Inferring Land Use from Remote Sensing Imagery
A context-based approach

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This doctoral thesis investigates the potential of classification methods based on spatial context to infer specific forms of land use from remote sensing data. The problem is that some types of land use are characterized by a complex configuration of land covers that traditional per-pixel based methods have problems classifying due to spectral heterogeneity. The problem of spectral heterogeneity is also present in classification of high resolution imagery. Two novel methods based on contextual information are evaluated, Spatial Relational Post-Classification (SRPC) and Window Independent Context Segmentation (WICS). The thesis includes six case studies in rural and urban areas focusing on the classification of: agricultural systems, urban characteristics, and dead wood areas. In the rural case studies specific types of agricultural systems associated with different household strategies are mapped by inferring the physical expression of land use using the SRPC method. The urban remote sensing studies demonstrate how the WICS method is able to extract information corresponding to different phases of development. Additionally, different urban classes are shown to correspond to different socioeconomic profiles, demonstrating how urban remote sensing can be used to make a connection between the physical environment and the social lives of residents. Finally, in one study the WICS method is used to successfully classify dead trees from high resolution imagery. Taken together these studies demonstrate how approaches based on spatial context can be used to extract information on land use in rural and urban environments where land use manifests itself in the form of complex spectral class and land cover patterns. The thesis, thus, contributes to the research field by showing that contextual methods can capture multifaceted patterns that can be linked to land use. This, in turn, enables an increased use of remote sensing data, particularly in the social sciences.

Keywords: land use, remote sensing, urban remote sensing, image analysis, segmentation, spatial context, land cover, land cover configuration, farming types, bark beetle, dead trees, forest inventory
List of papers

This thesis is based on the following papers, which are referred to in the text by their roman numeral.


III Nielsen, M.M. ‘Extraction of urban areas with different functions and underlying planning theories and practices using Window Independent Context Segmentation.’ Submitted to Environment and Urban Systems

IV Nielsen, M.M. ‘Socioeconomic residential profiles in urban areas classified by the WICS method.’ Manuscript

V Nielsen, M.M., Ahlqvist, O. ‘Classification of different urban categories corresponding to the strategic spatial level of urban planning and management using a SPOT4 scene.’ Submitted to Journal of Spatial Science

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## Abbreviations

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<td>GIS</td>
<td>Geographic Information System</td>
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<td>Object Based Image Analysis</td>
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Acknowledgments

Looking back it becomes clear that without the help and support of a number of persons and institutions this thesis would not have materialized.

First of all, I would like to express my deepest gratitude towards my supervisors Bo Malmberg and Anders Wästfelt. Thank you for believing in me and for all of the support, suggestions and patience throughout the years. I would also like to thank Professor Håkan Olsson for all of his helpful comments and suggestions during the final seminar. Thank you also to Ola Ahlqvist for your help and hospitality during my stay at Ohio State. I am also very grateful towards Camilla Årlin and Brian Kuns for all of the last minute language editing throughout all of these years. Thanks also to the co-authors whom I have not already mentioned: Marco Heurich, Tsegaye Tegenu and Anders Brun.

I also would like to thank the following institutions: Department of Human Geography at Stockholm University, Department of Geography at Ohio State University, the Sweden-America foundation, Riksbankens Jubileumsfond, Carl Mannerfelts foundation, Lillemor and Hans W:son Ahlmanns and Axel Lagrelius foundation for geographical research.
Introduction

The term remote sensing can be traced back to 1960 when it was first coined by Evelyn Lord Pruitt at the Office of Naval Research and Geography (ONR). The name of ONR’s aerial photo-interpretation project was too limited in its potential to incorporate the obvious future of the field, which included nonconventional photography (the term used at the time for multispectral images) and space-borne cameras/sensors.¹

Remote sensing can be defined as acquiring information on an object without actual contact with the object. The obvious example is how the human eye works. The term most commonly refers to observations of the earth’s surface from aircraft or spacecraft that gather information based on the electromagnetic energy reflected or emitted from the surface. Multispectral sensors measure the radiation in spectral bands with different wavelength ranges, meaning that each location has multiple values, one for each spectral band.

On July 23, 1972 the Earth Resources Technology Satellite (later known as Landsat 1) was launched. It was the first (civilian) satellite specially made for observations of the earth’s surface with multi-spectral-scanners. Landsat 1 acquired 300,000 images during its 6 years in service², and the research programs funded by NASA and the accompanying policies that allowed access to Landsat data regardless of political affliction³ were in many ways the starting point for the remote sensing research field.

As demonstrated by the number of articles registered with the topic ‘remote sensing’ in the Web of Science over the last decades (Figure 1), the remote sensing research field has grown at a notable rate since its early pioneer days.⁴

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¹ Pruitt 1979
² NASA 2011
³ Williamson 1997
⁴ Web of Knowledge 2014
Figure 1. Number of articles registered in the Web of Science with the topic 'remote sensing' (non-cumulative)

One important reason for this dramatic increase is the development of personal computers, which make it possible to analyze large datasets and the increasing plethora of geographical information available to the research and civilian communities. The emergence of powerful tools such as Google Earth and yellow pages types of homepages that not only address databases but also medium- to high-resolution satellite and aerial imagery have made the furthest reaches of the globe visible to the gaze of the public. In 2008 large portions of the Landsat satellite image library became available free of cost, and in Sweden, a free national satellite image database with continuous SPOT satellite data became available.

This increasing emergence of geographical data in recent years coupled with the continuous development of GIS software has led to enormous possibilities of geographical analysis. However, to a great extent, the social sciences have only been a sideline spectator (or non-contributor) instead of a willing participant in the remote sensing field, and the reasons for this seem to be numerous. In the book People and Pixels, Rindfuss and Stern\textsuperscript{5} present four key explanations.

I Many social scientists do not find the physical manifestations as interesting as the abstract variables that explain their appearance and transformation, which is not directly reflected in the electromagnetic spectrum.

II Social scientists tend to focus on why things happen instead of where things happen.

\textsuperscript{5} Rindfuss and Stern 1998
III  Difference in background and scientific tradition, technical barriers.

IV  A risk of marginalization for social scientist from their original field.

Point IV, the risk of marginalization for social scientists from their original field, must be put in a historical context. Rindfuss and Stern⁶ base their argument on interviews with scientists who made the ‘leap,’ presumably during the 1990s or earlier. In the 1990s, there was a heated debate between certain GIS scholars and human geographers, which was described by Nadine Schuurman⁷ as geography’s own civil war version of the 1990s ‘science war.’ The science war was a public debate raging between postmodernists and realists that became a part of mainstream culture after Alan Sokal’s⁸ fake publication ridiculing post-modernistic critiques.

In the geography civil war, the main argument from human geography against GIS was that it was a regression back to positivism while GIS users felt alienated and misunderstood. The intensity of the debate can be exemplified with Stan Openshaw’s statement that geographers that had disregarded the era’s computer developments were ‘technical cripples’⁹ and Peter Taylor’s assertion that GIS was ‘Positivist geography’s great revenge’¹⁰. The debate took a more gentle turn after the 1996 specialist meeting ‘Initiative 19: the social implications of how people, space, and environment are represented in GIS’ that was a mix of social geographers and GIS scholars. The essays from the meeting and a more nuanced debate, according to Schuurman, was a recognition that ‘GIS is a permanent feature in the geography landscape’ and ‘technology is always and irrevocably a social process.’¹¹

Subsequently, there has been a demand for implementing other forms of representation and geography within GIS. Michael Batty formulates this eloquently in the book Re-Presenting GIS:

‘If GIS is to be useful in articulating and operationalizing contemporary geographical theory, it must not only incorporate relations but also enable such representations to be focused on processes rather than structures. /.../getting such ideas into GIS is an enormous challenge for it is much easier to see GIS as providing some convenient form of visualization, data storage and manipulation technology rather than a vehicle on which to make contemporary geographical theory applicable and practicable.’¹²

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⁶ ibid.
⁷ Schuurman 2000
⁸ Sokal 1996
⁹ Openshaw 1991 p.624
¹⁰ Taylor 1990 p.211
¹¹ Schuurman 2000 p.583
¹² Batty 2005 p.150
Even though the citation above does not explicitly mention remote sensing, it might be an important key in understanding the lack of engagement from the social sciences in the remote sensing field.

As mentioned, the social sciences have not to a large extent been that engaged in the remote sensing field. Nevertheless important research has and is being done. For example, the influential collection of essays in the aforementioned People and Pixels summed up the research field at the time (1998) and focused on the issues of land cover and land use change, linking remote sensing images with census and survey data, urban attribute extraction and modeling, health, etc. More recently, Hall conducted an extensive survey of the use of remote sensing in the social sciences and identified five main categories: urban studies; demography, including population counts and population allocation; archeology; land use and land cover change; war and conflict studies.

In this thesis, an aspect of Rindfuss and Stern’s first point will be explored, i.e. that many social scientists do not find the physical manifestations as interesting as the abstract variables that explain their appearance and transformation, abstract variables which is not directly reflected in the electromagnetic spectrum. I would argue that the historical lack of methods that can extract information of interest for social scientists has been a factor for the lack of engagement. As more methods become available that incorporate spatial information (not just analyzing the electromagnetic spectrum) and are shown to be capable of extracting information of interest for the social sciences, there will be a possible opening for at least part of the social sciences. Thus, in this thesis, two novel methods are evaluated that utilize contextual information for image classification.

### Image classification

As a consequence of the enormous quantities of data produced by the Landsat program and its successors, semiautomatic methods were required for the classification and interpretation of the information as traditional visual interpretations were slow and subjective.

Gao lists seven photo elements that can be used to interpret/classify an image, and these are listed below with a short description of how they are represented in a digital image.

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13 Hall 2010
14 Rindfuss and Stern 1998
15 Gao 2009
16 Note that Olson 1960 lists nine basic elements for interpretation of photographic records, instead of location/association/contexture Olson differs between site and association, and also adds resolution as the ninth element
1. Tone/color: tone is the gray value representing the amount of radiation measured by the sensor in a specific spectral range. In a multispectral image, color is the combination of values from different spectral bands in an individual pixel.
2. Size: physical size of an object in the image. The spatial scale of the image determines how many pixels a given object is made up of.
3. Shape: outline or configuration of an object.
4. Shadow: shadow is often problematic for image classification.\footnote{This is not always true; see Comber, et al 2012b}
5. Texture: spatial variation in pixel values measured in a contiguous group of pixels.
6. Pattern: regular spatial arrangement of the same object.
7. Location/association/contexture: spatial relationship between features.

The main method used for classification has been per-pixel based, i.e., a classification based on each single pixel’s spectral characteristics treated in isolation without accounting for its spatial relationship. Thus, this type of classification only considers the tone/color photo element. Although the per-pixel based approach has been the dominant approach, alternative and complementary methods were part of the research field from early on. One example is texture, or the spatial variation in pixel values measured in contiguous groups of pixels. Haralick et al. published a seminal paper\footnote{Haralick, Shanmugam and Dinstein 1973 (see also Haralick’s 1979 review of different statistical and structural approaches to texture)} concerning the computation and use of textural features for image classification in 1973, just one year after the launch of Landsat 1. A context algorithm for image interpretation was presented by Welch and Salter\footnote{Welch and Salter 1971} in 1971 in which neighboring pixels influenced the final classification of the pixels, it was partly based on Chow’s\footnote{Chow 1962} pattern recognition work from the early 1960s. Another early example of the use of context was Swain et al.’s\footnote{Swain, Vardeman and Tilton 1981} paper in which they used context arrays to determine which neighboring pixels are allowed to influence the final classification, which capitalized on certain land covers being more likely to occur in certain configurations. Image segmentation most often refers to the portioning of an image into homogenous patches (segments) and has been used since the 1970s. In 1978, Sklansky\footnote{Sklansky 1978} published an overview of the then current segmentation methods, and in 1985, Haralick
and Shapiro\textsuperscript{23} published an influential paper in which a number of segmentation techniques were described and demonstrated. Ancillary data has also been used to enhance classification accuracy; for example, Stahler et al.\textsuperscript{24} used topographic data in the late 1970s for a rule-based classification to improve forest land cover classifications. Similarly, expert systems, a branch of artificial intelligence research from the 1960s\textsuperscript{25} that can be described as a computer system that can store human knowledge (commonly spectral, spatial and/or external) and utilize the knowledge in question to classify an image based on rules\textsuperscript{26}, have been used. Artificial neural networks have also been used since the late 1980s, mimicking how neurons act in the human brain (see Atkinson and Tatnall\textsuperscript{27} for a more detailed description).

When using per-pixel-based classifications, the goal is commonly to transform the pixel values in the raw image data into meaningful land cover classes\textsuperscript{28}. Land cover can be described as the physical material on the surface of the earth\textsuperscript{29}, and different physical materials have different characteristics and thus reflect, absorb and/or emit electromagnetic energy in a different manner, which makes it possible to classify remote sensed images\textsuperscript{30}. Per-pixel-based classification of land cover is then based on the assumption that the land cover to be mapped has identifiable spectral characteristics that can be extracted from the multispectral bands\textsuperscript{31}. The innate restriction associated with per-pixel based classification is that the analysis stops at the smallest unit of the image, the individual pixel. To extract more complex patterns or configurations of geographical phenomena consisting of a number of different land cover classes with varying spectral characteristics, you also have to take spatial information into account.

Van der Kwast et al.\textsuperscript{32} describe two main phases of methodology development since the 1990s that involve the use of spatial information. First are kernel-based contextual classification algorithms, such as Barnsley and Barr’s\textsuperscript{33} SPAtial Reclassification Kernel (SPARK), which uses a moving window reclassification procedure based on an evaluation of the configuration of adjacent pixels. Although these algorithms show promising results, they suffer from drawbacks, such as smoothed boundaries and the impact of different window sizes. The arrival of high spatial resolution multispectral

\textsuperscript{23} Haralick and Shapiro 1985
\textsuperscript{24} Strahler, Logan and Bryant 1978
\textsuperscript{25} Liao 2005
\textsuperscript{26} Goodenough, et al 1987, Gao 2009, Liao 2005
\textsuperscript{27} Atkinson and Tatnall 1997
\textsuperscript{28} Gao 2009
\textsuperscript{29} Di Gregorio 2005
\textsuperscript{30} Lillesand and Kiefer 2000
\textsuperscript{31} Gao 2009
\textsuperscript{32} van der Kwast, et al 2011
\textsuperscript{33} Barnsley and Barr 1996
imagery in the early 2000s combined with increased computational power paved the way for the introduction of object based image analysis (OBIA), which is also called object based classification.

OBIA’s roots can be traced back to the 1970s when it was all but abandoned in favor of more easily implemented per-pixel based classifications. However, the growing demand from GIS users to be able to extract meaningful objects from high resolution remote sensing imagery, especially in urban areas, led to a renewed interest and re-emergence of the term. Hay and Castilla propose that OBIA ‘is a sub discipline of GIScience devoted to partitioning remote sensing (RS) imagery into meaningful image-objects’. In OBIA, the goal is to make classifications based on attributes that mimic the human interpretation of an image, including size, shape, texture and context. In practice, these ‘meaningful image-objects’ are built up by patches of uniform tone and texture created by some form of segmentation routine. After the initial segmentation, the object can be built up using different measurements of shape, texture, topology, heterogeneity, and spatial relationships of the patches.

The success of OBIA indicates that there is potential for methods incorporating more than tone/color. In this thesis two novel methods are evaluated that are similar to OBIA as they also utilize contextual information, e.g., the spatial relationship between features, are evaluated: spatial relational post-classification (SRPC) and Window Independent Contextual Segmentation (WICS).

Spatial Relational Post-Classification
The SRPC method was developed by Wästfelt, and the method is partly inspired by Gurney and Townshend’s description of context:

‘the context of a pixel (or group of pixels) refers to its spatial relationships with pixels in the remainder of the scene/classification error might be reduced by using contextual information, but also that additional classes could be recognized by separating pixels with the same spectral properties into additional classes according to their context’.

SRPC is a post classification routine based on an initial standard spectral per-pixel based classification. SRPC utilizes geographical distances between spectral classes in a training area to construct a set of spatial relational crite-
ria that are used in a post-classification (post refers to the fact that a per-pixel based classification has already been conducted) process to identify places with the same spatial and spectral arrangement as the study area. Applying this concept means that it is possible to sort among pixels belonging to the same spectral class and to only retain pixels that have a specific spatial context, as described above by Gurney and Townshend.

Starting from a spectrally classified image, the training phase of the SRPC procedure consists of the extraction of spatial context information from training area(s). The context information used for the SRPC method as a spatial criterion is the largest nearest neighbor value for each class to all other classes present in the training area (see Figure 2).

In the post-classification stage, every pixel in the image that has a spectral class represented in the training area is evaluated based on its nearest neighbor distance to different spectral classes and the largest nearest neighbor distances found for the pixels in the training area. If a pixel outside of the training area has a nearest neighbor distance that is larger than the largest nearest neighbor distance found in the training areas for that spectral class, it is classified as having a different spatial context compared to the pixels of the training area. Therefore, although it has the same spectral class as a pixel in the training area, it is deemed to represent a different feature because of its different spatial context (see Figure 2).

Therefore, SRPC uses a spectral criterion and contextual criterion to determine what a specific pixel represents. Only pixels that have a spatial context that corresponds to the spatial context of pixels in the training area are considered as signaling the presence of on-the-ground features similar to those found in the training area.

Inherent to the SRPC approach is the extraction of the spatial configuration of pixels and an ability to consider relative patch size. Figure 3 is an example of two different patch configurations: the left example consists of two large patches and the right consists of 32 perfectly mixed patches. As shown in Figure 3, the largest nearest neighbor value differs, which implies that SRPC can differentiate between landscapes that consist of large spatial elements and landscapes that consist of small spatial elements.
**Spatial Relational Post-Classification**

1. The largest nearest neighbor value for each class to all other classes present in the training area is the context information that is used for the SRPC method as a spatial criterion. The largest nearest neighbor value is calculated by first calculating all nearest neighbor values between classes in the training area, keeping only the largest for each neighbor relation.

   ![Training area diagram](image)

   - Largest nearest neighbor values based on the training area:
     - A→B = 2
     - A→C = 3
     - B→A = 1
     - B→C = 1
     - C→A = 2
     - C→B = 1

   - Distance measured in pixels

   - 0
   - 1
   - 2

2. The largest nearest neighbor values from the training area are used as spatial relational criteria to identify pixels that have similar spectral characteristics and spatial context. The spatial relational criteria are applied by only keeping those pixels whose nearest neighbor values are equal to, or smaller than, the largest-nearest neighbor values extracted from the training area.

3. In this example the nearest neighbor values which are too high are grey and only the two pixels whose two nearest neighbor values both are within range pass all of the spatial relational criteria.

4. So why use the largest nearest neighbor instead of the nearest neighbor? If the nearest neighbor value based on the training area had been used instead of the largest nearest neighbor value, only the C pixel (third one down) would have passed the spatial relational criteria, as the nearest neighbor for A→B in the training area is equal to one and no A pixel outside the training area is within a distance of one from a B pixel. In fact, not even all of the pixels in the training area would pass the contextual criteria if the nearest neighbor value was used instead of the largest nearest neighbor.

Figure 2. Example of SRPC criteria extraction and implementation
Figure 3. Example of two different patch configurations

Window Independent Context Segmentation

The WICS method was developed by Nielsen, Wästfelt and Malmberg\(^{40}\). The WICS method is similar to SRPC because it starts from a spectrally classified image and derives its information on the context by finding nearest neighbor distances to different spectral classes. The main difference between WICS and SRPC is that nearest neighbor distances are not used in evaluations based on post-classification criteria; instead they are used to group pixels into classes that differ in spatial context. The WICS method is similar to the aforementioned OBIA methods because it utilizes spatial information and different because it uses the spectral information in individual pixels along with the geographic distances between pixels. The spatial information approximates how different pixels are spatially related to each other, i.e., the surrounding spatial context of each pixel. The final classification is then based on the similarity of the spatial context of pixels. This context-based classification explains the ‘Context Segmentation’\(^{41}\) in WICS. This method is ‘Window Independent’ because it is not a moving window method. WICS does not use a fixed window; instead, the method calculates an approximation of the spatial surroundings for each pixel based on the geographic distances between different pixel categories.

The WICS procedure is broken down into four steps (Figure 4) assuming that the input data are a multispectral satellite image or a CIR or RGB aerial photo. If the input data already have defined categories (not necessarily spectral based), the first step is skipped.

Step 1 reduces data (for example, a multispectral satellite image) to a manageable size. For example, this could be performed through a supervised or unsupervised spectral classification. Data reduction is a necessary procedure because the next step constitutes a calculation of distances between different pixels based on the spectral classes to which they belong.

\(^{40}\) Malmberg, Nielsen and Wästfelt 2011

\(^{41}\) In this case, segmentation is not used as it was in the aforementioned creation of image objects; rather, it is used in the broader sense of labeling pixels in an image.
Step 2 consists of the calculation the nearest neighbor distance to all of the spectral classes for each individual pixel in the image. These distances are then used to create a contextual feature vector in the next step. A distance threshold can be applied to limit the effect of extreme values. Distance transformations, such as log, can be used to give higher weights to shorter distances.

Step 3 creates a contextual feature vector for each pixel in the image. A contextual feature vector consists of the geographical nearest-neighbor distance from a specific pixel to pixels of all other spectral classes; therefore, it is a way of describing the contextual surroundings for each individual pixel. The distance to each individual class is a dimension in a multidimensional feature space, which means that all of the pixels in the image have a location in the multidimensional feature space that can be analyzed with the help of clustering techniques in the next step.

In step 4, the contextual feature vectors are classified using clustering techniques that group together those pixels with similar contextual feature vectors to create new classes that are based on contextual information. This can either be supervised or unsupervised. Supervised would entail the identification of a number of cluster centers with the help of training areas. A basic example is an area of forest that has been marked as a training area for the class forest and an urban area that has been marked as urban. Based on the contextual feature vectors covered by the training areas, a mean cluster center is calculated. All of the contextual feature vectors are then compared to the mean cluster centers and is assigned the closest center.

Unsupervised classification includes the common method of the K-mean cluster analysis. The user decides the number of clusters (output classes). For each cluster, a mean vector is in the multidimensional space created by the contextual feature vectors. The dimensions are the distance to each individual spectral class, so if there are ten classes, this equals ten dimensions, and each pixel has a position in this ten dimensional space. Then, all pixels (usually a sample is used) with the shortest Euclidian distance to a specific mean vector in the multidimensional space is assigned to that cluster. New mean vectors are then calculated based on the contextual feature vectors of the pixels belonging to the different clusters, and once again, all pixels are assigned a cluster based on the shortest Euclidian distance to the new mean vector. The process continues to move the means (migrating means technique) until the clusters are stable, i.e., a minimum number of pixels are changing clusters. (Jensen, et al 2009)
In Figure 5 the WICS procedure is described from the perspective of a single pixel, and the number of values it is associated with is specified at different stages.

One of the main differences between the SRPC method and WICS method is the difference of importance placed on an individual pixel’s spectral class (as a result of the initial spectral classification) for the determination of the final classification. In the SRPC method, the pixel’s initial spectral class is crucial because only the spectral classes found in the training area are
evaluated based on the relational spatial criteria. This then means that if a pixel belongs to a spectral class not found in the training area, it is not even considered. In the WICS classification, the pixel’s initial spectral class does not influence the final classification because the classification is based on the pixels distance to spectral classes in its surrounding\textsuperscript{44}. The WICS method can therefore be compared to a person who stands in one spot taking in the surroundings, not looking underneath their feet, and based on the information gathered, make a classification of the landscape. In contrast, the SRPC method can be likened to a person who looks for a specific phenomenon \(x\) and decides that the components are \(y\) and \(z\); so they travel to each place (in a given area) that contains \(y\) or \(z\) and are blind to all other land surfaces, and they decide that if \(y\) is within a given range of \(z\), and \(z\) is within a given range of \(y\), they are standing on phenomena \(x\).

Aim

The aim of this thesis is to investigate the potential of classification methods based on spatial context to infer specific forms of land use from remote sensing data. The problem is that some types of land use are characterized by a complex configuration of land covers that traditional per-pixel based methods have problems classifying due to the spectral heterogeneity associated with the land use in question. Closely associated to the problem of spectral heterogeneity is the classification of remote sensing data with a high spatial resolution. The six case studies presented in paper I to VI focus on the following three tasks:

- classification of different types of agricultural systems;
- classification different types of urban characteristics; and
- classification of dead wood in forest areas from high resolution imagery.

Classification of different types of agricultural systems

The complications of mapping different types of agricultural systems are connected to the concepts of land cover and land use.

Land cover refers to ‘the observed (bio)physical cover on the earth’s surface,’\textsuperscript{45} whereas land use is ‘the arrangements, activities and inputs people undertake in a certain land cover type to produce, change or maintain it’\textsuperscript{46}. Land cover can be determined by direct observation; this in contrast to land

\textsuperscript{44} this can be modified; for example, one could assign the distance of 0 to the spectral class to which the pixel belongs
\textsuperscript{45} Di Gregorio 2005 p.3
\textsuperscript{46} ibid. p.3
use, which can only be determined by proxy of a socio-economic interpretation of activities\textsuperscript{47}. While land cover has a major role in physical environmental models, the concept of land use is more relevant in the field of planning and policy\textsuperscript{48}. Fisher et al.\textsuperscript{49} argue that up until the 1970s, it was considerable more common to map land use compared to land cover. This changed in the early 1970s when the aforementioned Landsat 1 satellite was put in orbit. There were substantial advantages associated with satellite imagery because it was multi spectral and had a high temporal frequency and (relatively) low cost and covered large areas. The low spatial resolution of the early satellite images combined with per-pixel based methods used for classification led to problems of classifying land use, so the focus was shifted towards land cover. Consequently, we had a period of land cover mapping rather than land use mapping and a period that has been data- rather than demand or application driven\textsuperscript{50}.

Land cover is often mapped using per-pixel based spectral classification. This means that each image pixel in the remote sensing data is analytically evaluated and assigned to a spectrally distinct class and then associated with an identifiable real world concept. This assumes, as previously mentioned, that the land covers to be mapped have identifiable spectral characteristics that are possible to extract. However, even if this is the case, there is always the possibility of complications because no one classification system can accurately reflect the social or natural world\textsuperscript{51}, and notions of different types of land cover can be both politically and socially constructed\textsuperscript{52}. Similarly, Comber and Fisher argue that geographical information is interpreted from personal and group conceptualizations of the world, so it is always subject to indeterminacy and relativism\textsuperscript{53}.

Vejre et al. describe land use as a reflection of the physical consequences of societal demands on land territories\textsuperscript{54}. Although land use relates to physical form, Bibby and Shepherd argue that it actually is social purpose, so land use may therefore be regarded ‘as intension projected upon physical reality through the medium of natural language’\textsuperscript{55} [italics in original]. Similarly, Couclelis argues that purpose is fundamental to the semantics of land use and relative to the observer\textsuperscript{56}, and she further suggests that purpose might be seen as ‘the interface between the world of geospatial entities on the one

\textsuperscript{47} Fisher, Comber and Wadsworth 2005
\textsuperscript{48} Comber 2008, Fisher, Comber and Wadsworth 2005
\textsuperscript{49} Fisher, Comber and Wadsworth 2005
\textsuperscript{50} ibid.
\textsuperscript{51} Bowker and Star 1999
\textsuperscript{52} Crampton 2001, Perkins 2003
\textsuperscript{53} Comber, Fisher and Wadsworth 2005
\textsuperscript{54} Vejre, et al 2007
\textsuperscript{55} Bibby and Shepherd 2000 p.585
\textsuperscript{56} Couclelis 2010
hand and the social world of intentional agents on the other. Consequently, land use must primarily be seen as socially driven. Therefore, land use seen as social purpose cannot be reduced to a spectral characteristic, but its physical expressions/consequences can be recognized and thus inferred, analyzed and interpreted. Couclelis states that even if no human presence might be observed in a landscape scene (her example being an agricultural landscape and a streetscape), human purpose is ‘reflected’ and interpreted by an observer. In other words, the purpose can be interpolated through what Couclelis calls ‘functional spatial relations’. Therefore, it is often the results of a specific land use rather than the land use itself that can be observed. The relationship between land cover and land use can be exploited as land cover can be the cause, constraint or consequence of land use, but at the same time, land use cannot always be directly inferred from land cover. Thus, information on land use is often not readily observable from remote sensing data without insights into societal aspects connected to economic, institutional, cultural, legal, and historical factors. Some land cover has a one-to-one relationship to land use; however, most types of land use has a many-to-many relationship and may consist of a configuration of different land covers.

In rural settings, land use connected to agricultural systems produces a noticeable effect in terms of the impact on physical characteristics such as vegetation, ground cover, structures, etc. that may be readily described using land cover concepts. Therefore, different agricultural systems often produce a distinct spatial configuration of local land covers. For example, presupposing a theoretical flat landscape, most labor intensive and manure demanding land use is located close to farmsteads while less labor and manure demanding land uses are located farther away. Hence, Wästfelt and Arnberg argue that different agricultural production specializations are expressed in a specific (although not necessarily exclusive) spatial structure that can be interpreted as the agricultural specialization.

To analyze and classify land cover, which is the physical matter present at a given geographical location, the added information of its spatial surrounding is not needed because it has no bearing on the physical matter being classified. However, to classify land use connected to different types of agricultural systems, we need insights into societal aspects connected to economic, institutional, cultural, legal, and historical factors. Some land cover has a one-to-one relationship to land use; however, most types of land use has a many-to-many relationship and may consist of a configuration of different land covers.

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57 ibid. p.1796
58 Couclelis 2009 p.347
59 Cihlar and Jansen 2001
60 ibid.
61 Lillesand and Kiefer 2000
62 Cihlar and Jansen 2001
63 Comber 2008
64 Chisholm 1973
65 Wästfelt and Arnberg 2013
66 At least in theory; note that spatial surroundings can help manage misclassifications
tural systems, the spatial context is increasingly important because the same physical matter can be present in many different types of land use. Additionally, the same geographical location can be connected with a number of different types of land uses. These two characteristics of land use in which (1) the same land cover can be present in different types of land use and (2) the same location can be the site of different land uses\textsuperscript{67} complicates the classification. These two complications are what the SPRC method tries to solve by enabling the separation of similar land cover classes into different target classes and allowing for simultaneous overlapping land uses by the iterative use of different training areas.

To better understand the SRPC method’s use of spatial criteria to model the physical consequences of land use, it could be helpful to compare the SRPC method to Peter Gärdenfors\textsuperscript{68} metatheory of conceptual spaces. Although Gärdenfors’ work is a product of and for the cognitive sciences, it can be used to formally model geographical phenomena\textsuperscript{69}. Following Gärdenfors’ theory, a conceptual space is constructed of $n$ qualitative dimensions, and each dimension corresponds to a specific property of the concept being modeled.

‘The dimensions form the framework used to assign properties to objects and to specify relations among them. The coordinates of a point within a conceptual space represent particular instances of each dimension, for example, a particular temperature, a particular weight, and so forth.’\textsuperscript{70} [italics in original]

The concepts being modeled in the conceptual space are regions denoting the boundaries for inclusion or exclusion of a given object based on its properties. Applying conceptual space to the concept of land use, agricultural systems that are characterized by a specific configuration of land covers could be modeled in the following way using the SRPC method:

- The framework is the geographical distances to the different spectral classes;
- Each pixel is an object;
- The object is represented as a point whose properties are its nearest neighbor values, which produce a coordinate in the conceptual space;
- The largest nearest neighbor values extracted from the training area are used to construct the region in the conceptual space representing a specific concept, in this case a specific agricultural system; and

\textsuperscript{67} Fisher, Comber and Wadsworth 2005, Comber 2008
\textsuperscript{68} Gärdenfors 2000
\textsuperscript{69} For example, see Ahlqvist’s paper using fuzzy and rough sets; Ahlqvist 2004
\textsuperscript{70} Gärdenfors 2000 p.6
• All points inside of the region denoting the concept are identified with the specific concept, and these points, i.e., pixels, are reclassified and identified with the specific agricultural system.

Thus, the theory of conceptual spaces can shed some light on how the information from the training area is used to describe a concept, which is then applied on a larger data set.

To further understand how the SRPC method operates when identifying agricultural systems, parallels can be made to Couclelis’ plea for an inclusion of more modes of inference in GIS. Coculelis argues that the capabilities of GIS are limited by its ability to capture function and purpose and suggests that an inclusion of abductive modes of inference in GIS, in addition to the prevalent deductive and inductive modes, would lead to a more comprehensive approach to spatial thinking. Abduction was first expounded on by Peirce in the late 19th century and results in a possible explanation, or hypothesis, for a given situation such that the explanation fulfills a given set of criteria or constraints. To exemplify the three different forms of inference, Peirce suggests that the classical syllogism Barbara is not the most suitable and instead proposes the use of Rule, Case and Result. In the well-known bean bag case, Peirce uses the Rule, Case and Result scheme to exemplify the difference between deductive, inductive and abductive inference:

**Deduction**

*Rule:* you know that all beans are white in a specific bean bag.

*Case:* you take a handful of beans from the bag.

*Result:* you know that the beans in your hand are white

**Induction**

*Case:* you take a handful of beans from a bag not knowing the color of the beans in the bag.

*Result:* all beans in your hand are white.

*Rule:* you think it is probable that all beans in the bag are white.

**Abduction**

*Rule:* in a room full of bean bags, you know that one of the bags only contains white beans.

*Result:* on a table in the room, there lays a handful of white beans.

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71 Couclelis 2009
72 ibid.
73 At this stage, Peirce used the term hypothesis instead of abduction (see Peirce 1878 p.452); he started to use the term abduction later.
74 If x is y; y is z; thus x is z.
75 It is most suited for illustration of deductive inference.
76 ibid.
77 ibid. p.472, Nubiola 2005
Case: you think it is plausible that the beans are from the bag with only white beans in it.

Couclelis suggests that the practice of abductive inference could be used to ‘get at the hidden underlying plan that ties together functions and purposes of a human configured feature in the landscape, its spatial organization, and any activities relating to it that we may be able to observe’\textsuperscript{78}. I would argue that the plans surrounding agricultural systems are not hidden; instead, they are usually readily observable in the landscape as a consequence of a specific land use. However, one must know what to look for, meaning that the spatial relations must be codified into a Rule. For example, when surveying a landscape, if one has an idea of how different agricultural systems correspond to different spatial configurations (Rule), then observations of the spatial configuration at a specific place (Result) may lead one to make a plausible guess concerning the agricultural system present at the specific place (Case). Based on Couclelis’ description of how abductive inference can be used to identify land use\textsuperscript{79}, I argue that SRPC is an example of a method using abductive inference following the Rule, Case and Result scheme.

Rule: the specific land use $x$ in the training area(s) has the spatial configuration $y$ that is translated into the spatial relational criteria of SRPC

Result: the pixels $z$ pass the relational criteria from the training area, thus are sufficient similar to the spatial configuration $y$

Case: it is plausible that the pixels $z$ are land use $x$ as they are sufficient similar to the spatial configuration $y$

Note that abductive inference is subject to converse error (a.k.a., affirming the consequent); just because one land use has specific spatial configuration does not mean that other land uses or other geographical phenomena cannot have the same spatial configuration\textsuperscript{80}. Therefore, over classification using the SRPC method could be seen as a converse error, i.e. wrongly inferring that a pixel belong to the same land use that is found in the training area as a result of it having similar spatial relational characteristics. In other words, abduction results in plausible inference compared to the certain inference of deduction and the probable inference of induction\textsuperscript{81}. However, Couclelis argues that the amount of information to be obtained also differs be-

\textsuperscript{78} Couclelis 2009 p.353
\textsuperscript{79} ibid. p.354
\textsuperscript{80} Other bags might only contain white beans or the white beans on the table might be from multiple bags.
\textsuperscript{81} ibid.
between the modes of inference, with the smallest amounts for deduction and largest amounts for abduction\textsuperscript{82}.

In paper I and II in this thesis, the SRPC method is evaluated as a tool for the extraction and classification of specific types of land cover configurations produced by different types of agricultural systems. This concept differs from most other forms of land use mapping that are predominately general, focusing on urban/built up or agricultural landscapes, or specific, focusing on pasture/hay, row crops, small grain, etc. The SRPC method is used to combine the notion of many-to-many relations between land cover and land use with the understanding that different farming systems give characteristic spatial imprints in the form of land cover.

**Classification of different types of urban characteristics**

Urban remote sensing can be defined as the ‘measurement of surface radiance and properties connected to the land cover and land use in cities’\textsuperscript{83}. Fugate et al. argue that urban remote sensing data gives an unprecedented opportunity to understand the connection between the physical environment and the social lives of urban residents\textsuperscript{84}. Consequently, urban remote sensing has the potential to ‘lead to improved understanding of the relationship between the built environment and numerous urban demographic and social process’\textsuperscript{85}. Similarly, Longley\textsuperscript{86} describes urban remote sensing as a meeting place for the social and physical sciences. Nonetheless, urban remote sensing has primarily focused on the dynamics of biophysical features (i.e., land cover) rather than the social sciences per se\textsuperscript{87}. Thus, there is a need for new methods to be developed that extract information in such a way that they accommodate a number of research problems connected to the analysis of urban areas and different social processes\textsuperscript{88}.

The use of per-pixel based methods for spectral classification of remote sensing data in urban areas is challenging because of the high spectral variability in urban materials and the fact that a specific spectral signature might appear in a number of different contexts in the urban landscape. Consequently, the classification reliability has been lower in urban areas than in more rural settings.\textsuperscript{89}

\textsuperscript{82} ibid.
\textsuperscript{83} Netzband and Jürgens 2010 p.5
\textsuperscript{84} Fugate, et al 2010
\textsuperscript{85} ibid. p.133
\textsuperscript{86} Longley 2002
\textsuperscript{87} Gatrell and Jensen 2008
\textsuperscript{88} Netzband and Jürgens 2010, Schöpfer, Lang and Strobl 2010
Although the classified data delivered by per-pixel based methods are valid, they do not address the strategic problems and issues associated with urban settings. Therefore, even if the accuracy concerns of per-pixel-based classifications in urban areas are addressed, professionals in the urban field tend to be less interested in the resulting distribution of land cover. This is especially true in the social sciences where information on the spatial and structural properties and different indicators of social and economic functions are central to analysis. Therefore, it is typically the specific contextual arrangements rather than the spectral characteristics in the individual pixels that define urban features. Although the same problems associated with inferring land use from land cover in the aforementioned rural areas holds true in urban areas, Barnsley et al. argue that the many categories of urban land use can be recognized by the characteristic spatial patterns of land cover.

Longley’s statement in 2002 that the urban remote sensing field is ‘largely oblivious to function’ might be a valid observation; however, a number of studies have been conducted that analyzed the functions in urban areas based remote sensing data: Batty and Longley used fractal geometry in their publication on fractal cities; Barnsley and Barr conducted a number of studies focusing on inferring urban land use based on land cover using different methods; the SPatial Reclassificaton Kernel (SPARK) which examines the frequency and spatial arrangements of land covers inside of a square kernel, a graph-theoretic data model and an analysis of morphological properties of buildings to extrapolate land use; Herold et al. used spatial metrics and texture measures to map urban land use; Stefanov et al. used expert systems combining ancillary data with logical decision rules to monitor urban land cover change; Rahed et al. used spectral mixture analyses to map the physical composition of urban morphology; Wu and Murray used the vegetation-impervious surface-soil (VIS) model to monitor urban areas and argued that the distribution of impervious surfaces can be used for esti-

90 Donnay, Barnsley and Longley 2001, Longley 2002
91 Jansen and Di Gregorio argue that the problems might be more severe in urban areas because there are less one-to-one relationships between land cover and land use. Jansen and Di Gregorio 2003
92 Barnsley, Møller-Jensen and Barr 2001
93 Longley 2002 p.237
94 Batty and Longley 1994
95 Barnsley and Barr 1996
96 Barr and Barnsley 1997, Barnsley and Barr 1997
97 Barr, Barnsley and Steel 2004
99 Stefanov, Ramsey and Christensen 2001
100 Rashed, et al 2001
mating different socio-economic factors, such as population density and social conditions\textsuperscript{101}.

Since the early 2000s, the aforementioned field of OBIA\textsuperscript{102} has arguably become the most important field connected with classification of data from urban remote sensing. An early example is Bauer and Steinnocher’s study using eCognition for land use classification in urban areas\textsuperscript{103}. Comber et al. classified land cover with the help of OBIA and then used Walktrap, Spinglass and Fastgreedy algorithms to identify areas of homogenous land use\textsuperscript{104}. Ban et al. and Ban and Jacob used OBIA to classify urban land cover and land use from a fusion of multispectral imagery with high spatial resolution and synthetic aperture radar data\textsuperscript{105}. In a recent publication, Blashke et al. go so far as to propose that OBIA is a new paradigm in remote sensing and geographic information science\textsuperscript{106}.

One of the interesting aspects of the methodologies going beyond the per-pixel based approach in remote sensing is its possible theoretical consequences. Methodologies with the potential to include contextual information, such as OBIA, expert systems and the WICS method, are interesting in that they open up for a theoretical framework that goes beyond land cover.

I suggest utilizing Bibby and Shepherd’s call for a new ontology in GIS and remote sensing concerning land use questions, which was primarily founded on different writers’ interpretations of Aristotle\textsuperscript{107}. Bibby and Shepherd (and later Couclelis,\textsuperscript{108} who elaborates on their paper) evaluate the ontology surrounding remote sensing and GIS utilizing Moravcsik’s four-fold view of the meaning of objects\textsuperscript{109}, and they argue that the ontology has been conflated to only the Formal dimension in GIS, namely the ‘physical attributes that distinguish one type from another’\textsuperscript{110}. The other three dimensions are the Constitutive, i.e., the composition of things, the Telic, i.e., the function and purpose; and the Agentive, i.e., the processes that produce things. These dimensions are by nature of interest to a great spectrum of users of remote sensing data, especially within the social sciences. Couclelis suggests that GIS in its current form is limited in its ability to investigate phenomena associated with the Telic and Agentive dimensions as ‘\textit{the thinking behind the understanding of function and purpose is not analytic but synthetic and}\textsuperscript{110}

\textsuperscript{101}Wu and Murray 2003
\textsuperscript{102}Blaschke 2010
\textsuperscript{103}Bauer and Steinnocher 2001
\textsuperscript{104}Comber, Brunsdon and Farmer 2012a
\textsuperscript{105}Ban, Hu and Rangel 2010, Ban and Jacob 2013
\textsuperscript{106}Blaschke, et al 2014
\textsuperscript{107}Blaschke, et al 2014
\textsuperscript{108}Bibby and Shepherd 2000
\textsuperscript{109}Couclelis 2010
\textsuperscript{110}Moravcsik 1975
\textsuperscript{110}Bibby and Shepherd 2000 p.584
normative, whereas GIS is foremost an analytical tool [italics in the original].

I would argue that contextual methods can incorporate the Constitutive dimension into the already inherent Formal dimension (physical attributes that discern one thing from another, such as electro-magnetic reflection), and the combination reflects aspects of the Telic dimension that are interesting to the social sciences. The study of relationships enables the extraction of information with a more complex conceptual structure than traditional per-pixel based methods, and through the Telic dimension, such studies might shed light on urban remote sensing’s blind spot concerning function.

Two case studies in this thesis (paper III and V) identify different types of urban areas relevant for urban planning and management (UPM). Sliuzas et al. argue that urban planning and management operate on two spatial levels, local and strategic, with different urban remote sensing requirements. The local urban planning and management level is concerned with specific site planning and monitoring. The focus on the local level is therefore on the recognition of objects, such as individual buildings, and OBIA is commonly used for classification. A recent example is Bhaskaran et al.’s use of a combination of per-pixel based and object-based methodologies to increase the classification accuracy of white roofs and vegetation (important factors for heat islands) in parts of Queens and Brooklyn, New York.

The strategic urban planning and management level is focused on the planning and monitoring of general land use (zoning) and involves different categories of urban land use and functions, such as different types of residential, industrial and commercial areas on an aggregated city block scale. As a result of the poor results of standard per-pixel based classification methods in urban areas on the strategic level, visual interpretations of remote sensing data are often preferred.

Urban remote sensing is used for both spatial levels, but the levels require different data sources. Following the scheme of urban categories developed by Anderson for the classification of land use and land cover, the classification of urban categories such as residential and industrial (level II), which correspond to the strategic spatial level of UPM, requires a spatial resolution of ≤20 m. The classification of single family units and apartments (level III), which correspond to the local spatial level of UPM, requires a spatial resolution of ≤5 m. Consequently, the analysis of local spatial level of urban and planning and management has been facilitated by the increased availability

111 Couclelis 2009 p.344
112 Sliuzas, Kuffer and Masser 2010
113 ibid.
114 Bhaskaran, Paramananda and Ramnarayan 2010
115 Sliuzas, Kuffer and Masser 2010
116 ibid.
117 Anderson 1976
of high resolution imagery. In the two case studied in this thesis (paper III and V), the potential use for the WICS method on the strategic urban planning and management level is evaluated.

The underlying assumption motivating the evaluation of the WICS method as a tool that could be of use for urban analysis at the strategic level is that the local configuration (the Constitutive dimension) of various matter with different spectral signatures, such as asphalt, grass, concrete, etc. (the Formal dimension), could communicate something about planning and use (the Telic dimension). Analyses of this local configuration require going beyond the individual building and field of grass and aggregating them into more generalized concepts, such as different types of urban areas.

Similar to the SRPC, the WICS has similarities to Gärdenfors’ conceptual spaces. However, instead of a pixel assessed as part of a specific concept region, each pixel is evaluated based on its distance in the conceptual space. Depending on the status of the WICS classification as supervised or unsupervised, the creation of concepts is different. If it is supervised, the concepts are given meaning beforehand; if it is unsupervised, they are given meaning after the classification is completed. It should be noted that this concept is similar to the regular classification of multispectral image data, and the main difference is that the distance between different spectral classes are used as the input data instead of the radiation reflection in different image bands. Therefore, the borders are not definite, as in the SRPC case; instead, the concepts are defined more as cluster centers, and the objects are assigned the concept that it is closest to in the conceptual space. The three first points in the list below are the same as in the SRPC example:

- The framework is the geographical distances to the different spectral classes;
- Each pixel is an object;
- The object is represented as a point whose properties are its nearest neighbor values, which produce a coordinate in the conceptual space;
- If supervised, the mean distances of all of the training area pixels for each individual training class create a point representing the specific concept; each point is then evaluated and classified as belonging to the concept that it is closest to in the conceptual space;
- If unsupervised, all of the points are divided into the same number of concept regions as the number of classes in the unsupervised classification; the concept regions are constructed in such a way that the variation is smaller inside the region than between the regions, and each point is classified based on the concept region to which it has been assigned.
Therefore, depending on if the WICS routine is supervised or unsupervised, the mode of inference is different. If supervised, it uses the abductive mode.

*Rule:* the specific land use $x$ in the training area(s) has the spatial configuration $y$ that is translated into the cluster center $z$ in the multidimensional feature space

*Result:* the pixel $q$’s contextual feature vectors are closest to cluster center $z$

*Case:* it is plausible that the pixel $q$ is land use $x$ because it is closest to cluster center $z$, which is codifying the spatial configuration $y$

If unsupervised, the mode of inference would arguably be inductive.

*Case:* randomly selecting a number of pixels belonging to class $x$

*Result:* all of the selected pixels belonging to class $x$ are land use $y$

*Rule:* it is probable that all class $x$ pixels are land use $y$

A theoretical example of deductive inference would be as follow:

*Rule:* all of the pixels close to cluster center $x$ are called $z$ and known to be land use $y$

*Case:* you select a number of $z$ pixels

*Result:* you know that the $z$ pixels are land use $y$

The question remains of how this information fits with the notion of different levels of entropy (amount of information that can be obtained) for the three given modes of inference. The answer comes down to how specific one can be when looking for different types of land use. The most specific is the supervised approach corresponding to an abductive inference where one decides beforehand what type of land use one wants to classify. Following the logic from above, the supervised approach will carry with it the most uncertainty, which is a result of an inability to be sure beforehand that the cluster center created based on the training area(s) will not result in a class containing additional unwanted land uses as a result of the unwanted land uses them having similar spatial configurations. The unsupervised approach corresponds to the inductive method, is less specific (the number of cluster centers is assigned but positions are not assigned for the cluster centers in the multidimensional space). In the unsupervised approach, each separate class is surveyed and interpreted as corresponding to a certain land use. This might be a more certain approach because the land use in question is inter-

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118 Couclelis 2009
Interpretation based on the interclass variance\textsuperscript{119}, but there can be a loss of specificity\textsuperscript{120}, e.g., more general land use classes.

**Classification of high resolution imagery**

The increase in availability of high spatial resolution remote sensing data does not necessarily mean an increase in classification accuracy\textsuperscript{121}. Per-pixel based classifiers have problems handling the increased intra-class spectral variability among land covers in high resolution imagery\textsuperscript{122}, which is sometimes described as the H-resolution problem\textsuperscript{123}. As mentioned, the increase in spatial resolution and the problems associated with it has been a driving factor for the OBIA remote sensing paradigm\textsuperscript{124}.

In this thesis, a case study is conducted to evaluate the WICS method’s suitability to handle the H-resolution problem. WICS is evaluated as tool for monitoring deadwood areas in a forest park caused by insect outbreaks using high resolution aerial images (40x40 cm). High spatial resolution makes it more complicated to find homogenous vegetation classes using standard per-pixel classifiers. If the object that is to be classified consists of several pixels (such as a tree crown) there is the possibility of a large amount of spectral variability associated within that object. Consequently, the use of high spatial resolution imagery can make it difficult to find unique spectral signatures for vegetation classes. Therefore, spatial information is often needed. In the case of the classification of tree crowns, a mix of spectral information, shape and texture could be used instead of an analysis of the spectral signatures of individual pixels\textsuperscript{125}.

**Methodology**

The methods used for classification in the case studies are the SPRC method or WICS method. The SRPC method uses a training area that works as an example of the phenomena to be mapped. The training areas for paper I and II were thus chosen as examples of the agricultural system to be mapped. The WICS method can either be supervised or unsupervised. Paper III and V use an unsupervised version of WICS wherein the number of classes are set

\textsuperscript{119} Note that this is also usually done when performing a supervised classification.
\textsuperscript{120} At the same time there is an explorative element in the unsupervised approach that should not be underestimated.
\textsuperscript{121} Jensen, et al 2009
\textsuperscript{122} Gao 2009
\textsuperscript{123} Yu, et al 2006, Hay, Niemann and McLean 1996
\textsuperscript{124} Gao 2009, Blaschke, et al 2014
by the user, and some trial and error is required to find a working set of parameters. In paper VI, a supervised version of WICS is used that utilizes the training areas used to calculate the cluster centers for the different classes.

Common to the case studies in this thesis is that the land covers are not interpreted and connected to different geographical concepts; instead, land cover is treated as the spectral properties of objects\textsuperscript{126}, such as the input of a multispectral satellite image that is reduced by the help of unsupervised per-pixel based spectral classifications into a data set containing $x$ number of land cover classes (sometimes called spectral classes) that are not interpreted. This is also described as the data reduction of the multispectral image data that is required before using it as input for the WICS method (paper III, V and VI).

A number of data sets have been used for the verification of the classifications. In paper III, a preexisting data set of built environment characteristics based on historical context, architectural styles, planning theories and practices, and functions was used. In paper V, the parcel data gathered by the Franklin County auditor office were used. In paper I, a dataset with the coordinates for summer farms provided by the county administrative board of Dalarna was used. In paper II, field studies were performed to verify the results. Paper VI utilized independently produced datasets provided by the Bavarian Forest National Park administration.

Results

The results from the six different papers demonstrate how the contextual based classification methods can infer specific forms of land use in urban and rural settings from remote sensing data.

In paper I and II, the SRPC method is used to map agricultural systems consisting of configurations of land covers. In paper I, summer farms in Dalarna are mapped. The summer farms are in different states of abandonment, and the highest classification accuracy was for still-active summer farms. This is to be expected because the training area consisted of a still-active summer farm. In paper II, the SRPC was used to map the two different agricultural practices connected to different household livelihood strategies characterized by subsistence and cash crop types of farming in the Sodo district of Ethiopia. The study shows that socioeconomic differences can be identified in satellite images because different farming practices give a characteristic spatial imprints consisting of land cover, which in turn can be linked to differences in farming types.

Because the physical expression of land use can be recognized and inferred, the studies in this thesis have demonstrated the potential of the meth-

\textsuperscript{126} Comber, Fisher and Wadsworth 2005
ods utilizing contextual information, such as the SRPC, to map specific types of agricultural systems associated with different household strategies. This is of interest not only in fields of planning and management but also in land system science, which has requested new approaches to analyze socioeconomic functions of land from remote sensing data\textsuperscript{127}. In paper III and V, WICS is evaluated as a tool for classification of information that is relevant for the strategic spatial urban planning and management level. The method is tested in two different urban areas: the central parts of Stockholm and Columbus, Ohio. In paper III, the WICS classification is shown to relate to the built environment characteristics used by city planners to describe the building structure of Stockholm. In paper V, the WICS method is used to classify information corresponding to the strategic UPM level in Columbus, Ohio. Three different urban area classes are extracted: two types of residential categories and one commercial/industrial class. The main differences between the classes in the Stockholm and Columbus studies are a reflection of differences in the history and societal context between the two cities. The urban classes in Stockholm are identified as corresponding to different phases of planning history, theories, and practices, such as the garden-city movement and functionalism. In Columbus, the residential classes instead represent a shift in “suburbanization style” along a time axis\textsuperscript{128}. In paper IV, an analysis is presented that shows that the WICS classes in paper III have different demographic and socioeconomic resident profiles.

The urban remote sensing studies in this thesis showed how the use of contextual information in the form of the WICS method was able to extract information that goes beyond land cover in urban areas. Information was extracted that corresponded to different phases of the development of the urban areas in question. Additionally, it was demonstrated how the different classes corresponded to different socioeconomic profiles that could be seen as a direct response to Fugate et al.’s proclamation that urban remote sensing data gives an unprecedented opportunity to understand the connection between the physical environment and the social lives of urban residents\textsuperscript{129} and

\textsuperscript{127} Rounsevell, et al 2012

\textsuperscript{128} To ensure that the mean construction year of residential buildings for A and B could not be a product of chance, a 99.9\% normally distributed confidence interval was calculated for the mean construction year of the residential buildings based on all of the residential parcels (except the 7\% missing information) of all of the residential parcels using the following parameters; Alpha 0.001, standard deviation 25.7, sample size of A - 128720, and sample size of B - 119216. Because the sample size for both A and B are large, the confidence interval for parcels’ mean becomes narrow at 1966±0.24 for both A and B (corresponding number for C is 1966±0.65, sample size 16987). Therefore, as long as the mean of A and B is outside of the 1966±0.24 range, there is less than a 0.01\% chance that the A and B mean residential construction year could be a product of chance.

\textsuperscript{129} Fugate, et al 2010
‘lead to improved understanding of the relationship between the built environment and numerous urban demographic and social process’

In paper VI, the WICS method’s ability to perform a time-effective and accurate classification of deadwood areas caused by bark beetles in the Rachel-Lusen non-intervention zone was evaluated. Two high resolution infrared aerial images from 2001 and 2008 were classified. Despite the differences in generalization in the verification datasets, the accuracy values were high. In addition, the individual trees were mapped, which is not practical by means of manual visual interpretation on such a scale. The 2001 classification appeared to be unaffected by the borders present in the image, which indicated that the WICS could be effective when dealing with border problems associated with the analysis of image collections.

The problems associated with classifying land use consisting of a complex configuration of land cover are similar to the problems associated with classification of high resolution imagery, a.k.a., the H-resolution problem. In this thesis, the WICS method was able to successfully classify dead trees from high resolution imagery, which permits the consideration of other areas with the same underlying problem, such as at the local spatial level of urban planning and management.

Discussion

Since the early 1970s, there has been an increasing wealth of remote sensing data that has led to unprecedented opportunities to study the world. The data-driven approach required to handle the immense volumes of data has replaced an application- and user-driven approach. Consequently, there has been a shift from land use to land cover mapping (Fisher et al. 2005). During this time, the social sciences have mostly been a sideline spectator rather than a participant in the remote sensing field. To break this stalemate there is a need for methods, which focus on more multifaceted forms of information than land cover. A good example is land use that often takes the physical expression of a complex combination of land cover that is hard to extract using per-pixel based classification methods as a result of the heterogeneity and complexity in its spectral and conceptual dimensions. Social science demands can therefore be described as a shift away from the traditional pixel-based methods for satellite image analysis towards a methodology that can capture more aspects then the purely (bio)physical.

In this thesis, two methods that are based on contextual information are evaluated. The methods aim to incorporate the Constitutive dimension (the composition of things) into the already inherent Formal dimension (physical attributes that discern one thing from another, such as electromagnetic re-
flection). The purpose of combining the Constitutive and Formal dimensions is to be able to say something about the Telic dimension (the function or purpose of things), which is specifically stressed by Bibby and Shepherd as important for the definition of land use\textsuperscript{131}.

The methods presented in this thesis and similar studies have the potential to make possible a more prevalent use of remote sensing images as a data source in human geography (and the social sciences). Mats Widgren argues that ‘Through reading and analyzing landscapes we can understand social relations and social structures that are not evident for social scientists using other sources.’\textsuperscript{132} I would argue that by taking advantage of the concept of context information in the form of distance relationships, it will be possible to extract different forms of information in a way that have primarily only been possible by human visual interpretation of landscapes. However, Widgren also notes that ‘not all events in society and all aspects of power relations are expressed transparently on the ground’\textsuperscript{133} [italics in original]. Therefore, for contextual methods to work there has to be an underlying spatial pattern or a number of essential characteristics that shape the physical landscape in a discernible way.

The results from paper I-VI showcase the possibility of using semiautomatic methods for mapping specific forms of land use that accommodate a number of research problems connected to the analysis of different social processes. These results opens up for greater opportunities to map land use, which can counteract the current dominance of land cover as the dominant concept being mapped from remote sensing data\textsuperscript{134}. There would be a great benefit in the wider use of methods capable of mapping more complex forms of geographical phenomena using remote sensing data because one could take advantage of the high temporal frequency, low cost of production and large coverage of areas. This in turn could initiate the creation of classifications of remote sensing data that are more demand driven compared to data driven\textsuperscript{135} and might at least upgrade the social sciences from a sideline spectator to a part time player in relation to the remote sensing field.

Further work on the SRPC method would preferably focus on studying the impact of choice on the training area. In addition, steps should be made to handle the spatial criteria in a more ‘forgiving’ way, and instead of using discriminate rules for inclusion or exclusion, the spatial criteria could be used to calculate an index on the similarities between the spatial context of each pixel and the spatial context of the training areas. In that way, each pixel in the image would be given a number indicating how similar its spatial

\begin{footnotesize}
\begin{enumerate}
\item Bibby and Shepherd 2000
\item Widgren 2006 p.57
\item ibid. p.57
\item Fisher, Comber and Wadsworth 2005
\item ibid.
\end{enumerate}
\end{footnotesize}
context is to the training area. Further work on the WICS method should preferably focus on the effects that the number of input classes and output classes have on the final classification. Experimentation with different methods of measuring distance is also encouraged, such as log distance and one divided by the distance. Furthermore, the effect of spatial resolution in connection to the objects of interest to be mapped should also be studied.

Summary of papers

This section contains a summary of the six papers included in this thesis. The papers are in chronological order, or the order in which I worked on them. In the cases where there are multiple authors, I have also clarified my contribution to the paper.

Paper I

Formalized interpretation of compound land use objects mapping historical summer farms from a single satellite image

Ola Ahlqvist, Anders Wästfelt and Michael Nielsen.
Published in Journal of Land Use Science, volume 7, no. 1 2012.

The paper consists of two parts. The first part is a framework for analysis of the relations between two separate types of knowledge: machine-based knowledge and human mental knowledge; this was written by Ahlqvist and Wästfelt. The second part is a case study in which summer farms in Dalarna, Sweden were identified from a satellite image using the SRPC method. The second part was conducted and written by me and draws from my 2007 master’s thesis. In paper I, the spatial relational criteria (the largest nearest neighbor distance for each class to all other classes in the training area) were calculated manually using a print out of the training area. The criteria were then applied through a system of buffers applied pairwise between different class combinations. The main difference in this SRPC case study compared to the studies performed by Wästfelt was that I allowed for the pixels surrounding the training area to also effect the calculation of the criteria. This makes for more restrictive criteria but is also more ‘true’ to the spatial configuration found in the training area; otherwise, unwanted border effects are obtained. The verification was also performed by me except for the categori-

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136 Nielsen 2007. The case study was also mentioned in a 2008 peer-reviewed conference paper (Ahlqvist and Wästfelt 2008) which was cited by (Couclelis 2009, 2010).

137 Wästfelt 2004, Wästfelt 2009
zation of the summer farms into different levels of abandonment, which was performed by Ahlqvist and Wästfelt.

Paper II
Qualitative satellite image analysis: Mapping spatial distribution of farming types in Ethiopia

Anders Wästfelt, Tsegaye Tegenu, Michael M. Nielsen, Bo Malmberg
Published in Applied Geography, volume 32, no. 2 2012.

This paper used the SRPC method to identify two different agricultural and socioeconomic practices in the district of Sodo, Ethiopia. Qualitative information from field studies were used to select training areas and verify the results. The initial field studies were made by Wästfelt and Tegenu, on basis of this Wästfelt and Tegenu selected training areas to be used for the SRPC analysis. I carried out the SRPC analysis and developed a new way to implement the SPRC method. Instead of manually calculating the criteria from the training areas, I constructed, using distance transform and vector layers, a database containing the nearest neighbor distance for each pixel to all of the spectral classes in the entire study area. This meant that the spatial relational criteria could be sorted out by selecting the posts in the database connected to the pixels in the training area from which the largest nearest neighbor values used as criteria can be extracted. The criteria could then be used by applying SQL to extract subsets from the database and in that way implement the SRPC method. This significantly shortened the process time and made it practical to use more training areas. The verification was partly made by digitizing images from Google Earth, which was performed by me, and by field studies performed by Tegenu, with me assisting in the field.

Paper III
Extraction of urban areas with different functions and underlying planning theories and practices using Window Independent Context Segmentation

Michael M. Nielsen
Submitted to Environment and Urban Systems

Working with the distance database in paper II led to experiments using the database to create entirely new classifications based on spatial contexts. These experiments resulted in the development of the WICS method. Moving away from rural areas, I wanted to test the method in urban areas because I have a background in urban and regional planning. Therefore, in paper III, I tested the WICS method’s ability to extract urban categories corresponding
to the strategic spatial level of urban planning and management. Comparing
the WICS classes to the planning material Stockholms byggnadsordning\textsuperscript{138},
WICS was shown to extract urban area categories that correspond to the
strategic urban planning and management level and differ in function and
underlying planning theories and practices. One might argue that there is no
need for mapping Stockholm using satellite imagery because the city is al-
ready so well monitored. However, Stockholm works as an exemplary case,
showing that if it is possible here, it might also be possible in other places.
This was also something that reviewers commented on as they wanted to see
the method applied to other cities. Thus, Columbus was tested in paper V.
An early draft of the study was published as a peer-reviewed extended ab-
stract in 2011\textsuperscript{139}.

Paper IV
Socioeconomic residential profiles in urban areas classified by the WICS
method

Michael M. Nielsen
Manuscript

This is a short paper inspired by Fugate et al. who argue that urban remote
sensing data gives an unprecedented opportunity to understand the connec-
tion between the physical environment and the social lives of urban resi-
dents\textsuperscript{140}. The aim of this paper was to test if the WICS classes produced in
Paper III have different demographic and socioeconomic resident profiles.
That is to say, can contextual classification techniques applied to remote
sensing data say something about the socioeconomic variables associated
with different urban areas. The demographic and socioeconomic resident
profiles were created for urban area characteristics and WICS classes. A chi-
square test was performed to ensure that the outcome of the different vari-
ables were not just a product of chance and the resident profiles were made
using the proportional deviation from the expected value in the chi-square
tests. Finally the urban resident profiles for the built environment character-
istics and the WICS classes were compared by calculating the correlation
coefficients. The WIS method was shown to successfully capture informa-
tion that corresponds to different urban area characteristics, and they also
have different demographic and socioeconomic resident profiles.

\textsuperscript{138} Stockholms Stad 2012
\textsuperscript{139} Nielsen 2011
\textsuperscript{140} Fugate, et al 2010
Paper V
Classification of different urban categories corresponding to the strategic spatial level of urban planning and management using a SPOT4 scene

Michael M. Nielsen and Ola Ahlqvist
Submitted to Journal of Spatial Science

In this paper, the WICS method was tested in an urban milieu different from paper III. Through my contact with Ahlqvist and a grant from the Sweden America foundation, I was able to spend time in Columbus as a visiting researcher and conduct the case study for paper V. Similar to paper III, this study focuses on the extraction of information that was relevant to the strategic spatial level of urban planning management, including more general land-use descriptions using the WICS method to extract urban area categories from a SPOT4 satellite scene. Parcel data were used for the accuracy calculations. Three different urban categories were classified in Columbus, Ohio: one industrial/commercial and two residential categories that belong to different suburbanization phases. I was responsible for the empirical design, analysis of data and drafting of the paper, with Ahlqvist having a supervisory role.

Paper VI
Automatic mapping of standing dead trees after an insect outbreak using the Window Independent Context Segmentation method

Michael M. Nielsen, Marco Heurich, Bo Malmberg and Anders Brun
Submitted to Journal of Forestry

In this paper, the WICS method’s ability to map deadwood areas in the Bavarian Forest National Park in southeastern Germany, which has had an increase in spruce bark beetle population since 1980s, was tested. Two color infrared scenes with a spatial resolution of 40x40 cm from 2001 and 2008 were used for the study. I was responsible for the empirical design, the analysis of data and drafting of the paper and my co-authors made the following contributions: Heurich wrote the study area section, supplied the data used for the study and also produced input on other aspects of the text; Malmberg contributed to the initial design and commented on different versions of the text; and Anders Brun developed the algorithm that made it possible to use a supervised version of WICS.


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