address the contents of the entire probability vector, they fail to capture the distribution and extent of the uncertainties underlying a classification. Overall knowledge of the uncertainties involved, however, is imperative for acquiring in-depth insight in the quality of the classification. To exploit fully the information content of a probability vector for this purpose, additional measures of uncertainty are called for.

For a detailed exploration of the uncertainties underlying a remote-sensing classification, it is proposed to use a measure from among a class of measures that build on the notion of *weighted uncertainty*. A well-known example of such a measure is the *entropy* measure originating from information theory (Shannon, 1948; Kullback, 1954). The measure pertains to a statistical variable and the uncertainties in its various possible values, expressing in a single number the distribution and extent of these uncertainties. Goodchild *et al.* (1994b) and Maselli *et al.* (1994) have already briefly hinted at the use of the entropy measure for capturing the uncertainty underlying a remote sensing classification.

In the entropy measure, the uncertainty in a single value of a statistical variable is defined as the *information content* of a piece of information that would reveal this value with perfect accuracy. For a pixel in a remote-sensing classification, viewed as a statistical variable C, the uncertainty in class C_i is defined as:

$$-\log_2 p(C = C_i | X) \qquad [5.1]$$

for $i = 1,...,n$, where X denotes the available data; the uncertainty is measured in units of bits of information. Generally, the true class of the pixel is not known and, as a consequence, the amount of information required to reveal the pixel's class is unknown. The entropy of the pixel is therefore defined as the expected information content of a piece of information that would reveal its true class. To this end, the entropy measure combines the uncertainties in the various classes of the pixel by weighting them by their probabilities:

$$-\sum_{i=1,...,n} p(C = C_i | X) * \log_2 p(C = C_i | X) \qquad [5.2]$$

The pixel's entropy is minimal if the uncertainty as to its true class has been resolved. Thus, if $p(C = C_i \mid X) = 1$ for some class C_i, $1 \leq i \leq n$, that is, if class C_i has been established with perfect accuracy, then the entropy equals zero and there is no further information required to reveal the pixel's true class. Conversely, the entropy is maximal if none of the classes is preferred, that is, if there is utter ignorance as to the pixel's true class. So, if the probabilities $p(C = C_i \mid X)$, $i = 1,\ldots,n$, are uniformly distributed, that is, if for all classes C_i we have that $p(C = C_i \mid X) = 1/n$, then the entropy is at maximum. Figure 5.5 depicts the entropy of a pixel that can have one of two classes; the x-axis represents the probability of one of these two classes and the y-axis represents the pixel's entropy.

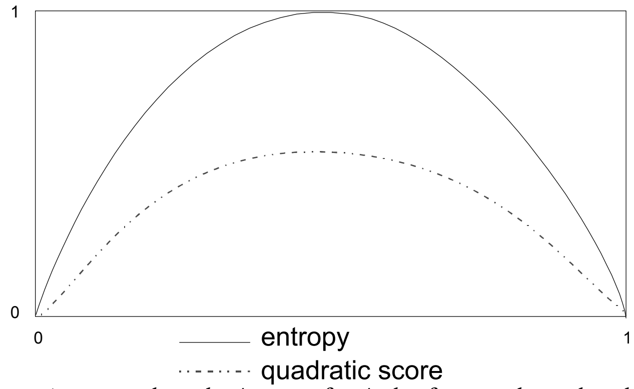


Figure 5.5: Entropy and quadratic score of a pixel (after Van der Wel et al., 1998)

The main advantage of the entropy measure over the simple quality measures mentioned before, is its ability to summarise all the information contained in a vector of probabilities in a single number. Entropy reveals information about the amount of information that is needed to improve the assignment of a single class to a pixel. Apart from its theoretical value, this measure possessed an obvious practical potential:

- its compactness supports a straightforward conveyance to users;
- it is far more easy to interpret one single number than a whole series of, partly insignificant, posterior probabilities;
- it requires very little storage capacity in a GIS.

The entropy measure is, however, not the only measure that exhibits these properties. In essence, any measure that builds on the notion of weighted uncertainty will do the same thing.

As another measure of weighted uncertainty, the *quadratic score* (Glasziou & Hilden, 1989) is briefly discussed here. The quadratic score builds on the notion of confirmation. The uncertainty in a single class for a pixel is the amount of *probability* required to establish this class with complete accuracy. The uncertainty in class C_i is defined as:

$$1 - p(C = C_i \mid X) \qquad [5.3]$$

for i = 1,...n, where x once more denotes the available data. The quadratic score of the pixel is then:

$$\sum_{i=1,\ldots n} p(C = C_i \mid X) * (1 - p(C = C_i \mid X)) \qquad [5.4]$$

This measure exhibits the same behaviour in its minimum and maximum values as does the entropy measure. The two measures differ, however, in their slopes as is shown in figure 5.5. The slope of the entropy measure is steeper than the slope of the quadratic score. As a result, the entropy measure for example more strongly weighs small deviations from probabilities equal to zero or one than the quadratic score.

Now that a number of uncertainty measures has been derived and explained, it is desirable to distinguish between situations or applications that prefer different measures. Before providing a scheme that summarises the contents of this chapter, attention will be paid to the *reduction* of uncertainty.

5.6 Reducing uncertainty: the role of a priori knowledge

Having assessed the uncertainty of a remote sensing classification, the user is faced with the fact that the results are diverging from the “truth value”. Instead of just accepting the classification *as is*, a number of strategies could be adopted, namely:

- rejecting the results and repeat the processing steps with other image data, alternative methods, or additional data;
- partially accepting the classification and improving results only at “hot spots”, locations where additional knowledge is likely to be required (indicated by high entropy values, for example);
- accepting the assessed amount of uncertainty but only to include it in a decision analysis procedure as a weighting factor.

The last option is dealt with in chapter 6, in which attention is focussed on the interpretation of uncertain data. The aim is not to reduce uncertainty any further, but rather to make the best decision given the quality of the data and the relevance of the decision itself. In fact, this heading refers to so-called *optimisation* procedures as well (e.g. Siteur, 1996), although this subject goes beyond the scope of the thesis.

Here, the role of *a priori* knowledge will be highlighted as a means to reduce classification uncertainty. It has been demonstrated that uncertainty can be expressed by the *posterior* probability vector and that this information can be summarised per pixel using weighted uncertainty measures. Conceptually, a next step would be the possibility to reduce the amount of uncertainty by adding knowledge. An important question can be defined as follows: **how can this knowledge be introduced in the classification process?** Even more pressing is the question: **when can this knowledge be applied?** Before, during or after the classification procedure? Hutchinson (1982) elaborates on the stages in which ancillary data could be used. It has been shown in section 3.3 that Bayes's Maximum Likelihood Rule allows for the inclusion of a *prior* or an *a priori probability*, representing the probability that an arbitrary case belongs to class C_i independent of its measurement vector (with i = 1..*n*):

> *"...prior probabilities are probabilities of occurrence of classes which are based on separate, independent knowledge concerning the area to be classified..."* (Strahler, 1980)

These *priors* are directly used **during** the classification, and can be derived from ancillary data according to a number of approaches. Very often, additional knowledge is applied through all stages of the classification process, although not always just as explicitly. The remaining part of this section will be dedicated to the description of some strategies to include extra knowledge in the classification process. These ideas have proved to be useful, and it appears that a strict distinction as to whether additional knowledge is used before, during or after classification is somewhat artificial. Chapter 9 will elaborate further on the practical usefulness of these methods in an extended case study.

Pixel-based assignment of priors per class

The most simple thing to do is of course not defining priors explicitly, assuming that each of the distinguished classes is equally likely to occur in the considered image - corresponding to equal area coverage in reality. This approach often results in disappointing classification results, especially when classes are not sufficiently distinctive from a spectral point of view. Assigning a *weight factor* per class can seriously improve this situation, but preferably after a stratification procedure as proposed by Strahler (1980), see the next section. If not, priors will be weighted for cases that are clearly not part of the considered class, e.g. maintaining a high prior probability for corn over water surfaces is nonsense (although this would not result in an error as water will be clearly separated spectrally from other classes). These *priors* are usually obtained by estimating the proportions of the area covered by the considered classes and originate from a study of maps, aerial photographs or former classifications of the same area, but possibly from the opinion of experts as well. A higher prior for class A as compared to class B means that there is a higher probability that a random pixel would belong to class A. In section 3.3 it is explained how extreme values of priors affect the performance of the classification as they tend to ignore the actual measurement values. Carefully designing prior probability vectors is a prerequisite for their assumed extra value. An advantage of this simple approach is the requirement that only one set of priors needs to be defined, one for each class to be distinguished.

Stratification

Strahler (1980) mentions the usefulness of additional information such as soil maps to distinguish between different sets of *priors* for separate image segments. Based on a process of *stratification*, each stratum receives its own set of priors, thus revealing a spatial distribution of the estimated classes. As an example, consider the presence of a rocky, arid soil type that would exclude the occurrence of particular crops. It doesn't make any sense to assign a *prior* to for example wheat for this part of the study area, except for a value of zero: P(wheat) = 0. Here, a relationship between soil type on the one hand and crop type on the other is assumed. In this way, **nominal** cartographic information (e.g. as stored in a GIS) is integrated with **ordinal** image data (digital numbers). An obvious disadvantage of this method is the large amount of *priors* that needs to be defined as Strahler (1980) admits: one for each class in each stratum! The derivation of the land cover database of the Netherlands (LGN) has been based on a stratification approach as well, by a visual and interactive interpretation of the satellite images before the actual classification (Thunnissen *et al.*, 1992). A more recent version of this database (LGN-2) has used digital databases for this stratification process (Thunnissen & Noordman, 1997).

The *context maps* that are used in this approach can also be derived directly from knowledge that is provided by expert users. By delineating strata in a sketchy way, the user can exclude the presence of particular classes beforehand without defining an explicit geographical relationship (for example, *"...from daily commuter-traffic, I know that this area lacks the presence of corn fields..."*).

Post-classification approaches

Harris & Ventura (1995) apply prior knowledge in a so-called *post-classification sorting* procedure, using conditional statements to re-classify the achieved results. For their classification of urban areas they employ e.g. the rule:

"...if the zoning is commercial and the classification industrial, then recode as commercial..."

with "zoning" referring to additional geographic data. This approach has as its advantage that it focuses only on so-called "problem areas" after classification, but its main drawback is the requirement of rather high-level zoning information.

Janssen (1993) also applies a knowledge rule in his proposed object-based classification: *only one crop type is grown within an object* (i.e. a parcel). His two-stage object-based classification consists of a straightforward pixel classification and subsequent GIS processing to determine the *mode* class (label with highest frequency of occurrence) within predefined object boundaries. Janssen (1993) shows that this approach works well for the Flevoland polder, characterised by relatively large and well organised parcels (90 % of the fields have been assigned a correct crop type!). In order to update the geometry of the parcel boundaries (although stored in a GIS, this cadastral information is not static by definition), Janssen (1993) further introduces a segmentation method based on spectral edge-detection to distinguish between field boundaries. Therefore, a combined intensity image is retrieved from bands 3, 4, and 5 of Landsat TM.

Segmentation

Edwards *et al.* (1990) give a somewhat different interpretation of segmentation. It is based on the idea that classification performance can benefit from the identification of homogeneous segments consisting of spectrally contiguous regions, geometrically relevant shapes or even significant contextual structures. They all correspond with the definition of different criteria according to which the partition takes place; in fact, both spectral and structural pattern recognition techniques can be applied to extract the information from the image data. The general problem that is met when adopting a segmentation strategy is that the partitions often fail to correspond directly with relevant objects in the image because of the degrading effect of, for example, image noise. Edwards *et al.* (1990) therefore introduce an extra band or feature in their classification, containing "fixed" objects such as (rail)roads and parcel boundaries (although Janssen (1993) shows that these boundaries do indeed change over time, at least in the Netherlands, and therefore makes a distinction between variable and fixed lot boundaries!). As a result, the cartographic information is applied in order to **guide** the segmentation process, which is more accurate than the posterior usage of this information as predetermined object definitions.

Transition matrices

Temporal information can be involved in land cover classifications by means of *transition probability matrices* expressing the expectation that cover types will change during a particular period of time. As exemplified by Strahler (1980) and Janssen & Middelkoop (1991) knowledge about the dependency of crops to seasons and their mutual sequences (agricultural crop rotation schemes), is valuable for defining the probability that:

given crop A at time t_1, crop B will occur at that position at time t_2

The sequences are the result of studies aimed at the increase of yields and the avoidance of plant diseases. An example is the succession of potatoes by winter wheat (Janssen & Middelkoop, 1991). An inventory of this type of relationships eventually results in the creation of a matrix representing in fact time-dependent prior probabilities:

$$p(\textit{winter wheat } 1999 \mid \textit{potatoes } 1998)$$

Obviously, land cover at an earlier time should be available, which might be easy when stored in a GIS.

The statistical concept of *Markov chains* is closely related to this issue, as it describes the (partial) dependencies between a state at t_2 and the preceding states (t_1, t_0, t_{-1},...).

Context information: logical rules

Not seldom, one has a certain idea of the nature of land cover classes: are they homogeneous or not (grass land versus mixed forest), are they delimited by sharp boundaries or characterised by fuzzy transition zones (water versus shrubs)? Clearly, a point located in the centre of a homogeneous class should be considered differently from a point close to a fuzzy boundary (figure 5.6). Stated in other words, it seems sensible to maintain these spatial relationships by assigning different *priors*. So the rule:

...high weights for class A only count at those places revealing high probabilities of occurrence for that class, according to the available prior knowledge...

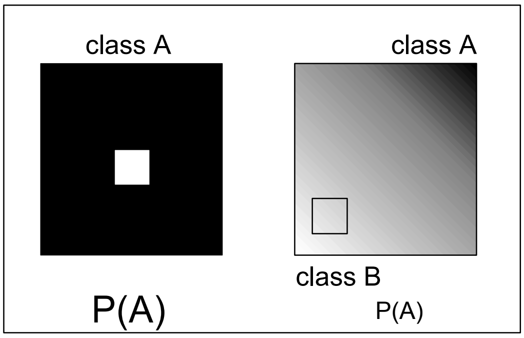


Figure 5.6: Example of considering context information

is directly derived from Strahler's (1980) stratification approach, but can be further refined such that it illustrates the involvement of logical relationships (figure 5.7):

...if - according to prior knowledge - class A occurs at point (x,y), the prior for class A at that position is dependent on the distance to its estimated boundary and the nature of that boundary....

or stated in another way:

...if according to GIS information point (x,y) is likely to be situated in forest area, than the prior for class forest will decrease inversely proportional to the distance of that point to its fuzzy boundary...

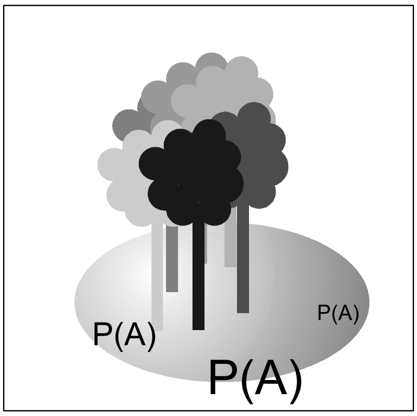


Figure 5.7: The use of logical relationships

In fact, this is an extension to the stratification approach, only adapted in order to conform to the definition of fuzzy delimited objects. Further refinements can be obtained if not only the assumption of, and the closeness to a fuzzy boundary is taken into account, but the nature of the neighbouring class as well (figure 5.8):

...if according to GIS information point (x,y) is likely to be situated in forest area, than the prior for class forest will decrease inversely proportional to the distance of that point to the boundary of the adjoining shrubland, but remain high if the neighbouring class is water...

Chapter 9 will elaborate on these logical rules in the framework of the CAMOTIUS case studies.

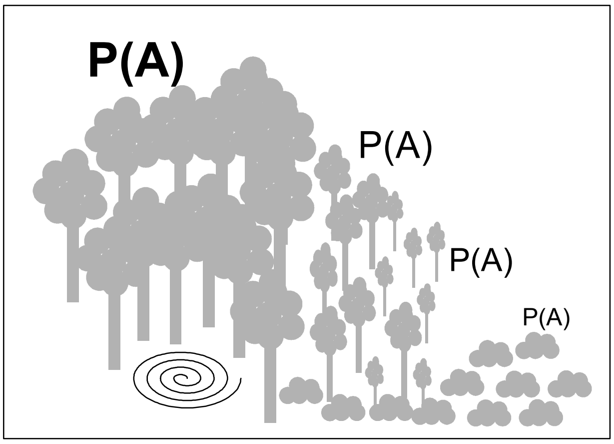


Figure 5.8: Inclusion of even more knowledge during the derivation of priors

Iterative calculation of prior probabilities

Gorte (1998) presents an iterative approach to the calculation of prior probabilities in the context of a *k*-Nearest Neighbour classification. The main assumption being made is that the total area being covered by a particular class is corresponding with the sum of the posterior probabilities for that class as computed over the whole study area. As a consequence, the entire probability vector derived from classification is stored in a GIS as it is required for further consideration. Figures 5.9a to 5.9g illustrate the derivation of prior probabilities according to the iterative method. Consider an image with 3 spectral bands and t pixels. For each of the t pixels a feature vector can be assessed consisting of the values in each of the 3 bands (figure 5.9a). Starting with a set of equal prior probabilities (e.g. $1/n$ with n representing the number of classes), a Gaussian *k*-NN classification is carried out. The *class probability densities,* $p(X_j|C_i)$ with $i = 1,...n$ and X being a measurement vector for pixel $j = 1,...t$ (figure 5.9b), are multiplied by the values of the *priors* (figure 5.9c):

$$p(X_j/C_i) * p(C_i)$$

The results (figure 5.9d) are normalised according to Bayes' Rule (see section 3.3) in order to obtain posterior probabilities, $p(C_i|X_j)$ (figure 5.9e). The interpretation of these results is as follows:

... assuming 100 pixels with the same measurement vector X_1, 2 are expected to belong to class C_1, 24 to class C_2, ..., and 26 to class C_n ...

a.

pixel number	1	2	...	k
band 1	12			
band 2	47			
band 3	88			
feature vectors	x_1	x_2	...	x_k

b. $P(X_j|X_i)$

feature vectors	x_1	x_2	...	x_k
$\mathbf{C_1}$	0.10			
$\mathbf{C_2}$	0.60			
...				
$\mathbf{C_N}$	0.20			

c. $P(C_i)$

	0.10	0.20	...	0.65

d. $P(X_j|X_i) \times P(C_i)$

feature vectors	x_1	x_2	...	x_k
$\mathbf{C_1}$	0.10			
$\mathbf{C_2}$	0.12			
...				
$\mathbf{C_N}$	0.13			

e. $P(C_i|X_j)$

feature vectors	x_1	x_2	...	x_k
$\mathbf{C_1}$	0.20			
$\mathbf{C_2}$	0.24			
...				
$\mathbf{C_N}$	0.26			

f.

	1	2	...	k
sum j	0.02			
sum j	0.24			
...				
sum j	0.26			

area

g. $P(C_i)$

	0.30	0.09	...	0.55

Figure 5.9 a – 5.9g: Derivation of a priori probabilities

Deduced from this is the statement that the posterior probability value for class C_i of pixel j corresponds with the contribution of that pixel to the total coverage of that class in pixels, see figure 5.9f (remember that the total area being covered by all classes is equal to t pixels). This pixel-by-pixel summation thus results in a number representing the area covered by a particular class. After normalisation (figure 5.9g) a new set of *priors* is made available; assuming that the earlier defined *priors* are just a guess, these calculated values should be more reliable and hence could be used in a second classification round. As long as there appears to be a significant shift in the values of the *priors*, the above procedure can be repeated. At a certain moment, the values seem to stabilise (*convergence*), heralding the end of the iterative classification process. Gorte (1998) demonstrates that his method contributes to a considerable improvement in classification accuracy for a stratified area in the Twente case study (91.3% as compared to 82% for a *k*-NN classification with equal priors), without the availability of prior probabilities! Obviously, a sound mathematical basis for this method is needed (see also Gorte & Stein (1998)).

5.7 Concluding Remarks

This chapter has dealt with the assessment and reduction of uncertainty in remote sensing classifications. If a comparison with the "real world" is possible, the derivation of an accuracy statement is feasible. This provides information about the correctness of the considered data set, although one may question the value of general figures like "85% correct". Therefore, a more specified error analysis is advocated, to start with the derivation of an error rate *per class*. The error or confusion matrix from which these figures can be deduced offers more valuable grips for the evaluation of a data set than most users would suspect!

A completely different situation arises when no reference data are available. In such a case, absolute accuracy numbers can not be assessed and an evaluation has to rely on the interpretative skills of the user (visually recognising unlikely occurrences given some *a priori* knowledge) and statistical information relating to the performance of the classifier. The latter requires that the posterior probabilities are stored (e.g. in a GIS) and at the disposal of the user. Once available, these probabilities reveal information about the height and distribution of uncertainties. The composition of the probability vector is a source of information within this respect and it has been demonstrated that the complete contents of such vectors can be summarised in one single number per pixel. In this way, a highly informative uncertainty information can be easily conveyed to the users, for example by visualisation approaches (see chapter 7).

Additional knowledge can help to reduce the amount of uncertainty in a remote sensing classification. In order to achieve this, different approaches can be adopted and it is difficult to judge their mutual merits. Obviously, some methods are more cumbersome than others while their extra value is not always easy to demonstrate. In general, it depends on the considered phenomenon as well as geographical area whether or not sophisticated approaches are worth trying (figure 5.10).

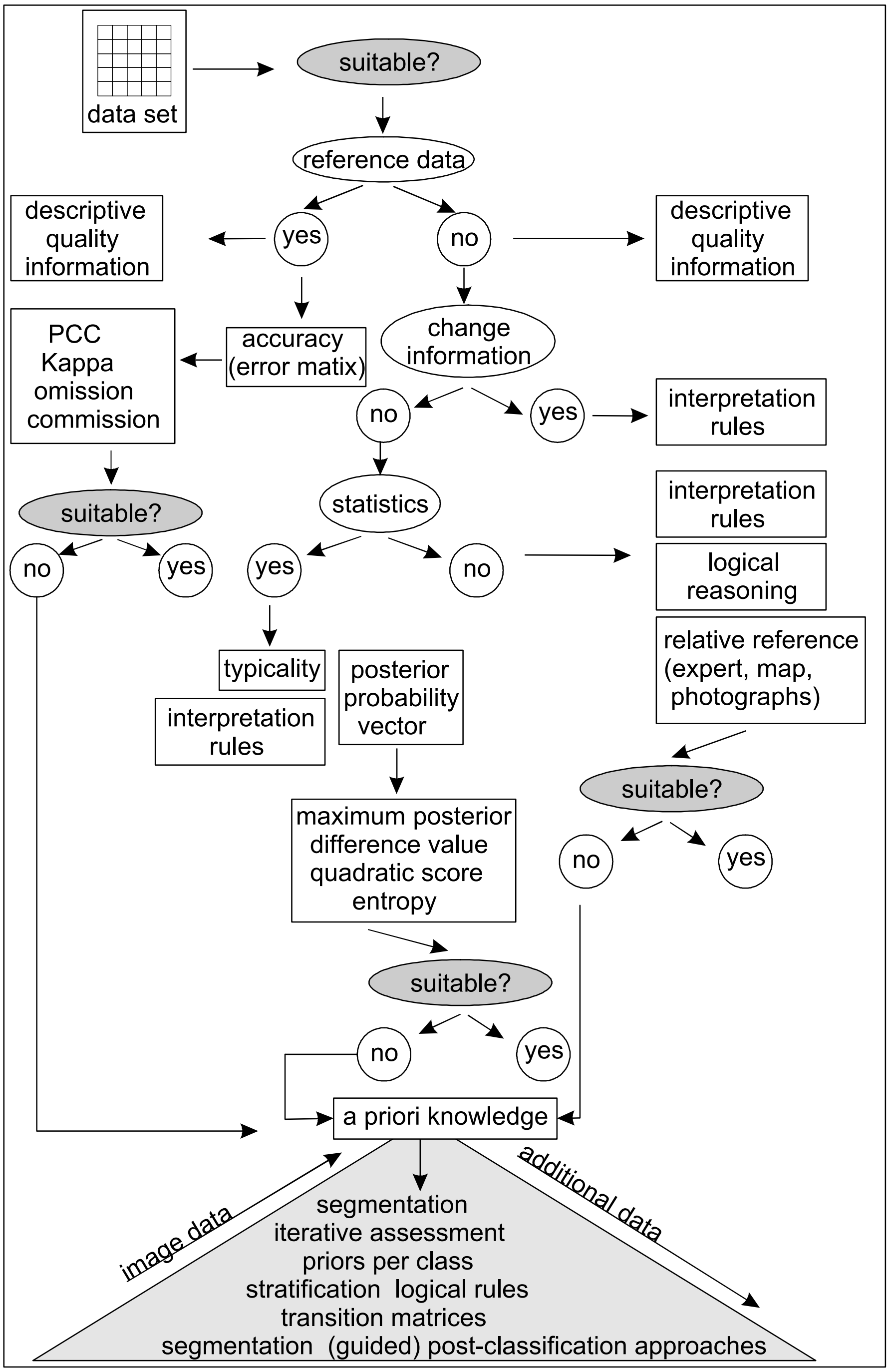


Figure 5.10: The role of a priori knowledge in the information process

6 Dealing with uncertainty: decision analysis

"...Decision-making is therefore something which concerns all of us, both as makers of the choice and as sufferers from the consequences, and there can be no doubt about the importance of the subject..."

Dennis Lindley (1990) - "Making Decisions"

6.1 Introduction

So far, four different approaches to uncertainty have been presented: "the do-nothing" option, accuracy assessment procedures, uncertainty measurement and uncertainty reduction strategies. In this chapter, another one will be added to the list although it is actually an extension to the latter two approaches. It refers to the "catchword" of Openshaw (1989), already quoted in section 1.4: *"...how to live with error and uncertainty in the spatial databases being manipulated by* GIS*..."*

Accepting that uncertainty is an inherent part of spatial data has some implications for the decisions that will be based on their expected information value. What if a class assignment turns out to be erroneous? Are the consequences for the application in mind serious or are they better than was expected? How can we make the best decisions under uncertain circumstances? All these issues will be touched upon in subsequent sections, and interesting parallels will be drawn between decision-making in the geographical field of interest and other, non-spatial, disciplines.

As an introduction to decision-making strategies, a simple example is given in section 6.2. From this, it is only a small step towards the understanding of some basic concepts underlying the theory of *decision analysis*. This has been described by Tom Spradlin (1997) in his *Lexicon of Decision Making* as:

"...a structured way of thinking about how the action taken in the current decision would lead to a result..."

The practical advantages of such concepts for deriving information from remotely sensed data will be elucidated according to several examples.

6.2 Life is full of priorities - decision-making comes natural

In everyday life, people take numerous decisions - one more important than the other - and often without really having an overall view of the consequences of the actions that result from these decisions. An example. Most people are quite well informed as far as the weather forecast is concerned and they are basing decisions on the likelihood of rain: taking a day off, leaving the car for the bicycle or organising a barbecue party. Although simple, this situation reveals some interesting approaches to decision-making:

- decisions are made with a particular objective in mind - *having fun*;
- decisions are often derived from uncertain information - *the weather forecast*;
- before decisions are taken, several alternatives can be considered - *organising a barbecue or not (watching television, reading a book,...)*;
- these alternatives result in different actions - *if organising a party, shopping is required*;
- actions have divergent consequences - *a barbecue means meeting people but also spending a considerable amount of money*;
- a good decision weighs the uncertainty of the information with the costs and benefits of the actions that result from that decision.

The above considerations have been systematically summarised in table 6.1.

Table 6.1: Example of decisions (barbecue or not) and the certainty of events (rainy weather), summarised in a decision table. The consequences of the different combinations are ranked according to their desirability (from 1 - 4)

	Rain	No Rain
Barbecue	"what a waste..."(1)	"what a party!" (4)
No Barbecue	"glad I canceled!"(3)	"too bad..."(2)
Probability	0.6	0.4

If someone intends to organise a barbecue and considers the probability of rain as provided by the newspapers or television channels, the costs and benefits of decisions taken under these uncertain circumstances should be taken into account. It will be demonstrated that decision analysis enables a well-considered judgement of possible decisions (the remaining part of this chapter explains why it is better not to organise a barbecue given the information provided!).

6.3 Decision-making: reasoning with uncertainty

If one would be absolutely certain about the occurrence of a particular land cover class (called *an event* in decision analysis - Lindley, 1990) the decision to assign a pixel to that class is easily taken, moreover without having to consider the consequences of a possible erroneous classification. However, chapter 4 has elaborated on the fact that uncertainty is an inherent part of spatial data. Concepts from probability theory have been proposed as a mechanism to handle these uncertainties, and the considered classification procedures appear to provide valuable statistical information for this purpose. Decision-making as pursued by a user of remotely sensed data, who needs to assign classes to pixels (or better: objects) and possibly base actions on the assumed presence or absence of information classes, has probability theory as one of its components. In order to broaden the understanding of the decision-making process, consider figure 6.1 that will be extended progressively in the remaining sections.

Figure 6.1 defines a set of events, or occurrences, represented by the symbol θ (all symbology is in accordance with the textbook of Lindley, 1990). Suppose these events are a set of possible land cover classes from which one has to be selected in order to make a decision about the updating of an outdated map, thus:

if selecting class C_1 then map needs to be updated, if C_2 or C_3 leave it as is

In this example there are only two decisions that can be taken, namely updating or maintaining the information of the old map (d_1 and d_2 respectively). For a sensible decision-making procedure both the list of events and the set of decisions have to be exclusive and exhaustive, as only one decision will be based on an occurrence and only after a thorough consideration of the whole range of events (see Lindley, 1990).

	θ_1		d_1	
	θ_2		d_2	
events	θ_3	**decisions**	d_3	**consequences**
	:		:	
	θ_n		d_m	

Figure 6.1: Simple presentation of the decision-making process with respect to remotely sensed data

Gorte *et al.* (1996) distinguish between *decision variables* and *chance variables*, where:

- a decision variable is defined as a variable representing viable decisions or actions that can be taken in the context of the problem at hand and
- a change variable refers to a variable representing the true "state of the world" (event); the value of such a variable cannot be selected by the decision-maker.

Now the uncertainty story enters the stage because events are accompanied by an amount of uncertainty that preferably needs to be quantified in order to be useful in the procedure. Acknowledging that the expression of uncertainty in numerical terms may be a problem in itself, this point is left for discussions in statistical literature as the considered statistical classification rules do result in uncertainty numbers. These are the values that are summarised by the posterior probability vectors, extensively dealt with in chapter 4. The probabilities represent degrees of belief in an event either

	θ_1	$P(C_1\|X) = 0.30$		d_1	update map
events	θ_2	$P(C_2\|X) = 0.45$	**decisions**		
	θ_3	$P(C_3\|X) = 0.25$		d_2	maintain map

Figure 6.2: Extension of the decision-making process with posterior probabilities defining the probability that class C_i occurs ($i = 1 \dots 3$), given evidence X

being true or false. Including these uncertainties can now continue the above example, resulting in the scheme that is provided by figure 6.2.

The events are possible land cover classes C_1 ... C_n, with n the number of classes, the uncertainties are represented by the vector of posterior probabilities for a particular pixel. Note that a standard maximum *a posteriori* classification approach is based on a decision procedure in which the event with the highest probability is selected:

$$d = \textit{assign class } C_i \textit{ for which } P(C_i|X) \textit{ is maximal}$$

In the above map revision example, the situation is somewhat more complicated; here, particular rules may exist that determine the necessity and urgency of updating. Consider for this part table 6.2 in which a table describes the situations in which actual class labels are required. The background of such a decision-making procedure is that one wishes to assess only specific and dramatic changes in land cover, in order to reduce costs and minimise efforts.

Table 6.2: Definition of actions to be taken if the land cover type appears to have been changed over time, given a specific amount of uncertainty.

Old	New		
	C_1	C_2	C_3
C_1	maintain	update	maintain
C_2	update	maintain	update
C_3	maintain	update	maintain

As can be seen from this figure, updating is only needed if class C_2 is selected from the posterior probability vector or if classes C_1 and C_3 are likely to replace former occurrences of class C_2. The latter seems to be critical for the pursued application; an imaginable example is the detection of suspicious objects by military surveillance satellites. The systematic survey of a particular area over time (*monitoring*) is based on the idea that as long as vegetation remains vegetation (whether it is coniferous or deciduous forest, C_1 and C_3 respectively), the signal is set at clear. A glaring contrast is formed by the situation in which vegetation is likely to be replaced by some building (C_2) or vice versa, possibly indicating strategic military moves or camouflage tactics!

So far, only the judgement about the likelihood of events has been considered (Pearl, 1988), by means of probabilities. There are, though, still other considerations involved in decision analysis, as can be understood from the above. What if no significant change in land cover is observed (probably woods at time T_1 and at time T_2) - and subsequently no efforts are made to revise the map - and this turns out to be a wrong decision? How serious are the consequences? Is it desirable or even better to accept a worst case scenario in which critical changes are always taken serious, even if there is only the slightest evidence? To answer these questions, another concept has to be introduced, namely the theory of *utilities*. Extensively used in the economical, social and medical fields, its application in the geographical realm is still very limited.

6.4 Decision-making: defining utilities

A decision results in an action, which in turn leads to particular consequences (also known as a *scenario*, Gorte *et al.*, 1996). If a particular event occurs (the barbecue example: it starts raining, the map revision example: coverage appears to be built-up area) the combination of this event and a decision (barbecue or update respectively) can be assigned a consequence. In fact, table 6.1 provides narrative examples of possible consequences. The idea of *utility theory* is to introduce a numeric measure to express the **desirability** of these consequences. The importance of this theory is lying in its ability to support a sound decision-making process as it determines the critical boundaries in the uncertain "decision space". Or, stated in other words, at what probability is it better to assign class C_2 (see the previous section), even if this fails to be the maximum value? Therefore, so-called utilities are assessed and assigned to combinations of a decision d_j and an event C_i:

$$u(d=d_j \; L \;\; C=C_i) \text{ or } u(c_{ji})$$

in which c_{ji} stands for the consequence of decision d_j and the actual occurrence of event C_i.

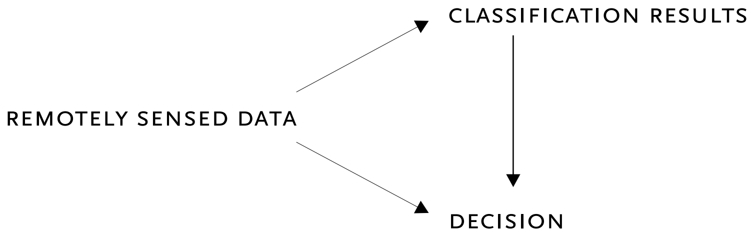


Figure 6.3: Founding decision-making on data (after Gorte et al., 1996)

The utility expresses the desirability of the scenario where the decision d_j is taken with regard to a spatial object O while it has C_i as its true information class. Actual utilities associated with the various scenarios depend upon the objectives that are being pursued with the interpretation. Note the usage of *interpretation* instead of classification; this is to make a distinction between situations in which decisions are made directly on the data and their uncertainties and **not** on their "hardened" thematic class assignments (see figure 6.3). For decision-making purposes only, a classification is no longer required and has even become obsolete(!) because not the classification **results** are needed but information on the extent and distribution of the **uncertainties** introduced by that classification.

Implementing the utilities in a decision table clarifies the relationship between decision, event and consequences (table 6.3).

Table 6.3: A decision table for the map revision example

	θ_1	θ_2	θ_3
d_1	$u(c_{11})$	$u(c_{12})$	$u(c_{13})$
d_2	$u(c_{21})$	$u(c_{22})$	$u(c_{23})$
	0.30	0.45	0.25

An alternative representation is provided by a *decision tree* (e.g. Gorte *et al.*, 1996; Lindley, 1990), a pictorial tree-like representation of the problem. The various variables and values of the problem are organised in a (rooted) tree. Each node in the tree models a variable; the branches emerging from a node represent the values of its associated variable. The topological structure of the tree is an explicit representation of all scenarios that can possibly arise from a decision. The root node of the tree represents the initial situation before any decision is taken and each path from the root node to the tip of a terminal branch corresponds with a scenario. Figure 6.4 demonstrates the decision tree for the data in table 6.3.

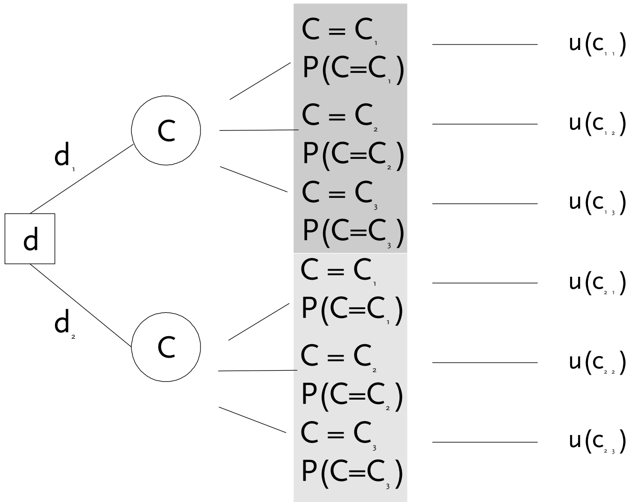


Figure 6.4: Example of a decision tree

The advantage of such a decision tree is that it becomes more understandable how the consideration of uncertainties and utilities leads to the best decision. Gorte *et al.* (1996) emphasise the role of *foldback analysis* to evaluate the decision tree. The basic idea is to start at the ends of the branches and work back to the base of the tree in order to assess the desirability of the decisions, $u(d=d_j)$. This is dependent on the true value of the chance variable that is, however, not known prior to the actual decision-making. Therefore, the utilities of all possible scenarios for a decision are weighted with the probability of occurrence of these scenarios. In fact, at each node of the decision-tree representing a chance variable, an *expected utility* is calculated. An expected utility defines the desirability of a decision d_j and can be formalised in a mathematical manner as (e.g. Gorte *et al.*, 1996; Lindley, 1990):

[6.1]

$$\hat{u}\ (d = d_j) = \sum_i u(d{=}d_j\ L\ \ C{=}C_i) * P(C{=}C_i)$$

The best decision that can be made is that with maximum expected utility (this explains why it is better not to organise a barbecue as stated at the end of section 6.2!). The obvious question that remains to be answered is of course how to assess utilities, and therefore section 6.5 will extensively deal with this issue.

6.5 Assessing utilities

According to Lindley (1990) the study of assessment of utilities is still in its infancy. Though he made his remark almost 10 years ago, it is true that a sound derivation of utilities is not unambiguously presented in the literature. By tradition, economic studies express utilities in monetary terms (benefits, pay-off...) because it seems that anything can be assigned a value or price. However, money possesses a *pseudo-stability*; its value changes over time and the conception of its value is not consistent among different persons. In other fields of interest the desirability of a decision is preferably assessed along another scale of reference. Medical specialists for example are confronted with such elusive issues as the *"utility of life of a diabetic after an amputation above the knee"* (Habbema & Bossuyt, 1990). Gorte *et al.* (1996) deal with utilities that express a combination of monetary, social and labour considerations.

The actual assessment of utilities can be performed in an increasingly complicated way. The easiest approach is to **visualise** utilities along an ordinal scale, thereby referring to one of the axioms of utility theory, namely **orderability** (Pearl, 1988). A decision-maker is forced to rank all possible scenarios on a linear scale, with the least desirable and most preferable scenario at the utmost ends of the scale bar (figure 6.5). All other scenarios are placed somewhere in between, according to the views of the decision-maker. "Distances" between scenarios are an indication of their relative appreciation. A straightforward projection of these positions on a numerical scale reveals utility values. Its simplicity notwithstanding, this methods has as its main disadvantage that it assumes the ability of a user to calibrate the relative differences in preferences in a direct way (Habbema & Bossuyt, 1990).

Another, yet more complicated and time-consuming strategy uses the *standard reference gamble* that aims at a direct quantification of the utilities. Applied in so-called global utility assessment methods (i.e. considering all aspects of a possible consequence at the same time), it is based on the idea that a rank-ordered sequence of three scenarios can be assigned a probability p for the best consequence and (1-p) for the worst, while an intermediate probability is reserved for the scenario that lies in-between both extremes, as far as consequences are concerned. Consider figure 6.6 in which an example is provided that embroiders further on the map revision theme from section 6.3. The decision to abandon map revision results in a highly desirable consequence if indeed a significant change in land cover is lacking. The question

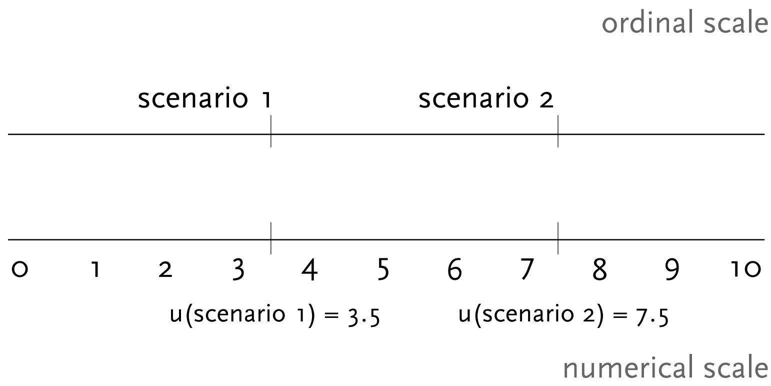


Figure 6.5: Visual approach to the assessment of utilities (after Gorte et al., 1996)

arises at what value of p the decision to maintain the map information changes into the decision to revise the map, so what is the reversal probability?

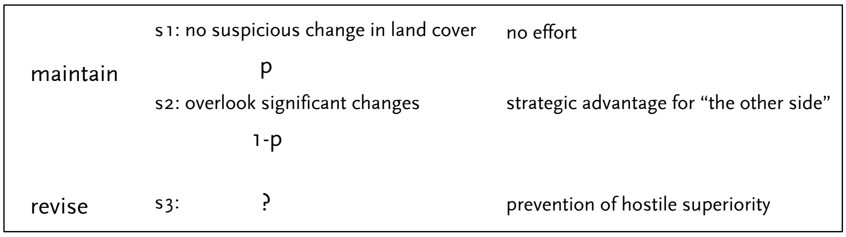


Figure 6.6: Decision tree with the probabilities for the consequences of each of the three possible scenarios

If this breakpoint is estimated as a value of 0.70, in other words, if the probability is less than 70%, then the map is revised by at least tagging the considered image elements. From this it follows that:

$$0.70 * u(s_1) + (1\text{-}0.70) * u(s_2) = u(s_3)$$

To finish the numerical example, substitute the utilities for scenario s_1 and s_2 by 1 and 0 respectively to see that a utility of 0.70 for scenario s_3 follows from the uncertainty that is expressed by p. The method of *standard reference gamble* tends to result in better calibrated utilities as compared to the visual approach (Gorte *et al.*, 1996) and is applicable to decisions with more than three (uncertain) consequences, although the evaluation of three-tuples of scenarios is indeed more time-consuming,

Other, more sophisticated methods to derive utilities are being developed, e.g. those in which all aspects of a particular consequence are considered separately and assigned a utility. This is the case if there are different calibration *commodities* such as time or money which are only difficult to compare with each other (Pearl, 1988). Von Winterfeldt & Edwards (1986) present an extensive study on these utility assessment procedures.

6.6 Concluding remarks

To conclude this section, a number of interesting observations can be made.

- **Decision theory appears to be a combination of probability theory and utility theory.** Both concepts oblige a user (here: *a decision-maker*) to structure and subsequently consider a wide range of decisions, given exclusive and exhaustive events. The uncertainty by which events are attended is expressed as a posterior probability in case of the considered remotely sensed data. The availability of these probabilities avoids cumbersome assessment techniques and hence the emphasis should be on the derivation of utility values. These utilities provide a numeric way of expressing the preferences of consequences of decisions.
- **Decision theory acts directly on the - uncertain - data and avoids the fuzzification of "hardened" thematic classes.** Decision analysis of remotely sensed data results in *interpretations* instead of *classifications* because the actual assignment of class labels prior to decision-making is superfluous. Probabilities are measures of belief as they express the strength of the assumption that a pixel or object (in the image) corresponds with an actual class C_j (in the real world). By focussing a decision around the selection of one class, the unjustified usage of probabilities as *partial membership values* (as in fuzzy set theory) is avoided.
- **Decision analysis results in the** best **decision, standard classifications lead to the** most probable **results.** Given the uncertainties at hand, and considering the desirability of the consequences of courses of action, decision-makers pursue the best decision, e.g. *"cheap but sufficient, expensive but safe, cumbersome but fruitful"*, etcetera. It is interesting to note that these ideas are directly applicable to standard maximum *a posteriori* classification procedures. The decision consists of selecting the class that has to be assigned to a pixel, the utilities represent the severity of possible erroneous classifications or confusions. In maximum *a posteriori* classification strategies the probability of a correct classification is maximised and hence each misclassification is considered **equally** adverse. In terms of utilities, for the decision d_j to assign class C_j to a pixel:

  $$u(d=d_j\ L\ \ C=C_j) = 1 \text{ for all } j = 1,\ldots,n \text{ (n is the number of information classes)}$$

  $$u(d=d_j\ L\ \ C=C_i) = 0 \text{ for all } i,j = 1,\ldots,n \text{ AND } i\ ^{1}\ j$$
- **Additional knowledge can improve the probability of occurrence of a particular class but at the expense of more costs.** The role of *a priori* knowledge in classification strategies has been stressed in section 5.6. Reducing uncertainty by the inclusion of extra knowledge can facilitate decision-making, but it involves possibly extra costs. Think of the efforts that need to be made in order to collect better, more recent data, or of the processing time needed to prepare the additional data. The utilities are affected by these extra costs, and therefore increasing probabilities do not always result in higher utilities, as adverse consequences could overrule the advantage of more certain data!

Figure 6.7 provides the position of decision analysis in the extended schema of chapter 5.

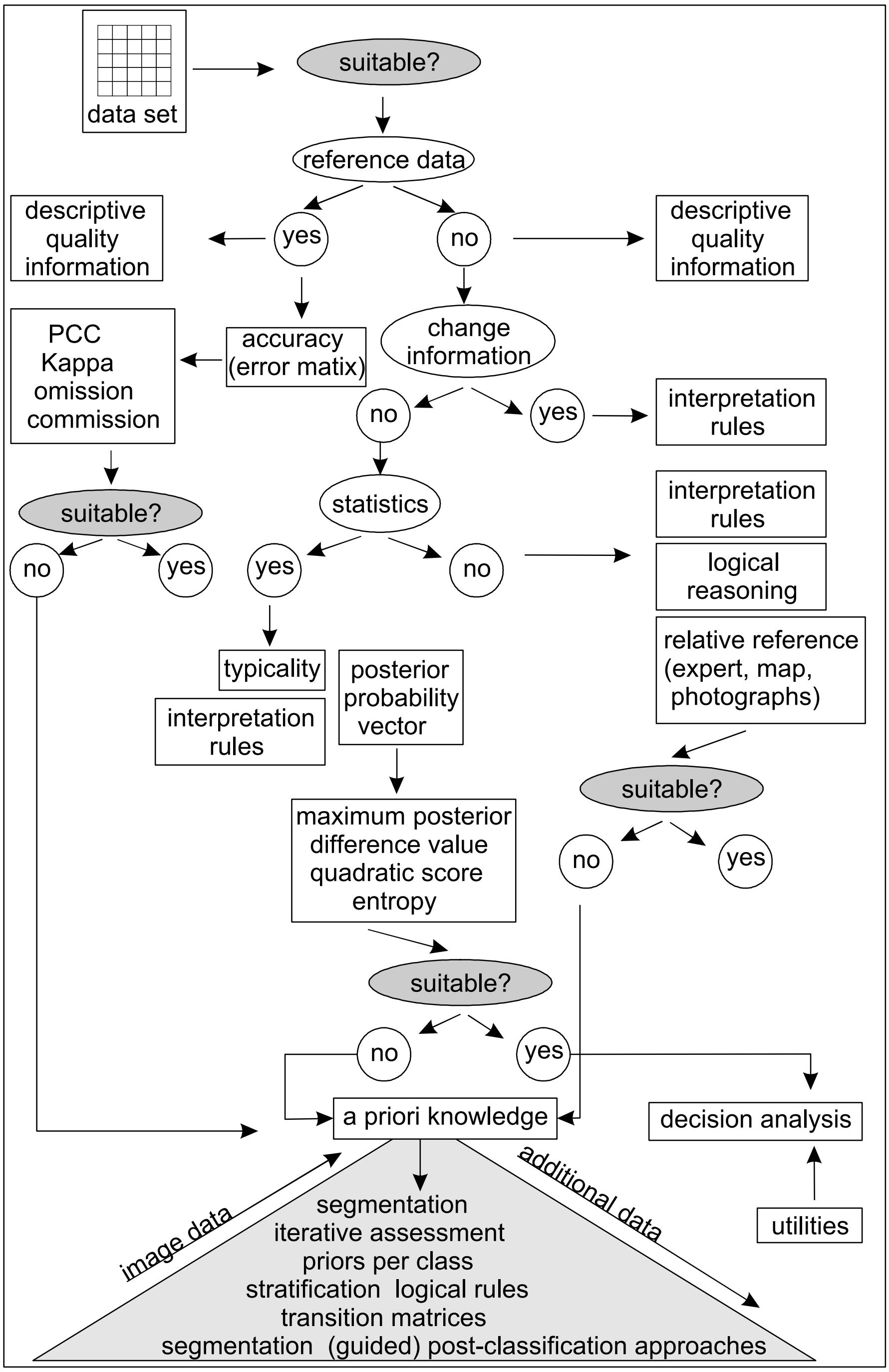


Figure 6.7: The role of decision analysis in the information process

7 Representation of uncertain information: from exploration to explanation

"...Ce n'est pas une image juste, c'est juste une image..."

Jean-Luc Godard – French cineast

7.1 Introduction

The value of information is judged by its ability to provide answers to predefined questions; in all its simplicity, this statement expresses the quintessence of the information process as dealt with in this thesis, the incentive to use remotely sensed data instead of alternative spatial data. Information about uncertainty and quality in general helps to determine the level of acceptance of assumed information. It is, unfortunately, often lost during the cartographic presentation of processing results because of both generalisation and practical limitations of the map making process. Deliberately hardening fuzzy boundaries and generalising heterogeneous areas is generally accepted in cartography as a means to facilitate and reinforce the communication of spatial information. This *"lying with maps"* is useful as Monmonier (1991b) points out, though the question arises how to map the "lies" that lurk in the character of spatial data? How to assess the information value in order to avoid wrong interpretations and unjustified usage?

Accepting that uncertainty is inextricably bound up with efforts to understand the real world by means of collecting, processing and visualising spatial data, the relevance of quality information has been stressed. An interesting point made in section 1.4 by Goodchild *et al.* (1994a) refers to the cartographic prospects of conveying this data quality because of its spatial extent:

"...the measurable aspects of data uncertainty will probably have a spatial component, since quality will be higher in some areas than others, or higher for certain features..."

Note that although data quality and uncertainty seem to be quoted without doing justice to their separate meanings, the concept of uncertainty is somewhat more generic - but indeed contributory to the idea of quality! Since the end of the 1980's, visualisation of data quality has gained an increasing amount of attention by the geographical community. The National Center for Geographical Information and Analysis (NCGIA) in the USA dedicated one of its research initiatives to this subject (Beard *et al.*, 1991). Without the support of some efficient and effective means to convey the intrinsic value of spatial data, the acceptance of quality information is doomed to failure.

Traditionally, the profession of cartography has been dedicated to the representation of the geographical extent of our surroundings, thereby reflecting a certain level of knowledge about the "real world". Obviously, this implies a process of abstraction for it is far too difficult and even undesirable to grasp the real world in its full extension, as its characteristics are subjected to the dynamics of time and space. Neither the data acquisition methods, nor men themselves can cope with such a complicated reality although the subsequent implications are quite different. Sampling strategies underlying such techniques as remote sensing and field work prove that the introduction of a certain amount of uncertainty is inevitable and related to both the nature of phenomena and the method which is used to describe them, while the intentional exclusion of data by cartographers is dictated by the rule of *seeing less to know more*. The visual transfer of information is at stake and the map happens to be the medium, not an aim in itself, as opposed to mere graphical design.

The skills and affinity of the mapmaker with the processed data happened to ensure the derivation of a reliable reflection of the geographical "truth" - at least with respect to the intended map use. Morrison (1995) calls this the *"...invisible stamp of approval of the quality on each created map..."* Uncertainty has always been considered by cartographers, although often in an implicit or non-informative way such as in the case of *imaginary cartography* (Thrower, 1996). Arisen during the Dark Ages, it added imagination to the map making process, *"...an imagination that flourishes especially at the boundary between the known and the unknown in maps old and new..."* as Hall (1993) puts it. Wild animals and fantasy tableaux were placed on continents to veil the lack of knowledge on their interior - and not seldom moved to other, still unexplored regions when more knowledge came available (Whitfield, 1994)! But uncertainty was also more seriously visualised by interrupted boundaries such as the eastern coast of "New Holland" (Australia) until its mapping by James Cook in 1770.

Of course, the uncertainty as considered in the preceding chapters is somewhat different - as are the ways in which cartographers have to deal with it. Nowadays, the cartographer digitally "assembles" data from different (sometimes unknown!) data sources that can be visualised in more than one way ("there is no true map" as Ormeling (1995) stated, see also section 2.1.2); in fact, the cartographer is increasingly replaced by a cartographic "utility" provided by geographical information systems. Clearly, the image of the cartographer as a *quality filter* needs some adaptation!

It may be obvious that the uncertainties that attend geographical data are spatially distributed and hence can be mapped cartographically, but it remains to be resolved what exactly needs to be visualised, let alone how and when! Chapter 4 has ended by concluding that probability information alone doesn't reveal all uncertainty in a classified remotely sensed data set and that there is a need for describing other quality issues as part of more extended meta-information. The challenge is to find out exactly what quality components are relevant and which of these can be visualised - or gain extra value by being visualised. The idea is that by doing so, a scheme can be elaborated that helps the communication of quality information according to a cartographically sound approach. This chapter pursues the construction of such a scheme based on the theory of graphic semiology.

7.2 The role of meta-data in defining quality

The concept of data quality is generally understood as *fitness for use*, indicating its relative meaning and dependency on the pursued application. This observation provokes an interesting statement; high quality is not simply related to highly accurate or more certain data. For some applications it is clear that high-resolution data are desirable and feasible (see example below), but only when the benefits are outranking the costs. It could be more sensible to invest in a cheap land cover map of the Netherlands and its regular updates instead of spending money on high-resolution data that are likely to absorb budgets for a long period of time!

Accuracy measurements or uncertainty indications tell the user of spatial data how good or bad these data are without considering the circumstances under which they will be applied. The point put forward in this thesis is that **better data need to be defined in terms of better decisions**. Decision analysis is one way of dealing with uncertainty in spatial data as has been elucidated in the previous chapter. Quality considerations add an extra value to this process because they explain why a particular data set has been selected in the first place. High *posterior* probabilities reflect the compliance to the classification model but obscure the reasons why particular data are given preference to other:

- why using Landsat TM and not SPOT-XS?
- why using up-to-date and therefore expensive scenes?
- why using remotely sensed data at all?

An example...

In precision farming everything hinges on a more efficient and economic use of agricultural resources and the reduction of adverse environmental effects by means of adopting different technologies. Remote sensing, as one of these, provides a mechanism to monitor fields on the condition that the spatial and temporal resolutions are sufficiently high - as a matter of fact as high as technically feasible. The rise of high-resolution earth imagery enables the detection of e.g. badly irrigated lots and the presence of crop diseases, and urges for a more dedicated cultivation of agricultural crops. In meteorology, however, high resolution is not always feasible; the derivation of albedo, or reflectivity of the Earth's surface, can be achieved from vegetation maps, which in turn could be obtained from remotely sensed data. As a parameter of the numerical models that are used to predict the weather, high resolution is desired but the models themselves are still so rough (in the range of kilometres) that the heterogeneity of vegetation within the grid cells as defined by the model can still be represented by relatively low (spatial) resolution data.

Before classifying an image, a number of choices has been made that require background information about the data set: at what day has the image been acquired, what level of processing has it undergone, is it resampled and if so, by what method, et cetera. Of course, choices are not always made on the basis of rationalism, but are rather overruled by pragmatic considerations. Though, if more additional data is made available for the description of data sets, according to a number of *quality components*, the resulting increase of *data consciousness* is expected to contribute to better decisions. In the literature, these quality components are generally considered a subset of metadata, so data about data, and placed in one of the following categories according to Moellering's (1987) classification for the National Committee on Digital Cartographic Data Standards (NCDCDS):

- *lineage* - describes the "pedigree" of a data set, including information about source, age and level of processing;
- *attribute accuracy* - refers to the correctness of a non-spatial characteristic that has been assigned to an object;
- *positional accuracy* - indicates the extent to which the location and height of an object have been correctly represented;
- *completeness* - describes the relationship between objects represented in a data set and *"...the abstract universe of all objects..."* (Morrison, 1988), which is dependent on a specific context and real world model (Brassel *et al.*, 1995);
- *logical consistency* - deals with the data set itself as it focuses on the validity of object representations, both from a geometric and thematic point of view, and the relationships between these objects (Kainz, 1995).

These quality components have been adopted by the International Cartographic Association (ICA) as the ingredients of quality reports (see the next section) which are in turn part of *de jure* spatial data standards. The European Committee for Standardisation (CEN) has published its guidelines for the description of spatial data (CEN, 1996) while the US Content Standard for Digital Geospatial Metadata of the Federal Geographical Data Committee (FGDC) legally prescribes the standardised documentation of spatial data (Clinton, 1994).

In addition to these components, several other aspects of quality have been discussed in literature, the most prevalent of them being semantic accuracy and temporal accuracy. The former refers to the success of translating a complex reality in understandable and pertinent chunks of geographical information, by way of some model. As such, the concept is closely knit with other quality components that are not easy to differentiate as Salgé (1995) concludes in his interesting paper on semantic accuracy. Temporal accuracy clearly relates to the dynamics of real world phenomena, so with the issue of currency and temporal consistency of spatial databases. Again, this concept is tied up with other quality components - lineage for example could include information about update cycles.

Quality information as described in the above should always accompany a spatial data set such that it can be consulted when applicable, e.g. when combining different data sets during an overlay analysis (Ormeling, 1998). Its visualisation could contribute to better decision-making as it reveals possibly relevant differences over space, helping users to be on the alert and recognise treacherous pitfalls well in advance. A cartographic representation of this information is not always feasible or significant, especially when only one quality parameter is available for the data set as a whole. Other approaches have to be used to accomplish the consideration of this information by a user, a task that challenges the creativity of the spatial metadata administrator or data custodian.

7.3 Non-cartographic ways to depict data quality: reports

A graphic representation of quality information is preferred to its non-graphic counterparts. As geographical data are generally processed in a GIS environment with a - by definition - (carto)graphic interface, spatial metadata is likely to be conveyed in some graphic format as well. However, a quality map that shows fitness for use at a glance is not always feasible or desirable, because:

- the available quality information lacks a spatial component - one number representing the attribute accuracy of a remote sensing classification, e.g. 75% of pixels correctly classified;
- the quality component is not *map-genic* - the processing history of a data set could be too comprehensive for a convincing map visualisation, in spite of its spatial variations.

Moreover, visualisation of spatial data quality is not a goal in itself; if the resulting quality map is too complicated and therefore not easily interpreted by a user, it misses its aim as explanatory background information!

Before dealing with visualisations in more detail, some attention is given to other, non-cartographic ways to depict quality information. One approach is to write a detailed report on a specific part of the processing history of a data set. An example of this is the paper by Ankum *et al.* (1987) that provides clues that help to assess the total error after rasterising the polygons of the Dutch soil map. A more often used and straightforward format is the *quality report*, a textual description of a data set conforming to some *de jure* or *de facto* metadata standard. An example is provided by figure 7.1 in which a Landsat TM image is described according to the guidelines of the metadata standard as issued by the Federal Geographical Data Committee. The role of such an extended data characterisation exceeds mere quality information conveyance; as part of metadata serving the efficient storage and retrieval of spatial data in (distributed) databases, it enables the early consideration of different data sets without actually accessing the data themselves.

The advantage of a report is its exhaustiveness; all information that is considered relevant for the assessment of the *fitness for use* is listed, although this may fatigue the innocent user who is not specifically interested in all this background information. Clearly, the contents of such reports contribute to the exploration of the most suitable data in a spatial database because of its structuring in a metadatabase (*"search database for all images with a cloud coverage of less than 30%"* could be a query that makes an appeal to **completeness**). But a decision-maker who is confronted with a

Data Quality Information

Attribute Accuracy Report

The identification of features is provided by the distinct electromagnetic energy it emits, reflects, or otherwise transmits. This is called the spectral signature. Other signatures are tone (lightness or darkness), texture (surface roughness or smoothness), pattern, shadow, shape and size are as important. Thus, through the use of Thematic Mapper, such elements as water features, soils, and vegetation can be identified and distinguished from each other.

Logical Consistency Report

All the Landsat satellites have been in sun-synchronous orbits with equatorial crossing times ranging from 8:30 a.m. for Landsat 1, 9 a.m. for Landsat 2, to 9:45 a.m. for Landsat 5. The Landsat system provides for global data between 81 degrees north latitude and 81 degrees south latitude.

Completeness Report

The Landsat platforms operate from a sun-synchronous, near-polar orbit imaging the same 185-km (115 miles) ground swath every 16 days. Thematic Mapper (TM) data are received directly from Landsats 4 and 5 by a network of 16 worldwide ground stations. The United States ground station in Norman, Oklahoma, receives TM downlinks daily, and records them on high-density tapes. These tapes are then sent to Space Imaging EOSAT's Image Processing Facility (IDPF) located in Lanham, Maryland. Also, data are transmitted via a Tracking and Data Relay Satellite (TDRS) to its ground terminal at White Sands, New Mexico, and then relayed via a domestic communications satellite (DOMSAT) to the Space Imaging EOSAT data processing facility in Norman, Oklahoma.

Lineage

Source Information

Originator: US Geological Survey

Publication_Date: 19720101

Title: Land Satellite Multispectral Scanner (Landsat MSS)

Geospatial Data_Presentation_Form: Remote-sensing image

Process Steps

The Space Imaging EOSAT Image Data Processing Facility in Lanham, Maryland, receives the HDT's from the Norman, Oklahoma, acquisition facility. The newly acquired data are manually and automatically screened for cloud cover and data quality through the Pre-processing and Data Classification System (PDCS). HDT's that are required for customer products continue through the image-processing stream. The remaining data are stored locally for approximately six months; after temporary storage, they are permanently archived in Jessup, Maryland. The HDT's are also shipped to the EDC where they are copied and the original returned to the Space Imaging EOSAT.

Figure 7.1: Description of a remote sensing image as far as quality components are considered.
Source: USGS *Geospatial Data Clearinghouse (shortened and adapted version)*

land cover map that is attended by a quality report of several pages is apt to disregard its information! In other words, an end user can benefit from a quality report because of its availability through the metadata information system, but the composition of such a summary for *presentation-purposes-only* requires too excessive efforts. A main advantage of a quality report is its standardised format, at least in the case of a metadata standard; as a consequence, metafile-generation software can be developed in order to accomplish an easy-as-possible recording of quality information. Moreover, a *generic template* could serve as a starting point for a description, such that the characteristics of e.g. a Landsat TM scene only have to be customised for the particular image when and where required.

7.4 Visualisation and cartography

"...During data analysis one will require simple, throw-away visual aids in order to establish the accuracy, completeness (...) of the data, to distinguish between what is spatial pattern and spatial nonsense..." This statement from Medyckyj-Scott (1991) makes an appeal to visualisation techniques to convey quality information without introducing redundancy. Of course, this information must be *visualisable* as stated in the previous section. Unwin (1995) considers the representation of error and uncertainty by visualisation one of the features that needs to be addressed by an *error-sensitive* GIS!

What exactly is visualisation? It is not synonymous with cartography as it goes beyond the domain of spatial data, although cartography has always dealt with the issue of making data visible (MacEachren & Kraak, 1997) or at least with transforming data into forms spatially meaningful to human beings (Olson, 1991). Krygier (1994) and Fisher (1994a) who applied sound as a non-visual, sensorial variable to depict data quality exemplify the latter. It is more probable, however, that Olson's remark refers to tactile maps or maps for the blind, stimulating feeling instead of vision. So, visualisation exceeds the field of interest of cartographers whereas cartography is not always about visualisation.

According to Muehrcke (1990), visualisation refers to *"...the use of computer graphics and image processing technology in data-intensive scientific applications..."* This emphasis on computer technology is put forward by Taylor (1991) as well, but cartographic visualisation is better distinguished from cartography by focusing on its **use** during the information process, as MacEachren (1994) clearly points out. DiBiase (1990) considers *cartographic visualisation* a scientific research tool that can prove its merit during several stages of data processing. In other words, visualisation not only pursues maps for the sake of presentation, but also serves as a means to facilitate analysis and decision-making based on spatial data. Figure 7.2 illustrates his ideas concerning the differing roles of visualisation during the research process. During a more exploratory stage a data set is visualised in several ways - in fact, a data set is scrutinised from as many sides as possible, similar to the observation of the facets of a turning diamond. The objective of these efforts - known as *visual thinking* - is the generation of knowledge such that the researcher better understands the phenomenon under consideration. In addition, an explicative stage can be distinguished during which visualisations are used to communicate information to a wider audience (*visual communication*). This is traditionally the domain of cartographers who use maps to synthesise, summarise and convey relevant spatial patterns. The conceptual dichotomy addressed by DiBiase's depiction of visualisation doesn't exclude cartography from the "visual thinking realm", on the contrary, it extends the possibilities of cartographers as it reveals an area in which they can develop a more cognitive mapping of spatial data. Their contribution is needed to improve the graphical imagination of the average person, a "knack" which is often over-estimated.

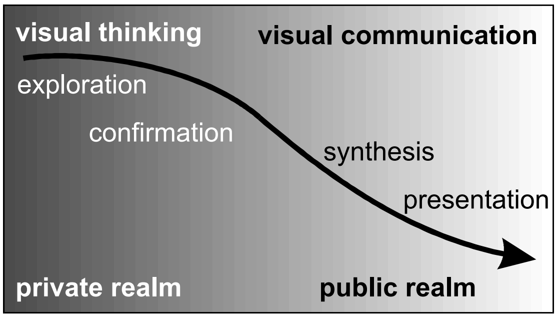


Figure 7.2: The roles of visualisation in the information process (after DiBiase, 1990)

The introduction of new - computer - technology and the deviation from the traditional communication paradigm generally accepted in cartography seem to be constantly recurring in the discussions on cartographic visualisation. MacEachren & Monmonier (1992), however, have proposed the appearance of another distinguishing characteristic of cartographic visualisation on the scene - one that clearly separates computer cartography from cartographic visualisation. From a user point of view they consider *human-map interaction* a critical component, enabled by present computer technology and provoking a completely different map usage as compared with mere communicative maps that support a one-way transfer of information, from the cartographer via the map to the map reader. When founding an ICA working group on visualisation, MacEachren (1994) has given shape to his ideas concerning map use in view of cartographic visualisation. His depiction of cartography corresponds with a cube (hence *cartography*^{3}) in which different types of map use can be identified according to their positions along the 3 axes, defining respectively (figure 7.3):

- the interactivity between map reader and map product (static versus dynamic maps);
- the identity of the user (researcher versus laymen);
- the pursued map use (exploration versus explanation).

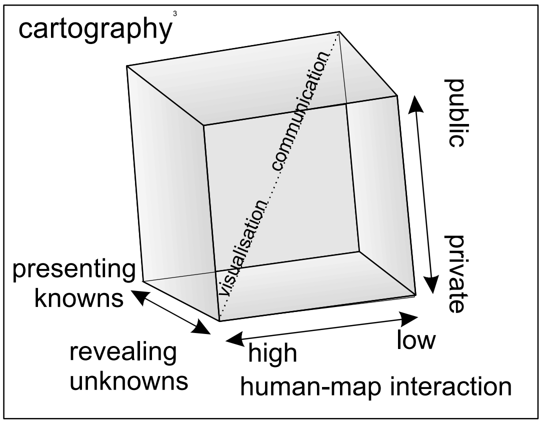


Figure 7.3: Cartography according to MacEachren (1994)

Starting from this representation, MacEachren & Kraak (1997) consider visualisation then the *complement* of communication. There is, however, no clear dividing line between both fields of interest as MacEachren (1994) notes; instead, map use can be characterised by an emphasis on either visualisation (e.g. revealing spatial patterns in probability vectors) or communication (e.g. presenting a land cover map based on highest probabilities).

One end of the cartography[3] space represents the traditional cartographic practice of presenting results of some sort of processing ("the known") to a broad public by means of maps with a mainly static nature. The other end is typical of an exploratory environment in which the individual researcher needs answers to questions in order to reveal - as yet - unknown spatial patterns, thereby highly interacting with the data as such. From this it becomes clear that efforts aimed at the mapping of spatial data quality are principally concentrated around the latter extreme. It is interesting to investigate the extent to which this visualisation can benefit from cartography, or more specifically, cartographic *rules*. **Which graphic variables can be used at what stage of the information extraction process?**

7.5 Graphic variables - Bertin's theory reconsidered

The question that concluded section 7.4 is addressed by Van der Wel *et al.* (1994) who present a framework for the visualisation of data quality components (figure 7.4). In a step by step approach they consider five issues relevant with respect to the conveyance of spatial data quality (and uncertainty). Some of the components have already been discussed in previous sections.

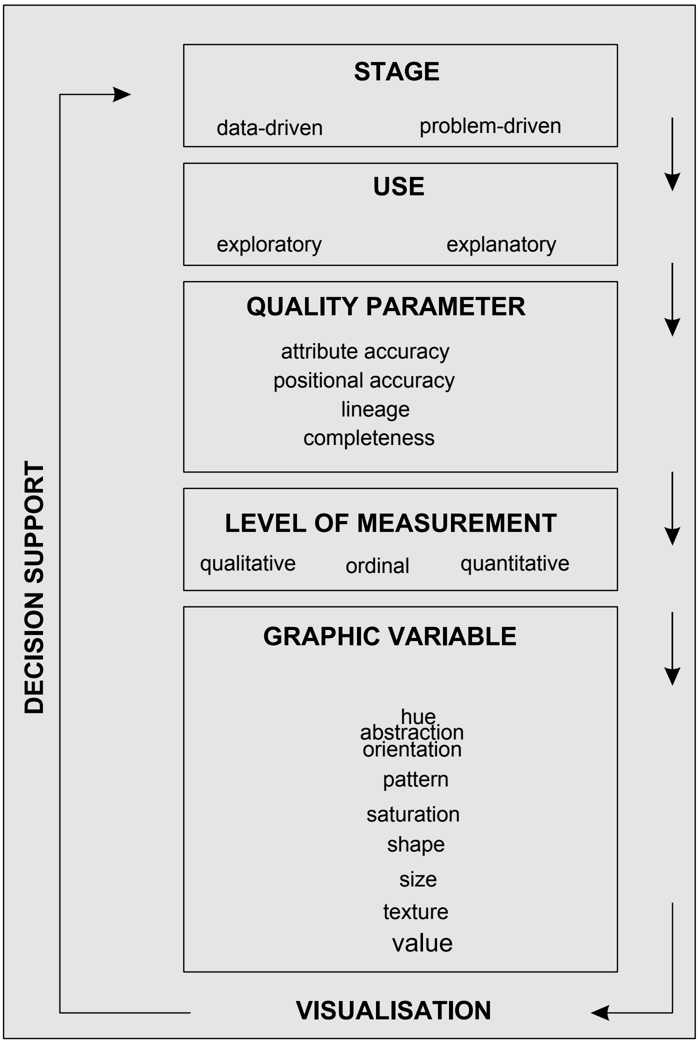


Figure 7.4: A framework for the visualisation of data quality components

The first distinction that has been made is between a data-driven and a problem-driven information process (Hootsmans & Van der Wel, 1992). The former applies to a process in which the selection of data is subjected to such criteria as availability, accessibility and costs. Hence, the generation of information (*"answers to questions"*) is directed by more or less pragmatic considerations. In a problem-driven approach, not data but questions are decisive for the information (*"answers"*) to be derived and, as a consequence, for the data to be processed. Ideally, solving a problem means processing only those data that meet specific requirements - or at least approach the prerequisites as close as possible. Quality information and its visualisation is of key importance during the complete problem-driven information extraction process because it helps to assess the extent to which a data set deviates from the pursued ideal. It allows for some adjustment if necessary whereas in a data-driven process visualised quality information serves a mere notification of the fitness for use of the data under consideration. The above distinction relates to the moment or **stage** in the information process at which particular quality information can be visualised.

After deciding what quality information has to be visualised, and at what moment and for which user group, this information has to be expressed graphically. Before doing so, it is important to take notice of the quantitative or qualitative nature of this information as this may affect the graphical working space. Quality information can be distinguished at four levels of measurement, to wit:
- nominal (descriptive lineage information about source and age);
- ordinal (relative assignment of *fitness for use*, e.g. A better than B but worse than C);
- interval (values defining the membership to a fuzzy class);
- ratio (classification accuracy values, posterior probabilities).

The above arrangement is of importance because it contributes to the assessment of relationships between quality components and graphic variables. Here, the latter two scales are summarised as "quantitative", although mainly ratio-scale data are treated in this thesis. This doesn't trivialise the point made by Wang & Ormeling (1996), namely that cartographic theories often assume the same position for both scales.

The resulting structure shown in figure 7.4 is taken as a starting point for the generation of quality maps according to the application of graphic variables, especially those proposed by Jacques Bertin who has exerted a tremendous influence on European cartography.

With his *Semiologie graphique* published in 1967, the Frenchman Bertin introduced a framework for a graphical language - a set of rules which application should contribute to an optimal stimulation of the visual powers of perception of a map-reader. The practical impact of the proposed semiology of graphics over the past years is difficult to assess, but its "virginity" with respect to the visualisation of quality information is beyond all doubt. Moreover, being in the very heart of the digital era, with computer cartography being almost becoming a pleonasm, one could even question the validity of the theory as Bertin has developed his work in the analogue 60's (Bertin, 1967):

"...on ne considérera donc que ce qui est représentable sur une feuille plane de papier blanc d'un format moyen, sous un éclairage normal, par tous les moyens graphiques disponibles..."

Initially, the ideas of Bertin will be examined by establishing relationships between his graphic variables and particular quality parameters in view of the construction of static quality maps. Here, s*tatic* means that the map representation is not guided by temporal variables (see section 7.8). In case the electronic equivalent of the static paper map is considered, one has to take into account that the perception is controlled by a different light source; features are observed by virtue of emitted instead of reflected light. In addition, computer screen maps can become part of a more dynamic visualisation, for example as part of an animated map series. Therefore the distinction between static paper and electronic maps calls for caution. Bertin's theory rests on three pillars that will be briefly discussed during the remaining part of this section. They are implantation, graphic variables and pursued perceptual effect respectively.

Implantation

The French term "implantation" refers to the classes of representation, i.e. point, line and area. American cartographers, such as Phillip Muehrcke (1983), simply call this "type of symbol".

Graphic variables

Bertin (1967) has made a distinction between 6 graphic variables (or *visual dimensions* as Muehrcke (1983) tends to mention them). Point, line and area symbols can vary according to these variables and subsequently evoke different perceptual sensations (see below). Not all types of data can benefit from the same graphic variables; some of them are more apt to transfer quantitative data while others do exhibit a qualitative nature. Moreover, some symbols can not change their appearance according to a changing graphic variable (i.e. area symbols can't change according to shape). Besides the position in the graphical plane (x,y) the original variables are:

- colour hue;
- value;
- orientation;
- shape;
- size;
- texture or grain.

Muehrcke & Muehrcke (1992) have added pattern arrangement (or structure) and colour saturation to this list. According to MacEachren (1992) the latter is *"...the most logical one to use for depicting uncertainty..."* Its application in so-called bivariate maps comes into mind as these maps allow for the simultaneous conveyance of thematic data (e.g. land cover classes characterised by different hues) and uncertainty (e.g. classification probabilities expressed by the extent to which a colour is saturated). Still other variables have been suggested as an addition to the original variables of Bertin, for example focus (MacEachren, 1992) and abstraction or realism (McGranaghan, 1993; Van der Wel *et al.*, 1994). Focus is considered in one of the following sections that deals with visual *effects* (section 7.8). Abstraction has already been recognised by cartographers as a powerful variable to communicate information (Muehrcke, 1990), but the link with quality components is rather new (higher quality corresponds with lower level of abstraction). Of course, to some extent this application of abstraction can benefit from a consideration of more general efforts such as the distinction of the mimetic to arbitrary symbol range by Robinson & Bartz Petchenik (1976). MacEachren's (1992) *degrading resolution* and McGranaghan's (1993) *(photo-)realism* are closely related to the concept of abstraction. The latter author urges for caution and he hits the nail on the head when stating that *"...greater realism may interfere with the abstraction that makes maps useful in the first place..."*

Pursued perceptual effect

The graphical transfer of spatial data involves the depiction of a phenomenon by a particular symbol that changes according to a graphic variable which, in turn, is controlled by the values or characteristics of the considered data at a specific position.

In a remote sensing classification, different land cover classes can be represented by area entities made up of pixels that are assigned different colours. If represented correctly, the result evokes a perceptual effect that helps to interpret the underlying spatial data. Taking again the land cover map as an example, it is possible to detect all occurrences of corn at a glance (e.g. the distribution of all yellow-coloured fields). This is called selection (*perception sélective*), a process of immediate recognition and isolation of all map elements of a particular class, thus perceiving the image formed by that class. But it is also easy to see which fields are part of the same class, in other words, to reveal similarities (e.g. the field in the upper part of the map belongs to the same class as the one in the lower left corner of the map). This is known as **association** (*perception associative*), a process of matching and grouping corresponding map elements distinguished by a variable. Two other perceptual effects are absolutely unattainable with this qualitative land cover map: **order** (*perception ordonnée*) and **quantity** (*perception quantitative*). It is of the utmost importance to understand that the successful stimulation of these effects is bound by a maximum number of levels or steps with which the graphic variable is applied!

It is an obvious next step to wonder whether or not these concepts are transferable to the realm of spatial data quality. The next section will touch upon these issues and propose a framework for the application of graphic variables to depict spatial data quality.

7.6 Graphic variables and the visualisation of data quality

Given a particular quality component, a decision has to be taken concerning the graphic variable to use for its representation. The five components from section 7.2 can serve as a starting point but need an adaptation because they fail to address the **classification uncertainty** that is pivotal with respect to the subject of this thesis! In fact, not attribute accuracy (*"correct or erroneous"*) but classification uncertainty (*"more or less probable"*) is relevant for this particular study, as are completeness and lineage. Examples will mainly concern the thematic or attribute component of quality that is currently attracting most attention in literature (Ormeling, 1998). The positional component is not part of the study as long as it isn't interwoven with its thematic counterpart, and will therefore be ignored. Logical consistency is not further discussed neither because of the absence of explicit topological relationships in the (raster) remotely sensed data, and the non-cartographic character of the reports on thematic inconsistencies (e.g. tables showing the frequency of adjacent classes or the 4/8 connectivity of a particular pixel). The eventual scheme will differ somewhat from the one originally presented in Van der Wel *et al.* (1994) because it is merely dedicated to the quality of classified remotely sensed data.

Although the research is still in its infancy, several authors have already prioritised the establishment of a framework for the visualisation of data quality. Buttenfield (1991) has made an attempt to construct a matrix in which the relation between quality components and data types is achieved through different graphic variables. McGranaghan (1993) provides examples that show how graphic variables can be applied to convey quality components as lineage and positional accuracy in an *"...explicitly symbolised..."* approach. This means that the quality information is retrievable through the dimension of a graphic variable as opposed to an *"...implicit symbology for data quality..."* (McGranaghan, 1993) that tells the user that the data need to be carefully interpreted without providing exact information (figure 7.5). This distinction is very helpful when structuring the graphic variables according to their suitability for depicting quality information **and** the level at which this information needs to be conveyed.

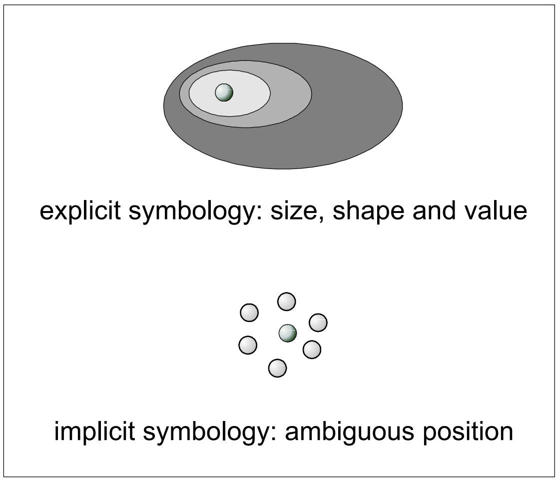


Figure 7.5: Explicit versus implicit symbology

Van der Wel *et al.* (1994) summarised their visions concerning the visualisation of data quality in a framework that defines the suitability of 9 graphic variables for the representation of 4 quality components at all measurement levels (figure 7.6, see appendix 1 for an extended explanation). It must be emphasised that they have considered visualisation merely from a theoretical point of view, in other words, no efforts have been made to gather results on the cartographic readability of the possible quality maps. Jiang (1996), on the other hand, has dedicated some of his research to perceptual issues and concluded that the selection of graphic variables should be the subject of constant concern. For example, a bivariate map in which different themes are assigned different colours (red = urban area, green = pasture) and the accompanying uncertainty is represented by different saturation levels (increasing saturation indicates more certain data) could be interpreted erroneously; saturated red is perceived as low certainty, while saturated green is perceived as high certainty. Brown & Van Elzakker (1993) have investigated the suitability of all three colour variables hue, saturation and (lightness) value for the depiction of quality information on both paper and electronic maps. They stand up for the possibilities of saturation but also recognise its pitfalls, for example the fact that colours of low saturation converge and hence are difficult to distinguish.

	nominal	*ordinal*	*interval*	*ratio*
positional accuracy	x	o	o	o
attribute accuracy	x	o	o	o
lineage	o	o	x	x
completeness	x	o	o	x

o = possible

x = not possible

level of measurement	nominal	ordinal				interval			ratio	
graphic variable	L	L	A	P	C	A	P	C	A	P (9)
colour hue	+ (2)	-	-/+	-/+	- (5)	+	+	-/+ (8)	-	-
orientation	+	-	-	-	-	-	-	-	-	-
shape	-/+ (3)	-	-	-	-	-	-	-	-	-
size	-	-	+	+	- (6)	+	+	-	+	+
texture	+ (4)	-/+	-/+	-/+	-/+	-	-	-	-	-
value	-	+	+	-	+	+	+	-/+	-	-
abstraction	-	-	-	+	+ (7)	-	-	-	-	-
pattern	+	-	-	-	-	-	-	-	-	-
colour saturation (1)	-	+	+	+	+	+	+	-	-	-

- = not suitable

-/+ = suitable under predefined conditions

+ = suitable

L = lineage

A = attribute accuracy

P = positional accuracy

C = completeness

Figure 7.6: An extended framework for the visualisation of quality information, see also appendix 1 (after Van der Wel et al., 1994)

Figure 7.7 presents the backbone of the visualisation framework, consisting of Bertin's original variables (**bold**) and suggested additions (*italic*). This iconic representation doesn't reveal any judgement or preference because this would require perception tests (see appendix 1 for an additional explanation).

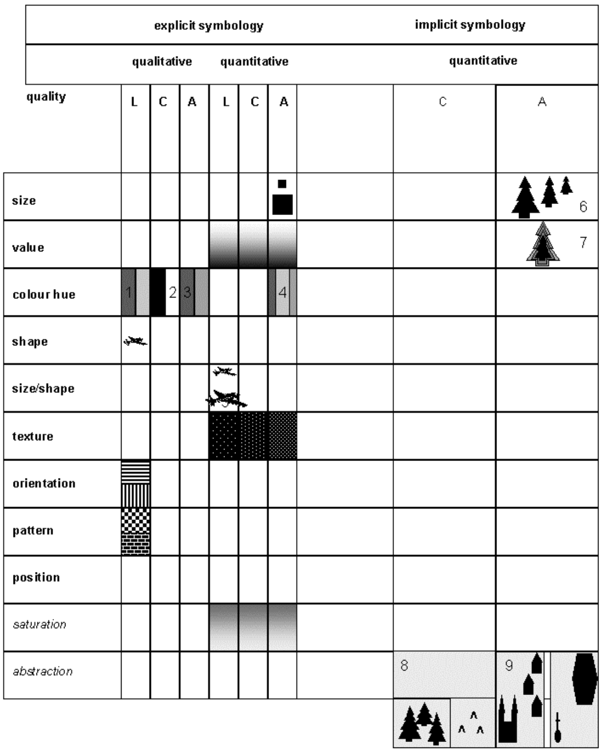


Figure 7.7: A framework for the visualisation of spatial data quality components lineage (L), completeness (C) and classification uncertainty (A), see also appendix 1

In practice, the selection of these graphic variables is controlled by the specification of the visual relation between data and quality (after MacEachren, 1992):

- combined
  - ◊ bivariate map (data and quality represented in one visualisation)
- separated
  - ◊ static map pair (data and quality represented separately but at the same time)
  - ◊ succeeding map pair (first data, then quality)
  - ◊ alternating map pair or animated map sequence (data, quality, data, quality...)

The most well known offspring of the first category is the bivariate colour map, based on a complex 2-dimensional colour scheme representing ranges of two variables, very often on population maps. Olson (1981) has examined the efficacy of such maps that focus mainly on colour hue as a graphic variable. More useful within the framework of quality is the qualitative/sequential scheme proposed by Brewer (1994), that cross-tabulates different hues (representing e.g. land cover) with different lightness values (e.g. posterior probabilities) in order to form the interpretation key of the resulting map. Jiang (1993) adopts a bivariate colour scheme for depicting uncertainty based on a random-dot approach that refers to an implicit symbology (see the above). He assumes certainty proportional to the density of dots instead of the percentage tint scale - a starting point that is proved useful as appears from a test conducted on a group of cartographers. Hootsmans (1996) presents an adaptation to the idea of a bivariate map for the visualisation of confusion, a measure of ambiguity applied on a fuzzy set. If the confusion between different classes is below a predefined threshold an area is assigned its corresponding class colour hue while uncertain areas are shown in a range of grey values. An advantage of this method is the clear distinction between what is known (hues) and what is still lacking (values).

Except for the first of the separated visualisations (static map pair), this type of representation exhibits a dynamic nature and therefore is subjected to further discussion in section 7.8. The construction of a static map pair is technically simple. In fact, the map pair can be positioned on the same sheet of paper (or computer screen) as in the case of reliability diagrams that reveal source information (lineage) or the *marginal maps* shown by McGranaghan (1993) that inform a map reader about several quality components concerning the main map.

The resulting framework (figure 7.7) may need some extension as research continues, but meanwhile it offers a grip for visualisation strategies based on sound cartographic concepts. Chapter 9 is dedicated to a practical application of some of the visualisation approaches in order to explore the uncertainty in remote sensing classifications. There are, however, some pitfalls to avoid and reservations to be made before one could conclude that particular graphic variables could be applied effectively to represent the quality counterpart of spatial data. Again, it is stressed that the most striking point is the lack of independent and well-organised perceptual research to assess the ability of **average map-readers** to perceive quality information through different graphic variables. Without identifying the exact target group, it is evident that its members should be able to interpret the quality information without experiencing too many difficulties. Of course, some training may be needed but efforts must definitely pursue an as simple as possible map representation - quality visualisations need to be a springboard to a better information extraction, not a hurdle that has to be cleared!

Viewed in that light, bivariate maps revealing both thematic and uncertainty information might be unnecessarily complicated and confusing, from a design as well as interpretation point of view (remember the earlier mentioned research by Jiang (1996) and Brown & Van Elzakker (1993)). An extenuation comes from MacEachren (1992) who correctly distinguishes these quality bivariate maps from the spectrally encoded two-variable maps discussed by Olson (1981). The fact that here one variable and its uncertainty is considered and represented by a well-balanced colour scheme (e.g. Brewer, 1994) gives reason to nuance. Following the rules of cartographic grammar helps to optimise the readability of maps, for example by dictating the maximum level of differentiation of a graphic variable in a map view such that it still yields the desired perceptual effect. In order to maintain for example the property of selection, no more than 6 or 7 grey values should be represented at the same time according to Bertin (1967), although Declercq (1995) increases this number to 7 or 9. The latter is considered more truthful because Declercq, contrary to Bertin, has done a thorough perceptual study among map users. Kraak & Ormeling (1996) make the important remark that the number of lightness values that a map reader is able to distinguish is dependent on the colour hue ("tint") that has been used; a bivariate land cover map depicting corn in yellow could only contain 3 lightness steps to represent its classification uncertainty!

7.7 Static visualisation of classification uncertainty in remotely sensed data

The graphic variables that are most suitable for conveying the quantitative character of uncertainty in remote sensing classifications are value (grey-scale map), colour saturation (bivariate map), colour hue (associative ranking map) and a combination of the latter two variables (dichotomy map, Van der Wel *et al.*, 1994, or maps with a "diverging colour scheme" according to Brewer, 1994). From figure 7.7 it appears that - strictly considered - even texture and size are eligible. Size, however, is dropped from the list because remotely sensed data are represented in an evenly spaced grid consisting of equally sized pixels, bound to the implantation class "area" (see section 7.5). Despite the fact that texture (or grain) can be applied to areas, its rank order effect is better achieved by value - and with less undesired side effects.

Probably the simplest visualisation of the uncertainties underlying a remote-sensing classification is in a **grey-scale map** depicting the maximum posterior probability per pixel as a colour value. The colour values used typically range from black for a low

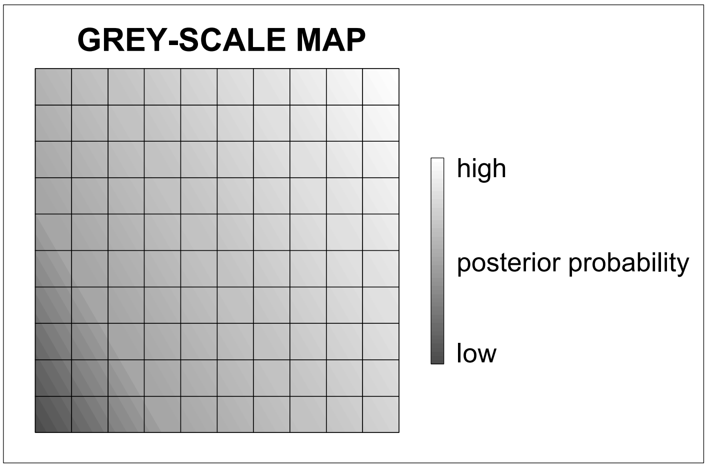


Figure 7.8: Example of a grey-scale map

maximum probability to white for a high one. An example grey-scale map is shown in figure 7.8. It will be evident that also grey-scale maps can be generated, which represent for each single qualitative class this class' probability per pixel. The information content of such maps, however, is rather restricted. This can be improved to some extent by the simultaneous representation of the classification itself in a separate map (MacEachren, 1992; Van der Wel *et al.*, 1994). Relating uncertainty to classes by means of a pair of static maps, however, is quite cumbersome.

Computer technology enables straightforward integration of the representations of qualitative classes and quantitative uncertainty in a classification by means of colour hue and colour saturation respectively. The resulting **bivariate maps** are highly informative, reflecting the strengths with which the classes have been assigned to the various pixels. The high information content, however, produces a complex interpretation key as discussed in the above.

By nature, colour hue fails to give an impression of order as required for conveying the quantitative character of uncertainty. It can, nevertheless, be applied for this purpose by taking advantage of the subjective associations by which people deal with a sequence of hues. An example is the *traffic light principle* (Monmonier & Johnson, 1991). Red, yellow (or orange), and green convey prohibition, alertness, and permission, respectively. From the probability vectors yielded by classification, an **associative ranking map** can be generated in which pixels having a high maximum probability in their vector and a large difference of this probability with the second ranking one are displayed in green and pixels with a low maximum probability and a small difference with the second ranking probability are displayed in red. Yellow spots in the map indicate ambiguous pixels, that is, pixels with a moderately high maximum probability in their vector but a hardly convincing difference value.

The associative capability of colour hue can also be exploited to convey deviation from a user-defined threshold value. Suppose that a minimal probability of 0.50 for class assignment to a pixel is considered critical for some application. Pixels with a maximum probability in their vector lower than or equal to 0.50 then are characterised by a blue colour hue (-), whereas pixels with a maximum probability above the threshold value are depicted in red (+), with the colours blue and red chosen so as to refer to an association with temperature ranges. The amount of deviation from the threshold value given by the user can in addition be represented by colour saturation. Figure 7.9 illustrates the basic idea of such a **dichotomy map**. Bertin (1967) dissuades his readers from this *"symbolique de la couleur"* if the associations are not logically linked with the phenomenon to be represented. This is only partly acknowledged here as the usefulness of these maps strongly depends on the acquaintance of the user with the selected association.

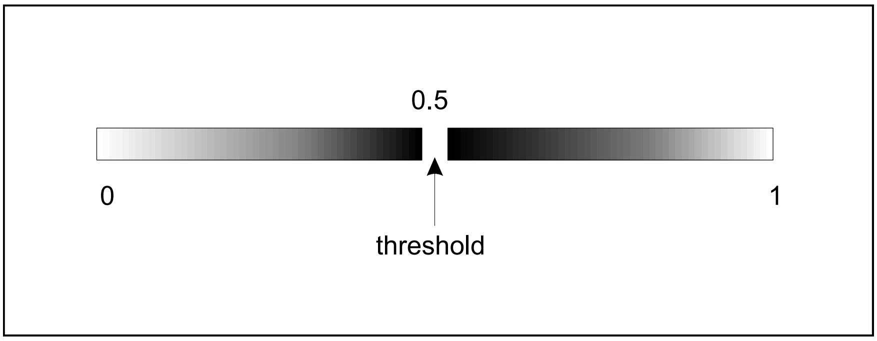


Figure 7.9: The basic idea underlying a dichotomy map

7.8 Towards dynamic and interactive mapping of data quality

The general acceptance of computer technology in cartography has extended the possibilities for the visualisation of spatial data quality. The inclusion of **time** as a variable enables the advent of a more dynamic cartography that contributes to a better perception of the fitness for use of a data set. Dynamic visualisation, in which time is added as an extra dimension, is rapidly gaining ground. MacEachren (1994) distinguishes between the use of temporal graphic variables to animate static maps and their use to depict dynamic processes in time. Because the uncertainties underlying a remote-sensing classification basically lack meaning in terms of evolution in time, the focus is on the use of temporal variables to make static maps more readily accessible.

Sometimes the explicit usage of graphic variables to depict quality is made superfluous by the temporal variable, as in the case of *blinking* in which the certainty of specific data elements is proportional to the duration of their display on a computer screen or their frequency of occurrence. A remote sensing example of the latter is given by Fisher (1994b) who uses the posterior probability vector during a randomisation procedure to determine the period of display time that a particular pixel should be represented with one of its possible labels. The "chameleon" map is changing continuously as class assignments with high posterior probabilities are shown longer than their less likely counterparts at that specific pixel position.

Time can also reinforce the effect of graphic variables to depict quality information, the reservations of Bertin (1967) notwithstanding. He considers the resulting dynamics so overwhelming that it could seriously mean a threat to the attention that has to be given to the graphic variables themselves! This opinion is long out of date judging by the considerable amount of literature dedicated to the topic of time as a cartographic variable (e.g. MacEachren, 1994). The alternating map pair that has been mentioned in the preceding section can be subjected to a process of *toggling* that is controlled by a particular time interval or duration. The retina of the human eye will record both data and quality information and induce a combined sensation. The selected time interval is, however, important because a fixed observation of only slowly interchanging images can cause an annoying colour after-effect as a result of the fatigue of cells in the retina. Staring at a many-coloured thematic map thus may cause an after-image that is projected onto the maximum probability map.

In case of a sequence of a considerable amount of images, an *animated map series* can be created that doesn't necessarily involve graphic variables (Kraak & MacEachren, 1996). To convey the uncertain position of class boundaries its range can be represented by a number of "frames"; when shown in succession, the impression of a continuously progressing and regressing boundary stresses the lack of knowledge concerning its exact location. The animation can follow different schemes, such as sequential, progressive, cyclic, and back-and-forth.

Interactive visualisation of data quality is even more challenging as it doesn't force the cartographer to summarise all information in a series of visualisations, but rather to design map tools to cartographically explore the (meta)database. Monmonier's (1992) idea of *authoring scripts* helps the user to get involved by "telling the story behind the data" in a step by step approach, these steps being visual slices in a dynamic cartographic sequence. His *brushing* approach, for example, contributes to the joint examination of two maps through a 2-dimensional scatterplot.

McGranaghan (1993) proposes the introduction of *quality sliders* on electronic quality maps. A threshold value can be set and only those elements that meet the required quality requirement (e.g. maximum posterior probability larger than 0.8) are represented or emphasised. In fact, the resulting images can be considered the offspring of a (static) dichotomy map!

A *clickable map* basically is a traditional many-coloured map of a classification of remotely sensed data with activatable extra information. The information concerning the uncertainty underlying the classification is not directly visible in the map but may be activated by pressing the mouse button at a pixel. Upon pressing the button the pixel's vector of probabilities is shown as a separate graphic (figure 7.10a). Alternatively, pressing the mouse button can reveal the second most likely class for the pixel, directly in the image, by changing the colour assigned to the pixel. By transecting the image with the mouse, an uncertainty profile can be created, displaying for every pixel visited the associated probability vector (figure 7.10b).

A logical step forward is to move from profiles to surfaces. Uncertainty may be represented by introducing a third dimension to produce an *uncertainty landscape* in which peaks express high probabilities and valleys lower probabilities. An uncertainty landscape may be draped with a many-coloured thematic class layer (Kraak (1988) has investigated the role of 3-dimensional mapping techniques in cartography and its relation with graphic variables). A *fly by* helps to explore this three-dimensional uncertainty landscape: skimming over its peaks and valleys can have a dramatic impact on the understanding of the uncertainty involved!

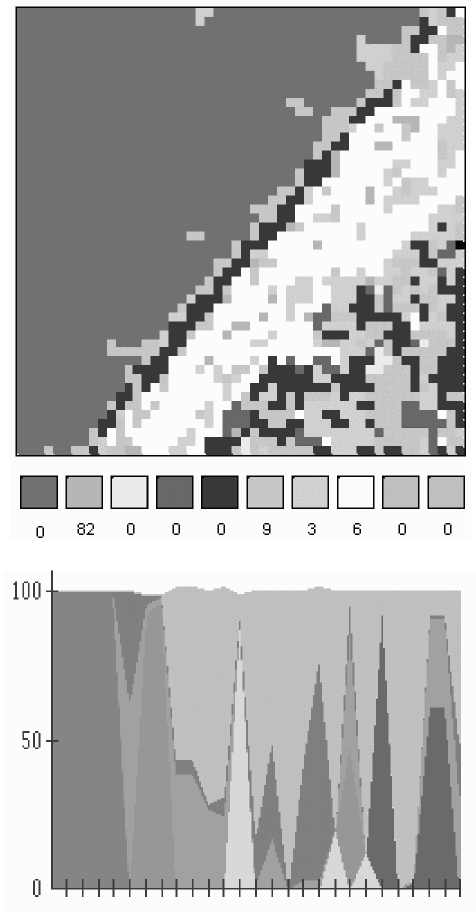


Figure 7.10: a. Representation of vector data as an array (top) and b. as a profile (bottom)

Finally, a quality maps can be the subject of **visual effects** that create an illusion of uncertainty. Van der Wel *et al.* (1994) propose *zooming* as a means to relate the amount of uncertainty - assumed to be present in a data set - to an imaginary viewpoint from which the data ought to be considered. If quality falls greatly short of expectations, a bird's-eye view can be used to give a general impression of a particular spatial pattern. For data with higher quality, a limited but detailed field of vision (close-up) seems appropriate. Although the concept can be confused with the graphic variable abstraction, their different meanings are striking. Abstraction literally leaves out data for further consideration whereas zooming conceals data for the interpreter. Theoretically, details will pop up after sufficiently zooming-in on the data set.

Another much-discussed effect is *focus* although some authors consider it a graphic variable (MacEachren, 1992). The reason why an objection is raised to this opinion is because focus can only be achieved by making use of one of Bertin's variables, such as value. This reservation notwithstanding, MacEachren's (1992) idea is fascinating and widely applicable as it enables the communication of uncertainties in position as well as attributes (*contour crispness* and *fill clarity* respectively). Nevertheless, such effects need to be subjected to perceptual tests because sometimes the pursued perceptual effect fails to show up, as appears from vision research (figure 7.11)!

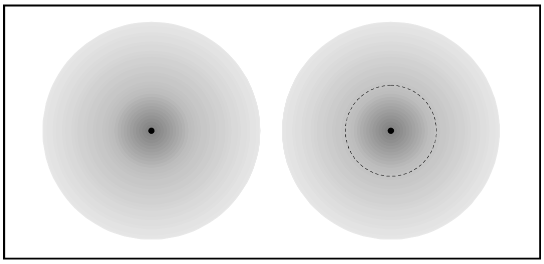


Figure 7.11: Filling-in illusion. When staring at the black dot in the left figure, the grey values around it will gradually disappear. In the right figure this effect won't occur because the gray ring helps to maintain the stimulus for visual perception

The proposed variables and dynamics are exceeding the realm of traditional cartography. This holds especially for the sometimes aired opinion to introduce sound as a variable to represent uncertainty information. Instead of graphically visualising the uncertainty underlying a remote-sensing classification, Fisher (1994a) applies sound as a sensory variable: a strident noise may be used to alarm a user whose cursor is entering a less reliable part of the map, relating uncertainty proportionally to tone. Sound can facilitate the visualisation of uncertainty while preserving the static graphic variables for the thematic information of the classification at hand. The perceptual consequences of exploiting sound for conveying information have, however, hardly been explored (Krygier, 1994). Here, it is stated that the application of sound is by all means "funny"; its practical value in a decision-making environment is negligible.

7.9 Concluding remarks

The relevance of quality information has been the subject of ongoing concern since the first chapter. The incentive to visualise this information - the spatial distribution of imperfections in a data set - has given rise to the structuring of several graphic variables that contribute to the communication of its extent (figure 7.7). In connection with that, it is interesting to wonder in what circumstances one ought to apply what graphic variable and in what map composition (static? dynamic?). This depends largely on user needs and user comprehension (Buttenfield, 1993) and this requires specific empirical, perceptual testing. Such tests are beyond the scope of the research but the next chapter will focus somewhat more on the needs of different user groups. Theoretically, a set of visualisations can be derived from this, although its success remains unproven as long as testing remains forthcoming. It is admitted that this is only partly resolving Ormeling's (1997) concern about the lack of concordance between methods to visualise data quality and the ways in which spatial information is used.

Computers have both enabled and necessitated the advent of new techniques to visually deal with quality information in a decision-making environment. Clearly, the same information can be visualised in many ways and at this stage, without having much practical experience, only general statements can be made concerning the effectiveness of some of these because it is still too early to expect sufficient feedback from the user community. The judgement of visualisations in general requires appropriate evaluation methods, as noted by MacEachren & Monmonier (1992). Some work has been done on the issue of perception, as can be concluded from earlier sections; in addition, Evans (1997) presents the results of an experiment involving people at different expert levels and from different sexes. Her study concerns the conveyance of the reliability of a land cover classification (based on a Landsat TM scene) and provides some valuable results:

- the graphical depiction of data quality is understood by the subjects;
- a sequence of quality and thematic maps ("animation") and a static bivariate map appear to be more effective than an interactive toggling approach; univariate quality maps showing only those objects that meet a particular quality threshold (again, an offspring of a dichotomy map) are experienced as less captivating;
- no significant differences are found between novice and experts during the observation of the offered visualisations.

Perceptual investigations eventually help the cartographer to determine the crossroads of cartographic validity, attractiveness, readability and usefulness in order to ensure the acceptance of this kind of visualisation - which is otherwise doomed to failure! This means an enormous challenge that cries out for co-operation, involving cartographers but also psychologists, computer scientists, vision experts, graphical designers and geographers. Cartography as a discipline is not dead, not even *almost* as Unwin (1994) incites, but is preparing itself for an even better visual information transfer. Another, even more challenging task is convincing GIS vendors of the usefulness of visualisation techniques for truly understanding the value of spatial data. The ability of GIS to deal with uncertainty and quality issues is already considered by both science (*error-sensitive* GIS, Unwin (1995)) and industry (e.g. ESRI, Idrisi, Ilwis). Such a system could hopefully be described in the following way (MacEachren, 1994):

> *"...having access to maps, graphics, statistics, images, etc. in a system that allows us to flexibly integrate the information in almost unlimited ways opens new possibilities for understanding our environment and the natural and human induced risks associated with it..."*

8 Towards a decision-supporting tool: the camotius project

"...Maps invite action..."

Stephen S. Hall - Mapping the next millennium (1993)

8.1 Introduction

The usefulness of remotely sensed data for the extraction of land cover (and indirectly land use) information is evident, although their successful acceptation seems to be hampered by a disproportionate emphasis on the visual appearance of the resulting images. It goes without saying that the sometimes spectacular pictures can easily excite the imagination, especially when some ingenious colour coding is applied. Unfortunately, this one-sided view seduces users to use the images as mere backdrops in their GIS applications instead of fully benefiting from the high information potential contained in these geospatial datasets.

The negligence concerning the appropriateness of these data is biased by the idea that the Dutch landscape is a too small-scale, diverse and frequently mapped patchwork of parcels to pursue a financially feasible application of remote sensing. Then what is the extra value of remote sensing for policy makers? Perhaps assessing the dynamic character of land use in the Netherlands, but the most interesting elements (e.g. built-up area) appear to be difficult to identify by spectral data alone. Of course, satellite remote sensing techniques do not always offer the best solution to a spatially related problem; more important, however, is their role **as part of** a vast information process, in which their possible contribution is evaluated in an objective way. One of the main advantages of remotely sensed data is for example the frequency with which they are collected. Yet another one is their ability to cover large areas of the Earth's surface.

The preceding chapters have dealt with theoretical issues concerning the collection, processing, visualisation and application of remotely sensed data. Handling the inevitable imperfections that accompany these data has been recognised as a task of vital importance. A next step would be to transfer theory into practice and provide guiding tools that help users to better balance the *pros and cons* of remote sensing in view of their anticipated application. In order to achieve this, the former chapters are synthesised in a structure that serves as the framework for a *decision-supporting tool*:

...a set of programs with functions that help a user to decide whether or not: to use remotely sensed data, to gather more data, to use a particular classification rule, to use the processed data for the eventual application - based on an evaluation of uncertainty and other quality characteristics...

The above description makes an appeal to the extension of (geographical) information systems with a quality module. The present chapter will elaborate on a study in which the development of such an extension has been given full attention. Besides systematically examining all its "ingredients", its practical usage and usefulness will be critically assessed. Issues such as the identity of possible users ("...*who is* the *user...*") and the need for quality information (*"...without considering it, no serious problems have occurred so far..."*) will be dealt with in this chapter. The role of utilities in decision-making (chapter 6) is also considered, although the derivation of sound utility values deserves more research.

8.2 CAMOTIUS: the project

In the spring of 1992 the CAMOTIUS project started with the first of its three stages (figure 8.1). By the summer of 1996, a demonstration version of the CAMOTIUS tool was presented as one of its main results. Initially, the study began as a follow-up of the HEIMON project (Moen *et al.*, 1991) that was aimed at the monitoring of grass dominance in Dutch heathlands by means of remote sensing techniques. As part of this study, the adopted method was subjected to an uncertainty analysis that revealed several aspects with an adverse effect on the results. Obviously, further research on the topic of errors and uncertainties was desirable. Therefore, the Cartography Section of the Faculty of Geographical Sciences of Utrecht University submitted a research proposal to the Netherlands Remote Sensing Board (BCRS) that aimed at a more generic approach to uncertainty. After approval, a three-stage project was carried out in close co-operation with partners from government, science and industry:

- the National Physical Planning Agency (VROM-RPD) - The Hague;
- the International Institute for Aerospace Survey and Earth Sciences (ITC) - Enschede;
- Eurosense BV - Breda.

The exploratory study CAMOTIUS *Preliminary Examination* (Van der Wel, 1993) was succeeded by an advanced theoretical discussion CAMOTIUS *Main Phase* (Van der Wel & Gorte, 1995) and practical developments were concentrated in CAMOTIUS *End Phase* (Van der Wel & Gorte, 1997), all being financially supported by the BCRS.

CAMOTIUS is an acronym for **C**artography-**A**ssisted **MO**nitoring - **T**owards an **I**nteractive **U**ser-friendly **S**ystem, a name that already implies its intentions.

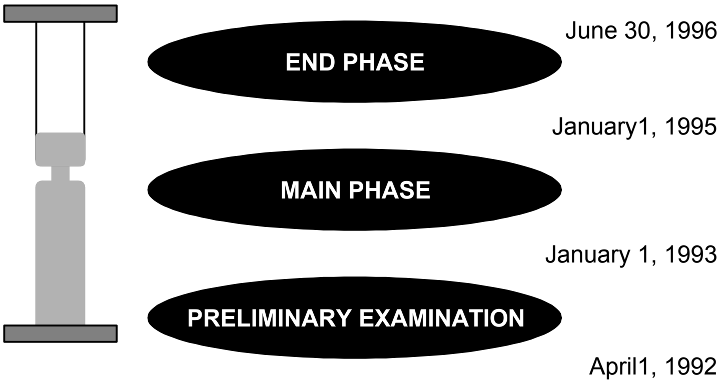


Figure 8.1: The three stages of the CAMOTIUS *project*

Moreover, it is the Latin name of Giovanni Francesco Camocio, a cartographer/publisher who lived in sixteenth-century Venice.

8.3 CAMOTIUS: definition of problems and objectives

The importance of considering different dimensions of data quality and its implications for subsequent decision-making has been recognised by the CAMOTIUS project. The main incentive originated from the observation that optimal information requires a more problem-driven approach to classification instead of the usual data-driven approach (figure 8.2). The latter aims at a straightforward classification, often controlled by practical considerations (time restraints, available data) and without the slightest notion of the suitability of the involved data, evoking a policy of *trying* instead of *thinking*. Fitness for use is assessed afterwards, for example by means of an accuracy assessment, the user being presented with a *fait accompli*; will he or she act differently when confronted with a proportion of correctly classified pixels of 70% instead of 90% (PCC, see section 5.3)?

Quality information, then, should control the problem-driven information extraction process and guide the user to the "best" solution, i.e. to results that at least meet predefined minimal requirements in terms of uncertainty and consequences. Often the highest possible accuracy is pursued because of a user's inability to exactly express the conditions the anticipated information has to fulfil. This possibly forces up costs of processing in a disproportionate way while the costs of wrong class assignments fail to decrease accordingly! Apparently, the "best" classification result is not only a function of allowed uncertainty ("truth value"), but an application-dependent parameter is clearly involved as well (utility!). Consequently, users of classified remotely sensed data have to form an idea of the information level they require and think over the consequences of failure (see example). Given the results of a classification, even if they are disappointing,

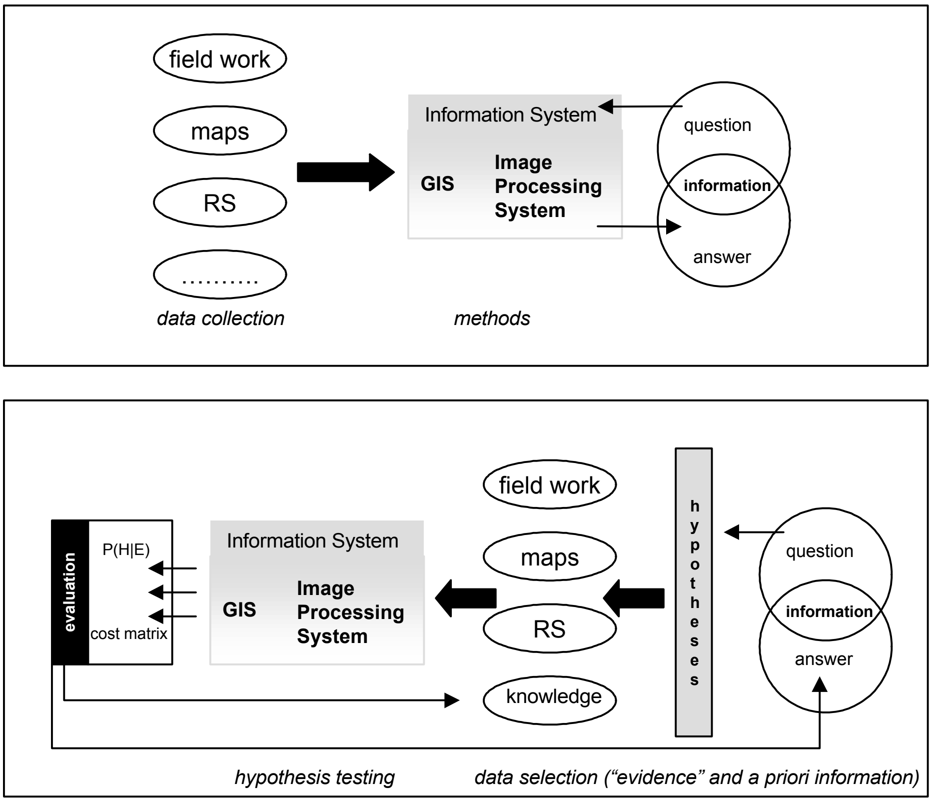


Figure 8.2: Data-driven (top) versus problem-driven (bottom) approach to the information extraction process

what decision can be made from them, if any? From this brief introduction, a number of problems can be defined that, in turn, incite the following actions:

- data uncertainty and general data quality need to be addressed by the adopted classification strategy;
- consequences of accepting wrong class assignments (or in reverse, rejecting correct ones) have to be considered when taking decisions based on uncertain classification output.

An example...

A user requires up-to-date and reliable land cover information as an indirect indication of soil type. From the classification of remotely sensed data, a land cover map results. Wrong class assignments, e.g. confusing potatoes and beets, are only considered serious if these crops are indicative of different soil types (moist or dry, sandy or clayey). The user could define his information requirement as follows:

“...if classified as crop A but actually crop B, there is no problem because both are grown on dry, sandy soils...

BUT

...if crop A turns out to be crop C then uncertainty arises because these crops require widely varying soil types...”

These two points can be split up in several sub-problems:

- introduction of appropriate classification strategies;
- assessment, reduction and handling of uncertainty;
- collection of information on quality components;
- conveyance of uncertainty and quality information to users of the data;
- definition of the risks that are related to the acceptance of a particular class assignment;
- accomplishment of a method to consider both uncertainty/quality and risks for the benefit of a sound decision-making process.

The above problems or challenges have led to the following definition of the general aim of CAMOTIUS:

"...the development of a tool that enables a decision-maker to derive classification results that are tuned to his or her requirements by explicitly considering information about uncertainty and utility..."

Such a "tool" is a piece of software that comprises all problem areas being addressed by the above points. Acknowledging the presence of uncertainty (**assessment**, **communication**) calls for countermeasures (**reduction, reasoning**). When arranging the required components of the pursued optimal information extraction process, it becomes clear that most issues have already been touched upon in the preceding chapters (figure 8.3). Six components are distinguished and considered relevant for the successful derivation of land cover information from remotely sensed data:

integration - the sensible amalgamation of remotely sensed and other data and (*a priori*) knowledge - before, during or after classification (chapter 5);

classification - the derivation of information classes based on spectral and possibly other, additional data (chapter 3);

formalisation - the translation of incomplete knowledge concerning the information extraction process to a workable format that enables interaction with a user (chapter 4);

documentation - the description (qualitative) and assessment (quantitative) of the qualities of data (and methods) according to a fixed set of criteria (chapter 5);

visualisation - the representation of the characteristics of the considered data in a cartographic way, for exploratory as well as explanatory purposes (chapter 7);

evaluation - the process that weighs the uncertainty of possible classification results with the desirability of the consequences of their class assignments, in such a way that a well-balanced decision is taken (chapter 6).

There is one important extension that has not being dealt with yet: time. When starting the CAMOTIUS research it was recognised that classifications are often used in a monitoring procedure to detect changes over time (the MO in the acronym!), indeed one of the most valuable applications of remotely sensed data (Barrett & Curtis, 1992). Therefore, considerable efforts have been made to extend the realm of uncertainty analyses from static land cover classification to monitoring. Monitoring is the systematic and chronological detection of spatial as well as thematic changes in phenomena (e.g. urban area, land cover) caused by some sort of process (e.g. population growth, forest

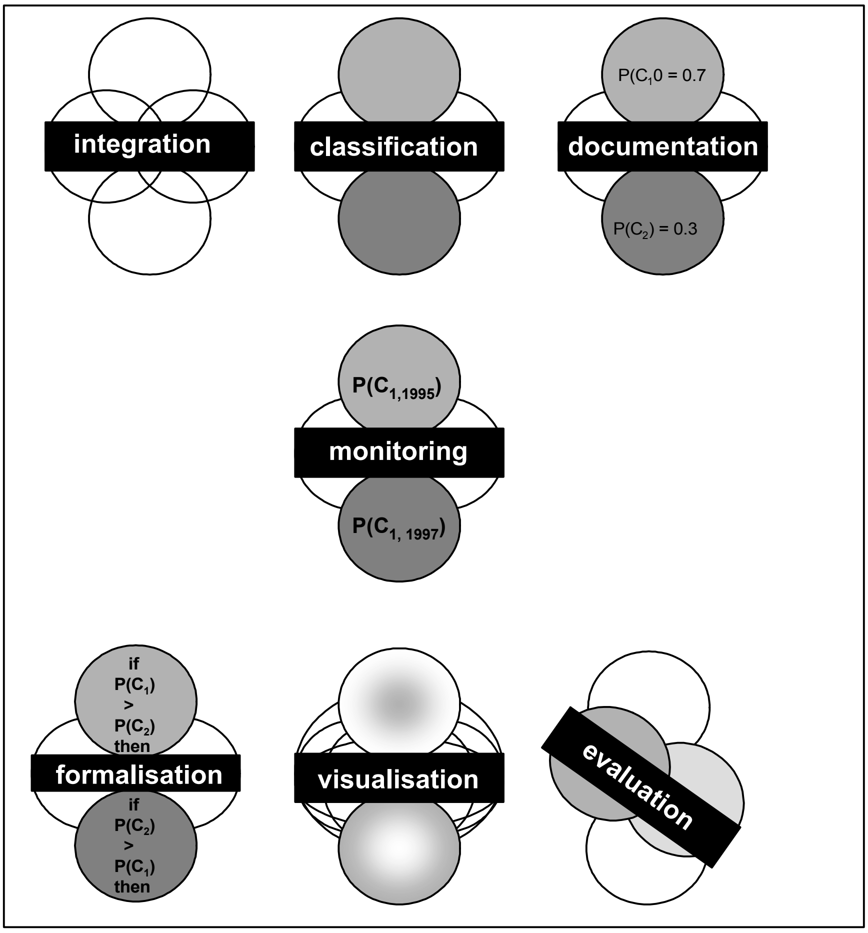


Figure 8.3: The main components of the information extraction process

fires). Periodic coverage of possibly large areas by satellites enables a reproducible "probing" of these phenomena as far as the extent, direction, nature and pace of changes are considered. Uncertainties in the source data are likely to be "propagated" during the evaluation of a time series.

Before elaborating further on the components of the pursued CAMOTIUS tool, the seventh component must be added (figure 8.3):

monitoring - the derivation of change information based on remotely sensed data covering the same area at different points in time, classified or not.

8.4 Detecting changes and assessing uncertainty

As from the Main Phase of CAMOTIUS, the research scope has been broadened with the inclusion of monitoring information, in addition to static inventories. The relevance of its need arises from the pace and impact of changes that man imposes, directly or not, on the environment, dictated by technological developments (Green et al., 1994). As a consequence of the often shared and even conflicting interests of nature, agriculture and urban areas, the need for a mechanism that helps to systematically detect, follow and analyse changes in land use and land cover has become urgent.

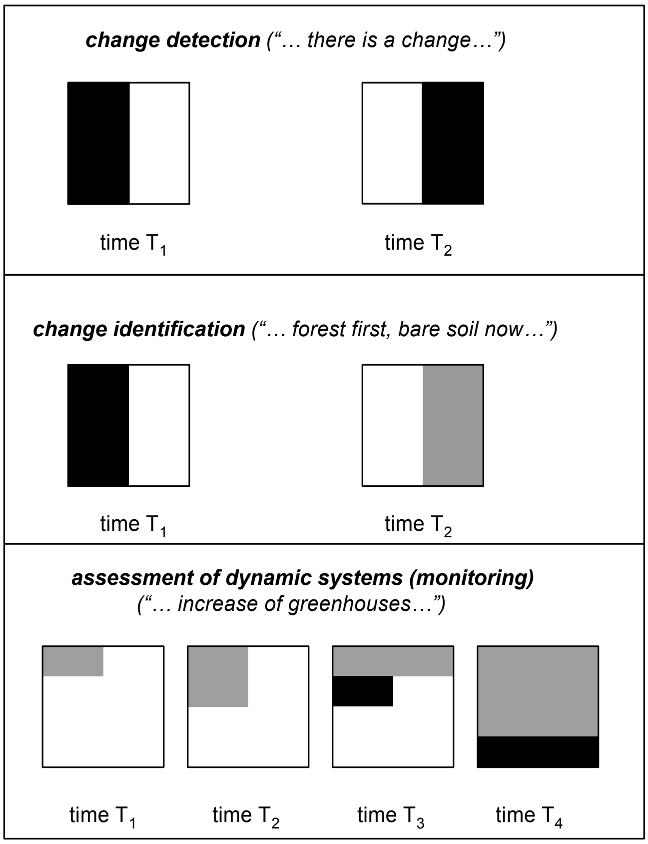


Figure 8.4: The distinction between change detection, change identification and monitoring

Figure 8.4 clarifies the different meanings of *change detection*, *change identification* and *monitoring*. They are all based on a comparison of different satellite images of the same area (Estes & Thorley, 1983). There exist a number of methods that help to detect changes over time, but in this thesis a restriction is made to those approaches that are actually used in the CAMOTIUS tool (interested readers, though, are referred to chapter 2 of Van der Wel & Gorte (1995) for an extended discussion). Within CAMOTIUS, both *image differencing* and *post-classification comparison* have been advocated, the latter being a true starting point for the identification of changes. *Image differencing* can be described simply as a computation of difference values involving two satellite images of the same area, but acquired at different points in time:

$$D_{i,j,b} = x_{1_{i,j,b}} - x_{2_{i,j,b}} \qquad [8.1]$$

in which:

D	difference value
$x_{1_{i,j}}$	measurement value at pixel(i,j) at time 1
$x_{2_{i,j}}$	measurement value at pixel(i,j) at time 2
i	row number
j	column number
b	band number

In order to avoid negative numbers (thus representing the results within the range 0-255), a constant is often added to the equation and the result is known as a differenced distribution. With no change in land cover occurring, the expected value of D equals this constant. In practice, a threshold value is selected that corresponds with assumed changes in the considered images. This evokes arbitrariness (Estes & Thorley, 1983), but a more interactive and empirical approach resolves most problems (Green *et al.*, 1994; Jensen, 1982). The simplicity of the method is the main reason for its presence in a tool like CAMOTIUS; without too much effort, one can quickly assess the stability of a particular area. Caution is called for, however, when the source images are not properly pre-processed (atmospheric corrections, for example!). Furthermore, the information level is low; only the occurrence of changes can be recorded.

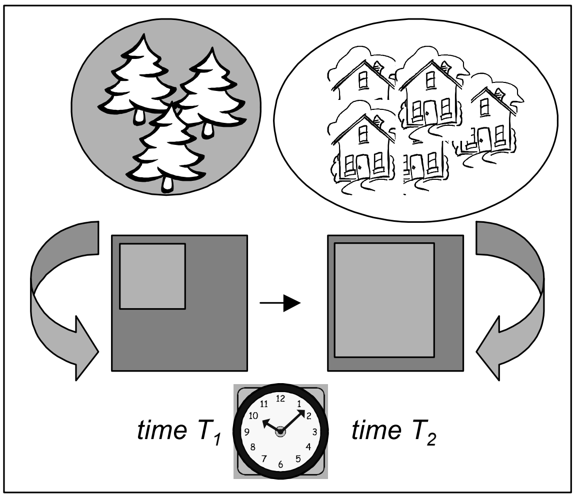


Figure 8.5: Schematical representation of post-classification comparison

Post-classification comparison not only enables the detection of changes, but also their identification (figure 8.5). The method is advocated because it links up best with the important role of classifications within CAMOTIUS. Once stored in a GIS, these classifications can be considered thematic layers, preferably enriched with their probability information. A multitemporal analysis based on such separate layers clearly runs parallel to the other functions of the CAMOTIUS tool.

Prerequisite for a post-classification comparison is a sufficiently high accuracy for the source layers in order to avoid the introduction of nonsense, for example as a consequence of mixed pixels. More than two classifications can be involved in such a procedure, as demonstrated by Jensen *et al.* (1995) who use up to five classifications for a wetland area in Florida to derive one change map revealing changes per year. Barrett & Curtis (1992) propose an interactive approach, in which two classifications are shown alternately on a computer screen, allowing for the possibility to extract a "virtual change map". Unfortunately, this probably functions only for simple classifications (or very distinctive classes in raw images, e.g. assessing the regressive shoreline of the Aral Sea).

The uncertainties that are present in the separate classifications that are used in a post-classification comparison can manifest themselves as apparent changes. Reduction of uncertainty by the addition of *a priori* information is one approach, taking it into account during interpretation is another one. Chapter 9 will analyse the causes of uncertainty in monitoring results and demonstrate several strategies to deal with it.

It must be noted that changes between time t_0 and t_1 can also be modelled explicitly by using process knowledge concerning the condition of an object at time t_1 (Abkar, 1999; Siteur, 1996). This approach is not adopted in the present research ("bottom-up approach").

8.5 The CAMOTIUS model

The model underlying the tool the development of which has been pursued during the CAMOTIUS research project, can be graphically represented in five schemes. Without going into too much detail (these are left for chapter 9) and assuming the theoretical issues from the previous chapters are taken notice of, the methodological framework is elucidated by means of an incremental approach.

classification and uncertainty

Figure 8.6 provides a familiar overview of the classification process. Within the data section, remote sensing is distinguished as a main input source but also GIS-data, field data, aerial photographs, paper maps, GPS measurements and expert knowledge can be applied during several stages of the process. The training of classes, the derivation of priors and the evaluation of classification results (*accuracy assessment*) all benefit from the addition of these extra data and knowledge. The output is the classification itself, obtained after statistical pattern recognition, and accompanied by *n* posterior probability maps that are indicative of the uncertainty in all *n* distinguished classes.

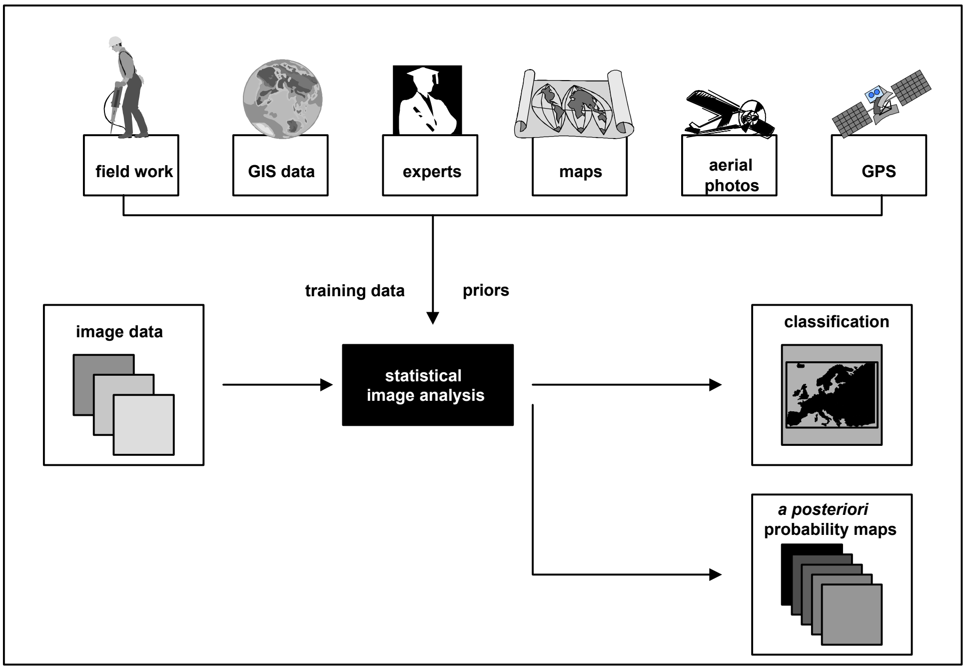


Figure 8.6: Schematical overview of the classification process

integration of a priori knowledge

The amount of uncertainty can be reduced by the introduction of *a priori* knowledge (figure 8.7). Different approaches have been considered that focus on possible ways in which this knowledge can be best integrated in the classification process. The iterative assessment of priors is promising, especially when extended to the idea of location-dependent *a priori* probabilities resulting in a so-called *context map* (Gorte, 1998).

monitoring

Figure 8.8 illustrates what happens if time is introduced in the information process. In case of a post-classification comparison at least 2 classifications of the same area are prepared and compared afterwards. The result is a *change map*, revealing not only the possible occurrence of altered land cover but the nature of these changes as well. This information places great demands on the quality of the source maps. Uncertainty information provided by the posterior probability vectors can, however, contribute to a detection of erroneous class assignments and hence improve the change map (see example).

An example…

Suppose that a user is interested in changes involving cornfields. Furthermore, assume that the time span 1997-1998 is of relevance. A distinction is made between decrease (corn in 1997, other crop in 1998), no change and increase. Isolated changes involving only 1 or 2 pixels are considered suspicious if they are smaller than the size of separate parcels. Possible confusion between corn and some other agricultural crop is evident from the probability vector and this could be held responsible for these "artefacts".

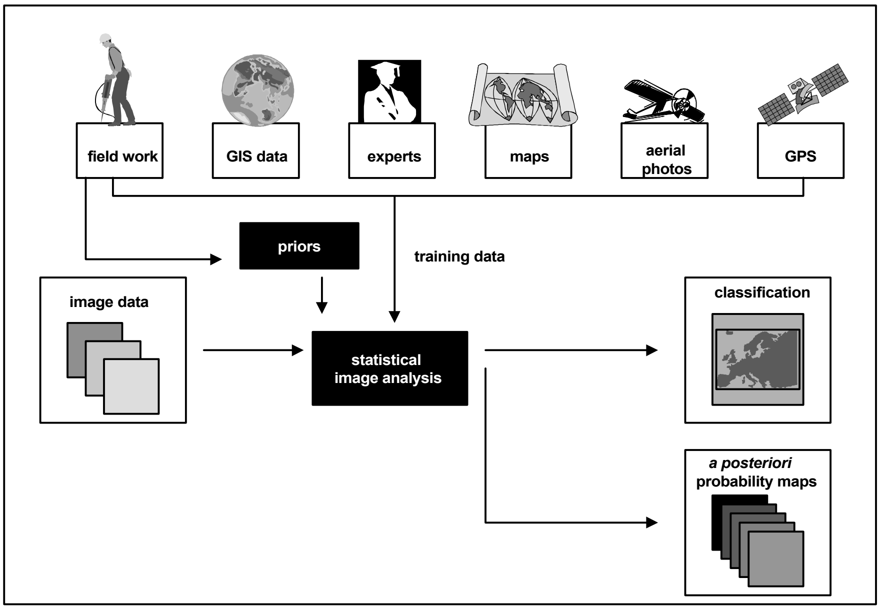


Figure 8.7: Adding a priori information to the classification process

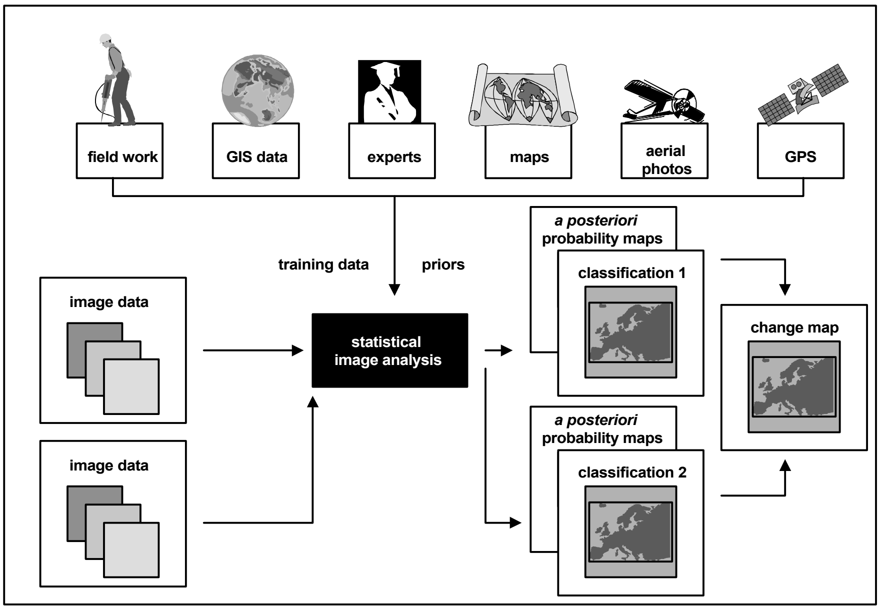


Figure 8.8: Monitoring based on the comparison of two or more classifications

assessing the quality of spatial data

Several measures of uncertainty have been introduced based on the information that is provided by the *posterior* probability vector. In addition, more descriptive quality information is needed from which the appropriateness of data for a particular application can be derived. This information is often summarised in a quality report.

evaluating interpretations by means of decision analysis

Accepting uncertainty as something that has to be dealt with during decision-making calls for appropriate methods that allow for reasoning with imperfect data (figure 8.9). Decision analysis has been stressed, but more simple interpretation rules in case of monitoring are worth considering as well (see chapter 9).

visualisation of uncertainty

A visual conveyance of uncertainty results in a range of cartographic products that are all derivatives of the posterior probability vector (figure 8.10). Approaches aiming at the simultaneous communication of as much uncertainty information as possible are based on dynamic visualisations and weighted uncertainty measures such as *entropy*.

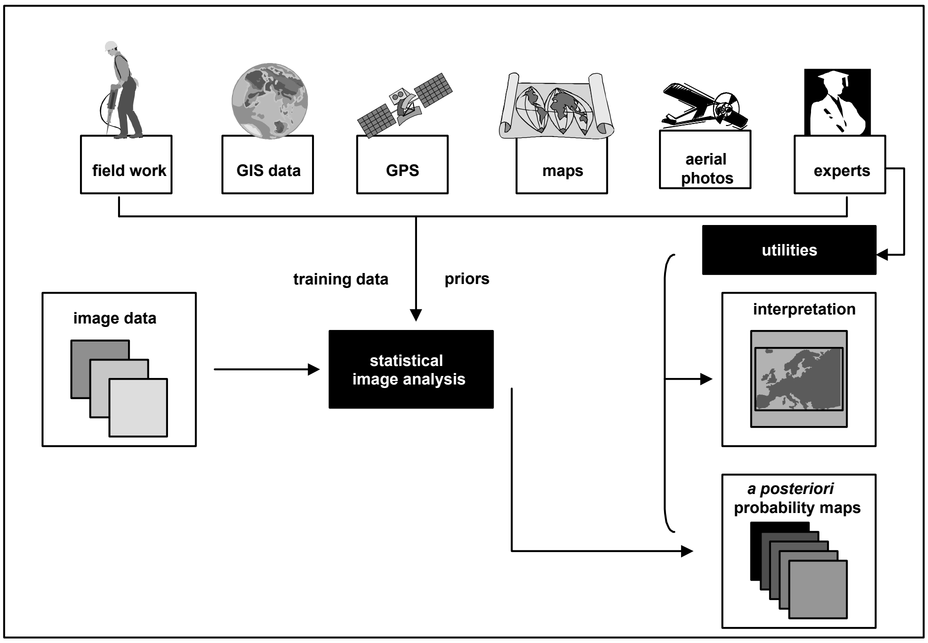


Figure 8.9: Decision analysis provides a grip to handle imperfect data

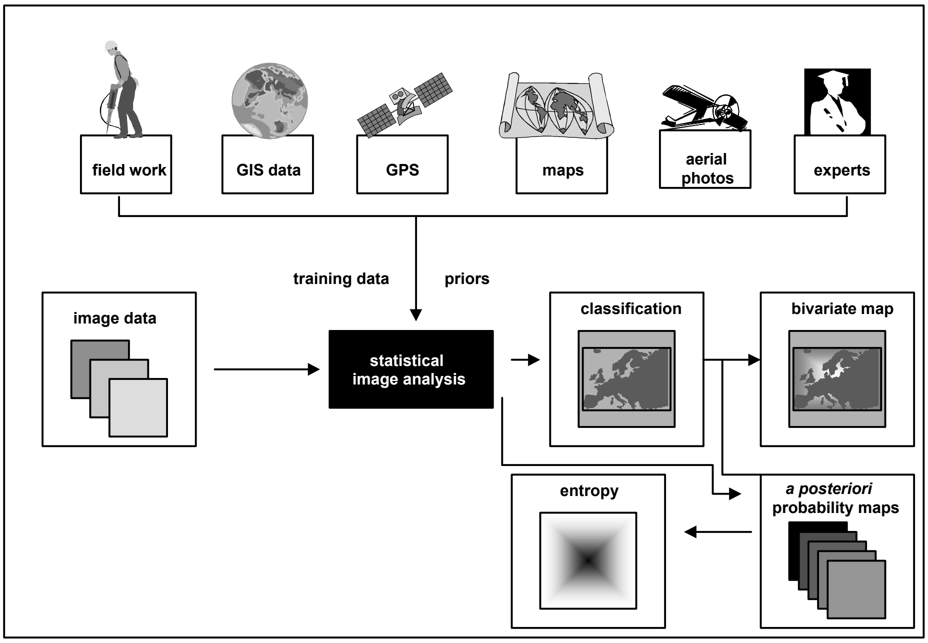


Figure 8.10: Visualisation of uncertainties supports the assessment of the fitness for use or quality of a data set

The pillars of the CAMOTIUS framework have hereby been elucidated and now their mutual relationships can be defined in order to arrive at a coherent decision-supporting tool. The blueprint of such a tool is outlined in figure 8.11. The integration of additional knowledge in the classification process, the subsequent derivation, formalisation and documentation of uncertainty and quality information, its visualisation and, finally, its role during the evaluation stage preceding actual decision-making - all are clearly distinguishable in this schematic figure.

Now that the *"looks and feels"* of the CAMOTIUS tool are taking a more definite shape, it is time to reconsider the original objectives encountered in section 1.5 and give them a moment's thought. Keeping in mind that the tool needs to demonstrate the methodological framework for which the foundations were laid in the second part of this thesis, the question arises right now: **demonstrate to whom?**

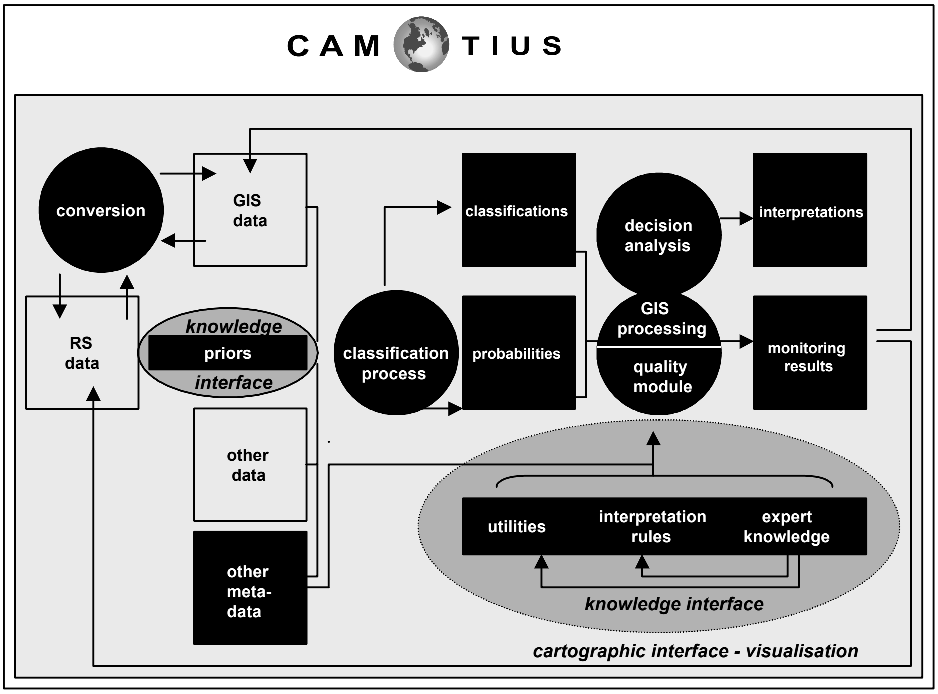


Figure 8.11: Structure of the pursued CAMOTIUS *tool*

8.6 The assessment of user profiles

The CAMOTIUS project has directed its attention principally at inventorying as well as monitoring of land cover at a regional scale, mainly determined by the limits of the Thematic Mapper data. At this level, between planning and realisation, the consequences of applying inappropriate data or taking bad decisions are making themselves felt by deviating from the "real world " model. At this scale individuals start to think in terms of political or social commitment, relating their own position to their surroundings and realise that any intervention could mean a threat to this present situation. In other words, it then suddenly becomes clear that the noncommittal government decision covers up an envisaged railway to be built right through a person's backyard...

Obviously, far-reaching decisions require a well-considered evaluation of the available information, the success of which is directly related to the validity of the representation of huge amounts of diverse data layers. Wang & Brent Hall (1996) note that current GIS fails to inherit the "fuzzy" or uncertain characteristics of boundaries during an overlay analysis, thus causing the resulting composite maps to reveal sharply but erroneously delineated elements. Not seldom, quality information is entirely lacking, a fact that is distinguished as one of the serious obstacles that hamper the true exploitation of "Geo-

IT" in physical planning (Geertman, 1996). But even then, the presence of a set of tools capable of handling uncertain data in a "GIS-like" environment could contribute to a more conscious usage and interpretation of the considered spatial data, e.g. by offering the possibility to report the "perceived quality" experienced by the user. This means that when confronted with a data set that lacks an adequate description, one should still be able to express his feelings about its usefulness, inspired by practical experience (*"classes A and B are not very reliable and seem to be confused"*) or accidental knowledge (*"a friend of mine grows crops in that region and therefore I know that soils are clayey right there"*).

A starting point for developing a tool like CAMOTIUS is that a user is likely to be scared off by unnecessary gadgets and a high extent of complexity. The latter is acknowledged by Geertman (1996) who believes that the results of scientific research into the field of spatial data quality are still so complicated that he considers their introduction in the practice of (GIS-based) strategic spatial policy premature. It is admitted that such investigations are attended by well-founded, theoretical discussions that are not easily transferred to a non-scientist's perception of the environment (e.g. the treatise of Hootsmans (1996) on fuzzy sets for visual decision support). Next to the more theoretical contributions, a pragmatic approach is needed as well - without making concessions to the soundness of the theoretical framework. Efforts should be directed at finding a balance between **attractiveness**, arousing a user's curiosity, and **effectiveness**, retaining his interest.

From the above, it becomes clear that policy makers at different levels are identified as potential users of a CAMOTIUS tool. In addition, the exploratory character of its functionality, fuelled by uncertainty and quality information, is likely to attract a more general "public"; engineering agencies could benefit from an exploratory stage in their information process to better tune the processed data to the required information, thereby probably saving money. From the very beginning of the CAMOTIUS project, emphasis has been laid on the definition of a few, general user groups and the distinction in three *profiles* has been acknowledged by the interest that has been demonstrated after accomplishing the project. From these profiles some general requirements for the tool itself have been derived that are successively listed in each of the following 3 subsections.

professional end user

policy maker, inexperienced with GIS and image processing, e.g. a governmental official at the Ministry of Housing, Regional Development and the Environment (VROM)

A user with little or no experience in the field of image processing and GIS places stiff requirements on the source data. Remotely sensed data, for example, need to be pre-processed to a sufficiently high level because it is assumed that the user lacks any specialised software other than a desktop GIS (e.g. Arcview) at his immediate disposal and, more important, is not trained as a geo-processing expert. Data specifications are defined in consultation with experts, for example concerning the required level of radiometric correction. Potential implementation of a CAMOTIUS tool has to be smooth - emphasis is on the adjustment to an existing geo-infrastructure. From this, the following requirements for the pursued CAMOTIUS tool are envisaged:

- separate application or extension of an available GIS package;

- no image processing capabilities but rather a wide range of input and output filters that improve data exchange with external partners who provide pre-processed image data;
- extended *help* functions and examples to support the user;
- emphasis on graphical user interface and visualisations.

Examples of possible applications:

- testing of hypotheses with respect to land cover in a particular area *("...area covered by potatoes has more than doubled over the past two years...")*;
- risk analysis (*"...are the costs of wrong class assignments still acceptable if more than 10% of the total area has been wrongly assigned to class corn..."*);
- attachment of quality information to classifications for the benefit of its prospective extraction from a meta-database (*"...the classification possessed 8 probability layers, defining for each of the distinguished classes the posterior probability..."*).

professional intermediary

operator of image processing and GIS systems, e.g. a GIS expert at a research institute or a university research school

A user who is situated at the other side of the data stream holds the position of supplier. As an expert in geo-information technology, appropriate hard- and software surround this type of user. Therefore, the addition of image processing tools to CAMOTIUS would mean a redundancy! The processing environment is characterised by speed and capacity. Large data sets need to be processed in a short period of time, deadlines are common. The consequences for the pursued CAMOTIUS tool are far-reaching; implementation on a personal computer is probably too cumbersome, workstations are preferred in the production line (although a Windows NT machine could be the future). Exploratory analysis is more important than cartographic (final) presentation. Again, some requirements for CAMOTIUS can be derived:

- software must run in compliance with and be subordinate to existing applications;
- large data volumes are no exception and a rapid processing is required;
- exploratory tools need more emphasis than explanatory tools;
- user support must be kept to a minimum;
- simple user interface satisfies the needs of an experienced user.

Some examples that clarify a practical situation:

- derivation of uncertainty information (*"...classification attended by a distribution of maximum posterior probabilities..."*);
- identification of doubtful assignments or "white spots" in the classification (*"...this location is labelled differently by each of three alternative classification scenarios, the maximum posterior probabilities being low, so perhaps the classification scheme is incomplete..."*).

occasional end user

member of a project team, e.g. appointed to an engineering agency

The application of a CAMOTIUS tool at *ad hoc* basis is another possibility. It is not difficult to imagine situations in which one wants to derive probability information, for example for a particular project, without immediately storing uncertainty information on a regular basis. The "looks" of a CAMOTIUS tool largely depend on the required functionality and the extent to which the user is equipped with information system technology. A separate program or a "plug-in" for an extended GIS package would be probable, but it remains difficult to anticipate this "nomad" user with his diverging needs and varying skills. Only a wide range of general functions is thought to meet the requirements of all these users, or a more customised approach must be chosen. Therefore, it is difficult to define the limiting conditions:

- preferably a separate, customisable module for an existing low-cost information system (comparable to the Uncertainty Subsystem of ILWIS);
- presence of visualisation tools;
- high level of interoperability with other information systems;
- the possibility to add extra functionality.

Examples:

- generation of a cartographic end product (*"...bivariate map showing classes as well as their presumed uncertainties..."*);
- comparison of different classification strategies (*"...method A clearly distinguishes this crop from other agricultural classes while method B results in confusion..."*).

These user profiles are far from exhaustive, on the contrary, but they incite a line of thought in which the user is at the centre. During development, user needs are kept in mind; of course, this is no guarantee for success but at least it helps to reveal the actual needs of users and the shortcomings of current information systems.

Chapter 9 presents the practical results of the efforts that have been put in the development of the eventual tool. It illustrates the extra value by focussing on a case study in which the detection and monitoring of particular land cover / land use is of key-importance in order to work out policy strategies. After reading this chapter, it is recommended to get some *hands-on* experience with the demonstration tool (see appendix 2).

8.7 Concluding remarks

A legitimate question that has not been treated so far, concerns the necessity of a tool such as pointed out in the above. Obviously, no doubt is cast on the role of quality information and uncertainty assessment. But why bother when there is no serious immediate cause for all the extra efforts that are involved? Still, no "geo-disasters" have occurred and it seems that everything works itself out... But, considering the following arguments may shed a different light on the issue:

- firstly, there have been some serious accidents as a consequence of errors and uncertainties in geographical data sets (see box), probably there are even more near-accidents;
- it is becoming common practice to download free spatial data sets with an unknown quality record from the Internet, their uncritical use being a source of blunders (a world data base that, once in an information system, allows for zooming and appears to lack one or two of the Dutch Friesian Islands);

- directly related to the above points is the question of liability in case of severe misuse - a sound quality report is likely to be a prerequisite for a data provider to protect himself against liability claims in the near future (Epstein *et al.*, 1998);
- quality information as part of more extended meta information will be inevitable to access the astonishing amount of spatial data that is coming available each day;
- quality statements can help to increase the credit that is attributed to particular data, which is especially welcome for the application of remotely sensed data.

It is admitted that quality statements could affect a product's market value in an adverse way because people often assume that data are "right". Apart from the above arguments, a producer could omit all documentation and simply provide a digitised map. A possible competitor adds some accuracy statements, which may cause a possible user to turn away from the data, even if they might be better! The psychological effect of this difference in foreknowledge should not be underestimated as long as high prices have to be paid for carefully prepared data sets while the vivid exchange of data via the Internet is already irrepressible.

It's the map...

Israeli army bombs UN-base Kana in the south of the Lebanon, killing 102 persons (April 18, 1996). According to the Israeli artillery, the consulted topographical map of the Lebanon revealed incorrect coordinates.

American naval aircraft cleaves cable of lift in Cavalese (Italy), killing 20 persons (February 3, 1998). The use of an outdated map of the area is believed to be one of the causes, as it failed to show all major cables.

NATO *plane unintentionally bombs Chinese embassy in Belgrade (May 7, 1999), killing 3 people. According to the US Department of Defense, a combination of erroneous interpretation and inaccurate map information may be the cause of this serious accident. Since then, news reports have suggested that insufficient funding and overwhelming workloads affect the ability of the National Imagery and Mapping Agency (*NIMA*), responsible for the map, to maintain databases currently and accurately.*

9 From theory to practice: a case study in the Westland area

"...Knowing is not enough; we must apply. Willing is not enough; we must do..."

Johann Wolfgang von Goethe - 1749-1832

9.1 Introduction

The development of a decision-supporting tool such as outlined in the previous chapter has been the ultimate goal of the CAMOTIUS research project. Eventually, the CAMOTIUS Demonstration Package (CDP) helped to clarify the concept of uncertainty, both for the researchers involved and for the anticipated user group. For this purpose a phased case study has been defined, the results of which are the subject of the remaining part of the thesis. The starting points of CDP are multiple and can be summarised as follows:

- elucidating the ideas that emerge from the scientific research efforts, as reflected in chapters 4 through 7;
- providing the research group with an environment in which their ideas could ripen;
- informing potential users about the possibilities of remotely sensed data for the Dutch situation;
- evoking feedback from these users in order to better define the prerequisites of a more definite uncertainty tool.

These users are divided in three rather general classes as can be learned from chapter 8 and their diverging interests seem to make an appeal to the development of different "CAMOTIUS-like" tools, each best meeting the requirements of that particular user group. However, after considering the limiting conditions of the project, it becomes clear that this is far from feasible and that efforts should be concentrated on the development of a *demonstration* application:

- given restricted budgets and strict deadlines, linking up with existing information systems was preferred;
- moreover, development tools had to be readily available because no additional investments were allowed;
- the case study had to cover issues that would probably gain the attention of a large

potential user group.
The strategy that is advocated here has an incremental character, meaning that the case study was first approached in an existing GIS environment, considering both inventorying and monitoring previous to its subjection to the CAMOTIUS tool itself. This has as its advantage that the development of the tool could benefit from experiences gained by analysing the first results of the investigations. Therefore, a considerable amount of work has been executed with ITC's ILWIS 1.4 package (ITC, 1993), not only because of the institute's partnership but also because of the flexibility of the software (e.g. ILWIS *mapcalc* allows for straightforward calculations on multiple data layers). Erdas software has been used as well, both the older 7.x PC version and the Unix Imagine 8.x package (Erdas, 1997). Simultaneously, efforts have been made to construct a tool on its own, first based on Borland's Turbo Pascal, later by means of Microsoft's Visual Basic (see appendix 2 for technical specifications).

The remaining part of this chapter is dedicated to the presentation of two case studies: inventorying and monitoring of greenhouses in the western part of the Netherlands. In this way, the theoretical framework is coming to life, giving the "sketchy" outline of the CAMOTIUS tool from chapter 8 its more definite appearances.

9.2 Managing space from space: assessing greenhouse development with remote sensing

9.2.1 The problem definition

The involvement of the National Spatial Planning Agency (RPD) in the CAMOTIUS project as a potential user of the pursued methodology has without doubt driven the selection of relevant "cases". In order to obtain a clear idea of the relevance of the case studies consider the illuminating "policy cycle" as distinguished by the agency (RPD, 1998). The spatial planners investigate present and future land use according to an obvious sequence of actions:
- formulation of spatial planning policy;
- implementation of that line of policy;
- monitoring of the actual results of realisation;
- exploration of new ideas to structure and manage the environment.

The observation of particular land use both in space and time can be classified under the monitoring activities (note that monitoring in this sense differs from its counterpart in image processing!). Eventually, the Westland area has been chosen as the main study area and its characteristic greenhouses as the study objects because of the relevance from a planning as well as methodological point of view (figure 9.1).

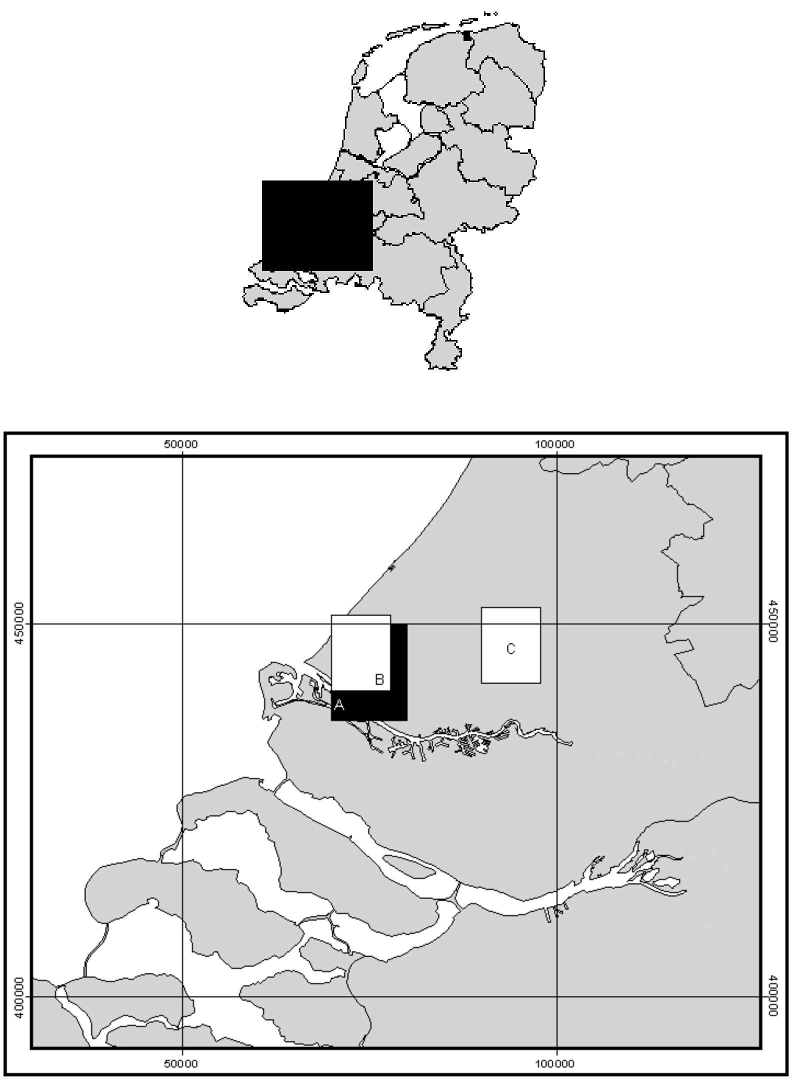


Figure 9.1: The study areas – Westland (A and B) and B-Driehoek (C), the first case study concerns area A, the second both B and C

The Westland is part of the so-called "Zuidhollands Glasdistrict" and as such one of the most important horticultural centres in the Netherlands. Maintenance and reinforcement of the significant geographical centres involved in this sector has been emphasised in the Vierde Nota Ruimtelijke Ordening Extra or Vinex (official document defining national spatial planning policy issued in 1993). Obviously, its considerable economic meaning requires an ongoing investment and expansion. In 1992 the value of products cultivated under glass amounted to more than 3.2 billion Euro according to figures of the Ministry of Agriculture, Nature Management and

Fisheries. In 1994, Statistics Netherlands (CBS) already noticed that 80% of the entrepreneurs in the region had no possibility to extend their glasshouses. Space is limited, especially in the western part of the country, and changes in land use in and around the Randstad area would immediately urge for a well-balanced response of the planning department. Opposite interests between urban area, horticultural regions and nature reserves are at stake: the expansion of cities is already seriously threatening greenhouses (in 1994 The Hague incorporated part of the territory of Wateringen!) whereas the relations between new greenhouse locations and the concern for the Green Heart are strained.

The problems that are connected with the spatial (re)structuring of the Westland offer a general planning framework in which more specific issues can be addressed. The total area covered by greenhouses is still increasing; in 1990, a total of 9.700 hectares were used (RPD, 1992). A more efficient use of available space can not prevent the sector from a shortage of 600 hectares by the year 2010, as far as the "Zuidhollands Glasdistrict" is concerned (LNV/VROM, 1992). The development of expansion areas has already been foreseen in the Vierde Nota Ruimtelijke Ordening Extra or Vinex. The Hogezandse Polder (Hoekse Waard) for example has been designated as a zone in which new greenhouses can be developed, according to the Actualisering Vinex 2005 – 2010.

Clearly, a planning agency could benefit from a topical and reliable overview of land use and its changing patterns. Statistical tables and reports as issued by Statistics Netherlands (CBS) are only partly providing such information as they fail to elucidate detailed spatial information about the nature and direction of particular developments. Are areas with a concentration of greenhouses increasing and conglomerating? Is the same area used more intensively, is the space developed more densely? Or is there a scattered occurrence of greenhouses without a substantial connection? At what expense is this type of land use expanding? When will the limits of this growth be reached given the present pace? Precisely this information is of the utmost importance for the decision-maker because it best reveals possible tense situations (RPD, 1992).

From a methodological point of view, both inventorying and monitoring are at stake here. The former helps to assess the actual location and extent of the area covered by greenhouses at a particular time T_1 while the latter reveals the direction, pace and character of any possible change at time T_2. The results of such static and temporal analyses are becoming even more valuable if they can be assigned an uncertainty label. Does the extent deviate considerably from the figures given in statistical tables as issued by e.g. CBS? Are changes really resulting from a different use of space or are they merely a consequence of bad data and careless processing? The information extraction approach adopted in the present research has been outlined in the previous chapters, although it is felt that the role of remote sensing as the data acquisition method needs some more elucidation.

9.2.2 Identification of greenhouses by means of remote sensing techniques

A method that enables the derivation of reliable, up-to-date and spatially specified land use information over time and space should meet the following requirements in order to be feasible:

- simple and fast (repeatable);
- cheap and purposive (cost-effective);
- accurate or at least as accurate as possible alternatives (competitive);
- directly applicable (operational).

In fact, an appeal is made for a synoptic approach that allows for an overview of relationships over time and space. Immediately, airborne and spaceborne data acquisition techniques come to mind because of their ability to cover large areas at a glance and at a regular basis (section 8.1). Aerial photographs clearly reveal the presence of greenhouses (figure 9.2a) whereas satellite images are considerably less explicit (figure 9.2b). This observation notwithstanding, aerial photography is considered too cumbersome and expensive to guarantee large scale coverage of greenhouses at significant time intervals (1-2 years). Moreover, as spectral resolution is normally low (panchromatic) the identification of the objects is largely dependent on visual interpretation (labour-intensive) or complicated automatic object recognition (e.g. Schutte, 1994). Satellite images could also be subjected to these information extraction approaches and the advent of high resolution satellites such as Ikonos (section 2.2.3) is without doubt promising within this respect. Remember, though, that the present case studies are inspired by an information need that is attended by practical limitations that are reflected in the above-mentioned requirements. Therefore, mature multispectral classification and post-classification comparison strategies (based on Landsat Thematic Mapper data) are investigated first. The extra value of remotely sensed data for the identification and monitoring of greenhouses was already pointed out by Eurosense b.v. in the framework of the national planning yearbook Ruimtelijke Verkenningen 1992 (RPD, 1992).

A. B.

Figure 9.2: a. Greenhouses on an aerial photograph and b. on a satellite image (light spot left from centre)

The usefulness of remotely sensed data to detect buildings and identify them as greenhouses is not undisputed. These objects could cause reflections that result in a temporary disorder of the scanner device on a satellite platform. The bad lines (figure 9.3) on the image attest to this malfunction and their subjection to several "corrections" notwithstanding, this lack of information is only blurred by cosmetic operations unless there is evidence for positive spatial auto-correlation. Moreover, it is not easy to associate the information class "greenhouses" with one spectral class. The confusion that results from the lack of characteristic spectral signatures is not strange if one realises that the information class itself is made up of different spectral classes that are indeed representative of separate land cover classes (Barnsley *et al.*, 1994). Without having an unambiguous spectral signature there is a serious danger for a residual class containing besides greenhouses also houses, industry, bare soil and more or less randomly assigned objects (see section 9.3).

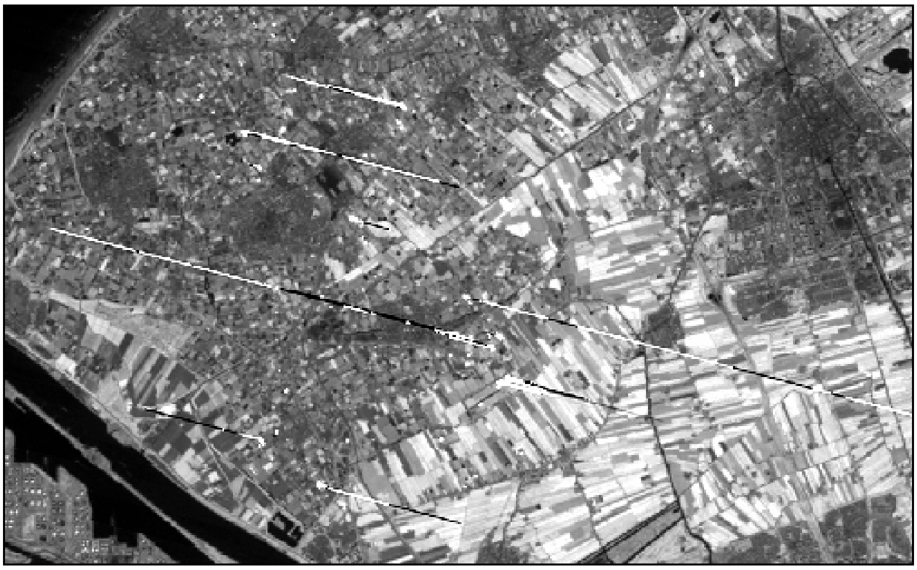


Figure 9.3: Bad lines in the satellite image

As a result of these burdens, the first version of LGN classified greenhouses in a general group of built-up area and roads. Thunnissen *et al.* (1992) noticed at that time that the separate inclusion of this horticultural information would be desirable in future releases of the data set (at that time the first stage of the CAMOTIUS project was started). As from LGN-2 this distinction has indeed been made (Thunnissen & Noordman, 1997), thereby adopting several strategies to accurately extract the extent of land covered by greenhouses from the remote sensing data sets. It is remarkable that neither automatic classification (maximum likelihood) nor visual interpretation of the images proved to be successful in their view. Instead an interactive classification procedure was advocated, heavily relying on existing topographical maps and land use databases. The question arises why CAMOTIUS held on to automatic classification, in spite of the LGN experiences. First of all, LGN pursues a national coverage of greenhouses and adheres to maximum classification accuracy, CAMOTIUS is rather concerned with the derivation of this information in the best, that is most feasible, way – as long as the inherent uncertainty is known. Furthermore, monitoring the amount of uncertainty enables the selective addition of geographical information (chapter 5!), which conforms to the idea behind CAMOTIUS: an efficient and customised information extraction. Tuning results to original requirements compares to providing answers to questions and thus information extraction. Last but not least, remember that greenhouses are chosen as an example, indeed with unique methodological and practical starting points. Nowadays, spatial planners probably tend to refer to regular updates of LGN for a straightforward extraction of greenhouse information (LGN-3 has been released in 1998).

9.3 Inventorying: assessment of the area covered by greenhouses in the Westland

9.3.1 Introduction

The first case study deals with the assessment of the extent of greenhouses in the Westland area. The questions that are addressed in this study are the following:

- are Landsat TM data suitable as the main source of information?
- what additional information can be used to improve classification results, and how is this information integrated?
- how are users – here: spatial planners – familiarised with the idea of uncertainty that is present in the eventual classification?

The main objective is defined as the development of a blueprint for the supervised and uncertainty-driven integration of extra information in the classification process.

9.3.2 Data and methods

In this stage of the project, a Landsat TM scene of 9 September 1988 was readily available, meaning without additional expenditures. As a precursor of the CAMOTIUS Demonstration Program, classification software has been developed in order to obtain the complete posterior probability vector (section 4.4). Its failure with regard to uncertainty information notwithstanding, the ERDAS image processing package has been used to carry out the necessary pre-processing steps. Next to radiometrical corrections, geometrical correction has been applied, eventually resampling the data set by a nearest neighbour approach to 25 meter in view of sequential data integration. From this, the above-mentioned subset was clipped and subjected to a Bayes' Maximum Likelihood classification procedure (section 3.3). This classification rule is widely accepted in the user community although it can be understood from chapter 3 that there are other (perhaps even better?) alternatives. The pragmatic lenience adopted here is inspired by the original objectives of CAMOTIUS. The development of new or the evaluation of existing classification procedures is not at all pivotal to CAMOTIUS, rather the adaptation of those methods with which users are most acquainted. The presence or absence in commercial image processing packages is thereby a criterion.

From the available spectral bands, only 3, 4 and 5 were selected for further processing. This combination is often used in land cover classifications (see the discussion by Thunnissen *et al.*, 1992, page 29), although bands 1, 2 and 3 contain latent information about built-up area (greenhouses!). However, given the high correlation values (often above 0.85 for the present data set) and the need to discern vegetation and crop classes, infrared information was required as well. To a lesser extent, the restriction to three bands as dictated by their distinguishing contribution was also preferable for computational reasons.

Three classification strategies were adopted, each involving a different approach to *a priori* knowledge (section 5.6):

- the probability of occurrence of all classes is equal, meaning no explicit knowledge is added to the spectral information;
- for each class, a *prior* probability was derived, proportional to the area it was assumed to cover in reality;
- *a priori* knowledge is not assigned per class but is spatially distributed according to context information and logical relationships.

Table 9.1: A comparison between the classification schemes of BARS and CAMOTIUS

BARS	CAMOTIUS
open water	water
agricultural land use (sports/recreation area/ park/orchard)*	grass-land
agricultural land use	arable land
forest, waste lands (recreation area, park, orchard)	deciduous forest
residential area (social/cultural/medical/educational/other public services)	urban area
greenhouse area**	greenhouses
industrial area (airfields, dump sites, purification installations, bio-industry, railway-yard)	industrial area
building site, waste lands	bare soil

* BARS classes that are less obviously assigned to a CAMOTIUS class are put between brackets
** *Greenhouse area* not only concerns greenhouses but also infrastructure and houses. It indicates the horticultural **function** of the area; greenhouses are an expression of this land use.

A priori knowledge was derived from existing digital data sets, more specifically BARS (BAsisbestand Ruimtelijke Structuren). BARS, maintained by the Spatial Planning Agency (RPD), contains information about land use and concentrates on urban areas. As an example, it makes a distinction between medical and social services but fails to specify agricultural land use. As such, it could be considered a true complement of the information that has to be derived from the remote sensing images. Therefore, the classification of greenhouses can draw inspiration from the urban and (agro)industrial BARS classes, given these are "translated" to camotius land cover classes (table 9.1). Clearly, this mapping of classes introduces uncertainty, as does the required rasterisation of BARS (see section 9.3.4). The next section will evaluate the results of each of the three approaches.

9.3.3 Results of three classification strategies

No a priori knowledge

A straightforward Maximum Likelihood classification relies completely on the spectral information in bands 3, 4 and 5. The result (appendix 3) is compared to the BARS data set. This is possible and sensible because BARS is updated in 1989 (the image is from 1988!) and BARS is not yet involved in the classification. Table 9.2 and figures 9.4 through 9.6 provide a numerical as well as graphical summary of the classification result. Obviously, the area covered by greenhouses is under-estimated in comparison with BARS (figure 9.4). The spatial overlap between BARS and the classification is shown in figure 9.5. About 50% of the area that is assigned class label greenhouses is indeed greenhouses in BARS, whereas more than 60% of the classification is recognised by BARS as far as greenhouses are concerned. These numbers correspond with producer's and user's accuracy respectively, if BARS is considered an absolute reference of reality (see section 5.3). Unfortunately, BARS is only a functional representation of our environment and susceptible to uncertainties. Moreover, remember that the definition of greenhouses in BARS and CAMOTIUS differs slightly, as a functional description could include not only the greenhouse itself but also water reservoirs, private houses and access roads. This discrepancy is partly responsible for the observed under-estimation.

Table 9.2: Numerical overview of the classification results (ha)

Classification	Greenhouses	Urban area	Industry	Bare soil	Not classified
1	3676	1632	1763	2782	176
2	6428	1162	373	1553	309
3	4651	1340	1180	2455	255

Pixel-based assignment of priors per class

BARS and the topographical map of the study area have served as the basis for the derivation of class-bound priors. Table 9.3 gives the values of the prior probabilities that are used in the classification.

Table 9.3: Prior probabilities for eight land cover classes

Class	Prior
Water	0.09
Grass	0.23
Arable land	0.12
Deciduous forest	0.01
Urban area	0.11
Greenhouses	0.37
Industry	0.06
Bare soil	0.01

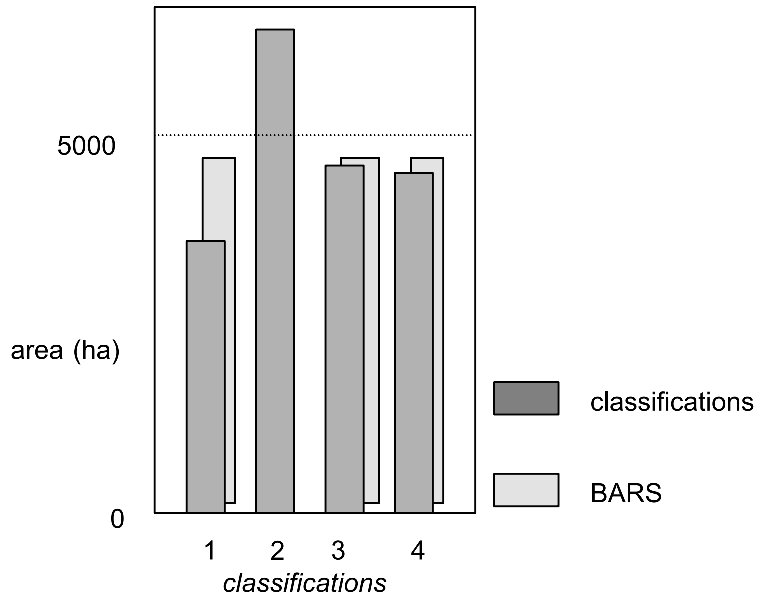


Figure 9.4: Area covered by greenhouses according to BARS *and 4 classifications*

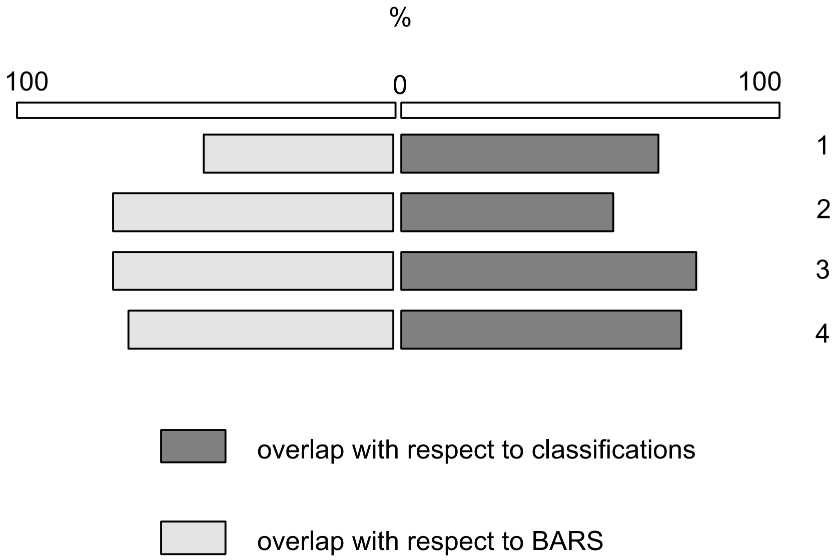


Figure 9.5: Correspondence of class greenhouses with respect to BARS *and separate classifications*

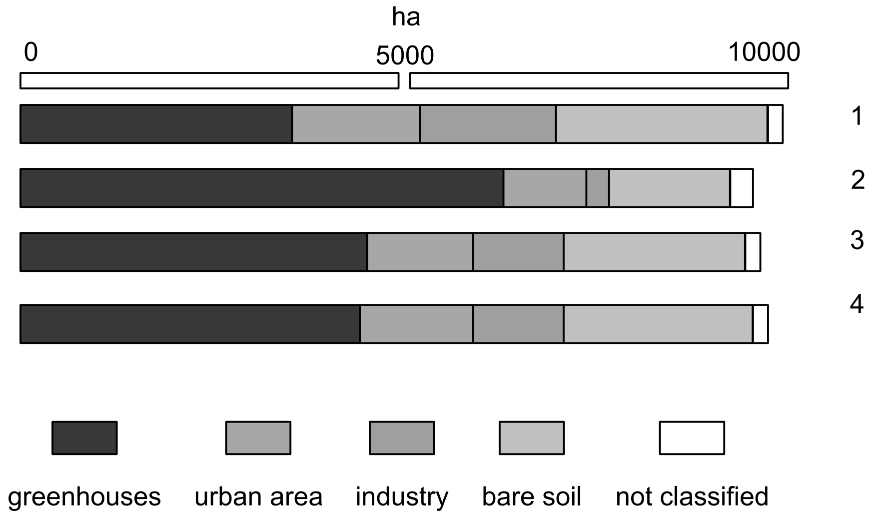


Figure 9.6: Area distribution of 5 classes according to 4 classifications

The most remarkable change with respect to the previous classification is the increase in the area covered by greenhouses: from 28% to 49% (appendix 4). From table 9.2 and figure 9.6 it can be learned that this is probably at the expense of the classes urban area, industry and bare soil. The high prior probability for the class greenhouses (0.37) and the subsequent lower values for the other "problem" classes (spectrally considered) is clearly responsible for the over-estimation of the area as compared with BARS (figures 9.4 and 9.5). Strongly diverging priors (close to 0 and 1) can endanger the reliable distinction of spectrally similar classes by totally neglecting the spectral information (see also the remarks at the end of section 3.3).

Context information and logical rules: BARS

Considering the simple way in which priors are used in Bayes' Maximum Likelihood Rule, namely per class, the question arises why this knowledge is not only used where required. Stratification approaches could contribute to a spatial distribution of this knowledge. Literally, strata are distinguished on the basis of some additional information and each stratum is assigned a set of priors which are no further spatially defined (section 5.6). Here, a somewhat different approach is adopted in which not only the presence of a point (x,y) in an information class A is taken into account but also its relative position with respect to a (possibly fuzzy) class boundary (figure 9.7). The assumed presence of such a point in a particular class and its distance to class boundaries is derived from a reference data set, to wit BARS, from which a priori images are derived that are subsequently weighted in the decision rule. Point 4 in the figure has a slightly higher prior than point 3 as far as class A is concerned. This is understandable from the point of view that the probability of occurrence of class A in the centre of the assumed class "not A" is likely to be low.

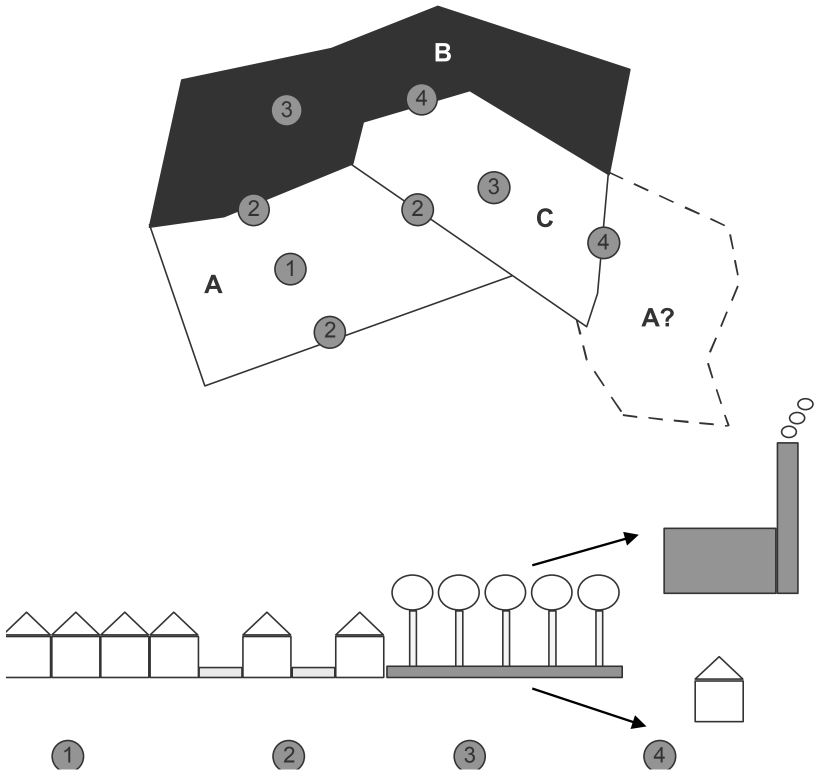


Figure 9.7: One approach to the derivation of priors for class "A" (e.g. greenhouses). A GIS data set is recoded to create an image in which only classes "A" and "not A" are distinguished. During an overlay, point (x,y) in the satellite image is assigned a prior according to its position relative to the assumed occurrence of class "A". It is assumed that: $P(A_1) > P(A_2) > P(A_4) > P(A_3)$

Figure 9.4 shows that the classification reveals almost the same area of greenhouses as the (reclassified) BARS. Moreover, figure 9.5 demonstrates the favourable spatial overlap between the two data sets while appendix 5 creates the impression that the class greenhouses is simply copied from the original BARS data! This striking resemblance notwithstanding, it is stated that this fact doesn't decrease the value of remote sensing data in the information process. The *priors* are sufficiently distinctive to describe the assumed class boundaries that clearly show up in the maximum *posterior* probability image (appendix 6). Moreover, this effect is merely observed in the spectrally difficult to distinguish urban and (agro-) industrial classes and this means that GIS information (e.g. BARS) takes only effect where remote sensing data alone are not sufficient. The classification rule continuously *"trades off the role of multivariate information for the role of prior information"* (Strahler, 1980) and this process is improved if the "unknown class" is taken into account (see also Gorte, 1998 – page 20).

9.3.4 Evaluation

The above strategies are examples of the way in which *a priori* knowledge can be considered during classification. It is not possible to select "the best" strategie because an absolute reference is missing and, more important, the definition of "the best" is dependent on the pursued usage. This simply means that the first classification works probably quite good as a *quick scan* without revealing accurate area figures and that the third classification seems to be very close to "reality" although requiring a considerable amount of efforts. What is at stake here is the discussion about uncertainty, or better, allowed uncertainty. Why bothering about wrong class assignments in areas that are easily recognised as erroneous or that are not of interest yet (or at all!) for the application in mind?

Obviously, this assumes knowledge about the spatial distibution of uncertainties. Since the posterior probability vectors are derived by the classification program and they are considered an indication of uncertainty (section 4.4), judgements about the value of the classification are made possible. As demonstrated in chapter 7, visualisations of these uncertainty patterns can seriously contribute to a better understanding of this value. It is becoming more interesting, though, when the posterior probabilities are used as the basis for decision analysis (chapter 6). Appendix 7 gives an example of a visual uncertainty analysis. It demonstrates how easy the idea of imperfect classifications can be conveyed to decision-makers. In the first stage of the CAMOTIUS project the importance of visual information transfer has been emphasised by the production of a project poster from which appendices 3 through 7 are taken.

9.4 Monitoring: development of greenhouses in the Westland area

9.4.1 Introduction

The above classifications and *interpretations* (according to the terminology in section 6.6) provide an overview of the spatial extent of greenhouses at a particular point in time. From a spatial planning point of view the detection of changes in the spatial composition of an area are considered more interesting. They could be indicative of certain "trends"or expressive of a line of policy set out for the years to come. Hall (1993) states that *"...there is information in the movement..."*, and indeed the character of a dynamic land cover class is best captured by Hall's *"time-lapse cartography"* consisting of several *"slices in time"* (Muehrcke & Muehrcke, 1992). A periodic coverage of extended areas is only feasible by means of airborne and spaceborne data acquisition techniques. The question that arises is to what extent possible changes can be detected and identified, and whether or not this change information can be reduced to uncertainties in the source data. For this second case study, the following goals have been defined:

- obtain a qualitative overview of the spatial change patterns as far as greenhouses are concerned,
    - ◊ for a number of areas-of-interest in the southwest of The Netherlands (figure 9.1);
    - ◊ based on Landsat-TM data;
    - ◊ between 1989 and 1993;
- represent the result in maps and qualitatively summarise them per community for the benefit of a comparison to CBS figures;
- attach a statement about the assumed presence of uncertainties to the monitoring results.

Emphasis is laid on the feasibility of using remotely sensed data for spatial planning purposes in The Netherlands. Special attention is paid to the description of change patterns as far as the development of greenhouses is concerned.

9.4.2 Data and method

Having demonstrated the use of Landsat-TM data during the classification of greenhouses, the step to monitoring by means of *post-classification comparison* is easy to bridge. Section 8.4 has already touched upon the idea of comparing two or more classifications in order to derive the extent and nature of changes. A prerequisite of this approach is that the source data (i.e. the classifications) are accurate or accompanied by quality information. If not, propagation of errors and uncertainties can cause artefacts that could be mistaken for change information.

The selection of suitable data for both reference dates (1989 and 1993) is accompanied by the following considerations:

- cloud-free coverage provides the most information for the application at hand;
- there is no strict dependence on seasons as far as greenhouses are concerned, although there is a preference for the growing season because of the possible spectral confusion with bare soil.

In practice, requirements with respect to content are often subordinate to pragmatic considerations that force users to make concessions to the desired acquisition dates. Eventually, this study has relied on data from 23 May 1989 and 11 May 1993. Erdas Imagine and Ilwis software have been used in order to execute the necessary pre-processing steps, as discussed in section 9.3.2. Figure 9.8 gives a schematical overview of the data flow and processing steps involved in the monitoring operation. It is assumed that the effects of the nearest neighbour resampling (after geometric correction) are not violating the classification results, in accordance with the findings of Smith & Kovalick (1995), see section 4.3. Besides, possible “edge effects” that are caused by a geometrical displacement (section 9.4.4.) would be clearly recognisable (by visual interpretation) on the change map.

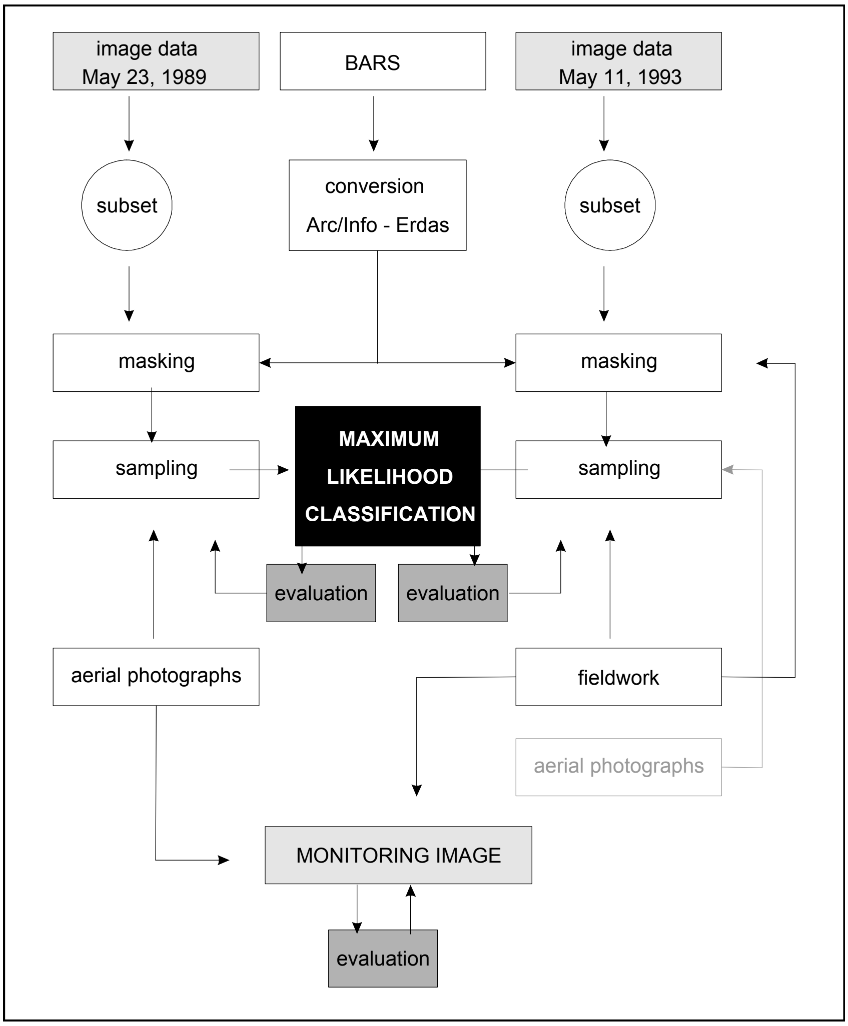


Figure 9.8: Steps involved in the monitoring operation

As a first step, the areas-of-interest are selected from the pre-processed data sets and subjected to a visual interpretation. Obviously, this can result in a rough estimate of the area covered by greenhouses, given that composite images are based on a sensible band combination. The display of bands 3, 2 and 1 in red, green and blue respectively certainly yields a striking and natural-looking image revealing greenhouses as white and greyish spots (see also figure 9.2.b). The role of visual interpretation for exploratory information extraction notwithstanding ("first impression", stratification), it fails as a basis for monitoring. The lack of objectivity, consistency and speed affects its feasibility. Supervised classification complies with the operational requirements (repeatable, fast, minimum user interaction) although the quality of the results remains to be assessed (section 9.4.4).

Continuing with the process flow of figure 9.8, the masking operation is worth mentioning. The BARS data set from the previous case study is rasterised and overlayed with the satellite images. The BARS information is considered *directive* for the 1989 image, meaning that areas are excluded from further classification if this GIS data reveals static land use at those particular places (remember that BARS has been revised in 1989 also). Clearly, a more *restrictive* masking is performed on the 1993 images because of potential new urban "outcrops" in the greenhouse areas.

Except for BARS, the role of *a priori* knowledge in this study is limited although aerial photographs and field data (relating to 1993 only) are used for a post-classification removal of highly unlikely or irrelevant occurrences. Correct assignments revealing greenhouses on allotments are not of interest and obvious errors such as greenhouses amidst industrial storage tanks can be better acknowledged during this stage.

The classification that serves as a starting point for the post-classification comparison is based on Bayes' Maximum Likelihood Rule. This approach offers sufficient grips for a feasibility study into the derivation of change information at low costs and without throwing existing approaches into confusion (see the remarks made in section 9.3.2). Classification results from 1989 and 1993 are evaluated and observed changes have been described systematically according to their spatial and thematic appearance. In addition, this change information has been subjected to critical uncertainty and error analyses.

9.4.3 Results of monitoring greenhouses between 1989 and 1993

Appendices 8 and 9 show the final results of the monitoring operation for two study areas. A simple colour key reveals the occurrence of changes as far as greenhouses are concerned: red (increase), yellow (no change) and green (decrease). This alerting colour scheme corresponds with an interpretation of the observed changes, meaning that an increase urges for caution because of the limited space that is available. In order to be suitable for spatial planning purposes, specific information about the appearance and behaviour of changes should be retrievable from the maps. In theory, changes over time can be distinguished according to different parameters, as outlined in figure 9.9. In this particular study, especially **location** and **extent** (*relocation, increase/decrease, presence/absence*), **nature** (*built-up area at the expense of greenhouses*), **direction** and **manifestation** (*fragmentation/coagulation*) help to structure the temporal information. From this, planners can derive relevant information to describe the spatial patterns:

- increases (red) within the yellow area (e.g. at the urban fringe) are considered forerunners of more **dense** and **intensive** land use, **enlargements** or increases at the outer limits of the yellow area possibly represent conflicting land use and **scattered occurrences** far from the yellow large-scale greenhouse concentrations perhaps mark the establishment of new centres;
- decreases (green) can be described in an analogous way in terms of **thinning**, **reduction** and **scattered decrease**.

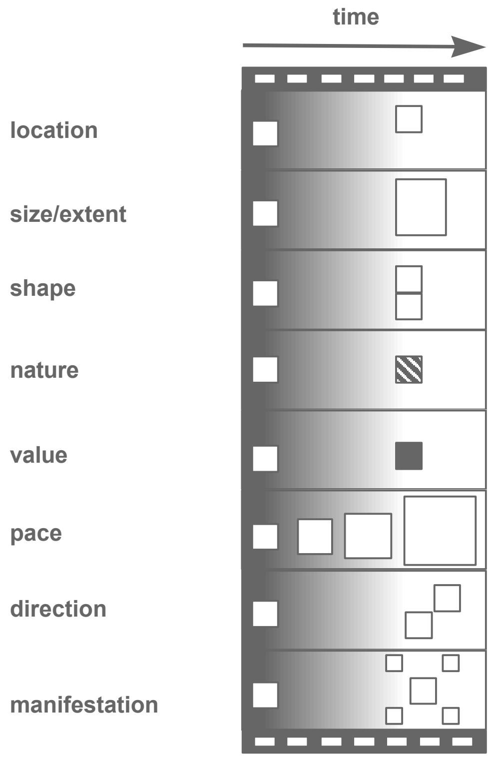


Figure 9.9: The different dimensions of change

Most of the attention is focused on the increases because of their major role in spatial planning policy. The study areas will be reviewed according to their structure and changes before being subjected to a critical discussion about the quality of the results.

Yellow - the structure

The map of the Westland area (appendix 8) demonstrates in an unmistakable way that it represents the largest continuous horticultural centre of the country. The area, roughly situated in the triangle constituted by The Hague-Hoek van Holland-Maassluis is with its 3500 hectares of glass indeed of considerable economic interest. Extended and contiguous occurrences of greenhouses ("complexes") are the rule rather than the exception. Naaldwijk is in the very heart of the region and its greenhouse coverage (over 50% of the area) is representative for the surrounding communities, causing the dominating "yellow image"!

The western boundary of the area is determined by dunes and beaches while the urbanisation of The Hague looms up in the north (just above Madestein). To the east and southeast the Westland reveals a somewhat more scattered appearance and this impression is partly reinforced by the ribbon development in the polders near

Maasland (not included in the map). This type of occurrence is best described as a "concentration" with a pattern that reveals a functional relationship with the Westland mainland.

North of Schipluiden more isolated settlements are detected (probably future concentrations) that seem to act as "stepping stones" in an approach to bridge the gap between Westland and B-Driehoek. This B-Driehoek, situated on the territory of Bleiswijk, Bergschenhoek en Berkel en Rodenrijs (appendix 9) shows a pattern that is less tight. Rather, it consists of small concentrations of greenhouses, except for Bleiswijk that reveals a relatively large and contiguous complex of glass. The observed potential aggregation of Westland and B-Driehoek seems to be continued eastward. The impression of a "greenhouse belt" comes into mind, functionally linking up the Westland with areas as remote as Boskoop /Waddinxveen (figure 9.10).

Red – the increase

The Westland complex appears to extend on the periphery of the area (*enlargements*), especially in the south and southeast. The size of the assumed new greenhouse settlements reveals information about the character of the development, for example planned (large) or more spontaneous (small and scattered). The latter urges for the utmost care because of the *confetti effect* that has been outlined in chapter 4. A condensation of the area, i.e. a more dense character of greenhouse development "from within" (at the edges of towns) is limited and possibly surrounded by uncertainty (see section 9.4.4).

Most striking on the B-Driehoek map is the enormous increase near Bleiswijk. In general, the open structure becomes somewhat more tight.

Green – the decrease

There is no clear pattern in the observed (and until the analysis of errors and uncertainties) assumed decreases. Given the relevance of the Westland and its tendency to expand, considerable changes are not expected, though. After 1993 the situation could be different as a consequence of the Vinex policy to allocate new expansion areas, but this is beyond the scope of the selected time frame (1989-1993).

Preliminary conclusions

The expectation that development would manifest itself mainly within or in the direct neighbourhood of existing complexes has proved to be true. The developments in both Westland and B-Driehoek reinforce the idea of a greenhouse belt representing an unprecedented horticultural activity. This is remarkable because precisely in this area space is scarce and the opportunity to develop it is likely to be claimed by different parties with incompatible interests (nature management, agriculture, recreation...).

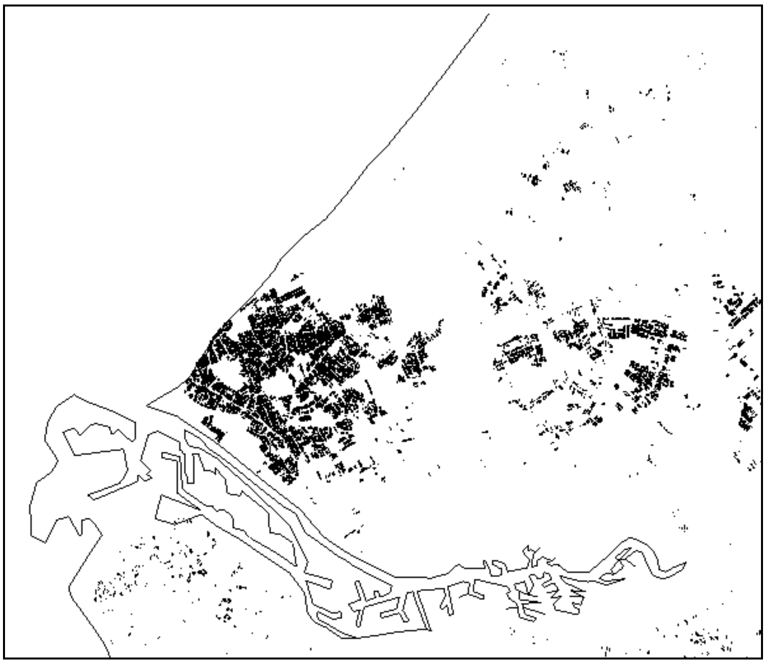


Figure 9.10: Greenhouses (black spots) appear to develop along a west-east "belt". The area is derived from LGN-*3 produced by* DLO-*Staring Centrum in 1998*

9.4.4 Analysis of errors and uncertainties

Monitoring of greenhouses by means of Landsat-TM image classification is not devoid of uncertainty as the previous section has already implied. A considerable amount of uncertainty can be easily discerned during interpretation of the results by critically considering the shape and context of changes. The former refers to increases and decreases along lines (*edge effect*) that are not seldom caused by (see chapter 4):

- mixed pixels along the boundary of two types of land cover;
- an incorrect masking by BARS or a geometrical displacement in at least one of the data sets (e.g. visible as "changes" at the urban fringe);
- the occurrence of bad lines that are assigned a value from neighbouring image samples;
- spectral confusion with linear objects, such as roads and dikes.

Preferably, most of this observed confusion should be removed or reduced during (pre-) processing. The approach adopted here, however, aims at handling uncertainty in **given** classifications (including their *posterior* probabilities) without necessarily having control over the "raw" data.

Context information can clarify part of the observed changes as well, for example small, isolated and scattered occurrences of greenhouses are less likely in the

Westland than in the B-Driehoek. Moreover, the character of neighbouring classes can provide further clues which demonstrates the value of the separate classifications during monitoring (also, the derivation of probability information during classification makes post-classification comparison more preferable than e.g. image differencing).

Fieldwork, though, remains inevitable when absolute error assessment is required. From these data and the visual interpretation of aerial photographs (1989) and satellite images (1993) the extent of greenhouses in the 1989 image appears to be somewhat over-estimated. As a consequence, decreases are observed with respect to 1993 and a simple explanation can't be given. It is suspected that spectral confusion between greenhouses on the one hand and industry, urban area and bare soil on the other plays a major role. But even the reflecting effect of plastic sheets, rolled out over agricultural fields to protect the crops, is not impossible. The addition of *a priori* knowledge during the classification process is one option to reduce this uncertainty as illustrated in the first case study. But also *before* (masking) or *after* classification, the role of such knowledge is evident. The above-mentioned interfering effect of linear objects, for example, can be easily overcome by the consultation of digital topographic data.

Figure 9.11 provides a summary of a theoretical uncertainty analysis, based on the assumption that spectral confusion and hence wrong class assignment is more likely to occur in one image than in both images for a particular point (x,y). Another assumption concerns the number of errors of commission or the unjust assignment to the class greenhouses; it is thought that they exceed the errors of omission

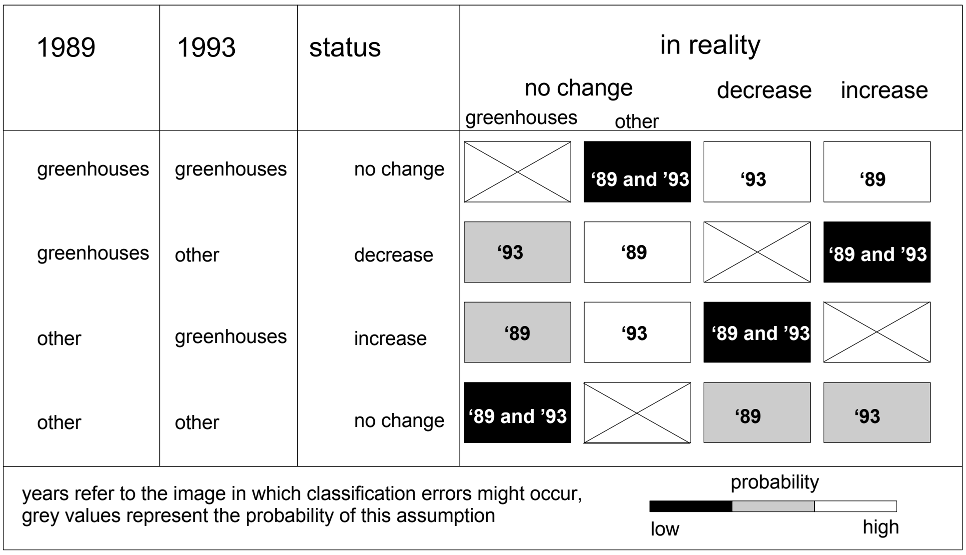


Figure 9.11: Example of a theoretical error analysis of the monitoring results. From this it appears to be probable that an unreliable "decrease" could be the consequence of a classification error in the image of 1989

(greenhouses are classified as something else). The latter position is to some extent confirmed by the observation of an over-estimation of greenhouses in the raw classification result. It is interesting to note what this simple scheme learns about the earlier mentioned uncertainty by which the observed decreases are attended. It reveals that this uncertainty is most likely a consequence of incorrect assignment of spectrally difficult to distinguish land cover to the class greenhouse. Fieldwork (i.e. “historical” interviews concerning the situation in 1989) and interpretation of aerial photographs definitely acknowledge this supposition. This type of reference data is not always readily available, such that uncertainty analysis has to rely on the probability information provided by each of the separate classifications. The *fitness for use* of monitoring information can be reconsidered after an investigation of the spatial distribution of the uncertainties. The posterior probabilities only exhibit their value as an indication of uncertainty if the classes are representative and exhaustively trained before the actual classification. In order to fully understand the uncertainty pattern, an error model is required that relates to the probability of occurrence of class C_i at time t_1, given class C_j at time t_0 - but this is beyond the scope of this thesis.

Visualisation of the uncertain information (chapter 7) is considered the most effective, user-friendly and persuasive tool to evaluate the value (*quality*) of the presumed information.

9.5 Final remarks

Both case studies have demonstrated methods to involve remotely sensed data in the spatial planning practice. It appears that classification and monitoring strategies based on these data can benefit from their large and repetitive coverage. The quality of static and dynamic information is dependent on *a priori* knowledge and its subsequent usage, and the availability of uncertainty information in view of a well-balanced interpretation. Visualisation of data as well as uncertainty is necessary in order to determine the usability of the information content of the derived product for the application pursued.

As long as extended areas of greenhouses are considered and spectral confusion is kept to a minimum by the use of additional knowledge, the role of satellite imagery is justifiable. The monitoring study exemplified the different dimensions of change information that are possibly revealed and that enable a more complete description of the ongoing developments in areas that are subjected to a serious pressure on the spatial arrangement of particular land use.

The emphasis on uncertainty information notwithstanding, users simply need tools to apply the presented ideas. One thing that CAMOTIUS has indicated is the fact that users refuse to consider new strategies unless they are provided with easy-to-use and straightforward tools. Especially for operational applications, e.g. in spatial planning, the CAMOTIUS Demonstration Program is just a blueprint for an uncertainty extension that needs maturation with the help of established GIS vendors.

10 Final conclusions and outlook

"...Cartography, however, is no idle pastime..."

James Cowan (1996) – "A mapmaker's dream"

10.1 Introduction

It is reassuring to know that already at the beginning of this century serious efforts were made to reveal the quality of bathymetric maps (Groll, 1913)! That particular investigation emphasised the scarcity of soundings (technology, costs!) and hence the uncertainty related to the represented isobaths (an indication of this uncertainty was obtained by reconstructing land topography by means of a limited sample data set, as is the case at sea). The bottom line of this most original study refers to what is now generally understood as *lineage*. Retracing the map to its raw data helps to improve the extraction of true information.

Lineage is just one of several **quality** components that form the quintessence of this thesis. Concern for the quality of spatial data is certainly not a new development, but it is increasingly attracting the attention as man is faced with intensified data flows from satellites. The basic assumption is that all geographical data are to some extent subjected to imperfections because of the insufficient precision and accuracy of instruments and observers, or the errors and uncertainties that are introduced along the way of processing. This text is meant as a primer on quality **awareness**, in order to convey the idea that one has to accept the fact that data are not always suitable for the pursued application. But after awareness comes **action**: the users of geographical data need directions from the **scientific community -** and that is where the shoe pinches. The adverse effects of consulting uncertain or even erroneous (mapped) data are more profound in the **geo-information market place**, i.e. where data are frequently and quickly exchanged, enriched and consulted. Here, appropriate or well-documented data sets are not always available and accessible at the right time and at acceptable costs. This fact notwithstanding, the engineer that is eagerly willing to use a flood map of sufficient accuracy before starting to plan construction works is forced to rely on other, less favourable though readily available sources. In other words, as long as data are distributed according to strict guidelines, there will be a tendency and sometimes even a necessity to apply inferior data. And with liability issues still not fully discussed (at least in Europe), bad data are maybe even worth the risk...

From this brief introduction and the literature that has been summarised during the previous chapters, the following conclusions can be derived:

- spatial data quality is mainly approached from a scientific perspective;
- there is no true incentive to use "better" data as long as they are more expensive, hard to get, difficult to recognise and legally equivalent to their inferior opposites.

The first point doesn't sneeze at the scientific efforts, quite the contrary, research has to provide the guidelines and grips that are necessary for handling uncertainty in spatial data. Rather, the practical feasibility of the research results is at stake. Numerous descriptive and quantitative quality indicators have been proposed, including the ones in this thesis, but there is hardly any feedback from the user community concerning the extra value of these statements.

The second point refers to user issues. The entire concept of spatial data quality is based on the assumption that data and application can be tuned to each other, that it is worth considering the information value of the data because it can save money, prevent misunderstandings or benefit otherwise. The advantages of providing data quality statements are undone if their meaning is badly understood and poorly conveyed. Moreover, unclear and inconsistent data policies hamper a situation in which data are at the right spot, at the right time.

The objective of this concluding chapter is to evaluate the achievements of the CAMOTIUS research, with the above critical remarks in mind.

10.2 What has been achieved?

Returning to the original objectives and reflecting on the previous chapters, the results will be subjected to a more elaborated evaluation. The main objective as defined in section 1.5 urges for *"...the development of a methodological framework..."* and is further divided in a number of goals. They all aim at a proper, well-balanced use of spatial data by an average user. Therefore, common processing is considered ("land cover classification") without introducing new methods ("widely-accepted maximum posterior classification strategies") and with an emphasis on feasibility instead of originality ("simple interpretation guidelines for change information and visual decision-support"). Are all ambitions sufficiently addressed in the course of the treatise?

Assuming Bayes' Maximum Likelihood Decision Rule one of the most applied approaches in classifying multispectral remotely sensed data, the emphasis on this method is justified. Commercial image processing software packages are still mainly supporting this classification, although the *k*-NN method has been put forward here as an interesting partner. The statistics underlying both approaches allows for the derivation of valuable probability information that could demonstrate its extra value in a GIS environment. It has been shown during the development of the CAMOTIUS Demonstration Package that a simple adaptation of existing classification procedures enables the storage of posterior probability vectors in a geographical information system. Stated in another way, it seems rather straightforward to extend image processing systems such as ERDAS Imagine with functions that can deal with this statistical information. In this case, the vendors have to become conscious of the fact that users will demand – sooner or later - tools that help to handle data uncertainty. More generally, users of remotely sensed data can benefit from a closer interaction with GIS as its technology offers solutions for the integration of additional knowledge during the classification process (see chapter 5). Such an involvement can be considered one of the approaches to a reduction of data uncertainty, although it is only sensible if the present uncertainty can be assessed in the first place. The proposed storage of the above-mentioned probability vectors allows for the application of measures that determine the strength of class assignments and thus the **fitness** of the classification for the pursued **use**. Its relative meaning notwithstanding, it reveals information about the suitability of the classification rule and the presence of spectral confusion, for example. It is admitted that probabilities are not telling the whole story, but they are basically readily available and therefore their ignorance should be considered "missing with an empty goal". In addition, more descriptive quality information can be provided, as part of geo-spatial meta-information, often summarising facts that are often known but not recognised as implicit quality indicators. By concentrating too much on more explicit clues, such as accuracy statements, one might overshoot the mark because this requires extensive fieldwork or at least the availability of an expensive reference data set. Of course, sometimes absolute quality information in terms of correctness is required, but not seldom knowledge about the limitations of the classification suffices. In these cases, it is far more promising to make sound decisions based on the assumed uncertainty and the anticipated use. Decision analysis has been introduced here in order to show its potential for the geographical field and its maturity for implementation in a GIS environment.

All these results would contain no value if not efficiently and effectively conveyed to the main figure acting in this thesis: **the user**. An appeal has been made to cartographic knowledge in order to develop guidelines for the transfer of particular quality information.

The methodological framework mentioned in the above, must be understood as the whole of classification rules, interpretation guidelines, uncertainty assessment/reduction/reasoning strategies, and cartographic grips that together cover the information process of remotely sensed data. Its implementation has resulted in the CAMOTIUS Demonstration Program, an example of how a "quality-based" information system would look like. In fact, the design of such a system has to be tuned to different anticipated user groups because a more or less "generic" system appears to be too cumbersome for demonstration purposes (while in general its feasibility remains questionable).

Chapters 4 through 7 have extensively dealt with the main issues that constitute the framework. The presence of uncertainty in a geographical data set and the subsequent consequences for the fitness-for-use of these data has been highlighted adequately.

Does a user now have the disposal of a clear step-by-step approach to handling uncertain data?

10.3 What remains to be done?

One of the most striking observations that can be made after consideration of the framework and its components relates to the lack of binding advises as far as quality measures and visualisations are concerned. In a sceptical way this can be interpreted as a deficiency of coherence, a "heap of bricks without a plan for construction". Indeed, the eventual picture of an *"error-sensitive information system"* still has to take definite shape. The concepts that have been outlined in the present thesis, however, can be put together in a logical way as is demonstrated in the CAMOTIUS study. But instead of offering a "corset" of rules and relationships that force a predetermined sequence of quality considerations, it is felt more desirable to provide components as separate, not necessarily interdependent building blocks that allow for a variety of user-defined constructions. This means for example that the evaluation of probability information remains optional, or that the level of quality information can be selected beforehand – in order to prevent a user from being deterred by the extra information. Specific user needs form an issue that deserves more attention, as the type of quality information and the ways in which it can be conveyed are decisive for the acceptance of this extra information and the success of their application. Take as an example the visualisation of uncertainty; the thesis founds the role of cartography in making the meta-information understandable but fails to provide clues about the preference of one visualisation above the other. From this point of view, the presented strategy might be too scientific and not directed at an immediate application. Considered more optimistically, it can be stated that the theoretical range of visualisations has been distinguished and awaits subjection to dedicated perception and feasibility studies.

The hope exists that research in the field of errors and uncertainty will eventually arouse the interest of the vendors of geo-information systems. Only then the ideas concerning better information extraction will be taken seriously by the majority of the user community. Until now, such research has still not led to large-scale implementations. Obviously, there is a gap between the scientific community on the one side and the GIS vendors and users on the other. This is partly caused by the complexity of the problem, but the lack of an incentive plays an important role as well. If one will be held responsible for wrong decisions due to the presence of imperfections in the data set, it can be expected that some kind of "liability disclaimer" is introduced - but only when a sound quality report has been provided. Another development refers to quality standards as part of more extended geo-spatial meta-data standards. Once they are sufficiently crystallised, their implementation in information systems will represent the start of explicit quality consideration. In a couple of years, the breeding ground for the inclusion of more statistical quality information, such as probabilities, is herewith assessed.

Afleiding en visualisatie van onzekerheden in remote sensing landbedekkingsclassificaties

Samenvatting

Instrumenten aan boord van satellieten en vliegtuigen zijn in staat om het uiterlijk en de toestand van onze planeet af te leiden door de hoeveelheid uitgezonden en gereflecteerde electromagnetische straling op te meten. De resulterende gegevensstroom is enorm en neemt nog immer toe, en vormt de basis voor een groot aantal computer-gebaseerde verwerkingsmethoden voor tal van toepassingen. De classificatie van deze *remote sensing* (rs) data in nominale klassen is bijvoorbeeld zinvol voor de extractie van kartografische informatie die gebruikt kan worden in thematische landbedekkingskaarten.

De *fitness for use* van een rs gegevensbestand is bepalend voor het zinvolle kartografische gebruik. De waarde van de classificatie voor een bepaald gebruik kan bepaald worden aan de hand van een nauwkeurigheidsbepaling. Daartoe wordt een foutenmatrix afgeleid voor de betreffende classificatie door steekproefgegevens uit het geclassificeerde bestand en uit een referentiebestand ("de werkelijkheid") aan elkaar te koppelen. Toch is een nauwkeurigheidsbepaling te beperkt omdat het geen ruimtelijke informatie verschaft ("waar zitten de fouten") en veelal slechts algemene statistieken omvat ("95% nauwkeurigheid voor het gehele beeld"). Verder veresit deze benadering veldwerk om actuele referentiedata af te leiden, een tijdrovende en dure bezigheid. Het gevaar is dat een gebruiker van deze data besluit dan maar helemaal niet om te kijken naar dergelijke "indicatoren van geschiktheid" zodat mogelijk ontverantwoord gebruik wordt gemaakt van het geclassificeerde bestand.

Behalve nauwkeurigheid wordt de term *kwaliteit* vaak gebruikt om te verwijzen naar de mate waarin de eigenschappen van het gegevensbestand overeenkomen met de eisen van de voor ogen staande toepassing waarin het gebruikt zal worden. Een hoge mate van kwaliteit geeft een relatief hoog informatiegehalte aan, opnieuw ten aanzien van de beoogde toepassing – een goede *fitness for use*. Daarnaast is onzekerheid een sleutelbegrip in de kwaliteitsbepaling en daardoor in de vaststelling van de *fitness for use* van een gegevensbestand.

Gedurende de "levensloop" van rs data worden onzekerheden geïntroduceerd en "voortgeplant", veelal op een onbekende wijze. Teneinde deze onzekerheden nader te onderzoeken moeten maten worden bepaald aan de hand waarvan een kwantitatief inzicht kan worden verkregen. Het doel dat in dit proefschrift wordt nagestreefd is het gebruik van dergelijke onzekerheidsmaten gedurende de exploratieve analyse van rs classificaties. Hiermee wordt getracht inzicht te verkrijgen in de sterkte van de klassentoekenningen. Kennis over onzekerheid is hierbij van doorslaggevend belang. Het classificeren van een rs bestand is veelal een iteratief proces dat profijt kan trekken van een tussentijdse rapportage van de hoeveelheid onzekerheid. Daar deze onzekerheden ook ruimtelijk verdeeld zijn ligt kartografische visualisatie als communicatiemiddel voor de hand. Een belangrijk deel van het onderhavige

proefschrift is dan ook ingericht rondom onzekerheidsmaten en kartografische visualisatiemethoden.

De onzekerheid die wordt geïntroduceerd gedurende de classificatie van een rs gegevensbestand wordt gekenschetst door de waarschijnlijkheidsvectoren die een produkt vormen van de meeste probabilistische classificatiemethoden. De nadruk ligt hier op zogenaamde *maximum a posteriori classificaties* waarbij voor iedere pixel in de data een vector van waarschijnlijkheden wordt berekend. De waarden vertegenwoordigen, voor elk van de onderscheiden klassen, de waarschijnlijkheid dat deze klasse de werkelijke klasse is. De vectoren geven de verschillen in onzekerheid weer die zich in de classificatie voordoen, en kunnen opgeslagen worden in een gis om als basis te dienen voor de afleiding van "gewogen" onzekerheidsmaten zoals *entropie*.

Naast de bepaling van onzekerheid moeten de inspanningen ook gericht worden op het terugdringen van de hoeveelheid onzekerheid in een rs gegevensbestand. De maximum *a posteriori* classificatieregels die hier worden behandeld geven ruimte aan het meewegen van *a priori* kennis in het classificatieproces, op een niveau dat het eenvoudig toekennen van een prior per klasse in bestaande beeldverwerkingsprogramma's ver overschrijdt. Een andere strategie behelst de toepassing van ideeën achter beslisanalyse, waarmee optimale beslissingen worden nagestreefd gegeven de onzekerheid in de informatieklassen. Het combineren van waarschijnlijkheidsleer en utiliteitentheory draagt bij aan de selectie van de beste beslissing onder de gegeven omstandigheden.

Zowel de probabilistische resultaten van de classificatieprocedure als andersoortige kwaliteitsinformatie kan worden onderworpen aan kartografische visualisatieregels teneinde tot een raamwerk te komen voor de communicatie van dergelijke ruimtelijke meta-data. Statische maar ook meer dynamische benaderingen bieden aanknopingspunten voor de gis gebruiker die eenvoudige maar overtuigende visualisaties nodig heeft om de *fitness for use* te achterhalen.

Commerciële gis programma's schieten nog steeds tekort wanneer het om onzekerheid in ruimtelijke gegevens gaat. Dit heeft geleid tot het starten van een projectgroep camotius waarbinnen de functionaliteit van een "onzekerheidsmodule" voor een "rs vriendelijk" gis is nagegaan. Een dergelijk systeem zou bijzonder waardevol zijn voor Nederlandse toepassingen waarbinnen de meerwaarde van rs data niet boven elke twijfel verheven is. Daartoe zijn 2 *case studies* uitgevoerd waarin de rol van rs voor ruimtelijke ordening is benadrukt: het volgen van ontwikkelingen in ruimte en tijd (*monitoring*) en het afleiden van actuele inventarisaties, beide gericht op de glastuinbouw in het westen van het land. Het expliciet beschouwen van onzekerheidsinformatie maakt de gebruiker bewust van de werkelijke meerwaarde van de rs data voor de beoogde toepassing. Om een en ander concreet te demonstreren is een software programma geschreven dat kan worden ge-*download* van:

http://cartography.geog.uu.nl/research/phd

Abstract

The ability of space- and airborne instruments to measure the amount of electromagnetic radiation reflected and emitted by the Earth's surface has proved to be valuable for the understanding of our environment, as it provides for an overwhelming flow of data on the appearance and condition of our planet. The data yielded by remote sensing can be subjected to various types of computer-assisted manipulation, to arrive at derived data sets tailored to different types of application. Computer-assisted classification of remotely sensed data into qualitative classes, for example, is useful for extracting information that can be exploited for cartographic purposes, such as in the generation of thematic maps of land cover types.

For a proper cartographic application, the *fitness for use* of a set of remotely sensed data needs be assessed. The practicability of the data and their classification can be established by means of an accuracy assessment procedure. An error matrix is created for the classification by matching a random sample and its counterpart from a reference data set representing the actual environment. Accuracy assessment based on an error matrix, however, has several drawbacks. Among these is the non-spatial and general character of a global statement like 95% accuracy for an entire classification; moreover, accuracy assessment is a time-consuming and cost-intensive process. As a consequence, it is easily omitted which, of course, is undesirable and may lead to the use of data that are unfit for the application at hand.

For assessing the fitness for use of a set of remotely sensed data, accuracy is not the only consideration. More generally, the phrase data *quality* is used to refer to the extent to which the characteristics of the data meet the requirements of the application aimed at by the user. A high quality indicates a relatively high information value for the considered application - a good fitness for use. Uncertainty is a key-issue in quality assessment and, therefore, in the assessment of fitness for use of a data set.

During the life cycle of remotely sensed data uncertainties are introduced and propagated in an often unknown way. For investigating uncertainty, effective measures need to be designed. To this end, it is relevant to consider the purpose to which these measures are to be employed. Here, the focus is on an exploratory perspective. Exploratory analysis of a set of remotely sensed data aims at acquiring insight into the stability of various possible classifications of these data. For this purpose, knowledge about the uncertainties underlying these classifications is imperative. As in exploratory analysis, classification is an iterative process, needing not only measures for assessing the uncertainty in a classification but also effective ways to convey this information to the user. Visualisation is generally considered a useful means of communication of potentially relevant information. In this thesis a class of measures of uncertainty is presented, tailored to the purpose of exploratory analysis of remotely sensed data, together with various ways of cartographic visualisation of uncertainty.

The uncertainty that is introduced during classification of a set of remotely sensed data is characterised by the probability vectors that are yielded as a by-product of most probabilistic classification procedures. Here, emphasis is laid on maximum *a*

posteriori classifications where for every pixel in the data a vector of probabilities is calculated that specifies for each distinguished class its probability of being the true class. The probability vectors reflect the differences in uncertainty in the resulting classification and can be stored in a GIS to serve as a basis for the derivation of weighted uncertainty measures such as entropy.

Besides the assessment of uncertainty, efforts can be aimed at the reduction of the amount of uncertainty present in a remotely sensed data set. The maximum *a posteriori* classification rules being dealt with in this thesis allow for the introduction of *a priori* knowledge in the classification process, at different levels of sophistication - thereby exceeding the simple approaches embraced in existing image processing packages. Another strategy within the realm of dealing with spatial data uncertainty is based on the idea of *decision analysis* that allows for an optimal decision-making given uncertain information classes. Combining probability theory (defining the uncertainty related to the occurrence of a particular class) and utility theory (defining the desirability of the consequences resulting from the actions that are taken assuming that particular class) contributes to the selection of the best decision under the given conditions. This idea is particularly interesting when dealing with huge data sets under uncertain circumstances and with far-reaching consequences for wrong decisions (e.g. agricultural fraud detection by European Union).

Both the probabilistic results from the classification procedure and other quality information are subjected to cartographic visualisation rules in order to develop a framework for the communication of this spatial metadata. Static as well as more dynamic approaches offer grips for the GIS user who needs to consider simple but persuasive maps to assess the fitness for use of a classification.

Commercial GIS packages are still failing when the sound consideration of spatial data uncertainty is at stake, a fact that has incited the participants of the CAMOTIUS project to look for the functionality of an "uncertainty-sensitive information system". Such a system is valuable for the Dutch situation in which the extra value added by remotely sensed data is not always beyond all doubt; the explicit evaluation of these data as well as their inherent uncertainty reveals their true information value. Two case studies have stressed the role of remote sensing for planning purposes by demonstrating its ability to monitor changes in the extent of greenhouses over space and time, and making inventories of their area. The inclusion of uncertainty information allows for an exploratory approach in which an appeal can be made to several levels of knowledge in order to improve the processing results. It is stated that a user will be encouraged to use remotely sensed data if their extra value is clearly demonstrable. The components that have been scrutinised in the methodological part of this thesis are formalised in a demonstration programme that could serve as a blueprint for commercial GIS packages. It can be downloaded from:

http://cartography.geog.uu.nl/research/phd

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Curriculum vitae

Frans van der Wel werd geboren op 25 november 1965 te Utrecht. Na afronding van het Atheneum aan het Utrechtse Sint Bonifatiuscollege in 1984 begon hij aan de studie fysische geografie aan de Universiteit Utrecht. Binnen de hoofdvakstudie kartografie specialiseerde hij zich verder in GIS en remote sensing technieken waarvoor hij in 1989 4 maanden aan het ITC te Enschede studeerde. De afstudeerstage werd uitgevoerd bij de Rijksplanologische Dienst te Zwolle, afdeling Informatievoorziening waar de basis werd gelegd voor het onderhavige onderzoek. Met een scriptie onder de titel "*de betrouwbaarheid van geografische gegevens - kwaliteitsinformatie ter ondersteuning van de GIS-gebruiker*" werd de studie in 1990 afgerond.

Vanaf het afstuderen tot medio 1996 was hij in dienst bij de vakgroep kartografie van de Faculteit Ruimtelijke Wetenschappen, Universiteit Utrecht. De aandacht lag sterk op het onderzoeken van de meerwaarde van remote sensing data voor de kartografie en de rol van geografische informatiesystemen als gegevensverwerkende technologie. Dit resulteerde in april 1992 tot de start van het derde geldstroomonderzoek CAMOTIUS dat uiteindelijk 3 fasen zou gaan omvatten. Na de afronding in 1996 werd aangevangen met het schrijven van de dissertatie.

Sinds maart 1997 is de auteur in dienst van het Koninklijk Meteorologisch Instituut (KNMI) in De Bilt. Als onderzoeker coördineert hij de introductie en verankering van GIS in de meteorologie.

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Appendices

1. Explanation of figures 7.6 and 7.7

Figure 7.6

1. Colour saturation can be used in combination with colour hue in bivariate maps.
2. By using colour hue, *selective perception* is maintained for a considerable amount of classes, for all types of *implantation*.
3. Point symbols representing field work (drill symbol), aerial photographs (plane symbol) and images (satellite symbol) can be used in a compilation graph in order to reveal the data collection methods used in a particular area.
4. Texture provides order as well.
5. Colour hues don't impose order except for the case that the colours are ordered according to their values. The reason for proposing this variable at an ordinal level of measurement lies in its ability to support the interpretation of meta-information. The "traffic light principle" (e.g. Monmonier & Johnson, 1991) at an ordinal level is in fact an interpretation of the underlying meta-information; accuracy values have been translated into "safety" classes. The map reader associates green, orange and red with increasing danger. The effectiveness of this principle depends largely on such issues as cultural background and therefore the term *subjective association* is justified.
6. For point and line features.
7. Different levels of abstraction correspond with different levels of completeness.
8. At an interval level of measurement is seems difficult to defend the use of different colour hues. Besides forcing order, the "distance" between classes must be assessed. The depiction of temperature (zones) on a map could benefit from the associations red-hot and blue-cold. Combined with red values and blue values such a map could be informative, but it is very difficult to derive such information as "the difference between the dark blue zone and the light red zone equals the difference between the light blue zone and the dark red zone". Only if a dichotomy has been defined, based on association (red-hot/blue-cold), interpretation at an interval level is enabled, but only within the two temperature ranges. For meta-information, an extension of the "traffic light principle" (e.g. Monmonier & Johnson, 1991) seems obvious. Bertin (1981) has a completely different point of view.
9. Visualisation itself is questionable for line and area features at a ratio scale of measurement. For area features, size could be used to create an *anamorphosis*, but thisis considered too complicated. Bertin's ideas on using size and number of repeated symbols within areas as a way to depict ratio-level information results in complex visualisations (see the graduated sizes in a regular pattern, Bertin 1983). Its effectiveness to depict meta-information is judges as low (-/+). Therefore, with the exception of point symbols, preference is given to visualisation at another level of measurement.

Figure 7.7

1. Colour hue can be used to distinguish between areas that have been mapped by satellites, aeroplanes and fieldwork.
2. Two different colour hues can reveal information about the completeness of a data set, e.g. black ("incomplete") and white ("complete").
3. Classification uncertainty can be represented on a nominal measurement scale by assigning associative colours, e.g. red ("bad") and green ("good").
4. On a quantitative level, classification uncertainty can benefit from the traffic light principle (Monmonier & Johnson, 1991). Colour hue normally fails to convey the impression of order, but *subjective association* can contribute to the establishment of some rank order: green, orange and red correspond with low, medium and high uncertainty respectively.
5. A combination of size and shape can be used to convey the data collection method (e.g. airborne), and the date of acquisition (larger symbols corresponding with more recent data).
6. In a more implicit way, size can be used to communicate the amount of uncertainty present in some attribute, e.g. deciduous forest.
7. More subtile is the use of "fuzzy symbols" depending on the assumed amount of classification uncertainty.
8. Part of the map that is based on a complete data set can be represented by a realistic representation of the considered class. Areas that are based on incomplete data can be assigned an abstract symbol.
9. Likewise, a more certain map can reveal a higher level of detail than its less certain counterpart.

2. Specifications of the CAMOTIUS tool

The CAMOTIUS Demonstration Programme (CDP) can be downloaded from the following internet address: http://cartography.geog.uu.nl/research/phd
Two zipped files contain the programme itself and test data sets respectively, while a third one covers the documentation in both Word and plain text files. The programme has been developed in Microsoft's Visual Basic. The functionality of the demonstration tool is best explored by working with the data of the Westland area that are added.

The CAMOTIUS programme is not an image processig package as it lacks the ability to (geometrically) correct and enhance the satellite images. Moreover, it can be considered an extension of a GIS, an "uncertainty module", characterised by userfriendly interfaces and openness as far as data formats are concerned. Remember, though, that it is a *demonstration* tool that fails to pursue completeness. The user interface is easy to understand; for example, all red text is *clickable* such that the user knows immediately where to expect actions. When a user descends further in the programme, the *navigator* helps to visually assess the processing steps so far. The main functions of the programme can be distinguished as:

- Conversion – ASCII, ILWIS and ERDAS LAN/GIS formats are supported;
- Meta-information / quality module – The *meta informer* allows for a preview of the imported data (up to 4 data sets at the same time) and a summary of statistical information, e.g. class percentages in a classified image. A user can add meta-information as well, for example by estimating the value of 6 quality components by moving scroll bars along a linear scale or by typing plain text.
- Classification – Both Bayes' Maximum Likelihood Classification and *k*-NN are supported and for these approaches the programme offers grips to include *a priori* knowledge, CDP can handle priors per class, per pixel and per segment. The latter approach comprises the iterative calculation of prior probabilities that has been explained in section 5.6. Besides classifications, CDP derives a number of additional maps showing e.g. maximum posterior probability, differences between maximum and second probability per pixel and entropy.
- Monitoring – CDP can derive a change map according to the methods of *image differencing* and *post-classification comparison*.
- Decision analysis - With CDP a user can define *utility values* that together with the posterior probabilities make up the decision tree.
- Visualisation – A considerable amount of attention is dedicated to visualisation of uncertainty as CDP supports both static and dynamic visualisation approaches. The former can be further subdivided into grey-scale maps and combined maps. Examples are *ranked probability* and *class probability maps* on the one hand and *bivariate* and *asscociative ranking maps* on the other. Dynamic visualisations explore the field of animated cartography by showing a series of mutually related maps in a particular order and at a specific speed. Also, the interactive clickable maps discussed in section 7. 8 allow for an exploratory analysis of the probability information.

Colour maps

Appendices 3 through 5 show classifications that are the result of different levels of *a priori* knowledge. Greenhouses are represented by the pink colour, while urban area is in red. Industry is depicted in an "aubergine" (purple) colour. A class "non-classified" is shown in grey. Water (blue), grassland (green), deciduous forest (dark green), arable land (light yellow) and bare soil (light brown) are also distinguished.

Appendix 6 reveals the maximum posterior probability map for the third classification ("scenario 3") in which the colour values typically range from black for a low maximum probability to white for a high one.

A comparison of all three classifications as far as class greenhouses is concerned, is summarised in the visual uncertainty analysis of appendix 7. Depicting the area of greenhouses for scenario 1 in red, scenario 2 in green en scenario 3 in blue results in a colour-mixing map. In the resulting map green means an over-estimation of the area of greenhouses in scenario 2 as compared to scenarios 1 and 3.

Appendices 8 and 9 show monitoring maps for the Westland and B-Driehoek area respectively. The colour key is simple as green represents a decrease of the area covered by greenhouses, yellow indicates no change between 1989 and 1993, and red reveals increases. The image at the background is a colour composite of one of the used Landsat TM images of May 11, 1993 with bands 4, 5 and 3 in red, green and blue respectively. In order to derive the monitoring information a post-classification comparison has been used.