CONTEXT SENSITIVE TRANSFORMATION OF GEOGRAPHIC INFORMATION

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Cover figure: Aspects of semantic uncertainty in a multiuser context

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ABSTRACT

This research is concerned with theoretical and methodological aspects of geographic information transformation between different user contexts. In this dissertation I present theories and methodological approaches that enable a context sensititve use and reuse of geographic data in geographic information systems.

A primary motive for the reported research is that the patrons interested in answering environmental questions have increased in number and been diversified during the last 10-15 years. The interest from international, national and regional authorities together with multinational and national corporations embrace a range of spatial and temporal scales from global to local, and from many-year/-decade perspectives to real time applications. These differences in spatial and temporal detail will be expressed as rather different questions towards existing data. It is expected that geographic information systems will be able to integrate a large number of diverse data to answer current and future geographic questions and support spatial decision processes. However, there are still important deficiencies in contemporary theories and methods for geographic information integration

Literature studies and preliminary experiments suggested that any transformation between different users' contexts would change either the thematic, spatial or temporal detail, and the result would include some amount of semantic uncertainty. Consequently, the reported experiments are separated into studies of change in either spatial or thematic detail. The scope concerned with thematic detatil searched for approaches to represent indiscernibility between categories, and the scope concerned with spatial detail studied semantic effects caused by changing spatial granularity.

The findings make several contributions to the current knowledge about transforming geographic information between users' contexts. When changing the categorical resolution of a geographic dataset, it is possible to represent cases of indiscernibility using novel methods of rough classification described in the thesis. The use of rough classification methods together with manual landscape interpretations made it possible to evaluate semantic uncertainty in geographic data. Such evaluations of spatially aggregated geographic data sets show both predictable and non-predictable effects. and these effects may vary for different environmental variables.

Development of methods that integrate crisp, fuzzy and rough data enables spatial decision support systems to consider various aspects of semantic uncertainty. By explicitly representing crisp, fuzzy and rough relations between datasets, a deeper semantic meaning is given to geographic databasses. The explicit representation of semantic relations is called a Geographic Concept Topology and is held as a viable tool for context transformation and full integration of geographic datasets.

Key words:Geographic information, geographic context, semantic models, conceptual models, interoperability, uncertainty, scale, classification , rough sets, fuzzy sets, decision support, uncertainty

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Chapter

1 FRAMEWORK AND OBJECTIVES

Our truth is the intersection of independent lies.
RICHARD LEVINS

Introduction

Current decision making with an expanding amount of information to take into consideration calls for an effective information service. The development of computer technology has implied considerable changes of work routines as well as an improved efficiency in a number of sectors. Computerized systems have the ability to handle large sets of information, which could assist the mental, human parts in completing the decision process. Future systems for decision support are expected to give quick overviews and extract necessary information based on questions, available facts and other considerations given. This would give the opportunity to concentrate the human resources on the overall visions and decisions.

A computerized treatment of geographic datasets is today made possible through commercial Geographic Information System-packages. The use of these software is however hampered by lack of information on data quality, the functions and processes included in the data and relations between the data. Variations in temporal and spatial scale are another major bottleneck when trying to integrate different data in a Geographic Information System.

One of the reasons why all these obstacles emerge when using a Geographic Information System is that the potential sources of information are so diverse. Given a certain location we may have to deal with material from a detailed level up towards highly generalized levels of information, each developed for a specific purpose and assembled in different ways. The use of Geographic Information System as a tool to handle all this data has been suggested for some time now.

The theoretical base for how to treat highly diverse data properly in an integrated fashion has not been developed as quickly as the technical tools available. In geography there is no such thing as a single representation of the world that incorporates every possible viewpoint. This is of fundamental importance and must be considered when we organize spatial data for integrated use in a Geographic Information System

From efforts to integrate geographic datasets in analyses from local to global scales, in which generalization constitutes one important process, we may conclude that we still lack a firm theoretical and methodological basis for this process (Wilkinson, 1998; Devogele et al., 1998; Thomlinson et al., 1998; Van Beurden and Douven, 1999). Increasing amounts of available data at increasingly better levels of detail give us theoretically an almost infinite possibility to choose at what spatial, temporal and thematic resolution we perform geographic analysis. This is a fairly recent turn into a data rich situation where each implementation raises some important questions.

The problem outlined above, indicates a substantial gap between geography and contemporary use of geographic information systems. This is used as an outset for this thesis.

Framework

This thesis project was initiated through the Swedish Centre for Geoinformatics as one of seven research foci carried out as PhD-student projects. The original title of this project was "Knowledge based digitisation of thematic maps”. This title wanted to emphasise that map reading is an intellectual process and as such would require a context-sensitive digitisation for further use as information in a Geographic Information System. The main goal of the project was formulated: “…to find a model how to digitise map symbols together with the mapping model so that the context can be exploited in a GIS.” An alternative interpretation of this goal is to look for an inverse to the mapping process in order to achieve more effective reuse of data in different situations.

As a PhD-student I was given relatively free hands to interpret this project focus into a research plan according to my own understanding of the problem. Coming from six years of professional practice within local and regional environmental planning and management, I naturally projected the research question onto these experiences. Together with my supervisor, ass. Prof. Wolter Arnberg, I also developed several contacts with other researchers and one of the more imortant ones has been the involvement in the "Sustainable Landscapes" project.

The Swedish research program Remote Sensing for the Environment (RESE) has highlighted the landscape perspective in the project "Sustainable Landscapes". In landscape studies a major concern is to integrate variables that depict structure and composition as well as operative processes within the landscape. As such the landscape as it is treated by the "Sustainable Landscapes" project seemed to provide a suitable testbed for the development of a conceptual model for geographic information handling. This dissertation may not show any concrete evidence from this collaboration but many of the discussions and work by other members within this group have certainly influenced my work.

Scope

This research is concerned with theoretical and methodological aspects of geographic information transformation between different contexts. My own academic and professional experience has affected this scope in two important ways:

1. Examples and discussions are restricted to certain parts of biology and earth sciences, mainly within the realm of ecological geography and landscape ecology.
2. The research questions are formulated from an application oriented view, emanating from my own experience of current practice in regional and local environmental management.

Thus, worked examples mainly concern information with relevance to managerial issues of nature conservation, such as the local implementation of global conventions on for example biodiversity (UNEP, 1992) and sustainable development (WCED, 1987). Tests uses information from vegetation maps, scalar, ordinal and categorical variables interpreted from maps and aerial images, and continuous data from digital elevation models. Findings are expected to be applicable to situations where any sort of categorization is applied to geographic data.

Objectives

The main goal of this study is to enable a context sensitive use and reuse of geographic data. In other words to make it possible to organize geographical information of different origin in such a way that this information can be used at other levels of scale and detail and in other contexts than those used to assemble the information. To reach this general goal it has been broken down into a handful of objectives toward which focused efforts have been directed:

- To review both theoretical and methodological aspects of integrating geographic data.
- To identify important deficiencies or gaps in contemporary theories and/or methods for geographic data integration.
- To identify approaches that consider geographic context information.
- To suggest a feasible solution to support a context sensitive use of existing geographic data.
- To demonstrate an application of a context sensitive integration of geographic data.

These objectives are to be interpreted within a framework of computerized geographic analysis. An important outset is the current ambition of geographic information science that tries to integrate geography, philosophy, physics and mathematics with the realms of cognitive and sociocultural sciences (Couclelis, 1999). Located within an admittedly complex intersection of separate sciences this work does not try to develop *the* general theory of spatiotemporal phenomena. I do however detail some important means of improving methods for transfer of geographic information between different user contexts.

Approach and thesis structure

The dissertation is divided into several chapters each addressing one or several of the research objectives. The chapter organization intends to lead the reader through a logical order of argumentation and findings.

This first chapter provides an overall introduction to the problem as well as the background for the study. It also intends to define the limits of the presented research and to give a general overview of the thesis.

To address the main goal of this dissertation I recognized early in my preliminary studies the problems that multiple world views will impose on any change of spatial or categorical detail or any effort to translate information from one context into another. These preliminaries are mainly articulated in chapter 2 and 3, which describe some of the problems associated with a computer-assisted analysis of geographic information. Chapter 4 and 5 were also part of the preliminary studies. The suite of chapters from 2 through 5 has been revised later on, and especially chapters 2 and 3 have been continuously updated during the entirety of this project.

Early in my work with this dissertation I also had to formulate an experimental design that was suitable for investigating transformation between different user's contexts. From the preliminary studies it seemed reasonable to assume that any such transformation would either change the thematic, spatial or temporal detail. I consequently decided to perform experiments on data that could isolate effects caused by either change in spatial or thematic detail. The limited amount of previous research on temporal aspects as well as the limitations in time for a dissertation led to a very restricted treatment of this dimension in my studies.

The continued preliminary work included data assemblage and two case studies presented in chapters 4 and 5. The findings from these studies both confirmed that the general experimental design gave interesting results and they also called for a methodology to handle categorical uncertainty. The continued studies therefore followed two parallel trails. One concerned with categorical detatil that searches for approaches to represent indiscernibility between categories, reported in chapter 6, and one concerned with further studies of effects caused by changing spatial detail, reported in chapter 7. Finally, in chapter 8, I pull together the initial discussions from chapters 2 and 3 with some of my experimental results to demonstrate a combination of map algebra with different extensions of set theories to define semantically certain, graded and indiscernible relations between geographic concepts.

Expected scientific contribution

I hold the most important contribution of this dissertation to be the *Geographic Concept Topology* construction. This is theoretically established in chapter 3 and demonstrated in chapter 8. Although still unverified in a wider setting, I claim that this structure enables an explicit representation of semantic relations for geographic concepts. In addition I propose that a Geographic Concept Topology can be used as a primary tool for a context sensitive transformation of geographic information. The Geographic Concept Topology acknowledges that different spatial representations may be used in concert and it is capable of handling important aspects of semantic uncertainty simultaneously. Still, the feasibility of the Geographic Concept Topology framework remains to be tested in a wider practical situation with large amounts of diverse, real data.

Furthermore, the Geographic Concept Topology serves as a first suggestion to formalize the due process and boundary object ideas first proposed by Star (1989) and introduced to the wider geographic decision and planning community by Harvey and Chrisman (1999). These notions are fully explained in chapters 2 and 3 but the actual achievement is the connection with the Geographic Concept Topology construct, as a concrete example of the ideas of "due process" and "boundary objects".

Geographic information science has only recently directed its interest towards the full suite of uncertainty aspects possible in geographic information. Among the least researched parts are uncertainty related to poorly defined objects or concepts, yet these are very common in the geographic discipline (Fisher, 1999). I view the research reported in chapters 6 and 8 as important theoretical foundations for further development of general considerations of imprecision in geographic information.

These findings and the experimental design in chapter 7 enabled the investigation of various aspects of semantic accuracy in a geographic data set. These aspects have only recently been acknowledged and so far a very limited amount of research on appropriate methods for measuring semantic quality aspects of geographic data has been conducted. In chapter 7 I describe a test design that uses manual interpretations at different resolutions. This design makes it possible to detect generalization effects other than purely statistical, and this has recently been acknowledged to be a neglected and problematic part of a quality report for geographic data (Weibel and Dutton, 1999).

Chapter 2

ENVIRONMENTAL MANAGEMENT AND INFORMATION SOURCES

Uncertainty sends the brave on the trail of discovery
and the coward on the route of the herd.
DARTWILL AQUILA, http://www.bentarz.se/me/dartwill.htm

An applied perspective

During the last 10 years or so the concept of spatial decision support systems (SDSS) has evolved to improve the performance of decision makers and managers when they confront semi structured spatial decision problems (Malczewski, 1999, p.277). Still the application of computerized geographical analysis is to many people an overwhelming task. Given a local authority, the department responsible for natural conservation may wish to use the information produced by some other department. Or it may even want to compare a new survey with an older one to identify changes in the vegetation. Besides problems of getting data to match into the geographic information system currently used by the department some profound questions will be articulated sooner or later. At what scale can we use this information? Do we need to perform some kind of generalization on these data? And if so, what generalization method should we use? And how accurate is the result? Some of these questions have been tackled to some extent but sufficient knowledge is still lacking to be able to recommend a standardized set of methods. Notably the issue of reliability or quality has received some well-deserved attention lately. One requirement is of course to minimize the error in the final output, but from an informational viewpoint we also need to make sure that the information is carried through the analysis process without being distorted in terms of the semantic content, the meaning of the data.

In the beginning of the work I came from an applied environment. Following my undergraduate education I was employed by the Åland Landskapsstyrelse, office for regional planning, to develop an environmental database with geographic references. The database was developed using the PC-network based Paradox software with loose coupling to a custom graphics software. The main issues were database design and integration of information from separate offices within the administration. This work gave me a thorough introduction into the problems of information sharing, database development, geographic data types and programming of user interfaces. Also the problems related to homogenization and integration of data from different users became evident to me.

Following this employment I held a substitute position as ecologist within the municipal administration of Järfälla, located just northwest of Stockholm. My main duties were the management of natural areas owned by the municipality and the management of two larger natural reserves. This also included management of the forest resources within the natural areas. I also had responsibility for nature conservation issues within the local planning process. In this I participated in the development of new management plans for the nature reserves as well as a municipality-wide water management plan. Much work was performed using traditional cartographic techniques and it included development of new cartographic products as part of geographic analyses and presentations.

The projects I have been involved in often required the production of a map of some kind depicting a situation of interest. One report wanted to define and delineate ecologically sensitive areas; another report included suggested areas for water conservation and protection purposes. Each report reflected a specific purpose and a specific question.

The title of this PhD project was in the beginning "knowledge based digitization of geographical information". The idea was to see if maps and other existing data could be digitized into a computer using the knowledge of skilled experts to enrich the database with some 'extra' information that made it possible to access these data for other purposes, to answer new questions than those used at the time of collecting this information.

I started out to try to compare my own exam-work from my undergraduate studies, a vegetation map (Ahlqvist and Wiborn, 1992), with another vegetation map collected over the same area 15 years earlier (Edberg, 1971). I found not only geometrical deviations, but also a large difference in classification systems, which specifically caught my attention. Could these two maps ever be used to answer the question if the vegetation had changed during this period? This question turned out to be a very researchable one, and the work with this dissertation finally landed in a study of translating the classification system of the new map into the old map producing two semantically similar maps (chapter 8). How similar they are is still a question, but the general idea to convert information from one context background into another has wide applications.

This and the next chapter will outline some general factors influencing the process of transforming geographic phenomena, or things "out there", into computer representations. First of all I will treat the issue of how models of the real world may be constructed as a way to describe and understand the world that surrounds us. This review of previous research will almost immediately acknowledge the second factor, which is the importance of the user context or the purpose behind the construction of a certain model. The third factor, the mode of observation acts as a kind of mediator between the other two. The mode of observation articulates the observational detail or granularity, which is directly related to the detail of the knowledge, and it also includes aspects of uncertainty in the observation. This outline parallels work by Couclelis (1996) who sketched a similar division between factors that are in part responsible for how we choose to create a computer representation of a geographic entity. Toward the end of chapter 3 the discussion has both summarized previous research as well as the findings in this dissertation. At that point the requirements for a context sensitive transformation of imprecise geographical data have been articulated together with some suggested solutions to these requirements. This is then finally brought into the proposed Geographical Concept Topology framework capable of supporting a context sensitive use and reuse of existing geographic data

Models of the real world

How to understand the real world has been an issue ever since the development of life on earth but from a shorter history-of-science perspective it seems to be a matter of "faith". When scientists try to make models of the real world they have different 'models' or perceptions of the real world, different 'world views'. At a very broad level Johnston (1999) list three types of science models, or "faiths" – empirical, hermeneutic and critical – that may be separated into a multitude of separate approaches with their own detailed exemplars, paradigm instances of how science should be done.

The simplified illustration in Figure 1 is an attempt to illustrate the relation between the real world, our perception of this as perceived reality, and the specification that ultimately leads to a data representation of the real world. From the geographic literature it could be assumed that 'perceived reality' or 'abstract view of the universe' (Salgé, 1995, David et al. 1996, Mark and Frank, 1996) is formed through some kind of understanding or modeling within the human mind. Also, a separation can be distinguished between a) a perceived reality which is inherently virtual, represented by human knowledge structures and b) a conceptual and logical specification which can be used to collect data into a database and which is somehow a subset of the perceived reality. The perceived reality might also be termed 'world view'. Since certain parts of every individual worldview are shared - both cognitive and bodily - with other individuals, some authors suggest that this overlap might be synthesized into a 'shared world' (Gould, 1994). This notion corresponds with the idea of experiential realism discussed by Mark and Frank (1996) that is based on a real world (shared world) that people share mental experiences within.

To start with the question of "what exists?" there is a problematic and old philosophical controversy between "plenum" and "atomic" ontologies (Couclelis, 1992; Couclelis, 1999). Is the world made up by discrete objects (atomic) or is it a continuum of named attributes (plenum)? Ontology is the branch of metaphysics that deals with the nature of being. The term has during the last five years or so been used in the geographic

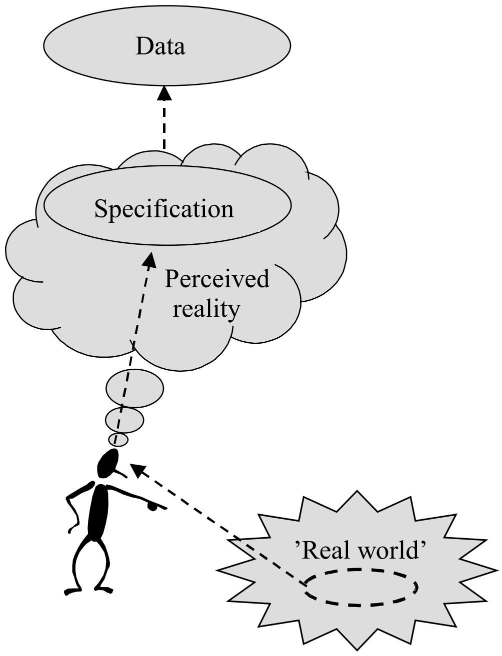


Figure 1 The abstraction process from perception of real world phenomena as entities in the perceived reality through a specification to an object representation in a database.

information science literature where its meaning ranges from the metaphysical science of being, to the more computer scientific view that ontology is a formalization of how to represent objects and concepts and their interrelations within an area of interest. These different interpretations led Smith (1998) to make a terminological distinction between R-ontology (referent) and E-ontology (epistemological). R-ontology refers to a theory about how a given referent-domain is structured, what sorts of entities it contains, relations and so on. This relates mostly to the short introduction above. E-ontology on the other hand is a theory about how a given individual or group or language or science conceptualizes a given domain. It follows from that definition that there are as many proper E-ontologies as there are conceptualizations, and it is this type of ontology that will be dealt with in this dissertation.

So, how does ontology take us any further? The experiential or cognitive perspective advocated by Mark and Frank (1996) suggests that humans deal with categories in a way that depart in a few fundamental ways from the traditional set-theoretic view that until recently has been the dominating idea for a formalized treatment of geographic information. I have no intention to go deeper into the philosophical or psychological sciences and theories of knowledge (epistemology). I will instead follow one of Pawlak's (1991) propositions and hold knowledge as being deep seated in the abilities of human beings and other species to classify anything; (apparently) real things, states, processes, moments of time and all other more or less abstract concepts we can think of. By this definition, knowledge is necessarily connected with the classification patterns related to specific parts of the real or abstract world and seen from the opposite direction classification is one of the fundamental tools of science (Mark, 1993). Knowledge thus consists of a family of classification patterns (conceptualizations or E-ontologies) of a domain of interest, which provide explicit facts about reality – together with a reasoning capacity able to deliver implicit facts derivable from explicit knowledge (Sowa, 1999). By a classification or conceptualization I mean any subdivision or partition of a real or abstract world using concepts and it is assumed from here on that classification is used to create categories which are also assumed to be basic "building blocks" of knowledge.

The terms 'category', 'class' and 'concept' are held synonymous although the common use of 'class' within computer implementations make this term ambiguous for this discussion and is the reason for me to prefer 'category' or 'concept' in this treatise. The term 'entity' refers to instances of concepts in the real world and as a consequence of Figure 1 that will be instances of concepts in the perceived reality. The related term 'object' refer to the digital representation of the entity and is therefore relevant to the specification and data in Figure 1. Entities and objects may also be termed grains and the term granularity is thus related to the resolution of the information. Unfortunately the term resolution is already associated with specific meanings for both spatial and temporal measurements (Veregin, 1999). I prefer here to use granularity as a more generic term in the sense that information contain grains such as classes, pixels and time units, that are limited in their spatial, temporal and categorical extent. Thus the granularity imposes restrictions on the possibilities to discern between entity/object elements within a grain.

The full process of creating a model of reality from the real world through human perception to a computer representation will be readdressed at the end of this chapter. For now it suffice to conclude that real world perceptions are inherently complex but seem to be possible to divide into building blocks that we call categories. Through E-ontology these categories may be defined and given significance and hopefully further organized in the framework of a geographical decision support system. Dealing with the where, when, and why of the real world, geography has developed some workable theories and methods to be able to conduct study and analysis of real world phenomena. It is impossible here to provide a full review of current methods or theories. In the following section I will simply elaborate on the notion of real world models in geography and the traditional use of a cartographic language to express geographical knowledge.

Real world models and Geography

Models of the real world have within geography a tradition of being space-time centered where descriptions of space seem to have dominated until work by Newton in the seventeenth century made it possible to treat time in a similar manner (Couclelis, 1999). The 'object' or 'plenum' views lead either to a world view focused on objects or on fields (Couclelis, 1992) which in turn may suggest a scale dependency of geographic space into for example small scale and large scale space (Mark and Frank, 1996). It is also commonly noticed that a separation can be made between true objects and humanly constructed objects, for example fiat vs. bona-fide objects (Smith 1995), non-geographic vs. geographic entities (Nunes, 1991). As a contrast one can also argue for a psychological definition of space where scale is defined not by the actual or apparent absolute size but on the basis of the projective size of the space in relation to the human body (Montello 1993). In this case a room in a house and the surface of the earth as seen from an airplane would belong to the same psychological space domain as they can both be apprehended from the same position. The lack of consensus on this issue indicates that we probably have to deal with some combination of these notions (Peuquet, 1988). The plenum and atomic (Couclelis, 1982) 'space paradigms' are probably at work in parallel in our way to use our own 'external models' of reality. The traditional map actually supports some of these ideas as it uses small-scale space to represent a large-scale space, extending the well known Euclidean geometry of everyday objects into a geographic space of realms and regions (Montello 1993) and geographic information systems have theoretically the ability to incorporate both plenum and atomic views represented as rasters (fields) and vectors (objects) respectively.

Geographical information includes indiscreet values, inaccurate attribute definitions as well as variations in temporal and spatial scale. Traditionally geography has been communicated through maps but also through texts and images. The latter becomes evident whenever visiting a geography library where books constitute a significant part of the information volume. During the last few decades increased use and availability of remotely sensed data has added a variety of new information sources for geographic analyses, for example aerial photographs, satellite images and radar data. Despite the fact that remote sensing devices provide an increasing amount of geographic information, I still regard the map as one of the most important sources of documented spatial information. It is also a well-refined model of communicating the atomic view of the real world. In addition, the fact that maps in many cases are the only available historical spatial record, the set of existing maps is an invaluable source for environmental information. Considerable amounts of geographical data collected in textual form with some sort of geocoding inherent, together with numerous inventories that have been carried out during the past few decades also form an extensive source, however mostly textual, for information on the environment (Frank and Mark, 1991).

Communication through a 'map-interface', which usually consists of a set of symbols, colors, text, is adapted to and designed for human-to-human communication. This communication process includes at least two steps where human interpretation is involved: first the real world is interpreted by the cartographer who produces a map using sets of well-known semantics and abstractions, then the user reads the map and tries to extract the necessary realism from the abstractions in the map. The map metaphor has been described and also further developed by several authors, among which Christopher Board and Arthur Robinson have made substantial contributions (MacEachren, 1995).

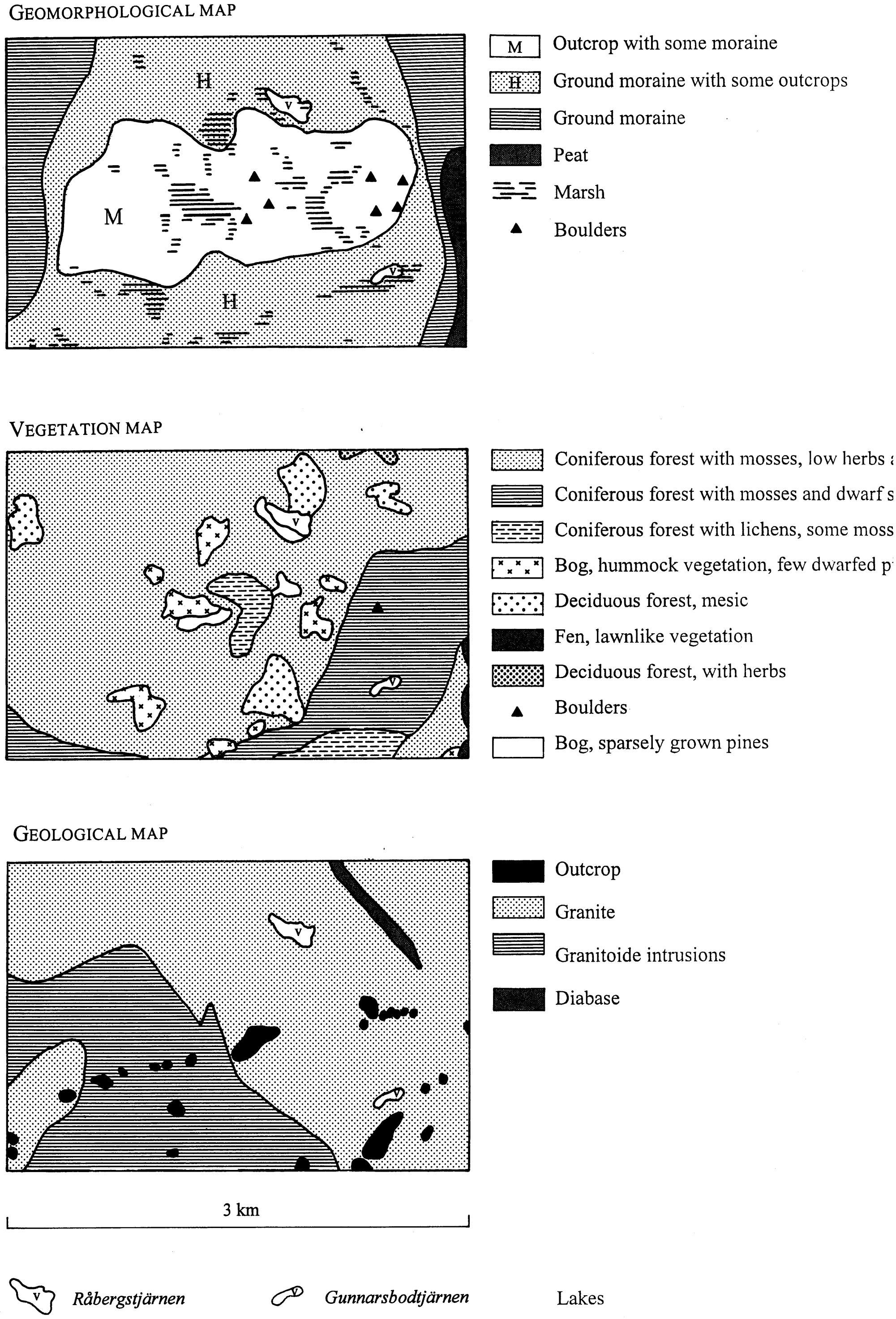


Figure 2 Three different thematic maps covering the same area compiled in 1:50 000 scale. The legends cover some common features among which the boulder concept is discussed in the text. (From Lind 1997)

The form a representation of geographic phenomena takes on a map or other display cannot be divorced from its purpose and the requirements of the society in which the visual language gains currency (Gombricht, 1977). This is essentially an expression of underlying faith, the hermeneutic science metaphor (Johnston, 1999) or the socio-cultural perspective on time and space (Couclelis, 1999). Still, we cannot ignore the fact that each spatial entity has been identified for a specific purpose and that the way this entity is visually represented on the map can be different according to the cultural preferences of the cartographer or the intended audience.

The examples in Figure 2 show the same geographic region as three different thematic maps compiled at1:50 000 scale portray it, and where some common features are shown.

Although the maps have been compiled in the same cultural setting and with mapmakers from the natural science disciplines, the representation of 'boulder' in Figure 2 within the mapped area differs from 0 to 7 symbol instances. The symbols should be interpreted as an indication of actual place for the feature and to some extent the areal coverage or frequency.

Some of the differences in Figure 2 might be held as interpretation inaccuracy during map compilation, but when we are given information on the purpose of each map the differences become understandable: For vegetation mapping the presence of boulders can be a significant character of the vegetation type and control the variation of the vegetation within one given class unit. The signs are to be taken as a secondary label indicating the presence of boulders within the area and the location should not be expected to be of high spatial accuracy. To a geomorphology map, boulders are of vital importance to the interpretation of the landforms and their genesis. In this map we can therefore expect a higher amount of boulder signs and relatively high spatial accuracy in their location. The geology map finally does use boulder signs, but we would expect them to appear only when the boulders are used as an indicator of actual bedrock.

So, we see that maps can serve a multitude of purposes. Important for this work is that maps can be considered as spatial representations of real world features which can in turn stimulate other spatial representations and all such representations are acts of knowledge-construction (MacEachren 1995). No matter how far this process is driven, the geometric representation of a feature on a map will always be a generalized abstraction of its current form and status (Livingstone and Raper 1994). The map as a representational model to communicate something of the nature of the real world is only able to deliver a fraction of the total amount of information present in the real world. So, we are either forced, or we deliberately choose to use different levels of detail in our representation of the features of interest. The example in Figure 3 taken from Board (1967) illustrates how representations of spatial features can be seen as organized along a gradient from an infinite reality to an ultimate ideal abstraction. It also indicates that relative abstraction levels can be identified as a function of two important components: dimensional scale and degree of complexity. Along this abstraction gradient we trade faithful complexity with distorted understanding (Board 1967). It is apparent that by chosing a certain level of abstraction a certain amount of detail gets lost. Still manual map reading may gain some of the lost detail through inference.

Given some knowledge of the purpose of an information collection, a knowledge based reasoning on the information value of each map element reveals more than can be read only be coupling the map legend to a concept definition. This is a kind of 'back-tracking' of the map-making processes by using some knowledge about the context in which the map features were assembled. The meaning of 'context' may vary among people but I intend to embrace a wide meaning of the term and define *geographic context* as the historical, social, physical, and disciplinary domain where geographic abstractions are formed. The geographic entities we try to describe such as those mentioned in the examples above own three special characteristics responsible for the shortcomings of current representational techniques according to Peuquet et al. (1995).

- The data volume needed to adequately represent geographic entities can be very large.
- Spatial relationships between geographic entities tend to be imprecise and application-specific, and the number of possible spatial interrelationships very large.
- The definitions of geographic objects tend to be inexact and context-dependent.

As if the volumes of data and complex relations were not enough, two of these three statements include formulations such as 'application-specific' and 'context-dependent', which illustrates the complex nature of geographic representations. In fact, that there can never be a single uniform representation of the geographic world is well known to geographers. The two latter statements also talk about imprecise relationships and inexact definitions, which will be subject for further elaboration in following sections about accuracy and knowledge representation.

To summarize, communication of geography through maps is traditionally a manual task that is now turning increasingly automated and information intensive. Nonetheless, any qualitative or quantitative spatial analysis need to

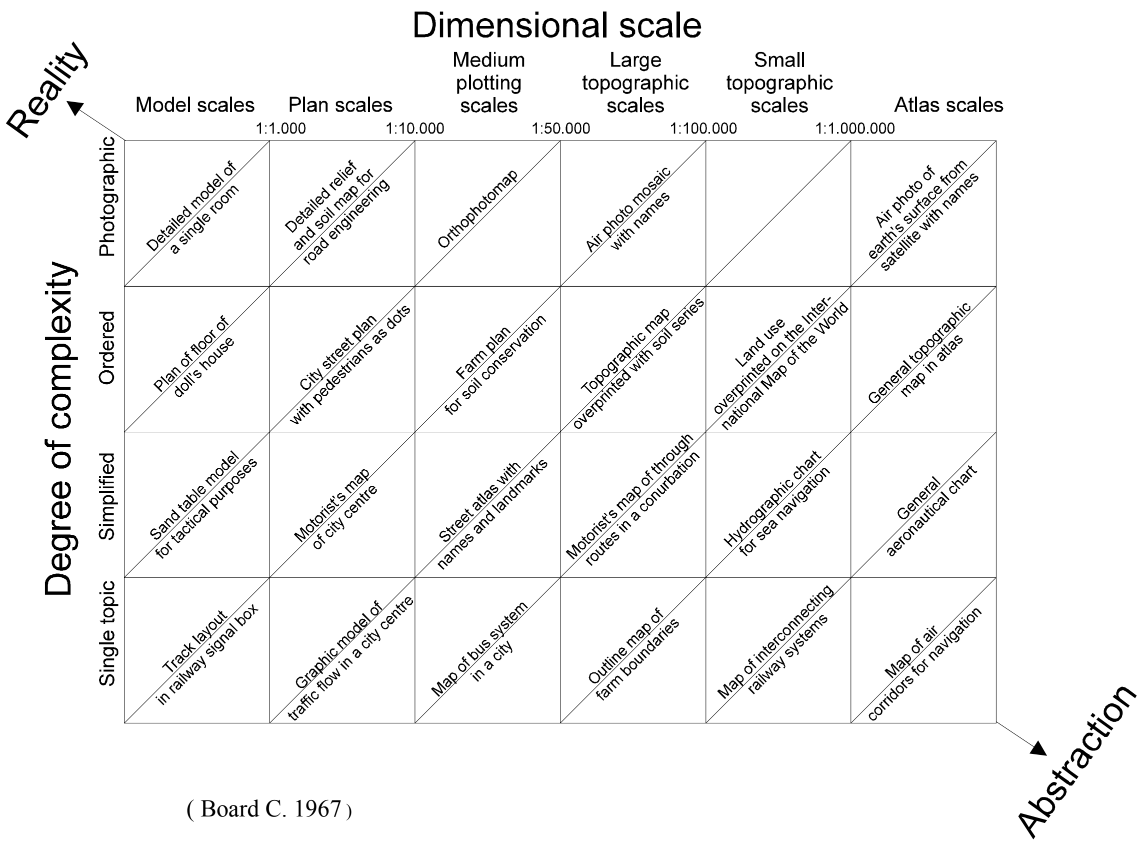


Figure 3 The gradient between reality and abstraction indicating examples of types of maps at their appropriate level of abstraction (after Board 1967)

consider that every representation of geographical features, be it on a map or in a digital database, is an abstraction of the reality, and as such they have been generalized for some specific purpose, therefore depending on the geographic context.

Real world models and geographic information systems

Apart from highlighting the context dependent nature of all geographic information, the map example in the previous section also shows how the cartographic language has been used to exploit the human ability to understand a situation by simultaneously overview a large area and pick up details. In Figure 2 a general pattern is given as colored areas and important details are given as symbols. Boulders would not really be visible in the given scale, but by using symbols one can indicate the presence and approximate location of these phenomena. It also makes sense to the map-reader, as it is possible to extrapolate cognitively the ‘boulders’ from the given location of the representation. This possibility of using a combination of detail and generalizations is not readily implemented in current geographic information systems but it might be possible to do, given that we can develop enhanced possibilities to express geographical meaning for entities in a geographical database.

In a geographic information system the visualization and the storage of data are separate. Possibilities to change scale by zooming in and out, reclassify data, create great opportunities for geographical analysis. In a geographic information system we are theoretically not constrained anymore by a paper map sheet with finite size and depth. ‘The map’ may instead be used as an abstract algebra paradigm (Tomlin, 1990) where the map elements are handled in a GIS toolbox to perform spatial analysis. The map itself will become a process as the on-screen map will play a key role as an interface to data in future GIS use (Kraak, 1995) GIS map-use is therefore two-way oriented in a way that include a large amount of user interaction with the data. In the light of the previous discussion on map communication and multiple world-views, the user-producer dialogue in a GIS makes it even more important that communication can be carried out within the ‘shared world’ of the user and the producer. On the downside, there is at least one serious concern that must be dealt with. There is no guarantee that the displayed information will appear in the same way as in the source material. The previous map example illustrated that many map features have a symbolic meaning, and these features have been designed for use with other map features in the scale and extent set by the paper map. This suggests that a straightforward transfer, that is digitization, of map features into digital format is a difficult task. A further aggravation is that the GIS user interface tends to mask the different origins of data, thereby leaving the user unaware of inherent limitations in the information. Even if the user should be aware of this problem it is not always possible to trace the origin and the limitations of the data stored in a GIS database. Nevertheless, digitized map data is widely used in geographic information systems.

Any attempts to use GIS to integrate data from environmental databases and to use models or analytical tools upon data need a full understanding of the origin and context of each data set used. Thus taking data using several different conceptualizations from different contexts the GIS integration process relies upon a transformation of this information into the desired conceptualization and current context. The issue of finding automated methods for that kind of GIS integration has been the focus of much work. Recently the above described integration process has been put into a comprehensive framework of interoperability of geographic information systems (see for example collections edited by Vckovski, 1998 and Goodchild et al. 1999). Interoperability has earlier been understood as a capability to transfer data from one computer system to another. It is only recently, and at a more general level, that the term has found its way to the wider geographic information science community. At the general levels of geographic information systems and applications, interoperability is concerned with the establishment of a smooth interface between multiple information sources (Harvey, 1999). At the GIS level, problems of interoperability can be created by different geometric syntactic representations, difference in class hierarchies, and different semantics (Bishr, 1998). Since different applications have different worldviews and semantics, interoperability at the application level is essentially a semantic problem (Bishr et al., 1999)

The discussion so far has elaborated on the fact that geographical data is subjected to major influences from various individual conceptualizations of the same reality. Furthermore I have argued that a geographic information system theoretically has the ability to do spatial analysis of integrated geographical data. Still there are apparently some fundamental aspects of context and semantics that need to be resolved. I now intend to resume the initial discussion on models of the real world in the context of modeling a computer representation of the real word and how the geographic context can be represented in this model.

Existing models in use

The individual worldview and the shared world concepts correspond to the external and conceptual models in the ANSI-SPARC definition, which has been used as a general framework for designing geographic information systems (Laurini and Thompson 1992, p.357). An overview of this model framework is given in Figure 4. The external models are defined by the potential user and their purposes and needs, the conceptual (or semantic) level is concerned with a synthesis of all external models, the logical level is a high-level description which is mathematically based and computing oriented and the internal level is concerned with the byte-level data structure of the database (Laurini and Thompson 1992, p.357f.)

Somewhere along this chain of model levels the supposedly chaotic real world is somehow systematized and made discrete for the purpose of digital handling. Apparently this step will have to be taken at a high level. The bridge between a concept/semantic model and a logical model is easier to create if a more formal mechanism is used at the conceptual level rather than narrative statements. However, the conceptual level will still need to hold both the deeper semantic notions of external models as well as synthesized concepts, which easily translate into logical level models. Clearly, the separation of models into a few levels does not solve this problem, but a short description from this more data modeling oriented viewpoint seems appropriate. Also, by explicitly identifying a semantic level in the data model stresses the importance of the actual meaning of data. I will return to this issue from many aspects since it is central for this thesis.

Proposed semantic level models

Seen from a GIS integration viewpoint the focus up until around 1995 was mainly on systems, data and to some extent information (Sheth, 1999).

Work on semantic or conceptual models for geographic information focusing on information and knowledge has received a significant amount of attention only in the past five or six years (Livingstone and Raper, 1994; Peuquet, 1994; Ruas and Lagrange, 1995; David et al., 1996; Usery, 1996). David et al. (1996) reported on early work to develop conceptual models for geometry within the European Committee on standards (CEN/TC287) and suggested that the main bottleneck in geographic information handling is the understanding of the semantic level and the way entity meaning affects the modeling of entity interactions over varying spatial and temporal scales.

Ruas and Lagrange (1995) outlined one possible logical model connecting the semantic models with the physical models. From their perspective of generalization, this should be seen as a process allowing us to perform a change in the perception level of geographic data. They also stated that the first generalization stage is the transition from one initial data schema to one corresponding at another level of perception. According to this the actual generalization decisions are made at the semantic level and further operations need 'only' be carried out on a rule base at the logical and physical levels. The issue of generalization is readdressed in the sections about spatial and categorical granularity in chapter 3.

Another relatively early idea proposed by Peuquet (1988; 1994) incorporates concepts from perceptual psychology and advocate a "triad" representation of spatiotemporal data in the later publication. It builds on the idea that the three "views", time based, location based and object based, all provide different aspects of the data and thus each facilitates a specific kind of query. The integration of these three views would enable for example objects to be explained by the spatial view and conversely spatial patterns to be matched against object based knowledge. The "triad"- view (Peuquet, 1994) is based on a dual framework of object- location integration (Peuquet, 1988) and the incorporation of time into this framework is still under investigation (Peuquet, 1999). This kind of simultaneous representation of multiple views of the same fact seem as a theoretically sound concept, and the following few paragraphs will show that much research verify the difficulty to find one common level of understanding. Instead it seems as if a

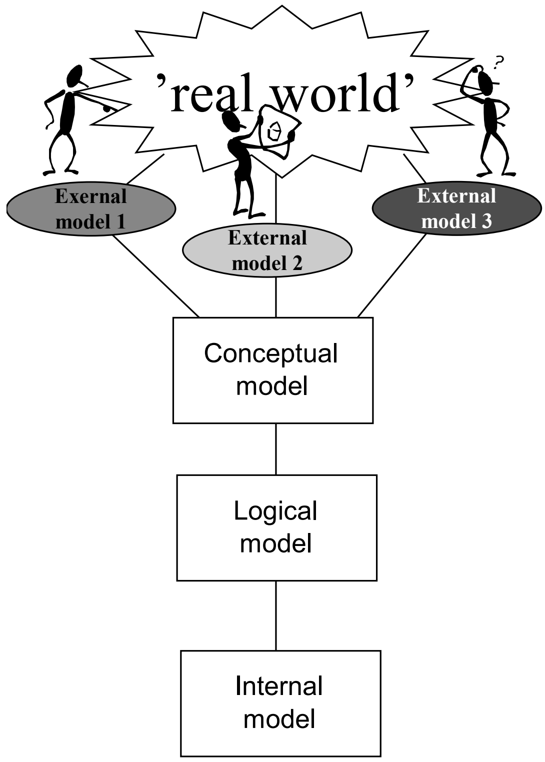


Figure 4 The four information modelling levels; external, conceptual, logical and internal, according to the ANSI-SPARC design methodology (After Laurini and Thompson 1992)

description of common and diverging points of reference are the most feasible way to give geographic entities more meaningful representations. In chapter 8 I argue that the integration of fuzzy, rough and crisp representations is a feasible implementation of the dual framework proposed by Peuquet (1988).

Usery (1996a, b) developed a feature based conceptual model along the same line of thought as Peuquet. Using an entity based view of geographic phenomena this model explicitly represents spatial, temporal and thematic attributes which can be directly accessed. A fuzzy set implementation of geographic features is proposed as a solution to capture some of the ambiguity inherent in features based on human perception and cognition (Usery, 1996b). The use of fuzzy set representation is a notable exception from the other proposed frameworks presented in this short review. Although this model seems very promising it remains to be tested. Also, to some extent noted by Usery, the mechanism for comparing multiple views of the same geographic feature has not been identified.

Livingstone and Raper (1994) argued for a semantic model where the entities should define the space they occupy and also guide the appropriate spatiotemporal representation. This view follow that of Nunes (1991) who claimed that the debate on concepts of space, shortly referred to earlier, show that no further specification of geographic space is possible unless the geographic objects can be defined. A semantic model theory developed form this viewpoint needs to be defined at a higher level of abstraction than the spatial and temporal models used to represent the phenomenon (Livingstone and Raper 1994). It has been argued that this would provide the necessary link between a GIS application, external process models and used spatial databases, and that an object-oriented approach using environmental metaclasses provide the means to perform co-ordination between different "world views" of the same "real world" entity (Livingstone and Raper, 1994; Raper and Livingstone, 1995). A metaclass is in object oriented wording an assemblage of data classes or model classes, it works independently from the subordinate data or model classes, at the logical model level, and it is concerned with the behavior and relationships of the class categories and available morphisms between the classes. One main problem with this construct seems to be that since a metaclass determine what objects it will be possible to represent one need to explicitly define at a metaclass level the attributes and methods of all current and future objects.

Recent work by Bishr (1998) and Bishr et al. (1999) have provided a useful formalized, approach for semantic modeling. Bishr in his thesis (1997) proposed a general framework for semantic translators capable of mapping between spatial database schemas while preserving their semantics. The main tool to connect semantically similar objects is in his framework based on common ontologies, essentially a standardized vocabulary for various domains of interest. Gahegan (1999) basically propose the same idea and both authors hold the use of interchange format (the term proxy context in Bishr's work) as a mediator to transform data from one information context to another. Gahegan also conclude that such a framework including categorization and transformation can achieve communication of meaning. However, Kuhn (1999), although involved in the work by Bishr et al. (1999), points out that existing approaches to semantic modeling such as semantic networks and first order logic are too limited for a rich and deep description of semantic meaning. That motivated him to suggest a connection between semantic nets and algebra that combines the best of these two worlds, a direction proposed as early as 1984 by Andrew Frank (Kuhn, 1999). One of the main achievements by this approach would be the possibility to provide links between two different semantic networks.

Semantic model integration

The original issue of modeling the real world has now turned into an even more challenging one of integrating different worldviews. In the above discussion several ideas based upon definition of common ontologies (Bishr et al., 1999; Gahegan, 1999) or metaclasses (Raper and Livingstone, 1995) were put forward. Such work will ultimately become a matter of getting groups of people together to negotiate their disagreements and consequently the issue of real world integration turns into what has been formalized as part of the sociology of science theory as Group or Organizational Decision Support Systems (King and Star, 1990). Bishr et al. (1999) uses the term "geospatial information community" to mean a group of spatial data producers and users who share an ontology of real-world phenomena. However, King and Star (1990) takes a broader stance, uses a social metaphor rather than a psychological one, as in e.g. Smith and Mark (1998), and address the entire decision making process in which "due process" and the construction of "boundary objects" is of particular importance (Star, 1989). Due process can be explained as groups and organizations constant struggle to recognize, gather and weigh evidence from heterogeneous conflicting sources (King and Star, 1990). Boundary objects is a structure for coordinating distributed work that not only involves heterogeneous actors, elements, and goals but also incorporates different research methods, values, and languages. A boundary object both supplies common points of reference *as well as differences* to enhance participant understanding of what world views other participants hold, and why they hold them. This theory has recently been brought into the geographic information science by Harvey (1997) and further discussed by Harvey and Chrisman (1998), Chrisman (1999) and Harvey (1999). It seems from their examples of wetlands mappings in the United States and the ATKIS standard database model in Germany that a definition of common ontologies and schema integration can at best reach some kind of associations and partial matching. Again this can hardly be represented by approaches based on binary relations but it can be constructively moved further if viewed from the ideas of due process and boundary objects. Vague, inconsistent, ambiguous and illogical information open the domain for concept negotiation, and there is enough proof that these situations are successfully handled within for example organizational decision processes (King and Star, 1990). Several types of boundary objects have been identified and King and Star (1990) list four such types; repositories, ideal types, coincident boundaries, and standardized forms. Repositories are "piles" of objects that are indexed in a standardized form such as a library or a museum. Ideal type or platonic object may be fairly vague but a good enough abstraction from all included domains of participants such as an atlas or a diagram. Coincident boundaries are terrain objects that have the same boundaries but different internal contents such as the delineation of the counties within Sweden. The last type of boundary objects, standardized forms or labels, are methods of common communication such as the standardized form used by the national forest inventory described in chapter 4. It is argued that boundary objects may serve as a mediator in negotiations around which similarities and differences can be articulated (King and Star, 1990; Harvey and Chrisman, 1998). If it turns out possible to formalize the idea of boundary objects into something that explicitly can represent commonalities as well as differences this would hopefully serve as a better means to represent geographical meaning in a geographic information system. A similar line of thought although never formalized in this way was proposed by Nyerges (1991a) for geographic data integration based on concept meaning and the full implication of these ideas will be more clear by the end of the next chapter.

To summarize; a geographic information model need to capture the vital components of geographic information. A host of authors conform in the outline of which the basic characteristics are that makes up geographic information. (Sinton, 1975; Peuquet 1994, Albrecht 1996, Gahegan, 1999) For example Albrecht (1996) state that in order to fully characterize geographic information it is necessary to simultaneously capture the basic spatiotemporal, thematic and topological aspects of the geographic entities and phenomena. Time, space (3D), theme, and their inter-/intraconnections thus can be viewed as a basic set of rather abstract properties that need to be described. How these characteristics should be modeled have been the focus for much research and development and it is only lately with increased demand for interoperability and data integration that the issue of meaning of the entity itself has gained focus.

Thus, in the next chapter I will start by examining the space, theme and time components separately. First of all though, I address in general the quality question, which in any use of data is an important concern. Quality issues include aspects of detail and accuracy and these have also become central in my thesis.

Chapter

3 DETAIL IN GEOGRAPHIC INFORMATION MODELS

Human knowledge is a process of approximation. In the focus of experience, there is comparative clarity. But the discrimination of this clarity leads into the penumbral background. There are always questions left over. The problem is to discriminate exactly what we know vaguely.
ALFRED NORTH WHITEHEAD, *Essays in Science and Philosophy*

In the previous chapter I concluded that aspects of time, space (3D), theme, and their inter-/intraconnections can be viewed as a basic set of rather abstract properties that need to be described to fully characterize geographic information. As a first step in the experimental design I decided to investigate these aspects separately in order to isolate and identify important deficiencies or gaps in theory and/or methods for geographic data integration. This chapter will treat the issue of detail and changing detail in space and theme.

As a preliminary I will go through some definitions pertaining to quality assessment and discuss their relevance to this dissertation. This is followed by an examination of spatial, temporal and thematic properties of geographic objects, reviewing other research efforts in the context of the work presented in this dissertation. By the end of this chapter I pull together most of the discussion and the findings reported further on in this dissertation in a discussion on a proposed solution to provide context information with geographic data. The proposed semantic model framework is labeled Geographic Context Topology, GeCoTope, and the work in chapter 8 demonstrates a partial implementation of this framework.

Quality – Detail, Granularity, Accuracy, Fitness-for-use and Uncertainty

During the last 20-30 years some well needed research efforts have been made to understand aspects of error and quality control in geographic data. Also, work to systematically define and standardize aspects of geographic data quality has been published (Guptill and Morrison, 1995).

Some attempts have been directed towards creating a common typology of quality. The two examples below both suggest a general typology for data quality or 'goodness' measures. Although they represent quite different fields of research they agree in much, and both works outline a separation between measurable and non-measurable aspects of quality.

Veregin (1999) in a recent treatment of the quality issue implicitly outlines a two dimensional matrix of geographic data quality components. Like any geographical phenomenon description, quality aspects may be divided into *spatial*, *temporal* and *thematic* components (Sinton, 1978; Veregin, 1999). Each one of these dimensions includes aspects of *accuracy*, *resolution*, *consistency* and *completeness*. So, we have for example an aspect of spatial resolution in a dataset, an aspect of thematic consistency etc Table 1. Interestingly, another and somewhat similar typology from the field of Modeling and Simulation (M&S) can be found in Meyer's (1998) definition of 'goodness' measures. In his definitions *(level of) Detail* is a measure of the completeness/complexity of a model with respect to the observable characteristics and behaviors of phenomena that the model represents. *(level of) Accuracy* is a measure of the exactness of a

Table 1 Data quality components

	Accuracy	Granularity	Consistency	Completness
Space	Spatial accuracy	Spatial granularity	Spatial consistency	Spatial completeness
Time	Temporal accuracy	Temporal graunlarity	Temporal consistency	Temporal completeness
Theme	Categorical accuracy	Categorical granularity	Categorical consistency	Categorical completeness

model's details with respect to the observable characteristics and behaviors of phenomena that the model represents. *(level of) Fidelity* is a measure of the agreement of a simulation with respect to perceived (i.e. within a specific context) reality. *(level of) Resolution* is a measure of the minimum degree to which accuracy and/or detail must coincide with the fidelity of the simulation. Accuracy and detail are relevant primarily in relation to models. Fidelity and resolution are appropriate to use in a simulation context. Meyer's terms *fidelity* and *resolution* are not directly related to any of the four aspects listed by Veregin, instead they are embraced by a broader quality term 'fitness for use'. These quality aspects have received very little attention from a geographic information science perspective. This may be due to the fact that they are hard for anyone but the data consumer to evaluate. Notably, both authors agree that fidelity, resolution or fitness-for-use are extremely hard to quantify, as they have almost no context-free meaning. This is probably already about to change with continued development of for example applied environmental models (Goodchild et al., 1993; 1996a; 1996b) but also as a result of designing an infrastructure that enables semantic interoperability (Harvey, 1999). In any case, following the argumentation of Meyer (1998), a necessary foundation for any such evaluation is that the aspects of detail and accuracy first can be properly measured.

So, if we turn to the quality measures that seem possible to quantify; detail/resolution and accuracy, we may note that Veregin's definition of resolution correspond with Meyer's definition of detail, whereas both authors use the term accuracy to mean the same thing. As for the use of the terms detail, resolution or granularity it is still a matter of discussion (Duckham et. al, 2000) and I noted earlier that I prefer to use granularity in this text to avoid confusion with detail and resolution. Occasionally I will also use the term resolution/granularity, mainly when reference is made to some specific work using the term resolution in the meaning of granularity.

Veregin (1999) and Meyer (1998) as well as several others (Salgé, 1995; Goodchild, 1995) treat accuracy as a relative measure since it is dependent on the intended form and content of the database. In addition to accuracy and granularity Veregin (1999) also include quality measures of consistency and completeness, Table 1. If we

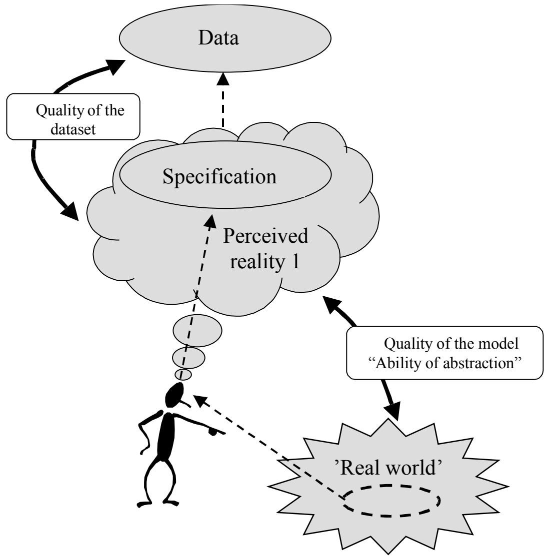


Figure 5 Two main aspects of semantic accuracy

consider the measurements in Table 1 as a minimum requirement to document we now need to suggest some viable ways to measure each property. It turns out that the matrix works fairly well for well-defined features (Goodchild, 1995; Veregin, 1999). We need to keep in mind though that measurement is always made against a logical specification of the conceptual model that was used to collect the data (Veregin, 1999). Goodchild (1995) noted that for poorly defined features it is not always possible to separate for example attribute accuracy from spatial accuracy. For example in the case of vegetation maps it is subjected to discussion whether the location of a boundary between two vegetation types is uncertain due to the problem of measuring the exact location of the vegetation types or if it is due to the problem of discerning between the two vegetation types at the correct location (Goodchild, 1995; Painho, 1995). Salgé (1995) provided the first treatment of quality measurements from this perspective in his seminal text on *semantic accuracy*. Semantic accuracy refers to the quality with which geographical objects are described in accordance with the selected model (Salgé, 1995). Figure 5 show a modified version of Figure 1. It illustrates the concepts of model quality or 'ability of abstraction' as a measure of how well a real world feature can be defined in the perceived reality. It also shows the meaning of an evaluation of dataset quality as how well geographical objects in a database correspond with the perceived reality. Veregin (1999) actually uses these notions but deviates slightly from the proper definition of completeness to produce a measurable situation in the case of completeness measures. Brassel (1995) in a similar way as Salgé (1995) defined completeness as the difference between the objects in a database and 'the abstract universe' of all such objects. This lead Veregin (1999) to consider both data completeness and model completeness but this is really a general problem for all four quality measures, and it is directly related to the nature of the object under consideration.

It is important not to restrict the discussion of quality to either well defined objects or poorly defined objects and an alternative way to treat the subject is to approach the quality issue from an uncertainty viewpoint. Fisher (1999) discusses uncertainty in general and separates uncertainty into two main categories depending on the difficulties to define object classes and instances of these. For well-defined objects the type of uncertainty can be characterized as error of some sort and this can be treated with probability-based methods, which typically produce true or false results. For this type of uncertainty there are today a collection of measures such as mean error, root mean square error, percent correctly classified, Kappa, sampling interval, sample resolution (pixel size or time collection interval for each measurement) (Veregin, 1999). For poorly defined or unresolved objects two types of uncertainty have been recognized, vagueness and ambiguity (Fisher, 1999). These latter types of uncertainty may be treated using concepts of fuzzy and rough sets. No general framework, such as the one described for well defined features (Veregin, 1999) Table 1; have been articulated for quality measures of poorly defined features. Salgé (1995) suggest that similar measures as for well defined objects should be used, for example commission and omission error. I would suggest that the framework of Table 1 could be used also in the case of poorly defined features with one reservation. The reason for this reservation originates from the experiment in chapter 7 where the degree of categorical completeness propagates into the analysis and is embedded in the following accuracy. We must bear in mind that for assessment of poorly defined objects as defined by Fisher (1999) the conceptual model is of primary importance. Thus, until further investigated quality assessment for poorly defined features need to commence from the lower right part of the matrix in Table 1 in order to acknowledge that the conceptualization of the real world governs the measurement of time and space. This also conform with Nunes (1991) referred to in chapter 2.

As already noted, which analytical approach to use for the uncertainty assessment is generally guided by the nature of the objects under study. With well-defined object classes and individuals the uncertainty is probabilistic in nature whereas poorly defined objects or classes are better handled by fuzzy set approaches (Fisher 1999). Rough sets is used where uncertainty comes in the form of indiscernibility, it is therefore suited whenever the granularity of the information is too limited to discern between sought alternatives. These later cases have been thoroughly explored in chapters 6 through 8. Although this general division might be argued it clarifies the complementary nature of these three approaches, and that a proper use of each method is decided by the data at hand. All of these uncertainty aspects will be further put into the context of representing geographical meaning in the last section of this chapter.

A central concern of this dissertation is use of data from different contexts and it is essential to admit that several instances of the same real world feature may be possible with equal relevance, since perceived reality often only exists as an intellectual construct. In Figure 6 I have included the additional aspect of semantic heterogeneity (Bishr, 1997) to give a more complete illustration of the semantic uncertainty involved in a translation between contexts.

If we recapitulate the earlier description of categories, conceptualization or E-ontologies, we see that semantic accuracy evaluation must be acknowledged as a fundamental part in the representation of knowledge through categorical data. The experiments and methods dealt with in this dissertation all pertain to the problem of transforming information from one context to another and it has been recognized that this is mainly a matter of semantics. So, a major scope in chapter 7 is measurements of semantic accuracy. There I demonstrate approaches that evaluate both the aspect of 'ability of abstraction' as well as an evaluation of the semantic accuracy of two different spatial generalization operators. By a careful measurement of attributes in a controlled environment, errors have been reduced to a minimum and remaining errors are controlled to enable a constructive interpretation of remaining

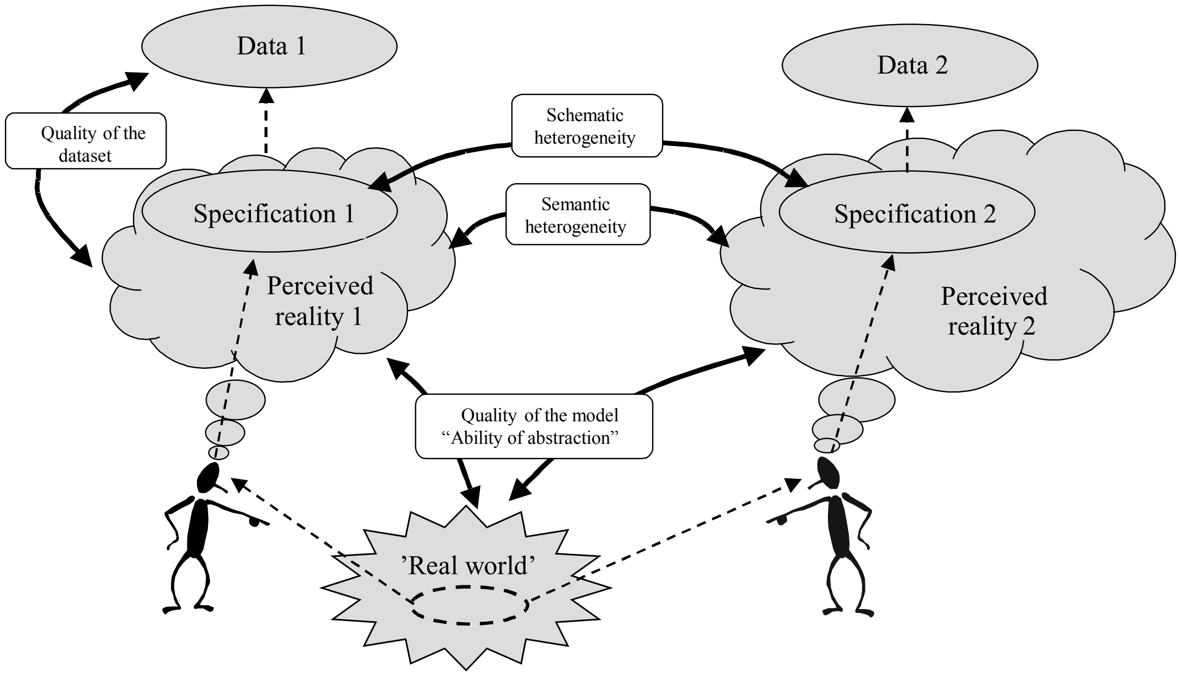


Figure 6 Aspects of semantic uncertainty in a multi-user context

deviations. A problem though is that any attempt to quantify semantic accuracy against perceived reality becomes extremely susceptible to subjectivity, but so will any assessment of translation results between user contexts be. A single measurement of semantic accuracy cannot accommodate for all different worldviews that might be at play and the use of these kind of 'closed' tests may very well be contested. In an environment of open systems operated by individuals who often use unresolved information we need a type of quality tests adequate for these conditions. Star (1987) argued in such a context for a different form of evaluation based on real time design, acceptance, use and modification of a system by a community and suggested the ideas of due process and boundary objects introduced earlier.

It will be important to keep the uncertainty discussion in mind through the following treatment of spatial, temporal and thematic granularity, as I will return to the space-time-theme dependence by the end of these following sections.

Spatial granularity

As I already noted, a well developed way to formalize and communicate space is the traditional map, and map scale has been one way to articulate a sort of spatial granularity. According to ICA (1973) the scale of a map is the ratio of distance measured upon it to the actual distances that it represents on the ground. Dent (1993, p.77) expands the term further by stating that scale relates to the size of precision and generalization applied in the study. He also sets out that the nature of the inquiry sets the scale, and the scale in turn determines the degree of generalization. This clearly relates to other dimensions than only spatial granularity but to a larger domain of generalization. This is probably due to the fact that scaling of geographical data has traditionally been made manually including all sorts of spatiotemporal and categorical considerations. With increased demand for automated tools for generalization, updates and revision of databases made at different scale levels the issue of scaling has gained a renewed interest.

The lack of an adequate definition of generalization in the context of digital processing environments motivated McMaster and Shea (1992) to suggested the following definition: 'Digital generalization can be defined as the process of deriving, from a data source, a symbolically or digitally encoded cartographic dataset through the application of spatial and attribute transformations'. In their definition they also stated that the objectives of a generalization process are to produce data that is consistent with chosen map purpose and intended audience; and to maintain clarity of presentation at the target scale. Since then the increased use of digital systems for storage and analysis of geographic data has widened the traditional meaning of generalization to encompass not only map output, but almost any transition between representational models of the real world (Weibel and Dutton, 1999). In order to be a generalization though, this transition is confined to one that decrease the level of detail but at the same time try to maximize the information content with respect to some application.

The 'value-added' aspect of digital generalization included in these definitions was rather lately added to the GIS research agenda (Müller, 1989; McMaster and Shea, 1992; Müller et al., 1995). The last decade has provided a multitude of fruitful discussions and investigations on generalization issues in a GIS context (Buttenfield and McMaster 1991; Müller et al 1995).

Even if a lot of the work reported so far on automated generalization has a cartographic flavor to it, a subset of the research labeled object and model generalization (Weibel and Dutton, 1999) is of direct interest to this discussion. Object and model generalization is the process of data abstraction dealing with the identities of geographic phenomena and their semantic relationships. This is essentially the same problem that has been outlined previously as a problem of GIS integration, interoperability and semantic modeling. An automated generalization process needs knowledge on object geometry, spatial and semantic relations (Ruas, and Lagrange, 1995). Thus the model generalization research needs knowledge on semantic relations in very much the same way as any other knowledge based technique. Today scale, granularity and generalization are receiving interest from researchers as generic issues. For example Goodchild and Quattrochi (1997) suggest a full science of scale that would include the ability to change scale in ways that are compatible with our own understanding of Earth system processes.

Apparently, generalization is concerned with changes of both thematic and spatial detail and a restricted focus on pure spatial granularity, as in this section, lead rather naturally to consider modern granularity limited data such as remote sensing images. With remote sensing images I include both aerial photographs and satellite images. In maps the concept of scale is set explicitly but the remote sensing image has no pre-defined scale as such. It does however have a concept of spatial granularity but this must not be confused with scale since there is no direct link between the two.

Resolution/granularity is a measure of detectable separation between objects in a visual field (Dent, 1993, p.260). This has only recently been noticed as a theoretical problem as the efforts to integrate and compare remote sensing data at different scales has shown problematic and therefore received some much needed attention (Wilkinson 1996). Studies of the effects of spatial data aggregation on grid data have often been performed using remote sensing images, simulated remote sensing images, and classified versions of the two. Those studies have provided a lot of useful insights into the effects imposed by a changed spatial granularity on grid data (cf Quattrochi and Goodchild, 1997).

Following the work by Woodcock and Strahler (1987), many studies have reported on the effects of spatial data aggregation. Most work employ methods and frameworks that provide global measures of the aggregation effects of changed spatial granularity and these effects can be evaluated from several aspects. One such aspect is to see how image statistics is changed over resolutions/granularity (Bian and Butler, 1999; Van Beurden and Douven, 1999; Milne and Cohen, 1999; Moody and Woodcock, 1994). One other evaluating certain landscape components (rural, forest) and their inherent responses to aggregation processes (Woodcock and Strahler, 1987, Turner et al, 1989). All these efforts may however be characterized as evaluations of truth in the model, where the model is a specially constructed set-theoretic reality surrogate whose relation to reality itself is left unspecified (Smith, 1995). The issue of evaluating how aggregation affects the semantic accuracy (as defined in previous sections) of for example land cover has not been worked upon as much.

This apparent gap in the literature about spatial granularity motivated me to look more into these aspects and the work presented in chapter 5 are the first efforts in this direction. I argue that from an application perspective the preservation of image statistics is not necessarily the goal. On the contrary, for example visualization often uses aggregation to reduce noise and enhance certain information, similar to the way we all 'low-pass-filter' a visual experience when we squint our eyes, which of course change the image statistics. It follows from the definitions above that the ultimate goal of any kind of generalization is that

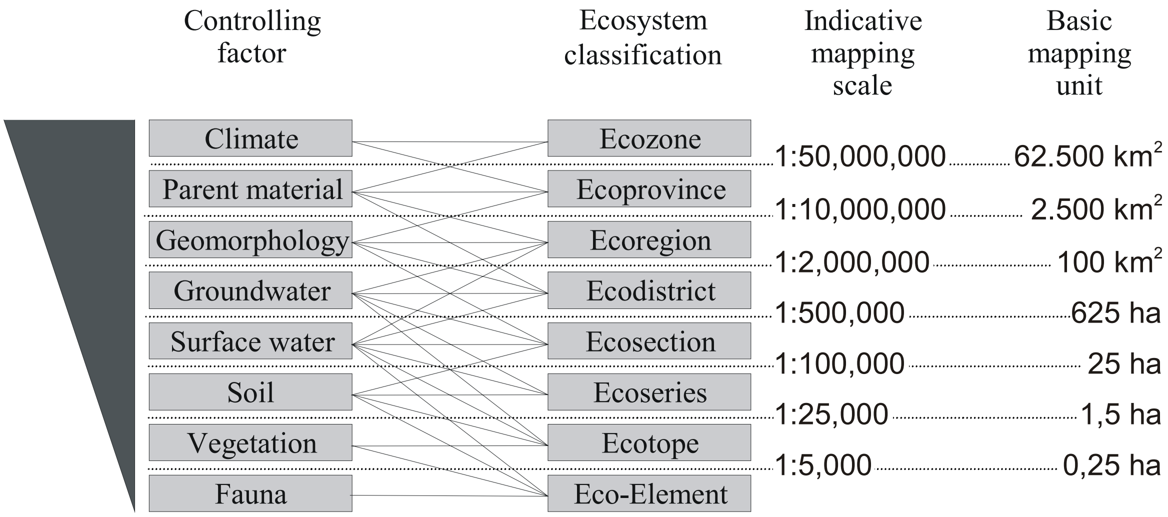


Figure 7 The relation between ecosystem components and spatial scales at which they are ecologically relevant. Lines connecting controlling factors and ecosystem classification indicate which controlling factors may determine the observed spatial pattern of ecosystems at each scale. Adapted from Klijn and Udo de Haes (1994).

the information we finally produce is appropriate to the task. But how do we make sure that this is the case?

This has connections to the issue of appropriate spatial granularity for study, which have been debated by geographers for some time now. As a result of these discussions there is today an agreement that a changes of analysis scale also changes the importance and relevance of specific variables (Meentemeyer, 1989). The recent development of landscape ecology (Forman and Godron, 1986) has not only brought an increased insight into the spatial domain of ecology but also some renewed attention to this as a geographical issue. Purely ecological studies have traditionally been biased toward particular spatial and temporal scales (Johnson 1996). In the development of landscape ecology as a field of research some general ideas of scaling up ecological processes (King 1990), to some extent based on a hierarchical concept of ecosystems (O'Neill et al. 1986) were put forward. Further work speculated that patterns and their relationships might be ordered into scale domains and that transitions between such domains might be relatively abrupt, much like phase transitions in physics (Wiens 1992). One example of a suggested framework uses a scale dependent hierarchy of classification systems where both abiotic and biotic factors are coupled to both space and time (Klijn and Udo de Haes 1994).

Figure 7 gives an overview of this idea in the spatial domain. The concept indicates the possibility of assigning certain granularity intervals at which controlling factors can be considered relevant for the spatial pattern of ecosystems. By identifying controlling factors for a specific variable it would be possible to delimit the scale interval within which this variable will exhibit an identifiable pattern. This can be seen as an effect of the 'constraint envelope' concept suggested by O'Neill et al. (1986). These ideas may be hard to verify (Schneider, 1994) but they have gained support and are now considered by several authors as one important key to making progress within the domain of geographic information science (Lam and Quattrochi 1992; Buttenfield 1995; Painho 1995; Jelinski and Wu 1996; Johnson 1996).

One of the problems to handle changes in levels of detail may be coupled to the way we measure this as an absolute space or as representative fraction as in maps (Goodchild, 1999). A possible candidate for a scale invariant measure of granularity is the "scope" (Schneider, 1994) or LOS, "large over small" (Goodchild, 1999) measure. Schneider (1994) define this as the ration of the range (extent) to the resolution/granularity and suggests that this relative measure is useful in comparing phenomena over spatial, temporal as well as thematic scales. The information value of this measure seem to be high since it in some sense incorporates two of the three most prominent scale concepts related to geographic information 'extent of a study' and 'operational scale' (Lam and Quattrochi, 1992). And if the third of these scale concepts 'cartographic scale' is too problematic for the digital domain (Goodchild, 1999) it seems as if the scope measure is a potentially powerful concept. It remains still to be tested in what way it might be applicable to the general issue of changed granularity of geographical data.

MacEachren (1995) also emphasize a need to investigate the possible psychological factors that may interact with such scale dependent real-world patterns. The latter has been discussed as part of the broader issue of scale and detail in the cognition of geographical information (Montello and Golledge, 1999).

Apparently a model of geographic reality that can be varied in scale must account for the variations in objects, attributes and relations that may be encountered as an effect of changing spatial granularity. In chapter 7 I follow this line of thought by demonstrating location specific methods for the estimation of generalization and spatial grain effects on categorical data sets. The study can be seen as an extension of the initial case studies reported in chapter 5. The design in these two studies still did not allow for an assessment of the influence of physically controlling factors such as hydrology, topography, climate et c. From the literature this still seem to be an important source for the conceptualization of a domain of interest (cf. Klijn and Udo de Haes, 1994; Johnson, 1996). Accordingly it should be possible to include these ideas in a framework for transformation of information between contexts. The demonstration in chapter 8 include wetness index as a determining factor for the target classification. I take this as affirmative proof that the proposed framework is capable of incorporating the idea of controlling environmental variables although this specific issue is not very much elaborated on in this thesis. Although chapter 7 failed to address the issue of controlling factors, it has attacked the problem of evaluating semantic accuracy due to changed spatial granularity. The hypothesis tested in both chapter 5 and 7 is whether the outcome of a changed spatial granularity of a dataset is the same as if data were instead collected at this desired level of granularity. The joint results from chapters 5 and 7 do not give any clear-cut answers which I take as evidence for that we have to deal with a multifaceted problem and that we miss an appropriate information theoretic model to handle aggregation operations. The case studies in chapter 5 showed a sensitivity of certain environmental variables to changed spatial granularity whereas the experiment in chapter 7 did not provide clear evidence for this.

Temporal granularity

Peuquet (1999) suggest that the goal of a temporal representation is to record change over time and the basic questions asked against a temporal database would be about states and changes. From an ecological perspective Huston (1994, p232) holds disturbance and successional changes as the primary landscape processes that are observed by humans and that regularly interact with human activities, and the intensity and frequency of disturbance are of major importance to community and ecosystem properties. Also from a more general perspective duration and frequency seem to be important concepts to describe temporal patterns (Peuquet, 1999). A disturbance regime often forms a dynamic equilibrium characteristic to a particular landscape (Huston, 1994). A landscape can in the same way be defined as the tangible and characteristic result of the interactions between a specific society, its cultural preferences and potential, the given physio-geographical conditions and biotic as well as abiotic processes (Sporrong 1993). Thus, a landscape is described by geographical boundaries and concepts ranging from physical objects such as houses, trees and rivers via processes like climatic variability and ecosystem succession to highly immaterial parts of the landscape such as land ownership pattern and human ideological structures. Once again we may note the problem to separate geographical information into its 'primary' components.

The time aspect of geographical information, although not as much investigated, seems to behave in a similar way as the spatial aspect. Both Langran (1992) and Klijn and Udo de Haes (1994) point at support for the hypothesis that the natural rate of change, that is frequency, for a natural process generally follows the spatial hierarchy outlined in Figure 7. In that figure the temporal scales are reflected by the most rapidly responding processes being located relatively low in the hierarchy.

Recent attempts on the formation of coastal geomorphology theories as well as other landscape ecological studies emphasize the use of space and time scales as an organizing principle

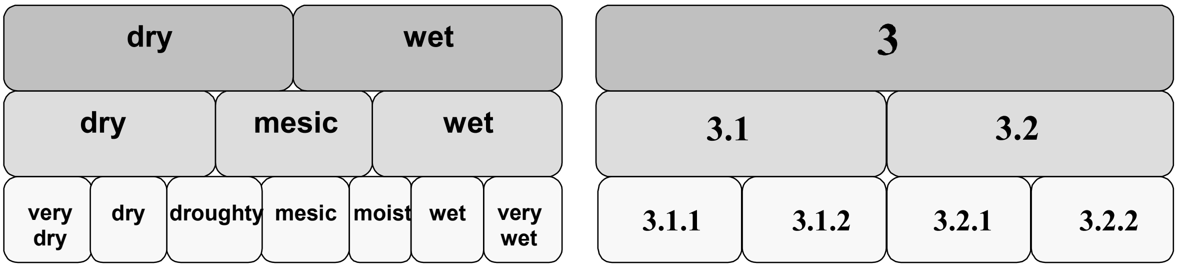


Figure 8 A conceptual hierarchy structure (left) adapted from Freksa and Barkowsky (1996) compared with a hierarchical tree structure (right) compatible with e.g. several vegetation classification systems (Påhlsson 1995)

(Raper and Livingstone, 1995; Turner et al., 1993). Both these works argue for a geographic model in which time and space are treated together in relation to the nature and behavior of the described entities. Peuquet (1999) review some approaches to the representation of spatiotemporal data in digital databases and divide these in groups of location-based, entity-based and time-based. She concludes that section by arguing for a combined representation such as the 'triad representational framework' treated in the previous section (Peuquet, 1994)

The scope concept was introduced in the previous section and I will use it here to speculate on how the spatiotemporal characteristics of a geographic phenomena might be expressed using the ideas reviewed so far. Given a piece of hemiboreal Scots Pine forest the spatial scale will have a lower limit of some 50-100m in order to call a piece of landscape a "forest" that also exhibit "foresty" properties such as influence on local climate and flora. The upper spatial limit might be set using the controlling factors soil and ground/surface water giving a spatial granularity interval of approx. 50-1000m. The temporal scope of forests depend on management, but for a Scots Pine forest the natural "disturbance regime", that is the turnaround interval, can be set somewhere between 50 and 100 years (Angelstam 1997). If these figures shall be as absolute values or on a relative scale as scope is still a matter of question as discussed in the previous sections.

The figures indicate appropriate ranges and the grains of the information, which govern the usage of this set of data. This information should for example be used to set limits for when the current data set is violated due to for example a zooming operation in a GIS.

What this short elaboration demonstrates is that regardless of the space-time strategy used, categories will always be guiding the space-time conceptualization and the granularity of the spatiotemporal representation. So, I therefore turn to the treatment of thematic detail and how this could be handled before the final two sections where I propose an integrated framework of a Geographic Concept Topology.

Categorical granularity

The theme of a geographical dataset is to be understood here as the domain of a study. It was defined earlier that knowledge was made explicit by classification patterns where categories are building blocks of knowledge. The treatment in geographic research of categorical granularity has not received as much direct interest as the issue of spatial granularity. For example Mark et al. (1999) list only four studies of geographical categories that have involved human subjects testing. But in the last few years a number of publications indicate an interest in category theory and ontology.

Categorical granularity or degrees of complexity in the terminology of Board (1969) is normally organized as concepts in a hierarchical structure. In such structures general and abstract categories can be found at the top and less abstract and more specific categories are found at the bottom of hierarchical organizations, such as the two hierarchies outlined in Figure 8. Increased complexity is found by climbing down to lower levels in the hierarchy. Such a hierarchical structure can be either constructed as a conceptual hierarchy (left) or a hierarchical tree (right) (Freksa and Barkowsky, 1996). There are some fundamental differences in the two hierarchy types of Figure 8 that will be examined below.

In the case of hierarchical trees Mark et al. (1999) separate between 'partonomies' and 'taxonomies' depending on the type of relation between categories at one level up or down the tree. Taxonomies relate to 'kind-of' relationships, such as an oak forest is kind of a deciduous forest. A taxonomy enable inferences about properties and class inclusion, which is fruitfully exploited in for example object oriented knowledge representation. A partonomy on the other hand is based on 'part-of' relations such as 'a tree is a part of a forest'. Although geographical concepts associate naturally with both partonomies and taxonomies, partonomies does not support property inferences (Mark et al., 1999). The lack of inferential power makes the application of partonomies as knowledge representational technique a question suitable for further investigation. A deeper investigation of the differences between partonomies and taxonomies will not be treated here.

In a concept hierarchy, refinement of concepts, that is increased complexity, is not merely done by a subdivision of individual concepts as in the hierarchical tree case. In a concept hierarchy we see that additional categorical detail is given by creating categories for borderline cases. Thus, each subdivision is also revised according to the horizontal neighborhood structure. Consequently each concept is defined at a specific place in the hierarchy and given a meaning by its position in both vertical and horizontal direction (Freksa and Barkowsky, 1996). We can observe this in Figure 8 where the immediate neighborhood of the concept mesic is dry/wet in horizontal direction. In vertical direction the concept neighborhood consists of dry/wet at the more general level and droughty/mesic/moist at a more detailed level. All of these neighborhoods are related to the meaning of the source concept moist.

Concept relations can also be defined between separate hierarchies in order to relate a category in one context with a corresponding category in another context. Building further on the idea of a meaningful neighborhood structure I will illustrate such a relation between two different contexts. This problem domain has been termed "the metadata folding problem" within computer science (Aslan and McLeod, 1999) where it is understood as the problem of partial integration of remote and local databases in the presence of semantic conflicts. And it seems to have set off a variety of efforts to resolve this problem although Aslan and McLeod (1999) list some serious shortcomings for most of these that are related to limited dynamics and considerable knowledge demands. The Cyc-project (Lenat, 1995) for example uses a global schema approach that today demonstrate some workable implementations, such as search engines for the internet, some 10 years after its start.

From a geographical viewpoint, any categorical mapping that fails to incorporate spatiotemporal aspects will fail to give a full geographic description. Thus approaches based solely on categorical matching will not qualify as a viable candidate in a geographical situation. In the following real example I use two different vegetation classification systems, and these actually represent instances of the two hierarchy types illustrated in Figure 8.

The upper part of Figure 9 shows the hierarchical tree of the forest vegetation types in a Nordic vegetation classification system (Påhlsson, 1995). It is separated into four levels of detail where the lowest level exhibits the highest degree of complexity. Enlarged squares give a few examples of the most specific categories, in this case vegetation types. The highlighted vegetation types have also been mapped onto a diagram decided by soil moisture and richness in the lower part of Figure 9. We may look upon this diagram as one level in a concept hierarchy that has been extended in two dimensions, guided by both nutrition status and moisture. In an object based view these are the attributes of a certain vegetation object but in a location-based view they are the physical conditions of a continuous space. The nutrition-moisture gradient forms the basis for several other classification systems commonly used within the Nordic countries (cf. Påhlsson 1972), and as such the linkages forms a mapping between these two classification systems.

By using the idea of a concept hierarchy such as the left one in Figure 8, each concept is now closely associated to its neighboring concepts in terms of both nutrition status and soil moisture, whereas in the original hierarchy (upper part, Figure 9) the horizontal neighborhood is not necessarily indicative of any specific property in the adjacent classes. Typically a geographic vegetation object should be regarded to have some internal heterogeneity, thus the mapping onto these continuous variables comes in the form of a more or less vague range, the elliptical shapes in the diagram of Figure 9.

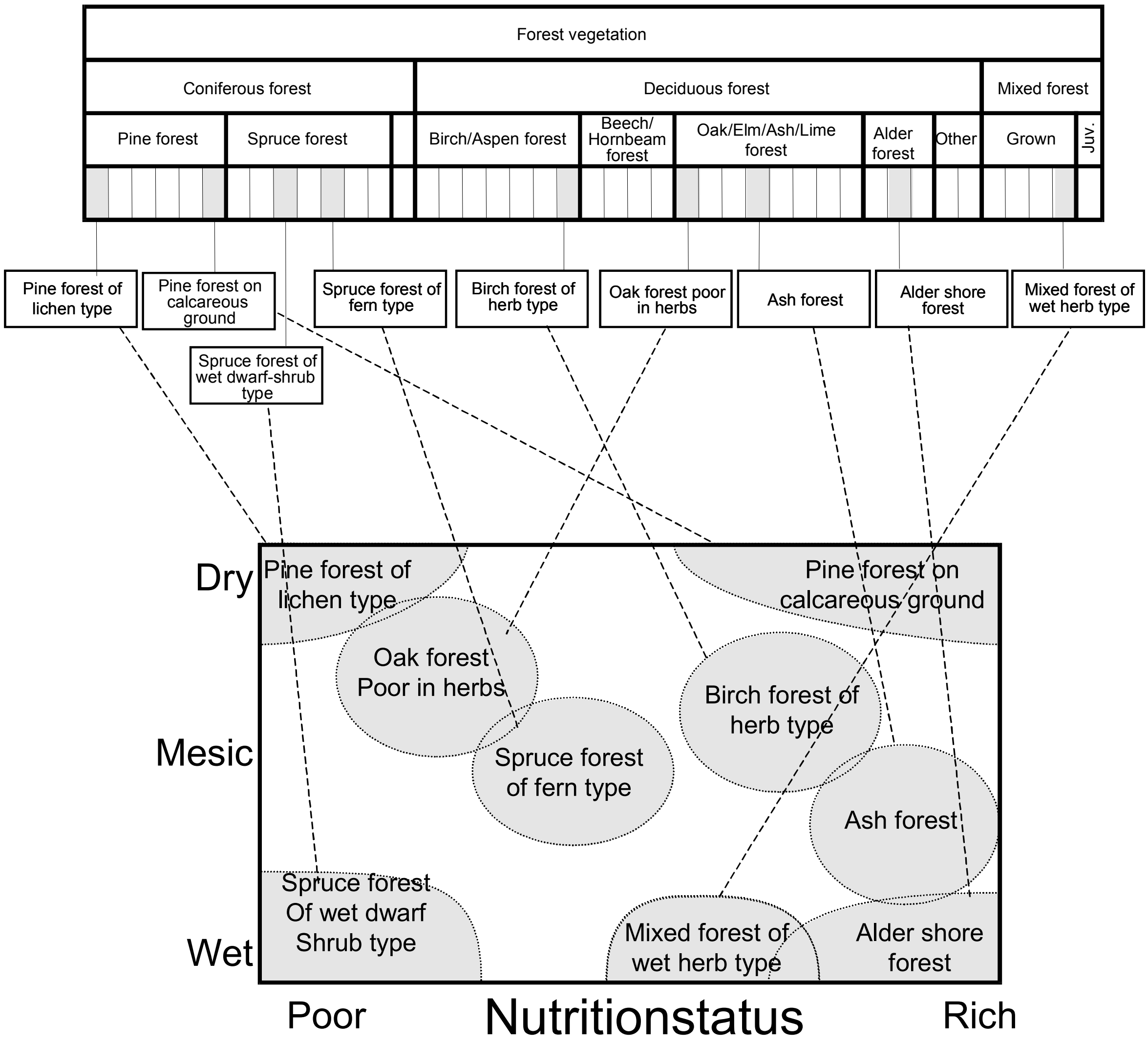


Figure 9 The taxonomy of forest vegetation classes (from Påhlsson 1995) is mapped onto a diagram using water and nutrition availability. Some of the vegetation-types are highlighted as enlarged boxes to exemplify the mapping.

The example has large resemblance with the work by Mark (1993) on the conceptual boundaries between similar categories of water bodies in English (lake, pond, lagoon) and French (lac, étang, lagune). In that experiment Mark showed that many categories for water entities may be discriminated using size, spatial relation to the ocean, salinity, presence of marshes at the edges, and whether it is man made or not. An important observation in these examples is that a mapping between similar concepts, but from different contexts, often cannot be achieved through a crisp relation. In the chosen examples there are components of uncertainty related to graded concepts and indiscernibility between competing concepts that cannot be fully described by a binary relation. These problems are approached in the following section and tackled in more detail in chapters 6 through 8 where I also propose and demonstrate a few solutions to handle them.

Although the examples so far deal with the horizontal neighborhood structure it is also conceivable to think of additional vertical neighborhood mappings as in Figure 8 left. The example in Figure 9 uses two dimensions at one concept hierarchy level, moisture and nutrition. The example by Mark (1993) explicitly illustrated the use of three dimensions, or controlling factors, size, edge marshiness, and man-madeness. Theoretically the dimensionality could be increased infinitely creating a multidimensional network of concept meanings provided by mappings between similar concepts and between concepts and controlling factors. Nyerges (1991a) outlines a general interpretation of this idea that he called a heterarchy of concepts, based on multiple, and interconnected conceptual hierarchies, forming a multidimensional knowledge framework of concept meanings. Thus, a heterarchy would be something similar to what linguists would call connected word maps. Such a heterarchy of concepts could be explored by e.g. generalization operations (Nyerges, 1991a) or be used to provide input to predictive geographical models (Nyerges, 1991b). I will now follow this general design and furthermore argue for some additions that I see as a prerequisite for a semantically rich representation of geographic concepts.

I have demonstrated in this section that categories from different contexts are often not related through crisp, binary relations. In such cases there is some amount of uncertainty involved in the relation. Now, uncertain concept relations, such as those illustrated in Figure 9 do not only extend the original notion of concept hierarchies (Freksa and Barkowsky, 1996) into considering a horizontal neighborhood in two dimensions. More important, it illustrates the general idea behind my proposed formalization of transformation between similar concepts from two different contexts. This idea acknowledges that geographical categories may use location-based, time-based as well as object-based views for their representation. Figure 9 illustrate how expert knowledge is used to produce an approximate mapping of categories that is accompanied by a definition of how target concepts are related to certain important spatial properties. I now claim that the arguments and discussions brought forward so far implies that the categorical aspect of geographic information is the proper starting point for any transformation of geographic information that involves a changed spatial, temporal or categorical granularity or any combination of these.

In the next two sections I will go into detail on available options to describe semantic uncertainty in (expert) knowledge representations. Here I will focus on crisp, fuzzy and rough sets as candidate frameworks for the representation of concept interrelations and the degree of uncertainty in the mapping. Thus, the remainder of this chapter outlines a core idea of *knowledge representation under semantic uncertainty*.

Knowledge representation and uncertainty

Integration, understanding and communication are essential concepts when we talk about knowledge. The previous section proposed that multiple interconnected conceptual hierarchies could be used to express a deeper geographical meaning of used concepts. Most efforts to implement semantic level models to date have proposed set theoretic approaches for its implementation (Nyerges, 1991b; Livingstone and Raper, 1994; Bishr, 1999; Gahegan, 1999). Related frameworks have also been proposed, such as 'mereotopology' (Smith, 1996) that uses mereology, referred to as the theory of part and whole, as an alternative to set theory to describe topological relations between parts and wholes of things. One reason to search for alternatives to set theory has been its limited capability to express semantic ambiguity of categories (Mark and Frank, 1996). Although uncertainty may have various sources, randomness and imprecision are two major types that are of importance in spatial knowledge representation and inference (Leung, 1997). Probability as a mathematical and statistical idea is well studied, understood and also well documented (Fisher, 1999) and its implementation within the field of geography is fairly well developed. I see no reason today to abandon the set-theoretic realm since the fuzzy (Zadeh, 1965) and rough (Pawlak, 1982) extensions of traditional set theory seem to be viable techniques capable of handling the types of category uncertainty or imprecision that previously was problematic from a representational viewpoint. As an example, the work by Usery (1996) has shown the possibility (sic) to represent features as fuzzy sets. I will explore this issue in more depth in this section, which finally by the end of this chapter blend into a general description of geographic knowledge representation under semantic uncertainty and a proposed solution.

There are a variety of views on the theory of knowledge but in order to build a spatial decision support system we need data that explicitly define at least parts of our current knowledge. Recent advances in data intensive methods, such as knowledge discovery through data mining (Fayyad et al., 1996), will probably gain in significance with the ever-increased amount and volumes of data. Although some pointers to the literature are provided by Pawlak (1991) and deeper treatments can be found in Fayyad et al.

(1996) and Leung (1997) I will neither go into detail into these, nor is my intention to cover all techniques to represent knowledge in spatial decision support systems. The following description tries instead to link the different views on knowledge representation with the previous discussion of different types of uncertainty.

There are today a few major approaches to represent knowledge and to make inferences from this in a formalistic manner (Leung, 1997). The first and maybe most known and used alternative is to use declarative knowledge represented through some kind of formalism such as first-order predicate logic, production systems built up by ordered sets of IF-THEN statements, semantic networks, frame-based hierarchies, object-oriented approaches or combinations thereof. These representations are adequate whenever knowledge can be expressed as clear-cut true or false statements such as 'this area is a swamp'. This also leads to clear-cut answers, 'yes' or 'no'. In this case uncertainty is essentially a stochastic event connected to well-defined objects. One frequently cited implementation uses a probabilistic approach to uncertainty representation (Goodchild, Guoqing and Shiren, 1992). From an error matrix we may produce probability vectors for each pixel given the actual estimate. Using such probability estimates it is possible to produce multiple realizations of the original interpretation and make the actual comparison of result upon these realizations.

However, human knowledge is often inexact and we therefore need some knowledge representation technique that is capable of handling uncertainty or imperfection related to poorly defined objects. Consider the three following expressions 'this area might be swampy', 'this area is rather swampy' and 'this area is either swampy or flooded'. They are all propositions that include aspects of uncertainty that are quite different in nature and therefore require different methods for representation.

The first proposition 'this area might be swampy' articulates a type of uncertainty that is caused by some degree of randomness and the validity of an inference under randomness can be expressed as the chance, or probability of the event. These measures are often produced through statistical testing and evaluation of frequencies of occurrence. To make inferences and to update previous knowledge with new evidence we may use Bayesian methods of updating. A geographic implementation of this can be found in Aspinall (1992). We may also use an extension of Bayesian probability theory called Dempster-Shafer theory, cf. Eastman (1997) and Leung (1997) for an introduction to the two approaches in a spatial information setting.

In the second proposition ' this area is rather swampy' we have expressed that the area might possibly be regarded as swampy. This type of inexact human knowledge led to the development of fuzzy sets and fuzzy logic (Zadeh, 1965). Fuzzy sets are a suitable representational tool to accommodate graded and subjective statements such as 'rather' to express partial belonging to a specific concept. As such fuzzy logic is suited to represent and infer with this type of imprecise human knowledge. In implementations of fuzzy systems we may translate the grade of belongingness of an object (this area) to the concept (swampy) into membership values, which can be used in propositions and inference. Gopal and Woodcock (1994) and Woodcock and Gopal (2000) present geographic implementations of this method where they use fuzzy sets for accuracy assessment and area estimation of thematic maps. Their approach enables a translation from linguistic terms of interpretation judgments into fuzzy memberships for further use in accuracy assessment. It follows that the validity of answers from a fuzzy system is depending on the meaning associated with the concepts used in the fuzzy propositions. It is important to note that membership values as such reflect an ordering that is not based on probability but on admitted possibility (Burrough and McDonnell, 1998).

The last one of the propositions 'this area might be either swampy or flooded' may intuitively be translated into a 50/50 % chance of either alternative. But in many situations this statement is based on the total lack of support for either of the two outcomes (a natural tag to the statement would be '… I don't know.'). To give both of the alternatives the same chance is to violate the fact that no such information is available. The recent development of rough set theory (Pawlak, 1982; Pawlak, 1991) has provided a viable tool to address uncertainty that arise from inexact, noisy or incomplete information. Also, rough sets and the concept of rough classification have demonstrated promising applications for geographic information handling (Schneider, 1995; Worboys, 1998a; Ahlqvist, Keukelaar and Oukbir, 2000a - chapter 6 this thesis).

In the previous section about categorical granularity I illustrated some examples that tried to associate categories in one context with similar categories in another context. This was known as mapping semantic similarity and it was acknowledged that this mapping needed to be able to represent graded concepts and indiscernibility between competing concepts. The concepts of probabilistic, fuzzy, and rough uncertainty can easily be confused but in light of the discussion above it should be apparent that these three concepts represents quite different facets of uncertainty. In the following chapters, especially chapters 6 through 8, this knowledge representation technique will be addressed in more depth.

It is also conceivable to think of combinations of these types of uncertain knowledge, for example 'this area might be rather swampy' stating that there is some probability of this area to be regarded as swampy, even though it might not be a full member of the 'swampy' concept. It would only be natural then to try to merge the different representational techniques into joint measures of uncertainty capable of expressing all combinations of uncertain knowledge. Formal descriptions of the relations between these different models of uncertainty have also been published (Dubois and Prade, 1992). This is where we reach the current forefront of the research on uncertainty in decision-making problems (cf. Pal and Skowron, 1999). In chapter 8 I present one effort to further develop these theories applied to the field of geographical data integration. Chapter 8 also goes further to include the wider problem of knowledge representation under semantic uncertainty. These last issues are the focus of the following section.

A geographical concept topology

Approaching the remaining problem of combining the different types of uncertainty represented by probabilities and possibilities there seem to exist workable approaches. The idea of using multiple sources to explain a specific concept has close similarity with multi-criteria decision analysis (Malczewski, 1999; Eastman, 1997). The multi criteria decision analysis framework enables a combination of separate lines of uncertain evidence such as deterministic, probabilistic and possibilistic (fuzzy) rules, into an answer or several scenarios. I propose here that these theoretical constructs can be used to perform a transformation from one context into another, using multiple sources of knowledge and interconnected concepts. I further propose that each concept involved in this transformation can be given a deeper meaning by explicitly defining mappings such as the examples related to Figure 9. These mappings can use either certain one-to-one, many-to-one relations or uncertain probabilities (not treated in this work) or possibilities. Above given examples have shown that semantic relationships very often is of an underdetermined character that is either graded or indiscernible of a type that is not probabilistic. Therefore implementations of context mediation based on first order logic are too restricted, and I propose instead to construct mappings using formalisms capable of expressing various forms of imprecision. In chapter 8 I present a method to integrate fuzzy and rough data into a result that can be generalized into a map. This implementation is a demonstration of the idea to use crisp, fuzzy or rough sets to define a complete or incomplete translation from one concept to another, and create a transformation between contexts from this. Since no information source provide a one to one mapping the idea is based on the integration of the multiple lines of evidence. It uses the concept of multi criteria decision support and the idea of fuzzy aggregation operations to extended the fuzzy approach to incorporate crisp, fuzzy and rough sets through conversions into bifuzzy sets.

I denote such mappings between concepts a *semantic topology* of available geographic databases. The notion of topology is within geographic information science normally understood as the spatial interrelations that describe how real world phenomena are linked together (cf. Burrough and McDonnell, 1998). Topology may also be generally understood as the study of interconnections (FOLDOC) and therefore include any type of connection such as spatial, temporal or categorical. I will thus in this thesis use a wide definition of topology and propose the use of a G*eographic Concept Topology*, a GeCoTope, to establish a formalized representation of semantic interrelations. A GeCoTope forms part of the metadata for each dataset and it also forms a higher-level metadata structure capable of connecting different datasets both semantically and functionally. The

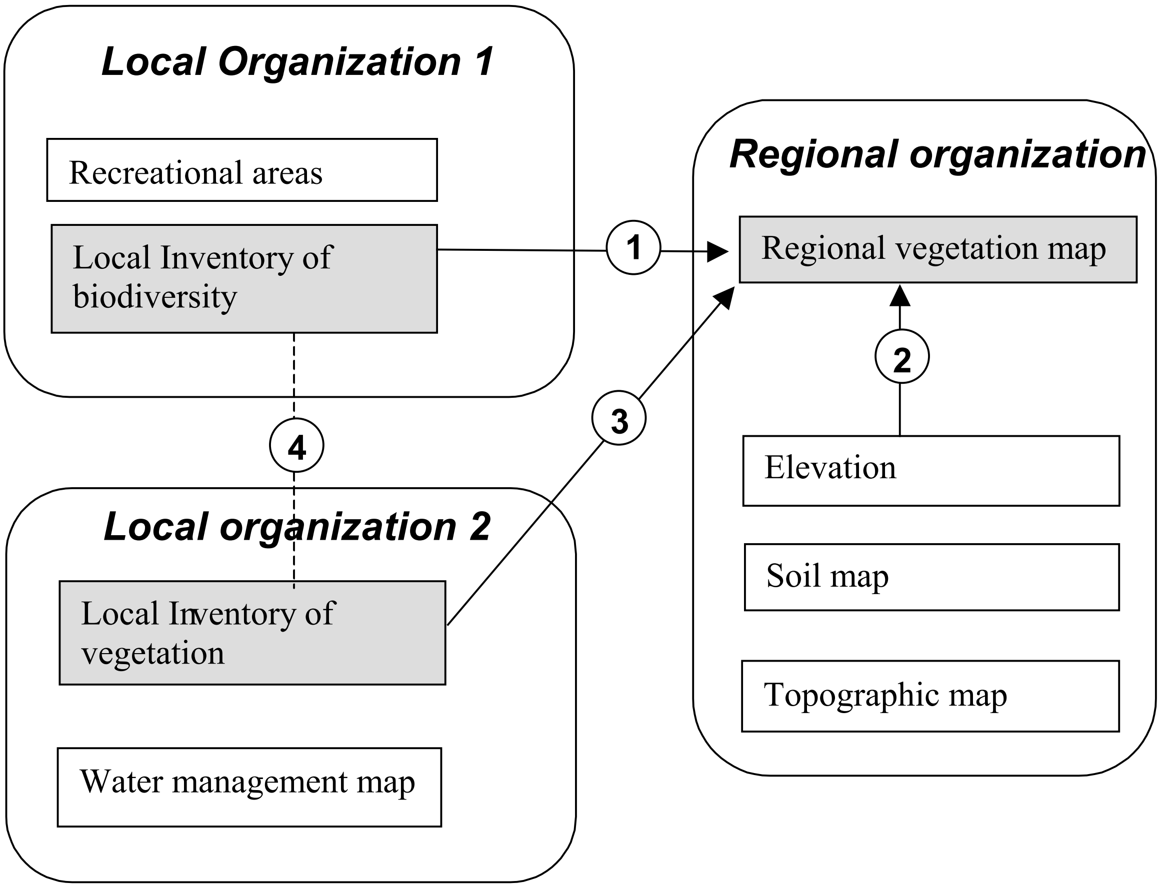


Figure 10 Organizational perspective on exemplified (1-3) and possible (4) transformations using the suggested approach.

GeCoTope is primarily intended to make explicit the semantic similarity between categories from separate contexts and I hypothesize that categories of controlling factors such as topography, hydrology, soils, are among the more important contexts to establish mappings to.

Figure 10 illustrate the implementation of the GeCoTope as a context transformation tool between (1, 3) and within (2) three hypothetical organizations. In the experiment in chapter 8 I show how the concept of multi-criteria evaluation can be used to transform local vegetation data into a regional vegetation classification (1) 'weighing' additional information about wetness into the decision (2). In chapter 8 I also suggest that other local organizations could produce similar mappings and that a network of such mappings give a possibility to transform data within and between organizations (4) realized through chained transformations. It may be discussed whether it is better to use 'controlling factors' such as the topography form an elevation model (2) as a bridge or 'proxy context' for these mappings rather than arbitrary classification systems. In any case, the framework of the GeCoTope allows for solutions based on 'arbitrary' common ontologies as well as controlling physical factors.

This issue connects to the use of federated data bases that in earlier work has been seen as a viable solution to establish bridges (proxy contexts) between localized contexts (Bishr, 1997) whereas others have argued for localized approaches (Aslan and McLeod, 1999). Here the proposed framework seems open for both federated and localized solutions. A combination of these may also be envisioned where a large number of transformation alternatives can be accomplished through chained transformations such as those outlined in chapter 8. The fact that these operations will often include transformations between measurement frameworks require careful consideration of the inherent meaning of each data set as transformation rules are formulated (Chrisman, 1999).

From a general geographical point of view, and following the argumentation in chapter 8, the GeCoTope framework enable the consideration of both location-based (wetness data) and object-based views (vegetation units) in a concept transformation process. This has other interesting connections to the ideas of Boundary object and Due process (Star, 1989) mentioned earlier in chapter 1. In chapter 8 I argue that the construction of fuzzy membership functions and rough classification rules in that chapter, can be interpreted as a “due process” where different groups or organizations constantly try to recognize, gather and weigh evidence from heterogeneous conflicting sources.

I also suggest in chapter 8 that many current techniques for spatial analysis, including the proposed framework, is a spatial implementation of the boundary object idea. Consequently, I suggest that multiple concept mappings, here termed a GeCoTope, can be used to negotiate semantic similarities and differences using a formalized framework of bifuzzy classifications.

Since the due process is supposed to be a dynamic and ongoing activity I hold it likely that it will require a fairly simple implementation structure. I anticipate that the GeCoTope framework, where each link is maintained by a limited number of participants, is a simple yet powerful implementation of the idea of a due process.

With this preview of the findings in my work I have given a summary of the entire thesis. I hope that this makes the argumentation in the following chapters easier to follow. I also hope that it enables a “high level browsing” of the following texts for those not interested in the details and particulars of each chapter.

Chapter

4 DISCRETE METHODS FOR INTERPRETATION OF LANDSCAPE INFORMATION

Introduction

In this work it has been of great importance to reduce the possible sources of error and to control those that are inevitable. It has also been a goal to be able to study changes in spatial and categorical granularity separately. This chapter is primarily devoted to a description of the data that was selected for analysis of changes of spatial granularity. For the studies of categorical granularity another set of previously described data has been used (Ahlqvist and Wiborn, 1986)

Most, if not all, studies on effects of changed spatial granularity in raster based data use data that in some way are a product of automated or semi automated data collection (Woodcock and Strahler, 1987, Turner et al, 1989; Moody and Woodcock, 1994; Bian and Butler, 1999; Van Beurden and Douven, 1999; Milne and Cohen, 1999). This has a positive effect in that a wide range of resolutions and aggregation levels may be covered by the study since the most detailed level of data can be collected in huge quantities, 10-100 thousands of pixels. The major drawback of the automated approach is that a translation has to be made between the information a machine/sensor captures and the information that humans preferably use. By focusing interest towards manually interpreted information it is possible to close up on scaling effects that pertain to the human mind and the concepts we use to understand the real world.

Interpretation of land cover information can be made with extreme variation using different data sources (maps, aerial images, satellite images), different spatial representations (point, area), and different measurement scales (continuous, ordinal, nominal). Early in the digital map age there were no standard method to collect information for digital spatial databases. Thus, textbooks on the subject from this time tend to have rather detailed descriptions of the procedures to capture data both manually and by automated methods, cf McDougall, 1976, p.57-60 for description of collecting rasterized data. The progress of technology has significantly reduced the amount of textbook space down to a few lines or paragraphs for consideration of manual methods to produce raster based, source datasets (Cromley, 1992, p.131; Jones, 1998, p.96). Manual production of geographic datasets is today mostly confined to the object/vector spatial model. This might be an issue of renewed debate since analyses of spatially regionalized data have been shown to produce difficult problems, such as the modifiable areal unit problem (Openshaw, 1983). Moreover, as most methods for spatial modeling are done in a raster model of space it can be argued that source data sets more often should employ a regular grid structure in the collection phase.

Against this background of a diminishing interest for manually collected grid data it may not be surprising that the data described in this chapter was collected using methods originally developed in the 1970’s. The described methods are based on manual inventory and interpretation of maps and areal images. Both methods also use a regular square grid as the basic areal unit. The content of these datasets therefore resemble contemporary datasets that today is assembled through satellite or airborne sensors followed by digital image analysis.

In 1996 a co-operation was initiated between MSc Rolf Ruben and BSc. Ola Ahlqvist. Ruben early had supplementary training additional to his university degree in forestry with two years of studies at the Royal Institute of Technology, dept. for Surveying and Mapping Engineering. During his 38 years within the silvicultural organization he worked with development of more effective site-specific methods for forest primary production. Parts of this work is documented e.g. the Reforestation assessment (Skogsstyrelsen, 1966). Other work is only available as internal reports, field protocols and other working papers. Thus, the main content of this chapter is a compilation and documentation of Mr. Ruben’s previously unpublished method development and results.

Consequently, this chapter has several objectives. Primarily it gives a thorough description of the datasets that have been used for studies of changed spatial granularity in this dissertation. Second, Rolf Ruben and myself want to present these two previously unpublished datasets. We also hope that a thorough description of the methods behind these data will initiate deeper discussions about methodological and statistic aspects. In this way this chapter may be of both public and scientific interest both in terms of actual information and the methods employed.

Structure of the method and data description

First I give a short background to the context in which the described methods were developed and data was collected. Information from the National Forest Inventory has been used as a basis for definitions and quality control. Therefore a description of that inventory is also provided as a background.

Both of these methods, the R-method and the classification of economic map sheets into landscape types are described in separate sections. Each of these sections consists of a Method sub-section and a Result sub-section.

The first dataset to be described, R-data of the PSU model, cover the Stockholm county and consist of landscape descriptions from 34,464 square shaped areas, each covering 25 hectares. The second dataset, classification of economic map sheets into landscape types, cover entire Sweden and contain information on landscape types within 18,000 square shaped areas, each covering 25km^2.

Planning support for the usage of the forested landscape and the R-method

In 1980 the Swedish National Board of Forestry started a long-term project called Planning Support for the Usage of the Forested Landscape, PSU. The aim was to develop methods to link strategic data from the National Forest Inventory with operative data often collected in the form of forest management plans. Another purpose for the project was to provide an information source for forest and land-use politics aiming at a better balance between central and local concerns. Stockholm County was chosen as a pilot example.

The project should be viewed from the forest industries' continuous need for both general and detailed planning and decision support in their management of landscape resources. Also, by the time of the initiation of the project the technical developments had enabled computerized treatment of areal information from remote sensing sources.

The method to provide a reliable source of information on a general level within reasonable time and financial limits was the same then as it is now. A statistically representative sample is measured with greatest possible accuracy with a consistent and thoroughly controlled method. The National Forest Inventory has in this way provided reliable information on the status of the forest resources in Sweden. The National Forest Inventory data can be spatially separated down to a spatial resolution corresponding to the county administrative level. This spatial resolution thus enables an illustration of the spatial distribution of certain forest variables. Regional authorities may also use this disintegrated information as an indication of the relation of the local region to the entire country. Because of statistical reasons it is not possible to get a higher spatial resolution directly from the National Forest Inventory.

The technique to collect similar information at the local level, e g municipalities or a single property has up until recently been characterized by a manual survey, estimation, and mapping of the entire area. In this way, a good documentation of the variation within the surveyed area has been collected. This documentation has then been used in forestry operations. The quality of these plans in terms of absolute values is however not as good as those achieved through systematic sampling. These local data sources are therefore not suited for integration over larger areas because of the variable and unknown bias included in each separate dataset. The comprehensive forestry inventory that was conducted during 1980 through 1993 aimed at producing county-wise collections of detailed forestry data. For reasons explained above some kind of correction of the individual bias would be required for comprehensive forestry inventory data. This correction would have been possible using the methods and data described in this report. The comprehensive forestry inventory was however never completed because of a change in the Swedish forestry statute in 1994 (SFS 1993:553)

In view of that the county and municipal authorities has been short of a reliable information source for planning purposes since these organizational levels require a higher spatial resolution than what the National Forest Inventory can produce. It is in this context that the described R-method was developed.

Classification of economic map sheets into landscape types

In the late 1980s The Swedish National Board of Forestry, Environmental Protection Agency, the National Heritage Board and the Nordic Council of Ministers co-operated on a project to investigate the relation between forestry and other interests in the Swedish and Finnish archipelago regions (Kihlbom, 1991). To ensure scientifically sound comparisons in cases like these it is important to produce a stratification of the landscape into regions, and several researchers have during the last century divided Sweden into regions based on a multitude of geographical or topic specific criteria (Hall and Arnberg, submitted). As one part of this effort, Rolf Ruben, made a delineation of the Swedish archipelago region in areal units of one Swedish economic map sheet. Furthermore, as a working material, the background information for this delineation was extended to cover entire Sweden. As a result this working material came to include estimations of constituting landscape types in 18,000, 5 by 5 km quadratic squares covering entire Sweden. Still, this material has never been documented, nor analyzed in any larger extent.

Description of the study area

Sweden

Sweden is located in northwestern Europe between Lat 55° 20′ N through 69° 4′ N and Long 10° 58′ E through 24° 10′ E. The extension from north to south is at roughly the same latitude as Alaska or—in the Southern Hemisphere—the stretch of ocean between Cape Horn in South America and the Antarctic continent. In terms of area it is similar to Spain, Thailand or California. In population, it is in the same league as Belgium, Ecuador or New Jersey. Its long coastlines, large forests and numerous lakes characterize Sweden.

Geologically, Sweden is located on the Precambrian Baltic shield and the geologic history extends as far back as the Archean orogeny some 2.8 billion years ago. The landscape still bears traces of many of the geological transformations that the land has subsequently undergone. Most of the interior of northern and central Sweden is dominated by 'Norrland terrain'. This terrain consists of scattered bedrock hills from 50 to 400 m high. This topography is mainly the result of millions of years of weathering and erosion of a previously flat rock surface. The western border between Sweden and Norway mainly follows the Scandinavian mountain range. It was folded up during the Silurian and Devonian periods in the Caledonian orogeny, later eroded and was then raised again during the Tertiary period and then eroded again. Now its peaks rise 1,000–2,000 meters above sea level. Drainage from the mountains flows in a southeasterly direction eventually forming the river valleys that feeds the Gulf of Bothnia. Much of southern Sweden is characterized by a sub-Cambrian peneplain, which in many places has been reshaped by tectonic movements and erosion. This peneplain has formed for instance the characteristic Stockholm region fissure-valley landscape, which extends into the Baltic Sea as an archipelago.

The two main natural soils, podzol and cambisol, are shallow, usually within the range 20-50 cm deep. These soils are formed in deposits mainly originating from the latest Weichselian glaciation. These glacial deposits are often found as till covering the bedrock surface. In lower parts of the terrain, especially below the highest shoreline, glacial or postglacial clay or silt has been deposited on top of the till cover. Peat is also abundant in the northern parts of Sweden.

Sweden's climate is determined by its northern position in the border zone between Arctic and warmer air masses as well as its location on the western rim of the Eurasian continent close to the Atlantic Ocean with its warm Gulf Stream. Annual mean temperatures range from +8°C in the south to -3°C in the north. Annual precipitation typically varies between 500 and 800 mm but in the mountain range annuals may reach as much as 2000 mm. Mean annual precipitation is on average more than twice as much as evapotranspiration. This, together with the influence of glacial deposits, gives Sweden numerous lakes of varying sizes.

The vegetation of Sweden is divided into four main zones. The Alpine zone is located along the mountains in the northwest. The boreal zone in northern Sweden is part of a vast coniferous forest belt, the taiga, which covers the northern Polar Regions. The boreonemoral zone south of the biological Norrland boundary, Limes Norrlandicus, is a belt of mixed forests consisting of coniferous trees and a significant amount of birch and aspen on till soil and groves of nemoral trees in the cultivated landscapes. In the far south and on the west coast is the nemoral zone with elm, ash, beech, maple, lime and oak trees, with beech being the most characteristic.

The most densely populated areas lie in the triangle formed by the three largest cities—Stockholm, Göteborg and Malmö—and along the Baltic coastline north of the capital. The interior of Norrland is very sparsely populated. The most distinctive agricultural districts appear as scattered 'islands' in a sea of forests.

Stockholm

The County of Stockholm is part of the relatively homogeneous central Swedish fissure-valley landscape, located within the boreonemoral zone. This region was entirely covered by ice during the Weichselian glaciation. During the deglaciation phase the region has changed from being completely submerged under the ice-sea lake

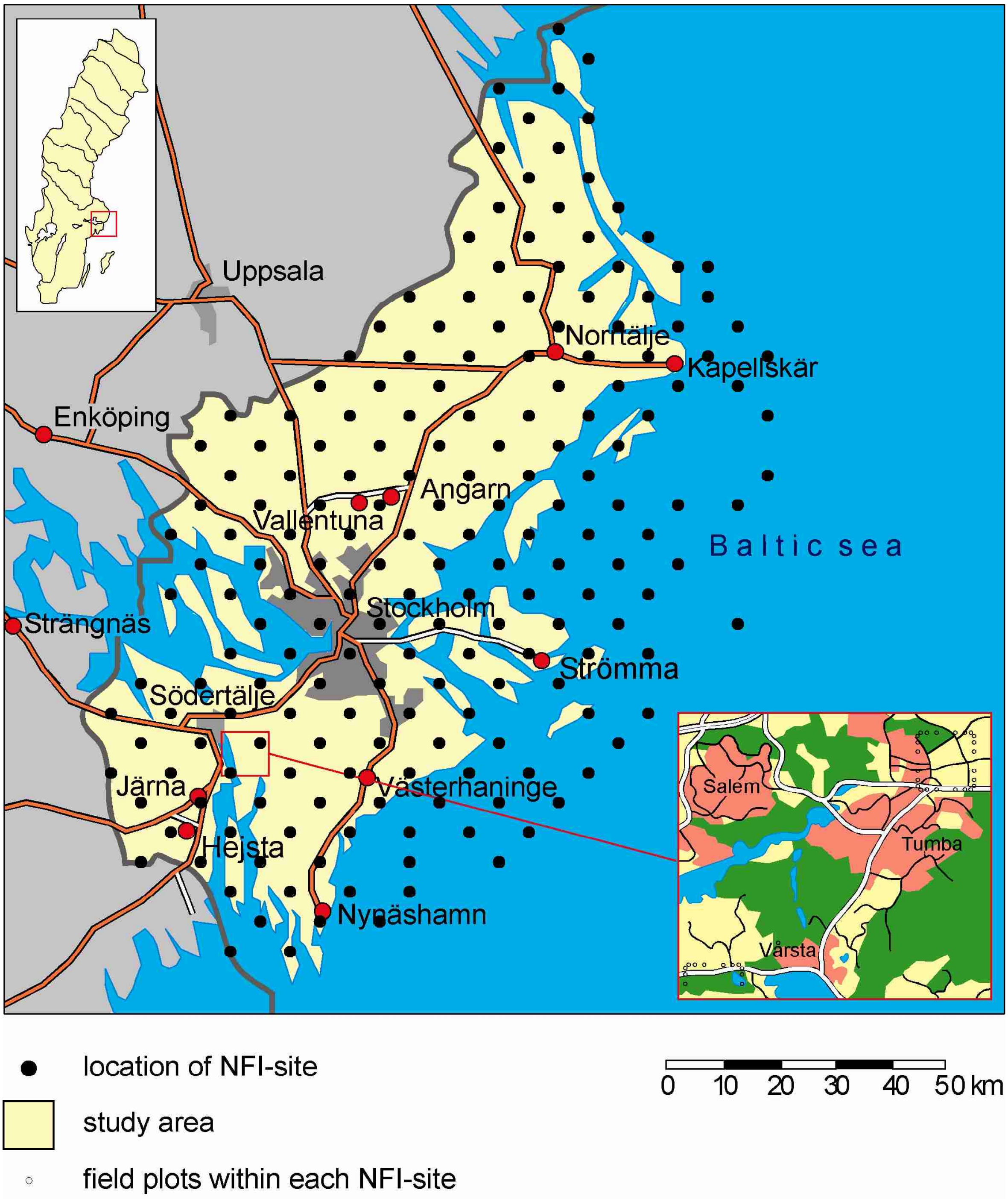


Figure 11 Map of study areas. Structure data were collected for entire Sweden (upper inset) and R-data collected for Stockholm County (main map). Dot symbols show the location of NFI tracts and plots within these tracts (lower inset) that were used for accuracy control.

surface into a region of scattered smaller and larger islands and lakes at the Baltic Sea coast. Governed by the fissure valley bedrock structure the glaciation and deglaciation has produced an areal pattern of lower and higher land, in which valleys are filled with sedimentary clays and higher ground is covered by till or consists of bare rock.

The southern shore of Lake Mälaren is mostly consisted of rocky cliffs, its northern shore rather flat. The city of Stockholm was founded in the 13th century on a small island at the entrance of Lake Mälaren. The southern region was sparsely populated and in the north the town met with farming settlements and villages. During the last few hundred years, Stockholm has undergone periods of rapid urbanization. In the second half of the 20th century the built up areas started to expand radially along the main roads and railways within a radius of 25-30 km. Between these suburban settlements there are still significant areas of forestland as well as some agriculture that reach fairly deep into the city center.

The National Forest Inventory

The following brief description is meant to give a background on the purpose of the National Forest Inventory, its content and the spatial and thematic resolution of the data.

Background

The goal of the National Forest Inventory is to provide information on the forest natural resource for planning and management on a national and regional level. It also aims at providing data for forestry research. Based on the National Forest Inventory it should be possible to present information on a regional level with adequate accuracy. It is on the other hand not possible to give estimates of smaller geographic units, for instance municipalities.

The first National Forest Inventory was conducted 1923–29 and the second 1938-52. Both these inventories were carried out one county at a time and in the form of a traverse sampling. Starting 1953 and until present entire Sweden is surveyed with a sparse sampling frame. At the same time the actual sampling was changed to an inventory of quadratic so called tracts with circular sample plots located along the tract edges Figure 11. Further refinement of the sample density has resulted in that from 1973 and onwards it is possible to make reliable estimates for several important forestry parameters based on the integration of 5 years of data.

The density of the sample has been chosen to provide a maximum standard error of 12% for estimates of forestland area and a maximum standard error of 5% for estimates of growing stock.

Method

The National Forest Inventory is an inventory based on sampling. The sample consist today of circular plots with a 10m radius (314m2). The plots are distributed along the sides of quadratic so-called assessment tracts. One such tract can under normal conditions be surveyed in the field in one workday. The tracts are systematically distributed over the entire country in a sparse network. To be able to use different sampling density Sweden has been divided into 5 regions. The distance between tracts and the number of sample plots may vary between these 5 regions. Stockholm County is located within a region where the side of the quadratic tract is 1200m, the average distance between the tracts in a 5-year sample is 7km, and the number of plots in each tract is 20. The field inventory is carried out during the summer from May trough August by some 20 inventory teams each consisting of 5 persons. In addition to this approximately 10% of the surveyed area is subject to control inventory. This is made to enable detection and correction of any errors in the data collection and to estimate the accuracy of the registrations.

There are two types of errors in the registrations, random errors and systematic errors. Random errors usually arise as a consequence of the sampling. These errors can be statistically estimated and they are presented with the data as a standard error for each variable. Systematic errors might occur due to deficiencies in the measurements, used factors in calculations of volume or individual variation in the interpretation of inventory methods and field interpretation.

For area calculations of some characteristic the following information is used; the total area of the county, the total number of field plots in the county and the number of field plots that have the wanted characteristic. First the area factor is calculated, that is the land area that each field plot in the sample represents. The area factor = total land area / number of filed plots. The area factor for Stockholm County for the period 1973-77 is 254ha. To calculate the area of for example

Table 3 The National Forest Inventory Site quality classes (Jonson, 1914)

Site quality class	I	II	III	IV	V	VI	VII	VIII
Ideal yield, m^3sk/ha and year	10,5	8,0	6,0	4,5	3,4	2,5	1,8	1,2

Table 2 The National forest inventory classification of cutting classes (Svensson 1979)

Cutting class	Meaning
A	Unstocked forest
B1	Thicket stage
B2, B3	Young forest
C	Young thinning forest
D1, D4	Old thinning forest
D2, D3	Final felling forest
E	Residual or creamed forest

swamp land supposing that we know from the field data that 100 field plots were found to be swamp. The total swamp area in the county would be estimated to be 254 * 100 = 25 400 ha.

Variables

The National Forest Inventory measures and calculates a host of variables out of which this introduction only considers variables also included in the R-method.

Land-use classes

Land areas are in the National Forest Inventory divided into the following land-use classes.

- Forestland
- Swamp
- Rock surface
- Power lines
- Various land
- Sub alpine woodland
- High mountains
- Roads and railways
- Agricultural land
- National parks, nature reserves, certain military areas etc. (NRS)
- Water
- Outside County

Site quality

Site productivity is a measure of the site specific, wood productive capacity. In the National Forest Inventory, Jonson's (1914) site productivity estimation method is still used. This is expressed as 8 ordinal classes divided by the ideal timber volume production for a 100-year growth period. Field estimation of site productivity is difficult and includes several subjective elements. This is why data such as local forestry plans and comprehensive forest inventories can be expected to include rather large errors in terms of absolute values. Results from the control inventory performed during 1973-77 show that site quality measurements are fairly consistent in the National Forest Inventory data (Svensson, 1980).

Cutting classes

The concept of cutting class is related to forestry application and it is a classification of the maturity within a field plot relative to the final felling age. It also indicates the next silvicultural measure to be conducted. The classification is based on information on crown closure, average tree diameter, age and height. Table 2 illustrates a slightly generalized version of this division.

Forest type

The forest type variable is derived by first specifying the constituent tree species fraction of basal area expressed in tenths. The classification rules in Table 3 are then applied on the derived species mixture, dividing the forest type variable into 5 classes.

Crown closure

The crown closure variable expresses to what degree an existing stand uses the site productivity as a consequence of the density of the stand. Crown closure is given on a relative scale from 0 to 1 divided into 10 classes. 1 denotes fully closed crown foliage that makes full use of the stand area. If a stand is so dense that it impedes the development it is classified as over-closed and is given a value of 1+. Crown closure below 0.3 is held as a regeneration area and a value between 0.3 and 0.5 is held as sparsely distributed forest.

Growing stock

Growing stock or standing volume is measured in m3sk, and is a measure of total stem volume over bark above stump height including top. The growing stock variable is only measured on trees higher than breast height, that is > 1.3m.

Material and methods – the R-method

Background

Table 4 The National forest inventory classification of forest types based on measured tree species mixture (Svensson 1979)

Forest type	Fraction of basal area or of number of stems/plants
Pine forest	Pine at least 7/10
Spruce forest	Spruce at least7/10
Mixed coniferous forest	Pine and spruce altogether at least 7/10
Mixed coniferous and broad leaved forest	Broad leaved trees 3/10-6/10
Broad leaved forest	Broad leaved trees at least 7/10

The basic idea behind the R-method (R=ruta, square in eng.) is a systematic summary of landscape information within quadratic, 25-hectare squares. One important feature in the design of the R-method is the ability to compensate for systematic bias. This is accomplished by comparison of the results with the corresponding estimates from the National Forest Inventory, which have statistically determined standard errors. The systematic bias in the R-data can hereby be quantified and corrected to the level of the National Forest Inventory. One of the main requirements has also been that the R-method shall produce objective data within a reasonable time and at a higher resolution than the National Forest Inventory. The described method is able to produce data for an area corresponding to Stockholm County within one man-year.

The definition of the R-data variables given below, allow for two variables to be directly related to the county estimates from the National Forest Inventory. These are ‘area of productive forestland’ and ‘growing stock’ per hectare productive forestland.

Method

The R-method involves the systematic summary of landscape information derived from aerial photographs. The collected R-data include all 500x500m squares delimited and specified by co-ordinates on the Swedish economic map and that also have at least 50% of the square area located within Stockholm county. This comprehensive summary of landscape information within a relatively large area is derived from large amounts of detailed information. This detailed information is derived through ocular inspection, which is interpreted and translated into 8 variables with 3 to 10 classes for each variable. These variables and classes are described in detail below.

The R-method has mainly used aerial photographs as information source for the database that has been created for Stockholm County. Regardless if the areal unit is 25 ha or 1 ha, aerial photographs, satellite images and also field studies are able to provide large quantities of landscape data of interest for various applications. The final choice of measurement method and the size of the areal unit is guided both by the purpose of the study and by available resources. There is however a fundamental difference between remote sensing and field based measuring methods. Both airplane and satellite carried sensors have the ability to give an overlook and detailed information at the same time. Field measurements on the other hand often demand time-consuming transportation in order to get close to the same amount of summarized information.

During the summer 1975 all of Stockholm County was surveyed by aerial photography at a low elevation, 9200m, using panchromatic film. The R-data described here used these images copied onto photographic transparencies at a 1:50 000 scale. For the interpretation the photographic transparencies were mounted on a light-table and interpreted through a mirror-stereoscope (Wild). An enlargement factor of 3 times was used during the interpretation. A constant source for additional information was also the Swedish topographic map, scale 1:50,000 and the Swedish economic map, scale 1:10,000. In addition a countywide map of forest landscape parameters, scale 1:50,000, was used. This map was compiled with the aid of silvicultural advisers from the local districts during a preparatory phase of the actual R-data inventory.

During the digital registration of the R-data each 25-hectare square unit was specified by its co-ordinates in the national grid. The boundary of each economic map sheet was transferred onto the aerial photographs using a mm-graded ruler and with the guidance of the land ownership pattern. The interpreted values for the 8 variables were written onto a transparent film with a 1cm^2 square grid, which in a 1:50 000 scale corresponds to the areal unit of the inventory, 25 hectare, Figure 12.

Thus, the inventory is conducted on a square-by-square basis. The entire area within the square and nothing on the outside is visually interpreted and classified according to the instructions below. Regardless of content, each square was always given an estimate of the area of productive forestland within the square. This estimate is given as tenths, 2.5 hectares, of the total square area. Thus the code 1 means 10,0-19.9% or 2,50-4,99 hectares. In cases of doubt, a direct measurement was performed on the economic map sheet.

The pilot study that was conducted as part of the PSU-project covers entire Stockholm county and it describes forest landscape variables for 34,464 quadratic, 25-hectare squares. The average interpretation performance using the R-method was estimated to about 4000 hectares/day.

Instructions for the inventory

The following section describes how the interpreted variables are to be classified and written down on the transparent inventory sheet.

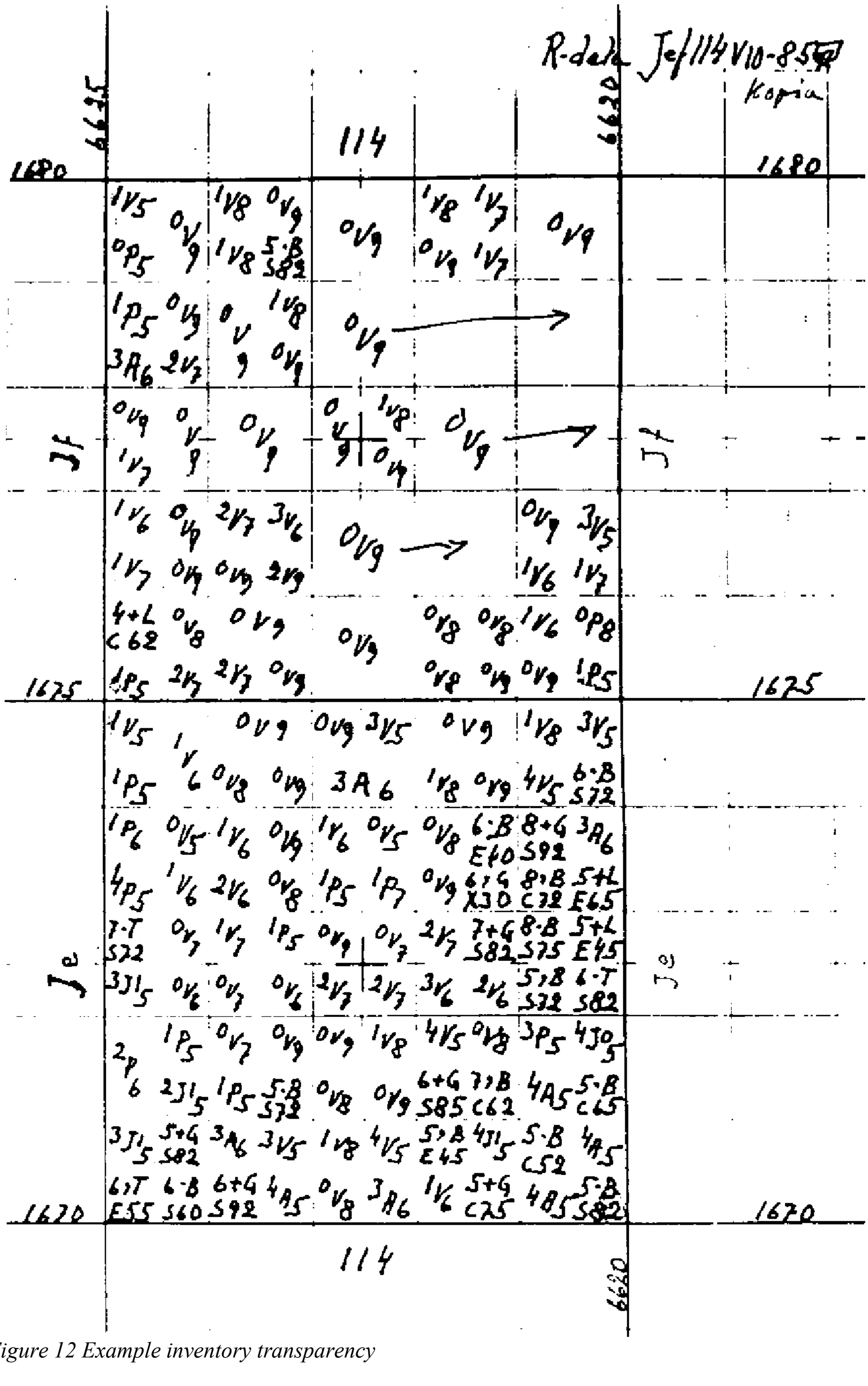


Figure 12 Example inventory transparency

Table 5 Land-use classes and corresponding codes in R-data

Code		Land-use class	
V		Water area also including smaller islands < 1ha	
P		Area planned for dense settlements	
J		Agricultural area with accompanying grounds. 10 classes are separated as follows:	
	J0	More than 50% of the area is settlement, farm center et c.	
	J1	≥ 50% of the area is field and accompanying buildings	
	J2	≥ 50% of the area is field of	good quality
	J3	"	normal quality
	J4	"	poor quality
	J5	"	varying quality
	J6	≥ 50% of the J-area is grazed	
	J7	"	and field on solid ground
	J8	"	and field on swampy ground
	J9	Other varying agricultural land	
A		Other land-use classes than forestland cover more than 50% of the area	

Table 6 Forest wasteland classes and corresponding codes in R-data

Code	Waste land type
H	Rock surface wasteland; at least 50% of the forestland is rock surface and other waste land
M	Swamp waste land; at least 50% of the forestland is swamp and other waste land

<u>Area productive forestland</u>

Codes 0-9 are given for each tenth of the total square area that is covered by productive forestland. Numbers are written in the top left part of the square on the inventory transparency.

<u>Land-use class</u>

If water, planned buildings, agricultural area or other land-cover types except forestland cover 50% or more of the square area, a code is given in the middle of the square on the inventory transparency. Codes are given according to Table 5.

For all squares coded as V, P, J or A the areal coverage of that land-use class is specified in tenths in the lower right part of the square on the inventory transparency.

<u>Forest wasteland</u>

Areas not classified, as V-, P-, J- or A-squares according to the specification above, are forestland squares. In these squares the total area of productive forestland, rock surface wasteland and swamp wasteland is always more than 12.5 hectares, that is more than 50% of the total square area. If the area of wasteland dominates, the square is classified as either rock surface wasteland or swamp wasteland according to Table 6. The code is written in the middle of the square on the inventory transparency.

For both types of wasteland the areal coverage of that type of wasteland is specified in tenths in the lower right part of the square on the inventory transparency. In addition, the crown closure and the bearing capacity of the wasteland is specified by a number next to the wasteland class code following the directions for these variables below. As usual, the remaining productive forestland is specified in tenths in the upper left corner of the square on the inventory transparency.

Visible roads, power lines, landfills etc. is not included in the forest area. Larger trails, ditches, telephone lines etc. should however never be excluded. This would require images of higher quality and a substantially higher level of ambition.

All other squares are evaluated on all 8 variables, which are specified with a six-digit code in the square on the inventory transparency. The first sign in this code is, as previously explained, a number that represent the amount of productive forestland within the square. All six signs describe forestry conditions in the productive forestland area. At the interpretation the signs are written down within the square area on the inventory transparency in two rows with three signs in each row in a systematic fashion, Figure 12.

<u>Site quality</u>

The second sign, written in the upper middle part of the square on the inventory transparency, represents the site specific, wood productive capacity. This is encoded according to Table 7.

Table 7 Site quality classes and corresponding codes in R-data

Code	Site quality class
+	Good productive capacity; site quality ≥ 6,0 m^3sk/ha*year is estimated to cover ≥ 50% of the productive forestland area
•	Normal productive capacity; site quality 4,0 – 5,9 m^3sk/ha*year is estimated to cover ≥ 50% of the productive forestland area
-	Poor productive capacity; site quality < 4,0 m^3sk/ha*year is estimated to cover ≥ 50% of the productive forestland area
,	Other productive forestland with varying site quality

Table 8 Tree species classes and corresponding codes in R-data

Code	Tree species class
T	Pine forest; pine constitute at least 70% of the growing stock
G	Spruce forest; Norwegian spruce constitute at least 70% of the growing stock
B	Coniferous forest; neither pine nor spruce dominates, coniferous trees constitute at least 70% of the growing stock
L	Deciduous forest and mixed forests where deciduous trees constitute at least 30% of the growing stock
∅	Regeneration area or area with unknown species composition

Table 9 Cutting classes and corresponding codes in R-data

Code	Cutting class
X	Final felled area with or without planting and nurse trees as well as other areas according to the old Swedish forestry statute SVL§ 5:1, 2, 3, is estimated to cover ≥ 50% of the productive forestland area.
U	Thicket stage forest is estimated to cover ≥ 50% of the productive forestland area.
C	Thinning stage forest is estimated to cover ≥ 50% of the productive forestland area.
S	Final felling forest is estimated to cover ≥ 50% of the productive forestland area.
E	Other combinations of cutting classes

Tree species

The third sign, written in the upper right part of the square on the inventory transparency, represents what tree species that is estimated as dominant on the productive forestland. Classification and encoding follows Table 8.

Cutting class

The fourth sign, written in the lower left part of the square on the inventory transparency, represents cutting class and is a classification of the maturity within a forest stand relative to the final felling age. Classes and codes used are given in Table 9.

Table 10 Growing stock classes and corresponding codes in R-data

Code	Growing stock class (m^3sk/ha productive forestland)
0	0-24
1	25-49
2	50-74
3	75-99
4	100-124
5	125-149
6	150-174
7	175-199
8	200-224
9	225-

Growing stock

The fifth sign, written in the lower middle part of the square on the inventory transparency, gives an estimation of the average growing stock. Values are given as one of ten classes according to Table 10.

Stand density and ground bearing capacity

The sixth and last sign, written in the lower right part of the square on the inventory transparency, represents the relative stand density measured as crown closure and the ground bearing capacity on the productive forestland. Classification and encoding follows Table 11.

Commentary on the instructions for the inventory

Land-use class

The first consideration at the interpretation of every individual square area is to determine whether or not other land-use classes than forestland, including forest wasteland, cover more

Table 11 Crown closure and ground bearing capacity classes and corresponding compound codes in R-data

Code	Crown closure and ground bearing capacity.	
0	Forests with markedly varying crown closure as well as ground bearing capacity	
1	Well closed forest stands	and high ground bearing capacity comprise > 50% of the productive forestland area
2	"	and normal ground bearing capacity comprise > 50% of the productive forestland area
3	"	and clay or otherwise wet ground with low ground bearing capacity comprise > 50% of the productive forestland area
4	Forest stands with normal closure	and high ground bearing capacity comprise > 50% of the productive forestland area
5	"	and normal ground bearing capacity comprise > 50% of the productive forestland area
6	"	and clay or otherwise wet ground with low ground bearing capacity comprise > 50% of the productive forestland area
7	Forest stands with sparsely distributed trees	and high ground bearing capacity comprise > 50% of the productive forestland area
8	"	and normal ground bearing capacity comprise > 50% of the productive forestland area
9	"	and clay or otherwise wet ground with low ground bearing capacity comprise > 50% of the productive forestland area

than half of the square area. If so, this square is assigned one of the four following land-use class labels:

- Water (V)
- Planned settlement area (P)
- Agricultural area (J)
- Other land-use (A)

If this is not the case, the square is regarded to be forestland. This procedure will generally reduce the frequency of land-use classes that already occur in lower frequencies or in smaller areal patches than the average. This is caused by the fact that such land-use classes less often covers 50% or more of the interpreted 25-hectare area.

No direct comparisons can be made between the estimates of land-use classes from R-data and the National Forest Inventory, unless the differences in classification can be eliminated, Figure 13. See also section Data analysis below.

V-squares - Larger water bodies such as the major bays of the Baltic archipelago, the lakes Mälaren and Erken, are not included in the inventory. On the other hand, pure V-squares in-between islands and the coastline are included for purposes of completeness. For the squares classified as water, the code 0V9 (0 forestland and 9 water) normally mean 100% water. The total number of such squares is rather large within Stockholm County. Theoretically, following the definition, the code 0V9 implies that 0-9% of the square area might be other than water, for example shoreline tree vegetation. However, these areas ore not considered holding any productive forestland.

V-squares encoded 0V5 through 8 indicate a certain proportion of other land-use classes than water of which some might be forestland. These scattered pieces of forestland close to water is not included in the total estimate of productive forestland in the county. It might be of interest to know that the total area of such scattered forestland with proximity to water within the county is probably around 3000 hectares.

Shoreline forestland has sometimes during the interpretation been considered as wasteland and therefore not been counted as productive forestland.

P-squares - In cases where half of the square area consists of planned settlements the economic map has been consulted in detail. From this the following areas have been included in the class: all plots whether built on or not, smaller adjacent parcels not suitable for forestry or agriculture, and areas such as sport fields, maintained beaches et c.

Forested areas an non-maintained agricultural land bigger than 0.5 hectares has been regarded as productive forestland even if these areas might have substantial other values such as recreational area for local residents. If more than half of the forest production theoretically could be harvested these areas have been classified as forestland even if it is situated with densely populated areas. Consequently parts of the Djurgården and

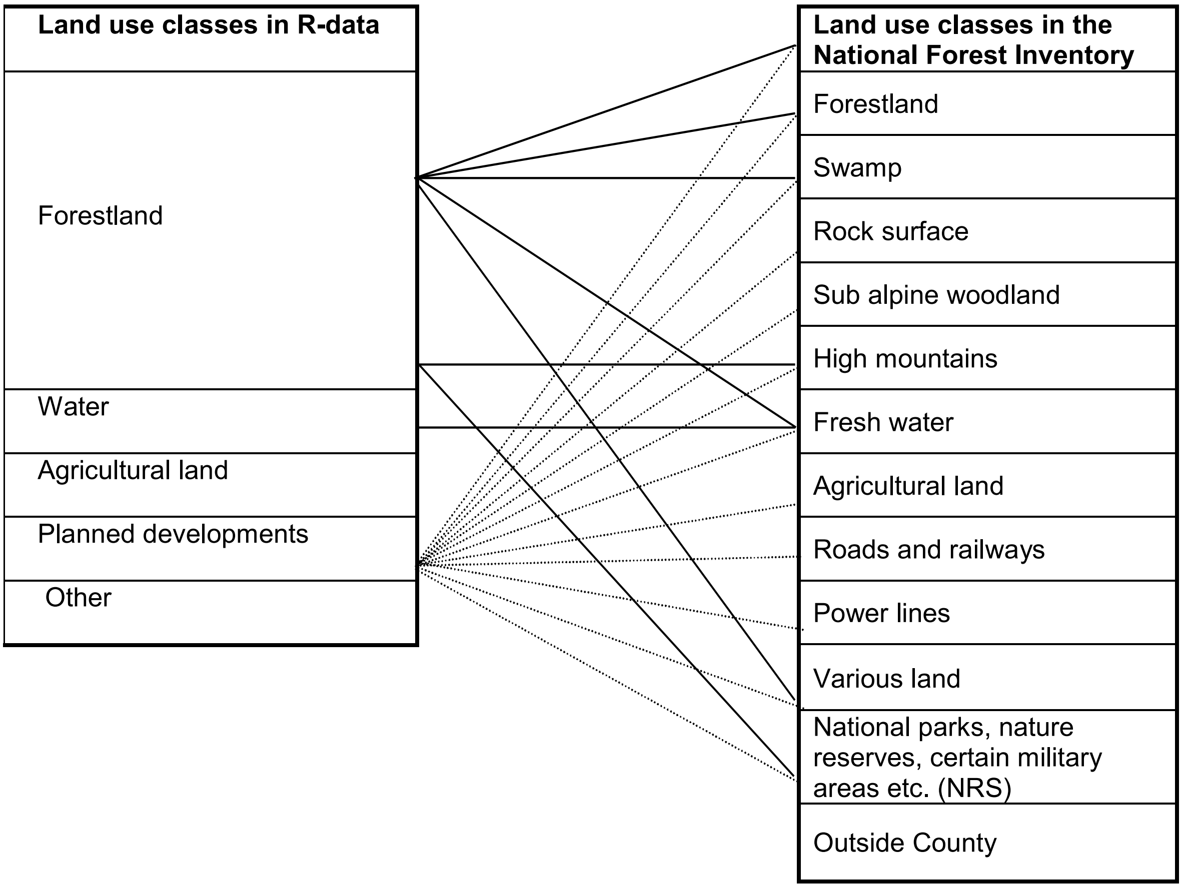


Figure 13 Corresponding land-use classes in R-data and the National Forest Inventory

Humlegården parks have been classified as forestland.

Residential plots in the forestland that are not yet built upon have been counted as P-land if it is anticipated that they may be built upon in a near future. Otherwise they have been considered as forestland. Old, non-developed, one-hectare sized parcels, frequently found in the Värmdö area, have been counted as forestland.

Squares encoded 0P9 (0 forestland, 9 planned settlement area) are pure built-up areas. P-squares encoded 0P5 through 8 have a certain proportion of other land-use classes. Smaller groves and parks are often present, probably covering some 800 hectares in the entire county, but they have not been counted as forestland.

There are 1,701 squares in the county encoded 1 through 4 P 8 through 5. These hold something like 9,000 hectares of productive forestland or almost 3% of the entire forestland in the county. It should be noted that this forestland has an average distance to dense settlements of 100m.

<u>J-squares</u>; The agricultural areas are in Stockholm county mainly concentrated as continuous areas such as those around Skeppstuna, Hölö and many others. In the archipelago and the forest districts the agricultural areas are markedly scattered. It was previously mentioned that this pattern might give some skewed results due to the fairly large basic areal units used in the inventory. This is especially true for the J-areas and to partly compensate for that fact the J class is subdivided into 10 subclasses according to Table 5.

"J0 - More than 50% of the area is settlement, farm center etc." are not very common but still viewed to be of particular cultural and historical interest. As soon as this situation has been conceived as possible, this code has been used.

"J1; [3] 50% of the area is field and accompanying buildings" has often been used, maybe too often.

"J2 - 50% of the area is field of good quality" is probably the most frequently used J-sub-class. The yield from the agricultural fields may sometimes be overestimated due to favorable field structures, proper maintenance or some indication of homogeneous and lush crops at the image interpretation.

"J3 - 50% of the area is field of normal quality" is not as common as one might suspect. The agricultural output of this class might be slightly overestimated in the archipelago region and underestimated in other regions.

"J4 and J5 - 50% of the area is field of poor or varying quality" probably should have been used more often, maybe the courage was missing! The support from the image for this delimitation is often rather weak.

Codes "J6, J7 and J8 - 50% of the area is grazed and field on solid or swampy ground" have maybe been used too liberally and these areas are very likely to have been interpreted as forestland in the National Forest Inventory.

"J9 - Other varying agricultural land" usually refers mainly to presently non-cultivated agricultural land with uncertainty about future land-use.

Similar with the V- and P-squares, no productive forestland has been recorded for the 1,381 squares encoded 0 J0-9 5 through 9. This unregistered area is estimated to be at the most 1,000 hectares for the entire county. These areas are mostly smaller forested plots adjacent to farm buildings, fields or small forest groves within enclosed pastures. They are probably as a consequence of their location especially valuable biotopes for the preservation of biodiversity within the cultural landscape.

<u>A-squares</u> comprise both concentrated occurrences of for instance golf courses, timber storage areas, bathing places and mixed V-, P- and J-areas that altogether cover more than 12.5 hectares. The definition of the A-class is therefore a bit more complicated than the previous ones.

As a consequence, one A-square can have a totally different mix of land-use classes than another. We do know however that neither the V-, P-, J- nor the forest area alone exceeds 12.5 hectares. The use of an A-class is to get 100% coverage of the entire county area.

By the technique of excluding the wasteland area in the A-square estimates, some information is gained. The code 3 A 5 for instance, give us the following information; at least 30% is productive forestland, at least 50% is A-class area and at least 10% is forest wasteland. This design enables a good estimation of the relation between productive forestland and forest wasteland.

<u>Forest wasteland</u>

<u>H-squares</u> - If forest wasteland is mostly made up of rocky ground or high hills the square is coded H. Stereo-interpretation of these areas requires good sense of observation and a good knowledge of the regional conditions. Big, high hills with steep slopes into the forests are easy to detect both on the economic map sheets and in the stereo images. This type of landscape is common on Södertörn, Värmdö and in the southern parts of the archipelago. In all other areas it is a lot harder to delimit areas of rock surface wasteland only with maps and stereo imagery.

The following method was employed to solve this problem: Two versions, one older and one newer, of the economic map was compared. If the older version on its orthophoto had a bright spot where the newer version had a height-curve, and the aerial imagery did not show any other sign of productive forestland, then this area was considered as rock surface wasteland. Smaller outcrops covered by mosses and shadowed by forest with north facing slopes are almost impossible to detect in the stereo imagery. And this may be the most common type of rock surface impediment in the county.

Rocky hill areas larger than 5 hectares have been mapped onto the countywide forestry inventory of 1972 and this information was of course of great help at the interpretation.

<u>M-squares</u> - Larger mires is relatively easy to identify in stereo images and they are also specifically marked on the new economic map sheet. However, on Scots pine bogs it may sometimes be hard to separate wasteland from forestland with poor productive capacity. It is likely that some of the M-areas have been classified by the national forest inventory as swamp forest of poor site quality. On the other hand, in the comprehensive forestry inventory the same areas would probably have been classified as wasteland.

These two wasteland categories occur as both densely and sparsely forested variants. This is why the code for crown closure and ground bearing capacity, explained below, has been used. The code 0 means mixed conditions and this code has been fairly frequently used.

<u>Area productive forestland</u>

For every inventoried 25 hectare square unit the share of productive forestland has been recorded as codes 0 through 9. Thus the code records tenths of the total square area and for example the code 1 means that there is at least 10.0% and at most 19.9% productive forest land within the square unit. The figure is a combined estimate using the economic map sheet and the stereo image.

Water, house lots, agricultural fields, buildings, roads, power lines were most easily

Table 12 Site quality class correspondence between the R-method and Jonson (1914)

Site quality class R-data	Good (+)		Normal (•)		Poor (-)			
Site quality class Jonson (1914)	I	II	III	IV	V	VI	VII	VIII
Ideal yield, m^3sk/ha and year	10,5	8,0	6,0	4,5	3,4	2,5	1,8	1,2

located on the economic map sheet. The map sheet does not however identify for example grazing areas and forest clear-cuts. These cases were settled by using the stereo image but even this may not result in a clear answer. In such cases the area was located on the old economic map sheet, which has a fairly good bottom imprint of the aerial image from the end of the 1940s. If the same land use pattern did not appear on this map it is probably a felling site area. If however the same land use pattern appeared on the older map it may be a grazed area. This might still be a recently abandoned grazing area and to resolve this possibility the areal image was consulted once again with specific attention to details. If brushes could be seen to encroach from the edges or along ditches and especially if signs of scarification or performed ground clearing could be found the area was classified as forest land. On the other hand, if grazing animals, areas of heavily trampled ground was detected in the image; the area was classified as pasture.

In remaining uncertain situations the decision between forest land or grazed agricultural land was based on considerations of the spatial configuration of the area under consideration and surrounding land parcels. Properties such as size, shape and especially relation to water and farm center were used as decision variables if it could be feasible to continue grazing or forestry on the area.

From this detailed description it is important to note two things. First, the areal estimate is made with great care in order to produce a reliable estimate for each areal unit. Second, there are a multitude of considerations of very different character and either one of these may determine the outcome of the classification.

As previously explained the areal distribution of land cover types is of importance for this classification system. First of all it is decided if the combined area of productive forestland and wasteland covers more than half the areal unit. After this the wasteland area is estimated and subtracted. The remainder is classified as productive forestland and that area is recorded as 10% classes. This procedure also enables not explicitly recorded land use areas to be calculated as the difference between given area and the total area of the square unit.

The following variables are solely determined based on the properties of the productive forestland area within the square area.

Site quality

Table 7 makes clear that the site quality variable does not refer to the average site quality within the square. Instead a mode-like measure is employed where a specific site quality class is chosen only if it covers 50% or more of the productive forest area. Site qualities may, especially within the County of Stockholm be very variable from one stand to another, and each stand is typically relatively small, only c.3 hectare. It is therefore argued that it is not meaningful to produce an average. The chosen measure is considered more expressive to people that are non-forestry experts.

The estimates are not based on measurements. A countywide map with site quality estimates from the local districts silvicultural advisers together with elevation information from the economic map sheet has been important information sources. With this information in mind it is a fairly easy task for a skilled forestry expert to use the aerial image to finally choose which of the four classes that best correspond with the picture.

It is anticipated that site quality information at this resolution could be very valuable information, especially for municipal planning purposes.

The approximate correspondence between the site quality classes used in the R-method and classes according to Jonson (1914) are illustrated in Table 12. The mixed class of the R-method has no equivalence in the Jonson system.

Tree species

All trained aerial image interpreters know that it is precarious to make estimates of tree species proportions in black-and-white images. Especially dicey are cases with younger and intermediate age

Table 13 Cutting class correspondence between the R-method and the Swedish National Forest Inventory

R-method cutting class		**National forest inventory cutting class**	
X	Felling site	A B1	Unstocked forest Thicket stage
U	Thicket stage	B2, B3	Young forest
C	Thinning stage	C D1, D4	Young thinning forest Old thinning forest
S	Final felling stage	D2, D3	Final felling forest
E	Other combinations of cutting classes	E	Residual or creamed forest

coniferous forest stands. So, for that reason the information from the local silvicultural advisers have been thoroughly studied before the aerial photo interpretation. Surprisingly often the background photograph on the old economic map gave additional information on the actual forest stand.

Squares with more than 3/10 deciduous forests (L-squares) appeared easiest to identify. After this, older, not too well closed spruce forests seemed easiest to identify. The dark shadow from these scrubby spruces was a contributing factor. On rocky substrates where normally pine trees prevail the code T was recorded, at least when the lighter gray shade of pine forests could be distinguished. Where the local silvicultural advisers had recorded pine trees this was taken as evidence to use the T class label even if the area was of young or intermediate aged forest. Spruce forests on good site quality locations were determined similarly.

In most cases, the images of the forest landscape were studied in a way that several squares could be compared in detail. When the joint information suggested the code L, G or T, this was recorded.

Cutting class

The managed forests in the Stockholm region have an average growth period of some 100 years. Because of this it is anticipated that information about the forest maturity or cutting class is of large interest for all use of the forested landscape. For forestry purposes information on the location of large volumes of forests ready for final felling is of course of interest. Furthermore, this information is of interest to all parties involved in the physical planning process, especially municipal and non-governmental organizations interested in for example the preservation of recreational values in the forested landscape. The design of the cutting classes in the R-method, X, U, C, S, and E is for that reason defined in order to enable all parties to participate in a constructive dialogue about the spatial issues of forest landscape information. The correspondence between these classes and the National Forest Inventory is illustrated in Table 13

During the air photo interpretation it can often be hard to tell between the S and C classes. If in doubt the photographic backdrop from the 1950s on the old economic map was compared with the stereo images. If there was a significant difference between the two the square was coded C, otherwise it was coded S. If the difference was substantial for some stands and not for other stands the square was classified as a combination, E. The X and U cutting classes stand out fairly well from the other classes in the image interpretation. It may, however, be hard to tell X and U apart. In those cases the records from the local silvicultural advisers have been an excellent information source.

The E cutting class has always been used when none of the classes X, U, C, or S alone have been estimated to cover at least half of the productive forest land area within the square unit. Due to the landscape structure in the Stockholm region, most if not all squares would have been classified as E-squares if the forests had been intensely managed for a longer period of time. This is not the case at the time of this inventory but it might very well be the case for many areas today except maybe for larger areas managed by large forest companies in the northern and western parts of the county.

Growing stock

The mean growing stock per hectare productive forestland was estimated for each square unit. These estimates were based on experience from measurements through the National Forest Inventory and especially estimates from forest management plans covering some 40,000 hectares, which were compared with the stereo image. In addition, information from other planning activities and related field sampling covering some 100,000 hectares of the county assisted the growing stock estimates.

The growing stock varies from stand to stand between 0 and 400m^3sk/hectare. Especially the cutting class value influences the amount of growing stock. The forest stand average for felling sites is somewhere between 0 and 10 m^3sk/hectare, not counting nurse trees, which have some 20-80 m^3sk/hectare. The thicket stage has a large variation in the range 10-120 m^3sk/hectare and in some cases even more at the transition to thinning stage forest. The values for thinning stage forests is between 60 and 250 m^3sk/hectare and forests ready for final felling usually lie in the range 80-400 m^3sk/hectare. In some extreme cases these stands may hold more than 400 m^3sk/hectare.

The second most important factor is the site quality. Poor site quality usually gives values at the lower end whereas good site quality result in values at the higher end of the intervals mentioned above.

Another contributing factor is how densely the forest grows and in the stereo images the crown closure is a measure of this. A well-closed stand with large crowns does not have as much growing stock as a similarly well-closed stand with small crowns that indicate a higher number of stems.

Also the tree species affects the volume of the growing stock. Deciduous stands have generally less volume than Norwegian spruce stands with similar conditions. Alder, Ash and Aspen might in thinning stage stands reach the same levels as comparable coniferous stands, whereas Birch and especially Oak stands normally have significantly lower volumes of growing stock.

An estimate of the growing stock volume using the described method is of course very subjective. Each person has different experiences, which become articulated through the series of considerations that are included in the estimation process. Systematic errors in the estimations may lead to an over- or underestimation of the total growing stock volume, maybe as much as +/- 15%. The quality control that has been performed as part of this report shows however that there is a very good agreement between the R-data estimates and the National Forest Inventory for the entire county.

Stand density and ground bearing capacity

Stand density is measured as crown closure since this is possible to detect in the aerial images. In the National Forest Inventory the stand densities is given as volume-density and is calculated from field measurements of basal area and mean height. The relation between the NFI measures and the R-data measure is not developed any further in this text.

The ground bearing capacity variable was recorded in the comprehensive forest inventory but not in the NFI. There are several reasons to include this variable in the R-data inventory. For forestry purposes this variable is of interest to road construction and logging planning. The indirect consequences for choice of plant species and silvicultural planning is however far more important. Also, this variable may be of interest to other interest groups such as for recreation purposes.

In the original R-data these two variables are found in the same position. This is the primary cause of the following mixed treatment of these variables.

Codes 0-9 have been used for all square units classified as productive forest and also for those squares where forest wasteland is dominant (H and M squares). Note however the special meaning of the code 0 in connection with the forest wasteland class.

For squares classified as productive forests the code 0 is used with a special meaning for felling sites that show signs of regeneration measures. Felling sites with no signs of soil cultivation or scarification or other regular point pattern, which may indicate seedlings, have been given the code 0. Felling sites with nurse trees and signs of ground clearing have often been coded 4, 5, or 7 although no seedlings have been identified.

The codes 1, 2, and 3 means that the forest stands are generally well closed with high normal or low ground bearing capacity. The interpretation may however have favored the normal case.

The codes 4, 5, 6, and 7 have also been applied with no significant deviations from the instruction. Though the code 5 "Forest stands with normal closure and normal ground bearing capacity" have been used in situations of a lack of indications for any of the other classes.

Squares given the codes 8 or 9 "Forest stands with sparsely distributed trees and {normal, low} ground bearing capacity" are usually areas that have been neglected or otherwise show signs of unsatisfactory forest conditions. A large amount of these areas may nevertheless be abandoned agricultural land or enclosed pastures that hold other specific values than those favored by this classification system. It may thus turn out useful from a nature conservation perspective to investigate these areas in more detail.

Data processing

During the period from 1981 until 1987 the Board for regional planning and industry within the Stockholm county council was the authority that specifically co-operated with the PSU-project leaders at the Swedish National Board of Forestry. This co-operation has largely consisted of registration and processing of original R-data performed by Gerd Lundström under the supervision of ME Björn Lindfeldt.

Registration control and corrections

Copies of inventory originals were continuously provided for computer registration. Printouts of the recorded data were similarly brought back to the interpreter (Rolf Ruben) for control and correction. This procedure was repeated until no errors were found.

By February 1986 the entire county was R-inventoried and computer registered. Finally the database was added the national grid coordinates for each registered R-data square. At the same time the codes from the inventory sheets were translated into number format.

To be able to evaluate a possible drift in the estimates, several square units were interpreted twice and even three or four times after some time. Also after a longer break in the inventory work some 1000 hectares were re-interpreted. These were all measures to evaluate any systematic errors from one period of inventory to another. Codes were given to these square units to be able to identify the most recently inventoried square.

Quality assessment

As soon as the following prerequisites can be fulfilled, the R-data can be compared with corresponding variables from the National Forest Inventory.

- R-data should be collected according to the above instruction for the inventory and for a geographical area that correspond to statistically verified data from the National Forest Inventory.

Furthermore data from the National Forest Inventory need to be processed so that the following information is available:

- The total area an the land use class proportions
- The productive forestland area, mean site quality and the areal coverage for each site quality class.
- The total volume of the growing stock, an overall mean value per hectare, areal distribution of growing stock classes and the mean growing stock per hectare for the three site quality classes <4m3sk/ha, 4-6 m3sk/ha and ≥ 6 m3sk/ha as well as for the cutting classes (A + B1); (C + D1) and (D2, 3, 4 + E).
- Areal distribution of cutting classes and the distribution for the site quality classes above, at least for the cutting classes (A + B1); (C + D1) and (D2, 3, 4 + E).
- The areal distribution of tree species and the growing stock distribution for tree species and for the three site quality classes that belong to the cutting class D2, 3, 4 + E) together with total figures.

If possible the standard error should be given.

The National Forest Inventory has not surveyed the entire county. The municipalities of Danderyd, Järfälla, Lidingö, Nacka, Sollentuna, Solna, Stockholm, Sundbyberg, Täby and parts of Vaxholm municipality, has not been surveyed in detail. The area of these municipalities is in the National Forest Inventory assigned to the land use class “Agricultural land”. Since this is a rather large area it would be hard to make any absolute comparisons between the two datasets if not some sort of adjustments were performed. To make a correct comparison between the two materials, the R-data not within the survey area of the National Forest Inventory needs to be removed.

The remaining difference between the National Forest Inventory figures and the R-data estimates may be related to that the distinction between productive forestland and forest wasteland has been different. There is also a possibility that deviation may occur due to the differences in spatial resolution of the two methods. The National Forest Inventory field plots are 314m^2 while the areal unit in R-data is 250,000m^2. This means that the two methods have different abilities to record properties of areal units, which size lie between these limits. In cases of systematic deviation in R-data from the National Forest Inventory data it is anticipated that using a correction factor can compensate for this deviation.

The area productive forestland is the only variable that is consistently given for all square

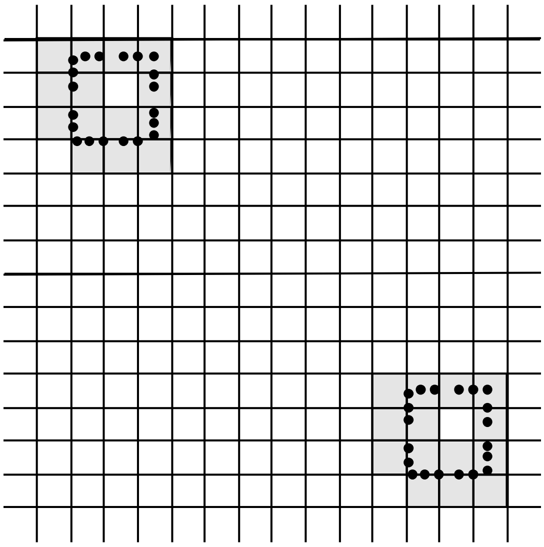


Figure 14 Conceptual layout of the condensed county square units. The square grid illustrates the grid of the 25 ha R-data inventory units. The small dots represent field plots in the National forest inventory, which usually come in square shaped tracts. The shaded 25ha units indicate those squares that intersect with one or more National Forest Inventory plots.

units no matter what land use class that dominates the square. Concerning the areal estimates of other land use classes, the purpose of the R-method is only to give a rough estimate of the land use structure by, for example, calculating the frequency of square units with a specific land use class or by examining the map image, Figure 16. For such areas the area of the specific land use class is given in tenths together with the estimate of productive forestland area. The remaining area, if any, is an indirect measure of the amount of other land use types.

Squares not covered by 50% or more productive forest land has not been specified according to the forest variables, site quality, tree species, cutting class, growing stock, stand density, and ground bearing capacity. The estimate of these variables is accordingly based on square units that have a 50% or more areal coverage of productive forestland. The truth of the overall estimates relies upon the assumption that the forests do not have entirely different properties for these different square units. This assumption may prove incorrect but is nevertheless the best estimate available.

For the quantitative summaries the class middle have been used as a mean value for each class. This means for example that for the variable "area productive forest land", the class 0, which by definition includes an interval 0-10% of the square area, is represented with the 5% value of the square area, 1.25 hectare.

Condensed-county method

The quality assessment was performed by concentrating the evaluation to those R-data squares that spatially intersected one or more of the National Forest Inventory field plots, Figure 14. In this way the spatial correspondence between the two data sets increase significantly. All National Forest Inventory field plots from the period 1973-77 thus determine the "condensed county". The sampling based National Forest Inventory is designed to give reliable estimates of county totals. It is therefore argued that the "condensed county" method gives an even better correspondence between the actual situation and the sample, due to the increased spatial correspondence.

Results – R-data

Quality assessment

The quality assessment is here restricted to total productive forest area and total growing stock estimates for the entire county. Other quality assessments are also possible but will require additional information from the National Forest Inventory according to the specification above. If possible though approximate figures from the National Forest Inventory have been given to give the reader an idea of the differences that may exist between the two data sets.

The total area of the "condensed county" is 46,750 hectare. It consists of 1,870 R-data square units and 3,091 corresponding National Forest Inventory field plots. The total area productive forestland for the "condensed county" is according to R-data 21,012 hectare. To produce an estimate of the total area within the whole county, the same technique is used as within the NFI. In 46,750 hectare of surveyed area we have 21,012 hectares of productive forestland. The ratio 21,012/46,750 is used against the known land area of the entire county, 649,000 hectares. This gives 21,012 / 46,750 * 649,000 = 291,696 ha. The National Forest Inventory estimates the area productive forestland to be 287,000, which means that the R-data estimate is 1.6% higher. We should expect some degree of overestimation when the areal unit for investigation is increased from 314m^2 of the NFI field plot to 250,000m^2 of R-data. Such circumstances generally suppress uncommon classes, in this case forest wasteland, and favor more common classes. It is however

Table 14 Summary of the quality assessment of R-data against the National Forest Inventory for Stockholm county estimates of area productive forestland and growing stock for the period 1973-77.

	NFI estimate	R-data Condensed County	R-data Total estimate
Area productive forestland (ha)	287,000	291,696	337,481
Average growing stock (m^3sk/ha)	121	120	126
Total growing stock (m^3sk)	34,100,000	35,003,520	42,522,606

Table 15 Areal coverage within Stockholm County of the 5 land use classes that was identified by R-data.

	Forest	Water	Planned buildings	Agricultural area	Other
Area (ha)	337,481	178,457	51,500	93,542	39,166

hard to predict the magnitude of this effect since it is dependent on the spatial properties of land use classes, such as the size and distribution of homogeneous areas.

The growing stock estimate is in R-data given as mean growing stock volume per hectare productive forestland within each 25-hectare unit. The mean growing stock in the "condensed county" is estimated to 120.17 m^3sk/ha, which can be compared with the National Forest Inventory estimate of 121 m^3sk/ha. The difference between the two estimates is thus <1%. The county total is in R-data estimated to be 35,003,520 m^3sk/ha, which deviates by 2.6% from the NFI estimate of 34,100,000 m^3sk/ha. Of course, the R-data estimate here includes the previous overestimation of the productive forestland area. A summary of the quality assessment is given in Table 14.

Clearly there is a very good correspondence between the estimates of area productive forestland and growing stock produced by the National Forest Inventory and the R-method respectively. The estimates of total growing stock will also be discussed further in one of the result sections below.

Land use class

Figure 16 illustrates the geographic distribution of recorded land use classes. A total of 337,481 hectares of productive forestland has been recorded in R-data for the Stockholm County. 250,643 hectares have been described regarding their site quality, tree species, cutting class, growing stock, stand density, and ground bearing capacity. This area is 78% of the total productive forestland area in the county. The remaining 22% is consequently not described in detail for these variables because it is located in square units that predominantly consist of other land use classes.

The National Forest Inventory states that the area productive forestland is 287,000 hectare. The reason for this large deviation is due to the previously mentioned fact that the National Forest Inventory does not survey significant parts of the county. The previous quality assessment showed the reliability of the R-data estimates for productive forestland. The estimates for the other land use categories given in Table 15 are only given as a rough estimate of the areal proportion of land cover categories within the county. For reasons explained previously these figures, except the figure for forestland, can not be used as an estimate of the absolute values of these land use types.

Site quality

Figure 17 illustrates the geographic distribution of the site quality classes. Out of the forest area that has been described in detail, 30.2, 28.8, 19.7 and 21.3% have been classified as good, normal, poor and other varying site quality in that order.

Studying the areal distribution of the site quality variable in Table 16 we see that 46% of the felling sites are on good site qualities. This relation is however not the case for the thicket stage forests. This result is not unexpected, but maybe a bit more pronounced than anticipated. That clear cuts during the 1960s and the 1970s were mainly done on the good sites have been known through information from local silvicultural management plans. The reason for this is partly the more aggressive logging policy during these years, partly due to the autumn storm in 1969 that fell large areas of high-grown forests on clay or otherwise wet ground, that is on good site qualities. During the 1950s the logging policy was different and many forest plantations were performed during this period. Markedly often it was forests on eskers and other higher hills that were logged during this period.

Table 16 Areal distribution of site quality classes over cutting classes. Numbers are given in hectares based on R-data from Stockholm county 1975.

	Cutting class					
Site quality class	Felling site	Thicket stage	Thinning stage	Final felling stage	Other combination	Total
Good	13,201	4,809	23,852	24,401	8,830	75,094
Normal	8,722	6,337	22,673	25,232	8,855	71,821
Poor	3,410	5,944	16,757	20,408	3,297	49,817
Other/varying	3,526	3,509	15,654	20,219	10,998	53,909
Total	28,860	20,601	78,938	90,260	31,982	250,643

Table 17 Comparison between R-data and NFI estimates of the areal distribution of recorded cutting classes. Numbers are given as percent coverage of the total forest area in the county 1975.

Cutting class	R-data (%)	NFI (%)
Felling site (A + B1)	11.5	14.2
Thicket stage (B2 + B3)	8.2	10.8
Thinning stage (C + D1 + D4)	31.5	29.8
Final felling stage (D2 + D3)	36.0	44.3
Other combinations, residual (E)	12.7	0.9

Table 18 Comparison between R-data and NFI estimates of the areal distribution of recorded tree species. Numbers are given as percent coverage of the total forest area in the county 1975. The NFI estimates pertain to the entire Svealand region and not only Stockholm County.

Tree species	R-data (%)	NFI (%)
Pine	31.8	36.6
Norwegian spruce	10.4	28.8
Conifer	44.0	22.8
Deciduous or mixed	6.7	11.8
Unknown	7.1	0

For the other cutting classes there are only minor deviations from the overall distribution for the entire county. It seems only logical that the felling stage forests have a slightly lower average site quality than the thinning stage forests.

Cutting class

The geographic distribution of the different cutting classes is shown in Figure 18. The areal distribution summarized in Table 17 seem to correspond well with the estimates of the National Forest Inventory acquired in a totally different manner.

Tree species

The comparisons of results for tree species are summarized in Table 18. These numbers indicate that the Norwegian spruce forest area have been largely underestimated in R-data. The spruce forests have probably been classified as coniferous forest due to the well-known difficulty to separate spruce from pine during the image interpretation. Stereo image interpretation of color infrared images would certainly lead to a more accurate result. The underestimation may also be a result of the size of the areal unit for measurement. If spruce forest stands generally occur as relatively small and dispersed units, this would result in a lower frequency in the R-data than in the reality. The geographic distribution of tree species according to R-data is illustrated in Figure 19.

Growing stock

The good correspondence between the R-data and NFI estimates of growing stock was previously established. This evaluation was based on a so-called “condensed county” assessment. One reason to perform this type of evaluation was that the National Forest Inventory does not cover the entire county with forest parameter evaluations, but R-data give an exhaustive evaluation of the entire county area. The average growing stock volume per hectare is estimated to 126 m^3sk/hectare in R-data, Table 14. This figure is higher than the county average for the areas covered by the NFI discussed earlier. From this we may draw the conclusion that the forests in the

Table 19 Areal distribution of stand density (crown closure) classes over cutting classes. Numbers are given in hectares based on R-data from Stockholm county 1975.

	Cutting class						
Crown closure	Felling site	Thicket stage	Thinning stage	Final felling stage	Other combi-nation	Total hectare	Total %
Well closed	892	6,690	52,728	46,505	8,909	115,723	46
Normal	1,428	6,976	19,826	37,046	11,539	76,815	31
Sparsely	2,471	1,327	1,835	3,799	3,357	12,788	5
N/A	24,070	5,608	4,549	2,912	8,178	45,317	18
Total ha	28,860	20,601	78,938	90,261	31,983	250,643	
%	12	8	31	36	13		100

Table 20 Areal distribution of ground bearing capacity classes over site quality classes. Numbers are given in hectares based on R-data from Stockholm county 1975.

	Site quality					
Bearing strength	Good	Normal	Poor	Other	Total (ha)	Total (%)
High	765	18,992	39,161	8,673	115,723	46
Normal	47,035	38,878	2,370	31,963	76,815	31
Low	11,780	1,980	1,612	2,118	12,788	5
N/A	15,515	11,971	6,675	11,155	45,317	18
Total (ha)	75,095	71,821	49,818	53,909	250,643	
Total (%)	15	14	10	11		100

municipalities of Danderyd, Järfälla, Lidingö, Nacka, Sollentuna, Solna, Stockholm, Sundbyberg, Täby and parts of Vaxholm municipality has a significantly higher average growing stock than other areas in the county.

Stand density

The general impression from Table 19 is that most of the thinning and final felling stage forests have a well-closed structure and only some 2% of the thinning stage forests hold sparsely distributed stands. No map of this parameter has been produced.

Ground bearing capacity

The areal distribution of the ground bearing capacity is summarized in Table 20 for each site quality class. This shows for instance that high ground bearing capacity occurs mainly on areas of poor site quality, these are often on rocky substrates. Low bearing capacity occurs largely in locations with good site quality, often in clay filled depressions and valleys.

Material and methods – Structural data; classification of economic map sheets according to landscape type

Background

As previously mentioned the classification of economic map sheets into landscape types was performed as a background material for the delineation of the archipelago region in Sweden. The extent of this working material came to cover entire Sweden in which four different landscape types have been identified. The idea behind this extended background data was that it could be used to differentiate for example forestry practices between different landscape types. The grid structure of the material was also anticipated to be possible to compare with other data such as national and regional summaries from the National Forest Inventory and data such as the R-data described previously in this chapter.

Method

In the working material four different landscape types have been identified, coastal district, urban/suburban district, agricultural district and forest district. As a result this working material came to include estimations of constituting landscape types in 18000, 5 by 5 km quadratic squares covering entire Sweden.

The term district above will be used throughout this description an is meant to be synonymous to the Swedish word 'bygd' which essentially mean a geographic region often in the countryside and populated to some extent. The spatial extent of this concept is not clear but from the translation above it follows that a 'bygd' or district in the context of this report embraces at least one or a few kilometers.

As source material the Swedish topographic map sheet series at 1:50 000 scale was used. The varying availability of the latest editions of these map sheets resulted in a time span from 1960 to 1980 in the used maps. Each map sheet is divided into 5 by 5 km squares corresponding to individual map sheets in the Swedish economic map sheet series in 1:10 000 scale. The areal coverage of certain land cover / land use types is estimated for each 5x5km square unit. On the basis of this estimation the square is classified as one of four landscape types. Furthermore the estimated areal proportion of all landscape types present in the square unit is also recorded. The estimates are given as tenths of the total square unit area. Thus, the smallest area registered is 2.5 km^2, which may in fact be a summary of many smaller areas summing to an area large enough to be registered.

Instructions for the inventory

Areal units corresponding to one entire economic map sheet is divided into four categories according to the instruction below. It is also possible to use other sizes of the areal unit following the occasional modifications detailed below.

The landscape types identified are:

1. **Coastal district, code K**, Archipelago covers at least 60% of the areal unit. Archipelago denotes the land area within 500 m from the seashore or from the shore of any of the four larger lakes in Sweden, Vänern, Vättern, Mälaren, and Hjälmaren. Included are also water bodies of these lakes. Code K is used within 500m from sea etc. no matter what the size of the areal unit is.
2. **Urban/suburban district, code T**, is used when at least 1/8 of the areal unit is covered by urban/suburban land, that is, built up land including house lots, streets, parks, industrial and commercial areas. Also golf courses, airfields, power lines, freeways and sports facilities (excluding slalom slopes) is counted as urban/suburban land.
3. **Agricultural district, code J**, is used when fields, meadows and urban/suburban land cover at least ¼ of the areal unit. By fields and meadows mean agricultural fields, grazed areas including tree patches within these areas. Also roads and buildings within or connected to these areas are counted. In addition to that urban/suburban land as defined above is included in this landscape type, though observing the sequence of work given below.
4. **Forest district, code S**, is used for all other areas, thus encompassing forested areas and other land cover types that do not belong to the other three categories

Sequence of work

In the classification process, first an evaluation is made whether the square should be classified as Coastal district, code K, or not. If this is not the case it is tested whether the requirements for Urban/suburban district, code T, is fulfilled. Again, if this is not the case it is tested if the requirements for Agricultural district, code J, is fulfilled. If the requirements for neither K, T, nor J is fulfilled the area is classified as Forest district, code S.

The areal estimates are always given as figures rounded to whole tenths of the areal unit. Occurrences less than 1/20 is recorded with a dot, • = incidence.

During the inventory, information is recorded as letter and number codes in geocoded squares on a separate interpretation worksheet. The class code is given in the middle of the square on the worksheet. In addition the areal share of each landscape type within the square unit is recorded as integer numbers in the four corners of the interpretation worksheet, each corner corresponding to one landscape type.

In the upper left corner, the coastal areal share within the square unit, rounded to whole tenths, is recorded. The lower left corner is in a similar manner used to record the areal coverage of urban/suburban area. The lower right corner records the agricultural area and the upper right corner is used to record the forest area. Inland lake area other than that included in the coastal area definition is not explicitly recorded but can be calculated as the remaining area between those recorded for the four landscapes type and the full area of the areal unit.

Results – Structural data

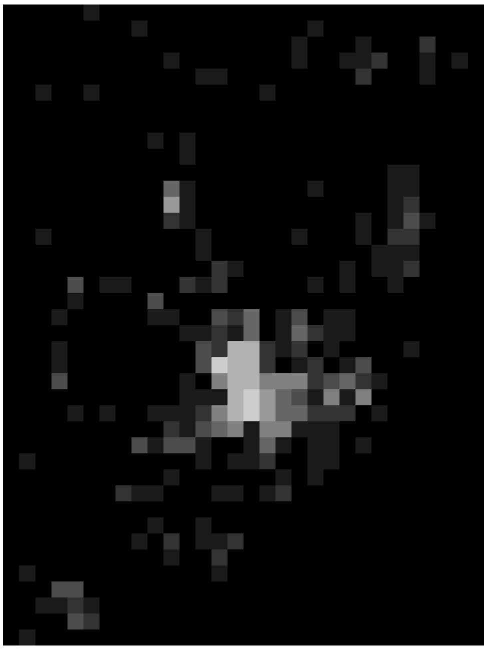
Most of the material is still only available as unprocessed interpretation worksheets. Due to the focus of the original project on coastal areas these have, however, been transferred into digital format. For the purpose of this work a portion corresponding to the Stockholm County has also been transferred into digital format. Figure 15 show the areal share estimates for each recorded landscape type for Stockholm County. Figure 21 illustrates the areal distribution of the final classifications into landscape types for Stockholm County.

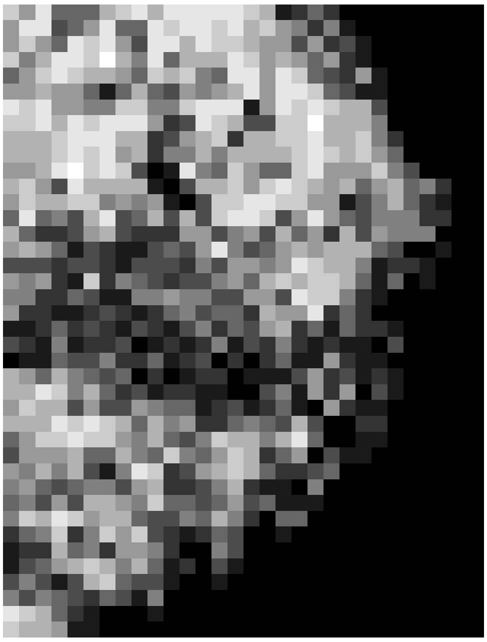
Discussion and conclusions

This chapter has given a detailed description of two previously unpublished data sets. The methods that was used to record these data sets and the final structure of these data resembles to a varying degree the structure used in contemporary techniques for digital analysis of landscape analysis.

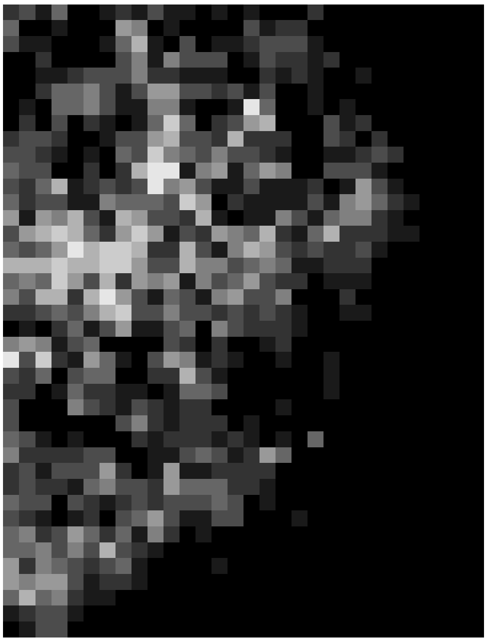
A primary goal has been to highlight these data as a possible source for further scientific studies. Another important goal has been to illustrate some interesting techniques to record and assess the quality of information about the physical landscape.

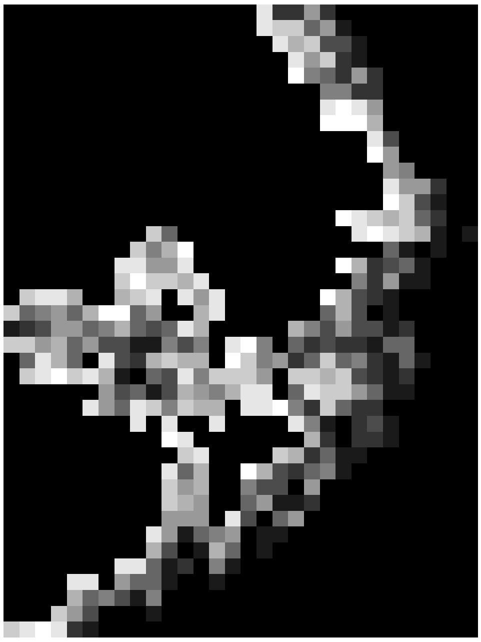
For the purpose of this dissertation the chapter has given a thorough description of the data used in chapters 5 and 7.





A – Urban/suburban B - Forest





C - Agricultural D – Coastal

Figure 15 Images illustrating the estimates of areal share of the landscape types, Urban/suburban (A), Forest (B), Agricultural (C), and Coastal district (D) form the Structural data inventory 1960-80. Each pixel represents an area corresponding to one Swedish economic map sheet, 5 x 5 km. Low areal share is given in dark tones and higher shares are given as increasingly whiter tones.

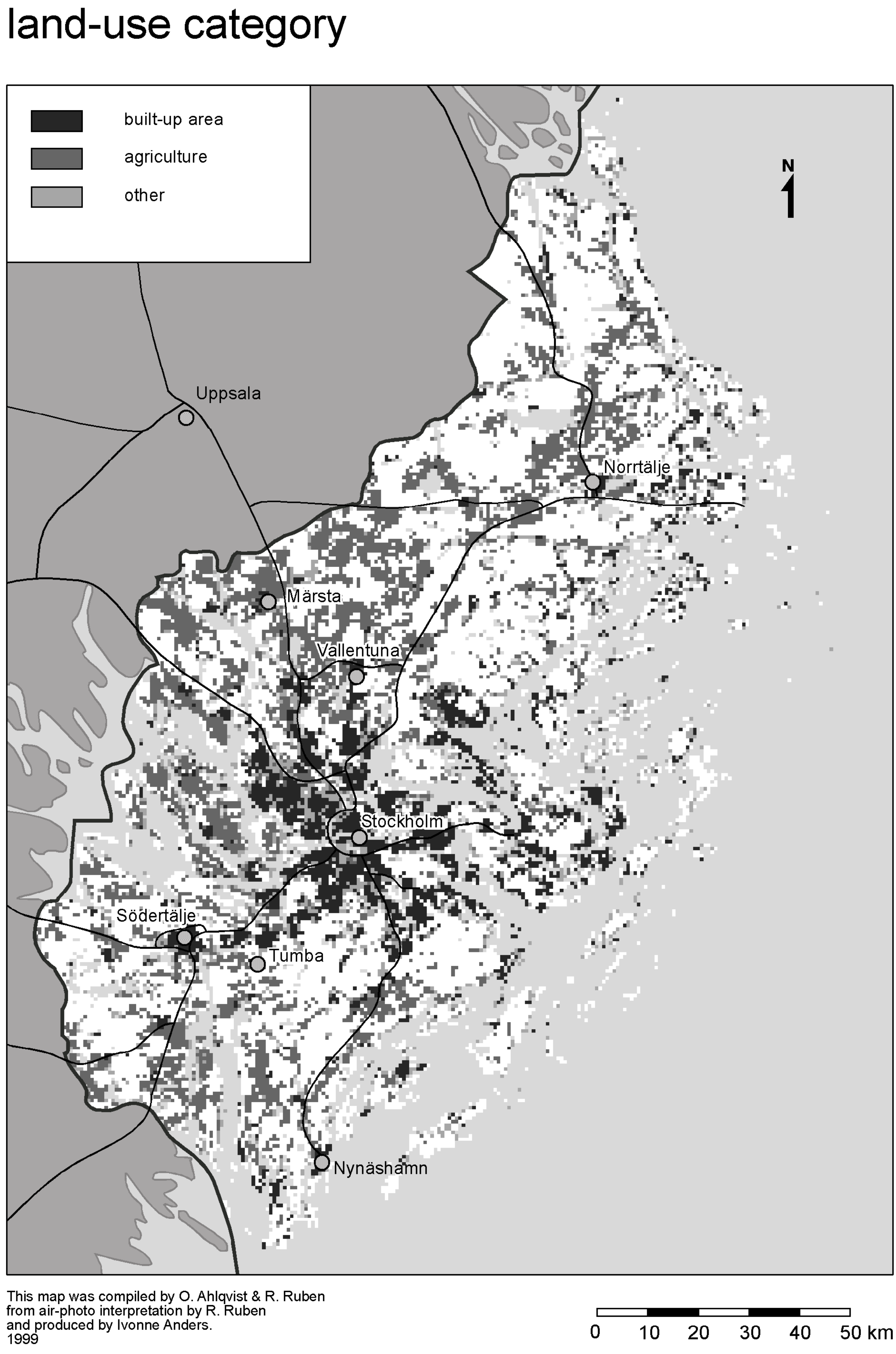


Figure 16 Map of land use categories in Stockholm County according to R-data from 1975

site quality

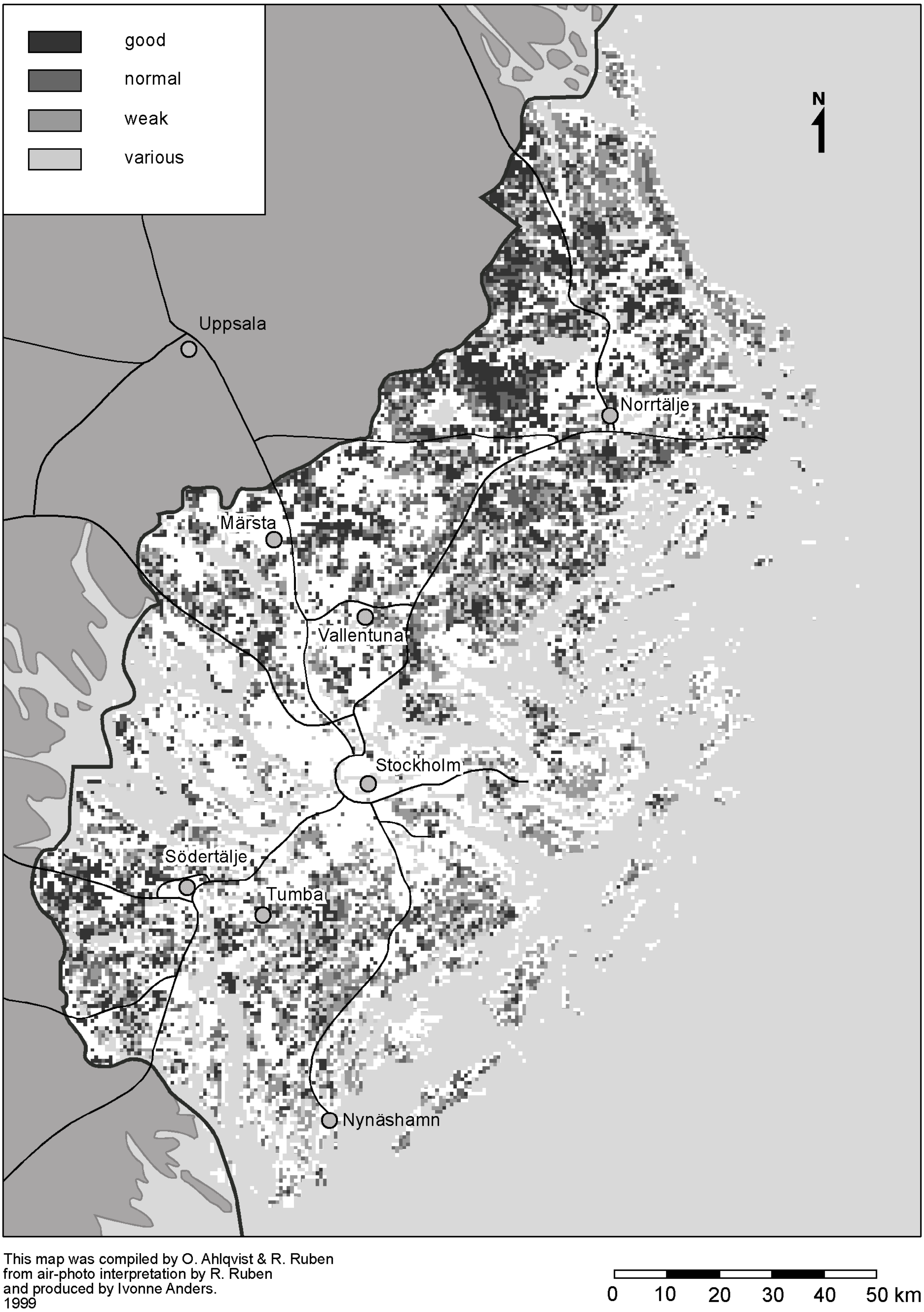


Figure 17 Map of site quality categories in Stockholm County according to R-data from 1975

cutting class

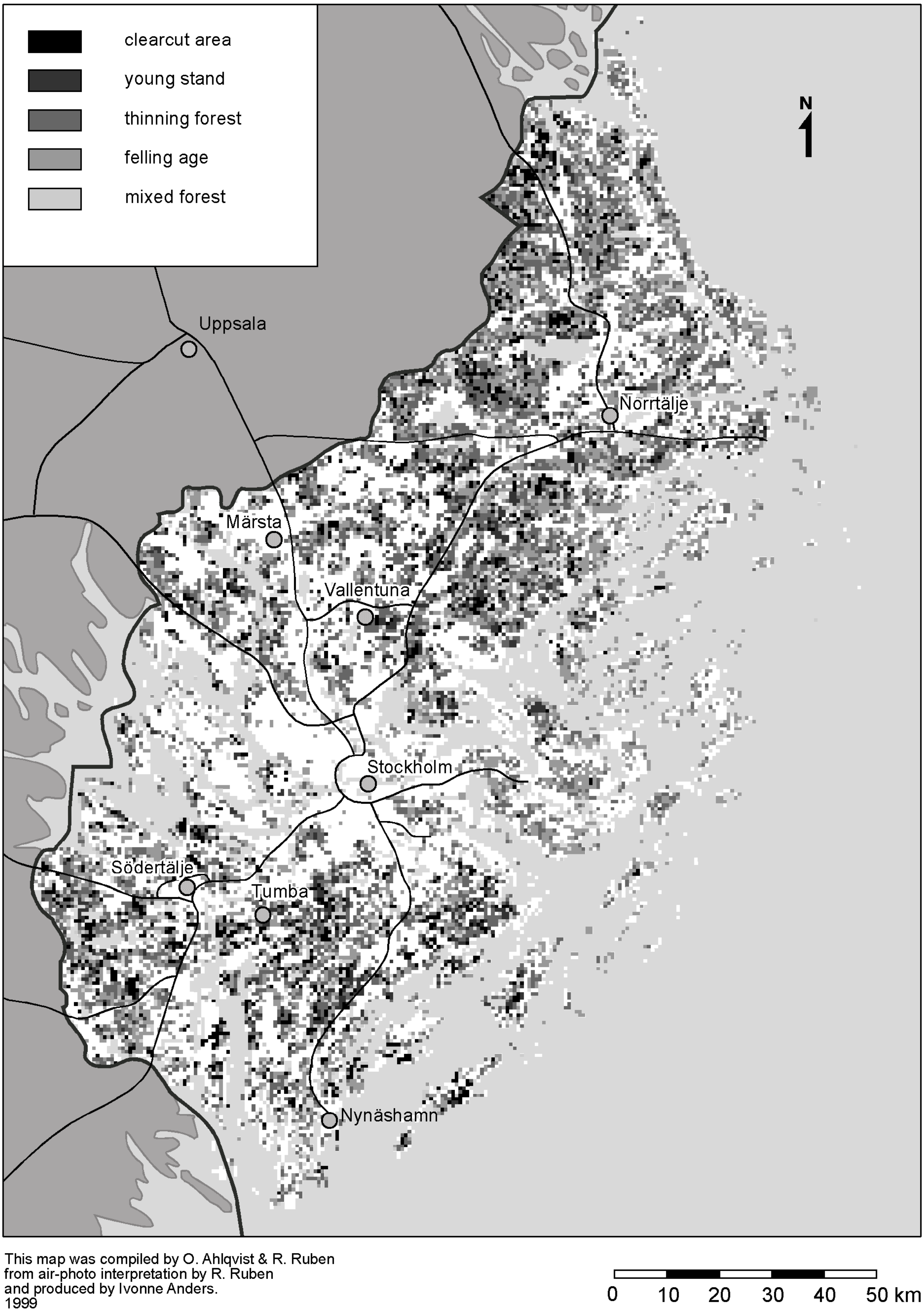


Figure 18 Map of cutting class categories in Stockholm County according to R-data from 1975

tree species

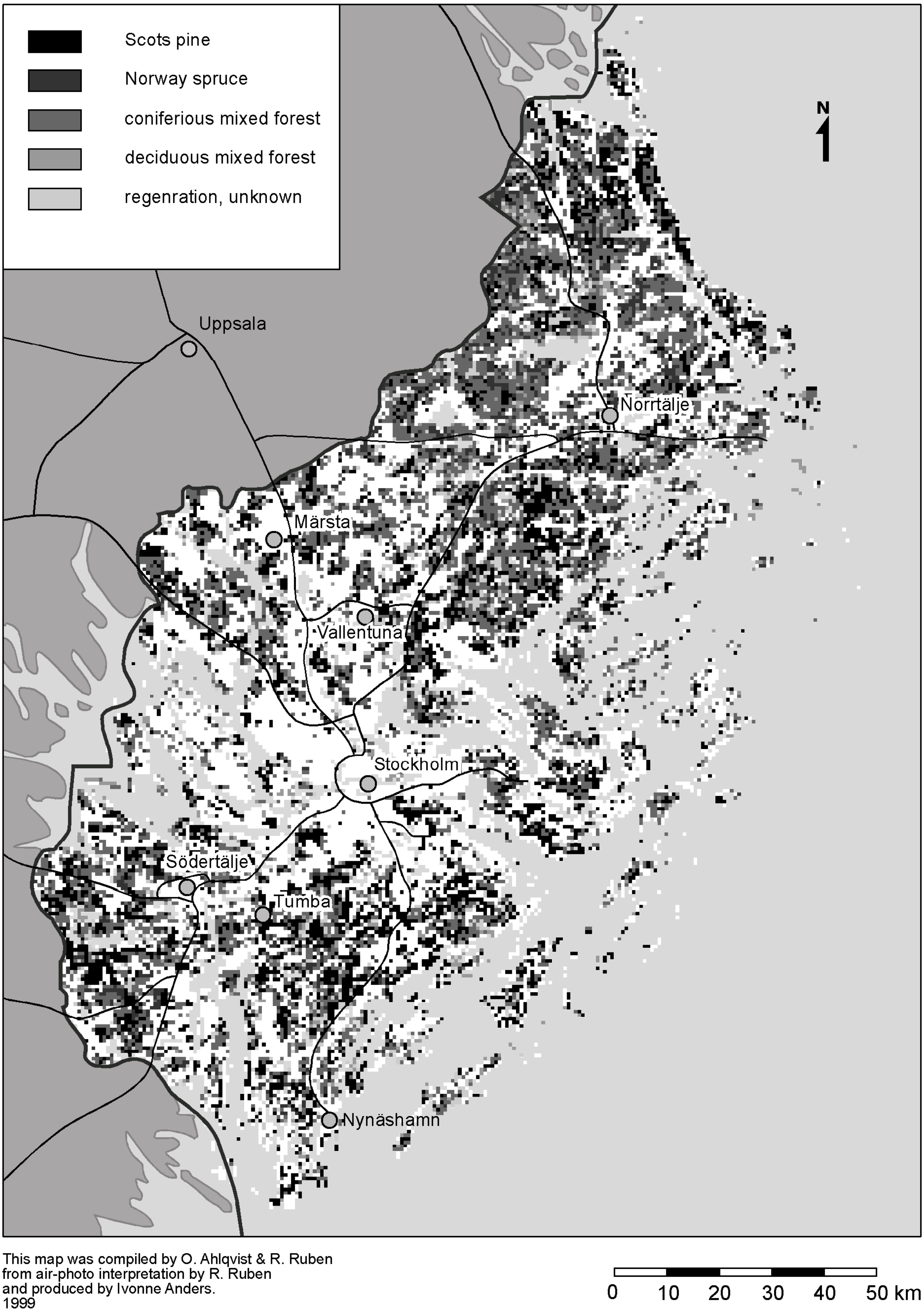


Figure 19 Map of tree species categories in Stockholm County according to R-data from 1975

growing stock

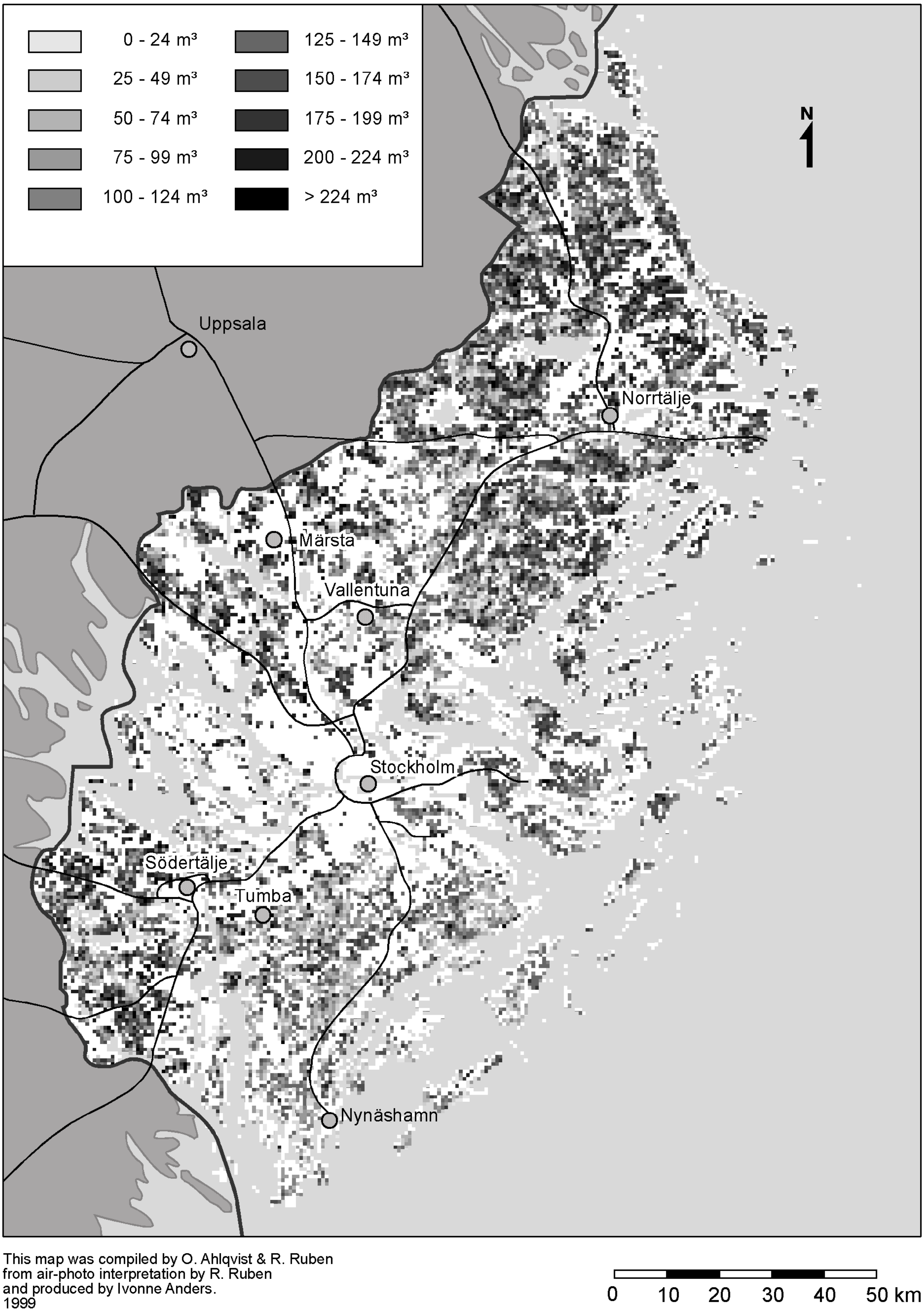


Figure 20 Map of growing stock categories in Stockholm County according to R-data from 1975

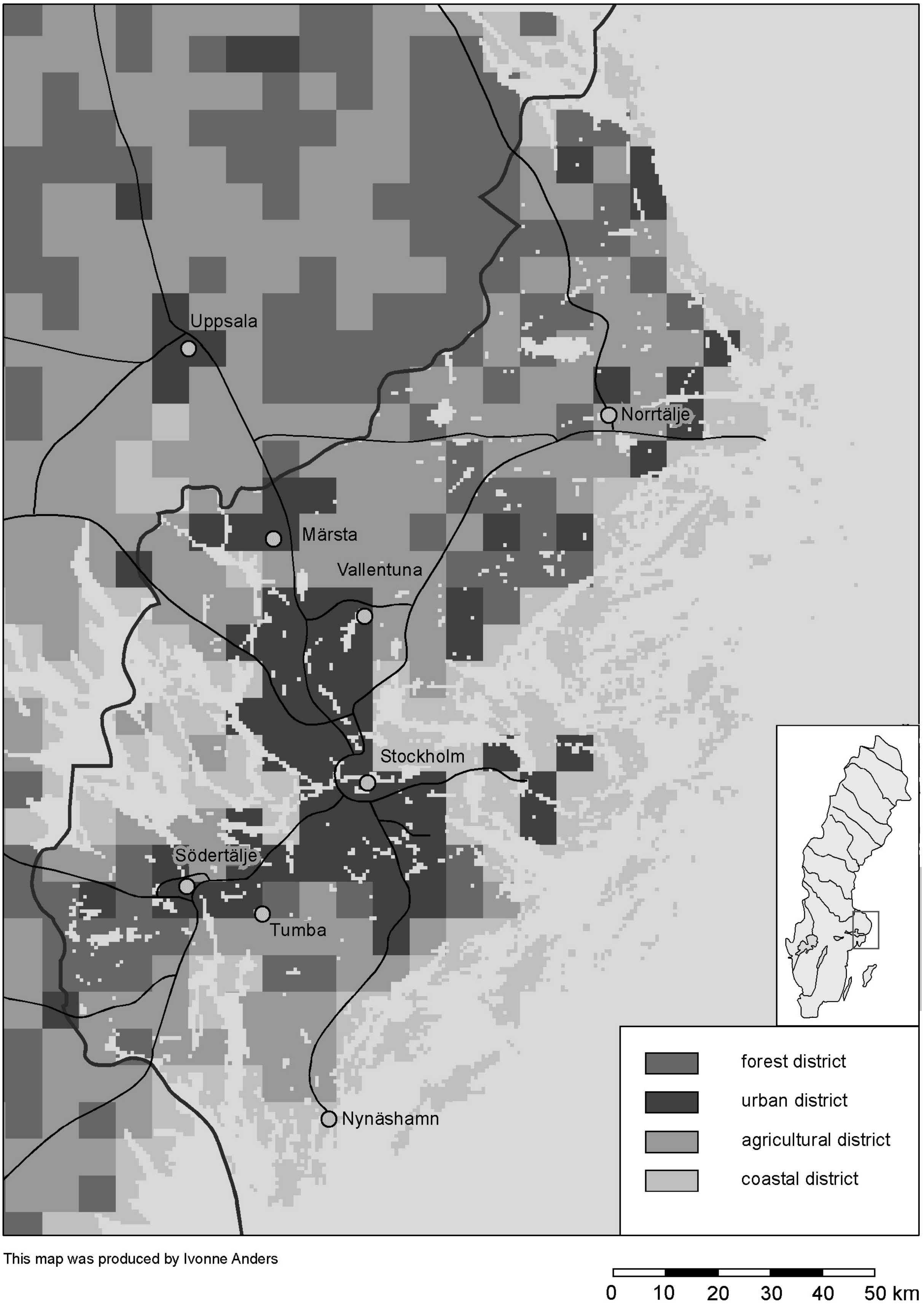


Figure 21 Landscape types in Stockholm County according to the Structural data inventory 1960-80

Chapter

5 PILOT STUDIES

Introduction

The following chapter presents two pilot studies that were performed during the first phase of this research. Parallel to the problem formulation it was essential to gain some insight into the problems associated with data transformations. As I have already mentioned I tried to separate the transformation problem into separate geographic dimensions. This chapter deals with the problem of transforming geographical data through a change of spatial scale.

Scaling of geographical data has traditionally been made manually, and the issue of aggregation and generalization has a long tradition within geography. There is today an increased demand for automated tools for generalization, updates and revision of databases made at differing levels of generalization. Several disciplines apart from geography such as ecology, land surveying, computer science and cognitive psychology are currently involved in research on this issue. A review of research within this field has been presented in the spatial granularity section of chapter 3.

The need for a general framework to deal with scale and complexity changes of geographical data was also indicated in chapter 3. The spatial pattern of various environmental variables and their relationships might be ordered into scale domains and it is also speculated that transitions between such domains might be relatively abrupt much like phase transitions in physics (Wiens, 1992). King (1990) denotes such domains as the ‘maximum extent’ in the context of ecological models. The fairly wide support for ideas of scale dependent controlling factors, on for example ecosystems, encouraged me to try to design experiments that investigated these theories as a tool for context transformation processes.

Both studies approach the scaling problem trying to isolate the change in spatial granularity, fixing the thematic and temporal granularity. Thus, they also make a first attempt to detect any evidence for a scale dependent perception of land cover categories. This research direction is further developed in chapter 7.

The first study considers both continuous and categorical data and uses both global measures as well as location specific analysis to estimate the spatial aggregation effects. For the categorical data this first study uses two different spatial aggregation strategies, one standard procedure using a majority decision and an alternative aggregation method based on confusion matrices. The second pilot study wanted to test the idea that physical controlling factors such as climate, hydrology and soils impose general and scale dependent constraints on other environmental variables. The second pilot study also considers both qualitative and quantitative data but focus more on the problem of how mixture classes and mixed pixels behave in the aggregation process.

Data for the pilot studies consisted of the R-data material presented in the previous chapter and additional data collected specifically for the purpose of the pilot studies, but in line with the same methodology. Of these two pilot studies, the second has been presented at the 8th annual GAP analysis meeting, 1998, Santa Barbara, USA (Ahlqvist, 1998).

Pilot study 1

Objective

The objective of this study is to evaluate the results of a straightforward aggregation of an initial dataset. This kind of assessment has been done before but in this study the initial dataset, as well as the reference dataset for testing the aggregation performance, is derived through manual classification at both levels of resolution. The basic hypothesis in this study is that the human perception of landscape features varies with field of view. If true this would imply that information gathered for a certain area would show differences depending on the spatial unit used for registering the information.

Method

To investigate whether or not there is a difference in interpretation depending on scale, data were needed from two separate interpretations of the same area using different spatial resolutions. Other studies of aggregation effects on grid data have mainly evaluated direct changes in spatial metrics such as local variance and pattern indices. This study uses an alternative approach based on manual interpretation at two resolutions using the same classification scheme. It is anticipated that the effect of different automatic data aggregation methods can be assessed in the right context if using manually classified data at different resolutions as reference data.

It may be speculated that the same piece of landscape might be differently evaluated as a result of the area of focus for interpretation and classification. The experimental design also has the profound difference with normal remote sensing image based tests that some of the information in this material has a sub-pixel resolution. Variables such as area productive forest actually gives the areal percentage of the class productive forest land within each pixel. Also the data actually contain gridded object information not spectral 'object-like' information and this is very important for the purpose for the investigation especially in the case of comparing aggregation results with a reference image. Aggregation of spectral signatures averages all sub-pixel object signatures and gives the integrated signature as an input to the classification algorithm to decide what class should be assigned to the pixel. In the interpretation process the interpreter actually summarizes the individual features on which the classification is based, and thus provides an object specific estimate for the pixel value. The use of manually interpreted data at two different levels of resolution is uncommon and as a result there are no guidelines on what methods might be appropriate for this kind of analysis. The methods used in the analysis are therefore a blend of techniques from digital cartographic generalization, remote sensing and statistical literature.

Study area and data used

The study area is located within the Stockholm County, Figure 11. There is a problem of doing multiscale studies with manually interpreted information and that is to collect a reasonably small but still representative sample. Three study sites were chosen so that both the physical properties of the landscape as well as different land ownership patterns should be represented within these samples. The total number of interpreted pixels was limited to n=675 at the higher resolution and n=27 at the lower resolution.

The low-resolution data set was extracted from the R-data described previously having a spatial resolution of 500x500m. To recapitulate quickly, this method is based on air photo interpretation and classification of 25 ha quadratic areas in a regular grid with full areal coverage. Interpretation is made using areal panchromatic photographic images at 1:50 000 scale.

The additional high-resolution data set was collected using the same method over the three study sites, Angarn, Hejsta and Strömma, indicated in Figure 11. The only thing that separates the two is that the second dataset was compiled using a spatial resolution of 100x100m. Data was thus assembled for 1 ha pixels and 25 ha pixels separately, giving two sets of data of different resolution distributed over the three study sites.

It may seem odd to use this kind of data in a study on modern automated generalization tools but it is anticipated that this data have some inherent properties that make them most suited for this kind of analyses.

As earlier mentioned, the classification system for R-data has been adapted from the Swedish National Forest Inventory classifications. This inventory is an annual survey covering the whole of Sweden. Part of the overall R-data approach is a ground truth calibration method. Using data from the nation wide National Forest Inventory R-data interpretations can be evaluated and adjusted for systematic bias in the interpretation. The accuracy evaluation is an important step to ensure that relevant conclusions can be made from the results. Also, calibration to reduce systematic bias is necessary whenever absolute accuracy is needed e.g. comparison with other datasets. Data used as ground truth in this study is a compilation of existing data from the Swedish National Forest Inventory.

Quantitative data – area productive forest land

The parameter 'Area productive forest land' is made up of 11 interval classes from 0=0-5%, 1=5-15% up to 9=95-100%. This parameter was digitized from manual interpretation protocols to produce the raster images shown in Figure 22 columns a) and b).

Accuracy assessment of absolute values was made by comparing averages of manually

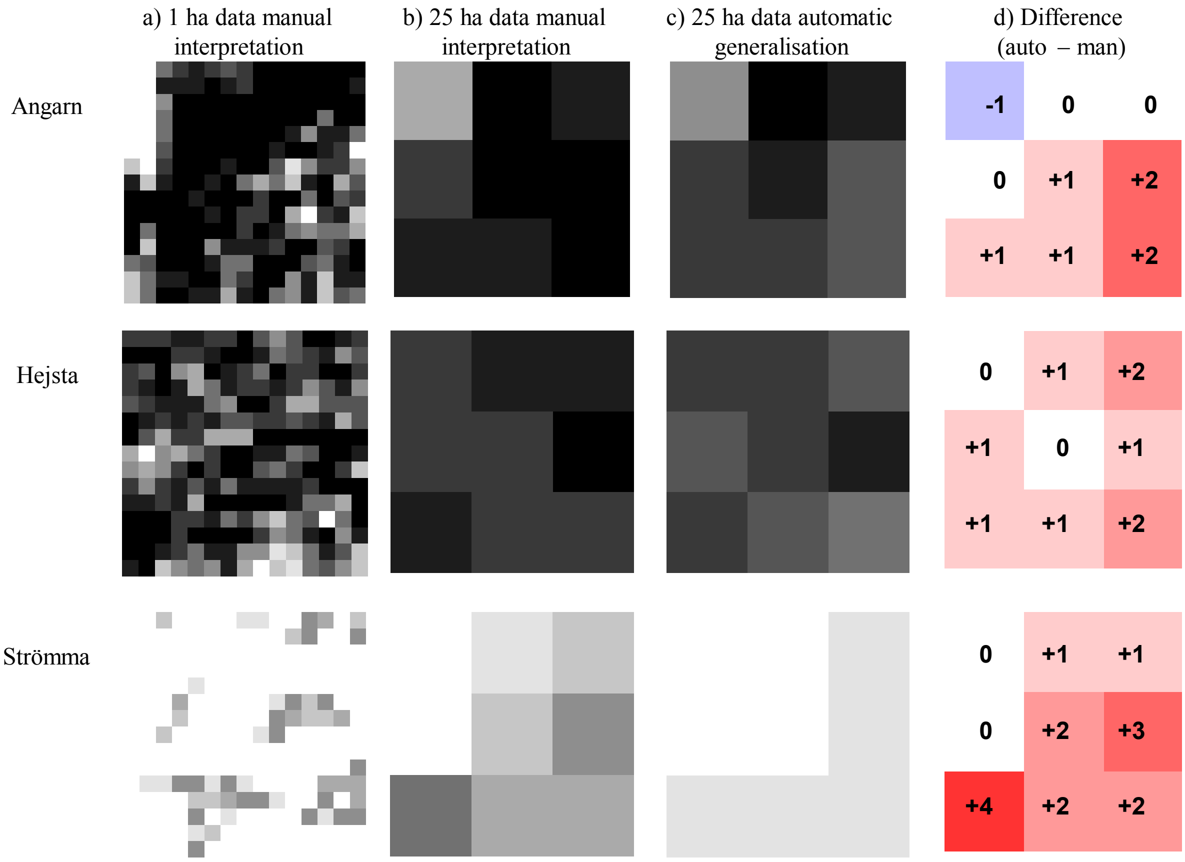


Figure 22 Results from manual interpretation with a) 1 ha pixel resolution, b) 25 ha pixel resolution, c) automatic generalisation of a) 1 ha pixels, and d) showing the difference between interpreted data and automatically generalised data at 25 ha pixel resolution. Increased tree cover is shown as increasingly darker tones.

interpreted data with ground truth data from the Swedish National Forest Inventory (NFI). Four total averages of productive forest land, two for manually interpreted data at 1 and 25 ha resolution and two averages for the corresponding NFI sites are given in Table 21. These averages are based only on those interpreted pixels and NFI field sites that overlap spatially.

Automatic generalization of 1 ha pixels were done by averaging 5x5 pixels into rounded integer pixel values producing images shown in Figure 22 c). This operation produces 25 ha pixel images with average values of area productive forest very close to the original 1 ha pixel images. Comparison of summary statistics from the manual and automatic data at 25 ha resolution is presented in Table 22.

During the analysis it was speculated that the interpretation accuracy could be affected by the spatial configuration of the landscape features. Therefore a range of spatial pattern indices was produced from the high-resolution data (1ha pixels) using the pattern module in IDRISI. The derived index images were then compared with the images showing differences between the automatic and manual interpretation, Figure 22 d), using simple cross tabulation.

Table 21 Accuracy evaluation results showing the accuracy of the manual interpreted data for the variable area productive forest land. Data from the Swedish National Forest Inventory serve as ground truth.

	Total error analysis area	NFI reference plot area	Average of man. Interpretation (%)	Average of NFI data (%)	Deviation	Error
1 ha pixel data	225 ha	21,4 ha	48.2	46.3	0.019	4.1%
25 ha pixel data	17125 ha	35,0 ha	45.1	43.6	0.015	3.4%

Table 22 Summary statistics from images produced by manual interpretation and automatic aggregation.

Site	Data	Average	Max. class	Min class	Stand.dev.
Angarn	1 ha man.	7	9	0	2.8
	25 ha man.	7.8	9	3	1.9
	25 ha auto.	6.9	9	4	1.5
Hejsta	1 ha man.	6.6	9	0	2.2
	25 ha man.	7.6	9	7	0.7
	25 ha auto.	6.6	8	5	0.9
Strömma	1 ha man.	0.6	4	0	1.3
	25 ha man.	2.2	5	0	1.7
	25 ha auto.	0.6	1	0	0.6

Table 23 Classification correspondence between the NFI system and classification system used in manually interpreted data.

NFI classes	R-data classes
Scots pine	Scots pine
Spruce	Spruce
Conifer Foreign conifers	Conifer
Mixed conifer/deciduous deciduous share 35-44% Mixed conifer/deciduous deciduous share 45-64% Birch Beech Broad leafed deciduous species	Deciduous mixed forest
	Undetermined species composition

Qualitative data – tree species

Data on tree species for the three test sites were collected in the same way as for quantitative data above. The NFI reference data contain 9 tree species classes that were aggregated into 5 classes to give corresponding classes with the manually interpreted data, Table 23. After this, the only discrepancy between the two tree species classifications is the undetermined class in the R-data classification. Pixels classified as undetermined in the R-data set have been excluded from the analysis to avoid erroneous results. Those NFI data that spatially overlap such undetermined pixels have also been excluded from the analysis.

The 1 ha data were aggregated into 25 ha data by categorical generalization using two different aggregation operators. The first strategy uses a majority method assigning the aggregated pixel a value of the most frequent class in the source 25 pixels. In this study it was possible to give two alternative answers in the case of ties with equal counts.

The other aggregation operator used confusion matrices for each individual tree-species class. NFI reference plots have been used to determine the mix of tree species within interpreted pixels. In this way it was possible to determine for example that pixels classified as Scots pine in average contain 39% Scots pine, 21% Norwegian spruce, 29% mixed conifers and 11% deciduous. For pixels classified as Spruce, Conifer, and Deciduous mix, other distributions were derived from the reference NFI data. In this way confusion matrices were produced for all tree species classes and at both interpretation levels, 1 ha and 25 ha resolution, Figure 24

We may look upon the diagrams in Figure 24 as class signatures. Consequently, this method is very similar to a supervised remote sensing image classification. So why is not the usual Image classification algorithm used from here?

The number of samples from the three test sites did not prove to be large enough to give a full estimation of the usefulness of the latter approach. The aggregation of 25 pixels into one proved to reduce the number of pixels in the lower resolution data too much. Nevertheless, these first results are included to give a general idea of the approach. From each set of 25 pixels to be aggregated, a species class signature was produced. This is illustrated as the nine

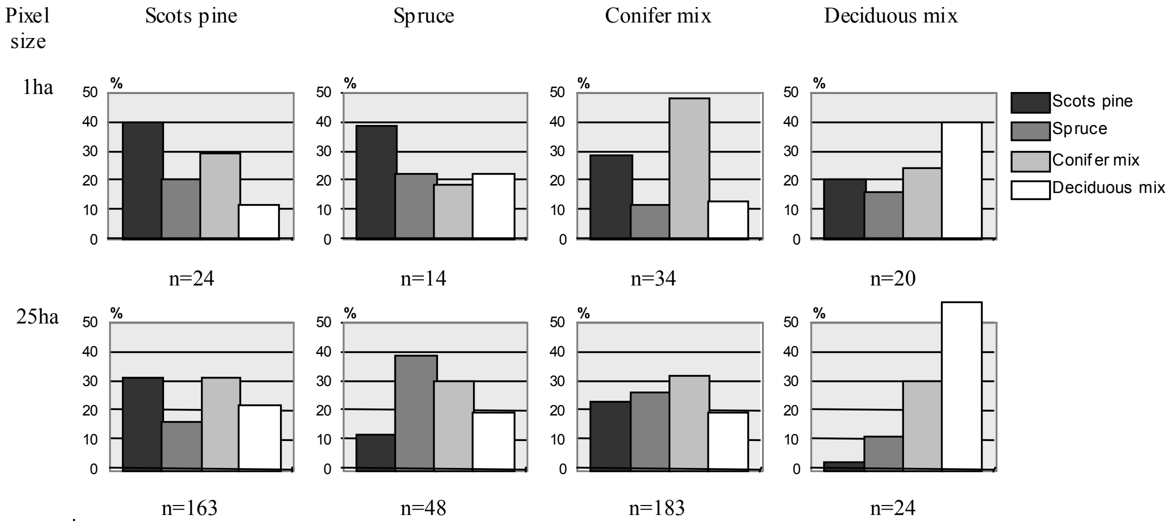


Figure 24 Confusion matrices showing the class signatures in data produced by manual interpretation at two levels of resolution 1 ha and 25 ha. Coloured bars show the relative distribution of actual tree species within each class according to NFI field control data.

histograms in Figure 23 a-i. Each histogram corresponds to the species distribution within one 5x5 pixel window

To get sufficiently large samples for a statistical testing of the scaling hypothesis stated in the beginning, more data was needed. One way to achieve this was to use low-resolution data from the entire Stockholm County. Compiling low-resolution R-data together with spatially overlapping NFI-reference data, gave an additional set of samples. Here only those R-data pixels that contain at least one NFI plot have been selected together with these NFI plots. This made it possible to examine the correspondence between samples of interpreted data at two different resolutions against a ground truth sample taken from the national forest inventory. Each pair of samples selected to overlap spatially as much as possible and at the same time to produce a sample large enough for significance test with Kolmogorov-Smirnov two-sample test. This test can be used to determine whether two independent samples may have been drawn from the same population or from populations with the same distribution. (Siegel, 1956)

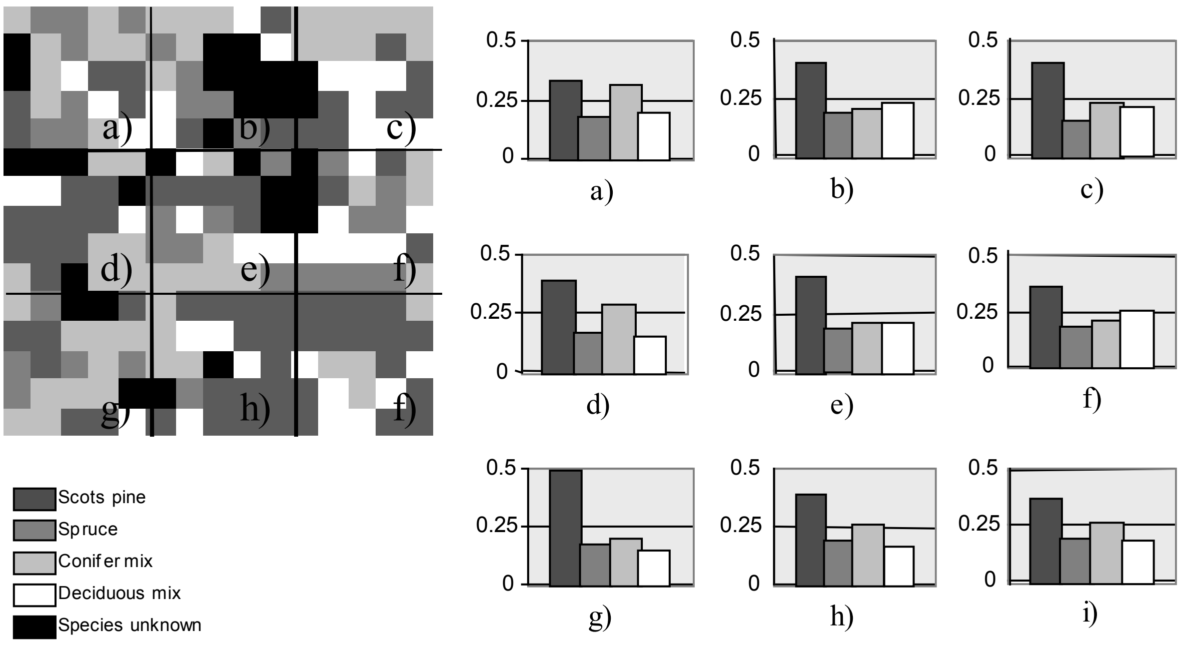


Figure 23 Image showing original 1 ha pixels in Hejsta study site. Histograms show class distribution within each 5x5 pixel set.

Results

<u>Quantitative data – area productive forest land</u>

The results form the accuracy evaluation for the variable "area productive forest land" is given in Table 21. It shows the correspondence of averages from manually interpreted data with the averages from field control data. We see from the left columns of Table 21 that the interpreted data for tree cover show an error of 4.1% and 3.4% respectively. We know from quality assessments of the NFI data that the standard error in Stockholm County may be as high as 4.3%. As none of the interpretations deviate more than the standard error from the NFI-data no calibration for systematic bias was made.

Generalized results were produced and compared with the manually interpreted data at 25ha resolution. These data are illustrated together with source 1ha data in Figure 22, columns a, b, and c. The difference images showing deviations between the manual interpretation and the automated aggregation are displayed in Figure 22, column d. Summary statistics from the manual interpretation and the automatic aggregation are presented in Table 22.

From the speculation that the spatial configuration of landscape features could influence the interpretation accuracy a certain correlation was found with some of the tested indexes. Using simple cross tabulations the strongest direct correlation was found with the index of diversity. The correlation figures are given below both as a cross tabulation table in Table 24 and as histograms in Figure 25. Here we see that the correctly classified pixels (deviation 0) occur over areas with a flat distribution of

Table 24 Cross-tabulation summary of all three sites with degree of misclassification (columns) against diversity index classes (rows)

	-1	0	1	2	3	4
1	7	38	21	19	3	9
2	0	25	12	9	6	2
3	1	16	8	0	2	2
4	0	14	24	14	1	0
5	7	17	22	15	4	4
6	3	18	33	11	7	4
7	4	19	60	15	12	4
8	2	23	53	29	14	0
9	1	5	12	11	13	
10	0	0	5	2	13	

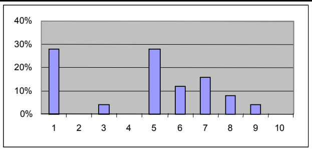
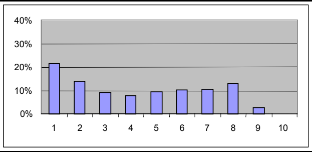
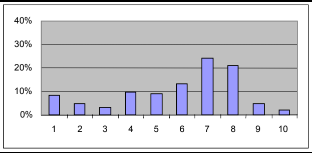
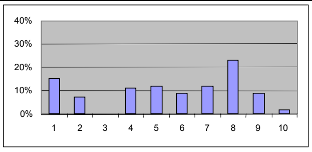
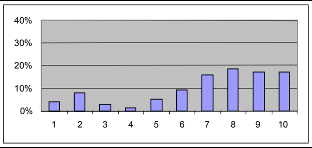
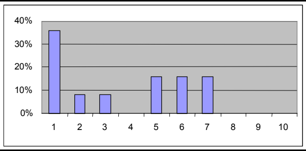
Dev	Distribution of diversityindex classes	
-1		n=1
0		n=7
1		n=10
2		n=5
3		n=3
4		n=1

Figure 25 Histograms over 25 ha classifications of productive forest land. Each diagram shows subset summary of those interpreted pixels deviating (Dev.) –1, 0, +1, +2, +3 and +4 from pixels derived through aggregation of 1ha interpreted pixels. N= Sample size.

diversity values with some weight on the lower diversity values. Pixels classified with a +1 to +3 class deviation from expected value show a distribution with more frequent high diversity values. For pixels classified as –1 and +4 the sample is only n=1 and these will therefore not be considered in further discussions.

<u>Qualitative data – tree species</u>

Data on tree species for the three test sites are shown in Figure 26 together with results from automated categorical generalization using the majority aggregation operator. Apart from the two aggregated data being quite different; we also see examples of pixels assigned to two classes by the automatic aggregation. These undetermined pixels are illustrated by splitting the square pixel diagonally using colors of the tied classes for the two halves.

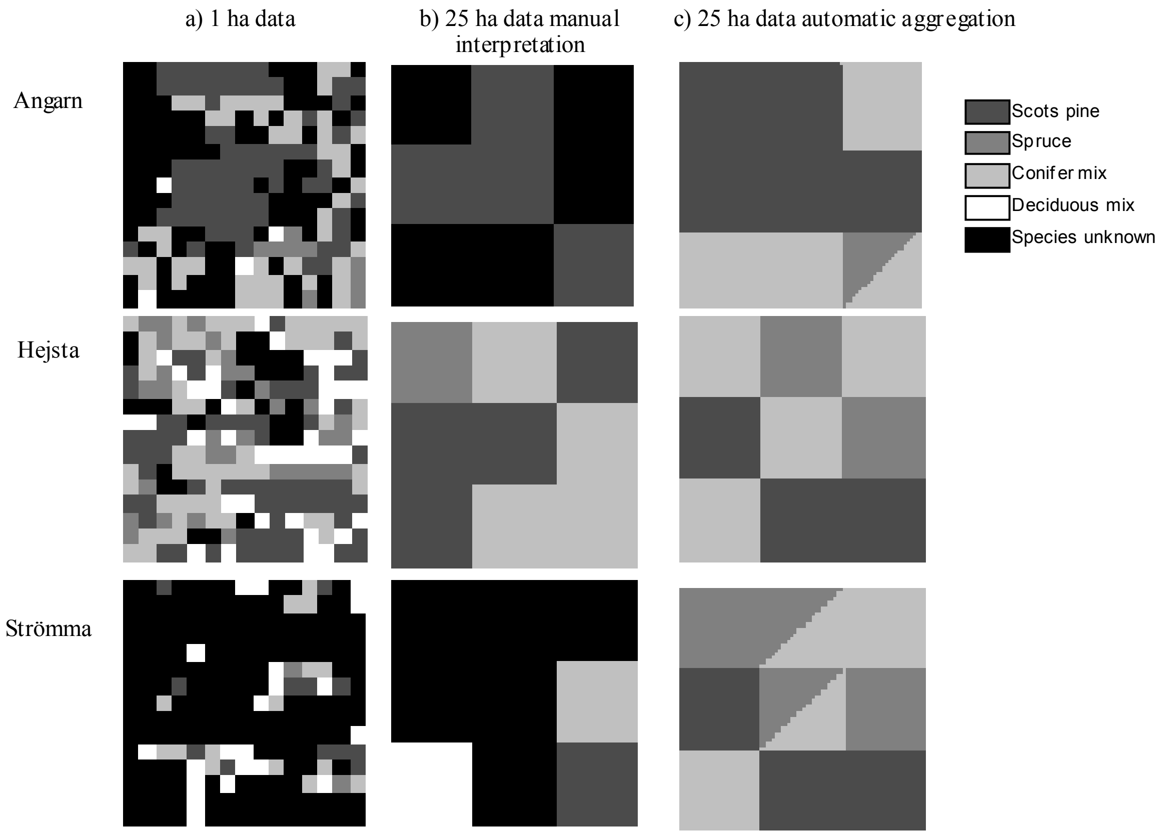


Figure 26 Results from manual interpretation of tree species with a) 1 ha pixel resolution, b) 25 ha pixel resolution, c) automatic generalisation of a) 1 ha pixels using most frequent class as classification criterion for aggregated pixels. Pixel count resulting in ties are illustrated by splitting the output pixel into multiple colors representing the tied classes.

Figure 27 exemplify the results from the categorical generalization using the second aggregation operator based on class signatures. For comparison purposes the previous result form the majority based aggregation operator and the manually interpreted low-resolution data are also displayed in Figure 27 c and d respectively. Aggregation based on class signatures derived from confusion matrices is problematic. Due to the small samples it is hard to reject the possibility that these distributions could be drawn from the same distribution as the reference distributions for the four species classes in a formal Kolmogorov-Smirnov test. In the example most pixels can be classified to belong to either Scots pine or Spruce classes at a 0.15 confidence level. Only the lower left pixel can be predicted the same way at a 0.05 confidence level. No pixel can be given only one class assignment based in this analysis.

The overall analysis of species distribution at the two levels of resolutions uses only global measures and are presented as histograms in Figure 28. The first two columns are the best comparison that could be produced having only fully overlapping R-data and NFI-data. The right column illustrates a similar result using all available information for Stockholm county, disregarding whether there is spatial overlap or not. The lower row of diagrams d-f all give the best ground truth estimate available. Figure 28 d) shows the species distribution for the three test sites that have been interpreted at 1 ha resolution. Figure 28 a) above are directly comparable as this show tree species distribution from those 1 ha data that are located over the same area. Moving to the next pair of diagrams Figure 28 b) and e) we can see that the distributions are very different. It is clear that the study regions are located at sites with more Scots pine and less Spruce compared with the total county average. The most apparent result of these diagrams is that classifications made at 25 ha resolution produce a far more erroneous result compared with NFI data than the 1 ha classification.

A formal estimation of the difference between interpreted data and ground truth NFI data was made using a Kolmogorov-Smirnov two-sample

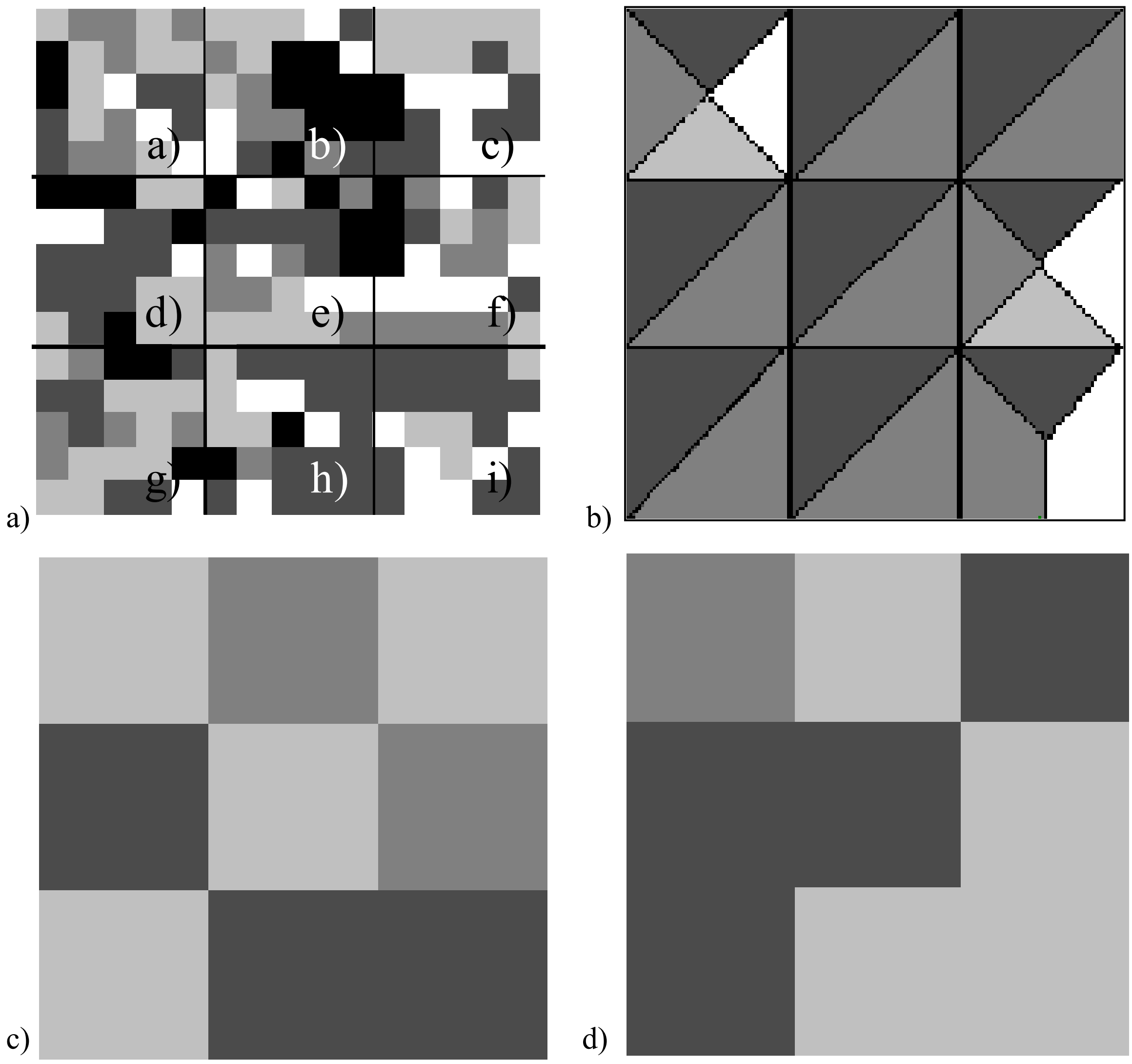


Figure 27 Images showing categorical generalisation over the Hejsta study site. Original 1 ha pixels (a), are aggregated using Kolmogorov-Smirnov two-sample test (b). Pixel aggregation resulting in ties are illustrated by splitting the output pixel into multiple colors representing the tied classes. For comparison, image (c) show the aggregation result using a majority operator and image (d) show the result from manual interpretation.

test. The test was able to reject the assumption that the distributions illustrated in Figure 28 b) and e) could be drawn from the same distribution at a 0.001 significance level. The same applied to the sample distributions in Figure 28 c) and f). The testing of 1 ha resolution data, Figure 28 a) and d) was however not able to reject the assumption that the samples are drawn from same distribution. Thus data at 25 ha resolution had deviated significantly from the initial distribution at 1 ha resolution.

Discussion

The results in Table 21 indicated that the relative difference between the manual and automatic data at 25ha resolution was small. Nevertheless all three test sites illustrated in Figure 22 show a relatively high degree of overestimation of productive forestland. A majority of the automatically generalized pixels show none or minor deviations from the expected result. In 9 cases areas show a difference in interpretation with as much as 20-50% productive forestland (classes +2 through +4). Considering that 1 ha and 25 ha data pixels were shown to be accurate with only 3-4% error these large deviations require some explanation. One reasonable suggestion would be that the spatial configuration of the areas influences the interpretation (Turner, 1989). The results from the cross tabulation indicate some degree of correlation between large deviations and index of diversity, Figure 25. It would be interesting to see if this result could be

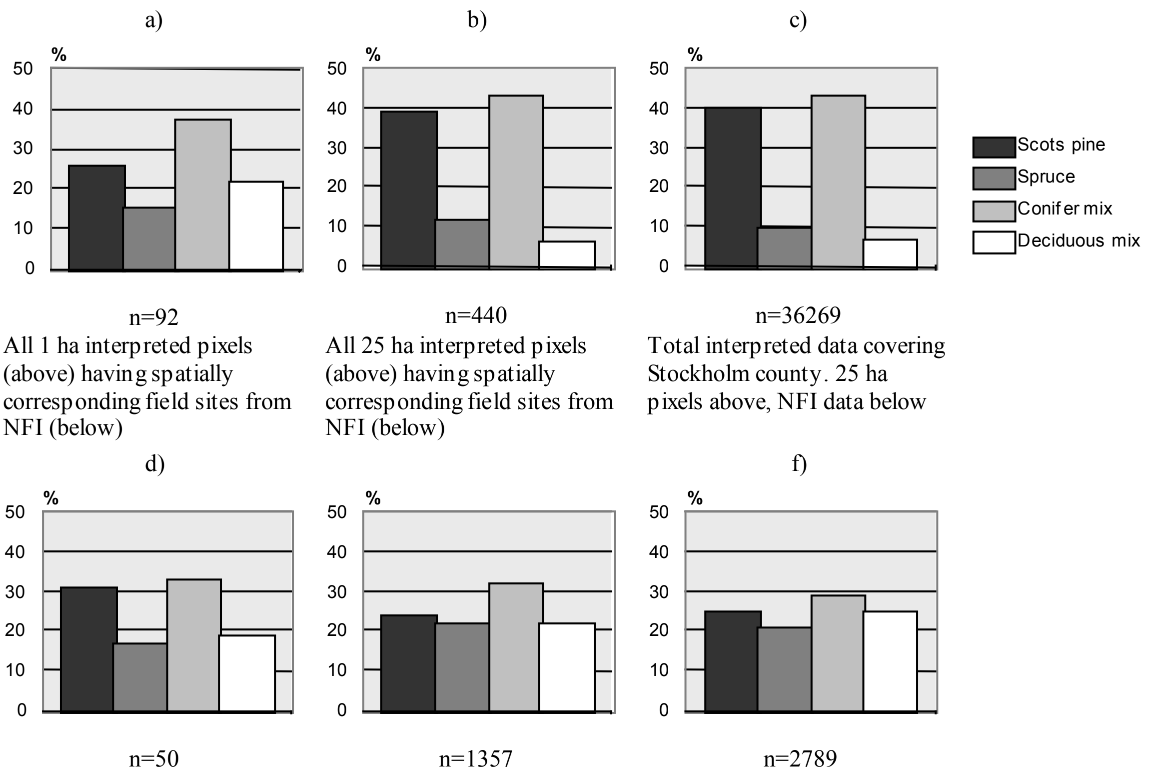


Figure 28 Tree species distribution histograms for spatially corresponding regions given for both interpretation resolutions. The total interpreted sample covering entire Stockholm county at 25 ha pixel resolution is given in column 3 together with the total NFI field sites covering same region.

further validated into a general pattern. If so it could be possible to model this kind of interpretation accuracy by measuring an index of diversity in the interpreted area. Further development of such neutral predictions of interpreter's reliability might also be used to construct a spatially differentiated uncertainty surface over a survey area.

Increasing grain size in raster data can be made by simple aggregation of groups of n adjacent pixels into one large pixel, which is assigned a value of the most frequent class. The effects of this has been shown earlier by Turner and others (1989). In essence their results show that increased grain size will decrease number of classes by eliminating less frequent classes. Furthermore the aggregation will produce an increase in indices such as dominance and contagion (spatial correlation). The test results follow these general rules. Even if no classes are totally eliminated Figure 28 show a decrease in less frequent classes for lower resolution data and originally more frequent classes get an increase.

The fact that the ground truth data from the NFI only cover a sub area of the classified area does of course have significant effect. The number of samples and the spatial distribution of the tree species is therefore of vital importance for the interpretation of the classification results.

Although the output image in Figure 27 b produces a result that is hard to interpret it has the advantage of keeping the actual species distribution in the original pixels as relative proportions of tree species classes. It may be an appropriate method to preserve some information through steps of data transformations.

Pilot study 2

Objective

The objective of this study is to investigate if the use of mixture classes and mixed pixels indicate a scale dependence of geographic concepts and if a scale dependency can be attributed to controlling environmental factors.

Method

The second pilot study has a lot in common with the first one. It uses the same input data from the same study areas. In this study however, focus has been shifted from analysis of the information change with respect to the National Forest Inventory data to go deeper into studying the site-

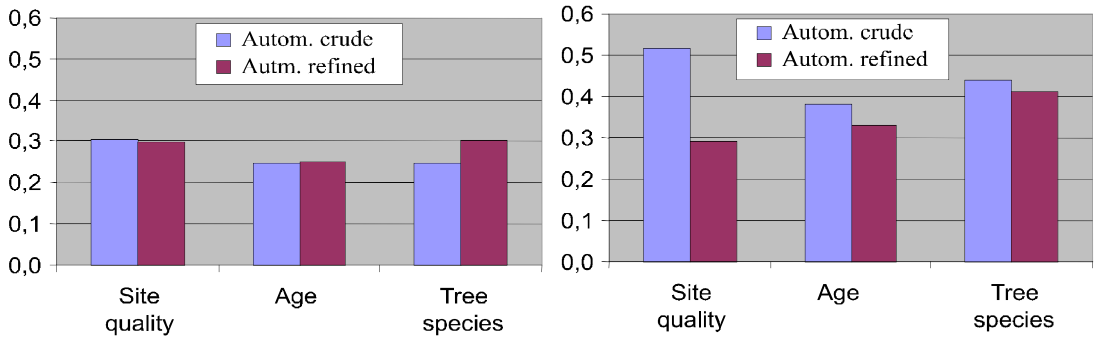


Figure 29 Diagrams showing overall kappa estimates for the automatically aggregated data using 1 ha data (left diagram) and 25 ha data (right diagram) as reference images. Values taken from Table 25.

specific correspondence between manually and automatically aggregated datasets.

Three quantitative and qualitative variables, site quality, age, and tree species were chosen for this study. All three variables have mixture classes in their classification definitions. The spatial aggregation is performed using a majority decision. Any class that reaches 50% or more areal coverage within the aggregated area is taken as class label for the aggregated pixel. If no class reaches the 50% limit the mixture class is chosen for the output. To investigate the effect that the application of mixture classes could have at different spatial resolutions, data were spatially generalized using two slightly different aggregation operators than those used in the first pilot study.

Crude aggregation simply sums up the different class areas and applies the classification rules on these sums. Refined aggregation uses the non-mixture classified pixels to provide information on the detailed distribution of e.g. tree species. This type of class detail enhancement is somewhat 'cartographic' enhancing some aspect of the information.

Accordingly, the Crude aggregation operator makes a strict evaluation of constituent classes. The Refined aggregation operator ignores the mixture class in the input thus assuming that these areas have the same class proportions as the rest of the area under consideration.

Both aggregation operators were applied on the data. This resulted in two images per variable making a total of six images of automatically aggregated data plus six manually interpreted images, three at 25 ha resolution and three at 1ha resolution.

The resulting images were compared both with the original images at 1 ha resolution and with the manually interpreted images at 25 ha resolution. The agreement analysis was performed using the grid-based geographical information system IDRISI. Crosstab analyses were made on all images to produce overall Kappa estimates for the agreement between each assessed image and two reference images. Here both 1ha and 25ha interpreted data were used as reference images.

Results

Automatic aggregation of the original 1ha resolution data resulted in two images per variable making six total images of automatically aggregated data. The overall kappa estimates using both resolutions of the interpreted data as reference are presented in Table 25, the same numbers are illustrated in the bar diagrams of Figure 29. The test of all variables against the high resolution 1ha data shows an overall performance of the manual 25 ha interpretation/aggregation as Kappa values in the range 0.22-0.25, and for the automatic aggregation: 0.25-0.31.

At the same time, the automatically aggregated data tested against manually interpreted 25ha data show much better agreement than against the 1ha-interpreted data.

Different aggregation strategies (crude and refined) perform differently for the three variables analyzed. Using 25 ha data as reference, the 'crude' method is undoubtedly more similar to the way the interpreter assesses the site quality than the refined method. The other two variables show the same tendency but not as strongly.

Discussion

The first impression is that all aggregations at the coarse 25 ha resolution are erroneous. However, using manually interpreted 25-hectare resolved data as a reference, the overall agreement increases, indicating that aggregations are

Table 25 Comparison of overall Kappa values from the evaluation of aggregation results using manually interpreted 25ha resolution data (first column) and 1ha resolution data (second column) as reference images.

Overall Kappa estimation results

		Ref.img. resolution	
Variable	**Aggregation method**	**25ha**	**1ha**
Site quality	Autom.crude	0.51	0.31
	Autom.refined	0.29	0.30
	Manual aggr./interp.	-	0.22
Age	Autom.crude	0.38	0.25
	Autom.refined	0.33	0.25
	Manual aggr./interp.	-	0.24
Tree species	Autom.crude	0.44	0.25
	Autom.refined	0.41	0.30
	Manual aggr./interp.	-	0.25

producing a result similar to the human interpreter's classification of the landscape.

The fact that the two methods of aggregation perform differently for the three variables in this study is of major interest for the development of scale dependent generalization methods. The indication that some variables seem to produce better aggregation results than others is also an important point that needs to be further investigated.

Hierarchical land cover classification schemes such as the US Federal Geographic Data Committee, National Vegetation Classification Standard (FGDC-STD-005), and EU´s CORINE land cover classification are intended to be applicable at a multitude of scales. This intention can only be fulfilled if the defined class hierarchies account for how accurately environmental factors/variables can be aggregated.

The taken approach made it possible to show the presence of scale dependent perception of a piece of landscape using classification schemes for three variables. It was also possible to assess scale related differences between manually and automatically aggregated geographical information.

Further analyses are needed to evaluate the strength of the indications pointed out here. The influence of spatial pattern metrics such as spatial auto-correlation of variables might for instance direct the choice of aggregation strategy. If these results can be firmly verified this would support the idea that constraints imposed by environmental factors act as controlling variables at different scales. This direction may be further investigated to find methods that can be used to evaluate the spatial domain of a given variable. Enhanced knowledge of a variable's spatial size is needed to promote the development of neutral measurements of abstraction levels.

Further research using the presented and similar methods will most certainly add to the knowledge base on which to build theories for the representation, analysis and communication of geographical data across multiple scales.

Overall discussion and conclusions

To summarize these studies the tests indicate a sensitivity of certain environmental variables to changed spatial granularity. The tests also indicate that these effects are not merely a result of aggregation. There may also be an effect of the human interpretation of landscape features at different resolutions. This is a multifaceted problem and computer models need to be able to adapt to a multitude of properties of the environmental variables registered.

As a general interpretation the results illustrate the problem with geographical data with specific attention to the scale effect. The difference between the automated and manual results could be held as an interpretation error due to the difficulty of correctly estimating an area of high heterogeneity. However, the result can also be taken to support a view that the automatic result needs to be adjusted to the perception of the manual interpreter in order to communicate the original information correctly. Although actual data values arrive at one result, this is not the result that corresponds to the current user's perception of this piece of landscape. The user may translate the entirety into something more than just the sum of the pieces. This again stresses the importance of a truthful linkage between the user and the automated system that takes into consideration a change of context, in this case scale.

The use of mixture classes in the classification system made it difficult to get full insight into the aggregation process since a mixture class reduces the thematic granularity in those instances of source data. Ideally, in cases of mixed conditions an explicit representation of this mixture would be preferable over the mixture class label. The mixture class problem was tackled to some extent by using different aggregation methods, such as the crude and refined procedure described in the text.

For the continued investigations of the spatial granularity effect, reported in chapter 7, I made two principal refinements of the experimental design. First, I decided to use the Structural data set from chapter 4, which does not make use of mixture classes in the same way as R-data. Second, after testing the interpretation consistency, it was possible to use methods of rough classification to represent the ambiguity that occurs in the spatial aggregation process due to the detected interpretation inconsistensy.

The explicit representation of the landscape type mixture for each spatial unit seemed more suited to the task of detecting differences in interpretation at different spatial granularity.

One main advantage of the R-data is that it was possible to do thorough quality tests. The result of the quality tests in chapter 4 made it possible to treat the R-data estimates as having the same accuracy as National Forest Inventory estimates.

Acknowledgements

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Chapter

6 ROUGH CLASSIFICATION AND ACCURACY ASSESSMENT

Introduction

This chapter investigates the thematic dimension. In the previous chapter, aggregation effects led to uncertainty due to indiscernibility. This chapter investigates the possibility to represent indiscernibility that occurs due to limited categorical granularity. The described theory and methods will then be used in the analysis of chapter 7. It is also an important method for the developnment of the proposed Geographic Concept Topology.

The chapter consists of a previously published paper, which here will be reproduced in its entirety thanks to the kind permission of Taylor&Francis.

My contribution to the following paper has primarily been the initial idea of using rough sets in a reclassification process. In writing, my contributions are mainly articulated in the Introduction, Categorization, and Discussion sections, and to some lesser extent also in the Experiment and Conclusion sections

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Research Article

Rough classification and accuracy assessment

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Abstract. In search for methods to handle imprecision in geographical information this paper explores the use of rough classification to represent uncertainty. Rough classification is based on rough set theory, where an uncertain set is specified by giving an upper and a lower approximation. Novel measures are presented to assess a single rough classification, to compare a rough classification to a crisp one and to compare two rough classifications. An extension to the error matrix paradigm is also presented, both for the rough-crisp and the rough-rough cases. An experiment on vegetation and soil data demonstrates the viability of rough classification, comparing two incompatible vegetation classifications covering the same area. The potential uses of rough sets and rough classification are discussed and it is suggested that this approach should be further investigated as it can be used in a range of applications within geographic information science from data acquisition and analysis to metadata organization.

1. Introduction

Generalization of information into groups is a common step in traditional as well as computerized geographical analysis. Classification into predefined categories is in many cases an important step to perform geographical analysis in order to measure or describe a phenomenon of interest. No matter what strategy we employ for the generalization procedure, this will lead to a loss of detail in one or more dimensions. This imprecision has to be treated in a controlled manner, and the issue of the representation of uncertainty in spatial data has become more and more of a concern (Goodchild *et al.* 1992, Burrough and Frank 1996). One of the reasons for this is that a current goal is to increase geographical information system interoperability. This need may partly be met by efforts to arrive at various standards such as the work by the Open GIS Consortium, CEN/TC287 and ISO/TC211 or research focused on the development of federated database systems (Devogele *et al.* 1998). Still there are a number of issues that remain to be solved before any of these approaches will become feasible implementations.

In this paper we focus on one of these underlying problems, that is, semantic

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imprecision as a result of categorization, exemplified by spatial vegetation and soil information. Building on existing theories of rough sets (Pawlak 1982), in §2 we discuss the causes of semantic heterogeneity in geographical data, fuzzy sets as one method to handle this heterogeneity and the idea of using rough sets and rough classes as an alternative. In §3 we develop a number of quality measures as well as methods for uncertainty assessment useful when comparing layers of roughly classified geographical information. We also discuss their relation to commonly used methods for accuracy assessment in remote sensing and geographical information systems, such as overall classification accuracy measures and confusion matrices. Finally in §5 these ideas are taken together in an experiment on geographic data to demonstrate our findings in a reclassification task followed by an accuracy assessment on the reclassified data.

2. Categorization

To make geographical analyses and presentations using computerized systems we need to assemble information about geographic phenomena in a quantifiable manner. Geographical data as geographic entities are quantified in terms of temporal, spatial and thematic dimensions (Lanter and Veregin 1992) and this complexity makes it practically impossible to measure all aspects on continuous scales. So, the assemblage of geographical data normally implies some kind of generalization of the basic dimensions. This generalization is often done by fixing one dimension, controlling another and measuring the third (Sinton 1978). The two main geographical data modeling paradigms used by contemporary geographical information systems could be looked upon as two cases of this general assumption. Both paradigms fix time. The spatial dimension is either controlled by a regular grid or measured as the position of 1-, 2- or 3-dimensional objects. Finally, the thematic dimension is either measured as field values or controlled by grouping objects into predetermined classes.

A geographical information category can be termed an 'abstraction' meaning a simultaneous focus on important content, structure and process while temporarily ignoring certain details, rather than eliminating details (Nyerges 1991a). From this it follows that abstractions, that apparently form in our minds, can not be regarded as crisply defined and delimited objects. We will not go any further into the increasingly large body of work on the theoretical basis for how categories are formed. For the purposes of this work we conclude that apparently there is a complex background for the formation of entities which are represented in geographic databases. To increase interoperability in terms of a better conceptual match between different databases we need tools to handle the conceptual and literal heterogeneity that occurs at the higher levels of geographic information modeling (Raper and Livingstone 1995, Bishr 1998). If we separate this heterogeneity into aspects of semantic, schematic and syntactic heterogeneity this article deals with methods to handle schematic heterogeneity, i.e. where classification and hierarchical organizations of real world categories vary across disciplines or contexts (Bishr 1998).

Turning now to the issue of how to represent and logically handle semantic heterogeneity, object oriented methods have been proposed as a viable alternative. For example Raper and Livingstone (1995) demonstrated how an object oriented geomorphologic spatial model enabled the representation of entities identified as a result of a categorization procedure, as well as providing the means to link process models to data models. Openshaw (1996) recently noted the evident linkage between geographical sciences with a multitude of linguistic knowledge expressions and the theory of fuzzy sets. Other authors argue in the opposite direction employing discrete models but using other organizing elements such as concept neighborhoods (Freksa and Barkowsky 1996, Bishr 1998). In the next section we will briefly go through fuzzy set theory, its current applications and the reasons we see for developing an alternative method to deal with imprecision and semantic heterogeneity.

2.1. *Fuzzy sets*

When considering uncertainty representation of geographic data in a digital environment we often find implementations in a field (raster) rather than an object (vector) environment. Fuzzy set theory (Zadeh 1965) is an extension of classical set theory. In fuzzy sets each data point has an associated membership value, which expresses the degree of membership of the data point in a particular set. The mapping of data points to degrees of membership is called the membership function. The theory is well known and contemporary geographic information systems usually include methods to handle data layers with attribute vagueness using fuzzy set theory. The fuzzy representation provides the means to express partial membership, not in the sense of a probabilistic attribute but in the form of an admission of possibility (Burrough and McDonnell 1998). Thus, it can be used to represent uncertainty about class membership.

So far, most implementations of fuzzy sets in geography have been focused on characterizing attribute ambiguity in data. However, during the last few years the issue of spatial vagueness has also been approached (Wang and Hall 1996, Burrough and Frank 1996, Brown 1998). Molenaar (1996) discusses fuzzy spatial objects using a semantic formalism but he also expresses some doubt as to whether this can be readily handled by existing tools. One major obstacle to the diffusion of fuzzy set based uncertainty handling is that the necessary membership function can be very hard to determine. In those cases, we anticipate that an alternative approach based on rough sets is more appropriate, since there will be no need to determine a membership function, or even resort to an arbitrary one. We might for instance end up with the following reclassification situation: given a categorical map with a map polygon labelled A, translate this into another classification system, given the alternative of assigning a label 4 or 6 according to the reclassification rule. Data in real situations are often of this discrete nature and membership values may be hard to determine.

2.2. *Rough sets*

Pawlak (1982) initially introduced the idea of rough sets but links between this theory and spatial applications have not until recently been elaborated. Rough sets, like fuzzy sets, are an extension of standard mathematical sets. In this extension an uncertain set is represented by its upper and lower approximation. If the data point is in the lower approximation, we are sure that it is in the set. If it is not in the upper approximation, we are sure that it is not in the set. The spatial representation of the rough set can be in the form of pixels or entire polygons which are given one of three possible values: not a member of the set (neither in lower nor upper approximation), maybe a member of the set (in the upper but not in the lower approximation) and absolutely a member of the set (in the lower approximation). Thus rough sets may also be used to represent uncertainty about class membership.

The use of rough set theory has not to any large extent been treated in the GIS literature but recent work by Schneider (1997) and Worboys (1998a, 1998b) has shown clear advantages of using a rough set approach in dealing with imprecise geospatial data. Schneider (1997) discusses rough sets in ROSE (Güting *et al.* 1995), in much the same way as we have implemented them below, but does not discuss classifications and related topics, focusing much more on the formal modeling aspects. Stell and Worboys (1998) reported on a formal approach to multi-resolution in spatial data handling using an approach similar to rough and fuzzy set theories. Their most recent findings are reported in (Worboys 1998a, 1998b) where rough sets are used to handle imprecision due to finite spatial or semantic resolution. Also the work of Cohn and Gotts (1996) on spatial relations between regions with indeterminate boundaries has much in common with rough sets.

3. Rough classification

This section builds on rough sets to introduce the idea of rough classification.

3.1. *Rough sets*

A *rough* set is a pair $(\underline{X}, \overline{X})$ of standard sets, the *lower approximation* and the *upper approximation*. In the representation we have chosen, $\underline{X} \subseteq \overline{X}$. The meaning of these two sets is that if a data point lies in $\underline{X}$, we are sure that the point is in the rough set, if a data point lies in $\overline{X} - \underline{X}$, we are unsure whether or not the point is in the rough set, and if a data point is outside $\overline{X}$, we are sure that the point is not in the rough set. These sets can contain either individual points, or continuous areas; we will use the term 'area' below. We will often call $\overline{X} - \underline{X}$ the *area of uncertainty* of a rough set. As opposed to rough sets, standard sets are often called *crisp*, a term that also applies to a rough set where $\underline{X} = \overline{X}$, which implies an empty area of uncertainty. Conversely, a rough set with an empty lower approximation and a non-empty area of uncertainty can be called *completely rough*.

According to Düntsch (1997), the basic set operations, union, intersection and negation, can easily be extended to rough sets. Union and intersection as follows: $(\underline{X}, \overline{X}) \cup (\underline{Y}, \overline{Y}) = (\underline{X} \cup \underline{Y}, \overline{X} \cup \overline{Y})$, $(\underline{X}, \overline{X}) \cap (\underline{Y}, \overline{Y}) = (\underline{X} \cap \underline{Y}, \overline{X} \cap \overline{Y})$. Negation can be extended in two ways: $(\underline{X}, \overline{X})^* = (-\overline{X}, -\overline{X})$ and $(\underline{X}, \overline{X})^+ = (-\underline{X}, -\underline{X})$.

3.2. *Rough classification*

A standard, or crisp classification C consists of a number of classes X_i, $i \in I$, each of which is a crisp set. I will be called the *index set* of a classification. For a crisp classification, $\forall i \forall j \neq i: X_i \cap X_j = \o$: the classes are pairwise disjoint. We will define the cardinality of C as $|C| = |\cup X_i|$, which, in this case, is equal to $\Sigma |X_i|$.

Likewise, a *rough classification* R consists of a number of *rough classes* $X_i = (\underline{X}_i, \overline{X}_i)$, $i \in I$, each of which is a rough set. In a rough classification, however, we would like to be able to express our uncertainty about which class, if any, a certain area belongs to. Therefore, instead of pairwise disjointness, we impose only the following restriction: $\forall i \forall j \neq i: \underline{X}_i \cap \overline{X}_j = \theta$. Of course, since $\underline{X} \subseteq \overline{X}$, this implies that $\forall i \forall j \neq i: \underline{X}_i \cap \underline{X}_j = \o$. We do not impose such a restriction on pairs of upper approximations, though, so there may be areas where two or more upper approximations overlap, but none where any lower approximation overlaps with anything else than the corresponding upper approximation. I will be called the *index set* of the classification. We will define $|R| = |\cup \overline{X}_i|$, which, in this case, is *not* equal to $\Sigma |\overline{X}_i|$. See figure 1 for an example of a rough classification.

In this way, we have expressed two fundamental types of uncertainty:

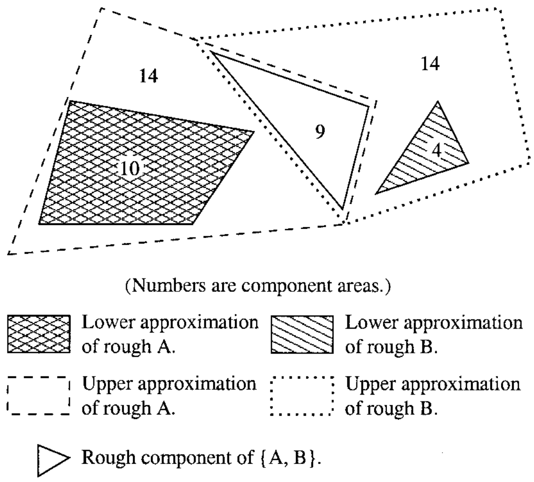

Figure 1. A rough classification.

- Uncertainty of spatial location: If, for a rough class $(\underline{X}, \overline{X})$, $\underline{X} \subset \overline{X}$, uncertainty about the spatial location of (part of) that class has been expressed.
- Uncertainty of attribute value: If a certain area is assigned to the area of uncertainty of more than one class, it is no longer certain to which class that area belongs. Thus, uncertainty of attribute value has been expressed.

Given a subset C of I, the index set of a rough classification R, we define its *rough component* as follows: $R_C = \bigcap_{i \in C}(\overline{X}_i - \underline{X}_i) - \bigcup_{i \notin C} \overline{X}_i$. *A rough component is the area that is in all the areas of uncertainty of the classes whose index is in* C, and in none of the areas of uncertainty of any of the classes of the rough classification whose indices are not in C. See figure 1 for an example rough component. The rough classes $(\underline{X}_i, \overline{X}_i)$ where $i \in C$ we will call the *founders* of the rough component R_C.

Rough components are defined such that they are always pairwise disjoint; furthermore, the union of all rough components of a classification and the lower approximations of all its rough classes is exactly the area covered by the classification.

4. Quality measures of classifications

In this section we will discuss the various ways that we can measure the uncertainty in rough and crisp classifications. Uncertainty in geospatial data is, as we stated above, divided into three major dimensions and since these dimensions are often dependent on each other, it may not be useful to explore thematic and spatial uncertainty independently (Lanter and Veregin 1992). The measures we will examine in the following discussion deal both with the thematic and the spatial aspect of uncertainty. This section is split up into four subsections, depending on what we base our measures. We can base our measures on a single rough classification, on the comparison of two crisp classifications, on the comparison of a rough and a crisp classification, or on the comparison of two rough classifications.

When comparing two classifications, we will sometimes assume that one of the classifications is the *reference* classification, containing our baseline data, whereas the other one is the *assessed* classification, the one whose quality we are trying to measure.

4.1. *Single rough classifications*

We define two measures that apply to single rough classifications: the overlap measure and the overall crispness measure. In each of these definitions, we will be talking about a rough classification R, consisting of the rough classes $(\underline{X}_i, \overline{X}_i)$, $i \in I$.

4.1.1. *The overlap measure*

The overlap measure can be computed as follows: $M_o = (\Sigma |\overline{X}_i| - |R|)/|R|$. Since all the area covered by the rough classification is included at least once in $\Sigma |\overline{X}_i|$, $M_o \geqslant 0$. If $M_o = 0$, there is no intersection between any of the rough classes. If $M_o > 0$, $\exists i \; \exists j \neq i : (\overline{X}_i \cap \overline{X}_j) \neq \emptyset$ (since the lower approximations are pairwise disjoint, this area of intersection must be in the area of uncertainty of said rough classes). M_o can grow if either the total area of intersection grows or (parts of) this area are shared by more rough classes. The upper bound for M_o is the number of classes in the rough classification minus one, as the maximum overlap occurs when all classes contain the whole area of the classification. For the example in figure 1, $M_o = ((14+9+10)+(14+9+4)-(14+9+10+14+4))/(14+9+10+14+4) \approx 0.17$.

Thus, the overlap measure measures the amount of overlap in the rough classification. This can be said to measure uncertainty in attribute value.

4.1.2. *The overall crispness measure*

The overall crispness measure can be computed as follows: $M_c = \Sigma |\underline{X}_i| / |R|$. Obviously, $M_c \geqslant 0$, and, since the lower approximations are pairwise disjoint, $M_c \leqslant 1$. If $M_c = 0$, all the lower approximations of the classes of the rough classification are empty, making the classification completely rough. If, on the other hand, $M_c = 1$, the areas of uncertainty of the classes of the rough classification are empty, and the classification is in fact crisp. For the example in figure 1, $M_c = (10+4)/(14+9+10+14+4) \approx 0.27$. This can easily be extended to a class based measure (one measure for each rough class), instead of an overall measure.

The crispness measure measures how much of the total area of the classification is assigned to lower approximations. This can be said to measure certainty in spatial location.

4.2. *Comparing two crisp classifications*

When comparing two crisp classifications, the standard first step is to compose an error matrix (Congalton 1991), so we start off with a description of this paradigm. Congalton (1991) also describes the various accuracy measures that can be computed from such a matrix, which we will briefly review.

4.2.1. *Error matrix*

We will consider the case where two crisp classifications A and B are being compared. A consists of the classes X_i, $i \in I$, while B consists of the classes Y_j, $j \in J$. Much of the following will only be valid if $|I| = |J|$ (let us define $N = |I|$), and will probably only make sense if, in fact, $I = J$.

The error matrix is now defined as an N by N matrix with elements $x_{i,j}$ having values $x_{i,j} = |X_i \cap Y_j|$. We will also assume that $\cup_i X_i = \cup_j Y_j$, i.e. that the two classifications cover exactly the same area. Because of that and the fact that all the X_i are pairwise disjoint, and all the Y_j are also pairwise disjoint, the error matrix has the following three properties:

- The *row-sum* property: $\Sigma_j x_{i,j} = |X_i|$, i.e. the sum of the elements in a single row of the matrix is the area of the corresponding class of A.
- The *column-sum* property: $\Sigma_i x_{i,j} = |Y_j|$, i.e. the sum of the elements in a single column of the matrix is the area of the corresponding class of B.
- The *total-sum* property: $\Sigma_{i,j} x_{i,j} = |A|$, i.e. the sum of all the elements of the matrix is the area covered by either of the classifications.

4.2.2. *Some commonly used measures*

Overall accuracy is defined as the total match between the two classifications divided by the total area of the classifications, i.e.:

$$A_o = \sum_i x_{i,i} / |A| \tag{1}$$

This can be split up according to the classes in the classifications, but in that case one is left with the choice of dividing by the column total or by the row total. Assuming that the reference classification is associated with the columns of the matrix, dividing by the column total gives the *omission error*, also called *producer's accuracy*. Dividing by the row total gives the *commission error*, also called *user's accuracy*. In other 'words':

$$O_j = x_{j,j} / \sum_i x_{i,j}, \text{ and } C_i = x_{i,i} / \sum_j x_{i,j} \tag{2}$$

A more complicated statistical measure, which makes various assumptions about the input data, is $\hat{K}$ (Congalton 1991):

$$\hat{K} = \frac{|A| \sum_i x_{i,i} - \sum_i \left(\sum_j x_{i,j} \cdot \sum_j x_{j,i} \right)}{|A|^2 - \sum_i \left(\sum_j x_{i,j} \cdot \sum_j x_{j,i} \right)} \tag{3}$$

Please note that, apart from the naming of omission and commission errors, these three measures are completely symmetrical with respect to the columns and rows of the matrix, i.e. transposing the matrix, by switching A and B, will have no effect on the computed value.

4.3. *Comparing rough and crisp classifications*

We first discuss how to extend error matrices to comparing rough and crisp classifications, and then we discuss the various measures we can compute from such a matrix. We also introduce a method by which we may apply any measure that can be applied to the comparison of two crisp classifications.

4.3.1. *Error matrix extension*

When comparing a rough classification, R, with a crisp one, C, such as in figure 2, we can start with constructing an *extended error matrix*, see table 1 for the example. For typographic reasons, we choose to associate the crisp classification with the rows of the matrix, and the rough classification with the columns of the matrix, independently of which one is the reference classification.

R consists of the rough classes $(\underline{X}_j, \overline{X}_j)$, $j \in J$ and C consists of the crisp classes Y_i, $i \in I$. Again, we will assume $|I| = |J|$ (and hope for $I = J$) and define $N = |I|$. We will also assume again that $\cup \overline{X}_j = \cup Y_i$. The matrix will be of size $2N \times N$, having

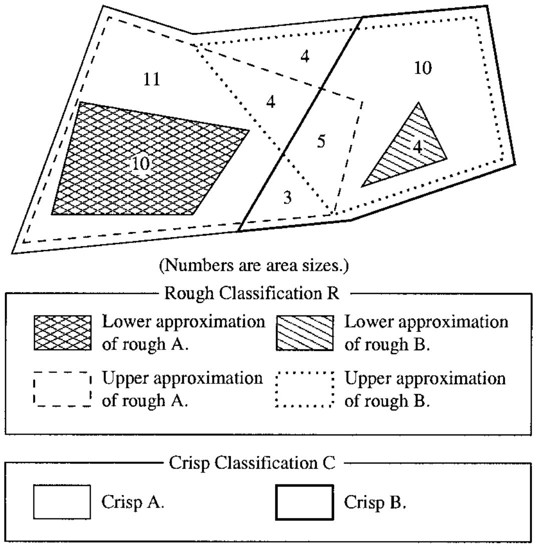

Figure 2. Comparing a rough and a crisp classification.

Table 1. An extended error matrix.

	$\underline{A}$	$\overline{A}-\underline{A}$	$\underline{B}$	$\overline{B}-\underline{B}$
A	10	15	0	8
B	0	8	4	15

elements $x_{i,k}$. The definition of $x_{i,k}$ depends on k. If k is odd, $x_{i,2j-1} = x_{i,j+} = |\underline{X}_j \cap Y_i|$. Otherwise, k is even, and $x_{i,2j} = x_{i,j?} = |(\overline{X}_j - \underline{X}_j) \cap Y_i|$. When we talk about the diagonal of this matrix, we will mean the elements $x_{i,i+}$ and the elements $x_{i,i?}$.

The column-sum property still holds: The sum of all the elements in a column is exactly the area of the corresponding part (lower approximation or area of uncertainty, as the case may be) of the corresponding rough class. However, the row-sum and total-sum properties do *not* hold any longer. If we compute the sum of a row of the matrix, $\Sigma_k x_{i,k}$, we do not, as we would like, get $|\cup_j \overline{X}_j \cap Y_i|$, but we get $\Sigma_j |\overline{X}_j \cap Y_i|$, thus counting all the overlapped areas multiple times, and similarly for the total sum of all the matrix elements.

4.3.2. *The relative crispness measure*

Assuming that the crisp classification is the reference one, the relative crispness measure compares the crispness of a rough classification in the areas where it corresponds to the crisp classification (where it is 'right') to its crispness in areas where it does not correspond to the crisp classification (where it is 'wrong').

If, on the other hand, the crisp classification is the one that is being assessed, the relative crispness measure measures whether the crisp classification is more correct in areas where the rough classification is certain than in areas where it is uncertain.

Given the following two definitions:

$$D=\begin{cases}\dfrac{\sum x_{i,i+}}{\sum(x_{i,i+}+x_{i,i?})} & \text{If } \sum(x_{i,i+}+x_{i,i?})\neq 0.\\ 0 & \text{Otherwise.}\end{cases} \tag{4}$$

$$O=\begin{cases}\dfrac{\sum_{i\neq j}x_{i,j+}}{\sum_{i\neq j}(x_{i,j+}+x_{i,j?})} & \text{If } \sum_{i\neq j}(x_{i,j+}+x_{i,j?})\neq 0.\\ 0 & \text{Otherwise.}\end{cases} \tag{5}$$

D measures the crispness in the diagonal elements of the matrix, whereas O measures the crispness in the off-diagonal elements. The crispness is not measured in a way compatible with M_c, since overlapping areas of uncertainty are counted twice.

The relative crispness measure can be computed as follows: $M_r = D - O$. Since $0 \leqslant D \leqslant 1$ and $0 \leqslant O \leqslant 1$, $-1 \leqslant M_r \leqslant 1$. If $M_r = -1$, that means that there is no crispness on the diagonal of the matrix, whereas there is perfect crispness off the diagonal of the matrix. Values between -1 and 0 mean that there is more crispness off the diagonal than there is on the diagonal. $M_r = 0$ means that there is no difference in crispness on or off the diagonal. Values between 0 and 1 mean that there is more crispness on the diagonal than there is off the diagonal. If $M_r = 1$, there is no crispness off the diagonal, while there is perfect crispness on the diagonal. Higher values of M_r are 'better' than lower values. For the example error matrix in table 1, $M_r \approx 0.31$, which tells us that the diagonal elements are significantly more crisp than the off-diagonal elements.

4.3.3. *Overall accuracy*

As stated above for the case of two crisp classifications, overall accuracy is the total correct area divided by the total area. This can be extended to the case of one crisp and one rough classification. However, we will not get one single answer, but, fittingly, an upper and a lower bound.

The upper and lower bounds for overall accuracy are as follows: $\Sigma x_{i,i+}/|R| \leqslant A_o \leqslant \Sigma(x_{i,i+}+x_{i,i?})/|R|$. We can be sure that we are not counting anything twice, since we only use elements from the diagonal of the matrix. The areas corresponding to these diagonal elements are all subsets of different classes of C, and those are disjoint. For the example extended error matrix in table 1, $0.27 \leqslant A_o \leqslant 0.86$.

The way to arrive at the bounds given above, is to think of the ways the rough classification can be converted to a crisp one. If the assumption is made that it is permissible not to assign (parts of) areas of uncertainty to any crisp class at all, the bounds given above are valid and tight. If this assumption is not valid, we will have to resort to the procedure outlined below.

4.3.4. *Error matrix parameterization*

Since the row-sum and total-sum properties do not hold for extended error matrices, it is hard to directly apply traditional measures that involve elements beyond those on the diagonal. For this kind of global measures, we will convert the rough classification into a crisp one. However, doing so in a consistent fashion is not straightforward, since there may be overlap in the areas of uncertainty, and this information is missing from the matrix. So, we will have to go back to the rough classification, R, and convert this rough classification to a virtual crisp classification, V, on which (together with the crisp classification, C) we will base our crisp error matrix. V will have the same index set as R, namely J. So there will be a one to one correspondence between the classes $(\underline{X}_j, \overline{X}_j)$ of R and the classes Z_j of V.

Since there is no unique way to convert a rough classification to a crisp one, and the value of the measure that we want to compute depends on exactly how we do this, we will have to parameterize our matrix depending on which classes of V, if any, we assign certain component areas. The component areas will be $Y_i \cap R_C$, the intersections of the classes of C with the rough components of R; in the situation in figure 2 these are the white areas that have numbers in them. We do not need to parameterize on the lower approximations of the classes of R, since we have no choice where to assign them; they will become zero-*th* order terms in our parameterized matrix.

Given the definition $\Gamma_j = \{R_C | j \in C\}$, the N by N parameterized error matrix has elements $p_{i,j}$ given by:

$$p_{i,j} = |Y_i \cap \underline{X}_j| + \sum_{K \in \Gamma_j} (x_{i,j,K} \cdot |Y_i \cap K|) \tag{6}$$

with the following two restrictions imposed upon the parameters:

$$0 \leqslant x_{i,j,K} \leqslant 1 \text{ and } \sum_j x_{i,j,K} \leqslant 1 \tag{7}$$

This last inequality assumes that it is permissible not to assign some of the area covered by the areas of uncertainty to any class of V. If this is not permissible, the inequality becomes an equality: $\Sigma_j x_{i,j,K} = 1$.

If we apply this to the example in figure 2, we get the parameterized error matrix in table 2, although we have simplified the indices somewhat. The additional restrictions that we should impose are $x_2 + x_3 \leqslant 1$ and $x_6 + x_7 \leqslant 1$.

Now we can apply any accuracy measure to this new matrix, and we will get a formula that gives us the value of the accuracy measure depending on exactly how we treat the areas of uncertainty in the rough classification. Theoretically, we could then maximize and minimize this equation within the bounds imposed on the parameters, and obtain the maximum and minimum values for the accuracy measure applied.

Let us look at an example. Omission and commission errors are the diagonal elements of table 2 divided by, respectively, the sum of the column and the sum of the row. In any parameterized error matrix, this comes down to a quotient of two linear expressions, combined with the appropriate restrictions mentioned above.

For another example, let us look at $\hat{K}$. Each of the $x_{i,j}$ is a linear expression in an unknown number of parameters in our case, the same goes for $\Sigma_j x_{i,j}$ and $\Sigma_j x_{j,i}$.

Table 2. A parameterized error matrix.

	A	*B*
A	$10 + 11x_1 + 4x_2$	$4x_3 + 4x_4$
B	$5x_6 + 3x_8$	$4 + 10x_5 + 5x_7$

$|A|$, meanwhile, is perhaps best translated as $|C|$, which is constant. Thus, the whole comes down to the quotient of two quadratic expressions which should be optimized over a hypercube limited by some hyperplanes.

For both these examples, at least local minima and maxima can be found with software such as Matlab. Since finding the extremes of a quadratic expression over an N-dimensional box is known to be NP-complete (Garey and Johnson 1979), optimizing the expression for $\hat{K}$ is at least that hard. We have been unable to find any mention about the complexity of finding the extremes of a quotient of two linear expressions, so have no such information about omission and commission errors.

4.4. *Comparing two rough classifications*

In the rest of this subsection, we will assume that we are comparing the rough classification R, consisting of $(\underline{X}_i, \overline{X}_i)$, $i \in I$, with S, consisting of $(\underline{Y}_j, \overline{Y}_j)$, $j \in J$. We will make the usual assumptions $|I| = |J|$ and $\cup \overline{X}_i = \cup \overline{Y}_j$ and the definition $N = |I|$. We first discuss the error matrix extension for this case and its properties, then explore measures for it, and finally parameterize it to apply conventional measures.

4.4.1. *Error matrix extension*

When comparing two rough classifications with each other, like in figure 3, we will use the *two-dimensionally extended error matrix*, or *2Deem*. The 2Deem for the example from figure 3 is given in table 3.

The matrix will be of size $2N \times 2N$, having elements $x_{k,l}$. The definition of $x_{k,l}$ depends on both k and l. If both are odd, $x_{2i-1,2j-1} = x_{i+,j+} = |\underline{X}_i \cap \underline{Y}_j|$. If k is odd, but l is even, $x_{2i-1,2j} = x_{i+,j?} = |\underline{X}_i \cap (\overline{Y}_j - \underline{Y}_j)|$. Symmetrically, if k is even, but l is odd, $x_{2i,2j-1} = x_{i?,j+} = |(\overline{X}_i - \underline{X}_i) \cap \underline{Y}_j|$. Finally, if both are even, $x_{2i,2j} = x_{i?,j?} = |(\overline{X}_i - \underline{X}_i) \cap (\overline{Y}_j - \underline{Y}_j)|$. When we talk about the diagonal of this matrix, we will mean the four sets of elements $x_{i+,i+}$, $x_{i+,i?}$, $x_{i?,i+}$ and $x_{i?,i?}$.

For a 2Deem, none of the row-sum, column-sum and total-sum properties hold

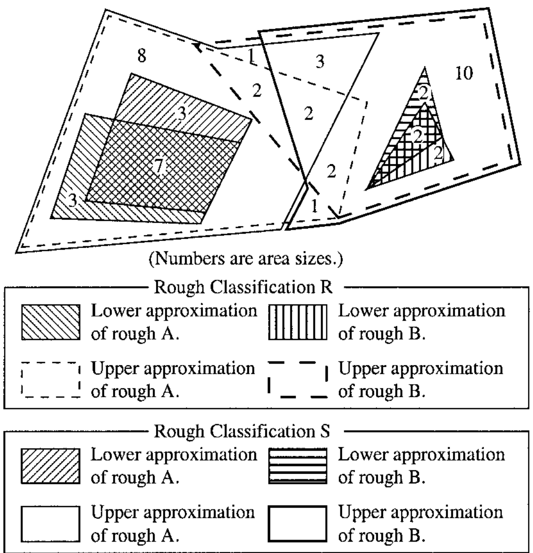

Figure 3. Comparing two rough classifications.

Table 3. A two-dimensionally extended error matrix.

$R\downarrow, S\rightarrow$	$\underline{A}$	$\overline{A}-\underline{A}$	$\underline{B}$	$\overline{B}-\underline{B}$
$\underline{A}$	7	3	0	0
$\overline{A}-\underline{A}$	3	12	0	5
$\underline{B}$	0	0	2	2
$\overline{B}-\underline{B}$	0	8	2	17

any longer, since neither the parts of classes associated with the individual columns nor the parts of classes associated with the individual rows are pairwise disjoint any more.

4.4.2. *Overall accuracy*

For this case, as well, an upper and a lower bound for overall accuracy can easily be computed.

4.4.3. *Error matrix parameterization*

To apply conventional crisp measures to this case, we can use an approach similar to the one we used for the rough-crisp case in §4.3.4.; constructing a parameterized error matrix. This time, we will parameterize on the intersections of a component of R with a component of S. We will repeat the definition $\Gamma_i = \{R_C | i \in C\}$ and add $\Delta_j = \{S_C | j \in C\}$. The elements of the $N \times N$ parameterized error matrix are now given by:

$$p_{i,j} = \underline{X}_i \cap \underline{Y}_j + \sum_{K \in \Gamma_i} (x_{i,j,K,\underline{Y}_j} \cdot |K \cap \underline{Y}_j|) + \sum_{L \in \Delta_j} (x_{i,j,\underline{X}_i,L} \cdot |\underline{X}_i \cap L|) + \sum_{K \in \Gamma_i} \sum_{L \in \Delta_j} (x_{i,j,K,L} \cdot |K \cap L|) \tag{8}$$

Of course, still

$$0 \leqslant x_{i,j,K,L} \leqslant 1 \text{ and } \forall K, L: \sum_{i,j} x_{i,j,K,L} \leqslant 1 \tag{9}$$

(or make that ... = 1 if you do not believe in not assigning parts of areas of uncertainty to any class). Like in §4.3.4., this parameterized error matrix is linear in its parameters, so the conclusions we have drawn there apply to this case as well.

The only difference is in the number of parameters. The maximum possible number of parameters is much larger for this case (on the order of 2^{2N} rather than 2^N, a quadratic difference). In practice, however, many, if not most of these parameters (in either case) will only ever occur in the matrix multiplied by zero, and can thus be dropped from calculations. It is harder to estimate this practical number of parameters, but it seems likely that it will be larger in this case than in the case in §4.3.4.

5. Experiment

The goal of our experiment was to use the idea of rough classifications to compare two vegetation maps, covering the same area of 1.8 by 2.3 km in Stockholm County, just north of Stockholm. The two maps had been produced for nature preservation tasks and different classification schemes were used to delineate vegetation categories on a categorical map sheet in 1:15 000 scale. The quality in terms of spatial and attribute accuracy of these maps are not known but for the purpose of this experiment that is of less importance, since the main idea is to demonstrate the technique of using rough classifications.

5.1. *Experiment description*

In our experiment we considered the two layers as two different representations of the same area. We started out with two vegetation maps which provided two crisp vegetation classification layers called veg9 and veg35. Building on vegetation concepts that were introduced by Påhlsson (1972), veg9 was classified using moisture and nutrient status as the classification basis giving nine different vegetation classes for the experiment area. Veg35 used a Nordic classification system described by Påhlsson (1995), giving 35 different vegetation classes for the experiment area. The class descriptions are given in tables 4 and 7. To compare the two, we needed to reclassify one of them; for obvious reasons, we picked veg35. This can be seen as a generalization operation where we reduce the number of classes from 35 to 9 and simultaneously change the classification system.

Reclassification of veg35 into the classification scheme used for veg9 would be a straightforward task if a one to one or many to one correspondence between the two classification systems existed. Since this is not the case, we used the idea of rough classification to represent the uncertainty in the reclassification operation. Rules to reclassify from the classification system given by Påhlsson (1995) to the one given by Påhlsson (1972) were constructed using both the guidelines given in (Påhlsson 1995) and our own knowledge about the association between the different vegetation classes. The re-classification rules are given in table 7. The reclassification rules can also be constructed using decision tables obtained through training data sets as described in (Skowron and Grzymala-Busse 1993).

Since the reclassification of veg35 into rough classes introduces a certain degree of uncertainty it will be of interest to see if this uncertainty can be resolved by using additional information about the area. Given that the veg9 classification system uses nutrition and moisture properties we could argue that more information on these properties could give evidence to resolve some of the areas of uncertainty. We decided to use soil information as proxy for the moisture component and provided this evidence in the form of a digitized soil map covering the experiment area. This required a reclassification from the soil map classes (table 5) into rough veg9 classes.

Table 4. Classes in veg9.

Id	Description
1	bare rock
2	dry heather
3	mesic heather
4	wet heather
5	swamp
6	dry meadow
7	mesic meadow
8	wet meadow
9	steppe alike

Table 5. Soil classes.

Id	Description
1	washed moraine
2	outcrop
3	moraine
4	sandy sediments
5	postglacial clay
6	clay sediments
7	muddy clay
8	mud peat

The rules for rough classification of soil classes in the soil map was entirely done by our own knowledge about the association between soil classes and vegetation classes in the veg9 classification scheme. These classification rules are given in table 6.

We proceeded as shown with non-dashed lines in figure 4, where single boxes are crisp layers and double boxes are rough layers. We took veg35 and the soils classifications and reclassified them into two separate rough classifications using the nine classes of veg9. Having this data, we produced some statistics about them and about their match with veg9, which are presented in §5.2.

5.1.1. *Merging two rough classifications*

The problem under consideration in this section is, given two rough classifications of the same area, with the same classification scheme, how do we combine them? For example, if, with respect to a specific piece of land, the one classification claims that it is either forest or city, while the other classification claims that it is either lake or forest?

Let us call the input classifications A and B, and let us say that we are looking at these classifications of point x. We will call the set of classes of A of which x is a member K; for B, we will call that set L. The output classification we will call C, and the set of classes of which x is a member in C we will call M.

Note that in this representation we can not differentiate between if x is in the area of uncertainty of exactly one class or in the lower approximation of exactly one class. This is acceptable, because we are looking at complete classifications, and in that case x being in the area of uncertainty of exactly one class does not really make sense. This is true for M, the set of output classes, too. If M contains more than one

Table 6. Rough reclassification from soils to veg9.

Soil class	veg9 rough classes
1	2, 6
2	2, 6
3	3, 7
4	3, 7
5	3, 7
6	4, 8
7	4, 8
8	4, 8

Table 7. Veg35 classes and rough reclassification to veg9.

Id	Description	Veg9 rough classes
1	pine forest type 1	2
2	pine forest type 2	2
3	spruce forest type 1	2, 3
4	spruce forest type 2	4, 8
5	spruce forest type 3	3, 7
6	spruce forest type 4	8
7	spruce forest type 5	4
8	mixed conifer forest type 1	2
9	mixed conifer forest type 2	2, 3
10	mixed conifer forest type 3	3, 7
11	mixed conifer forest type 4	none
12	broad leafed deciduous forest type 1	7
13	broad leafed deciduous forest type 2	8
14	broad leafed deciduous forest type 3	7
15	alder forest type 1	8
16	alder forest type 2	8
17	birch/aspen forest type 1	2, 3
18	birch/aspen forest type 2	7
19	birch/aspen forest type 3	2, 3
20	brushwood	7
21	mixed forest type 1	2, 3
22	mixed forest type 2	7
23	mixed forest type 3	8
24	early successional forest	none
25	clear cuts/non determined	none
26	alder scrub	8
27	geoliteral shore vegetation	none
28	subliteral shore vegetation	none
29	dry meadow type 1	6
30	dry meadow type 2	6, 7
31	meadow type 1	6, 7
32	meadow type 2	6, 7
33	meadow type 3	8
34	meadow type 4	3, 7
35	wet meadow type	8

class, x will be in the areas of uncertainty of all those classes. If M contains only one class, x will be in the lower approximation of that class.

There are two cases that have to be considered separately. Either the two classifications contradict each other (i.e. $K \cap L = \emptyset$) or they do not (i.e. $K \cap L \neq \emptyset$). It is quite likely that any two classifications will contradict each other in some points, if only in sliver areas along the not-quite-equal borders of classes.

Let us consider the non-contradictory case first. In this case, we will apply the rule that $M = K \cap L$. For a class c, if $c \notin K$ or $c \subseteq L$, that means that that classification says that it is certain that x is not in c. So only if $c \in K$ and $c \in L$ can we conclude that $c \in M$.

But what about the contradictory case? Here, we will adopt the reasoning that, even if they can not both be right, one of them probably is. Since we do not know which one, we will just say that $M = K \cup L$. So if classification A says that our point

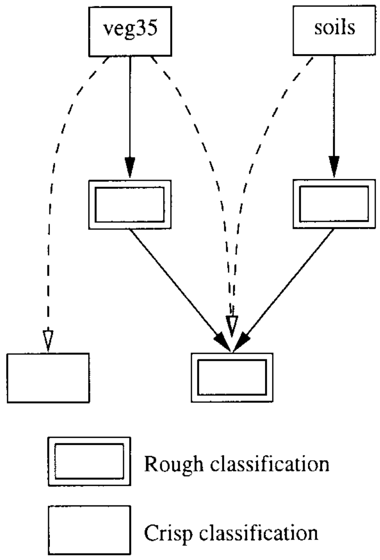

Figure 4. Process graph.

X is forest, while B says that it is really water, we will conclude that it must be either forest or water.

5.1.2. *Implementation details*

This work was carried out using a custom-built system, ROVer (Rough Object Visualizer), shown in the screenshot in figure 5. It is based on ROSE, the RObust System Extension, a library of spatial operators based on exact arithmetic, specially developed for integration into a spatial database system (Güting *et al.* 1995), with an extension to ROSE that deals with rough sets. The user interface was written with *gtk* +, a small, efficient and flexible GUI library for X11. Perl has been embedded as a programming language. ROVer can display any number of overlaid rough and crisp classes and classifications, even transparently, using a highly dynamic user interface, and is driven by Perl scripts, which call *C* routines in ROSE to do the actual computations. What is not apparent from the screen-shot is that as the user moves the mouse over the geometry shown, not only do the coordinates update, but also the little icons in the legend change to indicate which classes the mouse pointer is in (showing *a* '+' if the mouse is in the lower approximation, *a* '?' if it is in the area of uncertainty, and *a* '−' if it is outside the rough class).

5.2. *Results*

The reclassified veg35 layer has an overlap measure of 1.058 and a crispness measure of 0.308. That means that about 30% of the area is certain, and the remaining 70% is uncertain. On that uncertain area, there is overlap (overlap measure is greater than zero). In fact, the overlap covers a little bit more than the whole classification; there must, in other words, be areas which are in at least three areas of uncertainty. When comparing the reclassified veg35 layer with the veg9 layer, we get an overall accuracy in the range of [0.039, 0.461], not very good.

The merged classification has an overlap measure of 1.981 and a crispness measure of 0.168. That means that the certain area has almost been halved as compared to

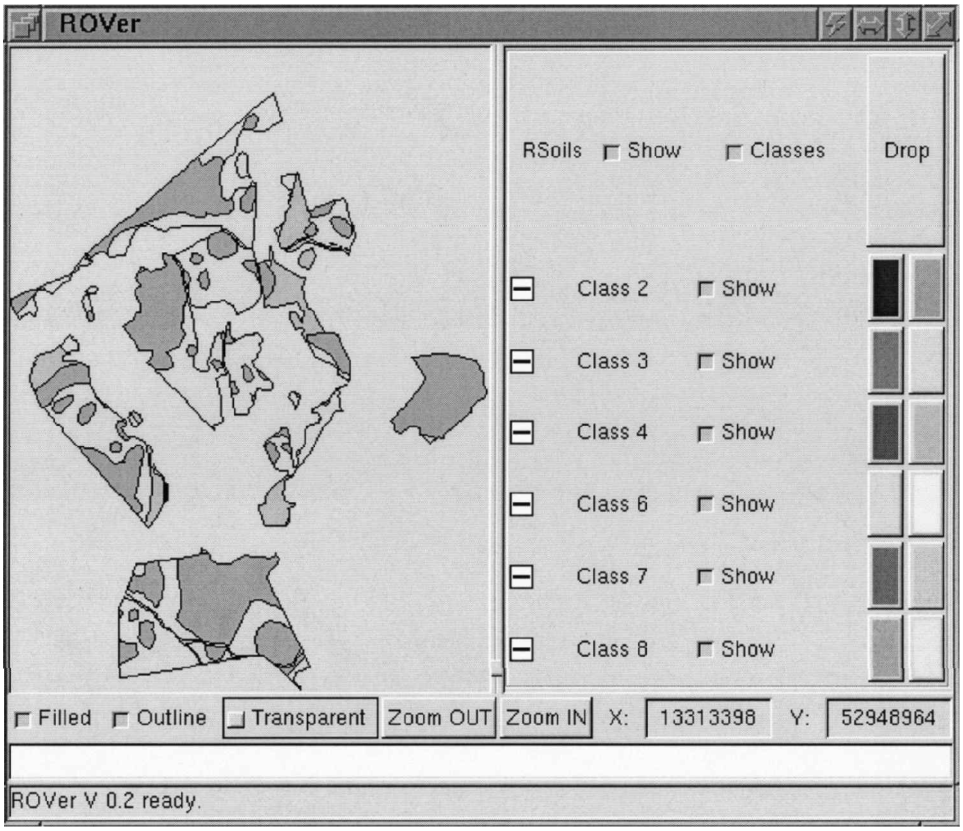

Figure 5. ROVer screenshot.

veg35, from about 30% to about 17%. About 83% of the area is uncertain, and on those 83% there is an overlap that covers almost twice the whole classification. Since $1.981 > 0.83 \times 2$, there must be areas where there is a triple overlap; in other words, there must be areas which are in the area of uncertainty of at least four classes. The overall accuracy when comparing this classification to veg9 is in the range of $[0.031, 0.697]$, still not very good. It does mean, however, that if we get more information about the area under consideration, we could improve the overall accuracy at most up to 0.697.

6. Discussion

Our experiment shows the simplicity of rough classification in situations where we have difficulties to associate a particular area with one specific category based on available information. The experiment shows the applicability of rough classification both to reclassification of existing datasets and to performing spatial analyses on these datasets. We also see a potential to work with rough classification in primary classification work such as surveying. To exemplify this we would like to highlight an example from the field of research in glacial geomorphology where we think that a rough classification would be well suited.

In a recent paper Hättestrand (1998) treated the formation and distributional characteristics of glacial geomorphological features, particularly ribbed moraines. As a basis for his study a survey of glacial landforms was done covering almost two-thirds of Sweden. One type of moraine that was mapped was the Veiki moraine, a type of hummocky moraine characterized by plateaus with rim ridges separated by depressions. In his survey Hättestrand used a narrower definition of this moraine type than previous work by other authors, and what came out was a more restricted distribution of this specific landform. Especially the spatial distribution of the ridges coincided with the distribution of other ice-marginal features and suggested an association between them. This finding together with other observations made a reinterpretation of the early phases in the latest glaciation of Fennoscandia possible. We suggest that surveying of geomorphological landform elements using rough classification would enable a rough assignment of nearly matching features to the upper approximation of the set. Subsequent analysis of for example the distribution pattern may then exploit this preservation of uncertainty and make findings as the one mentioned possible.

From a geographical information system users point of view the visual interface is a primary tool for interpretation, analyses and visualizations of geographical data. Most current geographic information system software provides ready to use functions to zoom in and out, regroup, aggregate and generalize the data. Still most people in the geographic information community now realize that the digital generalization process is still problematic and that research needs to develop methods for data abstraction and data reduction that keep track of data quality (Müller *et al.* 1995). The advantage of the rough set based approach is that one doesn't have to quantify uncertainty.

There is of course a risk of being too vague if every question is answered with a rough 'maybe'. A way to compensate for this vagueness is to provide additional information on the context of the concept or class. Freksa and Barkowsky (1996) discuss fuzziness in geographical objects and argue that a discrete model of spatial concepts that preserves the conceptual neighborhood has clear advantages in practice. A conceptual neighborhood means a situation where we either have compatible concepts on different levels of granularity or we have competing concepts on the same level of granularity. Some examples demonstrate this idea of conceptual neighborhood in the context of concepts for spatial relations (Freksa and Barkowsky 1996, Cohn and Gotts 1996). In our experiment we show that the same ideas can be applied to concepts such as vegetation classes. The rules we used to reclassify our initial data into rough layers apply the idea of conceptual neighborhoods either stated explicitly (Påhlsson 1995), or by using an expert decision approach. Of course, the neighborhood structure is not preserved as such in the data but in all cases of uncertainty each item is assigned rough set values according to the concept neighborhood. Thus, we see rough classification as a candidate approach for the representation of conceptual neighborhoods in a wider perspective.

The explicit definition of multiple conceptual hierarchies as a heterachy of concepts as part of the meta data may help to preserve the geographical meaning in databases (Nyerges 1991b). Such an idea to employ a discrete model on the semantic level is closely related to the mechanisms developed by Bishr (1998) to capture and handle concepts at a level of application semantics. Bishr (1998) presents a thorough background to the reasons why and how semantic similarity between concepts should be used to develop mediator concepts to resolve, for example, schematic heterogeneity.

The combination of two rough layers performed in our experiment in order to resolve some of the uncertainty can be compared to the use of inference network operations. Examples of commonly used methods include: fuzzy logic AND and OR operations, Bayesian updating of prior probabilities to posterior probabilities, and the related evidence theory or Dempster-Shafer theory. The latter divides a probability space into two parts, an inner measure given by a belief function and an outer measure given by a plausibility function.

There is an apparent similarity between Dempster-Shafer belief and plausibility, and the upper and lower approximations of rough sets. Let us, as an example, look at evidence of the influence of civilization. At the locations where one sees, say, grass, one can deduce that some external influence, be it a herded flock of sheep or a lawnmower, must keep out the trees from that location. This can be seen as positive evidence for the influence of civilization. At other locations, such as in a forest, such evidence may not be present, but this is not the same as evidence of the absence of civilization. Evidence of absence could be given by, say, extensive growth of reindeer moss, which is very fragile and grows very slowly. Dempster-Shafer belief and plausibility differentiate between these options, and so do rough sets.

This has motivated work on the relation between rough set theory and evidence theory, which has been reported in (Skowron and Grzymala-Busse 1993). It follows from their work that the overall crispness measure described in §4.1.2. can be interpreted as a belief value in the sense of Dempster-Shafer logic. However, much of their findings remain to be applied in a spatial context such as the one reported here. Combination of datasets in overlay operations is an important step to performing multi criteria evaluation where an attempt is made to combine a set of criteria for a decision according to a specified question. In such a set of criteria we may want to use boolean, fuzzy and rough set layers.

7. Conclusion

We have discussed rough set based classification, and have argued that it is a viable alternative to fuzzy set based classification when a classification with explicit representation of uncertainty is desired. We have introduced various useful concepts and measures related to rough classification, and have shown how to compare a rough classification to both a crisp and a rough classification. In our experiment, we have shown the practical use of this theory, by converting data from one classification system to another, so they can be compared with other data in the latter classification system, or be used for further processing that requires data in this classification system; the uncertainty in our data is explicitly represented at each step in the analysis. This experiment would not have been possible without the theory developed here.

It would be possible to perform uncertain reclassification based on fuzzy set theory. However, as stated previously, membership functions are either difficult to determine or rather arbitrary. When discussing rough sets, (Yao, 1998) states: 'Rough membership functions may be interpreted as a special type of fuzzy membership functions...'. One could argue then that the decision whether a data point 'is', 'is not' or 'is maybe' in a given class, for instance, is also rather arbitrary. However, in our case, given the reclassification rules, it is straightforward to determine the rough memberships for each data point of the classification.

7.1. *Future work*

Two alternate reclassification approaches, indicated with dashed lines in the graph in figure 4, which remain to be investigated, are:

- The 'classical' direct conversion: Converting the crisp classification veg35 directly to the nine classes of veg9, and comparing them. This would seem to be an inferior approach, since we cannot indicate our uncertainty when converting from one classification system to another: one input class must always map onto exactly one output class. It would, however, give us a baseline with which to compare the other approaches.
- The rough direct conversion: Converting the two crisp classifications into one rough classification in one single step, without any intermediate classifications. This way we can be sure that we do not lose any information in intermediate steps, which does happen in the indirect approach that we took in the experiment above, see figure 4. A closer matching between the conversion and the reference classification can probably be achieved this way, because we have the maximum amount of information available on which to base our conclusions, but it is more knowledge-intensive; making this mapping is much more difficult than making the two consecutive mappings.

We intend to look into more appropriate measures that can be derived directly from the rough and/or crisp classifications, without the need for converting the rough classification to a virtual crisp classification. We should probably also explore these alternate approaches to our experiment. It would be interesting to look at whether and how the reclassification approach and the measures developed in this article can be extended to fuzzy data.

Another direction one might take is to develop more high-level interfaces to rough set based systems. There would then, as we mentioned in the discussion, be a desire to use crisp and fuzzy data as well as rough data in such high-level systems. This would require some way of combining these three kinds of data in multi criteria analysis, for example. Combining crisp and fuzzy layers is rather straightforward, using crisp data as a mask on fuzzy layers. The question of how to combine rough data in such overlay operations is, as far as we see today, nontrivial.

A field that we have not covered here is the one concerned with spatial aggregation of raster data. The increased use and availability of different air-borne sensor imagery produces datasets on the environment from local to global scales. In order to exploit these data there is a current need for proper aggregation and generalization methods. In this paper we have used rough set classification to explore the possibilities to perform generalization using a thematic approach. An interesting question that remains to be studied is how to incorporate this with a spatial aggregation of for example satellite imagery or other grid datasets.

Altogether, our findings suggest that rough set theory and rough classification opens an interesting field for further studies as a complement to existing theories on the representation of uncertainty in geographical information.

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Chapter

7 ESTIMATING SEMANTIC UNCERTAINTY IN LAND COVER CLASSIFICATIONS

Introduction

After the pilot tests in chapter 5 it was concluded that the use of mixture classes in R-data made it difficult to fully investigate the effect of spatial aggregation. The aggregation experiments also called for a way to handle alternative or tied outcomes in the result. Further studies of aggregation effects using the chosen approach therfore required some solutions to these problems.

First, I chose to use the structural data described in chapter 4 instead of the R-data. This data set was more consistent in the interpretation of the different attributes and it consequently gave an areal estimate of each interpreted variable.

Second, the problem of mixed aggregation outcomes or ties was interpreted as a problem of indiscernibility due to a limited granularity in the information. Chapter 6 fruitfully developed the method of rough classification and rough accuracy assessment. These findings are now anticipated to be applicable to the previously problematic aggregation effect.

Thus, these two modifications are the major difference between this more elaborate study of spatial aggregation effects.

Scale change by spatial aggregation is technically a straightforward process. Harder though is to produce information from the aggregation that is consistent with the analysis purpose at the target scale. This chapter illustrates methods to search for semantic differences in a scale change from fine resolution, pixel based landscape data generalized into a coarse resolution data set.

Despite the large interest in data aggregation and generalization, very few, if any, studies have investigated digital generalization effects with a quantitative, location specific approach. This work anticipates that the use of a location specific assessment of aggregation results will provide an additional and sometimes more informative aspect of aggregation effects. The main purpose of this chapter is to demonstrate location specific methods for estimation of scaling and generalization effects on the semantic accuracy of categorical data sets.

Experimental design: Conceptual discussion

To define the general scope of this study, consider an initial measurement L_r at a spatial granularity of r spatial units and another identical measurement L_{10r} made with a granularity of $10 * r$. We would like to find the generalization function $g()$ that satisfies

Eq. 1 $$g(L_r) = L_{10r}$$

In other words, can we define a generalization procedure for a given variable so that the outcome of the generalization is the same as if measurement were performed at the desired level of generalization? The assumption of this work is that any deviation from a strict calculation of landscape content indicates scale dependence in the interpretation of used landscape concepts. Thus, if we can falsify Eq. 1 it strengthens the alternate hypothesis, that there is a scale dependent component in the use of the data concepts. In the context of this experiment, the definition of the digital generalization method is a digital implementation of a manual interpretation and classification instruction.

One large difference between this and other studies of aggregation is that it uses data acquired from manual interpretation of printed maps. The reference dataset is thus derived using exactly the same technique and exactly the same input information as the one used in the collection of lower resolution data. The major reason for this design is to evaluate whether there is a semantic effect involved in aggregation of geographic information. Semantic differences will here be estimated as differences in semantic accuracy.

The notion of semantic accuracy was introduced in chapter 2 and exemplified in Figure 5 and Figure 6. Semantic accuracy includes an evaluation of "ability of abstraction" as a measure of how well a real world feature can be defined in the perceived reality. It also includes an evaluation of how well geographical objects in a database correspond with the perceived reality. The specification in these figures serves as a framework for the hypothesis testing in this experiment.

The following experiment will try to evaluate both the above-mentioned aspects of semantic accuracy; "ability of abstraction" and "accuracy of the dataset". First the ability of abstraction is measured using differences between multiple interpretations as a proxy for an actual "ability of abstraction"-measure. The logic behind this is that a multiple interpretation of the same real world entity uses the same specification and would ultimately end up with the same data. Any differences at the data level would be possible to interpret as a difference at the level of perceived reality since the path from perceived reality to data is exactly the same and can be held as a constant factor.

The analysis of generalized versions against the manual reference to answer the main hypothesis (Eq. 1) uses the same logic in that it uses two versions from the same real world feature. Once again data is used as a proxy for the comparison between perceived reality and the real world. The degree of correspondence between the two can then be interpreted as the semantic accuracy of the dataset, that is the semantic accuracy of the translation from the original dataset to the generalized level.

Also, the experiment includes an estimation of the differences between generalization methods that use different levels of detail in source data. Automated spatial generalization of categorical data often uses the same categories at both input and output levels. Manual generalization on the other hand may use several levels of detail but there are few if any reported examples of how this can be made automatically. Hodgson (1998) propose a conceptual model of manual image interpretation. In this he speculates that a manual interpreter identifies intermediate level abstractions before the final classification. Of primary interest in order to make automated generalization possible is of course to determine the required spatial and thematic resolution of the input data in order to produce the desired output.

Since this work uses a site specific approach to the evaluation of aggregation effects the analyses will follow some of the standard procedures for performing site specific accuracy assessment, mainly those of Congalton and Green (1999). Due to the inevitable interpretation inconsistency, this study also implements methods to include classification uncertainty using rough classification described in the previous chapter.

Methods

Source and reference data

In chapter 4 it was concluded that the existence of mixture classes in R-data caused undesirable effects for the analysis of aggregation effects. Now, for the continued investigations of the spatial granularity effect, I made two principal refinements of the experimental design.

First, I decided to use the "structural data" set from chapter 4, which does not make use of mixture classes in the same way as R-data. The explicit representation of the landscape type mixture for each spatial unit is more suited to the task of detecting differences in interpretation at different spatial granularity. One main advantage of the R-data is that it was possible to do thorough quality tests. The result of the quality tests in chapter 4 made it possible to treat the R-data estimates as having the same accuracy as National Forest Inventory estimates. However, for these closed experiments it is of secondary interest to have absolute calibration of the interpretation values. More important is to assure an internal consistency in the interpretations, and this was possible to evaluate for the Structural data.

The second modification of the experimental design of chapter 4 is the use of rough set representations explained in chapter 6 (Ahlqvist, Keukelaar and Oukbir, 2000a). After testing for interpretation consistency, it was possible to use rough classification to represent the ambiguity that occurs in the spatial aggregation process due to the detected interpretation inconsistency.

Thus, for the purpose of this chapter, a portion of the original Structural data was selected. From the entire dataset, data covering two topographic map sheets (Swedish land survey, 1961, 1977) within the Stockholm County was selected for a detailed study, Figure 30. These study areas were interpreted once again using the same method as described in chapter 4, only this time using a smaller grid size, 500x500m. This gave two sets of data for the same area, both datasets using the same source information, same areal extent, same

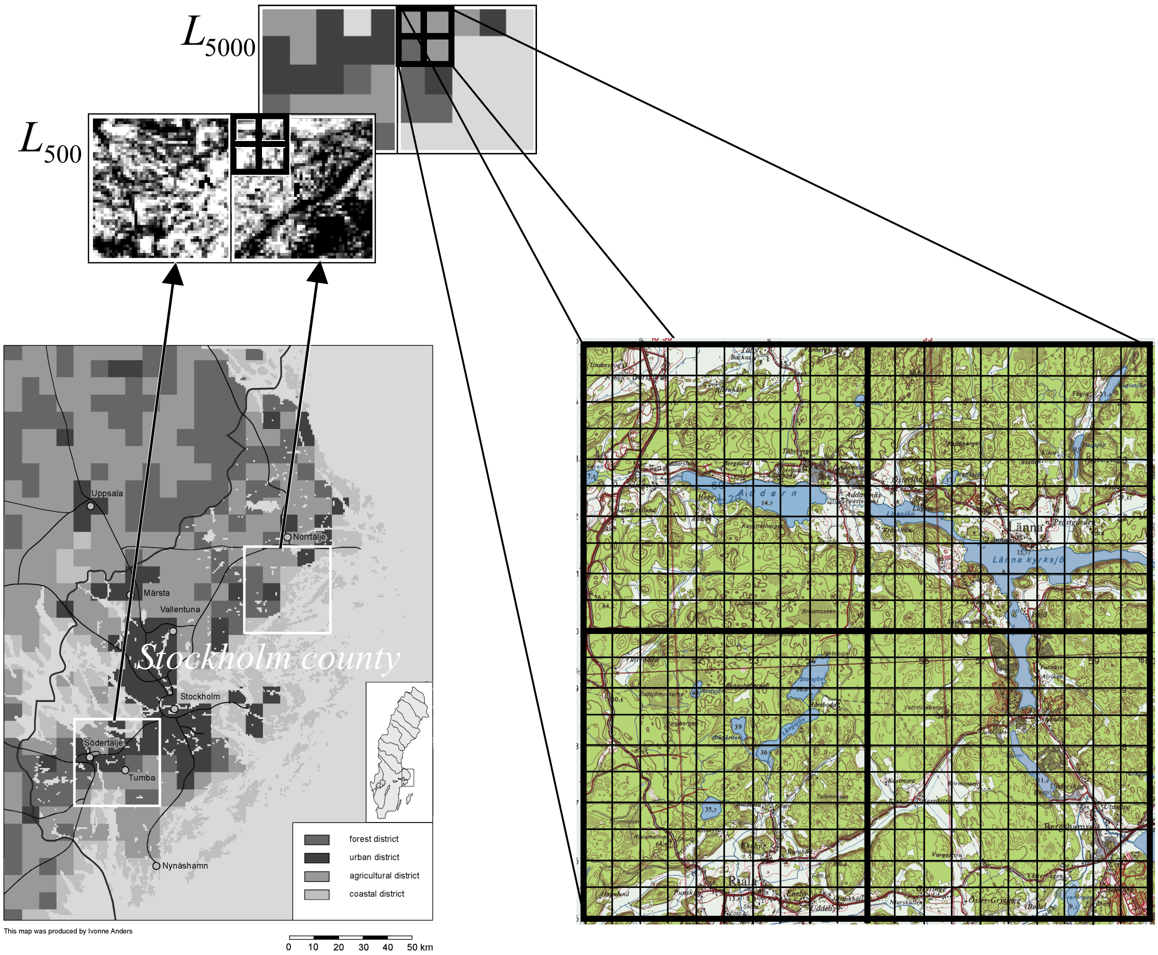


Figure 30 Study area interpretation and tiling. Topographic maps (right) from NE and SW parts of Stockholm County (left) were interpreted at two different grid resolutions L_{500} *and* L_{5000}*. The two separate study areas were tiled and analyzed together.*

interpreter (Rolf Ruben), and same classification scheme. The only thing that differs in the two pieces of information is the areal unit of investigation.

The interpretation of landscape types uses topographic maps to determine the proportion of land cover types within each areal unit. Using these estimates a classification of the areal unit into one of four different landscape types is made. The areal units consist of a regular quadratic grid where each map sheet is digitized into an array L of square grid cells. As already noted this study uses two different cell sizes, 500x500m called L_{500} data and 5000x5000m called L_{5000} data.

One problem of this kind of approach is to achieve enough data in order to provide a statistically valid result, as each pixel at the low resolution corresponds to 100 pixels at the high resolution. According to general suggestions in Congalton and Green (1999) we need c. 200 pixels for the assessment. This would in turn require interpretation of another 20000 pixels at the L_{500} resolution. Clearly some kind of trade off between the statistical requirements of the analysis and the practical limitations for this study had to be made. Since sampling is not used for the assessments of correspondence it may be argued that a smaller number of target pixels can be sufficient. I have decided to include an area corresponding to two topographic map sheets in this study, giving N=5000 for the fine resolution L_{500} data and N=50 for the coarse resolution L_{5000} data. The study areas, and the layout of the interpretation grid are illustrated in Figure 30. The study area is comprised of two separate areas each corresponding to one topographic map sheet 5x5km and in a 1:10000 scale. For purposes of analysis and visualization the two map sheets have been tiled side by side to produce one virtually contiguous study area. All further aggregation processes and analyses are made without any involvement of the border zone between the two maps thus making sure that no artificial effects arise. Figure 31 shows images

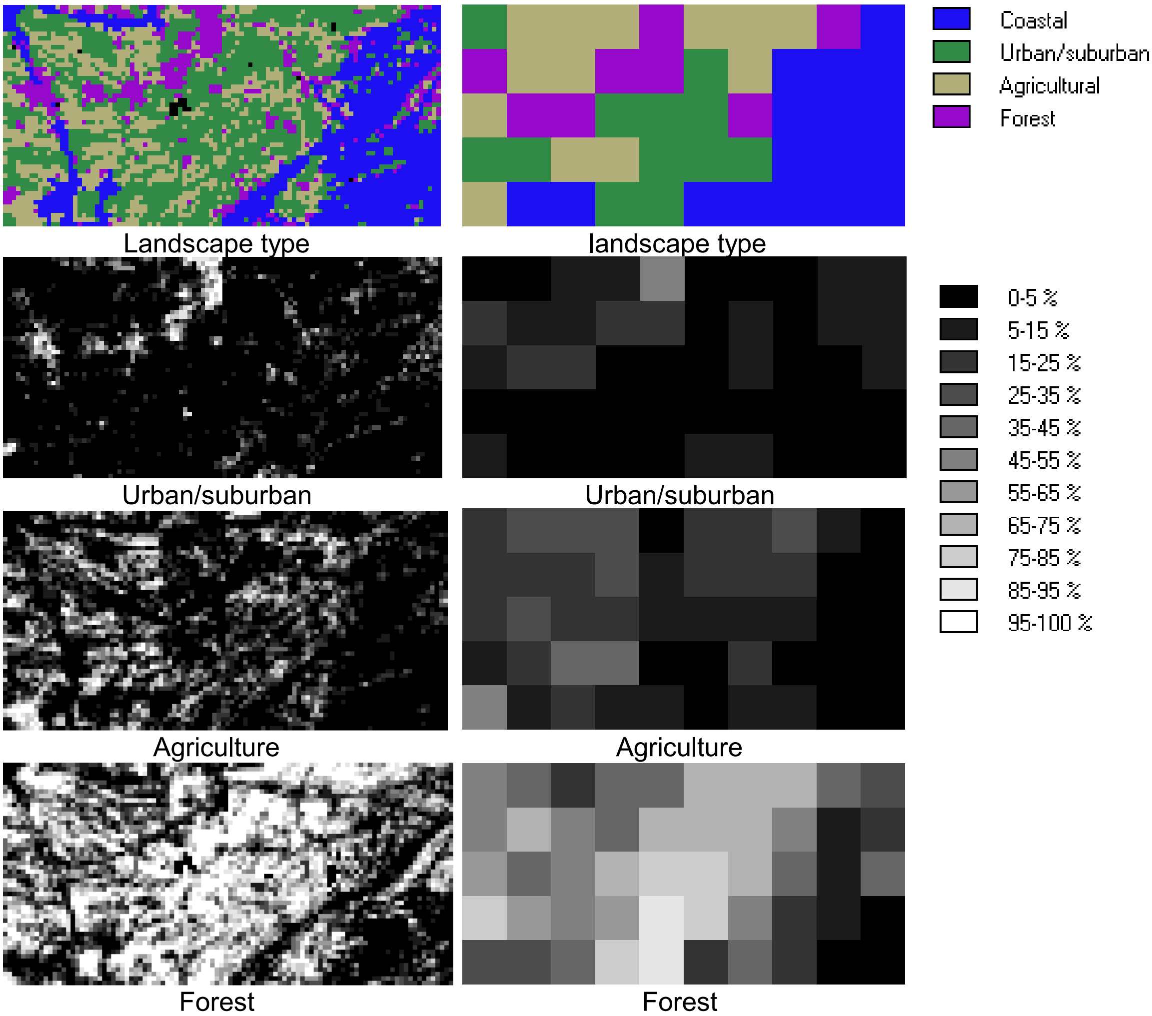


Figure 31 Interpreted source data at the two resolutions L_{500}, left column, and L_{5000}, right column. The upper two showing landscape type classifications (Blue= Coastal landscape, beige= Agricultural landscape, green= Forest landscape, purple= Urban/suburban landscape). The lower six showing areal coverage of assessed land cover types, black=0-5% coverage, and increased coverage shown as increasingly whiter shades.

that portray the interpretation result at both resolutions.

Congalton and Green (1999) state some necessary steps to ensure proper collection of data for accuracy assessment of a map:

- Accuracy assessment sample sites must be located on both the reference data and on the map
- Sample units must be exactly the same area on both the reference data and the map
- Reference and map data must be collected for each sample unit to create reference and map labels based on the map classification scheme.

Since these recommendations pertain to applied accuracy assessment the reference data may be collected from a variety of sources, and may be captured either through observation or measurements (Congalton and Green, 1999). These first three requirements are fulfilled by the data collection procedure explained above.

<u>Classification scheme</u>

A detailed description of the classification scheme was described in chapter 4. The description given below is in a translated and more formalistic form. As can be seen from the images in Figure 31 the collected data includes both nominal and continuous variables. The following section will more thoroughly explain the basis for classification and its formal implementation. The same scheme was used in all datasets.

For each cell location l in L an estimation is made of the areal coverage of four land cover categories by visually examining the paper topographic map sheet. Only the area within the spatial limits of the cell is considered at any one time. Categories and their definitions are given in Table 26.

Table 26 Land cover categories assessed for areal coverage in the study

Land cover category	Definition
Archipelago	Actual sea area and land area within 500m from the seashore
Urban/suburban	Built up land including residential ground, streets, parks, industrial and commercial areas
Agriculture	Agricultural fields, grazed areas and tree patches. Also roads and buildings connected to these areas.
Forest	Forested areas and other land cover types that do not belong to the other three categories

Table 27 Classification scheme followed in the study

Step	Landscape type	Classification rule
1	Coastal district	At least 60% of the areal unit (pixel) is covered by archipelago
2	Urban/suburban district	At least 1/8 of the areal unit (pixel) is covered by urban/suburban
3	Agricultural district	At least ¼ of the areal unit (pixel) is covered by Inägor and urban/suburban
4	Forest district	All other combinations

Associated with each cell location l in L is an array of variables $\{LT, PC, PF, PA, PU\}$ assigned values in the following manner. The first variable in the cell array $l\{LT\}$ is assigned a class label from the total set of landscape type classes *LT =[Coastal, Urban/suburban, Agricultural, Forest]* according to the classification scheme in Table 27. The classification procedure starts by assessing the areal coverage of land cover type archipelago as step 1. If the classification rule is fulfilled the array variable is assigned $l\{LT\}$=Coastal landscape, if not the classification proceeds with steps 2 through 4 until $l\{LT\}$ has been assigned one of the four possible landscape type values.

After the assignment of landscape type class, the cell array is also given the values from the initial estimation of land cover *proportions* for the four categories in Table 1 to cell array elements archipelago $l\{PC\}$, forest $l\{PF\}$, agriculture $l\{PA\}$, and urban/suburban $l\{PU\}$. The array elements are assigned to one of 11 possible areal coverage classes $[0,1\ldots9,10]$. These values represent an interval of 10%, where $l\{Px\}*10$ is the middle of the interval in percent. Thus a value $l\{Px\} = 4$ represents an interval from 35%-45% areal coverage. Note that this does not apply for classes 0 and 10 where values represent 0%-5% and 95%-100% areal coverage respectively.

The values for archipelago $l\{PC\}$ are according to the interpretation instruction and classification system (Chapter 4) not consistently given as the areal coverage of this land cover type. This circumstance made that particular variable unsuited for the study and it was therefore excluded from the analysis. Necessary information on the areal coverage of the archipelago cover type was derived from the $l\{LT\}$variable instead. The implication of this circumstance will be discussed in detail in the next section.

The study thus focuses on the distribution and areal proportion of the estimates of urban/suburban, agriculture, and forestland cover types. These three variables are used to analyze the effects of aggregation on quantitative pixel values.

The process described above provide two sets of data $L_{500}[LT, PF, PA, PU]$, N=5000 and $L_{5000}[LT, PF, PA, PU]$, N=50 interpreted from the same source. Thus in the sense of Eq. 1 we now have the two measurements $L_r = L_{500}$ and $L_{10r} = L_{5000}$.

Generalization strategies

The data collection has this far provided two measurements of the same area at two different spatial granularity levels L_{500} and L_{5000}. To answer the question if Eq. 1 holds, a definition is needed of the generalization function $g(\;)$ that will be tested. The following section gives a brief background on the various methods for raster generalization described in the literature followed by a detailed description of the aggregation procedures that were used for our analysis.

Doing aggregation of data is not a trivial task and a large literature is concerned with aggregation and the wider field of generalization. Following the definitions in McMaster and Shea (1992) raster-mode generalization can be divided into four fundamental categories.

Structural generalization refers to a spatial rearrangement of the raster matrix and normally produces a cell size that represents an increased area.

Numerical generalization is the type of generalization often referred to as spatial filtering or convolution.

Numerical categorization is a process referred to as image classification in the remote sensing literature.

Categorical generalization is confined to generalization of categorical data.

In the following analysis of raster data I will use a combination of numerical generalization and numerical categorization. Two different generalization strategies are used to evaluate difference in performance. The difference between these two strategies is that they use input data at different levels of detail.

The first step of both digital generalization strategies is to define the spatial tessellation for the output to be exactly the same as the data we already have interpreted at the lower resolution L^{5000}. Thus a 5000x5000m quadratic grid of non-overlapping cells is produced, where each cell embraces 10x10 = 100 original L^{500} data cells. Now a *numerical generalization* is made $g\left(L^{500}\right)$. It takes L^{500} data as input and calculates numerical averages for the four land cover type variables $\{PC, PF, PA, PU\}$, which are output to the coarse resolution grid. The next section will describe exactly how the numerical generalization step uses two different strategies to produce these averages. One called *Proportion based* generalization Eq. 2 and the other called *Category based* generalization Eq. 3.

Eq. 2 $g_P\left(L_{500}\right) \quad \left[PG_C, PG_F, PG_A, PG_U\right]$

Eq. 3 $g_C\left(L_{500}\right) \quad \left[CG_C, CG_F, CG_A, CG_U\right]$

The output from the averaging procedure is assigned to vector variables identified by the subscript. PG and CG denotes the two generalization strategies, *Proportion based (PG)* and *Category based (CG)*. The Proportion based generalization is using all of the available primary information to produce images on areal coverage for the variables at the coarser resolution. The Category based generalization uses only the class category information from each cell in the original data to produce images on areal coverage for the variables at the coarser resolution. It was suggested earlier that a manual interpretation might use intermediate level abstractions in the classification process. The purpose of the second approach in this study is to simulate one possible set of such intermediate level abstractions and to use them as input to the following generalization process.

The implementations of the two strategies thus make use of different inputs from the original cell vector variables $L_{500}\left[LT, PF, PA, PU\right]$ and the following examples will illustrate in detail how they work.

Figure 32 a illustrates the *Proportion based (p)* numerical generalization procedure from Eq. 2. It uses all the available information in the vector variables so that for each variable $x = \{PC, PF, PA, PU\}$, a mean value is calculated for each 10x10 cell frame, which is passed on to the corresponding vector variable in the target resolution PG_x.

Figure 32 b, illustrate how the category based numerical generalization procedure from Eq. 3 only uses the nominal cell classification $L_{500}\{LT\}$ and calculates the frequency of each class within each 10x10 cell frame as a measure of spatial coverage for each land cover type. The frequency for each class is output to the corresponding vector variable in the target resolution CG_x.

After the averaging process a *numerical categorization* is performed on the result. This can be expressed as a function using the areal proportions in the coverage variables at each location to produce a classification given as nominal values to the generalized landscape type variable PG_{LT}.

Eq. 4 uses notation for the proportional generalization strategy but it also applies to the categorical generalization strategy. This numerical categorization function is the automated implementation of the classification

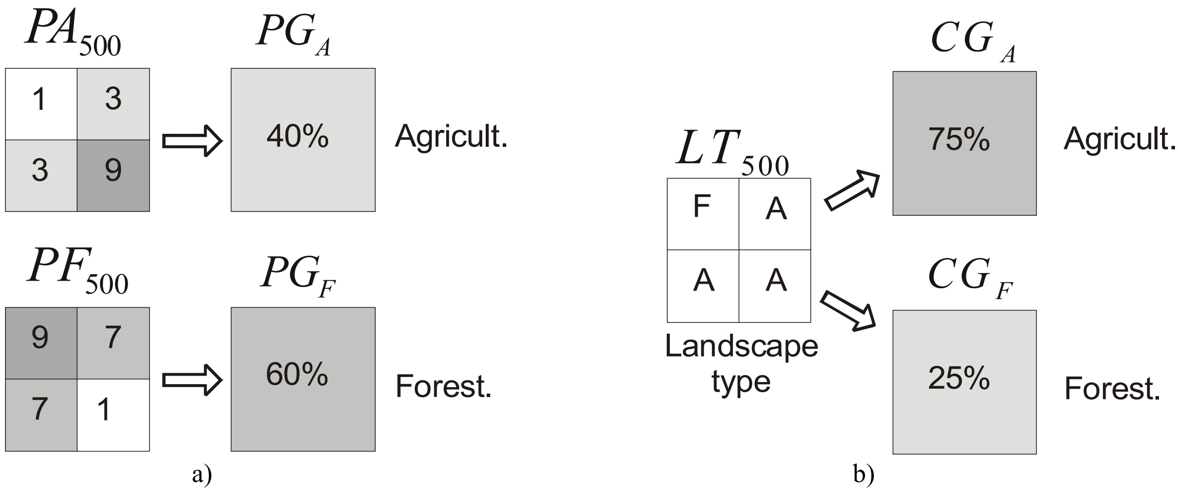


Figure 32 Illustration of the proportion based (a) and category based (b) numerical generalization procedures over a hypothetical 2x2 source pixel window. The proportion method calculates the average of the source proportions for the window and the category method takes the proportion of each class in source data for the window. Values are output to the corresponding cover type variables.

into landscape types used for the source data compilation described in chapter 4. It uses exactly the same rules and since the discrimination between the classes is not exclusive we need to follow the same flow in the classification process as in Table 27.

Data quality assessment

So far several measures have been taken in the design of the data collection to ensure the quality of the final data for analysis. These are:

- Use of spatially exhaustive measurements instead of sampling to eliminate sampling uncertainty
- Balancing the number of measurements with practical considerations to reach reliable conclusions
- Retrieving reference data using exactly the same method as for the source data
- Use of only one interpreter for both datasets thus eliminating need to calibrate interpretations
- Use of a clearly defined interpretation procedure to enable a consistent interpretation process

Some additional steps are still needed to further control the quality of the empirical data. These receive extended treatment in the next section.

Interpretation consistency

In general, consistency refers to the absence of apparent contradictions in a database (Veregin, 1999). An important part of any study using manually classified information is the sensitivity of the classification scheme to observer variability. This can also be referred to as data collection consistency.

The use of only one interpreter during the data collection and a clearly defined interpretation procedure serve the purpose of reducing the inevitable variance in any estimation process. But even if these steps manage to reduce variability we will still be facing some variation in the data that is hard to control. Manual image interpretation variability has been reported (Ihse, 1978; McGuire, 1992), and it would be reasonable to assume that a certain amount of interpretation variability would be present in map interpretation also. Apart from pure mistakes one source for this variation can be due to a lower ability of abstraction in the used concepts. Although interpretation variability is difficult to control it is often possible to measure it and incorporate information on the variation into the data. In doing so the results of further analyses are likely to be more reliable since the uncertainty of each estimation can be explicitly stated. According to

Eq. 4 $$PG_{LT} = f\left(PG_C, PG_F, PG_A, PG_U\right) = \begin{cases} Coastal & PG_C \geq 6 \\ Urban\ /\ suburban & PG_U \geq 1/8 \\ Agricultur\ al & PG_A + PG_U \geq 1/4 \\ Forest & otherwise \end{cases}$$

Table 28 Example error matrix from the assessment of interpretation consistency for the forest variable PF_{500}. *Rows=interpretation #1, columns=interpretation#2. Class 0=0-5%; class 1=5-15%... class 10=95-100% forested area. Major diagonal shaded, extended diagonal bold outlined.*

Forest	0	1	2	3	4	5	6	7	8	9	10	Total	Class accuracy
0	16	2										18	0.89
1	1	2	1									4	0.5
2		2	2									4	0.5
3				1	1							2	0.5
4					2	1						3	0.67
5					1	1						2	0.5
6						1						1	0
7								1	1			2	0.5
8								2		2		4	0.5
9									1	4	1	6	0.67
10									1	2	24	27	0.89
Total	17	6	3	1	4	3	0	3	3	8	25	73	

Table 29 Assessment of interpretation consistency

Classification	Overall accuracy	KHAT	Extended overall accuracy
PF	0.73	0.65	0.99
PA	0.85	0.63	1.00
PU	0.90	0.64	0.99
LT	0.93	0.89	N/A

Congalton and Green (1999) there are two options to measure interpretation variability in the context of reference data collection for accuracy assessment of remotely sensed images. One is to measure each variable at reference sites to provide an exact reference for the complete interpretation. The other option is the use of multiple interpreters of reference sites. Both alternatives seem viable alternatives to measure the ability of abstraction. In this case, the first option would be feasible since we are using paper sheet maps and do not need to perform extensive field measurements. Using map originals and measuring the total areas of interpreted map elements would probably provide a fairly exact measurement of ground truth. Although the first option was possible the second option was chosen because of its simplicity and since data already were available as multiple interpretations distributed over the study area.

Thus, an estimate of interpretation consistency as proxy for ability of abstraction was performed. By doing multiple interpretations of the same area at different times. A total of 73 areal units (cells) were interpreted twice at L_{500} resolution and the multiple samples were assessed using error matrices for the variables PC, PF, PA, and PU. Table 28 shows one of the error matrices, variable PF_{500}, that was generated from the multiple interpretations.

The overall accuracy of the example error matrix is as low as 72% meaning that on average every 4th pixel is differently interpreted from time to time. Table 29 provides a summary of the statistics from the four error matrices that were generated for the four variables. From the overall accuracy and KHAT statistics in the first two columns of Table 4 we can see that the absolute fit of the analysis is moderate. There is a 73% - 93% agreement between the two interpretations in terms of overall accuracy measures. The KHAT statistics that compensate for chance agreement is as low as 0.63-0.65 for the proportion variables. But it is much better, 0.89, for the final classification into landscape types, LT_{500}. The general picture from all error matrices is that the final classification is most consistent between the two interpretations. This can be explained by the larger tolerance of this variable to minor deviations in areal coverage interpretation.

The derived error matrices now give us some useful information on how severe the interpretation uncertainty is, and what measures may be taken to incorporate the uncertainty into our analyses.

According to the error matrix in Table 28 the uncertainty is restricted almost entirely within +/- one areal coverage class. Since the variables are scalar intervals there is a transition around the error matrix diagonal from totally consistent interpretations, almost consistent interpretations through non-consistent interpretations. Congalton and Green (1999) describe a simple but useful variation of the error matrix that is appropriate for this situation. Given that we are dealing with classifications on a continuous scale it can be justified to expand the major diagonal in a normal error matrix. Such an extended diagonal is outlined in the Table 28 error matrix with bold lines. This fairly simple extension allow for some consideration of the idea that class boundaries are not totally crisp since it accepts plus or minus one class as a correct classification. In Table 29, extended overall accuracy measures, based on the extended major diagonal, show a substantial increase of the overall accuracy. In other words, if we are willing to accept a variation in the interpretation of areal coverage within + or – one cover class the interpretations will be totally consistent, 99%-100% overall accuracy, from time to time.

What we also see in the error matrix, Table 3, is that the error is not evenly distributed among the classes. Class 0 and 10 that accommodate values of no or full areal coverage are more accurate (89%) than the other classes. The average for classes 1-9 is 48%. This type of skewed class accuracy can be analyzed through accuracy assessment using of fuzzy logic (Gopal and Woodcock, 1994; Woodcock and Gopal, 1999). This technique will not be used here since the data does not require this method at the stage of interpretation consistency evaluation. The issue of fuzzy logic will however be returned to in the aggregation procedures and in the analysis of the results. To some extent the assessment in this section provides a proxy for the "ability of abstraction" measure discussed earlier.

Spatial autocorrelation

Knowledge of the degree of spatial autocorrelation, or the correlation of a variable with itself through space, is important for any analysis of scale change. Also, if the analysis is made using any kind of sampled reference data, we need to consider the spatial autocorrelation to choose an appropriate sampling scheme that fulfills the criterion of independent samples. Since the analyses in this work is made on spatially exhaustive data, the risk of uncertainty introduced by sampling is eliminated, and the spatial autocorrelation is not of primary interest for the production of the reference data. More important though is the effects that spatial autocorrelation has on the outcome of any spatial aggregation performed. It is therefore necessary to know the degree of spatial autocorrelation for the analyzed variables in order to do a correct interpretation of the results.

The concept of a spatial correlogram (Cliff and Ord, 1981) was used to analyze the presence and range of spatial autocorrelation. The spatial autocorrelation was estimated as King's case Moran I index using the AUTOCORR module in IDRISI for Windows 2.0. In the analysis the original images was analyzed separately (image #1 and #2) to avoid artificial effects due to the concatenation of non-contiguous landscapes. Also a binary mask was produced for the coastal landscape type. The rationale behind this was to eliminate bias caused by the low and constant levels of the forest, agriculture, and urban/suburban cover types in these areas.

In Table 30 and Figure 33 we see that the autocorrelation quickly tapers off from 0.23 –

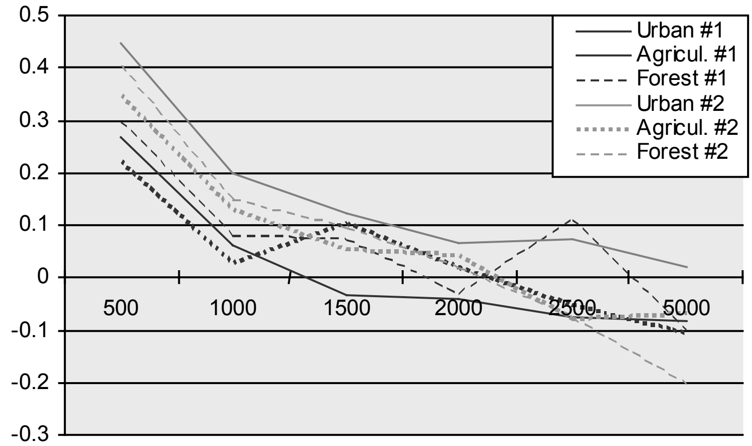


Figure 33 Autocorrelation for both analyzed images, #1 and #2, and for the three variables Urban, Agricultural, and Forest landscape types. 1st lag at 500m through 10th lag at 5000m.

Table 30 Moran's I autocorrelation index of the original L_{500} interpreted data. I is given for 1st and 10th lag autocorrelation corresponding to 500m and 5000m lag distance respectively.

	1st lag		10th lag	
	Image #1	Image #2	Image #1	Image #2
Urban/suburban	0.27	0.45	-0.08	0.02
Agriculture	0.22	0.35	-0.11	-0.07
Forest	0.30	0.40	-0.10	-0.20

0.47 at 500m lag distance to –0.20 – 0.02 at 5000m lag distance. This means that we can expect that cells at the lower resolution of 5000 m will be a spatial mix of land cover types from the higher resolution, 500m. The forest and agriculture variables exhibit a small increase in the autocorrelation at a lag distance of 1-3 km. This is probably due to the fact that the landscape in this region is dissected by fairly long fissure valleys. There are a few more dominant such fissure valleys in the study area. These extend in a SW-NE direction and are about 1500m across. The spatial pattern of forest, agriculture and in some sense the urban areas are of course guided by these major fissures thus providing the bumps in the autocorrelation plot.

The analysis does not suggest that the different land cover variables would behave differently in the generalization due to effects caused by differences in autocorrelation.

Interpretation uncertainty propagation

After the previous definition of the digital generalization methods we now turn back to the earlier assessment of interpretation uncertainty. For the following analysis of scale dependent interpretation it is important to incorporate the uncertainty in interpretation in order to draw correct conclusions. Figure 35 builds further on Figure 31 to illustrate the two different generalization strategies over an example 2x2 pixel matrix of source data.

The initial proportions of land cover variables in this example are very close to the classification threshold for landscape type "Agricultural district". The areal estimates of the land cover types after the first numerical generalization differs by 50% units. Despite this large difference the final classification of landscape type is the same. We see by this example that the overestimating effect of the classification rules by using the category based generalization is even more pronounced than in Figure 32. Furthermore, the final classification step is clearly very tolerant to misinterpretations in the landscape type variables at certain levels. Despite the large differences in land cover proportions, "Agricultural district" is still chosen as the landscape type in both generalization strategies. Simply because the classification threshold is not within the range of the differences in this particular situation. Now, in Figure 34 when the tolerance of +/- one areal coverage class is applied to the same generalization situation we see that both strategies fail to decide upon the class label.

Figure 34a shows how the initial data is averaged into an interval of possible areal coverage for the land cover type at hand. Since the interval crosses the classification threshold for the agricultural and forest landscape types the output classification has to accept that either one of these class labels can be correct. Figure 34b shows the same situation for the category-based strategy. Remember that this generalization strategy try to simulate a construction of intermediate level abstractions used in the final classification. The input information is in the form of classified landscape types. Application of the same logic as the illustration in Figure 34 will produce borderline cases where a +/- one-class interpretation consistency may yield different final landscape type classifications. The information from the land cover type variables can be used in this way to determine if the landscape type classification of the source data is certain or if several classes are possible. In Figure 34b the input data has undecided classifications in 3 of 4 cells due to the information we have from the land cover type variables Figure 35b.

Uncertainty handling

In the previous sections the concept of an extended diagonal in the error matrix was introduced. The following analysis of the results from the numerical generalization will use the same method to handle the detected inconsistency in the interpretation of the source data. Summary results will therefore include overall accuracy measures for both the major diagonal and the extended major diagonal of the error matrices. It was also concluded previously that the use of an

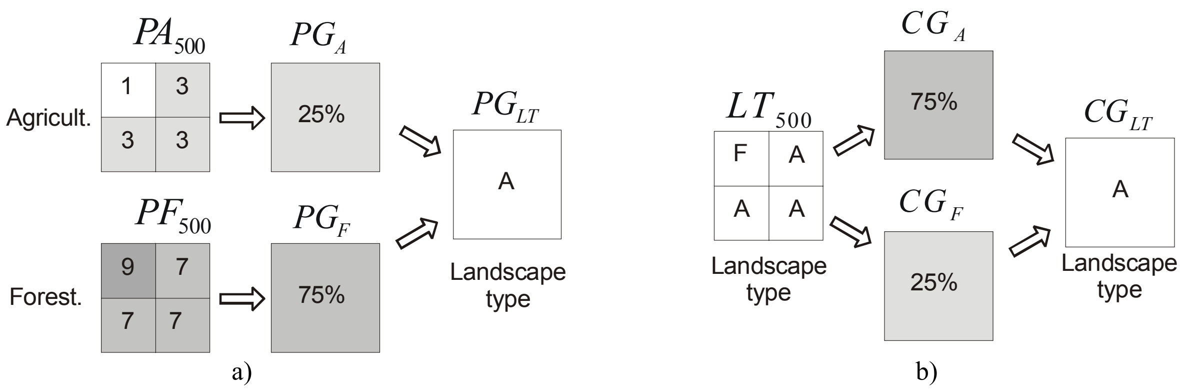


Figure 35 Illustration of the numerical generalization followed by numerical categorization into landscape type classes. The proportion based generalization strategy (a) uses averages from the land cover type variables Eq. 2 and the category based generalization strategy (b) uses landscape type frequencies Eq. 3 as input to the final classification step Eq. 4

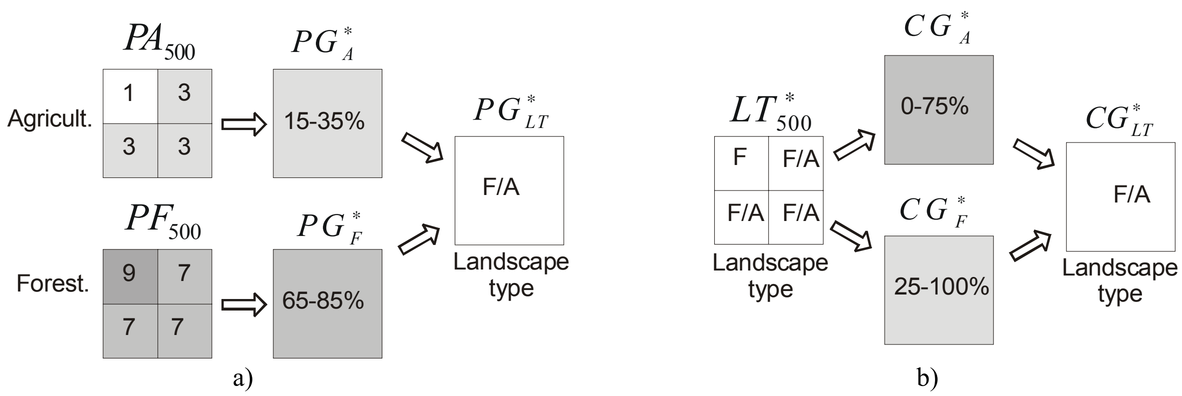


Figure 34 Illustration of the numerical generalization followed by numerical categorization into landscape type classes accounting for +/- 10% classification accuracy in the input data. The proportion based generalization strategy (a) uses averages from the land cover type variables and the category based generalization strategy (b) uses landscape type frequencies as input to the final classification step.

extended major diagonal is not suited to nominal, qualitative data such as the landscape type variable in the final classification. To be able to analyze ambiguous generalization outcomes such as those illustrated in Figure 34 some logic is needed that can handle the classification ambiguity in a location specific accuracy assessment. We face here the same situation as in the experiments reported in chapter 5, however this time it is my ambition to confront this particular problem.

The review of methods for uncertainty representation in chapter 3 suggested fuzzy sets as a suitable method for data with poorly defined objects or individuals. The definitions above may not seem as poorly defined. Still, the objective of this study is to reveal differences in the interpretation of a concept with respect to an object, i.e. the areal unit. This fuzziness is what Freksa and Barkowsky (1996) describe as a lack of detail that result in fuzziness. Fuzziness cannot be viewed as a property of a single object: *rather it is the property of a relation between a concept and an object*. Using the terminology established previously, this could be interpreted as the accuracy of the model or “ability of abstraction”. As a consequence of this follows that the concept of ability of abstraction can be approached using fuzzy set reasoning. As already noted there have been examples of evaluating crisp classifications against a fuzzy reference (Gopal and Woodcock, 1994; Woodcock and Gopal, 1999). Their methods are capable of answering questions of the accuracy of a crisp map using a fuzzy reference, but the inverse situation is not easily inferred. As it turns out in this chapter, we have a fuzzy classified map, which we want to evaluate against a fuzzy reference.

It has been pointed out previously that one difficulty with the use of fuzzy sets is the need to determine a proper membership function. The fuzzy set approach also requires that there is some kind of gradual transition from non-membership to full membership. This is the situation in for example an ordered set of linguistic concepts: [‘short’, ‘medium’, ‘long’]. In the case of non-ordered linguistic concepts such as [‘forest’, ‘urban’] we do not even have the necessary information to build a membership function. In fact, it would be inappropriate to build one since there is no evidence for a gradual transition from none to full membership. The only thing known is that the information is not detailed enough to provide a unanimous decision. This non-quantified uncertainty has until recently been hard to handle. However, the recent advances on rough set theory (Pawlak, 1982) and the previous examination of the use of rough sets to represent uncertainty in geographic datasets will now come useful. The following analysis will use the novel methods of rough classification and calculation of overall accuracy measures using extended error matrices described in the previous chapter.

The uncertainty propagation in the numerical generalization and categorization was outlined in Figure 34. This uncertainty can now be represented using the rough set based logic to create rough classes. Consider for example a generalization that results unambiguously in the landscape type class 'Coastal'. This result will be assigned a label of $\underline{C}$ meaning that it is in the lower, certain approximation of the rough set $\left(\underline{C}, \overline{C}\right)$. If however the result was ambiguous, that is the numerical categorization found that both landscape type class 'Coastal' and 'Forest' was possible, the cell would be assigned two labels; $\overline{C}-\underline{C}$ and $\overline{F}-\underline{F}$. This means that the cell is in the area of uncertainty for both the coastal rough class and the forest rough class. Thus, the numerical categorization into landscape type classes was performed once again, now using the logic of rough classifications. The two outcomes from the proportion and category based rough numerical categorizations PG_{LT}^{*} and CG_{LT}^{*} respectively, were compared against both the crisp L_{5000} and a rough version L_{5000}^{*} of the interpreted data in extended error matrices. The logic behind the construction of a rough version of the reference dataset was the same as for the generalized versions.

Table 31 Extended error matrix for proportion based generalization (a) and two dimensionally extended error matrix, 2Deem for proportion-based generalization (b). Major diagonal shaded.

Proport.	Coast.	Forest	Agri.	Urb.
$\underline{C}$	14			
$\overline{C}-\underline{C}$				
$\underline{F}$	1	3	2	
$\overline{F}-\underline{F}$	3	5	8	4
$\underline{A}$			3	5
$\overline{A}-\underline{A}$	3	5	8	4
$\underline{U}$				2
$\overline{U}-\underline{U}$				1

The rough classification is then used in an extended error matrix for a site-specific accuracy assessment Table 31. In an extended error matrix we have a rough representation of either target data or reference data. In the example below, the generalization has produced a rough classification (rows), which is compared against a crisp reference (columns). The error matrix extension will mean that some of the properties of a 'normal' error matrix do not hold since we will have overlapping areas in the upper approximations. This property will make it harder to calculate for example user's and producer's accuracy (Congalton, 1991) but it can be done using a parameterized error matrix as explained in chapter 6. However, one measure, the overall accuracy, will still be easy to calculate but it will be given as an interval with an upper and a lower bound, Eq. 5.

Eq. 5 $$x_{i,i+}/|R| \le A_O \le \left(x_{i,i+} + x_{i,i?}\right)/|R|$$

In other words the lower bound of the overall accuracy is calculated dividing the sum of the certain, lower approximation areas in the diagonal $x_{i,i+}$ by the total area $|R|$. Dividing the sum of the certain and uncertain, upper approximation areas, $\left(x_{i,i+} + x_{i,i?}\right)$ by the total area, give the upper bound.

As mentioned, we may have either target data or reference data in the form of a rough classification. Furthermore, we may have *both* target and source data as rough classifications. We only need to extend the error matrix in both directions producing a *two-dimensionally extended error matrix*, or *2Deem* (chapter 6) as shown in Table 32. From the 2Deem it is still hard to calculate producer's and user's accuracy. The overall accuracy is still possible to calculate, although a bit more elaborate than in Eq. 5.

Analysis

Up to this point the methods for data collection have been firmly established, the generalization strategies used to produce two target datasets have been defined, and methods to handle the

Table 32 Two dimensionally extended error matrix, 2Deem for proportion-based generalization. Major diagonal shaded.

Proport.	$\underline{C}$	$\overline{C}-\underline{C}$	$\underline{F}$	$\overline{F}-\underline{F}$	$\underline{A}$	$\overline{A}-\underline{A}$	$\underline{U}$	$\overline{U}-\underline{U}$
$\underline{C}$	10	4		4		3		2
$\overline{C}-\underline{C}$								
$\underline{F}$		1		6		6		1
$\overline{F}-\underline{F}$		2	1	17		17	2	8
$\underline{A}$				3	2	3	3	2
$\overline{A}-\underline{A}$		2	1	17		17	2	8
$\underline{U}$							2	
$\overline{U}-\underline{U}$		1		1		1		1

interpretation accuracy have been described. The analyses in the following result section uses several, well described, methods as well as some novel methods based on rough classification.

The first result section tries to answer if the original hypothesis, 'Eq. 1 holds', can be justified. Many techniques may be used to assess the outcome of a spatial aggregation of data. A simple but useful method that was used here is to produce histograms of the distribution of class values in the original and aggregated images. Error matrices were also produced to provide overall accuracy measures such as the overall accuracy and $\hat{K}$ (KHAT-estimate) (Congalton, 1991). The Kappa analysis method is widely used to statistically determine if one error matrix is significantly different from another. Also the KHAT statistic provides a measure of actual agreement between reference data and estimated data. This measure of agreement is based on actual agreement in the error matrix compensated for the chance agreement indicated in row and column totals. This analysis technique is therefore similar to Chi square analysis. Chi square analysis may raise problems if cell values in the matrix equal zero (Congalton, 1983). An analysis of difference images was seen as a powerful, location specific method for evaluation of the outcomes from the different generalization strategies. The joint outcome of these methods was used to answer the original hypothesis.

The implementation of rough classification and extended error matrices section goes deeper into the results. The concept of rough classification and extended error matrices from chapter 6 makes it possible to do a site-specific evaluation of the final landscape type classifications. The use of 1- and 2-dimensionally extended error matrices is here further demonstrated in a thorough analysis of possible explanations for the results.

Results

Semantic correspondence analysis

The two source data sets interpreted at 500x500m and 5000x5000m pixel resolutions together with two digitally generalized sets of data at 5000x5000m pixel resolution were used in the following analyses. Examples of the source interpretations and results of the two

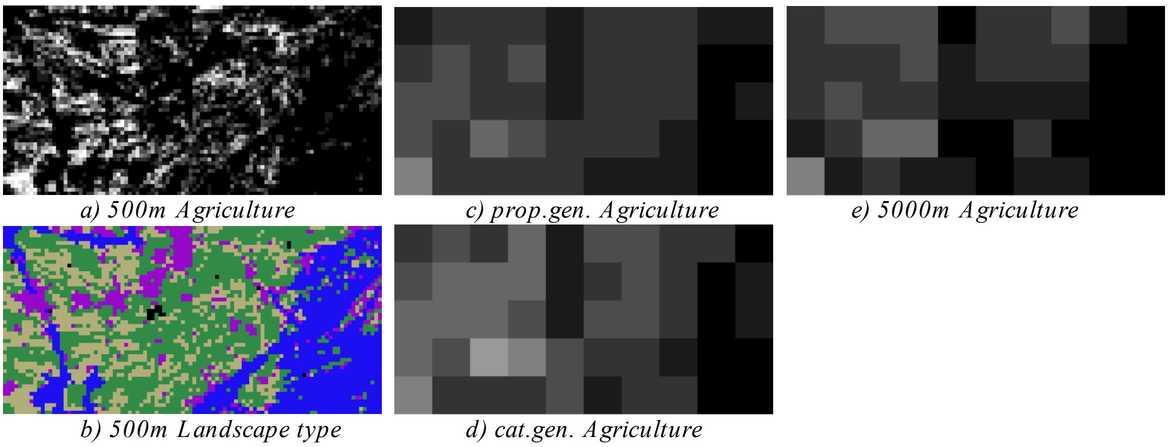


Figure 36 Example source PA_{500} data (a), LT_{500} data (b), results from the proportion based PG_A (c), and category based CG_A (d) digital generalization for land cover type variable Agriculture, and reference PA_{5000} data (e).

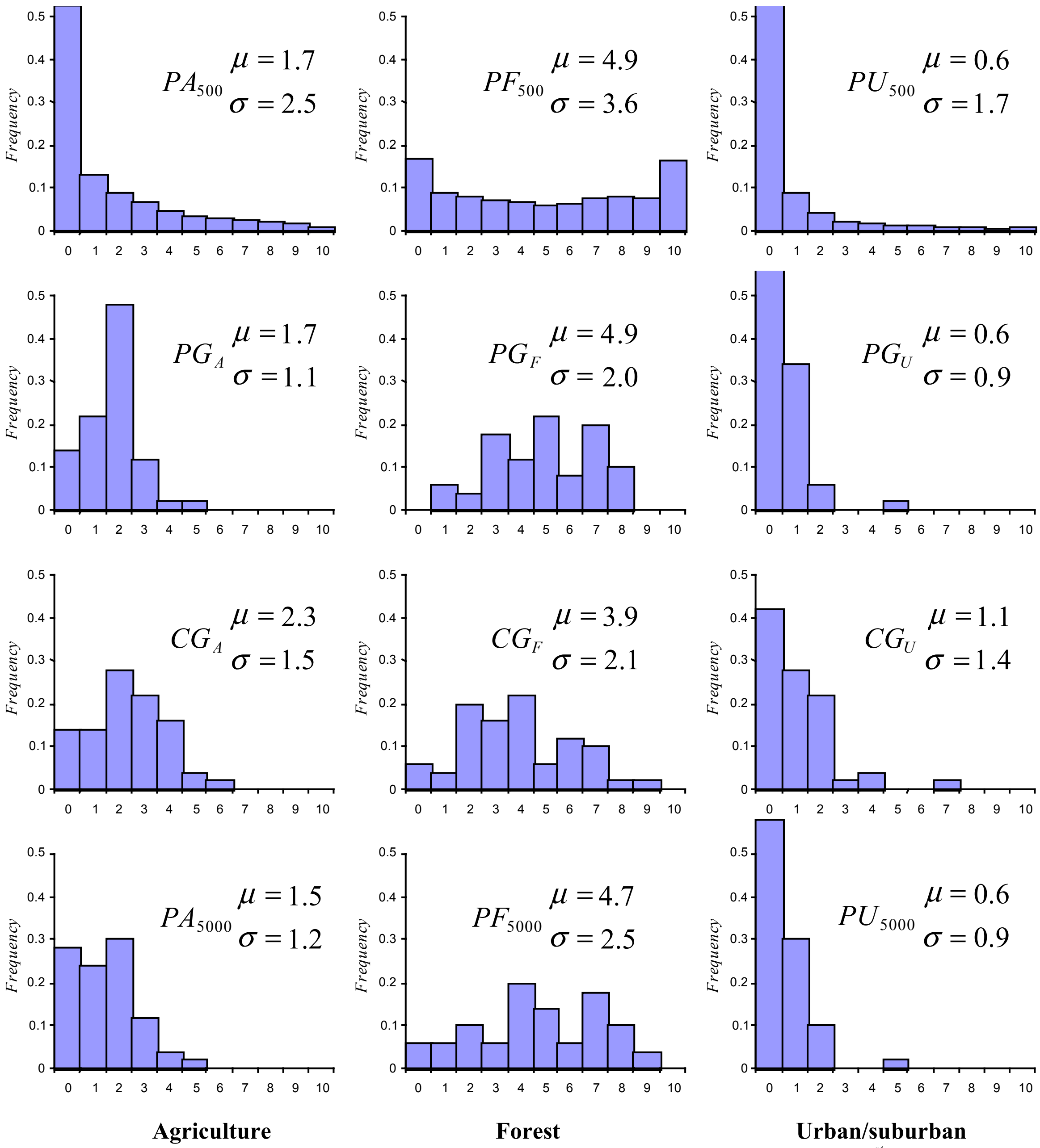


Figure 37 Histograms of the scalar variables Agriculture (a), Forest (f), and Urban/suburban (u). 1st row show source data at 500x500m pixel resolution, 2nd row show generalized data at 5000x5000m pixel resolution using proportion based averaging, and 3rd row show generalized data at 5000x5000m pixel resolution using category based averaging. The 4th row shows the reference interpretation at 5000x5000m pixel resolution.

generalization processes are illustrated by the images in Figure 36. The upper left image (a) is source data for the Agriculture land cover type. The lower left image (b) shows source data for the landscape type variable. The middle column images show the generalized output for land cover type agriculture, using the proportion-based method (image c), and the category based method (image d). Image (e) shows the manual interpretation of the agriculture land cover type variable at the low spatial resolution.

Quantitative variables

Histograms of the distribution of the classes in interpreted data and the generalized output is shown in Figure 37. In general the two digitally generalized outcomes in rows 2 and 3 show large similarities with the interpreted reference data in row 4. In the Px_{500} interpreted data, both the Agriculture variable and the Urban/suburban variable show a unimodal distribution with low mean values, whereas the forest variable show a more flat almost bimodal distribution. We know from the autocorrelation analysis, Figure 33 and

Table 33 Summary accuracy statistics for correspondence assessment of proportion based (PG) and category based (CG) aggregation of land cover type data, $CG_x \Leftrightarrow Px_{5000}$.

	Archipelago		Forest		Agriculture		Urban	
	PG_C	CG_C	PG_F	CG_F	PG_A	CG_A	PG_U	CG_U
Overall accuracy	N/A	0.54	0.50	0.24	0.56	0.32	0.88	0.54
Overall kappa $\hat{K}$	N/A	0.41	0.43	0.14	0.41	0.16	0.78	0.29
Rough Overall Acc.	N/A	0.90	1.00	0.94	1.00	0.96	1.00	1.00

Table 30, that the aggregation window is greater than the autocorrelation range. As we then would expect (Bian and Butler, 1999), the generalization changes the distribution of the classes and tend to eliminate low frequency values far away from the mean. A reduced variance is also apparent throughout all generalization outcomes. The proportion based generalization in 2nd row, retains the mean but reduces the variance. Theoretically this should be the case for this type of generalization and the result only confirms this.

The category-based generalization though, changes both the mean and the variance values. The mean values here suggest a tendency to over estimate the Agriculture and Urban/suburban areas while the forest area is underestimated if we use Px_{500} interpreted data as a reference. Since this study is more interested in the differences between the manual interpretation and the digital generalization at the same resolution I will mainly use the Px_{5000} source data as a reference. As we can see in the 4th row, the Px_{5000} data produce mean and variance values that differ slightly from the high-resolution data. The Agriculture and Forest variable is interpreted with a lower mean value than the high resolution data whereas the Urban/suburban variable retains the mean.

The category based generalization apparently makes an underestimation of the forestland cover type but makes an overestimation of the Agriculture and Urban/suburban land cover type. The statistical summaries also suggest that the category based generalization method retain more of the variation in the data. Variance estimates does not drop as much as in the proportion based generalization. Although not apparent, the variance estimates suggest a pattern where the proportion based generalization method follow the low-resolution manual interpretation better than the category-based generalization.

So far the generalization outcome has only been analyzed using global measures. Figure 36 gave examples of the spatial outcome of the interpretations and the generalizations. To make a location specific analysis, error matrices were produced, assessing the outcomes of the generalization against the manually interpretation as reference data. Example of one error matrix has already been given in Table 28. Overall accuracy, $\hat{K}$, and extended overall accuracy statistics were calculated from all error matrices. Table 33 displays these statistics from the proportion based and category based generalization strategy respectively. The overall accuracy shows a relatively bad correspondence between the digital generalizations and the manual estimate. The $\hat{K}$ value only confirms this having values in the region considered as “poor agreement” by Landis and Koch (1977).

Since both overall accuracy and $\hat{K}$ statistics will be influenced by the +- 10% interpretation accuracy found in data they will not be used for further discussion. They are only provided here for comparison purposes. The lower row with rough overall accuracy measures show accuracies compensated for interpretation inconsistency. These were produced using a 2-dimensionally expanded error matrix with rough versions of both source and reference data. These tables together with the previous histograms give us more information on how differently the two methods of aggregation agree with the manually interpreted reference. The general picture from the histograms is repeated here. The proportional generalization works best, capable of producing estimates of the different land cover types with a 100% correspondence with the reference images. The category-based strategy manages to produce 90-100% correspondence with the manually interpreted reference images. It should be noted for the category strategy that the best result of 100% for the urban land cover category is an effect of the narrow range of this variable in combination with the interpretation consistency of

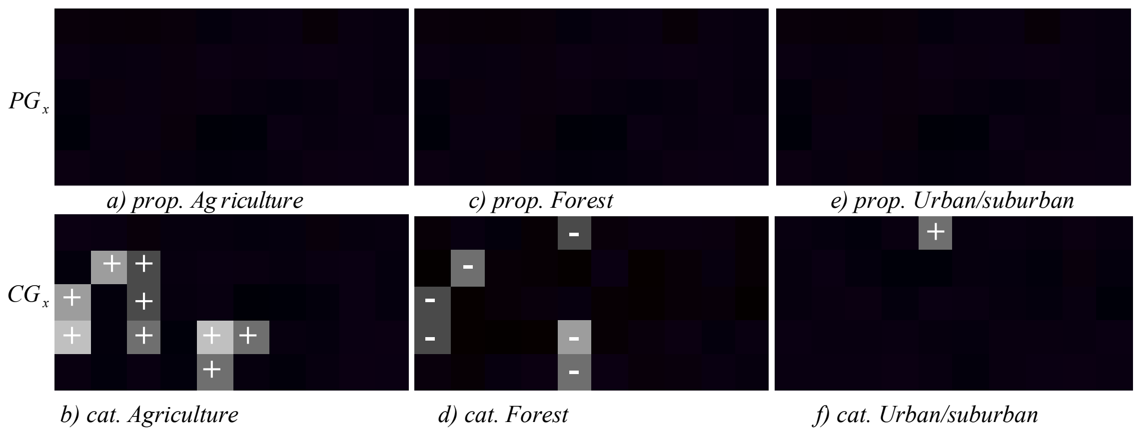


Figure 38 Difference images for cover type variables Agriculture (a,b), Forest (c, d), and Urban/suburban (e, f). The images were produced by subtracting the interpreted reference image from the digitally generalized image. First row are results from the proportion-based generalization $PG_x - Px_{5000}$, second row category based generalization $CG_x - Px_{5000}$. Grays are set to show significant deviations from the reference image in increasingly brighter shade. Signs show if deviations are positive or negative.

+/- one cover class. This has the effect of embracing most of the range for this land cover variable. The accuracy estimates for the three other land cover variables, 90-96% are more likely to give a correct estimate of the accuracy for this generalization method. The same reasoning applies for the proportion-based estimates although accuracies for the other land cover variables also produce 100% correspondence with the reference. Thus a correspondence of up to 100% is likely to be representative for the proportion based generalization method. These highest figures of course only apply if all the interpretation inconsistencies turn out in a favorable direction.

To illustrate how these differences in interpretation and generalization are distributed in space, a spatial residual analysis was made. In Figure 38 Px_{5000} data have been subtracted from the generalized outcomes PG_x and CG_x to produce difference images showing the generalized deviation from the reference image, $PG_x - Px_{5000}$. Gray shades are set to show deviations from the reference with brighter shades representing higher deviations. The shades have been set to indicate only significant deviations that exceed the uncertainty interval of +/- 1 class. Signs show if deviations are positive or negative.

The images in Figure 38 give a spatial version of the histograms in Figure 37 and accuracy measures in Table 33. For example the forest variable in the reference interpretation has a mean of μ=4.7. The category based generalization mean is lower, μ=3.9. Figure 38 d illustrate the spatial distribution of the significant deviations from the reference image as the gray pixels. The proportion based generalization mean is μ=4.9 which is slightly higher than the reference image mean. In Figure 38 c however we see no gray pixels. This means that the deviation from the reference image is not anywhere of a magnitude greater than the bounds of the +/- 10% interpretation accuracy. This goes for all variables in the proportion based generalization outcome, Figure 38 a, c, and e. Figure 38 f, show that the category based generalization produce only one significant deviation from the reference image and this is positive.

<u>Qualitative variables</u>

Figure 39 illustrate different versions of the landscape type classifications. First two images Figure 39 a and b, show the landscape type, high-resolution LT_{500} interpretation and low-resolution LT_{5000} interpretation respectively. Figure 39 c and d, show the two generalized classifications, PG_{LT} and CG_{LT} that were produced using generalized land cover images and the classification scheme defined earlier. The visualizations of these images do not account for the +/-10% interpretation accuracy that of course also affect the final landscape type classification discussed earlier. A visual inspection of the images in Figure 39 c and d is nevertheless instructive in that it confirms the pattern that the previous images and statistics so far have only suggested.

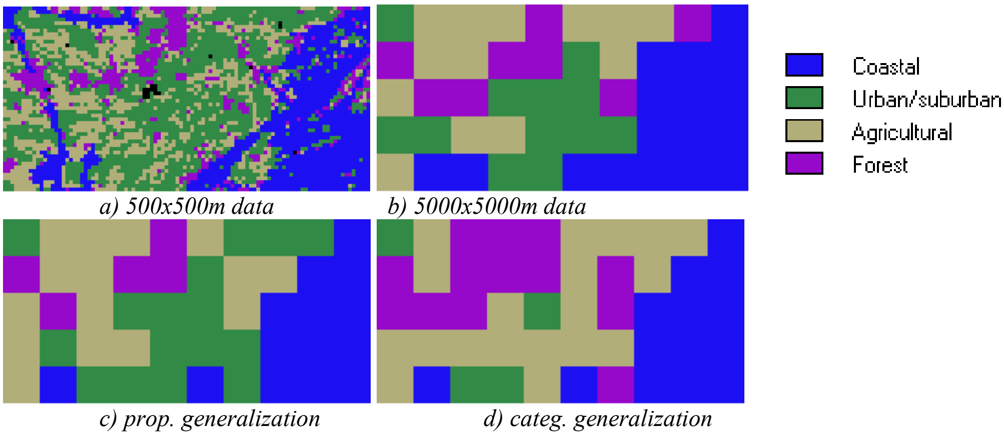


Figure 39 Landscape type classifications. Manual high-resolution interpretation LT_{500} *(a), manual interpretation* LT_{5000} *(b), outcome of proportion based generalization* PG_{LT} *(c), and category based generalization* CG_{LT} *(d)*

Both generalization outcomes, Figure 39 c, d, are visually different from the reference image Figure 39 b. The proportion based strategy produce fewer areas of the urban landscape class and more areas of the forest landscape class compared with the reference image. The category-based generalization apparently overestimates the agricultural landscape type and the urban landscape type class whereas the forest landscape class is underestimated. A location specific accuracy assessment was performed on these images also, using error matrices and calculating overall accuracies. It was earlier concluded that the method of using an expanded major diagonal is not appropriate for these categorical data. Instead rough classifications have been used to represent the uncertainty and accordingly the overall accuracy measure will be an interval within which the classification accuracy is definitely located.

As we can see from the standard overall accuracy, none of the generalization strategies produce a good correspondence with the reference, 82% and 64% respectively. This result only confirms the visual inspection of the images in Figure 39. Since there is a certain amount of uncertainty hidden in the crisp classification, an analysis of the rough set based classification provide valuable additional information. The rough overall accuracy row in Table 34 tell us that the overall accuracy for both generalization methods may reach as much as 100% correspondence with the manually interpreted reference. As before, these highest figures only apply if all the interpretation inconsistencies pull in a favorable direction. We may actually end up with an overall accuracy as low as 28% and 26% for the two generalization strategies respectively if the uncertainty pulls in a completely unfavorable direction.

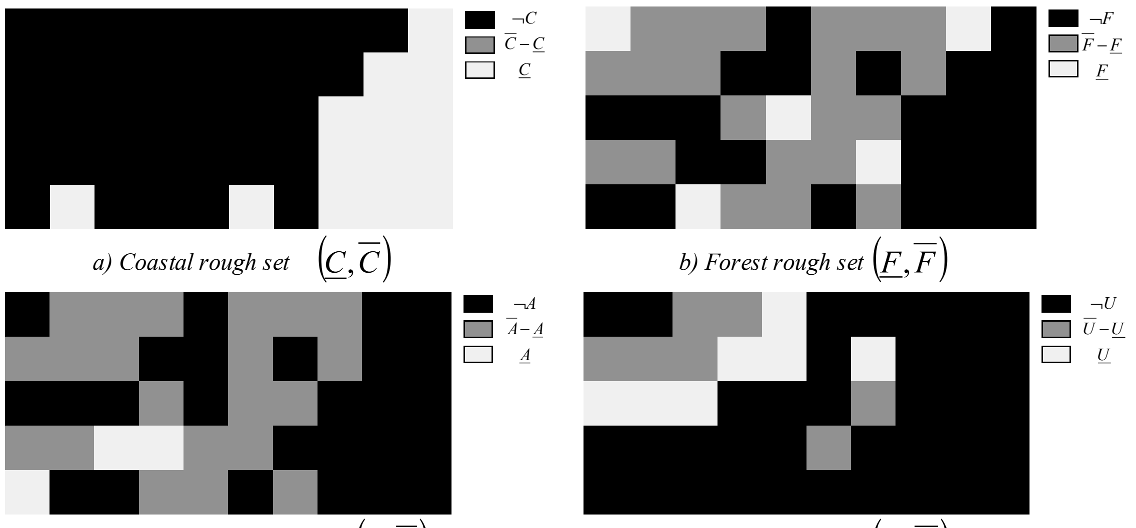
Implementation of rough classification and extended error matrices

The above results have considered two cases of uncertainty. One where source and reference data are both regarded as totally crisp and the other where both source and reference data incorporates interpretation uncertainty represented as rough classifications. After a brief illustration of the implementation of rough classification this section will further illustrate the possibilities to use 1- or 2-dimensionally extended error matrices (referred to below as 1Deem and 2Deem) with rough classified data.

The actual implementation of rough

Table 34 Summary statistics from a traditional crisp error matrix (overall accuracy and overall Kappa) and a 2Dimensionally extended error matrix produced from the comparison of generalized landscape type classifications.

	Proportional Strategy	Category strategy
Overall accuracy	0.82	0.64
Overall kappa $\hat{K}$	0.75	0.52
Rough Overall Acc.	0.28-1.00	0.26-1.00



a) Coastal rough set $\left(\underline{C},\overline{C}\right)$ *b) Forest rough set* $\left(\underline{F},\overline{F}\right)$

c) Agricultural rough set $\left(\underline{A},\overline{A}\right)$ *d) Urban rough set* $\left(\underline{U},\overline{U}\right)$

Figure 40 Rough classification CG_{LT} *implemented as IDRISI for Windows 2.0 images.*

classifications has been made using the IDRISI for Windows 2.0 GIS and Microsoft Excel 2000 spreadsheet software. The representation of rough classes in IDRISI uses separate images for each variable in each rough classification. For example, the landscape type classification PG_{LT} consists of four images PGLTCOA, PGLTFOR, PGLTAGR, and PGLTURB. Each image uses values of 0, 1 and 2 to represent $\neg\overline{X}$, $\overline{X}-\underline{X}$, and $\underline{X}$ respectively.

This representation is very similar to the way fuzzy measures may be accommodated by raster GIS. In the example images shown in Figure 40 we see the outcome of the category-based generalization into rough classifications. Lower approximations $\underline{X}$, that are the certain areas, show as white pixels, areas of uncertainty $\overline{X}-\underline{X}$ show as gray pixels and areas that certainly not belong to the class $\neg\overline{X}$ show as black areas. Figure 40 illustrate that the rough classification allow overlapping pixels in the area of uncertainty of the rough classes, but lower approximations never overlap with anything else than their corresponding upper approximations.

To further demonstrate the use of 1- and 2-dimensionally extended error matrices Table 35 show the previous analysis results under two different assumptions. If one of the data sets is crisp and the other is rough we can use a 1Deem in the accuracy assessment. This is illustrated by the upper and lower left 1Deems. These matrices use rough versions of the generalized outcomes from the two different strategies and a crisp version of the reference data, that is assuming that reference data is totally confident in its classifications. For the 1Deem case we may use Eq. 5 to calculate an overall accuracy interval. For the shown data these measures would be $0.50 \le A_O \le 0.90$ for the Proportion based generalization (upper left table), and $0.50 \le A_O \le 0.88$ for the category based generalization (lower left table). In the upper and lower right tables the same two generalization strategies are compared against a rough version of the reference data in 2Deems. The overall accuracies for these two tables, $0.28 \le A_O \le 1.00$ for the Proportion based generalization (upper right table), and $0.26 \le A_O \le 1.00$ for the category based generalization (lower right table), have already been presented in Table 34. The increase of the accuracy interval is an effect of the uncertainty added by the rough version of the reference data set.

In addition to the overall accuracy, an examination of the error matrices reveals additional information on the nature of the uncertainty in this specific case. One important aspect of a rough classification is the precision of the lower approximations since these estimates are regarded as certain under the given information. Both P- and C- classifications are 100% correct for the coast class, but as we can see in the 2Deem the reference data is not totally confident in its classifications. 4 of the cells are assigned to the upper approximations of one or more other classes. Three of the cells attributed to the lower approximation of class ‘Forest landscape’ in the P-classification was not correct according to the 1Deem, but from the 2Deem it is

*Table 35 Extended error matrices for both generalization strategies. a): Proportion based (**P**) classification against crisp reference, b): Category based (**C**) classification against crisp reference, c): P-classification against rough reference, d): C-classification against rough reference*

.

P	$\underline{C}$	$\underline{F}$	$\underline{A}$	$\underline{U}$
$\underline{C}$	14			
$\underline{F}$	1	5	2	
$\overline{F}-\underline{F}$	1	7	10	5
$\underline{A}$			3	
$\overline{A}-\underline{A}$	2	7	10	5
$\underline{U}$				3
$\overline{U}-\underline{U}$			1	3

P	$\underline{C}$	$\overline{C}-\underline{C}$	$\underline{F}$	$\overline{F}-\underline{F}$	$\underline{A}$	$\overline{A}-\underline{A}$	$\underline{U}$	$\overline{U}-\underline{U}$
$\underline{C}$	10	4		4		4		2
$\underline{F}$		1	1	5		5		
$\overline{F}-\underline{F}$		1	4	20		20		12
$\underline{A}$				1	2	1		
$\overline{A}-\underline{A}$		1	4	20		20		12
$\underline{U}$				2		2	1	2
$\overline{U}-\underline{U}$				4		4		4

C	$\underline{C}$	$\underline{F}$	$\underline{A}$	$\underline{U}$
$\underline{C}$	14			
$\underline{F}$		3		1
$\overline{F}-\underline{F}$	3	9	8	2
$\underline{A}$			3	
$\overline{A}-\underline{A}$	2	9	8	2
$\underline{U}$			2	5
$\overline{U}-\underline{U}$		1	4	2

C	$\underline{C}$	$\overline{C}-\underline{C}$	$\underline{F}$	$\overline{F}-\underline{F}$	$\underline{A}$	$\overline{A}-\underline{A}$	$\underline{U}$	$\overline{U}-\underline{U}$
$\underline{C}$	10	4		4		4		2
$\underline{F}$				5		5		1
$\overline{F}-\underline{F}$		1	5	16		16		7
$\underline{A}$				1	2	1		
$\overline{A}-\underline{A}$		1	5	16		16		7
$\underline{U}$				6		6	1	
$\overline{U}-\underline{U}$			1	6		6		6

clear that the reference data is very uncertain in this class. Only one cell in the reference is assigned to the lower approximation of Forested landscape and this specific cell was actually given a partly correct label of $\overline{F}-\underline{F}$ and $\overline{A}-\underline{A}$ in the proportion based generalization. This last specific fact cannot be read directly from the error matrix. Both the proportion based and the category-based generalization corresponds in their lower approximations with the lower approximations of the reference interpretation. This means that when each generalization method is confident about its classification, the reference data does not reject a correspondence. There is confusion between the forest and agricultural landscape types, which is evident if we look at the upper approximations of these sets for both generalization strategies. Cells assigned to the area of uncertainty for the forest landscape class, are also assigned to the area of uncertainty for the agricultural landscape class. This confusion is an effect of the classification scheme that forces areas assigned to the upper approximation of agricultural landscape to be in the upper approximation of the forest landscape as well. This produces an artificial symmetry in the lower approximations rows of Agricultural and Forest landscape types. In general terms, the detail and accuracy of the information is not enough to produce confident answers in many of these cases.

Discussion and conclusions

The main focus of this study was to investigate if a changed spatial resolution also changes the interpretation of a certain landscape concept. The original hypothesis stated that the outcome of the generalization is equal to a manual interpretation at the target level. The large accuracy intervals may seem hard to draw any conclusions from. Indeed this is a problem and in this study one of the reasons can be found in the rather low crispness of the interpretations. The uncertainty of the interpreted images are caused by the recognition of a limited ability of abstraction represented as a +/- one areal cover class accuracy in the interpretation. This uncertainty interval forces the overall accuracy interval to be quite big. In fact, it is never possible to reach a better overall accuracy interval than $0.36 \leq A_O \leq 1.00$. Following terminology in Chapter 6 (Ahlqvist, Keukelaar and Oukbir, 2000a) this measure can be translated as the overall crispness measure, M_C = 0.36, meaning that only 36% of the reference data is unambiguously classified into lower approximations. Similarly, uncertainty in the input to the automated generalization causes the output to have overall crispness measures of M_C = 0.50 for the PG_{LT}-generalization and M_C = 0.58 for the CG_{LT}-generalization. In spite of the low crispness and high uncertainty, the results do allow for some general conclusions to be drawn.

For the classification into landscape types, the overall accuracy of up to 100% indicate that Eq. 1 may hold for any one of the two suggested generalization strategies. Thus we have no evidence to falsify the original hypothesis. This can also be translated as a high semantic accuracy of the dataset. But if we consider the outcome from the analysis of land cover proportions in Table 33 the picture is a bit different. The proportion-based classification did produce a 100% correspondence with the reference for all variables. The category based method though, did not produce a full agreement with the reference images. The estimates of areal coverage departed significantly from the reference in up to 10% of the cases. The characteristic of the category based generalization method is the use of a secondary classification of the original information as input data. Figure 37 and Figure 38 showed that this secondary classification exaggerates the amount of urban and agricultural areas. Clearly this skewed information has a negative impact on the correspondence with the reference interpretation. In this case study the skewed areal land cover information has in spite of this no proven effect on the final classification into landscape types. This is mainly due to the rather broad limits set by the classification system. Other classification situations may be more susceptible to this kind of bias though.

It was speculated earlier that an interpretation at a coarser spatial resolution might use intermediate level abstractions before the final classification is made. The type of intermediate level abstraction used here in the category-based generalization does not support this idea but it still does not reject such a possibility. The pilot studies in chapter 5 indicated that the automated aggregation of high-resolution data and the low-resolution interpretation does not correspond very well. Some of the errors in those studies may be attributed to interpretation inconsistency but the general picture from all analyses carried out is that some of the analyzed parameters may well be aggregated to satisfy Eq. 1 whereas other parameters may not.

Increased granularity in remote sensing information

In the light of this it is appropriate to discuss the idea of using one single high-resolution database as a primary source for information derivatives. This can be held as a feasible and highly desirable solution in that source data will be possible to translate into different concepts according to the current needs (Müller 1989; Albrecht 1996; Gray 1997). The approach would be ideal for data that can be collected through quantitative measurements of field like parameters such as temperature, topography but also perhaps individual plant species occurrences. Remote sensing information is well suited to this kind of treatment but there are still some fundamental problems that need to be resolved before this kind of framework can be made operative for environmental monitoring and management (Wilkinson 1996).

Remote sensing through satellites is continually producing environmental information of more and more accurate and fine-grained resolution both in terms of spatial and spectral resolution. Over the next ten years we can expect the complexity of remotely sensed datasets to grow significantly through the use of multi-sensor, hyper spectral, multi-view angels and multi-temporal time series. Given that future remote sensing systems will provide even more detailed data, each call for automated interpretation or classification of these fine-grained data into larger spatial and thematic groupings will need a thorough understanding of the generalization steps needed for such operations. The problem, for example with mixed pixels, will not disappear with increased resolution, instead the high resolution pixels will become mixtures of different things than we are used to today and accordingly call for other conceptualizations. Key questions here will be to identify what actual variables that should be considered as defining a more abstract concept.

For complex category definitions such as vegetation types Gray (1997) propose a method of keeping information as disaggregated fields in order to be able to use different class concepts in other contexts. The fine grained dataset given by remote sensing devices will of course give us unique opportunities to study the meaning of varying concepts in relation to one another. Such studies would also have the potential to provide an increased understanding of our own mental models of the real world entities (Gray 1997). Given such an understanding of our conceptualizations methods, to translate field-based information into objects has been described by Mackay et al. (1994).

Still there is also a need to approach the problem with an integrated view of the landscape where we will deliberately expose ourselves to the thematic inaccuracies represented in e.g. historical maps and cultural heritage descriptions. Looking at the landscape as a whole, errors and loss of information will not necessarily be the case. The use of summary concepts such as “agricultural district” gives an instantaneous idea of the landscape properties. It may be full of errors and cannot provide estimates of the actual field area and the spatial distribution of individual fields, but on the other hand the concept “agricultural district” will most likely give the reader more immaterial notions of ownership structure and land use traditions which are complicated to communicate in more formal terms. Of course the term “agricultural district” might mean something rather different in a north-American than in a European context for example. This is exactly the reason for the current efforts to develop richer models on a semantic level that have been pointed out in chapter 2.

This field of research has been of interest to geographers for a long time now and with the current developments within the field of cognitive psychology and computer science there are openings for further findings. Being able to handle multiple perceptions of the environment is not only important for visualization of data. It is also of great importance when dealing with environmental models e.g. for wildlife habitat management.

Implications for image classification

It is also interesting to discuss these results in the context of current techniques to produce land cover maps from remotely sensed data. Most multispectral classification procedures still use location specific classification based on the spectral information from one image pixel location. At the same time, it is often recommended that training data for a supervised classification be given as larger regions of several hundred pixels in order to capture the total range of the spectral signature of a specific class. This standard procedure requires that there is a 100% consistency in the use of a specific class concept at the two levels of resolution used in a normal supervised image classification.

The great variety of currently used categories at different levels of resolution has never been tested to confirm or reject this fundamental assumption. I therefore argue that more extensive tests using similar methods and data illustrated in this work need to be made as part of any normal data quality report. It has been argued that this approach is neither rigorous nor always possible (Weibel and Dutton, 1999). The problem is that the other alternative would be to ignore the problem. There is today no documented knowledge if there is a semantic variation in the use of a specific concept at different scales.

So, why insist on comparing results with other interpreted results when a digital reference might be used for accuracy assessment? The major purpose of this chapter is not to show how well the human interpreter manages to summarize pieces of data compared with the 'right' answer that the computer might give us. The purpose is to find out whether the human mind makes different assessments of an area if we apply different scales for our investigation. Of course a baseline of digital numbers could be of interest to see if we over- or under estimate at various resolutions. This might also give some clues of what causes the differences. The aspect covered by the correspondence assessment translates into to the semantic accuracy of the dataset. I can only suggest that the use of manual interpretations at different resolutions is a viable method to make the necessary evaluation of generalization effects other than purely statistical.

Rough classification method

The analysis of the final classification results and the demonstration of data in 1Deeem and 2Deems show the power of rough classifications to represent and illustrate a type of uncertainty often found in geographic datasets. The three levels of memberships that can be represented by the lower approximation, the area of uncertainty and the negation of the upper approximation, translates quite intuitively into the statements ‘absolutely sure’, ‘maybe’, ‘absolutely not’. In cases where more levels of gradual certainty is needed, methods using fuzzy sets have proven to be a feasible alternative (Gopal and Woodcock, 1994; Woodcock and Gopal, 2000). The rough set approach to uncertainty thus enriches the existing suite of methods to represent uncertainty in geographic datasets. The inherent type of information uncertainty should guide the use of probability or fuzzy/rough set based representations of uncertainty.

One drawback of the rough classification method is of course the problems of generating measures of per-class accuracy or a KHAT-like statistic. Although both a crisp-rough and a rough-rough comparison can produce an overall accuracy interval, applied questions will often take advantage of some more summary measures.

Conclusions

This chapter has successfully demonstrated the evaluation of semantic uncertainty in manually interpreted land cover classifications. The analysis illustrated how categorical uncertainty could be translated into rough classifications. This made it possible to do assessments of the correspondence between two datasets using semantically uncertain data in one or both of the assessed data sets.

The evaluation of scale dependency in the use of certain landscape concepts provided no evidence for a scale dependent use of these concepts. Still, the results from chapter 5 indicate the opposite possibility. It is therefore too early to draw any general conclusions other than a broad recommendation of caution. Consequently, it was argued that more extensive testing is required of a possible scale dependency of commonly used land cover mapping concepts. Used methods were here suggested as a way to estimate semantic accuracy in such tests.

Using methods of rough classification and error matrix extensions developed earlier, the potential for these methods to perform generalization and accuracy assessments was further illustrated.

The findings also raise important questions for future quality assessments of digitally aggregated data. Issues of semantic accuracy assessments as well as contemporary techniques to produce digital land cover classifications were discussed.

Chapter

8 CRISP, FUZZY AND ROUGH DECISION SUPPORT IN GIS

Introduction

In chapter 2 it was established that separate views on the real world result in two general distinctions. One view where the world is considered to be made up of discrete objects and another view that consider the world as being made up of a continuum of named attributes. From a semiotic perspective Sowa (2000) holds symbolic and image like reasoning as two necessary components of a complete system of reasoning. Geographic information systems have theoretically the ability to incorporate both plenum/image like/field and atomic/symbolic/object views represented by rasters and vectors respectively.

It was further recognized that this theoretical basis is reflected in several proposed conceptual modeling frameworks for geographical databases (Peuquet, 1988; Nyerges, 1991; Peuquet, 1994; Livingstone and Raper, 1994; Mark and Frank, 1996; Usery, 1996; Bishr, 1998; Mennis et al., 2000). Most of these works suggest that it is necessary to simultaneously represent field-based, object-based and time-based views to be able to provide a full description of a geographic phenomenon.

Although some of the proposed frameworks never have been extended towards the actual database representation, those that were have proposed set theoretic approaches for its implementation (Livingstone and Raper, 1994; Usery, 1996; Bishr, 1998; Mennis et al., 2000).

In this chapter I will suggest one possible implementation structure that not only integrates object and plenum spatial views, but also is capable of considering vagueness and ambiguity in these views. I also discuss how this further opens up possibilities for improved interoperability of geographic information systems.

Current and emerging techniques for geographic data integration

We can presume that future geographic questions will need information not explicitly represented in available databases. One large challenge is therefore to derive implicit facts from explicit geographic knowledge, and to produce a statement about the uncertainty in the presented information.

Multi criteria evaluation (Carver, 1991; Eastman, 1997) or multi criteria decision analysis (Malczewski, 1999) is a group of methods that can be used to face this challenge. Such analyses are often implemented in geographic information systems by using two or more pieces (layers) of attributes or constraints for a certain objective. The multi criteria decision analysis framework enables a combination of separate lines of certain or uncertain factors such as Boolean, probabilistic and possibilistic (fuzzy) information combined through a set of rules into an answer or several scenarios. Standard multi criteria decision analysis can for example make use of fuzzy set membership factors and Boolean constraints that may be summed together to produce an output result.

Current multi criteria decision analysis implementations still lack the indiscernibility aspect of uncertainty. In brief, indiscernibility refers to the granularity of the knowledge whereas vagueness (fuzziness) arises due to gradual notions of categories (cf. Fisher, 1999; Duckham et al., 2000). Indiscernibility may be explained in the context of a reclassification situation when one or several of the source classes do not translate directly into the target classes. For example, elements of source class A could be elements of both classes 2 and 3 in the target classification.

It has been shown in chapter 6 that rough set theory and rough classification is capable of representing indiscernibility. It was also illustrated how proxy information could be used as additional evidence for the target classification and resolve some of the unresolved areas of uncertainty. That is, information on soil moisture was in chapter 6 taken from a soil map to either support or reject ambiguities in the first rough reclassification. I will now readdress this problem, which in essence can be formulated as a decision function: given the old class and some additional evidence, calculate the new class.

A suggested approach

The main problem addressed in this chapter is the combination of nominal and continuous data in the decision rule. In standard multicriteria evaluation this is often solved by a conversion of continuous variables into grades of membership in a specified set.

This work uses a similar approach, and uses the concept of bifuzzy sets to represent two different facets of imprecision and these ideas are illustrated in an experiment. In this it is demonstrated how to use crisp, fuzzy or rough sets to define a complete or incomplete translation from one concept to another, and create a transformation between contexts. Since no information in the experiment provides a one to one mapping between the source data and the target classification the idea is based on the integration of multiple lines of evidence. It uses the concepts of multi criteria decision analysis and fuzzy aggregation operations, extending current fuzzy approaches to incorporate crisp, fuzzy and rough sets through conversions into bifuzzy sets.

Merging together information about a certain concept using object-based and location-based views, the experiment not only illustrates the use of this method to make transformations of information from one context to another, it also suggests this framework as a solution to the wider problem of integrating different representations of geographic space (cf Peuquet, 1988; Peuquet, 1994; Couclelis, 1996; Couclelis, 1999; Mennis et al. 2000).

Method development

The final experiment will use continuous *(z)* wetness data converted into fuzzy membership values $MF_j(z)$ corresponding to the target classification *(j)*. We also convert indiscernible nominal classes *(i)* through reclassification into rough classes corresponding to the target classification *(j)*. The theoretical basis for combining rough and fuzzy *(z+i)* classifications will be referred to below and it includes the conversion of data into bifuzzy classifications before the actual integration is performed through an intersection overlay operation. The experiment illustrates all this in an application that integrates bifuzzy classifications into a final image that combines both vague and indiscernible information. A more detailed description of the formal development of the bifuzzy representation has been presented at GIScience2000 (Ahlqvist, Keukelaar, and Oukbir, 2000b).

Transforming fuzzy and rough into bifuzzy data

It is of interest to see how the two facets of imprecision that rough and fuzzy data represent can be integrated. It is tempting to convert rough sets to fuzzy ones by assigning membership value 0 to elements not in the rough set, membership value 1 to elements in the lower approximation of the rough set, and perhaps membership value 0.5 to elements in the area of uncertainty of the rough set. We could even use some conditional probability instead of the value 0.5. However, Dubois and Prade (1992) argue that these attempts can be only partially in agreement with fuzzy set theory. It seems, therefore, that a different approach is called for.

Two methodologies have been proposed to unify rough sets and fuzzy sets (Dubois and Prade, 1992). Both result in a mathematical object which is a pair of fuzzy sets $M = (\underline{F}, \overline{F})$, each determined by a membership function $\mu_{\underline{F}}$ and $\mu_{\overline{F}}$. This will hereafter be called a bifuzzy set or BF-set, and this mathematical object is able to express both uncertainty due to indiscernibility as well as uncertainty due to vagueness (Ahlqvist, Keukelaar, and Oukbir, 2000b). In the same way as with rough sets and rough classifications (chapter 6) is possible to define a bifuzzy classification as a set of bifuzzy sets and to develop useful quality measures that can be applied on a single bifuzzy classification (Ahlqvist, Keukelaar, and Oukbir, 2000b).

Bifuzzy representations and multi-criteria evaluation

Having defined a formal representation for vagueness and indiscernibility, let us now move directly further toward the question where we have several classifications that we want to evaluate together. In the context of this work this can be formulated as a problem of combining different types of uncertainty such as vagueness and ambiguity, and to this there seem to be existing and workable approaches. The idea of using multiple sources that partly explain a specific concept has close similarity with multi-criteria decision analysis (Eastman, 1997; Malczewski, 1999). In the following discussion I will in the last few paragraphs of this section first summarize some of the work in Ahlqvist, Keukelaar, and Oukbir (2000b). It illustrates the conceptual idea of using the multi criteria analysis framework to integrate fuzzy and rough data through the use of bifuzzy classifications. After that I will exemplify this approach in an experiment with geographical data.

Imagine a situation with three classifications that we want to use in a multi-criteria evaluation, one crisp, fully determined classification, a second fuzzy classification with vague information and a third rough classification with ambiguous information. All three classifications are defined on the same universe U, and on the same index set I. The first classification is a crisp classification, C, consisting of a number of crisp classes X_i^C. The second classification is a rough classification R, consisting of a number of rough classes $X_i^R = \left(\underline{X}_i, \overline{X}_i\right)$. Finally we have a fuzzy classification F, consisting of a number of fuzzy classes X_i^F, each of which is a fuzzy set, determined by the membership function $\mu_{X_i^F}$.

To use these three classifications together in a multi-criteria evaluation, we convert all of them to bifuzzy classifications. The conversion of the three existing classifications proceeds in the most straightforward way: A crisp class X_i^C is converted to a bifuzzy class $X_i^M = (\mu_{X_i^C}, \mu_{X_i^C})$, with $\mu_{X_i^C}(z) = 1$ if $z \in X_i^C$, 0 otherwise. A fuzzy class X_i^F is converted to a bifuzzy class $X_i^M = (\mu_{X_i^F}, \mu_{X_i^F})$. A rough class X_i^R is converted to a bifuzzy class $X_i^M = (\mu_{\underline{X}_i}, \mu_{\overline{X}_i})$, with $\mu_{\underline{X}_i}(z) = 1$ if $z \in \underline{X}_i$, 0 otherwise, and, similarly, $\mu_{\overline{X}_i}(z) = 1$ if $z \in \overline{X}_i$, 0 otherwise.

To be able to proceed with a multi-criteria evaluation, it is necessary to define some logic for this, and for the purpose of this work only the intersection and union operations on bifuzzy sets will be defined. The intersection of two bifuzzy sets is defined as $A \cap B = (\min(\mu_{\underline{A}}, \mu_{\underline{B}}), \min(\mu_{\overline{A}}, \mu_{\overline{B}}))$. The union of two BF-sets is defined similarly as $A \cup B = (\max(\mu_{\underline{A}}, \mu_{\underline{B}}), \max(\mu_{\overline{A}}, \mu_{\overline{B}}))$.

Similarly, other operations such as product, bounded sum, bounded difference and convex combination defined for fuzzy sets (Burrough and McDonnell, 1998) seem possible to extend to bifuzzy sets.

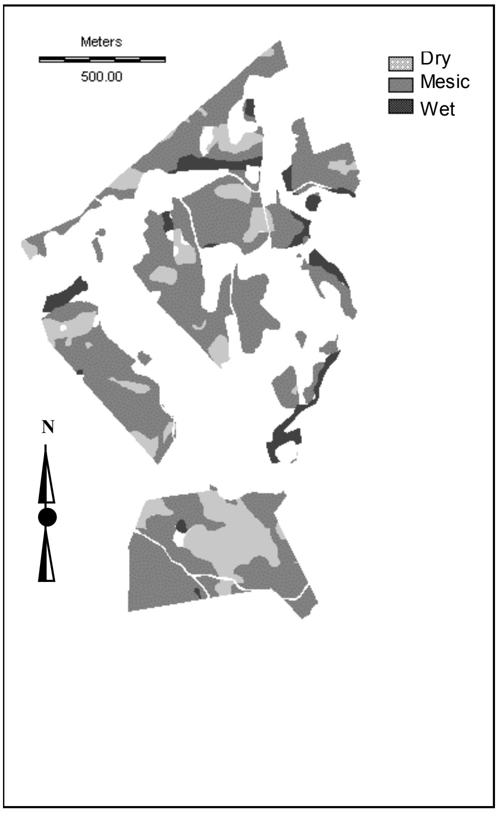
It is also possible to define something like an overall accuracy measure (Congalton, 1991) for bifuzzy classifications. Let us assume that the reference classification, R, is compared with a classification M. We could then compute M_{WA}, the weighted accuracy measure, Eq. 6

Here, the function $W(a,b,c,d)$ defines what it means for a point to be correctly classified. If we desire exact equality of the uncertainty intervals, we could use $W_{exact}(a,b,c,d) = (2 - |a-c| + |b-d|)/2$. Any deviation in the evaluated data from the reference will here result in a decrease of the global accuracy value. It does not make any difference if the discrepancy is in the necessary membership value or the possible membership value. Other functions may also be defined for $W(a,b,c,d)$ (Ahlqvist, Keukelaar and Oukbir, 2000b) but is not necessary for the purpose of this chapter.

Experiment

The map data used in this illustration was taken from two separate investigations covering the same area (Edberg et al. 1971; Ahlqvist and Wiborn, 1992). These two vegetation maps had been produced for nature preservation tasks. However, they used different vegetation classification systems to produce the final categorical map sheet. These two maps were digitized by scanning and segmentation into two GIS raster images with pixel values representing vegetation class labels, Figure 41. Data entry and all subsequent GIS operations were performed using the IDRISI for Windows v.2.0 software. The left map from 1971 uses originally 9 classes but has been thematically aggregated to 3 classes; wet, mesic and dry vegetation. This map is called VEG3. The right map of Figure 41 is from 1986, it uses 35 classes and will be called VEG35.

Eq. 6 $$M_{WA} = \sum_{i \in I} \int_U W(\mu_{\underline{R}_i}(x), \mu_{\overline{R}_i}(x), \mu_{\underline{M}_i}(x), \mu_{\overline{M}_i}(x))dx \Big/ \sum_{i \in I} \int_U \mu_{\overline{R}_i}(x)dx$$



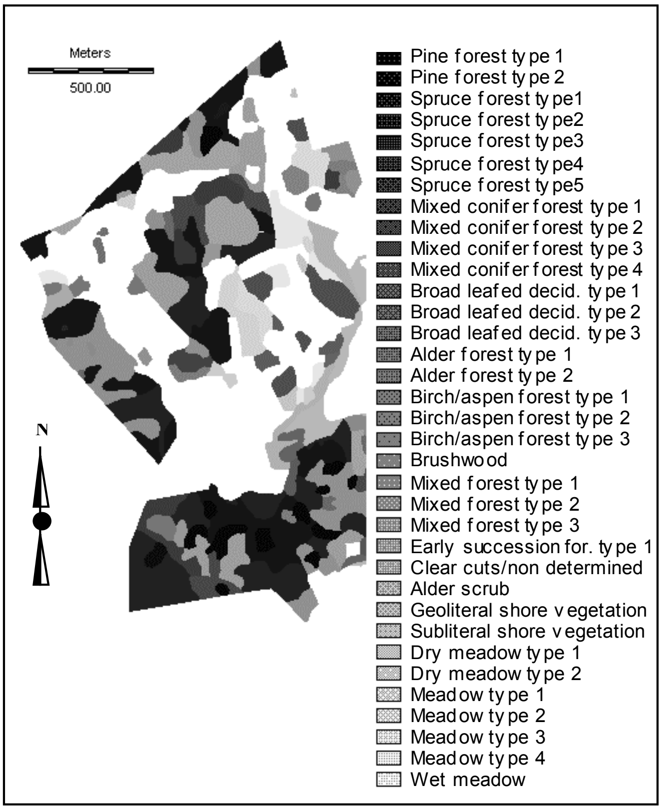


Figure 41 Original maps used in this study. Left, the VEG3 map produced by Edberg et al. (1971) thematically aggregated into dry, mesic and wet vegetation types, and right, the VEG35 map produced by Ahlqvist and Wiborn (1986).

The following experiment demonstrates the combination of two different types of knowledge in a geographic analysis. Using the concept of multi criteria analysis, we take two different sources of information and combine them into the final image. The two data sources are converted to rough and fuzzy classifications to express the different kinds of semantic uncertainty these data have in the context of the target classification system. A digital elevation model is used to produce an image with gradual transitions from non-membership to full membership in the target classes given as fuzzy membership values. The other line of information comes from the detailed vegetation map, VEG35, which is reclassified into a rough classification. In the rough classification, membership, non-membership, and possible membership in the target classes are represented by the upper and lower approximation of rough classes. The combination of the two is a bifuzzy representation that accounts for both gradation and indiscernibility. The bifuzzy representation is finally visualized by thresholding membership values, which produce the final image of the transformed information.

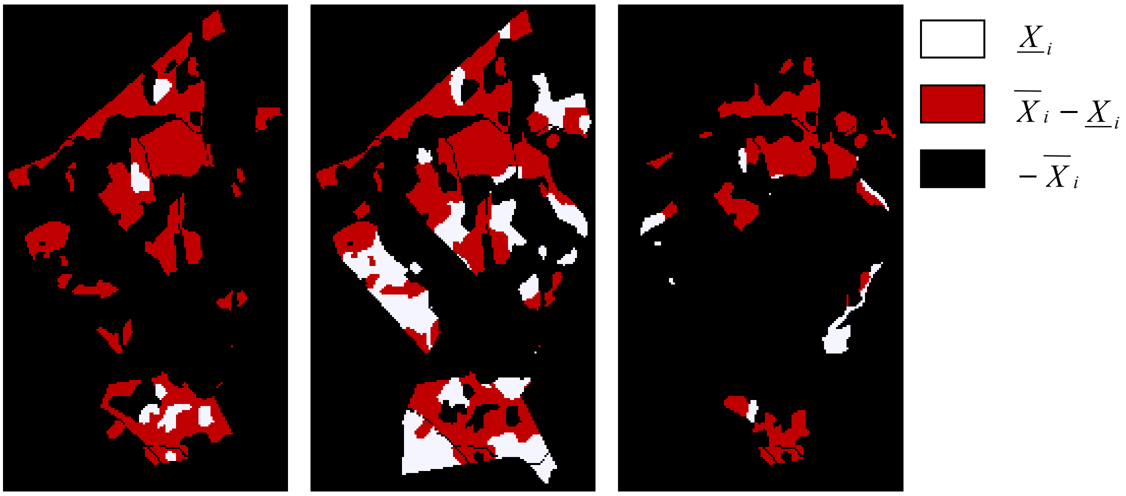
From fuzzy and rough to bifuzzy representations

The following sections will explain how the original data was translated into rough and fuzzy representations. It also shows how these two, the fuzzy and the rough classifications, were transformed into bifuzzy classifications. The whole operation can be seen as the general procedure of getting two pieces of information compatible for assessment of for example changes in vegetation between two times.

<u>Rough information – reclassification of crisp data</u>

The rules for rough reclassification were established deductively using domain knowledge. Each original VEG35-class was evaluated against the target VEG3 classification system and translated into rough classification rules, Table 36. Rules such as these could also be set up by induction using a collection of ground truth samples from each original class.

Table 36 shows that a majority of the classes in the original crisp classification cannot be reclassified directly into lower approximations of the target classification system. Following the reclassification rules set up in Table 36 the rough classification R is produced. This is built up by 3



i = dry | i = mesic | i = wet

Figure 42 Images showing the outcome of the rough reclassification using the reclassification rules set up in Table 36. Lower approximations are colored white and areas of uncertainty are shaded for each of the 3 classes in the rough classification R.

rough classes $X_i^R = \left(\underline{X}_i, \overline{X}_i\right), i \in \{dry, mesic, wet\}$, each being a rough set and represented in this experiment by 6 separate images.

Figure 42 illustrates the resulting rough classification. In this, lower approximations are white and areas of uncertainty are shaded for each of the 3 classes in the rough classification *R*. In Table 36 we noticed earlier that a majority of the original classes in the crisp classification *I* cannot be assigned to a lower approximation in the rough classification *R*. Figure 42 shows the spatial outcome of this, from which it becomes obvious that the spatial overlap is fairly high.

The overlap and overall crispness measures described in chapter 6 are here calculated to be M_o= 0.64 and M_c=0.41. In this case a totally crisp classification would yield M_o=0, M_c=1 and a totally rough classification M_o=2.0, M_c=0. Obviously the categorical granularity of the crisp classification *I* has not enough detail to discern between the different lower approximations in *R*. But still, the rough classification is not short of information. It is often able to exclude one of the classes as a possible alternative, leaving only two alternatives to choose from. This information will be used later on together with location-based information about the possibility that a certain location belongs to one of the target classes. This second piece of information is introduced next.

<u>Fuzzy information – wetness index</u>

The VEG3 classification system is based upon vegetation moisture. Thus, additional information about soil water content may resolve some of the indiscernibility that was a result of the rough reclassification in the previous section. One commonly used source of information on soil

Table 36 Original VEG35 classes and corresponding rough VEG3 classes

Original classification I (VEG35)	Rough classification R (VEG3)
1 : Pine forest type 1	{Dry}
2 : Pine forest type 2	{Dry, mesic}
3 : Spruce forest type1	{Dry, mesic}
4 : Spruce forest type2	{Mesic, wet}
5 : Spruce forest type3	{Mesic}
6 : Spruce forest type4	{Wet}
7 : Spruce forest type5	N/A
8 : Mixed conifer for. type 1	{Dry}
9 : Mixed conifer for. type 2	{Dry, mesic}
10 : Mixed conifer for. type 3	{Mesic}
11 : Mixed conifer for. type 4	{Dry, mesic, wet}
12 : Broad leafed dec. type 1	{Mesic}
13 : Broad leafed dec. type 2	N/A
14 : Broad leafed dec. type 3	{Mesic}
15 : Alder forest type 1	{Wet}
16 : Alder forest type 2	{Wet}
17 : Birch/aspen forest type 1	{Dry, mesic}
18 : Birch/aspen forest type 2	{Mesic, wet}
19 : Birch/aspen forest type 3	{Dry, mesic}
20 : Brushwood	{Mesic, wet}
21 : Mixed forest type 1	{Dry, mesic}
22 : Mixed forest type 2	{Mesic}
23 : Mixed forest type 3	{Wet}
24 : Early succession for. type 1	{Dry, mesic, wet}
25 : clear cuts/non determined	{Dry, mesic, wet}
26 : alder scrub	{Wet}
27 : geoliteral shore vegetation	{Wet}
28 : subliteral shore vegetation	N/A
29 : Dry meadow type 1	N/A
30 : Dry meadow type 2	{Dry, mesic}
31 : Meadow type 1	{Dry, mesic}
32 : Meadow type 2	{Dry, mesic}
33 : Meadow type 3	{Mesic}
34 : Meadow type 4	N/A
35 : Wet meadow	{Mesic, wet}

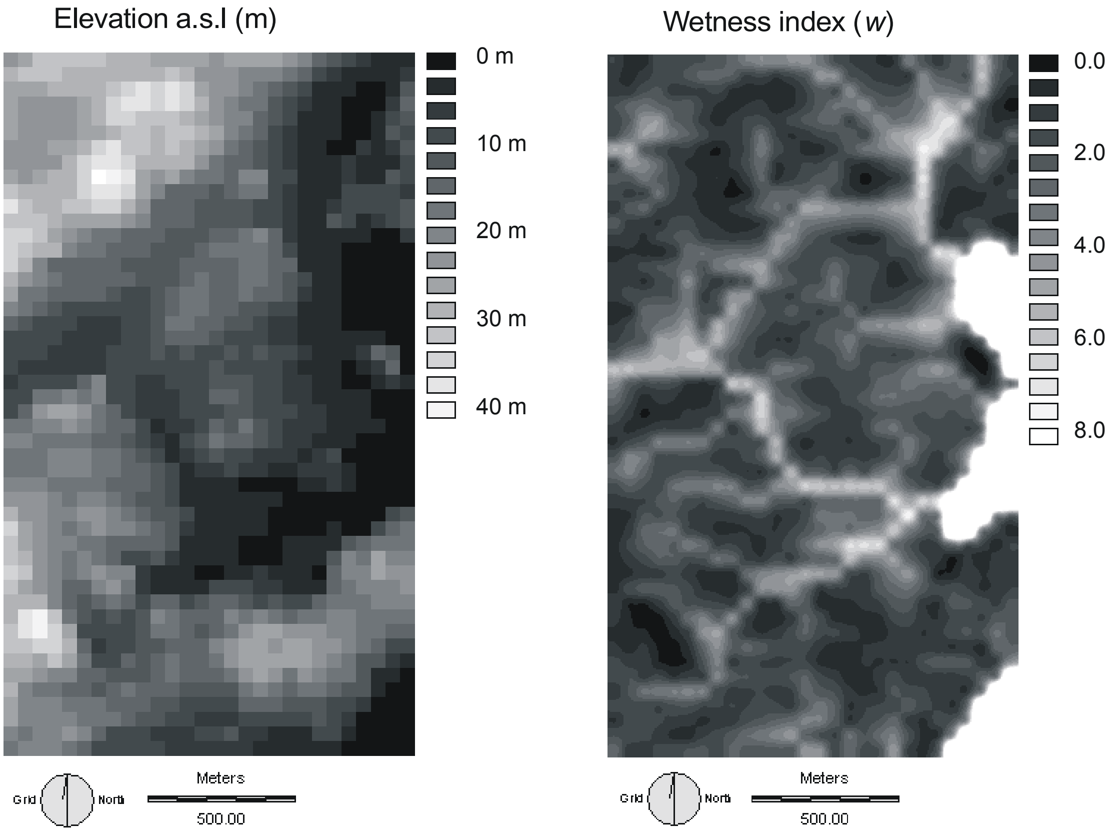


Figure 43 Original digital elevation model over the study area together with the wetness index image produced using Eq. 1 (Medgivande Lantmäteriverket 2000. Ur GSD - Höjddata, ärende nr L2000/646)

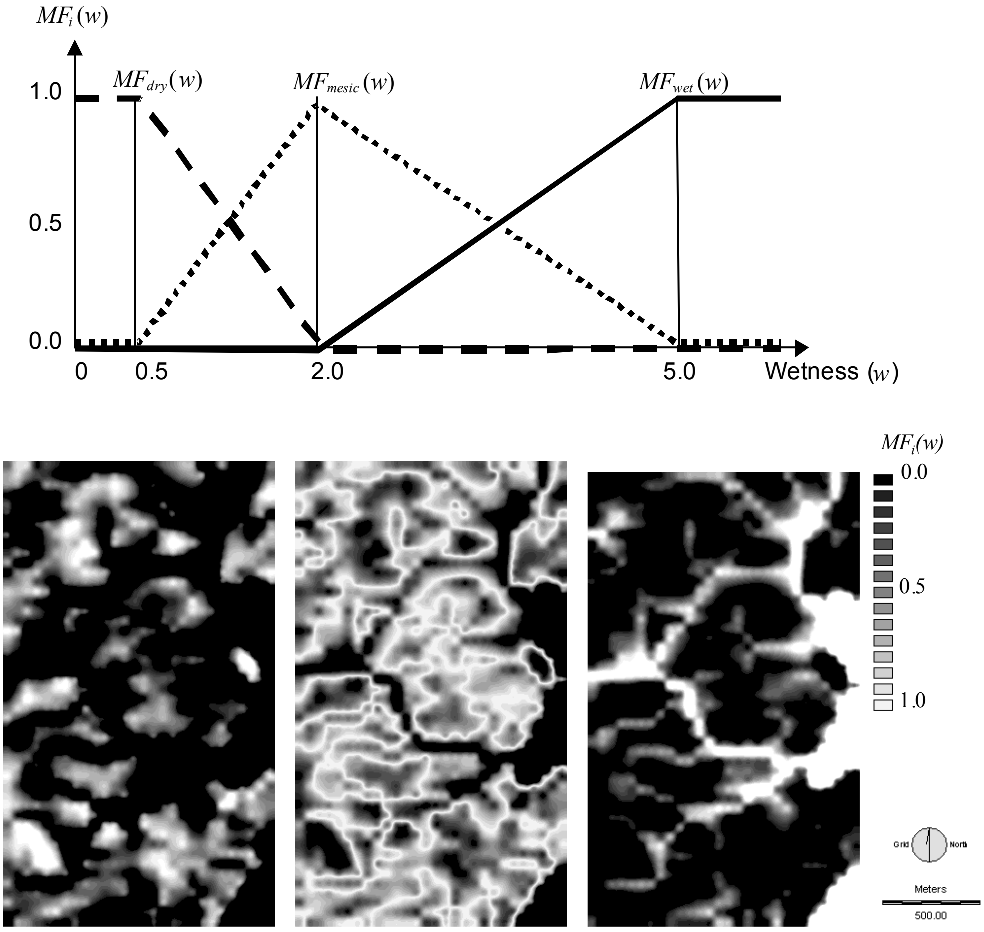
water content is the topographically based wetness index, *w*, Eq. 7 (Moore et al. 1991). This index is calculated for each cell in an elevation image using the following formula:

Eq. 7 $$w = \ln\left(\frac{A_s}{\tan\beta}\right)$$

Here A_s is specific catchment area defined as the upslope area draining across a unit width of contour, and β is the slope of the cell. So, a wetness index image was calculated from an original digital elevation model from Geographic Swedish data (GSD) provided by the Swedish National Land Survey, using the TAPES-G software (Gallant and Wilson, 1996). The used digital elevation model had a spatial resolution of 50x50m. The calculated wetness index values were interpolated over a 5x5m resolution image. The purpose for this was to transform the original 50x50m resolution into the map data at 5x5m resolution. The accuracy of the output images is of course questionable, but the intent of this experiment is only to demonstrate the principles behind a rough-fuzzy data integration, not to produce a fully accurate representation. The DEM together with the derived wetness image are displayed in Figure 43.

The fuzzy membership functions used to transform the wetness image into fuzzy information were established using the semantic import approach (cf. Burrough and McDonnell, 1998). This method is suitable in cases where there is a fairly good qualitative knowledge about how to group data. The two major issues in the semantic import approach are the choice between linear, sinusoidal or some other function defining the class membership, and the definition of the transitions zone limits and widths. To make things simple I have chosen linear transition functions and to support the establishment of transition zone limits and widths, information from the older vegetation map was used as a guiding reference.

The established membership functions displayed in Figure 44 were used to produce the fuzzy classification *F*. This consists of 3 fuzzy classes $X_i^F, i \in \{dry, mesic, wet\}$, each being a fuzzy set and represented here by the three images displayed in Figure 44. These 3 images show the membership values at every pixel location in each of the 3 fuzzy classes, dry, mesic,



a) X^F_{dry} b) X^F_{mesic} c) X^F_{wet}

Figure 44 Membership functions for the fuzzy reclassification (top) and the three images showing the three fuzzy classes $X^F_{\{dry,mesic,wet\}}$. In the images black areas represent no membership and higher degree of membership is increasingly brighter reaching white at full membership.

and wet. In a sense they convey a location-based view of the target classification.

Transformation into bifuzzy data

After the conversion of source data into one rough classification and one fuzzy classification it is time for the last step before the actual integration of the two pieces of evidence to produce a final output. Here I only follow the definition in one of the previous sections on how to produce bifuzzy classifications from the fuzzy and rough classifications. This results in two bifuzzy classifications M^F and M^R originating from the fuzzy and rough classifications respectively. This transformation does not change the actual information, it only translates it into the notation of bifuzzy classifications. Therefore the bifuzzy classification M^F is now represented by a set of 6 images but 3 of those are identical to one of the other 3 images. Consequently the bifuzzy classification version of the original fuzzy classification still looks exactly as in Figure 44, and similarly the bifuzzy classification of the original rough classification could be illustrated as Figure 42.

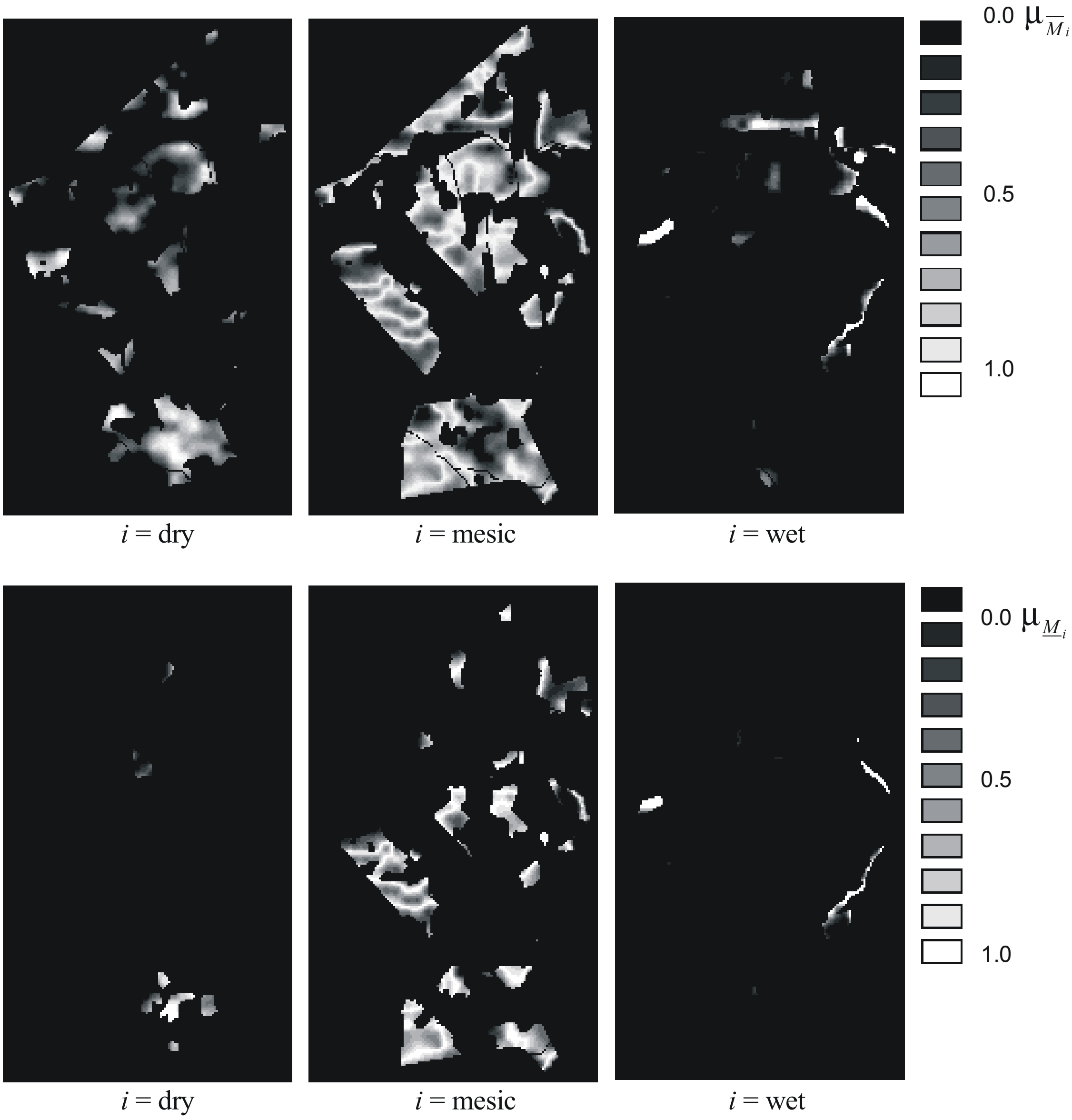


Figure 45 Images of the bifuzzy classification showing the degree of possible (upper row) membership and necessary (lower row) membership in each of the target classes; dry, mesic and wet vegetation respectively.

Bifuzzy data integration

The subsequent integration of bifuzzy classifications used the concept of multicriteria evaluation discussed earlier through an intersection operation $M^F \cap M^R = \left(\min\left(\mu_{\underline{M}_i^F}, \mu_{\underline{M}_i^R}\right), \min\left(\mu_{\overline{M}_i^F}, \mu_{\overline{M}_i^R}\right)\right)$.

The result can be represented as a set of 6 images, Figure 45. The grade of membership in these images is to be interpreted as the degree of possibility and necessity for the target classes. At this stage the previously defined quality measures were calculated for the integrated bifuzzy classification. The roughness of the integrated information was calculated to be $M_r = 0.67$, which obviously gives an overall crispness $M_c = 0.33$. The bifuzzy overlap measure was calculated to be $M_o = 0.18$.

If these measures are compared with the bifuzzy classifications from the initial rough and fuzzy data, Table 37, we see that the integration of the two data sources reduces the overall crispness as well as the bifuzzy overlap. Given that the original fuzzy classification introduces degrees of necessary membership in the lower approximation areas of the rough classification (Figure 45), this of course reduces the overall crispness. At the same time the bifuzzy intersection operation reduces the amount of overlap since it uses a minimum operation on the membership values. What is achieved is a result with less spatial confusion about the target classes. We also get an explicit representation of the spatial variation within each vegetation unit with respect to the belongingness to a specific class, Figure 45.

It is also possible that we for some reason wish to de-fuzzify the result into a crisp result. To illustrate how this can be done the six images have been combined to produce a final crisp classification C'. The logic followed in this combination is to let all bifuzzy lower approximations $\mu_{\underline{M}_i}(z) > 0$ at location z result in crisp classes $z \in X_i^{C'}$ in C'. This is possible since all lower approximations of bifuzzy sets are disjunct and will not result in locations being assigned to multiple classes. The remaining areas that may include overlapping areas are assigned to crisp classes in C' based on the maximum value of the upper approximations at each pixel location. If for example a location has the following values $\mu_{\overline{M}\{dry,mesic,wet\}}(z) = \{0.1, 0.4, 0.5\}$ this will produce the output classification $z \in X_{wet}^{C'}$. The resulting image is given in Figure 46A and can be compared by the original VEG3 map from Edberg et al. (1971) to the right, Figure 46B. If the standard overall accuracy is calculated using these crisp maps we will find that it is 0.62.

Table 37 Quality measures for the bifuzzy classifications M^R, M^F, and $M^{F \cup R}$ that were produced respectively from the rough and fuzzy original information, and through bifuzzy data integration.

Classification	BF-Crispness	BF-Overlap
Rough M^R	0.41	0.64
Fuzzy M^F	1.00	0.32
Bifuzzy $M^{F \cup R}$	0.33	0.18

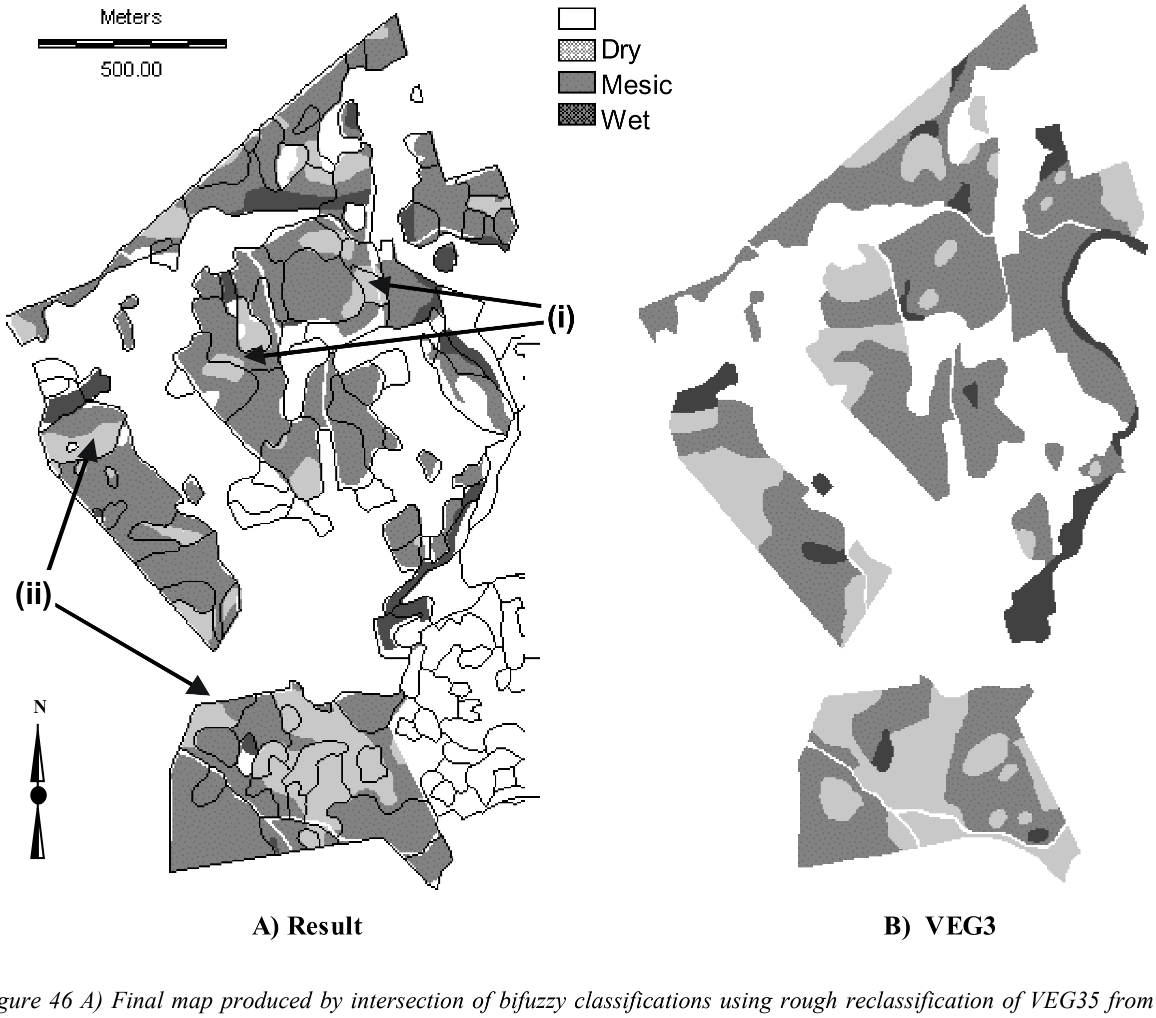


Figure 46 A) Final map produced by intersection of bifuzzy classifications using rough reclassification of VEG35 from Ahlqvist and Wiborn (1986) and fuzzy classification from wetness index image. B) Original VEG3 map from Edberg et al. (1971). Arrows show examples of i) vegetation units in the final map that was previously boundary areas, and ii) new boundaries within original vegetation units as a result of moisture heterogeneity within these units.

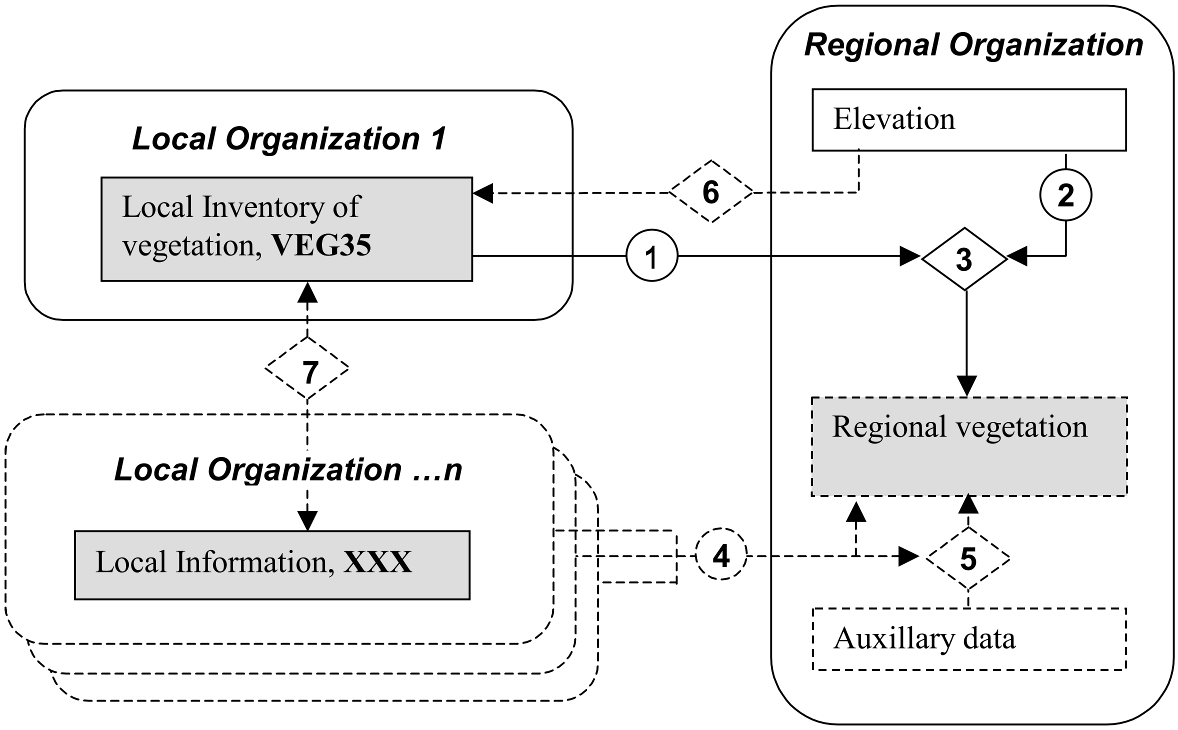


Figure 47 Organizational perspective on exemplified (1-3) and possible (4-7) transformations using the suggested approach.

Discussion and conclusions

The relation between this approach and existing theories and methods has been indicated throughout the text. The illustrated example serves as a backdrop against which the proposed ideas have been presented and explained. In Ahlqvist, Keukelaar and Oukbir, (2000b) some of the ideas of the method development and details of the experiment results were discussed. In this work I prefer to elaborate on the wider application of the described methodology in the context of this thesis.

Geographic information systems interoperability

The example demonstrated that the bifuzzy classification is able to integrate data with different aspects of uncertainty, such as vague and ambiguous information. This has wider applications as it can be seen as a general transformation mechanism between different user contexts. In Figure 47 the experiment has been put into an organizational context. Let us assume the VEG35 map to be an existing inventory produced within a local authority for management purposes. Now suppose a regional organization wants to produce a map with lower categorical resolution covering the entire region using existing local information. The transformation of local information can be made using methods of rough, Figure 47 (1), fuzzy (2) and bifuzzy multi-criteria evaluation (3) outlined in the previous experiment.

If we picture several local organizations, their local information could be made accessible through similar mappings either directly, Figure 47 (4) or through some mediation with other auxiliary data (5). It is also possible to transform information from the elevation data through the ontology of VEG3 using the fuzzy membership functions and then further reclassify it into the ontology of VEG35, Figure 47 (6). In this process fuzzy wetness information, (2), is transformed into a bifuzzy representation using a reversed version of the rough reclassification rules (1) in Table 36. The result of this is essentially 35 bifuzzy classes where the lower approximations of these are empty and the upper approximations could be illustrated with Figure 44.

Using the class numbers from Table 36, the fuzzy class dry, X^F_{dry}, would be reclassified into the upper approximation of bifuzzy classes {1-3,8-9,11,17,19,21,24-25,30-32} and would look like Figure 44a. Similarly, X^F_{mesic}, would be reclassified into the upper approximation of bifuzzy classes {2-5,9-12,14,17-22,24-25,30-33}, Figure 44b, and X^F_{wet} would be reclassified into the upper approximation of bifuzzy classes {4,6,11,15-16,18,20,23-27,35}, Figure 44c. Since this is a rough classification there are overlaps, that is two or more contributing membership functions that need to be resolved.

The most reasonable solution seems to be to apply the union operation on the contributing fuzzy membership values. Accordingly, for example the derived VEG35 bifuzzy class 2 would be assigned $M_2 = \left(0, \mu_{X^F_{dry}} \cup \mu_{X^F_{mesic}}\right)$ and using the max-operator for fuzzy union the result of this would look like Figure 48. The same idea could be applied to other transformations through already defined relationships. In Figure 47 a transformation between the two local organizations (7) therefore could be realized through already established links (1-5).

The suggested chained transformations in Figure 47 require a careful consideration of the original formulation, the meaning of each piece of information, as the transformation rules are constructed. A similar framework has been proposed by Bishr (1998) and Bishr et al. (1999) as a general framework for semantic translators capable of mapping between spatial database schemas while preserving their semantics. The main tool to connect semantically similar objects in Bishr’s work is based on common ontologies, essentially a standardized vocabulary for various domains of interest. Very much the same idea is reflected by Gahegan (1999) and both suggest the use of an interchange format (the term proxy context in Bishr’s work) as a mediator to transform data from one information context to another. As pointed out in the introduction, the use of traditional set theory in these and other works imposes severe limitations on the ability to represent semantically meaningful relationships (Kuhn, 1999; Mark and Frank, 1996). The use of fuzzy and rough extensions to traditional set theory is primarily what makes the illustrated approach substantially different from previous work. It is anticipated that this improvement enables the representation of semantically richer relations between concepts

<u>Bifuzzy data integration and generalization</u>

In the beginning of this thesis it was argued that the traditional meaning of generalization has been widened in the digital world to include not only map output, but also almost any transition between representational models of the real world. Thus, digital generalization can be seen as

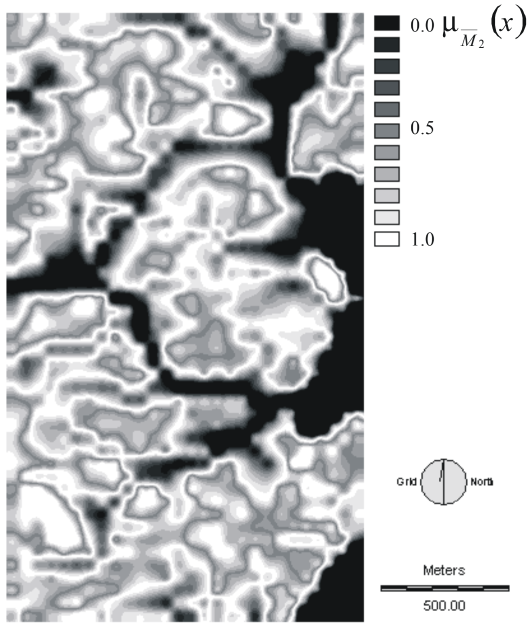


Figure 48 Example illustration of the upper approximation of bifuzzy class 2 in the VEG35 classification system after reclassification from fuzzy wetness classes.

a process that changes the context of geographic data.

The experiment is an example of one such change of context where the initial data was a categorically detailed vegetation description. This source data set was transformed into a context that emphasized vegetation wetness information at a low categorical granularity. This transformation of the VEG35 source data into the VEG3 classification system included use of additional wetness information into the bifuzzy representation.

These steps all relate to the process of *model generalization* introduced earlier in chapter 3, which is a data reduction process that preserves a geometrically and semantically correct object model. The normal understanding of the model generalization process is that it that can be modeled completely formally (Weibel, 1995). However, this view fails to address the important issue of semantic accuracy (Salgé, 1995), which will be an issue as soon as the model-generalized output is to be translated into any other model of reality that can be understood by humans. Semantic accuracy has been thoroughly discussed in previous chapters. Hence, it suffices to repeat that measurements always are made against a logical specification of the conceptual model that was used to collect the data (Veregin, 1999). Against this background it is instructive to look at some of the accuracy values, remembering that the absolute values should not be taken too seriously.

The original VEG3 map evaluated to be $WA_{esxact} = 0.42$ compared with the derived bifuzzy classification. Let us for one moment imagine that the derived bifuzzy classification $M^{F \cup R}$ was the full set of information that was available to the surveyor/cartographer who produced the VEG3 map. That is, knowledge about the vegetation was at a fairly high thematic granularity and there was also information on the wetness for the entire area. Under these assumptions the accuracy value of 0.42 can be seen as a measure of the amount of generalization that has been applied on the original data when it was transferred into a vegetation map with crisply delineated polygons. Also, the fuzzy information in the wetness image can be said to represent the heterogeneity within vegetation units from the aspect of wetness, that is within the context of the target classification.

This experiment exemplifies the discussion in chapter 3 on accuracy measurements for poorly defined objects. It becomes obvious in this case of poorly defined features that the attribute accuracy is tightly connected with the spatial accuracy. In the final step it was shown how the bifuzzy classification could be hardened into a map-like image, Figure 46A, that uses the same cartographic manner as the original VEG3 map shown in Figure 46B. This produces a change of geometry in the result, as new boundaries are created within original map units Figure 46A (i), and new vegetation units are created at original boundary locations Figure 46A (ii). In chapter 3 I referred to the discussion whether the location of a boundary between two vegetation types is uncertain due to the problem of measuring the exact location of the vegetation types or if it is due to the problem of discerning between the two vegetation types at the correct location (Goodchild, 1995; Painho, 1995). In this example the uncertainty of the location of the boundary between two vegetation types has been treated primarily as a problem of discerning between the two vegetation types.

The examples illustrate transformations between different measurement frameworks (Chrisman, 1999) and also that different measurement frameworks imply decisions about information granularity and accuracy. Accommodating for semantic accuracy means to produce a representation that is correct both with respect to the original model as well as the conceptualization of the target model. To address model generalization from this perspective is somewhat conflicting with current understanding of the concept (Weibel and Dutton, 1999) and maybe the division into model and cartographic generalization needs a revision. Anyhow, semantic considerations ultimately ask the generalization process to look for methods that convey geographic meaning and understanding of spatial processes, a direction that has been proposed by several authors (Müller, 1989; Ormsby and Mackaness, 1999; Van Beurden and Douven, 1999).

Controlling variables

The demonstrated example shows how use of process knowledge from the wetness image is used to discern between the different wetness classes in the VEG3 classification system. The idea of scale dependent controlling factors was introduced in chapter 3 and Figure 7. In this experiment the use of an elevation image converted to wetness information is a way to utilize a 'controlling variable' to guide the delineation in the target context. I therefore anticipate that the proposed methodology can be used to define links between concepts and controlling processes.

However, this procedure is not as straightforward as it might seem, and a comment on this is appropriate. The spatial granularity of the VEG35 map was 5m whereas the source elevation model used a 50m spatial granularity of the original measurement. In order to fit the elevation data to the grid of the map, it was interpolated over a 5m grid and in this process a smoothing effect was achieved. The selection of this data set, the following spatial transformation and wetness index calculation are all explicit decisions about how the original measurement framework can be transformed without putting the credibility of the final result at risk.

These decisions will be articulated in the final process of hardening the bifuzzy maps into a crisp final result. Many of the boundaries in the final, crisp map are drawn as a result of these decisions and might have been located differently using for example other sequences of these operations (Van Beurden and Douven, 1999). To be able to use process knowledge in this manner requires careful consideration of these issues. It also requires explicit representation of these considerations as part of the metadata that explains in detail how a data set may be transformed. Reclassification tables and fuzzy membership functions as those used in this experiment is one way to make such considerations explicit and open for revision.

Bifuzzy sets and conceptual modeling

In chapter 2 it was established that a conceptual level geographic information model need to capture the vital components of geographic information. I have also referred to a host of authors that all outline, time, space (3D), theme, and their inter-/intraconnections as basic characteristics that makes up geographic information. (Sinton, 1975; Peuquet, 1994; Albrecht, 1996; Usery, 1996; Gahegan, 1999)

The "triad"- view proposed by Peuquet (1994) is based on a dual framework of object- location integration (Peuquet, 1988) with the incorporation of time. This kind of simultaneous representation of multiple views of the same fact raises the question of how to find one common level of understanding. The example has provided an interesting illustration of this question. Something that in the object based view was held as a wet vegetation type was a matter of graded membership in the field view. The integration of these two views through a bifuzzy set intersection created the joint field/object based view illustrated in Figure 45. The most important step to achieve the bifuzzy representation is that both the field based and the object-based view is mapped onto a common ontology. The choice of common ontologies is still open for discussion. It may either be domain specific and standardized ontologies as suggested by Bishr (1998) or sets of scale dependent ontologies of physically controlling variables as suggested earlier. The mapping from the original data onto the chosen common ontology may with the suggested approach be defined crisply, vaguely or indiscernibly through crisp, fuzzy or rough sets respectively.

We see that the fairly dry mathematical idea of a bifuzzy set has turned out to be able to negotiate common and diverging points of reference. This turn my discussion into the even more challenging issue of integrating different worldviews and what has been formalized as 'Group or Organizational Decision Support Systems' (King and Star, 1990) introduced earlier in chapter 1. There the ideas of "due process" and "boundary objects" were introduced. The identification of important concepts such as different vegetation classes and wetness information make it possible to think about the spatial units as "boundary objects" (Star, 1987) for the negotiation of different aspects of uncertainty.

It was described in chapter 1 that boundary objects come in different types. It appears clearer now that a standard multi criteria evaluation performed as an overlay operation in a geographic information system makes use of the boundary object "terrain with coincident boundary". When such an evaluation is conducted it evaluates the joint outcome of the overlay operation for each spatial unit, be it a polygon or a pixel. The spatial unit essentially acts as a boundary object within which similarities and differences are articulated and negotiated by the overlay operator. Also the case with a multi spectral image classification process uses the boundary object idea, although not usually acknowledged that way. Each location pixel acts as a boundary object for the evaluation of the information from the different spectral bands in the image data.

It seem reasonable to think that the demonstrated technique may be used in the kind of negotiation that can be expected from divergent viewpoints held by different people in organizations. Such negotiations may often reach agreements around vague or imprecise terms as suggested by (King and Star, 1990). In the case of this experiment, space served as a boundary object around which the different aspects of uncertainty where integrated. The regional organization, and the two local organizations may, according to King and Star (1990), exchange their information only through the process of continuous identification, gathering and weighing of heterogeneous information into something here formulated through bifuzzy classifications. This is an articulation of a "due process" (Star, 1987; King and Star, 1990), which has been described in a similar geographic setting by Harvey (1999). Within the due process, boundary objects sit in the middle of a group of participants trying to negotiate their divergent viewpoints. I imagine that the use of space as a boundary object will make it possible to apply multicriteria evaluation to perform concept mediation and thus perform a transformation between contexts within and between organizations. This remains to be fully tested, as also whether other types of boundary objects such as 'repositories', 'ideal types' or 'standardized forms' prove to be suitable for geographic applications.

Returning to the situation of a polygon overlay, this is actually a two-step process where the first step consists of identifying the lines that define the spatial limits of the boundary objects, and the second step is the actual negotiation process. That view of the polygon overlay process also conforms with the transformational view of GIS operations described by Chrisman (1997).

To conclude, spatial boundary objects are defined and used in current digital geographic information analysis. I therefore propose that the boundary object idea can be used for coordinating a specific objective, for example in a data transformation process from one context to another. Yet, it remains to prove whether the idea based on bifuzzy data integration presented here will contribute to a successful implementation of this proposition. It also remains to be verified in a wider setting if the proposed framework is capable of negotiating the different spatial conceptual frameworks, field and object based views.

Chapter

9 CONCLUSIONS

Summary of findings and objective fulfillment

Spatial decision support using geographic information systems has been severely limited by the problems of integrating different types of geographic data. Efforts directed towards formal specifications of data structures, increased access through data warehouses and content standards has made important contributions. Still, the problem of conveying the actual meaning of geographic phenomena across different databases has not until recently been tackled. This study has tried to investigate the matter of using old information to answer new geographic questions. First of all I made clear that many questions need to be answered using existing data and in most cases these will first need to be adjusted to fit the question. For geographic data an adjustment of existing data may involve changes in five dimensions, three spatial, time and theme.

Review of both theoretical and methodological aspects of integrating geographic data

In chapters 2 and 3 it was argued that spatial decision support using geographic information systems requires integration of geographic data. Presented examples and cited literature made clear that the process of geographic data integration still lack a firm theoretical basis and a full suite of tools based on such theories.

A translation between geographic abstractions of real world features was determined to, at least potentially, include changes of spatial, temporal and categorical resolution of constituent data sets. The apparent complexity of such translation processes motivated a research approach where each dimension of a geographic dataset was studied separately. Appropriate data for the experiments were compiled using already existing data described in chapter 4 and supplemental data collection.

Identification of important deficiencies or gaps in theory and/or methods for geographic data integration

Important deficiencies in current methods for geographic data integration were found. The issue of semantic uncertainty as an important quality aspect has received relatively little attention so far. Thus, the theoretical background on this issue was examined in detail in chapters 2 and 3. Also, the use of a traditional set theoretic approach to the semantic level modeling of geographic information was reported as problematic in these chapters. As a consequence, these questions initiated the research reported in chapters 5 and 6.

The classification and reclassification ambiguity found in chapters 5 and 6 can be seen as a kind of semantic uncertainty.

Chapter 5 demonstrated how changing the spatial resolution of a geographic data set cause both predictable and non-predictable effects and how these effects may vary for different environmental variables. The mixed pixel situation causes effects in the thematic dimension.

In the introductory parts of chapter 6 it was concluded that current representational techniques using crisp and fuzzy sets fail to address situations of classification uncertainty due to indiscernibility.

Identification of approaches that consider geographic context information.

Solutions and recommendations that promote a context sensitive use of existing geographic data were proposed in chapters 5, 6, 7, and 8.

In chapter 5 the studies of changing spatial resolution made clear that different environmental concepts vary in their sensitivity to changes of spatial resolution. This issue was further studied with a refined experimental design in chapter 7. From these studies no general solution to the spatial aggregation problem could be deduced. It remains clear however that any change of the spatial resolution of a dataset must evaluate the sensitivity to semantic effects for this change.

Chapter 6 demonstrated the possibility to represent (re)classification ambiguity due to indiscernibility using rough set theory. This method finds applications whenever operations involve changes in the categorical resolution of a geographic dataset and when the categories are translated by one-to-many relations. This chapter also showed how rough spatial data may be compared with other crisp or rough spatial data using extensions to the normal error matrix paradigm.

Chapter 7 presented a testing technique to evaluate semantic uncertainty often found in geographic data. The used method uses concepts of rough classification together with manual interpretations of landscape variables. The test design was suggested as a way to estimate semantic accuracy of commonly used land cover or land use categories at different scale levels.

Chapter 8 proposed the concept of bifuzzy classifications to enable data integration with different types of semantic uncertainty involved. This technique was proposed to be used together with existing methods of multi criteria evaluation to create a joint representation of crisp, vague and indiscernable uncertainties.

Suggested solution to support a context sensitive use of existing geographic data.

The theoretical background given in chapter 2 and 3 led to the construction of the Geographic Concept Topology. The arguments for this construct were given throughout these two chapters. The Geographic Concept Topology is a formalized representation of semantic interrelations. I suggest a joint use of fuzzy and rough extensions to traditional set theory as demonstrated in chapter 8. I further argue that this enable explicit representation of semantically richer relations between geographic concepts. The collected set of such explicit links consequently provides all interconnected data sets with a deeper geographical meaning.

From a general geographical point of view I propose that the GeCoTope framework enable the integration of location-based and object-based views. It was shown in chapter 8 that it is possible to extend several crisp, fuzzy, and rough transformations into a general transformation mechanism between different user contexts and hence between different groups or organizations. I also argue that the GeCoTope framework may serve as a mediator around which similarities and differences between different worldviews can be negotiated.

Demonstration of an application of a context sensitive integration of geographic data

In chapter 8 I demonstrate that the explicit representation of crisp, fuzzy and rough relations between independent datasets is a feasible alternative to translation and full integration of geographic datasets. I also argue that such a translation using predefined crisp, fuzzy and rough relations illustrate a kind of model generalization. The proposed framework enables the use of common ontologies and/or physically controlling factors at the desired level of abstraction.

Conclusions

- Spatial decision support using geographic information systems requires integration of geographic data and this process still lack a firm theoretical basis and a full suite of tools based on such theories.
- Geographic data integration requires translation between abstractions of real world features, which often include changes of spatial, temporal and categorical resolution of constituent data sets.
- Changing the spatial resolution of a geographic data set cause both predictable and non-predictable effects and these effects may vary for different environmental variables
- When changing the categorical resolution of a geographic dataset, it is possible to represent (re)classification ambiguity due to indiscernibility using rough set logic.
- Rough spatial data may be compared with other crisp or rough spatial data using extensions to the normal error matrix paradigm
- The use of rough classification methods together with manual interpretations makes it possible to evaluate the semantic uncertainty often found in geographic data.
- Integration of crisp, fuzzy and rough data enable spatial decision support systems to consider various aspects of categorical uncertainty.
- Explicit representation of crisp, fuzzy and rough relations between datasets is a viable alternative to translation and full integration of geographic datasets.
- Translation using predefined crisp, fuzzy and rough relations enable model generalization using controlling factors at the desired level of generalization.

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