RESEARCH

Hendrik Herold

Geoinformation from the Past

Computational Retrieval and Retrospective Monitoring of Historical Land Use

Springer Spektrum

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Dresden, Germany

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Preface

Cartographic documents are considered to be unique storages for geospatial information; storages basically for centuries since *Ptolemy's Geographike Hyphegesis*, if not earlier. This characteristic makes historical maps exceedingly valuable resources not only for geoscientific, geographic, and landscape research, but also the digital humanities. In particular, archival maps can give spatially explicit evidence of the dynamic land change that has taken place during the last two centuries, a crucial period proposed as the Anthropocene. However, this geohistorical information is concealed in the documents and usually only visually accessible. This book summarizes more than ten years of research on the computational acquisition of retrospective geoinformation from topographic maps and is based on the author's doctoral dissertation. Although it is a work of an individual, such an endeavor is always accompanied and supported by numerous people. I want to thank my academic advisors Prof. Dr. Elmar Csaplovics from Dresden University of Technology and Prof. Dr. Nguyen Xuan Thinh from University of Technology Dortmund for reviewing this work and their valuable comments. I am especially in Dr. Gotthard Meinel's debt, my mentor and head of the land use monitoring research group at Leibniz Institute of Ecological Urban and Regional Development for initiating this research, for supporting me during the past years, for the space for free thinking and eventually for his patience while finishing this work. I thank Prof. Dr. Dr. Bernhard Müller as the head of the Leibniz Institute of Ecological Urban and Regional Development for the institutional support of my research, conference stays, and trainings. Furthermore, I owe thanks to all my institute's colleagues. Although it is impossible to address them all here, I want to name a few: Dr. Marco Neubert, whose work on image segmentation initiated not only my first thesis, but also led to various publications on the evaluation of image segmentation algorithms. Some of the shortcomings identified in that earlier work inspired parts of this research. Thanks to all the institute's fellow doctoral students, while special thanks go to my office mate and PhD fellow Dr. Robert Hecht. I think we have learned a lot during these years of highly intensive work, about both science and life. Further I thank Dr. Martin Behnisch for his advice, particularly while finishing this work. Sabine Witschas and Ulrich Schumacher for sharing their knowledge about historical and international maps. For providing excellent

technical support regarding all hard- and software issues I thank Jörg Gössel and Carsten Hantzsch. Anja Heller and Albrecht Rostowski for the support as librarians, Sieglinde Sauer for the organizational support. Dr. Gerd Lintz for his advice during my time as the representative as well as member of the doctoral committee board. I also thank my Diploma, Master's and Bachelor's students, amongst them Ulrike Schinke, Benjamin Richter and Patric Röhm, for their support regarding laborious data collection, preparation and processing. I thank Dr. Christine Wessollek, Dr. Rico Vogel, and Dr. Pierre Karrasch from Dresden University of Technology for their comments on parts of the work. Furthermore, I want to thank some people from all around the world, who have contributed with their advice, motivation or inspiration: Dr. Hermann Kux from Instituto Nacional de Pesquisas Espaciais I owe thanks for perfectly organizing my research visit at Brazil's INPE and the inspiring discussions. Dr. Prashant Reddy Marpu from Masdar University for the discussions on image segmentation algorithms that inspired some of the methodological approaches. Prof. Dr. Stefan Leyk from University of Colorado for sharing his expertise in the field of automated map analysis, and together with Prof. Dr. Yao-Yi Chiang from University of Southern California for inspiring discussions on the perspectives and state of the art in the research field. Dr. Petr Přidal from Oldmapsonline.org and Dr. Lynn Usery from U.S. Geological Survey for encouraging talks on the future digital map repositories. Dr. Manon Kohler from the National University of Singapore I thank for her valuable hints and the language support. I thank Anita Wilke from the publisher Springer Nature for the helpful comments on the manuscript as well as the support concerning the final book layout. Last not least, I deeply express my gratitude to all of my family for their loving support and understanding for all the time I dedicated to this research during the past years. I am especially in my parents' and grandparents' debt for their efforts in teaching me both holistic and reductionistic views, intrinsic curiosity, but also persistence and commitment, needed to cope with the challenges of such a scientific endeavor.

Abstract

Land use changes have become a major contributor to the anthropogenic global change. The ongoing dispersion and concentration of the human species, being at their orders unprecedented since its appearance, have altered Earth's surface and atmosphere. The effects are so salient and irreversible that a new geological epoch, following the interglacial Holocene, has been announced: the "Anthropocene". While its onset is by some scholars dated back to the Neolithic revolution, it is commonly referred to the late 18th century. The rapid economic and demographic growth since the industrial revolution and its implications gave rise to an increasing awareness of the pervasive anthropogenic land change and led to an urgent need for sustainable strategies for land use and land management. By preserving landscape and settlement patterns at discrete points in time, archival geospatial data sources such as remote sensing imagery and historical geotopographic maps, in particular, could give evidence of the dynamic land use change during this crucial period.

In this context, this book set out to explore the potentials of retrospective geoinformation for monitoring, communicating, modeling and eventually understanding the complex and gradually evolving processes of land cover and land use change. Currently, large amounts of geospatial data sources such as archival maps are being worldwide made online accessible by libraries and national mapping agencies. Despite their abundance and relevance, the usage of historical land use and land cover information in research is still often hindered by the laborious visual interpretation, limiting the temporal and spatial coverage of studies. Thus, the core of the thesis is dedicated to the computational acquisition of geoinformation from archival map sources by means of digital image analysis. Based on a comprehensive review of literature, available data sources and proposed algorithms, two major challenges for long-term retrospective information acquisition and change detection were identified: first, the diversity of geographical entity representations over space and time, and second, the uncertainty inherent to both the data source itself and its utilization for land change detection.

To address the former challenge, image segmentation is considered a global non-linear optimization problem. The segmentation methods and their parameters are adaptively adjusted using a metaheuristic, evolutionary approach. For preserving adaptability in high level image analysis, a hybrid model- and data-driven strategy, combining a knowledge-based and a neural net classifier, is recommended. To address the second challenge, a probabilistic object- and field-based change detection approach for modeling the positional, thematic, and temporal uncertainty adherent to both data and processing, is developed. Experimental results indicate the suitability of the methodology in support of land change monitoring. In conclusion, potentials of application and directions for further research are given.

Keywords: Land Change Science, Land Use, Long-Term Monitoring, Anthropocene, Historical Maps, GIScience, Adaptive Image Analysis, Evolutionary Algorithms, Neural Nets, Uncertainty Modeling.

Résumé

Les changements d'occupation des sols imputables à l'homme et ses activités sont devenus un contributeur majeur des changements globaux actuels. La dispersion de l'espèce humaine sur Terre ainsi que sa concentration en certains lieux sans précédent depuis l'apparition d'Homo Sapiens, ont altéré la surface terrestre et l'atmosphère. Les effets sont d'une telle magnitude et irréversibles qu'une nouvelle époque géologique, suivant l'époque interglaciaire Holocène, a été promulguée : l'Anthropocène. Alors que certains chercheurs considèrent la révolution néolithique comme date de début de l'Anthropocène, il est plus communément admis que celle-ci débuterait soit à la fin du 18e siècle soit en milieu du siècle dernier au commencement de la dite « Grande accélération » période. La croissance démographique et économique rapide depuis le début de la révolution industrielle ainsi que son implication dans les changements actuels a entrainé une prise de conscience croissante de l'intensité des changements d'occupation des sols inhérents à l'homme ainsi que de l'urgence de stratégies de gestion durable des terres. En conservant les informations relatives aux paysages et aux peuplements en des points discrets du temps, les sources archivées des données géospatialisées comme les images satellites et les cartes topographiques historiques peuvent fournir des indices précieux quant à la dynamique paysagère de cette période cruciale.

Dans ce contexte, le présent livre entend explorer le potentiel des informations géographiques rétrospectives pour suivre, communiquer, modéliser, et éventuellement comprendre les processus des changements d'occupation et d'utilisation des sols. Actuellement, d'importante quantité de données géospatiales tels que les carte-archives sont mises à disposition en ligne au travers des bibliothèques et instituts cartographiques nationaux. Malgré leur abondance et leur pertinence, l'utilisation en recherche de ces informations historiques est souvent entravée par leur interprétation visuelle laborieuse, limitant ainsi la couverture spatio-temporelle de telles études. Aussi, le cœur de cette thèse est dédié à l'acquisition automatisée des informations géographiques contenues dans les carte-archives au moyen d'analyse digitale d'images. Basée sur une revue de littérature exhaustive ainsi que sur les bases de données et algorithmes existants, deux défis majeurs ont été identifiés à l'acquisition rétrospective d'informations géographiques et à la détection des changements paysagers : tout d'abord la diversité des représentations dans le temps et l'espace des entités géographiques, et ensuite, l'incertitude inhérente aux sources de données et à leur utilisation pour la détection des changements d'occupation du sol.

Afin de relever le premier défi, la segmentation d'image est considérée comme un problème d'optimisation globale non linéaire. Les méthodes de segmentation et ses paramètres sont ajustés de manière adaptative au moyen d'une approche métaheuristique. Pour préserver l'adaptabilité dans l'analyse d'image haut-niveau, un modèle hybride et des stratégies orientées données combinant un classificateur à la fois expert et à la fois neuronale sont recommandés. Afin de relever le second défi, une approche probabiliste basée objet et terrain de détection de changements pour la modélisation de l'incertitude positionnelle, thématique et temporelle est développée. Les résultats expérimentaux de cette étude confirment la pertinence de la méthode dans le suivi des changements paysagers. En conclusion, des potentialités d'application de la méthode et futurs champs d'investigation sont données.

Mot-clés: Dynamique paysagère, Occupation du sol, Observation de longue durée, Anthropocène, Cartes historiques, Système d'Information Géographique, Traitements et analyses adaptatives d'image, Algorithmes évolutionnistes, Réseaux de neurones artificiels, Modélisation d'incertitude.

Kurzfassung

Landnutzungsänderungen haben wesentlichen Anteil am anthropogenen globalen Wandel. Die seit seinem Auftreten einmalige und weiter fortschreitende Verbreitung des Menschen hat zu bedeutsamen Veränderungen der Erdoberfläche und Erdatmosphäre geführt. Die Einflüsse sind so deutlich und irreversibel, dass die Einführung einer neuen, das interglaziale Holozän beschließenden, geochronologischen Epoche in Betracht gezogen wird, der des „Anthropozäns". Während dessen Anfänge teilweise bereits in der neolithischen Revolution gesehen werden, wird das späte 18. Jahrhundert als Beginn angenommen. Die rapide Entwicklung seit der industriellen Revolution und deren Folgen haben zu einem dringenden Bedarf an nachhaltigen Landnutzungsstrategien geführt. Durch das Bewahren von räumlichen Landschafts- und Siedlungsmustern zu bestimmten Zeitpunkten, können Fernerkundungsdaten und insbesondere alte topographische Karten dazu beitragen, den Landnutzungswandel innerhalb dieses entscheidenden Zeitraumes nachzuvollziehen.

In diesem Kontext untersucht das vorliegende Buch zu Beginn die Potentiale retrospektiver Geoinformationen für das Monitoring, die Modellierung, die Kommunikation und das Verstehen des komplexen und graduell verlaufenden Landbedeckungs- und Landnutzungswandels. Weltweit werden derzeit durch Bibliotheken und nationale Kartographiebehörden große Bestände historischer Kartenquellen über das Internet zur Verfügung gestellt. Trotz ihrer Verfügbarkeit und Relevanz wird ihre Nutzung in der Forschung durch die aufwändige visuelle Interpretation limitiert, die den räumlich-zeitlichen Betrachtungsbereich von Studien beschränken. Der Kern der Arbeit widmet sich deshalb Methoden der digitalen Bildanalyse für die automatische Gewinnung von Geoinformationen aus den archivierten Kartenquellen. Basierend auf einer umfassenden Literaturstudie sowie einer Analyse vorgeschlagener Algorithmen und Daten werden zwei grundsätzliche Herausforderungen identifiziert: Erstens die Vielfalt in der Repräsentation geographischer Entitäten in Zeit und Raum sowie zweitens die dem Ansatz immanente Unsicherheit, die sich zum einen aus den Datenquellen selbst und zum anderen aus deren Verwendung für die Veränderungsdetektion ergibt. Um der ersten Herausforderung zu begegnen, wird die Bildsegmentierung als nicht-lineares globales Optimierungsproblem aufgefasst. Dabei werden Methoden und Parametrisierungen unter Verwendung eines metaheuristischen, evolutionären Ansatzes adaptiv angepasst. Zur Übertragung der Adaptierbarkeit in die High-Level-Bildanalyse wird eine hybride modell- und datengetriebene Strategie empfohlen, die einen wissensbasierten und einen neuronalen Netz-Klassifikator kombiniert. Zur Modellierung der räumlichen, thematischen und zeitlichen Unsicherheit wurde ein probabilistischer Ansatz entwickelt. Experimentelle Untersuchungen legen eine Eignung der Methodik nahe. Schlussfolgernd werden Anwendungspotenziale, Weiterentwicklungsmöglichkeiten und zukünftige Forschungsbedarfe aufgezeigt.

Schlagworte: Landnutzungswandel, Langzeitmonitoring, Anthropozän, Historische Karten, GIScience, Adaptive Bildanalyse, Evolutionäre Algorithmen, Neuronale Netze, Modellierung von Unsicherheit.

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Acronyms

ABM . . . . Agent-Based Model

AI . . . . Artificial Intelligence

ANN . . . . Artificial Neural Network

AHVRR . . . . Advanced Very High Resolution Radiometer

ASTER . . . . Advanced Spaceborne Thermal Emission and Reflection Radiometer

BPA . . . . Basic Probability Assignment

CA . . . . Cellular Automata

CIE . . . . Commission Internationale de l'Éclairage

CIPM . . . . Comité International des Poids et Mesures

CIS . . . . Color Image Segmentation

COGIT . . . . Conception Objet et Généralisation de l'Information Topographique

DNA . . . . Deoxyribonucleic Acid

DST . . . . Dempster-Shafer Evidence Theory

DTC . . . . Decision Tree Classifier

EA . . . . Evolutionary Algorithm

EDA . . . . Exploratory Data Analysis

EO . . . . Earth Observation

ES . . . . Evolutionary Strategy

ERTS . . . . Earth Resources Technology Satellite

ESA . . . . European Space Agency

FCM . . . . Fuzzy C-Means

FNEA . . . . Fractal Net Evolution Approach

GA .... Genetic Algorithm

GEOBIA .... Geographic Object Based Image Analysis

GEOSS .... Global Earth Observation System of Systems

GCP .... Ground Control Points

GIS .... Geographic Information System

GIScience .... Geographic Information Science

GKD .... Geographic Knowledge Discovery

GLCM .... Gray-Level Co-occurrence Matrix

GMES .... Global Monitoring for Environment and Security

GOFC-GOLD ...... Global Observation of Forest and Land Cover Dynamics

GSD .... Ground Sampling Distance

GUF .... Global Urban Footprint

HALE .... High Altitude Long Endurance

HGIS .... Historical Geographical Information Systems

HSV .... Hue, Saturation, and Value

HVS .... Human Visual System

HYDE .... History Database of the Global Environment

ICA/ACI .... International Cartographic Association/Association Cartographique Internat.

IFOV .... Instantaneous Field of View

IGBP .... International Geosphere-Biosphere Programme

IHDP .... International Human Dimensions Programme on Global Environmental Change

IGN .... Institut Géographique National

INSPIRE .... Infrastructure for Spatial Information in the European Community

IOER .... Leibniz Institute of Ecological Urban and Regional Development

ISO .... International Organization for Standardization
KDD .... Knowledge Discovery in Databases
LiDAR .... Light Detection and Ranging
LBP .... Local Binary Pattern
LGN .... Lateral Geniculate Nuclei
LCCS .... Land Cover Classification Systems
LULC .... Land Use and Land Cover
LCML .... Land Cover Meta Language
LCS .... Land Change Science
LULCC .... Land Use and Land Cover Change
MAS .... Multi-Agent Systems
MCDA .... Multiple-Criteria Decision Analysis
MERIS .... Moderate Resolution Imaging Spectrometer
MM .... Mathematical Morphology
ML .... Maximum Likelihood
MLP .... Multi Layer Perceptron
MRS .... Multi-scale/Multi-resolution Segmentation
MST .... Minimum Spanning Tree
MVTec .... Machine Vision Technologies
NALCMS .... North American Land Change Monitoring System
NMA .... National Mapping Agency
NASA .... U.S. National Aeronautics and Space Administration
OCR .... Optical Character Recognition
OSM .... OpenStreetMap
PCA .... Principal Components Analysis
RCB .... Recognition-by-Components Theory
RGB .... Red, Green, and Blue

RMSE . . . . Root Mean Square Error
ROC . . . . Receiver Operating Characteristics
SA . . . . Simulated Annealing
SAD . . . . Absolute Gray Value Differences
SAR . . . . Synthetic Aperture Radar
SE . . . . Structuring Element
SEMENTA . . . . Settlement Analyzer
SDSS . . . . Spatial Decision Support Systems
SDI . . . . Spatial Data Infrastructure
SLEUTH . . . . Slope, Land Use, Exclusion, Urban Extend, Transportation and Hillshade Model
SOM . . . . Self-organizing Map
SPOT . . . . Système Probatoire d'Observation / Satellite Pour l'Observation de la Terre
SPSS . . . . Spatial Planning Support Systems
SSD . . . . Squared Gray Value Differences
SVM . . . . Support Vector Machines
UAV . . . . Unmanned Aerial Vehicle
UN-GGIM . . . . United Nations Global Geospatial Information Management
UNESCO . . . . United Nations Educational, Scientific and Cultural Organization
USGS . . . . United States Geological Service
VA . . . . Visual Analytics
VGI . . . . Volunteered Geographic Information
VHR . . . . Very High Resolution
WCRP . . . . World Climate Research Programme
. . . .

1 Introduction

1.1 Scope and Rationale

Human habitations worldwide have grown and continue to grow at an extensive rate. The beginning of the twenty-first century has marked a new threshold, witnessing more than half of mankind living in urban areas. By the year 2030, more than sixty percent of the human population will reside in cities, estimates propose (United Nations, 2012, p. 4). The continuing dispersion and concentration of the human species, being at their orders unprecedented, have indisputably altered Earth's surface and atmosphere. The impacts are so salient and irreversible that a new geological epoch, following the interglacial Holocene, has been announced: the "*Anthropocene*" (e.g., Crutzen & Stoermer, 2000; Crutzen, 2002).

While its onset is sometimes dated back to the neolithic revolution (e.g., Ruddiman, 2003), it is commonly referred to the late eighteenth century, reflecting the tremendous human impacts caused by the industrial revolution. While the increasing urbanization offers new opportunities and benefits, it contrastingly causes numerous socio-economic and environmental problems. The ecological issues involve, to name a few only, the loss of natural resources due to an extensive land take and soil sealing, the emergence of heat islands, excessive air pollution, and, more generally, a growing vulnerability of human settlements to natural hazards.

Increasing awareness of these issues during the second half of the twentieth century has lead to the adoption of the sustainability concept in human development strategies. A concept which had already been introduced more than 300 years before to forestry by Carlowitz (1713) in his *Sylvicultura oeconomica*. The study *Limits to growth* by the Club of Rome (Meadows et al., 1972) as well as the United Nations report *Our common future* by the World Commission on Environment and Development (1987), also referred to as the *Brundtland report*, emphasized the importance and inevitability of a global sustainability concept for all natural resources and the further development. This awakening interest and the emerging demand for sus-

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tainable development strategies also raised awareness of the implications of the extensive anthropogenic land change, caused by both the land take for settlements and the increasingly industrialized agriculture to feed a growing population. These issues underpinned and manifested the relevance of land cover and land use change observation and research. While pure quantitative measurements should never supersede qualitative approaches to landscape change research (Csaplovics, 1999, p. 132), they provide an essential foundation to the understanding of the dynamics and complex interdependencies of natural and anthropogenic changes.

Computational and spatially explicit Land Use and Land Cover Change (LULCC) models have been developed to predict future developments by studying the patterns and underlying drivers of the spatial urban and landscape dynamics. Spatially explicit management tools such as Geographic Information and Spatial Planning/Decision Support Systems (GIS, SPSS/SDSS) can assist planners and decision-makers with evaluating land use policies or with developing strategies aiming at the reduction of the extensive land take such as induced by urban sprawl. Global, continental, and national monitoring initiatives allow to observe development trends and, thus, to control effects of measures. At a global level, these efforts are coordinated and channeled by the United Nations Global Geospatial Information Management (UN-GGIM) and the intergovernmental framework Global Earth Observation System of Systems (GEOSS) by the Group on Earth Observation (GEO). This system of Earth observation systems is underpinned by the Copernicus program, formerly Global Monitoring for Environment and Security (GMES), a joint endeavor of the European Space Agency (ESA) and European Community (EC) or the Global Change Master Directory (GCMD) of the U.S. National Aeronautics and Space Administration (NASA), amongst others.

Fundamental to all spatial and quantitative environmental monitoring, modeling, and data mining endeavors are digital spatiotemporal data ***at appropriate spatial and temporal scales and scopes***. Both the spatial and temporal scale and scope depend on the process to be investigated and explained. Anthropogenic impacts such as the human-induced components of land and climate change are – in terms of human perception – gradually proceeding long-term processes (cf. figure 1.1).

Hence, *short-term* (including human life time) observations may explain only shares of these processes and do not cover the long-term interrelations and inertia of Earth's systems. Analogously, in climatology, direct short-

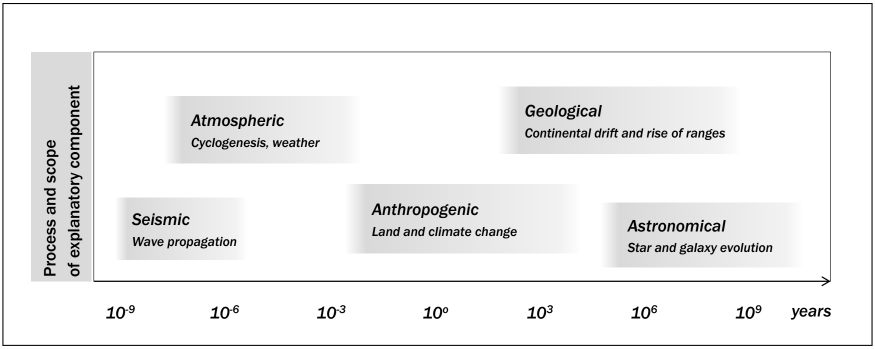

Figure 1.1: Temporal scopes (time scales) of natural and anthropogenic processes. Source: Author's own.

term observations are extended by indirect measurements on ***isotopes in ice cores (up to hundreds of thousand of years)***, in biology, evolution is reconstructed by paleogenetics and ***the fossil record (up to millions of years)***, or, in geology, ***lithostratigraphy (up to billions of years)*** is used, for instance, to explain plate tectonics.

Based on this coupled Earth systems perspective, a long-term oriented, integrated and interdisciplinary research field on land use and land cover change has emerged: Land Change Science (LCS, cf. Lambin et al., 2001; Rindfuss et al., 2004). The research efforts are mainly driven by the four Earth system science initiatives: International Geosphere-Biosphere Programme (IGBP), the International Human Dimensions Programme on Global Environmental Change (IHDP), the International Programme of Biodiversity Science, and the World Climate Research Programme (WCRP). The *land system* component of Earth system science seeks to improve at various spatiotemporal scales: (1) monitoring of land-use and land-cover patterns and dynamics, (2) understanding of these changes as a coupled human-environment system, (3) disentangling the complex suite of biophysical and socioeconomic forces, (4) spatially explicit land change models that are compatible with Earth system models, and (5) assessments of system outcomes, such as vulnerability, resilience, or sustainability (cf. Rindfuss et al., 2004; Verburg et al., 2004; Turner et al., 2007). In contribution to this efforts, this thesis research aims to investigate the potentials, possible sources, and computational acquisition methods for the long-term retrospective analysis of land change.

1.2 Challenges and Objectives

Long-term land use and land cover change studies aiming at covering the *Anthropocene* immanently base on a combination of multi-source geoinformation. The sources may include up-to-date hyperspectral and radar data, digital land use/land cover maps, archival optical monochromatic airborne and multi-spectral satellite imagery as well as historical cartographic documents. While the former provide high spatial and temporal resolution with up to global coverage, the latter are – in terms of the historical context – often the only data source for spatially explicit land use and land cover information. Cartographic documents such as historical cadastral and topographic map series, in particular, are considered unique and efficient "storages devices" (Roberts, 1962, p. 12) for geospatial information; basically for centuries since *Ptolemy's Geographike Hyphegesis* or even earlier.

Numerous studies have demonstrated archival topographic and cadastral maps as valuable and crucial sources for deriving spatially explicit historical land use and land cover information for both landscape change and urban growth research, for example Antonson (2009), Cousins (2001), Geri et al. (2010), Haase et al. (2007), Hamandawana et al. (2005) Kienast (1993), Meinel & Neumann (2003), Neubert & Walz (2002), Nikodemus et al. (2005), Pearson (2006), Petit & Lambin (2002), Podobnikar & Kokalj (2006), and Skokanová et al. (2012). However, the efforts of the laborious visual interpretation, which is commonly referred to as map digitization or vectorization, may seriously limit the spatial and temporal scope of investigations (cf. Bolstad & Smith, 1992, Khotanzad & Zink, 2003, Reger et al., 2007).

Thus, there is a remarkable body of research dedicated to the automated acquisition of computationally usable information from maps, for example the early works of Morse (1969) and Mor & Lamdan (1972), or later studies such as Suzuki & Yamada (1990), Lichtner (1985), Mayer et al. (1992), Ablameyko & Frantskevich (1992), Leyk (2005), Raveaux et al. (2008), amongst many others. Some of the developments have led to commercially available or academic expert systems such as PROMAP (Lauterbach et al., 1992), MAGELLAN (Samet & Soffer, 1998), KAMU (Frischknecht & Kanani, 1998), SEMENTA (Meinel, 2008; Meinel et al., 2009), and STRABO (Chiang & Knoblock, 2011a). From a research history perspective, three research stages or drivers for these developments can be identified:

- the early exploration of the capabilities of computer systems, artificial intelligence and recognition algorithms applied to maps,
- later the need for digital spatial and 3D (terrain) information accompanied by the advent of geographic information systems and geospatial analysis tools, and
- recently, the increasing interest in historical geoinformation (e.g., land use) and the soaring digital availability of historical maps through libraries and mapping agencies.

In particular the latter stage has introduced new challenges to the research field such as distortions and a degraded quality of graphical representations in the archival documents. The two major challenges, however, pose the spatiotemporal heterogeneity and uncertainty of the "***historical evidence***" (cf. van den Heuvel, 2006) for the LULCC, which is to be retrieved from the map documents (cf. figure 1.2).

In this context, this research aims at providing conceptual and methodical contributions to the long-term retrospective monitoring of the spatiotemporal land change dynamics. In detail, the research agenda for this thesis includes the following objectives:

1. Identification of the potentials of long-term retrospective geoinformation for understanding gradually proceeding geographical phenomena such as land use and land cover change in support of Land Change Science (LCS).
2. Review and comprehensive synopsis on the state of research in spatial information acquisition from archival map image data sources.
3. Identification of research needs based on the findings of the analysis of potentials, requirements and the research review.
4. Developing a methodical approach for adaptive image analysis to address the representational heterogeneity in archival data sets (Challenge 1).
5. Developing a conceptual framework to model the uncertainty caused by incomplete and fragmented historical evidence (Challenge 2).
6. Evaluation of the capabilities and potentials of the approach.
7. Identification of directions for further research.

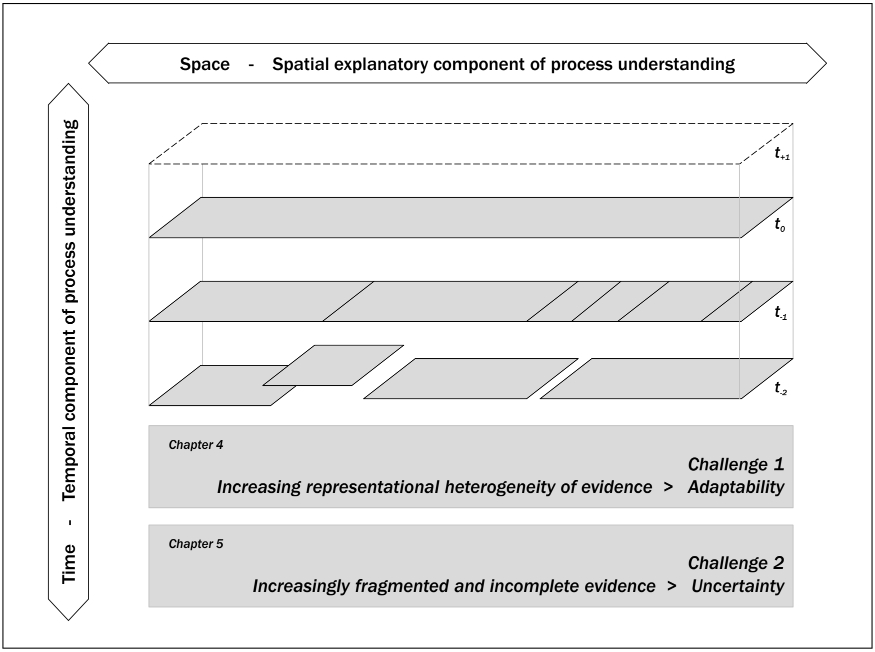

Figure 1.2: Research challenges for the automated acquisition of long-term retrospective land change evidence.
Source: Author's own.

The research presented in this thesis is part of the long-term land use change research, conducted at the Leibniz Institute of Ecological Urban and Regional Development (IOER). It contributes to the continuous development of the GIS-based tool Settlement Analyzer and its spatiotemporal extension SEMENTA®- CHANGE (Meinel et al., 2009; Herold et al., 2010). The results of both systems support a web-based land-use monitoring system (cf. Meinel, 2010). The research agenda encompasses the investigation of both up-to-date and archival data sources with regard to their potentials and operational application for studying the spatiotemporal dynamics of land use and land cover changes.

1.3 Research Questions and Hypotheses

The rationale and the objectives stated in the previous sections pose the following five research questions (RQ) for this thesis research:

RQ 1: *What potentials offer long-term retrospective and spatially explicit observational data for understanding and predicting of land use and land cover changes?*

RQ 2: *What data sources enable long-term retrospective land change monitoring and what approaches and challenges exist to access the geoinformation contained in these sources?*

RQ 3: *How can the historical geoinformation be retrieved considering the spatiotemporal heterogeneous representation of geographical entities caused by the long-term coverage?*

RQ 4: *How can the uncertainty inherent to the data source itself as well as to the information acquisition and change detection process be modeled in order to build time series?*

RQ 5: *What potentials indicate the evaluation of the proposed methodology and what perspectives for further research can hence be identified?*

To answer these research questions, an **interdisciplinary research approach** is pursued. The approach at the interface of the natural, engineering, human, and formal sciences encompasses research fields such as quantitative geography, complex systems theory, sustainability research, mathematical optimization, digital humanities, remote sensing, cartography, image analysis and visual pattern recognition as part of computer vision and artificial intelligence research as well as the computer science related geographical information science (e.g., spatial modeling, spatiotemporal reasoning under uncertainty). Thereon, the following seven *hypotheses* (H) are stated and evaluated in this work:

H 1: *Long-term and spatially explicit monitoring and modeling are key to perceive, understand, and forecast long-term geospatial phenomena such as land cover and land use changes.*

H 2: *Historical geospatial data sources such as a combination of archival remote sensing imagery and trigonometry-based geotopographic maps can document the land change during the past 200 years through preserving the geospatial landscape and settlement patterns of their respective time of origin.*

H 3: *Methods of digital image analysis such as color-, texture-, morphology-based segmentation and pattern recognition can be used to acquire spatially explicit data from the archival map sources and, thus, may be able to reduce the efforts of visual interpretation.*

H 4: *The utilization and processing of map sources for long-term retrospective land change detection pose two challenges, namely: (1) the spatiotemporal heterogeneity of geographical entity representations, and (2) the uncertainty inherent to both the data source itself and its non-intended utilization. The challenges have not yet been adequately addressed in research.*

H 5: *Image segmentation can be considered a non-linear optimization problem. A stochastic search algorithm may be used to find (quasi-)optimal parameter combinations in order to reduce the laborious and time consuming efforts of manual adaption.*

H 6: *Adaptive segment-based classification can, depending on the representational heterogeneity, be addressed by using a model- or a data-driven strategy. For less heterogeneous representations a model-driven strategy is suitable, which makes use of a-priori knowledge, represented in a Hierarchical Decision Tree (HDT). For higher adaptability at the cost of higher training efforts, a data-driven strategy using an Artificial Neural Net (ANN) is suitable.*

H 7: *A probabilistic object-based approach to change detection has to be used to model the positional uncertainty inherent to both the historical material and its non-intended use in multitemporal change analyses.*

The research hypotheses will be evaluated by a profound data source analysis, a comprehensive literature review on the state of research and by conducting experiments probing the proposed conceptual and methodical approach.

1.4 Research Organization and Structure

The work at hand is organized as follows: after an introductory view on the research scope, rationale, and objectives in the preceding sections, **chapter 2** (▷ page 11) investigates the theoretical background and relevance of long-term and spatially explicit information for understanding gradually proceeding geospatial processes. Figure 1.3 provides a graphical outline of the work.

Chapter 3 (▷ page 43) reviews the foundations and state of research in the area of automated acquisition of geographical information from digital images. The chapter concludes with a comprehensive summary of existing approaches and challenges for research.

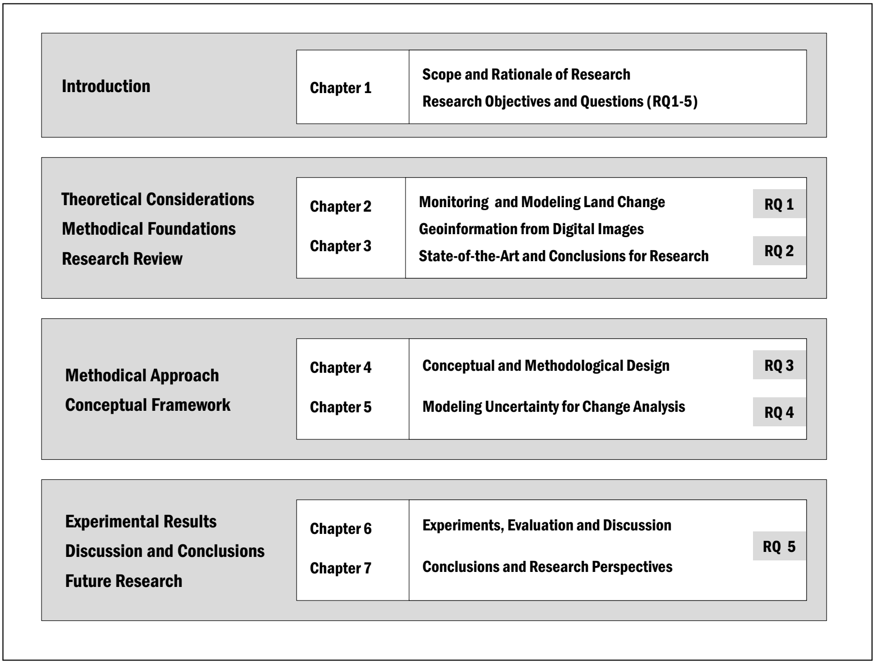

Figure 1.3: Outline of the research organization and structure of the work. Source: Author's own.

Chapter 4 (▷ page 67) proposes a methodical approach to adaptive image analysis for retrieving information from spatiotemporally heterogeneous data sources.

Chapter 5 (▷ page 87) contributes a conceptual framework for modeling the spatial, thematic and temporal uncertainty inherent to the multi-source data by proposing a data quality depended probabilistic object- and field-based approach.

Chapter 6 (▷ page 115) describes the evaluation of the proposed methodology by means of experiments and accuracy assessment using sample sets of real-world data. Based on these investigations strengths and limitations of the methodology are discussed.

Chapter 7 (▷ page 135) sums up the main findings and contributions of the thesis research in the scope of the initially stated research questions and hypotheses. It concludes with an outlook on potentials and perspectives for further research.

2 Monitoring and Modeling Land Change

Long-term and spatially explicit monitoring and modeling are key to perceive, understand, forecast, and eventually govern complex and gradual geospatial processes such as land cover and land use change (*working hypothesis one*). Figure 2.1 depicts the conceptual framework underlying this chapter, which focuses on the analytical evaluation

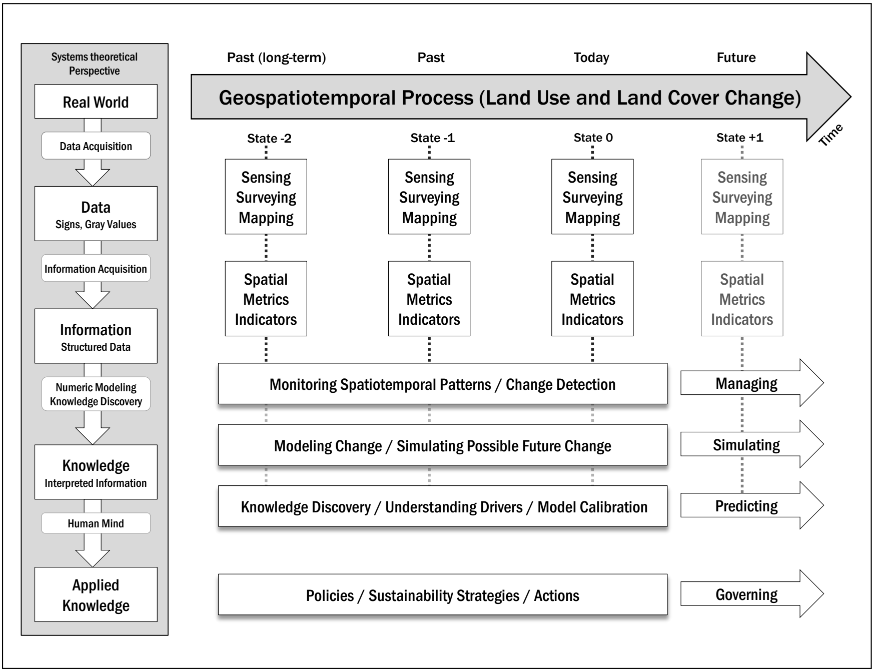

Figure 2.1: Conceptual framework underlying the investigation of long-term observations for mapping, measuring, monitoring and modeling complex and gradually proceeding geospatial phenomena such as land change.
Source: Author's own.

H. Herold, *Geoinformation from the Past*,
https://doi.org/10.1007/978-3-658-20570-6_2

To answer the first and second research questions concerning the potentials and sources of long-term observational land use and land cover information the chapter is structured from an inductive perspective: section 2.1 presents the capabilities and sources for mapping the land use and land cover, section 2.2 introduces an integrated concept for monitoring and measuring land change and section 2.3 seeks to explore the potentials for spatiotemporal modeling and knowledge discovery aiming at understanding the drivers of land change. In conclusion, potentials and research needs are identified.

2.1 Mapping Land Use and Land Cover

The terms *land cover* and *land use* are often used ambiguously or mutually interchangeable. In this work, the notion according to Lambin et al. (2003, pp. 213-216) is followed: the land cover is defined "by the biophysical attributes of the Earth's land surface and immediate subsurface, including biota, soil, topography, surface and groundwater, and human structures." In contrast, land use is defined by the purposes for which humans exploit the land cover and thus includes the land management practices (cf. Barnsley & Barr, 2000, p. 271; Verburg et al., 2009, p. 1328). The specifications of the Infrastructure for Spatial Information in the European Community (INSPIRE) further distinguish land use into existing and future planned land use (Joint Research Centre, 2013, p. 1). A more detailed and integrated view on land use and land cover as a coupled system is given in section 2.2.1 on the dynamics of land change.

Thematic mapping of the land use and the land cover implies a systematic classification approach. In literature, there exists a multitude of varying classification systems such as the:

- USGS Land Use/Land Cover Classification Systems (1972/1976),
- EC CORINE/Land Cover System (1990/2000),
- UNEP/FAO Land Cover Classification Systems (1993),
- IGBP-DIS Land Cover Legend (1996), or the
- GOFC/GOLD Land and Forest Cover Classification (1998),

amongst others, varying in scale, semantics, and number of classes (cf. Gomarasca, 2009, pp. 561-595). Efforts to harmonize and correlate the various land use and land cover classification systems have led to standardization through the International Organization for Standardization (ISO). ISO 19144-2:2012 provides a general framework by defining a Land Cover Meta Language (LCML). In the following, the major sources of recent and historical land use and land cover information are briefly discussed.

2.1.1 Space- and Airborne Remote Sensing

The most effective and thus predominant technique for the acquisition of information about vast areas of the Earth's surface characteristics is remote sensing. *Remote sensing* may be defined as "the science and art of obtaining information about an object, area, or phenomenon through the analysis of data acquired by a device that is not in contract with the object, area, or phenomenon under investigation" (Lillesand & Kiefer, 2000, p. 1). While this broad definition applies to a wide range of non-*in situ* techniques such as astronomical, microscopical, or biomedical imaging, it shall here be narrowed to the context of Earth observation (EO). Depending on whether the remote device (i.e., the sensor) is mounted to a satellite platform or an aircraft (including unmanned aerial vehicles, UAV), the terms *space-* and *airborne* remote sensing apply, respectively.

Fundamental Principle

For the remote acquisition of information exist two basic design principles: *active* and *passive* sensing systems. The former employ an artificial electromagnetic radiation source and measure the characteristics of the backscattered signal. The latter make use of either the naturally reflected radiation of the Sun or the radiation that is emitted from the terrestrial ground and atmosphere (cf. Schowengerdt, 2007, p. 10). Both active and passive systems base on the energy of the electromagnetic radiation that is received by the sensor. As the radiation can be described as discrete quanta (also referred to as photons), the quantum energy Q in joules (J) is given by:

$$Q = \frac{hc}{\lambda}, \tag{2.1}$$

where h denotes Planck's constant $(6.6261 \times 10^{-34}\ \mathrm{J \cdot s})$, c denotes the speed of light $(2.9998 \times 10^{-8}\ \mathrm{m \cdot s^{-1}})$, and λ the wavelength of the radiation. For passive systems, in particular, the knowledge about the magnitude and spectral composition of the radiation emitted from a matter, for instance, the Sun's or Earth's surface, is essential. The radiant emittance M from the surface in watt (W) per square meter can be described in a blackbody's approximation using the *Stefan-Boltzmann* law:

$$M = \sigma T^4, \tag{2.2}$$

where T the absolute temperature of the emitting surface in K and σ denotes the Stefan-Boltzmann constant $(5.6704 \times 10^{-8}\ \mathrm{J \cdot s^{-1} \cdot m^{-2} \cdot K^{-4}})$ (cf. Landgrebe, 2003, p. 33; Lillesand & Kiefer, 2000, pp. 6-8). Figure 2.2 shows the different types of information (namely, spectral, spatial, and intensity), which can be derived from the characteristics of the received emitted, transmitted, and reflected electromagnetic energy by the corresponding types of sensors.

Spectral and spatial information is of particular interest for land use and land cover mapping. For EO, the relevant part of the continuous electromagnetic spectrum is conceptually subdivided into the following ranges: Visible (VIS): 0.4 - 0.7 μm, Near Infra Red (NIR): 0.7 - 1.1 μm, Short Wave Infra Red (SWIR): 1.1 - 2.5 μm, Mid Wave Infra Red (MWIR): 3 - 5 μm, Thermal or Long Wave Infra Red (TIR or LWIR): 8 - 14 μm, and Microwave/Radar at the range from millimeters to meter wavelengths (cf. Schowengerdt, 2007, p. 10). The number, width, and location of bands along these spectral ranges is referred to as the spectral resolution of a sensor. The Ground Sampling Distance (GSD) of a sensing system is defined by the properties and the flight altitude or orbit of the sensor, which also define the Instantaneous Field of View (IFOV). The temporal resolution refers to the time between two visits of a sensor to a location and, hence, is of great importance for any environmental monitoring efforts (Weng, 2010, p. 7). For further details on the physics of the acquisition of remotely sensed data, the reader is referred to Kraus & Schneider (1988), Schowengerdt (2007), Landgrebe (2003), Lillesand et al. (2008), Elachi & van Zyl (2006), and Tso & Mather (2009). As the focus of this chapter is the exploration of sources for land use and land cover mapping and their temporal availability, the data analysis part of the remote sensing science – such as computational data interpretation methods – are later discussed in section 3.2.1.

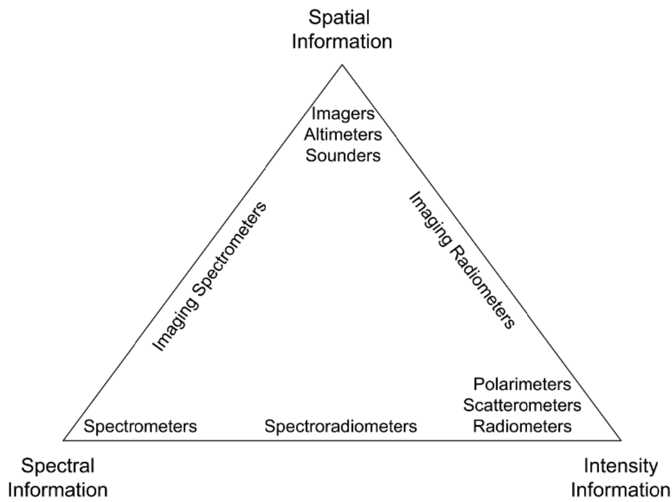

Figure 2.2: Types of information derived from the sensed radiation and the corresponding types of sensor.
Source: Adapted from Elachi & van Zyl (2006, p. 3), © 2006 Wiley, Inc.

Available Data and Temporal Coverage

The first known aerial photography was acquired in 1859 during a balloon flight over Paris by Gaspard Félix Tournachon, known as Nadar. Since, the development of airborne remote sensing techniques had been closely associated with military technology (Théau, 2012, p. 175). First spaceborne remote sensing imagery is available since 1959 through film based military reconnaissance satellites such as CORONA KH-1 (USA) and ZENITH (Soviet Union), which was later declassified for public use (Jacobsen, 2005, p. 490). Civilian spaceborne remote sensing started in 1972 with the launch of the Earth Resources Technology Satellite (ERTS-1, later renamed to Landsat-1) and has since been rapidly developing (cf. Table 2.1[1]).

[1]Spatial resolution given for PAN/MS, if applicable. Temporal resolution may be higher due to off-nadir acquisition.

Table 2.1: Important spaceborne remote sensing systems used for land use and land cover mapping at global to local level. The abbreviations for the system names are explained in the text. Ordered according to the first data availability. Source: Author's own, compiled from Jacobsen (2005), Gomarasca (2009), and Patino & Duque (2013).

System	**Spatial Resolution** GSD or pixel size in m	**Temporal Resolution** revisit in days	**Archival data available** since year
Passive Optical/Thermal			
ETRS-1/Landsat-1 MSS	80	18	1972
TIROS-/NOAA-AVHRR	1,100	<1	1978
Landsat TM	80/30	16	1982
SPOT 1-3	10/20	26	1986
IRS-1C	6/24	24	1995
SPOT 4	10/20	26	1998
Landsat ETM+	30/15	16	1999
Terra-ASTER	15/30	16	1999
Terra-MODIS	250/500	8/16	1999
CBERS-1	20/80	26	1999
IKONOS(-2)	1/4	3-5	1999
QuickBird-2	0.6/2.4	1.5-2.5	2001
SPOT 5	2.5/5/10	26	2002
EnviSat-MERIS	300	3	2002
WorldView-1/2	0.5	1.7	2007/09
RapidEye	6.5	1	2008
Pléiades-1A/B	0.5/2.8	26	2011/12
Sentinel-2	10/20/60	5/10	2015
Synthetic Aperture Radar			
ERS-1	10-30	35	1991
RADARSAT-1	10-100	24	1995
Envisat-ASAR	28	35	2002
TerraSAR	1-18	2	2007
Sentinel-1	5-40	12	2014

The application and selection of an appropriate remote sensing system for land use and land cover mapping depends on the scope and target scale of the mapping task. According to Weng (2010, pp. 6-7), Gomarasca (2009, pp. 59-61), and Möller (2005, p. 2), the following resolutions and systems for the corresponding application and mapping scales are suggested:

On the **local to regional mapping scale** (< 1 : 500), extremely high resolution (0.1 to 0.5 m) airborne such as acquired with the High Resolution Stereo Camera Airborne Extended (HRSC-AX), Airborne Digital Sensor (ADS 40), and UltraCamX or very high and high resolution spaceborne imagery (0.5 to 4 m), such as available through IKONOS, QuickBird, WorldView or the Pléiades constellation, is most effective.

On the **regional to continental scale** (> 1 : 250,000), medium to low resolution data (4 - 50 m), such as that provided by the imaging sensors of the Système Probatoire d' Observation de la Terre/Satellite Pour l' Observation de la Terre (SPOT), the Landsat Thematic Mapper/Enhanced Thematic Mapper Plus (TM/ETM+) or the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) on the Terra satellite, is used most frequently.

On the **continental to global scale** (< 1 : 250,000), very low and extremely low resolution imagery (> 50 m), such as provided by the Advanced Very High Resolution Radiometer (AHVRR) on the TIROS/NOAA series, the Moderate Resolution Imaging Spectrometer (MODIS) on Terra, or the Medium Resolution Imaging Spectrometer (MERIS) on EnviSat, is most suitable.

In particular for urban land cover and land use mapping, night time observations of the Defense Meteorological Satellite Program/Operational Linescan System (DMSP/OLS) show a great potential for mapping and characterizing populated places (e.g., Zhang & Seto, 2011 and Pandey et al., 2013). Active remote sensing systems such as Light Detection and Ranging (LIDAR) and high-resolution, interferometric Synthetic Aperture Radar (SAR), emphasizing the three-dimensional (3D) characteristics, have been increasingly used for urban land cover mapping, such as the *Global Urban Footprint (GUF)*, and land use pattern analysis (e.g., Henderson, 1997; Gamba et al., 2009; Esch et al., 2010; Taubenbock et al., 2011).

As urban environments – due to their high spatial and spectral diversity of surface materials that far exceeds natural environments – are considered as one of the most challenging areas for remote sensing analysis (Herold et al., 2003, p. 1907), hyperspectral (20-250 spectral bands) and ultraspectral (> 250 bands, cf. Ehlers et al., 2009, p. 722) remote sensing will gain further importance for land cover and land use mapping tasks. A comprehensive overview and further potentials of remote sensing data, particularly for urban land use mapping, are elaborated in Gamba & Herold (2010).

A complementary component to space- and airborne remote sensing may provide solar powered *High Altitude Long Endurance* (HALE) unmanned aerial vehicles with flight altitudes at around 20,000 meters, which are still mainly used for military reconnaissance (Jacobsen, 2005, p. 495), but may soon find their way to civilian applications.

2.1.2 Thematic Land Use and Land Cover Maps

Thematic land use and land cover maps are digital maps, explicitly describing the land cover and land use at a defined cartographic scale and geographical scope. In contrast to the previously discussed remote sensing data, the land cover and land use information has not to be extracted by visual or computational interpretation, but is ready-to-use. However, the temporal availability is much more limited. In the following, a brief introduction to the production principle and an overview on available data sets is given.

Fundamental Principle

The predominant source for deriving digital thematic land use and land cover maps is remote sensing data (cf. section 2.1.1). The information is extracted by visual or computational interpretation. While the land cover is directly detectable by the biophysical manifestations, the land use is derived or supported by *in situ* measurements, socio-economic statistics, and the land cover information. The approach of linking remotely sensed information with socio-economic knowledge of the social sciences is euphemistically termed as "socializing the pixel" and "pixelizing the social" (Geoghegan et al., 1998, pp. 51-52).

Another source for thematic land use and land cover mappings are digital geographical data. This data source may include *Volunteered Geographic Information* (VGI, cf. Goodchild, 2007) or *Collective Sensing* (Blaschke et al., 2011) as well as authoritative national geotopographic datasets. The capabilities of the former have been demonstrated on the basis of OpenStreetMap (OSM) by Hagenauer & Helbich (2012), Arsanjani et al. (2013), Hecht et al.

(2013), and Comber et al. (2013). The capabilities of the latter in form of a national digital landscape model have been shown, e.g., by Meinel (2010) and Krüger et al. (2013). Further sources such as historical cartographic records are discussed in section 2.1.3.

Table 2.2: Examples of important land use and land cover classification systems (classification level I).
Source: Author's own, compiled from Anderson et al. (1976), Gomarasca (2009) and FAO (2014).

Class	LC/LU USGS (1976)	CORINE LC (1990)	ISO LCCS3 GLC (2014)
01	Urban or Built-up Land	Artificial Surfaces	Artificial Surfaces
02	Agricultural Land	Agricultural Areas	Croplands
03	Rangeland	Forest/Semi-natural	Grassland
04	Forest Land	Wetlands	Tree Covered Areas
05	Water	Water Bodies	Shrubs Covered Areas
06	Wetland	-	Herbaceous Vegetation
07	Barren Land	-	Mangroves
08	Tundra	-	Sparse Vegetation
09	Perennial Snow or Ice	-	Bare Soil
10	-	-	Snow and Glaciers
11	-	-	Water Bodies

The thematic mapping of the land use and the land cover requires a classification system. As previously shown in section 2.1, there exists a multitude of classification systems varying in scale, semantics, and number of classes, but are mainly based on the hierarchical four-level Land Use/Land Cover Classification System of the US Geological Survey (USGS, Anderson et al., 1976). In 2012, a successor of the first UN/FAO Land Cover Classification System (LCCS) has been certified as international ISO standard (LCCS3, ISO 19144-1, cf. table 2.2).

Available Data and Temporal Coverage

The availability of thematic land use and land cover maps is closely related to the development of remote sensing techniques and thus, in the sense of long-term observations, temporally limited to some decades. However, there exist some approaches to reconstruct global and spatially explicit historical information on certain land use classes such as cropland and pastures. Examples are for the past:

- **12,000 years (Holocene)**: the History Database of the Global Environment (HYDE, cf. Klein Goldewijk et al., 2010, 2011),
- **6,000 years (Mid to Late Holocene)**: the global permanent and non-permanent agriculture data by Olofsson & Hickler (2007),
- **300 years (Late Holocene / Anthropocene)**: the global land use, wood-harvest activity, and secondary land data by Hurtt et al. (2006).

These long-term retrospective land use maps are typically of low resolution (0.5 degrees) and are based on assumptions on the historical population of *Homo sapiens* and its land use practices. Fuchs et al. (2013) present a high-resolution model to reconstruct the land use in six categories before 1990 (1950 and 1970) on a pan-European level, which is validated using aerial imagery. Recent digital land use and land cover maps are available on a global, a continental/national and a regional/local scale. The FAO Global Land Cover (GLC-SHARE) is the first global database created using the ISO standard for land cover classification and Land Cover Meta Language (FAO, 2014, p. 15). Table 2.3 gives an overview of recent thematic land use and land cover maps at various scales and their temporal coverage.

2.1.3 Geotopographic and Cadastral Mappings

A third important – and for long-term retrospective studies even a *conditio sine qua non* – source are cartographic records such as historical cadastral and, in particular, topographic map series. A topographic map, from Greek *τοπος*, *place*, and *γραφω*, *write*, depicts the geographic variation of height and shape over the Earth's surface as a two dimensional representation at a defined cartographic scale (cf. Hendricks, 2008, p. 479). Due to the terminological ambiguity of the term topographic map in the context of physics, medicine, and computer science such as describing the *Fast Level Set Transform* (e.g., Atif & Darbon, 2009), the author suggest the term ***geotopographic map*** in this geographical notion.

Cadastral maps, from Greek *καταστιχον*, *line-by-line*, refer to large scale thematic maps that record, based on measurements, attributes of land parcels such as location, size, value, and ownership (the land register or cadaster). The history of cadasters can be traced back more than 2,000 years before present to the land surveyors *(agrimensores)* of the Roman Empire (Stubkjaer, 2008, pp. 65-66). The long-standing tradition of both cadastral and topographic mappings have turned these historical cartographic documents into valuable source of historical land use and land cover information. In the following, a brief introduction to cartographic mapping process and an overview on the available map data is given.

Fundamental Principle

Emerson (1906, p. 461) conceived maps as "a kind of written language by which an immense amount of information may be conveyed in a brief space and, like any other language, maps must be thoroughly understood before their facts can be well appreciated". The cartographic production and communication process can, according to Hake et al. (2002, pp. 22-24), be conceptualized by a three-tiered model (cf. figure 2.3). The primary model includes the acquisition and storage of the primary geoinformation using terrestrial surveying or photogrammetric measurements. The secondary model comprises the design and storage processes such as the cartographic generalization and the actual map production.

The tertiary model refers to the map usage and application encompassing the visual and automated map interpretation as well as the spatial cognition in the users' mind. Comprehensive descriptions on the psychology and cognitive representation of maps can be found, for example, in *How Maps Work* by MacEachren (1995). For computational approaches to the acquisition and usage of map information, the reader is referred to section 3.2.2.

Available Data and Temporal Coverage

For centuries, cartographic documents have been unique and efficient "storages devices" (Roberts, 1962, p. 12) for geospatial information. Evidence of earliest cartography have been found in the prehistoric and historical civilizations of the Near and Middle East more than 4,000 years ago. A *graffito* on a clay tablet, found in northern Mesopotamia, representing the Euphrates and a tributary river, the bordering mountains and the cities, is currently perceived as the first cartographic document, which has been dated between 2,400 to 2,200 BCE (Gomarasca, 2009, p. 20; Kasturi & Alemany, 1988, p. 671).

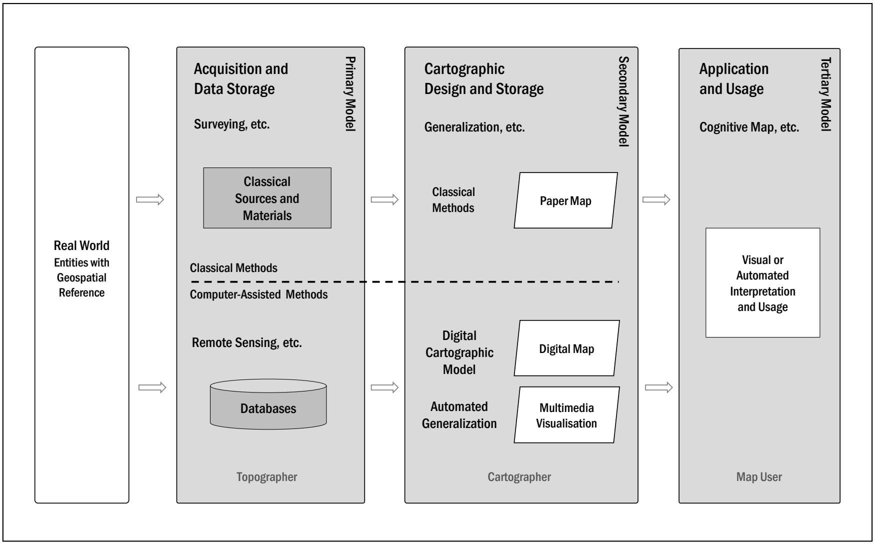

Figure 2.3: The three-tiered model of the cartographic mapping and communication process.
Source: Modified after Hake et al. (2002, p. 22), © 2002 De Gruyter.

Milestones of historical cartography are considered, amongst other, the *Hipparchus*' map (around 150 BCE) as the first geometric representation using a geographical equidistant grid, *Ptolemaeus/Ptolemy's Geographike Hyphegesis (or Geographia/Cosmographia)* at 150 CE, the *Tabula Peutingeriana*, the medieval *Mappae Mundi*, and the Ptolemy-based *Tabulae novae/modernae* of the renaissance, including the *Waldseemüller* map *(or Universalis Cosmographia)* from 1507, as the first map showing the continent name America (cf. Gomarasca, 2009, pp. 21-28). A comprehensive synopsis and application of early, medieval to renaissance maps for a long-term topochronological landscape analysis can be found in Csaplovics (2005).

The era of trigonometric land surveys started in 1744 with *Cassini de Thury's* new projection and surveying, resulting in the *Carte géométrique de la France* (cf. Cavelti, 1989, p. 2). Numerous land surveys followed all across Europe as well as later also in the spheres of the colonial powers. Examples are the Austro-Hungarian surveys (e.g., Josephine military survey, 1763-1787, at scale 1: 28,800), the Ordnance Survey (1791-1850, at scale 1 inch : 1 mile), the Gaussian survey (1821-1825, at scale 1: 21,333), the Prussian survey (1830-1865, at scale 1: 25,800), or the Saxonian survey (1780-1806, at scale 1: 12,000) (cf. Haase et al., 2007; Walz, 2008; Podobnikar, 2009; Skokanová et al., 2012). Given a temporal coverage of ***more than 200 years before present*** and a sufficient geometrical accuracy, the maps of these land surveys became an unique and valuable source for the reconstruction of historical landscapes, land cover and land and use data. Table 2.4 gives an overview and temporal coverage of studies using historical maps.

Table 2.3: Global, continental, national, and local land use and land cover maps. Source: Author's own, compiled from Schneider et al. (2009), Esch et al. (2011) and FAO (2014).

Name and Temporal Availability (Years)	Source, Provider, or System (No. of classes)	Spatial Resolution (approx.)
Global		
IGBP-DISCover 1992/93	NOAA-AVHRR, IGBP-DIS, IGBP (17)	1000 m
GLC 2000	SPOT4-VGT, EC-JRC, FAO LCCS (22)	1000 m
GlobCover 2005, 2009	ENVISAT-MERIS, ESA, FAO LCCS (22)	300 m
GLC-SHARE 2014 (beta)	Regional LC/Landsat, FAO, ISO LCCS3 (11)	1000 m
Global (urban)		
LITES 1992, 2012	DMSP-OLS Nighttime, NGDC-NOAA (1)	1000 m
Global Urban Extend 2001	MODIS, SAGE UW-Madison, IGBP (1/17)	500 m
Global Urban Footprint 2014	TerraSAR-X/TanDEM-X, DLR (2)	12 m
GHSL 1975, 1990, 2000, 2014	Landsat 1 - Landsat 8, EC-JRC (3/4 temporal)	38 m
Continental/National		
EU Copernicus CLC 1990-2012	Landsat/SPOT/IRS, EC-EEA, CORINE (44)	25 ha / 100 m
AFRICOVER 1992-2002	LandsatTM 5, UN FAO, LCSS (Var)	-
US NLCD 1992-2011	Landsat, USGS, MRLC (16)	30 m
Local/Regional (harmonized)		
EU Urban Atlas 2000-2012	SPOT5/RapidEye, EC-EEA, CORINE (44)	5 ha / 2.5 m

Table 2.4: Map-based, spatially explicit reconstructions of historical land use and land cover. Abbreviated types refer to land use (LU), land cover (LC), explicit urban land use (ULU), and forest cover (FC). The temporal coverage gives the study coverage, maps may in use partly only for the oldest datasets.
Source: Author's own.

Study / Publication (Year)	Country / Region (Type)	Temporal Coverage (Time Steps)
Antonson (2009)	Sweden (LU)	1637 - 1952 (3)
Cousins (2001)	Sweden (LU)	1678 - 1881 (4)
Petit & Lambin (2002)	Belgium (LU/LC)	1775 - 2002 (7)
Levin et al. (2010)	Palestine/Negev Desert (ULU)	1799 - 1948 (8)
Hamre et al. (2007)	Norway (LU)	1865 - 2002 (2)
Raet et al. (2008)	Estonia (FC)	1850 - 2002 (3)
Walz (2008)	Germany (LU)	1780 - 2000 (4)
Neubert & Walz (2002)	Germany (LU)	1780 - 1993 (4)
Stäuble et al. (2008)	Switzerland (LU)	1802 - 1979 (6)
Pearson (2006)	Great Britain (LU)	1836 - 1850 (2)
Skanes & Bunce (1997)	Sweden (LU)	1741 - 1993 (4)
Geri et al. (2010)	Italy (FC)	1933 - 2000 (2)
Haase et al. (2007)	Germany (LU)	1784 - 1993 (4)
Kirk et al. (2011)	USA North Carolina (ULU)	1907 - 1990 (6)
Meinel et al. (2009)	Germany (ULU)	1984 - 2005 (5)
Seiler et al. (2013)	Germany (FC)	1842 - 2000 (3)
Meinel & Neumann (2003)	Germany (LU)	1790 - 1998 (7)
Hamandawana et al. (2005)	Botswana / Okavango (LU)	1921 - 2001 (6)
Bieling et al. (2013)	Germany (LC)	1824 - 2009 (4)
Swetnam (2007)	Great Britain (LU)	1930 - 1998 (6)
Syrbe & Ullrich (2011)	Germany (LU)	1794 - 1994 (3)
Skaloš et al. (2011b,a)	Czech Republic (LC/FC)	1780 - 2007 (4)
Skokanová et al. (2012)	Czech Republic (LU)	1836 - 2006 (5)
Plieninger (2012)	Germany (FC)	1901 - 2009 (9)
Thinh & Vogel (2005)	Germany (LU)	1780 - 1998 (8)
Podobnikar & Kokalj (2006)	Slovenia (LU)	1800 - 2000 (3)
Witschas (2003)	Germany (LC)	1880 - 2000 (4)
Zhou et al. (2011)	USA Maryland (FC)	1914 - 2004 (6)
Bender (2005)	Germany (LU)	1870 - 1990 (3)
Nikodemus et al. (2005)	Latvia (FC)	1911 - 1990 (3)
Lung et al. (2012)	Kenya / Kakamega (FC)	1912 - 2003 (5)
McChesney & McSweeney (2005)	USA Ohio (LC)	1961 - 1994 (2)
Kienast (1993)	Switzerland (LC)	1888 - 1982 (12)

Table 2.5: Selection of important international collections of digital historical maps (partially georeferenced).
Source: Author's own, compiled from the given websites as of July 2013.

Name of the Online Digital Repository Link to Resource	**No. of Maps** (approx., as of July 2013)
Bibliothèque nationale de France (BnF numérique) http://gallica.bnf.fr/html/cartes/cartes	42,000
Cartography Associates (David Rumsey Map Collection) http://www.maps-charts.com; http://www.davidrumsey.com	48,000
Charles University in Prague (PřF UK mapová sbírka) https://www.natur.cuni.cz/geografie/mapova-sbirka	36,000
Deutsche Fotothek (Kartenforum) http://www.deutschefotothek.de/kartenforum	22,000
Harvard College Library (Harvard Map Collection) http://hcl.harvard.edu/libraries/maps/	14,000
Institut Cartogràfic de Catalunya (Cartoteca Digital) http://cartotecadigital.icc.cat/cdm/	58,000
National Library of Scotland (NLS) http://maps.nls.uk/index.html	86,000
New York Public Library (Map Division) http://maps.nypl.org/	20,000
USGS (Historical Topographic Map Collection) http://nationalmap.gov/historical/index.html	180,000
Old Maps Online (Meta-Collection) http://www.oldmapsonline.org	> 500,000

In recognition of this scientific and cultural value of the historical cartographic documents, many national mapping agencies as well as libraries provide not only access to the archival map documents, but also make them digitally available through web portals. The above table 2.5 gives an overview of some important international map collections freely accessible via the internet. Since 2006, these efforts are fostered and channeled by the commission on *Digital Technologies in Cartographic Heritage* of the International Cartographic Association/Association Cartographique Internationale (ICA/ACI), which is related to the United Nations Educational, Scientific and Cultural Organization (UNESCO).

Computational approaches to automatically access the geoinformation "concealed" in the archival maps are addressed in the chapters 3, 4, and 5 of this work. In the following, the potentials of these sources for monitoring and modeling the land change are discussed.

2.2 Monitoring and Managing Land Change

Repeated mappings of land use and land cover allow the documentation and analysis of changes. The process of purposeful repeated tracking of changes is referred to as *monitoring*. Two categories of changes in land use and land cover are distinguished: *conversions* and *modifications* (Meyer & Turner, 1994, p. 5). Conversions are defined as changes from one class to another, modifications as changes of the conditions within a class, e.g., intensification of a land use or the thinning of land cover. The long-term and gradual changes of land uses are also described as *transitions*. Generally, land use and land cover changes (LUCC) are referred to as *land change* (e.g., Jansen & Veldkamp, 2012; Bieling et al., 2013).

2.2.1 Towards a Land Change Science

Land use and land cover changes have become a major driver of the global environmental change. Research of the last decades has shown, that both natural and anthropogenic changes of the terrestrial surface interact with the climate, the global carbon cycle, the biodiversity, and landscape ecology (Petit & Lambin, 2002, p. 117). However, up to the 1990s, land use and land cover change were studied from a disciplinary perspective (Verburg et al., 2009, p. 1327). In the context of a new understanding of coupled Earth systems, a long-term oriented, integrated and interdisciplinary research field on land use and land cover change has emerged: *Land Change Science* (cf. Lambin et al., 2001; Rindfuss et al., 2004).

Land change science (LCS) investigates the complex dynamics of land cover and land use as a coupled human-environment system and seeks to develop new concepts and tools for improved understanding and management of land resources (Turner et al., 2007).Verburg et al. (2009) extend the integrated land cover and land use concept to the land function as provider of goods and services. The objectives of LCS can be summarized, according to Rindfuss et al. (2004), Verburg et al. (2004), and Turner et al. (2007), to improve:

1. observing and monitoring of land change patterns and dynamics,
2. understanding of these changes as a coupled human-environment system,
3. disentangling the complex suite of biophysical and socioeconomic forces,
4. spatially explicit land change models compatible with Earth system models, and
5. assessments of system outcomes, such as vulnerability, resilience, or sustainability.

The research efforts are mainly driven by the four Earth system science initiatives: International Geosphere-Biosphere Programme (IGBP), the International Human Dimensions Programme on Global Environmental Change (IHDP), the International Programme of Biodiversity Science, and the World Climate Research Programme (WCRP). The following section addresses the first objective of LCS, namely the monitoring of the land change patterns and dynamics.

2.2.2 Monitoring and Measuring Land Change

In a general sense, monitoring refers to the observation of an entity, system, or phenomenon at discrete points in time. In the context of earth observation and land change, the central components of monitoring can be described (cf. Lang & Blaschke, 2007, p. 311) as:

- Long-term observation of natural and anthropogenic influenced systems,
- Observing, quantifying, and evaluating changes at different scales,
- Identification of trends and predictable patterns,
- Use of a unified methodology and of harmonized approaches,
- Scientifically consistent and unbiased metrics for status and integrity of systems,
- Identification of anthropogenic-induced changes and local-global feedback loops.

Environmental monitoring may encompass climatological parameters, soil, water, agriculture, forests, carbon fluxes, natural resources, land cover and land use, as well as entire ecosystems such as wetlands. To capture the complex nature of the systems and to measure changes over time, ***indicators*** (from Latin *indicare*, to point out) are used.

In the (geo-)spatial context, indicators are often basically spatial metrics, representing values and quantities of an entity per spatial unit. Comprehensive overviews, proposals and applications of such spatial metrics for landscape and urban research can be found in McGarigal & Marks (1994), Galster et al. (2001), Thinh (2003a), Herold et al. (2005), Irwin & Bockstael (2007), Jaeger et al. (2010), Schwarz (2010), and Inostroza et al. (2013).

These basic scientific indicators can be further aggregated to policy-relevant "meta-indicators" such as vulnerability and integrity (cf. Lang, 2008, p. 8), which are useful for decision making. Lang et al. (2008, 2014) propose the *geon* concept for an integrated high-level monitoring, which enables the transformation of information on specific systemic components to policy-relevant information. Figure 2.4 shows the outline of an hierarchical, indicator-based environmental monitoring concept.

Environmental monitoring efforts in general and land change monitoring activities, in particular, are channeled, coordinated and supported by the United Nations Global Geospatial Information Management (UN-GGIM), the intergovernmental framework Global Earth Observation System of Systems (GEOSS) by the Group on Earth Observation, and the international initiative on Global Observation of Forest and Land Cover Dynamics (GOFC-GOLD). Continental activities such as the European Copernicus Land Monitoring Services, formerly Global Monitoring for Environment and Security (GMES), the North American Land Change Monitoring System (NALCMS) of Canada, Mexico, and the United States, as well as national and regional efforts underpin these global land change monitoring initiatives.

2.2.3 Managing and Controlling Land Change

Human populations have transformed their environment and thus have affected the structure and function of the Earth system since their evolution as a distinct modern species (cf. Moran et al., 2004, p. 1). The development of land for settlement is one of the most remarkable human activities in terms of impacting the natural environment (Hasse, 2007, p. 117). While the increasing urbanization offers new opportunities and benefits, it contrastingly causes a wide gamut of socio-economic and environmental issues (cf. Kalnay & Cai, 2003, pp. 528-531, Foley et al., 2005, pp. 570-573). However, these

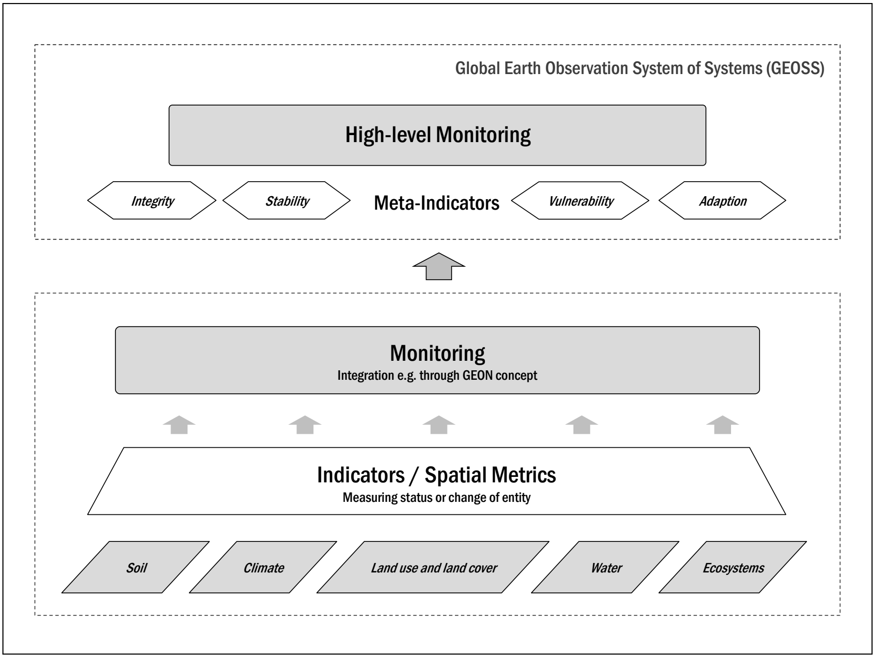

Figure 2.4: Outline of an hierarchical indicator-based environmental monitoring concept and its components.
Source: Modified after Lang (2008, p. 8), © 2008 Springer Nature.

concerns were not new, and have been expressed before in various poems and paintings of the industrial age (e.g., cf. figure 2.5).

In particular the increasing share of the private motorized transportation in the twentieth century propelled the rate of urban land take, unprecedentedly. Figure 2.6 summarizes some impacts of the dispersed urban growth, also referred to as sprawling. Increasing awareness of these evident issues during the second half of the twentieth century have lead to the adoption of the sustainability concept in development strategies (cf. section 1.1). This includes not only to measure and monitor land system states and changes but also to control and influence the ongoing land take using sustainable land management practices.

Taking up the early studies *Limits to growth* (Meadows et al., 1972), the United Nations report *Our common future* by the World Commission on

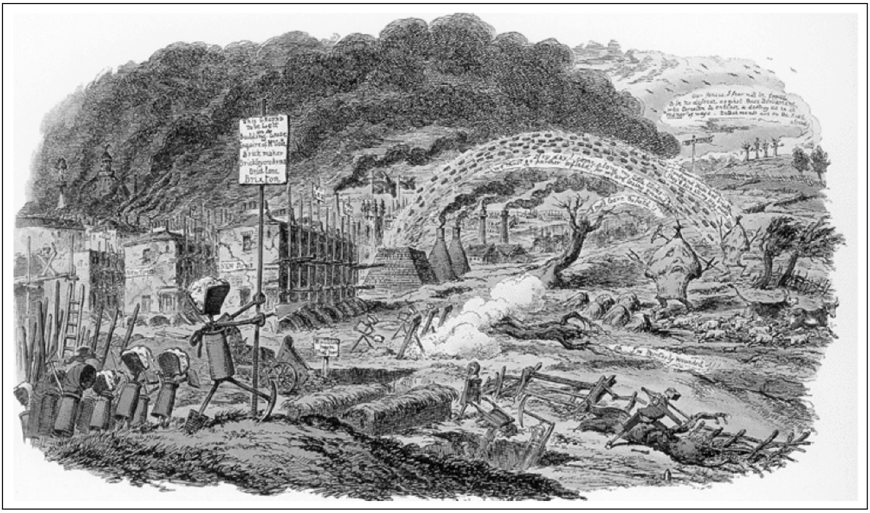

Figure 2.5: "London Going Out of Town or the March of Bricks and Mortar", etching by George Cruikshank, 1829.
Source: Adapted from Goldstein et al. (2004, p. 126), © 2009 The Harvard Art Museums, President and Fellows of Harvard College, ID 2009.156.

Environment and Development (1987) and the commitment *Agenda 21* by United Nations Conference on Environment and Development (1992), most nations have adopted national sustainable development strategies (NSDS), with some setting tangible aims to limit their land take (e.g., Germany, Bundesregierung, 2002, p. 68). Continuously controlling these aims and managing land use accordingly necessitates suitable instruments such as regional environmental information management systems (cf. Siedentop, 2006, pp. 69-70). Figure 2.7 depicts a general outline and basic components of a regional information system for controlling and managing land change.

Central components on both the strategic and the operational level are a monitoring, a controlling, and a reporting element. Efficient systems can have – besides the controlling function – also communication, marketing, and early-warning capabilities (cf. Siedentop, 2006, p. 70). Regional systems may be conceptually extended to form Spatial Planning and Spatial Decision Support Systems (SPSS, SDSS) for sustainable land use management (cf. Klosterman & Pettit, 2005, Malczewski, 2006, and Geertman & Stillwell, 2009).

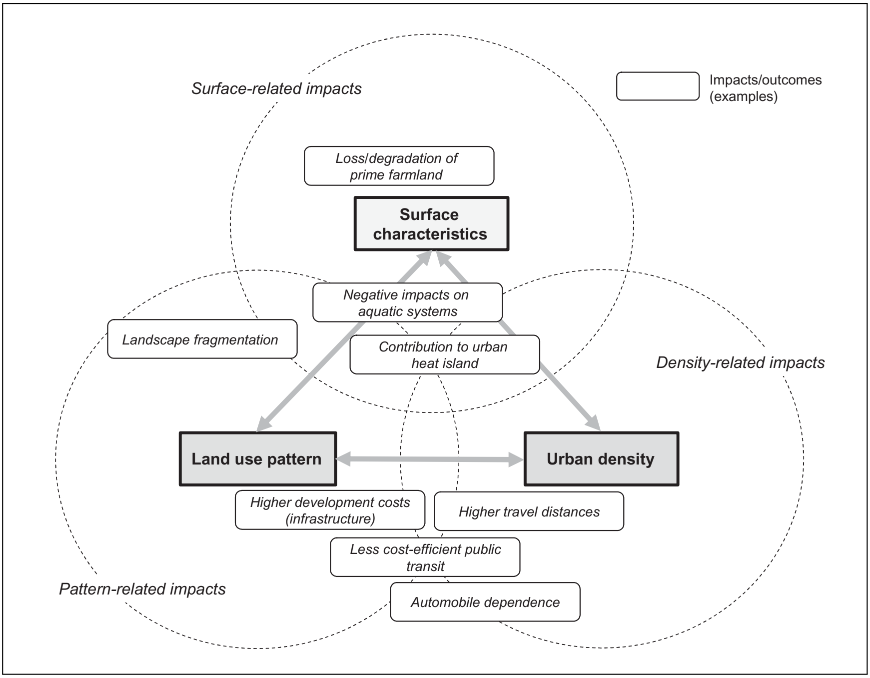

Figure 2.6: Impact phenomena caused by changes of land cover, land use pattern and density.
Source: Adapted from Siedentop & Fina (2010, p. 79), © 2010 Taylor & Francis.

2.3 Modeling and Understanding Land Change Dynamics

Thus far, potential data sources, theoretical foundations and methods for mapping, quantifying, monitoring and managing land use and land cover change were discussed. This section investigates theories and methods to understand the underlying causes and temporal dynamics of land change and, thus, one of the major aims of Land Change Science (cf. Turner et al., 2007, and section 2.2.1). Land change models have proven "to be an important tool, both to conceptualize and test our understanding of the role of different drivers in land use and land cover change and to explore scenarios of possible future developments" (Verburg et al., 2009, p. 1327). Modeling can be understood as "the process of identifying appropriate theory,

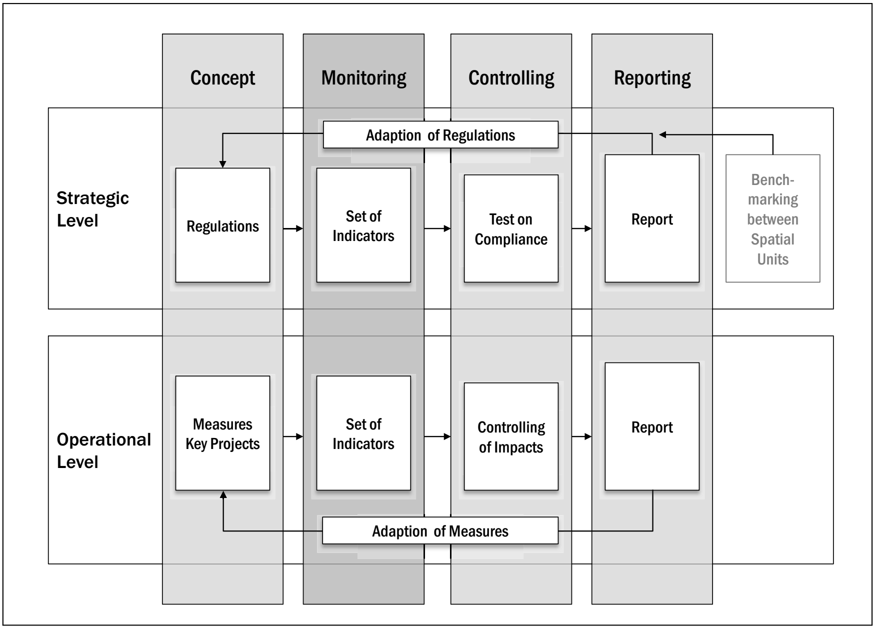

Figure 2.7: Components of an information management system for controlling and managing land change.
Source: Adapted and modified after Siedentop (2006, p. 72) and based on Frick et al. (2001, p. 38), © 2006 ARL.

translating this into a mathematical or formal model, developing relevant computer programs and then confronting the model with data so that it might be calibrated, validated and verified prior to its use in prediction" (Batty, 2009, p. 52). Thus, land change models are built to (1) understand *proximate* and *underlying* causes and forces of change (cf. Lambin et al., 2003, pp. 216-217) and to (2) simulated possible future developments under different initial conditions. Because of the latter, predictive spatial modeling is also referred to as ***geosimulation*** (e.g., Benenson & Torrens, 2004a). In the following, spatial modeling approaches as well as their proper calibration and validation are briefly discussed.

2.3.1 Spatial Modeling Paradigms

There exists a multitude of diverse modeling approaches. Comprehensive reviews and attempts to the classifications of approaches can be found in Agarwal et al. (2002), Briassoulis (2000) and Verburg et al. (2006). Briassoulis (2000) distinguishes four main categories:

1. statistical and econometric models,
2. spatial interaction models,
3. optimization models, and
4. integrated models.

Basically, models can be spatially explicit or non-spatial (Verburg et al., 2006, p. 118). In the context of this work, the focus is set to spatial explicit models. In terms of the scale of application, the approaches can be global or regional models. Most land use and land cover change models are designed for regional applications with extents from local case studies to country or to continental level with resolutions between 50 square meters up to 1,000 square kilometers (Verburg et al., 2006, p. 118). The most prevalent and most favored paradigms for implementing high-resolution regional models for dynamic spatial systems are ***cellular automata (CA)*** and ***agent-based models or systems (ABM)***, also referred to as models of ***multi-agent systems (MAS)***, cf. White & Engelen (2000, p. 384), Benenson & Torrens (2004b, p. 1), and Irwin et al. (2009, p. 1223).

Cellular automata are a class of basic automata (a *Turing* machine, a finite-state-machine, or central processing unit), originally developed by Stanislaw Ulam and John von Neumann, that are defined within the discrete confines of a cellular boundary (Torrens, 2006, p. 253). The states of these spatially and temporally explicit cells are typically discrete and "evolve according to simple transition rules. These rules determine how the cells within a local neighborhood (or at varying spatiotemporal scales) influence the state of each cell at a particular point in time and illustrate how global patterns emerge from local spatial interactions" (Irwin et al., 2009, p. 1231). Thus, CA consist of five basic elements (cf. White & Engelen, 2000, p. 386, Liu, 2009, p. 28): (1) the *cell*, which is the basic spatial unit in a cellular space, (2) the *state*, which defines the attributes of the system, (3) the *neighborhood* (e.g., the *von Neumann* or the *Moore neighborhood*), which is a set of cells with which the cell interacts, (4) the *transition rule*, which defines how the state of one cell changes in response to its current state and the states of its neighbors, and finally (5) the *time*, which specifies the temporal dimension in which a cellular automaton exists.

Mathematically, CA can be described as follows: If $S^t_{x_{ij}}$ is the state of a cell x_{ij} at the location i, j at time t where $S^t_{x_{ij}}$ commonly belongs to a finite number of states of cells in the cellular space, and if $S^{t+1}_{x_{ij}}$ is the state of the cell at time $t+1$, then

$$S^{t+1}_{x_{ij}} = f\left(S^t_{x_{ij}}, S^t_{\Omega_{x_{ij}}}\right), \tag{2.3}$$

where $\Omega_{x_{ij}}$ denotes the set of cells in the neighborhood of cell x_{ij}, $S^t_{\Omega_{x_{ij}}}$ is a set of states of cells $\Omega_{x_{ij}}$ at the time t, and f is a function representing a set of transition rules (Liu, 2009, p. 29). Accordingly, if the cell itself is considered as a member of its neighborhood, then equation 2.3 can be reduced to

$$S^{t+1}_{x_{ij}} = f\left(S^t_{\Omega_{x_{ij}}}\right). \tag{2.4}$$

CA were first introduced to geospatial modeling by Tobler (1979) as "Cellular Geography" and later further investigated and applied in the geographical context, e.g., by Couclelis (1985), White & Engelen (1993), Batty (1997), Clarke & Gaydos (1998), and Batty et al. (1999). Thinh (2003a) extended the standard CA concept to a multivariate CA model. The concept enables assigning each cell a vector of discrete or continuous variables and multivariate states. Thinh (2003b) and Thinh & Vogel (2006) link a CA model with compromise programming (CP) and multiple-criteria decision analysis (MCDA). Li & Yeh (2002) and Almeida et al. (2008) combine a CA model with an artificial neural network (ANN). Li et al. (2012) integrate a genetic algorithm (GA) and Feng & Liu (2012) a simulated annealing (SA) approach for CA model calibration (cf. section 2.3.2).

Agent-based modeling (ABM) refers to the modeling of systems using agent automata, which constitute another class of basic automata, with origins in artificial intelligence (AI) research (cf. Benenson & Torrens, 2004a, p. 6, Torrens, 2006, p. 254). In contrast to CA, the – autonomously acting – basic entities (the agents) are not restricted to a lattice nor have necessarily to be spatial or spatially aware. Agent automata are (1) autonomous, i.e., they have control over their actions and internal state in order to achieve goals, (2) share an environment through agent communication and interaction, and (3) make decisions that tie behavior to the environment. The generality and flexibility of this generic approach has attracted many disciplines using agent-based modeling to study the behavior of entities in various system, including atoms, biological cells, humans, organizations (Parker et al., 2003, p. 317), and also in the field of ***geocomputation*** (e.g., Clarke, 2003). Multi-agent systems are increasingly used in modeling and simulation of land use and land cover change (cf., Parker et al., 2003, p. 320 and Zou et al., 2012, p. 1917), particularly due to theoretical, but also technological advancements such as the increased computational power and the object-oriented programming paradigm. Recent application and advancements of MAS for land change modeling can be found, for example, in Manson & Evans (2007), Ligmann-Zielinska & Jankowski (2010), Perret et al. (2010), Haase et al. (2010), Chen et al. (2012), and Zou et al. (2012). Remaining key challenges of agent-based modeling in the geographical context are discussed in Crooks et al. (2008). Comparing both modeling approaches, the advantages of cellular automata can, according to White & Engelen (2000, p. 384), be summarized to:

- CA are inherently spatial; typically defined on a raster cell space and thus compatible, or can be made compatible, with most spatial data sets,
- CA are dynamic, and can thus represent spatial processes in a direct way,
- CA are highly adaptable and can be set up to represent a very wide range of situations and processes,
- CA are rule-based, and can thus capture a wide variety of spatial behaviors,
- CA are simple, and thus computationally efficient,
- in spite of their simplicity, CA exhibit extraordinarily rich behavior, and
- some CA have shown to be formally equivalent to a Turing machine, i.e., they can represent and execute any possible algorithm.

Multi-agent systems, in contrast, provide:

- a straightforward way to represent spatial entities or actors having relatively complex properties or behaviors,
- inheritance of properties from class to subclass, so that they represent hierarchical systems in a natural way, and
- a way to capture directly the interactive properties of many natural and human systems, as well as the complex system behavior that emerges

from this interaction (cf. White & Engelen, 2000, pp. 384-385, Verburg et al., 2004, pp. 310-311).

Because of the complementary advantages of CA and MAS, both modeling paradigms are often combined (cf. Benenson & Torrens, 2004a, p. 21). An overview of combined CA/MAS models can be found in Parker et al. (2003). The integration of these models with GIS (e.g., Takeyama & Couclelis, 1997) is viewed the most effective for developing process-based models to simulate geospatial dynamics from the bottom up (Irwin et al., 2009, p. 1232).

2.3.2 Model Calibration and Validation

Model calibration and validation are often the most important and computationally most expensive steps in spatial modeling (cf. Longley et al., 2005, p. 376, Silva & Clarke, 2002, p. 528, Herold et al., 2005, p. 370, and figure 2.8). However, in many studies both terms are used interchangeably or only a model calibration is conducted. ***Calibration*** refers to the parameter fitting, i.e., the adjustment of the model parameters such that the modeling result fits real system states at discrete point in time as good as possible. ***Validation***, in contrast, refers to evaluation of the adjusted model against unseen data, i.e., data that where not used for calibration (Verburg et al., 2006, p. 130). That is, the calibrated model has to be tested against data of another area or/and another point in time. In the past, this validation process has been neglected in the development and application of land change models (Wu, 2002, p. 795; Goetzke, 2011, p. 34). Nonetheless, there exists a wide variety of model calibration and validation approaches such as described in Li & Yeh (2001), Silva & Clarke (2002), Almeida et al. (2003), Straatman et al. (2004), Alkheder & Shan (2008), Al-Ahmadi et al. (2009), Onsted & Clarke (2012), Birkin et al. (2011), Li et al. (2012), Feng & Liu (2012).

Thus, the issue of insufficient model validation (Wu, 2002, p. 795) is in many cases primarily due to a lack of sufficient historical records, i.e., the lack of sufficient long-term spatiotemporal data (Goldstein et al., 2004, p. 128). The effects of long-term model calibration and validation based on historical geographical data (cf. figure 2.8) have been investigated and quantitatively assessed in Goldstein et al. (2004) and Akin et al. (2014).

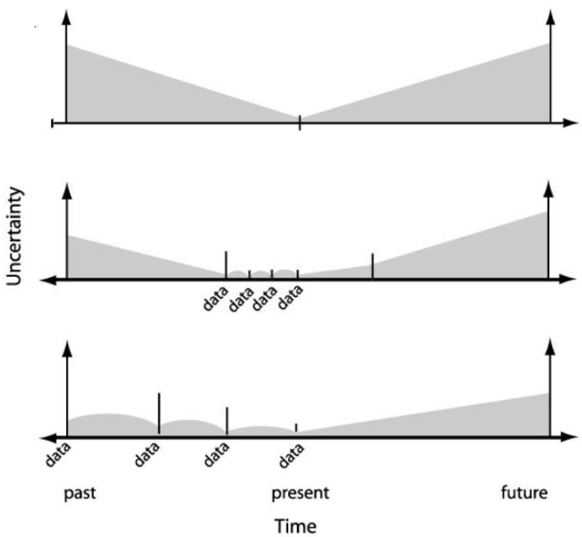

Figure 2.8: Effects of long-term calibration and validation of numerical models on the prediction uncertainty.
Source: Modified after Goldstein et al. (2004, p. 129), © 2004 Elsevier B.V.

2.3.3 Geographical Knowledge Discovery

Thus far, the potential of long-term monitoring and modeling for hypothesis testing for understanding the proximate and underlying causes and forces of land change have been discussed. Another promising approach to generate knowledge and to develop hypothesis about the dynamics of spatial systems provides the field of ***spatial data mining*** and ***geographical knowledge discovery (GKD)*** (cf. Miller & Han, 2001, Miller & Han, 2009b, Mennis & Guo, 2009). The advent of spatially and non-spatially explicit massive data sets, which are in case of unstructured data also referred to as *big data*, has recently drawn much awareness to this research field. The availability of vast spatial and spatiotemporal data provides opportunities for gaining new knowledge to better understand complex geographic phenomena, such as human-environment interactions (Mennis & Guo, 2009, p. 403).

However, traditional spatial analytical methods are confirmatory and require the researcher to have *a priori* assumptions. Thus, these techniques can not readily discover new and unexpected patterns, trends, and relationships that can be hidden within large and diverse geographical datasets (Miller & Han, 2009a, p. 2). Additionally, when facing massive data, traditional analysis methods reveal their limitations, as they (1) focus on a limited perspective (such as univariate spatial autocorrelation) or a specific type of relation model (e.g., linear regression), and (2) are not designed to process very large data volume or newly emerged data types such as trajectories of moving objects (Mennis & Guo, 2009, p. 403). GKD has its roots in knowledge discovery in databases (KDD), introduced in the AI research by Fayyad et al. (1996). The potential of spatial data mining and GKD for urban phenomena is shown in Behnisch (2007). Long-term historical data could enrich spatiotemporal databases and, thus, widen the temporal scope of the knowledge that is to be potentially discovered.

2.4 Summary and Conclusions for Research

The first aim of this chapter was to introduce the theoretical and methodical foundations for evaluating hypothesis one (H1) regarding the relevance and value of spatially explicit long-term monitoring and modeling. The second objective was the identification and analysis of potential data sources for historical LULC information in order to evaluate the second hypothesis (H2). This section sums up the main findings to answer the first and second research question. In contrast to the organization of the chapter (cf. figure 2.1, p. 11), this concluding section is structured from a deductive perspective, starting with arguments for long-term retrospective land change observations and concluding with the potential data source and challenges they pose for the computational information acquisition.

Supporting Modeling and Understanding of Land Change Dynamics

Long-term retrospective observational data may support spatiotemporal data mining and geographical knowledge discovery by providing a wider temporal scope for hypotheses generation and, hence, the investigation of driving forces of land change (e.g., Miller & Han, 2001; Behnisch, 2007; Mennis & Guo, 2009). Thus, the data may also contribute to objectives of Land Change Science (LCS), in particular the ones aiming to improve the monitoring of land change patterns and dynamics, the understanding of these changes as a coupled human-environment system, the disentangling the complex suite of biophysical and socioeconomic forces, and the spatially explicit land change modeling compatible with Earth System Models (cf. Rindfuss et al., 2004; Verburg et al., 2004; Turner et al., 2007).

Modeling as one major tool for understanding and forecasting the behavior of systems may be supported through the provision of data for long-term calibration and independent validation. This can improve the understanding of the *proximate* and *underlying* causes of change (cf. Lambin et al., 2003, pp. 216-217) as well as help to reduce the prediction uncertainty in simulations of future developments (cf. Goldstein et al., 2004 and section 2.3.2). Although spatial modeling has experienced a revival since the "Requiem for Large-Scale Models" announced by Lee (1973, 1994), there are still challenges in the methodology (cf. Wu, 2002; Crooks et al., 2008) as well as the process understanding: "Despite a century of effort, our understanding of how cities evolve is still woefully inadequate." (Batty, 2008, p. 769).

Supporting Monitoring and Managing of Land Change

Long-term retrospective observational data may support the retrospective monitoring and change detection using spatial metrics. That is, spatially explicit indicators such as suggested in McGarigal & Marks (1994) or Jaeger et al. (2010), for example, may be applied to quantitatively track changes over long periods of time (e.g., cf. Antrop, 2005). This also implies the visualization and communication of long-term LULCC process by means of web-based visualization systems (e.g., Meinel & Neumann, 2003), 3D Virtual Reality (VR) models (e.g., Walz, 2008), or Historical GIS (HGIS, e.g., Knowles, 2013). In the context of spatial planning and land management, long-term observational data may support spatially explicit management tools such as regional information and monitoring systems, which can be further extended to form spatial planning/decision support systems (SPSS/SDSS). These systems may assist planners and decision-makers with the *ex-post* evaluation of spatial planning practices, the analysis of the resilience of ecosystems and urban systems against perturbations (e.g., Müller, 2011), or the development of sustainable land management strategies (e.g., Siedentop, 2006; Bock et al., 2011).

Potential Data Sources for Long-Term Land Change Monitoring

Summing up the research conducted in sections 2.1.1 to 2.1.3, the following data sources provide a base for long-term retrospective land change monitoring. The primary and most efficient source for recent and retrospective land change monitoring is remote sensing. In particular, spaceborne remote sensing imagery from civilian and formerly military platforms provides a high spatial and temporal coverage. Airborne imagery may regionally provide a valuable data source prior to the space era. However, either way, the availability of this data source is limited to the 20th century. Another important source are thematic land use and land cover maps. These digital maps explicitly depict the LULC at a defined cartographic scale. That is, the information has not to be extracted but is ready-to-use.

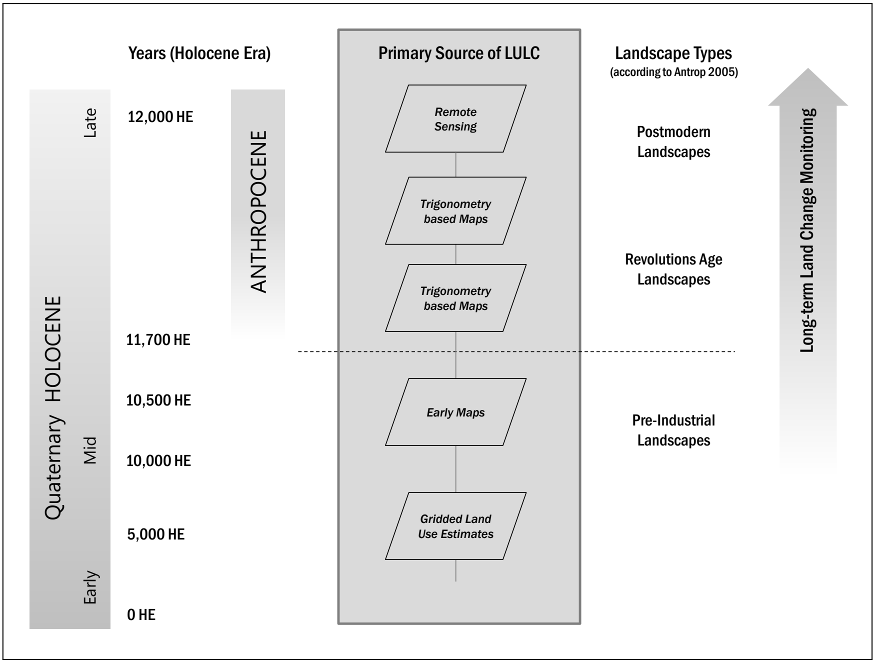

Figure 2.9: Overview of potential data sources for long-term retrospective land change monitoring.
Source: Author's own.

A further advantage over the remote sensing data, which basically detects the land cover as the biophysical manifestations, the land use is derived by *in situ* measurements and socio-economic statistics, a process termed as "socializing the pixel" (Geoghegan et al., 1998, pp. 51-52). Existing data sets are temporally limited to some decades before present (cf. section 2.1.2). However, there exist some long-term approaches to reconstruct historical information on certain land use classes such as for the past 12,000 years (Holocene, cf. Klein Goldewijk et al., 2010, 2011) or the past 6,000 years (Mid to Late Holocene, Olofsson & Hickler, 2007). These long-term retrospective land use maps are typically of low resolution and are based on assumptions of the historical population and land use of *Homo sapiens*.
A third important – and for studies covering the entire Anthropocene even essential – source are cartographic records such as historical cadastral and, in particular, topographic map series. These cartographic documents have been for centuries a storage for geospatial information and thus, also for the Anthropocene, which is largely covered by trigonometry-based maps (cf. section 2.1.3 and figure 2.9).
In conclusion, the wanted retrospective LULC information has to be ***retrieved from geospatial imagery***, particularly scanned maps. Hence, the following chapter introduces the methodological foundations and the state of the art in the acquisition of geoinformation from digital images.

3 Geoinformation from Digital Images

The computational acquisition of both quantitative and qualitative information from digital images is the research domain of image analysis and computer vision. Their methods are applied and constantly enhanced by a wide range of scientific disciplines, such as medical imaging, machine vision, remote sensing, material sciences, and physics, to name a few only. This chapter provides at the outset an overview of some basic principles of image analysis that are key to understand and approach the problem under investigation (cf. section 2.4). The second part is dedicated to recent theoretical and methodical advances in the acquisition of information from images in the geospatial context, focusing mainly on the quantification and characterization of land cover and land use change. To address the second research question, the chapter concludes with the identification and summary of research needs.

3.1 Methodical Foundations of Image Analysis

3.1.1 Human Visual Perception

Many concepts in image analysis are explicitly or implicitly inspired by the visual perception of human beings, which takes place in the part of the brain referred to as the *human visual system* (HVS). Thus, advancements in computer vision and image analysis have always been closely related to the deeper understanding of the primates' paragon, largely driven by the scientific fields of cognitive psychology and computational neuroscience.

The visual perception process can be subdivided in three components: the acquisition, the processing pathways, and the interpretation of the sensory input. The acquisition takes place at the photoreceptors, the *cones* and *rods*, of the *retina*. From the retina the signal is projected via the optic nerve and the optic *chiasm* to the *lateral geniculate nuclei* (LGN) inside the *thalamus* region, referred to as the ***retino-geniculate pathway*** (cf. Gazzaniga et al., 2002, p. 153). From the LGN neurons the signals are further projected via

H. Herold, *Geoinformation from the Past*,
https://doi.org/10.1007/978-3-658-20570-6_3

the ***geniculo-cortical pathway*** within the optic radiations mainly to the *primary visual cortex* (V1, *striate cortex*) and further to the *estriate cortex* with the visual areas V2, V3, V4, and the middle temporal visual area V5/MT (cf. Tovée, 2008, pp. 64-69). According to Hyvärinen et al. (2009, p. 55), the entire visual cortex encompasses about one fifth of the total cortical area in humans, which reflects both the importance and neuronal expense of visual processing.

While the acquisition and neural pathways in visual perception are less disputed in literature, the higher level interpretation of the visual stimuli via bottom-up and top-down neural processing is not yet fully understood. Instead, there is a range of partially controversial explanatory theories. For the perception and recognition of single objects, Goldstein (2008, pp. 61-72) offers four theories from a cognitive psychological perspective:

- *Template Matching Theory*,
- *Interaction Activation Model*,
- *Feature Integration Theory (FIT)*,
- *Recognition-by-Components Theory (RBC)*.

The perception and grouping of multiple entities is explained by the Gestalt psychological approaches (e.g., Wertheimer, 1923). The so-called *Gestalt laws of perceptual organization* are described by Wertheimer (1923, pp. 301-350) and Goldstein (2008, pp. 74-78) as follows:

1. *the **law of simplicity** (or "Prägnanz" in German, cf. Wertheimer, 1923, p. 318): every pattern is seen such a way that the resulting structure is as simple as possible.*
2. *the **law of similarity**: similar things appear to be grouped together.*
3. *the **law of good continuation**: points when connected in straight or smoothly curving lines appear to belong together.*
4. *the **law of common fate:** things moving in the same direction appear to be grouped together.*
5. *the **law of proximity**: objects that are close together appear to be grouped. The law of proximity overrides the law of similarity.*
6. *the **law of familiarity**: things are more likely to form groups if they appear familiar or meaningful.*

A milestone in linking the theories of human visual perception and computational approaches is marked by Marr's ***computational theory of human vision*** (Marr, 1982). Figure 3.1 shows a visualization of the analogies between the HVS and computational image analysis.

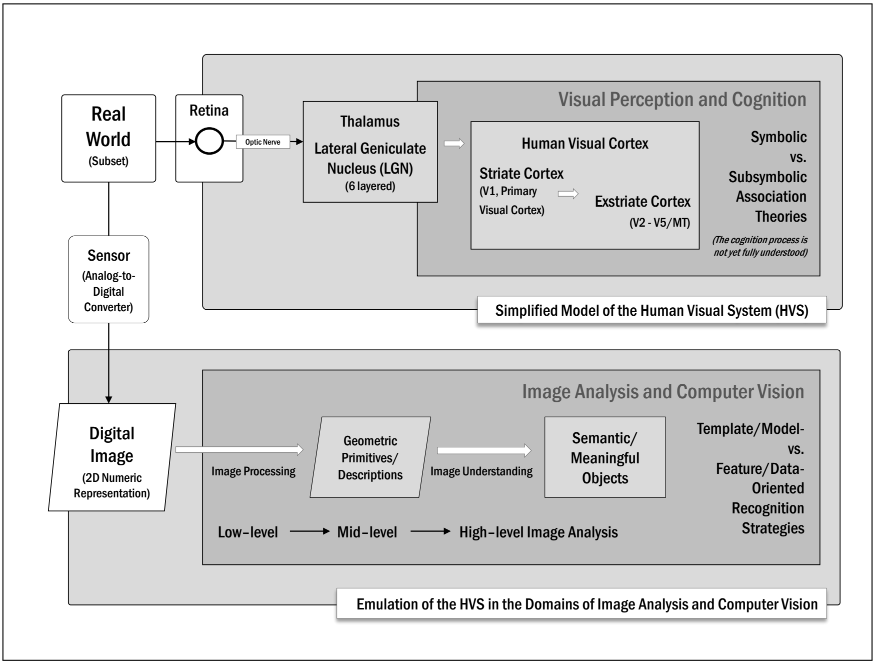

Figure 3.1: The principle of human visual perception and its emulation in image analysis and computer vision.
Source: Author's own, upper part inspired by the descriptions in Gazzaniga et al. (2002, pp. 150-153).

Marr (1982, pp. 24-26) proposed three levels for visual information processing: the computational, the representational or algorithmic, and the implementational. At the representational level, Marr introduced four stages of vision: from the *retinal image* to a *primal (low-level)* sketch to a *2½-D (mid-level)* sketch to a the *3D (high-level)* model representation (cf. Marr, 1982, p. 37). Many concepts in image analysis are based on this representational framework. Terminologically, low-level image analysis is generally referred to as image processing, high-level image analysis is referred to as image understanding. However, this terminology is not used consistently; while in electrical engineering image processing often comprises both fields, in (bio-) medical imaging the term *analysis* is also used for *processing*. In computer science, high-level image analysis is frequently referred to as *Machine* or *Computer Vision* and perceived as a field of artificial intelligence research. As the focus of this work is the computational image (content) description, the term image analysis is consistently used.

In the following sections, major components and methods of image analysis relevant for the research in this work, namely image segmentation, classification and pattern recognition, are briefly discussed.

3.1.2 Image Segmentation Algorithms

An analogy and direct consequence of the visual perception theories introduced above is the research effort devoted to *image segmentation*. Segmentation is defined as the partitioning of a digital image into non-overlapping component regions or constituent parts which are homogeneous with regard to some characteristics such as intensity, shape, texture, or context (cf. Haralick & Shapiro, 1985, p. 100; Gonzalez & Woods, 2002, p. 576). The segmented entities or regions are considered to be meaningful for the further high-level processing and the result of image analysis process (cf. Pal & Pal, 1993, and section 3.1.1). Thus, image segmentation of non-trivial images is one of the ***most crucial and most difficult tasks*** in digital image analysis (Gonzalez & Woods, 2002, pp. 27, 576).

A digital image may be defined as a two-dimensional function $I(x, y)$, where x and y are spatial coordinates and where all amplitude values of I at any pair of coordinates (x, y) are finite and discrete quantities (Gonzalez & Woods, 2002, p. 1). Hence, the segmentation of a digital image $I(x, y)$ can be formally defined as the grouping of the image pixels in a set S of n segments $(S_1, S_2, ..., S_n)$, such that:

$$S_i \subseteq I(x, y), \tag{3.1}$$

$$S_i \cap S_j = \emptyset \quad \forall\, i \neq j, \tag{3.2}$$

$$\bigcup_{i=1}^{n} S_i = I(x, y), \tag{3.3}$$

and, where the homogeneity predicate ψ is:

$$\psi(S_i) = \textit{True}, \tag{3.4}$$

$$\psi(S_i \cap S_j) = \textit{False}, \tag{3.5}$$

for any adjacent subsets S_i and S_j in S (cf. Fu & Mui, 1981, p. 3; Raut et al., 2009, p. 421). In literature, there exists a multitude of various algorithms and different approaches to the problem of image segmentation. However, there is no general theory nor any standard methodology for this field of research (cf. Haralick & Shapiro, 1985, p. 100; Pratt, 2007, p. 579). Many approaches are basically ad hoc, differ in the way they emphasize and balance the homogeneity criteria, and have to be partially supplemented by heuristics. By way of explanation, Fu & Mui (1981, p. 4) argue, that the "image segmentation problem is basically one of psychophysical perception, and therefore not susceptible to a purely analytical solution". Hay & Castilla (2008, p. 84) describe segmentation as an ***ill-posed problem***, in a sense that is has no unique solution, i.e., human image interpreters would not delineate exactly the same segments. Smeulders et al. (2000, pp. 1356-1359) distinguish between strong and weak image segmentation. Some authors consider segmentation as a form of classification, namely spatial-spectral image classification (cf. related discussion in section 3.2.1).

The differing conceptualizations and the lack of a general theoretical framework immanently cause various categorization schemes for the proposed algorithms. Here, an alternative and certainly disputable three-tiered scheme is suggested. The segmentation algorithms are organized according to the used:

Type of geometric primitive: *point-, edge- and region-based segmentation (e.g., edge detection algorithms such as Sobel or Prewitt operators; watershed transformation, energy-minimizing active contour, region-growing, region split-and-merge, and hybrid approaches);*

Homogeneity criterion: *intensity-, i.e., gray value- and color-, and texture-, morphology-based segmentation;*

Grouping method: *clustering-, graph-, threshold-, and hierarchy-based segmentation (e.g., clustering methods such as k-means, fuzzy c-means (FCM), mean shift, Kohonen self-organizing maps (SOM); optimal thresholding methods such as Otsu and SEaTH; graph-based methods such as minimum spanning tree (MST); hierarchical methods such as multi-scale/multi-resolution (MRS) segmentation).*

Extensive elaborations of the algorithmic details, alternative typologies, and evaluations of the above listed approaches can be found in Chen & Pavlidis (1979, 1980); Fu & Mui (1981); Rosenfeld (1984); Haralick & Shapiro (1985); Pal & Pal (1993); Zhang (1996); Rosenfeld (2000, 2001); Cheng et al. (2001); Neubert et al. (2006, 2008); Zhang et al. (2008); Marpu et al. (2010) and Sharma & Aggarwal (2010).

For the specific image analysis problem discussed in the work at hand, applications of various image segmentation algorithms will be described in section 4.2 of this work.

3.1.3 Classification and Pattern Recognition

Higher-level computational image analysis (and so the visual cognition process) encompasses the grouping of the segmented geometric primitives into a set of categories or contextual meaningful objects. This labeling process is referred to as *classification*, or more generically and comprehensively, as *object* or *pattern recognition*. While classification comprises the categorization of entities into a set of classes, the term pattern recognition, as a scientific research field, semantically also encompasses the pre-classification procedures *feature extraction* and *reduction* as well the post-classification evaluation (cf. figure 3.2).

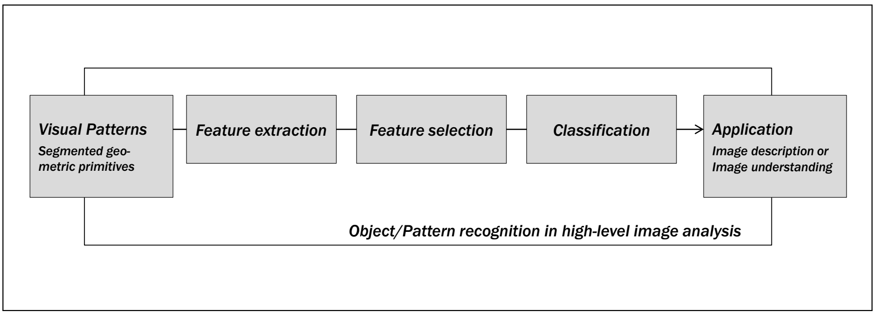

Figure 3.2: Components and process of (visual) pattern recognition in high-level image analysis.
Source: Modified after Waske et al. (2009, p. 7), © 2009 John Wiley & Sons.

In a general sense, a *pattern* can be, a sound, a sequence of sounds representing a spoken word, a deoxyribonucleic acid (DNA) sequence, a texture, or a character. In the domain of computational image analysis a (visual) pattern is an object or a constituent of an image object representing some real world entity or phenomenon. While the applications of pattern recognition are manifold, the underlying concepts and used techniques are fundamentally the same and universal. However, there exist basically different strategies to pattern recognition:

Philosophically and epistemologically, a *Platonic* and *Aristotelean* viewpoint can be distinguished (cf. Duin & Pekalska, 2007, pp. 226-231), which may be perceived as the top-down and bottom-up ways of building and representing knowledge in a high-level image analysis system. Thus, they are related to the ***deductive or holistic*** and the ***inductive or reductionistic*** reasoning principle, respectively.

Conceptually and methodically, Mantas (1987) distinguishes *syntactical* and *statistical* and hybrid approaches. Hybrid and syntactical approaches are frequently also referred to as *structural* pattern recognition. Whilst the field of syntactical pattern recognition is dominated by formal grammars, statistical approaches use wide range of methods, commonly categorized by the type of classification method: *unsupervised* and *supervised* classification.

Unsupervised classification encompasses various clustering algorithms. For supervised classification *parametric* and *non-parametric* methods are known. Parametric methods assume that the conditional class probabilities are known. Non-parametric methods are either probability density-based or geometric approaches (cf. Jain et al., 2000, p. 17). The latter can be further distinguished by the geometry of the constructed decision boundary, i.e., *linear* and *non-linear* approaches. Figure 3.3 gives an overview of the major classification algorithms, categorized by the different recognition approaches. Thus, statistical pattern recognition is closely related to the field of *statistical/machine learning*, which extends the concept by an automated classifiers design and optimization. In this context, supervised classification refers to *supervised learning*, unsupervised classification to unsupervised statistical learning as part of the fields of *data mining and knowledge discovery*. Algorithmic details and applications of the listed pattern recognition strategies and the respective classification methods can be found in Mantas (1987), Duda et al. (2000), Hastie et al. (2008), and Bishop (2006).

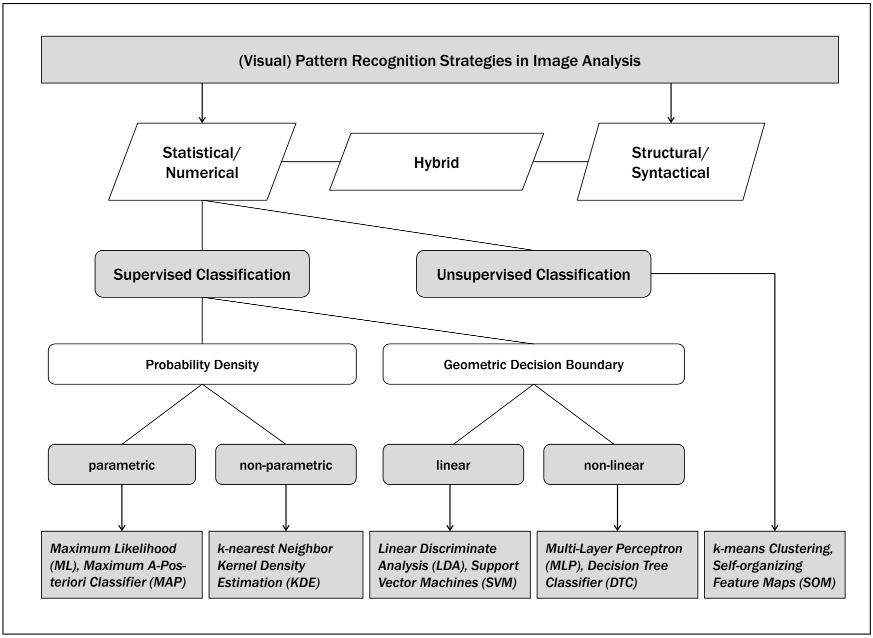

Figure 3.3: Categorization of major classification algorithms for statistical pattern recognition in image analysis.
Source: Modified after Waske et al. (2009, p. 5), © 2009 John Wiley & Sons.

For the classification and recognition problem regarded in this work, the application of a knowledge-based decision tree classifier and a non-parametric artificial neural net (ANN)-based classifier is described and discussed in section 4.4.

3.2 Image Analysis in the Geographical Context

The major application and research fields of computational image analysis in a geographical context are the automated acquisition of (geo-)spatially explicit information from remote sensing and cartographic image data. Based on the generic conceptual and methodical fundamentals of image analysis described in the preceding section, in the following a brief overview and review of concepts and methods in both fields of research are given.

3.2.1 Remote Sensing Image Analysis

Remote sensing image analysis aims at the automated acquisition of quantitative or qualitative information about the Earth's surface, lithosphere, or atmosphere from remotely sensed imagery. The basic principle, applications, and major sensors including non-optical systems have been discussed in section 2.1.1 of this work. The following overview on the fundamentals and recent advancements in the analysis of optical remote sensing data is based on Kraus (1990), Schowengerdt (2007), Lillesand et al. (2008), and Tso & Mather (2009).

There are two basic approaches to the analysis of remote sensing data, the *image-centered* and the *data-centered* view. While in the former the focus is on the spatial relationships among features, the primary interest in the latter is the data dimension itself, e.g., the measurement of spectral absorption or fractional abundance parameters for each image element (cf. Schowengerdt, 2007, pp. 7-8).

Corresponding to the specific characteristics of space- and airborne imagery, traditionally much research effort is devoted to the pre-classification, data preparation and enhancement. Sophisticated methods for low-level image analysis steps such as image rectification, restoration, and enhancement have been developed. According to Lillesand & Kiefer (2000, pp. 474-532) image rectification and restoration methods comprise:

- ***geometric rectification*** *for reducing geometric distortion,*
- ***radiometric rectification*** *for reducing atmospheric/topographic effects etc., and*
- ***image restoration*** *for reducing noise such as striping or bit errors.*

Methods for image enhancement, feature extraction, and feature reduction encompass:

- ***contrast manipulation****, e.g., level slicing and contrast stretching,*
- ***spatial feature manipulation****, e.g., convolution filtering, morphological filtering, edge enhancement, the Fourier transformation, and*
- ***multi-image manipulation****, e.g., multi-spectral band rationing and differencing, Principal components analysis (PCA), canonical components, image fusion, color-space transformations, and decorrelation stretching.*

The interpretation of remote sensing imagery mainly follows a statistical approach to pattern recognition. The patterns are of either spectral, spatial, or temporal nature. For ***unsupervised classification*** of remotely sensed data the *k-means* clustering algorithm, its modification the *ISODATA* algorithm, the *fuzzy-c-means* algorithm *(FCM)*, and – more recently – also *Kohonen's self-organizing (feature) map* algorithm *(SOM)* are used.

Commonly used ***supervised classification*** methods encompass parametric methods, such as the *Maximum Likelihood (ML)* and the nearest-mean classifier, and non-parametric methods, such as *the Parallelepiped classifier*, *the k-nearest neighbor algorithm*, *artificial neural nets (ANN)*, and more recently, *support vector machines (SVM)* and the *random forest (RF)* classifier. The latter three are particularly suitable for high-dimensional, i.e., high ***spectral resolution***, multi-, and hyperspectral image classification problems. Recent developments include the extension to machine learning algorithms (cf. section 3.1.3) for feature reduction and classification, in particular for hyperspectral image analysis.

The increasing ***spatial resolution*** of the imaging sensors over the past decades has challenged the traditional pixel-by-pixel analysis of remotely sensed imagery. At very high resolution (VHR) imagery for example, the patterns, i.e., the relatively small objects of interest in data-centered investigations, may be represented by a group of pixels. Whilst the alternative concept, *segment- or object-oriented* image analysis,

- has a long tradition in computer vision (e.g., Haralick & Shapiro, 1985; section 3.1),
- has been described in remote sensing literature (e.g., Kraus, 1990, pp. 566-567), and
- has been applied to remotely sensed imagery before (e.g., Kettig & Landgrebe, 1976),

the broad adoption and application in remote sensing has started with the beginning of the 21st century. Besides the advent of the VHR imaging sensors and the increasing dissatisfaction with the results of pixel-based analysis approaches (cf. Blaschke, 2010, p. 3), another reason may be the commercial availability of object-based implementations such as the *Fractal Net Evolution Approach* (*FNEA*, cf. Baatz & Schäpe, 2000). Various further approaches have been developed specifically for remote sensing imagery. A comprehensive overview can be found in Neubert et al. (2006, 2008). In this context, the term ***(geographic) object-based/object-oriented image analysis*** *(OBIA/GEOBIA)* has been coined in literature. While firstly introduced as OBIA, Hay & Castilla (2008) suggested to extend the term to *geographic* object-based image analysis (GEOBIA) in order to identify and distinguish the scientific community from other disciplines using the object-based analysis concept such as biomedical imaging, astronomy, and microscopy (cf. Hay & Castilla, 2008, pp. 78-88). Some authors have argued to use the term *object-oriented* (Baatz et al., 2008, p. 32), while others argue for *object-based* instead to distinguish it from the *object-oriented programming paradigm* in computer science (e.g., Castilla & Hay, 2008, pp. 104-105). In recent publications, the terms *geographic* and *object-based* image analysis are used, e.g. in Blaschke et al. (2014).

Specific to segmentation-based remote sensing image analysis are two characteristics. First, in contrast to general image analysis literature, pixel-based segmentation approaches such as optimal thresholding are usually not considered as segmentation algorithms. Second, the segmentation and classification algorithm can usually not be separated in the proposed approaches and should be perceived as interlinked concepts (cf. Lang, 2008, p. 12; Baatz et al., 2008, pp. 31-32), because of the multi-scale character of the interpretation schema. By linking the pixel and vector world, GEOBIA relates remote sensing to *geographic information science* (*GIScience*, cf. Blaschke, 2010; Blaschke et al., 2014). Hay & Castilla (2008, p. 77) define GEOBIA even as a sub-discipline of GIScience.

Application-oriented evaluations of various segmentation-based analysis approaches explicitly developed for remotely sensed imagery can be found in Neubert et al. (2006, 2008) and Marpu et al. (2010). Although studies suggest a superiority of object-based over pixel-based approaches not only for high and very high resolution imagery, the final decision always depends on the type of imaging sensor, scope and aim of a study.

In the following, the second field of image analysis in the geographical context, namely the analysis of cartographic map images, is described by focusing primarily on the differences in the data characteristics and their methodical implications.

3.2.2 Cartographic Map Image Analysis

Cartographic map image analysis aims at the automated acquisition of spatially explicit information from scanned cartographic, i.e., topographic, cadastral, or thematic paper map documents. The computer-based analysis of cartographic images is in the literature variously referred to as ***map processing*** (e.g., Kasturi et al., 1989; Ebi, 1995; Chiang & Knoblock, 2010), ***map recognition*** (e.g., Suzuki & Yamada, 1990; Samet & Soffer, 1998; Dhar & Chanda, 2006), ***map interpretation*** (e.g., den Hartog et al., 1996; Mayer et al., 1992; Ogier et al., 1998; Deseilligny et al., 1998), ***cartographic pattern recognition*** (e.g., Lichtner, 1988; Stengele, 1993; Leyk, 2010; Herold, 2013), ***inverse cartographic engineering*** (Walter, 2011), or, following the computer vision term *image understanding*, also as ***map understanding*** (e.g., Kasturi & Alemany, 1988; Ilg, 1990; Deseilligny et al., 1995; Pezeshk & Tutwiler, 2011b). The common denominator of all approaches behind these descriptions is the application of image analysis methods to a set of digital images, i.e., scanned maps in raster data representations, in order to derive structured information. Thus, in this work, the overarching term ***cartographic map*** or plainly ***map image analysis*** is used. Many basic image analysis concepts used in remote sensing can analogously be applied to maps. However, as discussed earlier in this work, cartographic documents represent - in contrast to remote sensing imagery - a secondary data source, exclusively designed for human interpretation and spatial cognition. That is, the contained spatial information is of abstracted and structured form, defined by the cartographic model. Due to the semi-structured representation as raster image data, however, the structured information is not computationally accessible and has to be retrieved by an algorithm (e.g., field-to-object-transformation or object extraction, cf. Goodchild et al., 2007, p. 249). Additionally, for recognizing single entities in the abstracted, standardized, and symbolized representations of the reality, the object form is more important than the limited set of object/map colors, which corresponds to the spectral resolution and signature in remote sensing imagery. Therefore, many cartographic image analysis approaches follow basically a knowledge-based and object-oriented recognition strategy, making use of both color and morphological characteristics of map objects.

A concept not yet discussed in this work but widely used in cartographic image analysis is ***correlation-based template matching***. Image template matching exploits the symbolic character of the cartographic representation and relates to some of the human visual perception theories introduced in section 3.1.1. The basic principle of the top-down concept at the image representation level can be described as following: a template $T(u, v)$ is found in an image $I(x, y)$ by computing the similarities for all relevant poses of the template (cf. Steger et al., 2008, p. 211). The similarity can be formalized using a simple similarity measure such as the *absolute gray value differences SAD*:

$$SAD(x, y) = \frac{1}{n} \sum_{i=1}^{u} \sum_{j=1}^{v} |T(u_i, v_j) - I(x_i + u_i, y_j + v_j)| \tag{3.6}$$

or the *squared gray value differences SSD* between the template and the image:

$$SSD(x, y) = \frac{1}{n} \sum_{i=1}^{u} \sum_{j=1}^{v} |T(u_i, v_j) - I(x_i + u_i, y_j + v_j)|^2 , \tag{3.7}$$

where n denotes the number of pixels in the $T(u, v)$. More advanced similarity measures such as the *normalized cross correlation (NCC,* cf. Steger et al., 2008, p. 214) can be used to achieve invariance to linear illumination changes in the image.

However, the standard template matching methodology is not invariant to the orientation and the size of an object within a template. As maps contain manifoldly sized and inclined representations, approaches to ***fuzzy*** (e.g., Stengele, 1995; Frischknecht & Kanani, 1998; Frischknecht et al., 1998), ***deformable*** (e.g., Valveny & Martí, 2000), and ***multi-stage template matching*** (e.g., Leyk et al., 2006) have been proposed. While template matching is predominately used to recognize toponym characters and map symbols, linear or areal map features are separated and detected with image segmentation algorithms using either color-, morphology-, or texture-based homogeneity criteria. In the following, a research review of proposed approaches within the active research field of cartographic map image analysis is given.

3.3 Geoinformation from Maps - A Research Review

3.3.1 Research Advancements

The idea of automatically retrieving geoinformation from analogue cartographic documents ranges back to the early days of the computer era. Roberts (1962) gave a visionary view on the potentials of extracting information from topographic maps as rich data storages, while their realizations were still limited by the hardware capabilities of its days. First computational approaches followed by Morse (1969) and Mor & Lamdan (1972), mainly focusing on the automated detection and vectorization of contour lines in topographic maps.

The rise of spatial analysis research (GIScience) and its tools (GIS) triggered an increasing need for spatial information. Besides remote sensing imagery, scans of traditionally produced topographic and cadastral paper maps became important and accessible data sources, in particular for small objects such as buildings and three-dimensional terrain data. In 1992 Bolstad and Smith stated that “map digitization is currently the most common form of spatial data entry, and as such has the greatest impact on spatial data accuracy” (Bolstad & Smith, 1992, p. 24). To reduce the arduous and costly manual digitalization, a wealth of approaches and sophisticated methods for automated map interpretation have been developed (cf. sections 3.3.2 and 3.3.3). Some of the developments have led to commercially available or academic expert systems such as PROMAP (Lauterbach et al., 1992), MAGELLAN (Samet & Soffer, 1998), KAMU (Frischknecht & Kanani, 1998), SEMENTA (Meinel, 2008; Meinel et al., 2009), and, STRABO (Chiang & Knoblock, 2011a), amongst others.

With the advent of new high-resolution spaceborne sensors, progresses in image analysis techniques, and the paradigm shift to digital cartography, the digitization and interpretation of contemporary maps has become less important for generating up-to-date geoinformation. In contrast, archival topographic and cadastral documents have been (re-)discovered as valuable sources of historical geoinformation (e.g., historical land use for landscape change analyses), introducing new challenges to the research field such as distortions and a degraded quality of graphical representations. This development is fueled by another recent phenomena: public libraries and national mapping agencies (NMA) give digital access to vast amounts of cartographic documents as parts of the human cultural heritage. Thus, from a research development perspective, three research stages or drivers can be observed:

- *the exploration of the capabilities of computer systems, artificial intelligence and recognition algorithms applied to maps;*
- *the need for digital spatial and 3D (terrain) information accompanied by the advent of geographic information systems and geospatial analysis tools;*
- *the increasing interest in historical geoinformation (e.g., land use) and the soaring digital availability of historical maps through libraries and mapping agencies.*

In the following, the attempt is made to categorize and review the multitude and large diversity of proposed approaches within this active field of research. In the first part, the approaches are categorized according to the field of application, i.e., the geographical features that are addressed by the object extraction algorithm (section 3.3.2). In the second part, the approaches are reviewed according to the methodology, i.e., the strategies used for segmentation and recognition (section 3.3.3). In conclusion, research needs are derived from the survey and methodical analysis.

3.3.2 Application-Oriented Review

Approaches to map image analysis can be categorized and investigated by the geographical features that are automatically extracted by an image analysis algorithm. This review procedure may support geographers and landscape ecologists building historical geographical information systems (HGIS) to find an appropriate map vectorization algorithm. Basically, there are two types of studies: first, studies focusing on one or multiple specific geographical features (e.g., vegetation) or map objects (e.g., toponyms), and second, studies that propose a generic system for complete map interpretation.

From the perspective of the *geographical reality*, table 3.1 gives an overview of studies categorized by the dominating geographical feature that is addressed in the study. The geographical features include the terrain (represented by the contour lines), the vegetation, the hydrography, the geology, and anthropogenic features such as road networks and buildings. The survey shows, that early approaches mainly focused on urban features and in particular on the terrain, representing the efforts to build three-dimensional digital models of the Earth's surface.

From the perspective of the *cartographic representation*, table 3.2 gives an overview of studies categorized by the map feature that is addressed in the study. The generic systems in the upper part of the table are compiled by the map type for which the system is developed. Most systems are built upon topographic maps (e.g., Ebi et al., 1992; Yamada et al., 1993; Frischknecht & Kanani, 1998; Lacroix, 2009), followed by systems for large-scale cadastral maps (e.g., Bruger, 1988; Lichtner, 1988; Ogier et al., 1993b; Keyes & Winstanley, 2001a; Viglino & Pierrot-Deseilligny, 2003). Thematic maps such as geological or soil maps are less included in the research for automated map analysis. The interpretation of digital maps comprises either previously digitized topographic maps (e.g., Esposito et al., 1997; Malerba et al., 2003) or natively digital maps (e.g., Walter, 2011).

A special category of cartographic representations constitute maps retrieved from online mapping services, which are natively digital, but represented as raster map for screen visualization and, thus, have to be analyzed as scanned paper maps (e.g., Knoblock et al., 2010; Chiang et al., 2013). In the lower part of the table, recognition algorithms for specific map objects such as the lettering, i.e., mainly *toponyms* (from Greek, "$\tau o \pi o \varsigma$" and "$o \nu o \mu \alpha$", place name), and map symbols are compiled. The studies addressing toponyms are separately listed for Latin characters (majority, e.g., Pezeshk & Tutwiler, 2011b), Chinese and Japanese signs (e.g., Yamada et al., 1993; Nakamura et al., 1993). For the semantic recognition of characters, segmentation approaches are sometimes combined with *optical character recognition* (OCR) algorithms. Map symbols may represent natural features such as single trees, hedges, and forests or anthropogenic objects such as towers or orchards (e.g., Boesch, 1996). Complex map symbols are considered to constitute from more than one entity such as dotted or dashed national borders or transmission lines (e.g., Gamba & Mecocci, 1999).

Table 3.1: Application-oriented survey of extraction approaches according to dominant geographical features.
Source: Author's own

Geofeature	Extraction Approaches (References)
Terrain	
Contour lines	Morse (1969); Mor & Lamdan (1972); Dupont et al. (1998); Arrighi & Soille (1999); Khotanzad & Zink (2003); Chen et al. (2006); Salvatore & Guitton (2004); Helvaci & Bayram (2004); Xin et al. (2006); Samet & Namazov (2008); Sandhya et al. (2009); Gul & Khan (2010); Ghircoias & Brad (2011); Hancer & Samet (2011); Banda et al. (2011); Oka et al. (2012)
Vegetation	
Forest cover	Lawrence et al. (1996); Leyk et al. (2006); Leyk & Zimmermann (2006); Leyk & Boesch (2008); Leyk & Boesch (2009); Szendrei et al. (2011a); Pezeshk & Tutwiler (2011b); Zhou et al. (2011);
Hydrography	
Rivers, Waterbodies	Fernandes & Leite (1996); Mariani et al. (1997); Podlasov et al. (2006); Ageenko & Podlasov (2006); Shaw & Bajcsy (2011); Kirby & Henderson (2013)
Geology	
Pedology, Soil types	Wise (1995); Wise (2002); Qi & Zhu (2003)
Urban areas	
Parcels, Urban blocks	Lichtner (1985); Mayer et al. (1992); Ogier et al. (1993a,b, 1998); Janssen et al. (1993); Katona & Hudra (1999); Roux & Maître (1998); Viglino & Pierrot-Deseilligny (2003); Ogier et al. (2000b); Raveaux et al. (2008); Muhs et al. (2013)
Roads, Road network	Ilg (1990); Kim et al. (1991); Labiche et al. (1993); Watanabe (2000); Deseilligny et al. (1995); Watanabe & Oshitani (2001); Yin & Huang (2001); Chiang et al. (2005, 2008); Knoblock et al. (2010); Henderson & Linton (2009); Chiang & Knoblock (2011a,b); Chiang et al. (2011, 2013); Callier & Saito (2012);
Buildings	Lichtner (1988); Suzuki & Yamada (1988); Suzuki & Yamada (1990); Illert (1991); Yamada et al. (1993); Maderlechner & Mayer (1994, 1995); Brügelmann (1996); Frischknecht & Carosio (1997); Frischknecht & Kanani (1998); Kwon (2000); Graeff & Carosio (2002); Miyoshi et al. (2004); Tuia & Kaiser (2007); Meinel (2008); Chernov & Chupshev (2009); Meinel et al. (2009); Herold et al. (2010); Herold et al. (2012)

Table 3.2: Application-oriented survey of extraction approaches for different map types and objects.
Source: Author's own

Map Objects	Extraction Approaches (References)
Map Type	
Topographic Map	Illert (1991); Ebi et al. (1992, 1994); Yamada et al. (1993); Ablameyko et al. (1993); Lauterbach & Anheier (1994); Maderlechner & Mayer (1994, 1995); Stengele (1995); Smeulders & ten Kate (1996); Frischknecht & Carosio (1997); Frischknecht & Kanani (1998); Frischknecht et al. (1998); Graeff & Carosio (2002); Levachkine (2004); Angulo & Serra (2003); Dodt & Lechtenbörger (2004); Dhar & Chanda (2006); Lacroix (2009); Chiang et al. (2008); Leyk & Boesch (2009); de Boer (2010)
Cadastral Map	Bruger (1988); Lichtner (1988); Suzuki & Yamada (1990); Mayer et al. (1992); Boatto et al. (1992); Janssen et al. (1993); Ogier et al. (1993a); Yamada et al. (1993); Katona & Hudra (1999); Ogier et al. (2000b); Keyes & Winstanley (2001b); Miyoshi et al. (2004); Viglino & Pierrot-Deseilligny (2003); Chernov & Chupshev (2009)
Thematic Map	Ansoult et al. (1990); Wise (1995); Lawrence et al. (1996); Centeno (1998); Wise (2002); Qi & Zhu (2003); Zhang et al. (2011); Kerle & de Leeuw (2009)
Digital Map	Anders & Fritsch (1996); Esposito et al. (1997); Sester (2000); Malerba et al. (2003); Steiniger et al. (2008); Walter (2008, 2011); Hecht (2014)
Toponyms	
Characters (Latin)	Lichtner (1988); Luo et al. (1995); Rhee et al. (1995); Li et al. (2000); Deseilligny et al. (1995); Kim et al. (1996); Tofani & Kasturi (1998); Roy et al. (2008); Gelbukh et al. (2004); Pouderoux et al. (2007); Pezeshk & Tutwiler (2011a); Chiang & Knoblock (2011b); Herold et al. (2011); Weinman (2013)
Signs (Chinese)	Nakamura et al. (1993); Chen et al. (1999); Yin & Huang (2001)
Signs (Japanese)	Yamada et al. (1993); Watanabe & Zhang (1997)
Map Symbols	
Simple, Complex	Stengele (1993); Bhattacharjee & Monagan (1994); Boesch (1996); Samet & Soffer (1996, 1998); Reiher et al. (1996); Myers et al. (1996); Frischknecht et al. (1998); Gamba & Mecocci (1999); Cordella & Vento (2000); Delalandre et al. (2002); Zhang et al. (2006, 2011) Szendrei et al. (2011a,b)

3.3.3 Methodology-Oriented Review

Another possibility to categorize and review approaches to cartographic map image analysis is to investigate the methodology, i.e., the conceptual and methodical strategies used for the segmentation, recognition, and description of the image content (e.g., as in Chiang et al., 2014). This type of review supports researchers and developers aiming to build map vectorization algorithms for a given geographical feature recognition problem. As the focus of work at hand is the object segmentation and recognition in multi-source map images with heterogeneous object representations, the adaptability of the approaches is primarily considered.

The review is divided into the analysis of the segmentation and the (more general) recognition strategy. Table 3.3 gives an overview of approaches according to this twofold categorization. The segmentation strategies are subdivided by the type of homogeneity criteria , as suggested in section 3.1.2. Corresponding to colored layer design of many cartographic representations, color image segmentation is the predominant method (e.g., Ablameyko & Frantskevich, 1992; Lacroix, 2009). However, for some map or map object types, color is not a discriminative characteristic. Therefore, methods of *mathematical morphology* (MM) and *texture analysis* are employed (e.g., Stengele, 1995; Szendrei et al., 2011a). In numerous studies various segmentation strategies are combined to extract the objects of interest.

The used recognition strategies for the extraction of map objects and geographical features may be roughly categorized in top-down and bottom-up strategies (cf. sections 3.1.1 and 3.1.3). However, this categorization can not always be strictly applied as many bottom-up strategies do comprise some top-down component for the representation of knowledge (here referred to as hybrid strategy). Corresponding to the symbolic and rather formalized character of cartographic representations, top-down, i.e., model-oriented or template-driven strategies prevail in the survey (cf. section 3.3.3). Only few studies are – at least partially – based upon a bottom-up, i.e., feature-oriented, data-driven recognition strategy (e.g., Leyk, 2010; Herold et al., 2012); mainly to address the challenges associated with the analysis of historical map documents.

Table 3.3: Methodology-oriented survey of proposed approaches to cartographic map image analysis.
Source: Author's own.

Recognition Methodology	Sample Approaches (References)
Layer Segmentation Strategy	
Color Image Segmentation CIS	Ablameyko & Frantskevich (1992); Bucha (2005); Lauterbach & Anheier (1994); Lawrence et al. (1996); Angulo & Serra (2003); Dhar & Chanda (2006); Xin et al. (2006); Lacroix (2009); Gul & Khan (2010); Ageenko & Podlasov (2006); Kerle & de Leeuw (2009); Samet et al. (2010); Henderson & Linton (2009); Leyk (2010); Banda et al. (2011); Herold et al. (2012); Callier & Saito (2012); Chiang et al. (2013)
Mathematical Morphology MM	Luo et al. (1995); Brügelmann (1996); Stengele (1995); Meinel et al. (2009); Herold et al. (2010)
Texture Analysis	Heutte et al. (1992); Ogier et al. (1993a, 2000a); Szendrei et al. (2011a)
Object Recognition Strategy	
Model-/Template-oriented (top-down)	
Image Template Matching	Lichtner (1985); Mayer et al. (1992); Stengele (1993); Frischknecht & Carosio (1997); Li et al. (2000); Graeff & Carosio (2002); Leyk et al. (2006)
Syntactical/Formal Grammars	Ogier et al. (1993a); Ablameyko et al. (1994); Deseilligny et al. (1995); Raveaux et al. (2008)
Bayesian Nets/Frames	Kasturi et al. (1989); Ebi et al. (1992, 1994); Maderlechner & Mayer (1994); Weinman (2013) den Hartog et al. (1996); Keyes & Winstanley (2001a);
Feature-/Data-oriented (bottom up) or hybrid	Leyk & Boesch (2009); Leyk (2010); Herold et al. (2012); Pezeshk & Tutwiler (2011b); Chiang et al. (2011, 2013)

3.4 Summary and Conclusions for Research

In this chapter, the fundamental methods and recent research advancements in the acquisition of geoinformation from digital images have been discussed. This section sums up the main findings in order to identify research needs, implications, and conclusions for the conceptual and methodical approach developed in this work.

In summary, the computational acquisition of information from digital images has been an active and innovative research fields for decades. The conceptual foundation of the field is closely related to the theories of the human visual perception. Sophisticated methods for digital image processing and higher level image understanding have been developed. To date, however, the principles of the primates' higher level visual perception are neither fully understood nor are the capabilities of the human brain in ***complex and invariant visual object recognition*** nearly achieved using computational approaches. Closing this gap is a major research effort in computer vision and computational neuroscience.

There exists ***no consistent terminology*** in the field. Sub-disciplines and technical terms such as image processing, image understanding, image analysis, and machine/computer vision are semantically not clearly delimited and thus diversely used (cf. section 3.1.1). In this work, for the computational image content description the generic terms *low- and high-level image analysis* are used.

In the geographical context image analysis methods are primarily applied and adapted in the field of remote sensing (cf. section 3.2.1) and cartographic map image analysis (cf. section 3.2.2). While many concepts for the higher level interpretation and object recognition are similar in both fields, there are major differences in characteristics of the image data source, which have some fundamental methodical implications. In optical remote sensing, the acquired image represents a ***primary geodata source***. In contrast, the cartographic map image is a ***secondary geodata source***, i.e., the analysis result relates to an abstracted, generalized, and symbolic representation, the cartographic model, and thus only indirectly relates to the real world entity (at the time of survey, cf. section 2.1.3). Therefore, slightly different strategies for integration and representation of *a-priori* knowledge can be applied.

Recent methodical challenges in remote sensing image analysis comprise the increasing spatial (VHR imaging sensors) and spectral resolution (hyperspectral imaging sensors). The former is addressed by the object-based analysis paradigm, which is underpinned by the active research field of *geographic object-based image analysis* or shortly GEOBIA. For the latter, non-parametric classification methods such as *support vector machines* (SVM) and *random forests* (RF) are increasingly used and often extended to statistical/machine learning approaches (cf. section 3.1.3).

Recent methodical challenges in cartographic image analysis comprise the adaptability to varying graphical representations, the automation of the georeferencing process, and the robustness of the recognition strategy towards the sometimes degraded quality of the graphical representations in historical map documents. This challenges arise from the current development of the research field, for which three stages and drivers have been identified (cf. section 3.3.1). For the acquisition of land use information from multi-source, heterogeneous image data for retrospective change analysis, which is the focus of this work, the following ***major conclusions for research*** can be drawn:

1. *There exists a plethora of approaches to the automated extraction and vectorization of specific geographical features, symbols, and toponyms from various map types.*
2. *Although the capabilities of human interpreters are not achieved, some algorithms that are exclusively designed for a certain map type or feature, yield high recognition rates.*
3. *Only few approaches aim to the analysis of different types or versions of maps and thus the problem of the varying graphical representations is rarely addressed.*
4. *So far, only a few approaches are explicitly developed for historical maps and thus address the problem of degraded quality of the cartographic representation.*
5. *The varying representational scales of contemporary and historical data sources require a multi-scale conflation concept for spatiotemporal data integration.*
6. *Neither the information contained in the historical documents nor the historical real world situation that is represented, can be retrieved perfectly, causing uncertainty.*

7. *Uncertainty has to be perceived as an inevitable and inherent property of the retrieved historical land use information and has to be adequately modeled for change analyses.*

In the following, a conceptual and methodical framework for addressing some of the research needs, namely, (1) the adaptive image segmentation and the adaptable representation of knowledge for the recognition process (chapter 4), and (2) a concept for modeling the uncertainties inherent to the data and non-indented application in land change analysis (chapter 5), is proposed.

4 An Adaptive Map Image Analysis Approach

Based on the findings and conclusions given in the preceding chapters two and three, this chapter presents a generic methodical concept for extracting geoinformation from heterogeneous, multi-source image data such as archival maps. It addresses the third research question concerning the representational diversity and builds upon the hypotheses three (H3) and four (H4), stated in section 1.3. In the first part, some conceptual considerations about the methodological design are given (section 4.1). The second part is dedicated to the development of a methodological approach for adaptive image analysis (sections 4.2 to 4.4). The chapter concludes with a comprehensive synopsis of the proposed methodology.

4.1 Conceptual Considerations

4.1.1 Data Characteristics and Prerequisites

In order to profoundly investigate and address the issues posed in the preceding chapters and to evolve an adequate methodology, it is crucial to understand and analyze the characteristics of the data under investigation. As stated earlier, in contrast to natural color scenes and remote sensing imagery, map images as a secondary data source are generally easier to handle in the automated, i.e., computational interpretation. This is mainly due to the abstracted and symbolic graphical model, which generalized the complex nature of the geotopographical reality (the cartographic model, cf. section 3.2.2). That is, the map content comprises a limited set of symbols, forms, or colors, for instance, which ***can be mathematically formalized*** and, thus, be represented in a computational recognition system.

However, in the context of a long-term oriented retrospective acquisition of geoinformation, three distinct characteristics complicate the formalization and computational interpretation:

H. Herold, *Geoinformation from the Past*,
https://doi.org/10.1007/978-3-658-20570-6_4

1. the ***amount, density, variation, and complexity of the contained information*** is, in comparison to other artificially generated images, extremely high (cf. Roberts, 1962, p. 12). Graphical variations, artefacts, and deviations from the cartographic model due to the manual production may pose no issue to the recognition by the robust human visual system (HSV).
2. a prevalently ***degraded and reduced graphical quality*** due to the document age, the material aging, or/and the digitization process (i.e., scanning or photographing), and
3. an enormous ***diversity in entity representations over time and space***, driven by technological, historical, cultural differences, changes and advancements.

Particularly the latter challenge has yet been little addressed in previous studies (cf. section 3.3 and 3.4). To describe the representational diversity it is important to know the degrees of freedom, i.e., in which ways the representations may vary. Considering the remote sensing image analysis, Weng (2010, p. 8) identifies seven elements, which are used for image interpretation: (1) tone/color as the most relevant, (2) size, (3) shape, (4) texture, (5) pattern, (6) shadow, and (7) association.

Analogously, Bertin (1967, p. 69) defined in his *Sémiologie graphique* seven graphical variables which are relevant for cartographic image analysis, namely (1) location, (2) size, (3) value, (4) texture, (5) color, (6) orientation, and (7) shape. MacEachren (1995, p. 279) extended this syntactic typology to eleven ***visual variables***, namely: ***location***, ***size***, ***crispness, resolution, transparency, color, value, color saturation, color hue, texture, orientation, arrangement***, and ***shape***. Thus, a computational visual pattern recognition system (cf. section 3.1.3) has to be capable to address variations of these variables. For the different variables different methodological strategies have to be used. This increases the amount of formalization and necessary problem knowledge. Empirical investigations of the stylistic diversity of topographic maps for different purposes have been conducted by Kent & Vujakovic (2009), Kent & Davies (2013) and Schinke et al. (2013).

Because of the wide range of variations between maps from different sources, the guiding design principle for any map understanding system has been formulated by Pezeshk & Tutwiler (2011b, p. 3) as "should (1) ***be easily modifiable*** and (2) ***require only minimal user interaction***". In table 4.1 the attempt is made, to quantify and evaluate the amount of user

Table 4.1: Conceptual levels of required user interaction and problem knowledge for the methodological design.
Source: Author's own.

Level	Human-machine interaction	Problem knowledge
1	Development of a suitable algorithm based on given data	Maximal
2	Selection of predefinded algorithm and its parameterization	High
3	Parameter adaption for automatically selected algorithm	Low
4	Provision of few labeled training samples	Minimal
5	No interaction needed	None

interaction using five problem-specific levels. At the lowest level, the interaction encompasses the development of a methodology from scratch, which necessitates expert knowledge in the domain of image analysis and computer vision. At the highest level, the full automated interpretation algorithm needs no interaction from the user, even if the representation of geographical entities changes. This work aims to evolve a methodology for a level four human-machine interaction approach. Following the second requirement of adaptability, the knowledge for the higher lever image analysis tasks has to be easy modifiable and thus has to be represented flexibly.

That is, combining both fundamental requirements (adaptability and minimal interaction), the methodology should be capable of ***adapting and learning*** strategies for segmentation and higher level pattern recognition ***from a few labeled samples***. As the necessary accuracy of historical geoinformation that is to be retrieved greatly depends on the research question and topic under investigation, a hierarchical approach to adaptive image analysis is suggested (cf. section 4.4).

4.1.2 Data Preparation and Automated Georeferencing

Prior to the acquisition of geoinformation, the archived paper maps have to be digitized and preprocessed. For the digitization process, the ***Nyquist-Shannon sampling theorem*** (cf. Nyquist, 2002, and Shannon, 1998, reprints of the original works from 1928 and 1949) has to be taken into account. Preprocessing encompasses both enhancement and georeferencing of the scanned or photographed map document. Considering long-term monitoring studies, hundreds of map sheets have to be included. Thus, the preprocessing step may be an extremely laborious task and may already limit the spatiotemporal scope of a study. To overcome this limitation for long-term monitoring studies, the task has to be included in the methodological development but is in most studies either not considered or underestimated.

For an automated image enhancement and color homogenization between different map sheets Podobnikar (2009) suggests a method using global and local gray value histogram statistics. In order to access the valuable spatial component of the information contained in documents, the maps have to be georeferenced. That is, real world coordinates are assigned to the image coordinates (cf. figure 4.1). Hence, the retrieved historical geoinformation can later be used in GIS and spatially explicit land change monitoring and modeling.

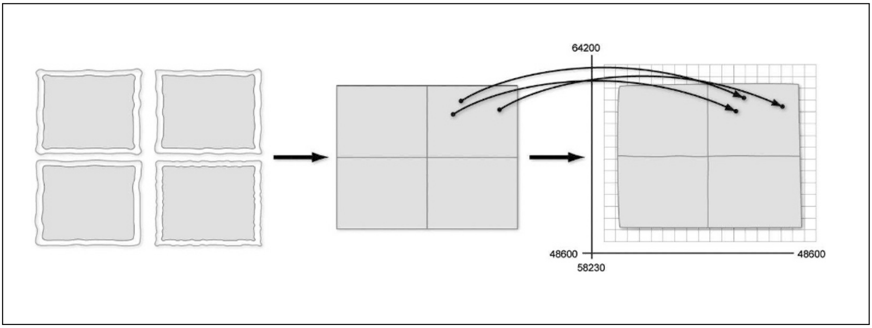

Figure 4.1: Fundamental workflow for map mosaicking and georeferencing using ground control points (GCP).
Source: Adapted from Podobnikar (2009, p. 53), © 2009 Springer Nature.

Basically, there exist two different strategies for georeferencing. One possibility is, analogously to remote sensing image referencing, to make use of ground control points (GCPs), which are either directly referred to known real world coordinates or to known geospatial locations of an already geocoded image (as depicted in figure 4.1). Advantageous of this strategy is that map image distortions can be corrected (e.g., Neubert & Walz, 2002, or Walz & Berger, 2003). However, the formalization and automation of identifying corresponding GCPs in different images is still a challenging task in image analysis and computer vision.

Another possibility is to make use of the information on map projections and coordinate systems, which is typically contained for cognitive georeferencing by the human map user. Advantageous of this strategy when aiming to an automation of the process is, that the reference points are homogeneously distributed, readily identifiable, and their real world coordinates are given by the map coordinate system. The reference points can be, e.g., intersections of coordinate lines, represented by either single crosses or a grid over the entire map (Herold et al., 2011, p. 2). Titova & Chernov (2009) propose a method for the identification of these grid crosses in binary and gray scale map images. The method enables an automatic search for parameters of image errors of topographic plans to accomplish automatic image correction. Another approach to automated map referencing is presented in Rus et al. (2010), which requires a completely delineated coordinate grid.

Herold et al. (2011) and Röhm et al. (2012) present an adaptable method for automated georeferencing, which is based on the detection of the four map corners of the inner frame as well as the map identifier. The map identifier, comprising a name and number, is detected by an OCR algorithm using a neural network (a multilayer perceptron, MLP) based classifier. Despite the flexibility, the approach only allows affine transformations, which may be not sufficient for older and distorted map images.

4.1.3 Conceptual Workflow for Information Acquisition

Figure 4.2 gives a graphical summary of the conceptual consideration presented in section 4.1 and 4.1.2. The methodical approach to adaptive image analysis is described in sections 4.2 to 4.4. The modeling of uncertainty is described in the subsequent chapter 5.

4.2 Methods for Map Image Segmentation

The theoretical and methodical concepts of image segmentation have been introduced in chapter 3. Region-oriented segmentation has been defined as the spatial partitioning of an image into sets of regions that meet a defined homogeneity criterion. In the following, methodical approaches to map image segmentation based on the predominant homogeneity criteria, namely color (section 4.2.1), texture (4.2.2), and morphology (4.2.3), are presented.

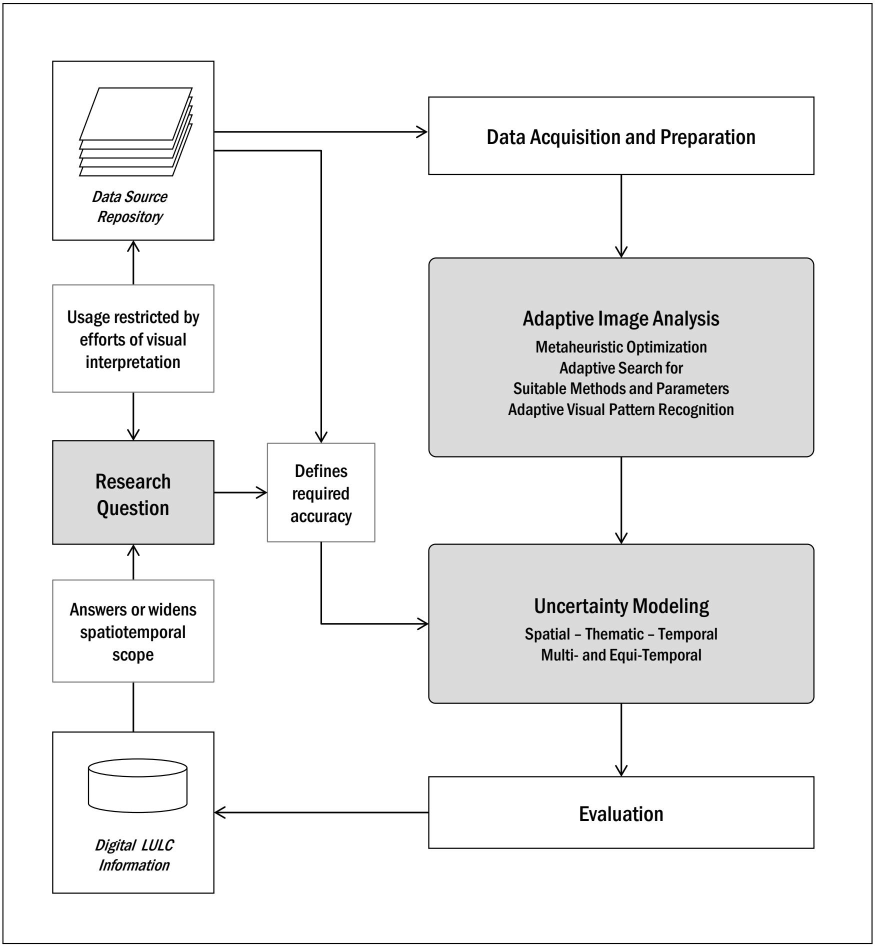

Figure 4.2: Conceptual workflow for information acquisition to reduce manual interpretation and adaption efforts.
Source: Author's own.

4.2.1 Color-Based Segmentation

Image segmentation based on color or tone, also referred to as *color image segmentation* (CIS), is one of the most important and widespread concepts in literature (cf. section 3.3). Topographic maps are traditionally built on a layer concept. That is, each topographic topic such as vegetation, water bodies, and urban features, are engraved in a distinct layer or slide (cf. section 2.1.3 on the map design process). When a map is updated, the layers may be updated separately. The single layers are combined and printed in different colors into the map. However, the final map color may contain various distinct layers (cf. section 4.2.3). For separating the features during the interpretation of the scanned paper maps, the color, frequency, and spatial domain may be used. To represent colors, different models can be used.

Color Representation Models and Region Formation

There exist various models of color spaces, each with distinct characteristics. Hence they are applied for different purposes. Prevalent color models are the ***RGB model*** (red, green, and blue; cf. figure 4.3), the ***CMYK model*** (cyan, magenta, yellow, and key=black), the ***HSV model*** (hue, saturation, and value), the ***HSI model*** (hue, saturation, and intensity), as well as the ***CIE spaces*** *L*u*v** and *L*a*b** (Commission Internationale de l'Éclairage). Details on the color spaces and the transformations between the models can be found, e.g., in Gonzalez & Woods (2002). The partitioning of the image may be based on a combination of information of the color, the frequency and the spatial domain. Most CIS algorithms are based on gray level image segmentation approaches such as feature space clustering, histogram thresholding, as well as region- or edge, fuzzy, neural net, and physics based approaches (Cheng et al., 2001, p. 2266), using different color models. Methods for CIS may either use an unsupervised clustering algorithm such as *k-means* or a supervised classifier (cf. section 3.1.2 on image segmentation).

Example approaches for map interpretation using different color models can be found in Leyk & Boesch (2009) for the RGB and in Herold et al. (2012) for the CIE *L*a*b** space. An implementation of a color-based segmentation algorithm for color map image analysis using a supervised neural network classifier is suggested, evaluated and discussed in chapter 6.

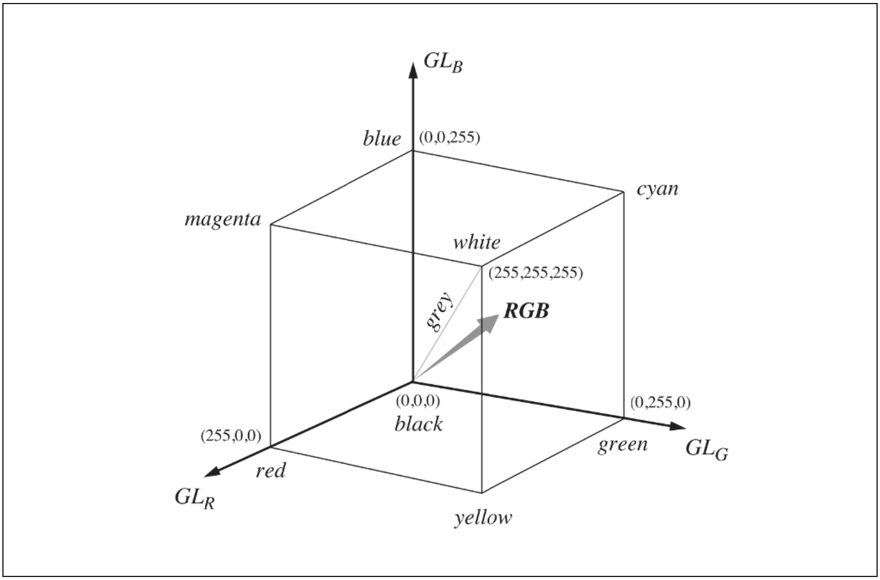

Figure 4.3: Visualization of RGB color space model. *GL* refers to the 8-bit gray levels of the color components.
Source: Adapted from Schowengerdt (2007, p. 38), © 2007 Elsevier, B.V.

4.2.2 Texture-Based Segmentation

Another important and widely used visual variable for the representation of entities is the *texture*. In literature, there exists a multitude of different definitions of texture. In the context of image analysis, texture may be conceived as as the "visual roughness", if an image is considered as a tangible, physical surface defined by digital numbers at each pixel position (Schowengerdt, 2007, p. 152). Pratt (2007, pp. 545-546) further distinguishes between artificial texture as arrangements of symbols such as lines or dots, and natural texture in natural scenes containing semi-repetitive arrangements of pixels. For texture-based segmentation, descriptors such as the ***gray-level co-occurrence matrix (GLCM)*** (cf. Haralick et al., 1973), ***Laws' texture energy measures*** (cf. Laws, 1980), ***fractal geometry*** (cf. Mandelbrot, 1983) or the ***local binary pattern (LBP)*** (cf. Ojala et al., 2002) may be used. Basically, there are statistical, spectral, and structural approaches to texture analysis.

Texture Measures of the Gray-Level Co-Occurrence Matrix

The most widely used descriptors for image segmentation are the spatial texture measures of the GLCM, e.g., the (cf. Haralick et al., 1973, pp. 618-619; Schowengerdt, 2007, p. 165):

$$\text{Angular Second Moment} = \sum_i \sum_j p_{i,j}^2, \tag{4.1}$$

which relates to the homogeneity of the image, the

$$\text{Contrast} = \sum_i \sum_j (i-j)^2 p_{i,j}, \tag{4.2}$$

which relates to the semivariogram of the image, the

$$\text{Correlation} = \frac{\sum_i \sum_j ijp_{i,j} - \mu_i \mu_j}{\sigma_i \sigma_j}, \tag{4.3}$$

which relates to the covariance, the

$$\text{Inverse Difference Moment} = \sum_i \sum_j \frac{p_{i,j}}{1+(i-j)^2}, \tag{4.4}$$

and the

$$\text{Entropy} = -\sum_i \sum_j p_{i,j} \log(p_{i,j}), \tag{4.5}$$

where $p_{i,j}$ denotes the [i,j]th entry in a normalized GLCM and μ_i and μ_j are the means and σ_i and σ_j the standard deviations of p_i and p_j (Haralick et al., 1973, pp. 618-619).

Laws' Texture Energy Measures

A second important descriptor for texture is suggested by Laws (1980), which is based on image filtering and the variation within a fixed size window.

Three heuristically developed basic vectors (L3, E3, S3) are combined to form five vectors L5, E5, S5, R5 and W5, which semantically represent levels, edges, spots, ripples, and waves (Sumer & Turker, 2013, p. 51):

$$L5\,(Level) = \begin{pmatrix} 1 & 4 & 6 & 4 & 1 \end{pmatrix} \tag{4.6}$$

$$E5\,(Edge) = \begin{pmatrix} -1 & -2 & 0 & 2 & 1 \end{pmatrix} \tag{4.7}$$

$$S5\,(Spot) = \begin{pmatrix} -1 & 0 & 2 & 0 & -1 \end{pmatrix} \tag{4.8}$$

$$R5\,(Ripple) = \begin{pmatrix} 1 & -4 & 6 & -4 & 1 \end{pmatrix} \tag{4.9}$$

$$W5\,(Wave) = \begin{pmatrix} -1 & 2 & 0 & -2 & 1 \end{pmatrix} \tag{4.10}$$

An implementation of a texture-based segmentation algorithm for textured map information using Laws' texture energy is tested, evaluated, and discussed in chapter 6 (see p. 115).

4.2.3 Morphology-Based Segmentation

A third important visual variable is *shape* (cf. section 4.1). That is, a great deal of information is coded only by the shape of the entities and thus can not be distinguished otherwise by color, grayvalue, or texture. This is frequently the case in the base layer of a map (e.g., Frischknecht & Carosio, 1997; Meinel et al., 2009). To address the shape (and size) of image objects in mid-level image analysis, methods of Mathematical Morphology (MM) are applied. While the term morphology is also used in Geography, Biology and many other disciplines, here, it is referred to a field of image analysis. Mathematically, because it is based on the set theory, topology, lattice algebra, and random functions (Serra, 1982, pp. 3-9).

Mathematical Morphology (MM)

The theoretical concept and field of mathematical morphology has been founded and developed by Georges Matheron and Jean Serra at the *École Nationale Supérieure des Mines* in Paris, which led to the foundation of the *Centre de Morphologie Mathématique* (cf. Serra, 1982). Since, MM has been spread and widely used in image analysis and computer vision in general (Rosenfeld, 2001, p. 307) as well as in remote sensing (e.g., Valero et al., 2010). The basic morphological operators, which are used in this work, can be conceptualized as non-linear image filters. The most important filters can, according to Gonzalez & Woods (2002), be formalized as follows: the morphological opening (an erosion followed by a dilation) is defined as:

$$A \circ B = (A \ominus B) \oplus B, \tag{4.11}$$

where A denotes an image matrix and B denotes a structuring element. Analogously, the morphological closing (a dilation followed by an erosion) is definded as:

$$A \circ B = (A \oplus B) \ominus B. \tag{4.12}$$

An implementation of a morphology-based segmentation algorithm for map interpretation is tested, evaluated, and discussed in section 6.2 (see p. 116).

4.3 Adaptive Segmentation Using Metaheuristic Optimization

The stylistic diversity of maps, which is certainly of high cultural value and interest (e.g., Kent & Vujakovic, 2009), poses a major challenge to mid-level image analysis, namely, finding a suitable segmentation algorithm and adapting its parameters appropriately (cf. figure 4.4). The problem is well known to other fields of image analysis such as remote sensing analysis. For remote sensing imagery, the challenge consists in the adaption of the segmentation parameters – which are typically based on spectral homogeneity and segment size – to the characteristics of the imagery and the image objects (Hay et al., 2005, p. 341). For geographic object-based image analysis, methods for reducing the manual parameters search have been suggested (e.g., Dragut et al., 2010). Cartographic image analysis extends the algorithm and parameter search from color- to texture- and morphology-based segmentation approaches (cf. sections 4.2.1 to 4.2.3). Hence, as the representational heterogeneity increases over space and time, the algorithm and parameter search space massively grows, leaving manual search a laborious or even an unfeasible task (cf. Herold et al., 2014, and figure 4.4).

Considering both the abstracted representation as well as the fact that a user could readily provide a minimal set of entity reference samples, image

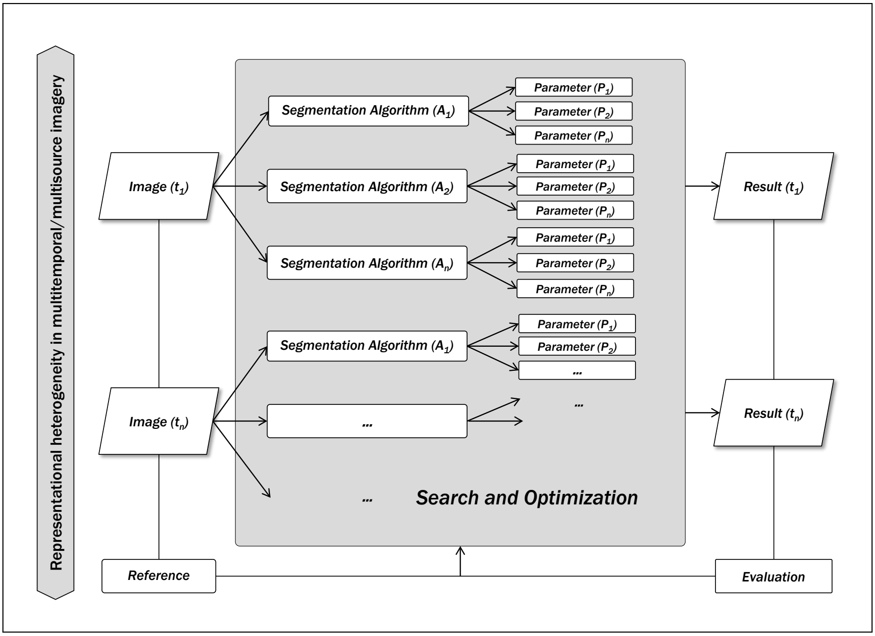

Figure 4.4: Challenge of algorithm and parameter selection using multitemporal and mulitsource imagery.
Source: Author's own.

segmentation can be ***mathematically conceptualized as an optimization problem***. In the following, a solver for this typically non-linear optimization problem is suggested.

4.3.1 Non-Linear Optimization

There exists a wide range of optimization problems as well as approaches and solvers to them. Optimization problems can, according to Yang (2010, p.18), be classified regarding their objective (single-/multiobjective), constrains (un-/constrained), landscape (uni-/multimodal), function form (linear/non-linear), response (discrete/continuous), and their determinacy (deterministic/stochastic). Basically, for all problems the optimization task consists in finding – depending on the formalization – global/local minima or maxima of an objective function $f(x)$:

$$\min_{x \in \mathbb{R}} \; f(x), \text{or,} \tag{4.13}$$

$$\max_{x \in \mathbb{R}} \; f(x). \tag{4.14}$$

The image segmentation optimization problem is typically a non-linear and multimodal problem containing various local minima or maxima (figure 4.5). For solving this mathematical problem, there exist a wide range of deterministic ***analytical or numerical iterative methods*** such as *Conjugate gradients* or *Quasi-Newton methods* (e.g., cf. Bishop, 2006).

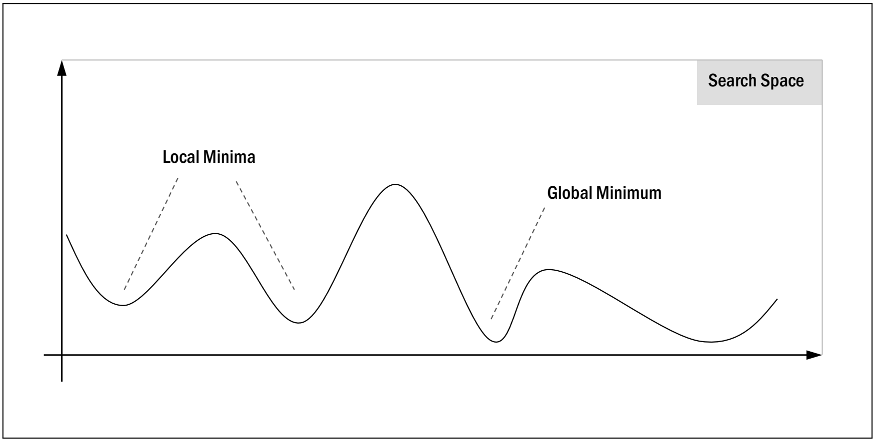

Figure 4.5: Global and local minima in non-linear optimization.
Source: Author's own.

An alternative approach, which does not presuppose differentiability (first or second derivate), provide ***stochastic metaheuristic methods*** such as the population-based Evolutionary Algorithms (cf. figure 4.6).

4.3.2 Evolutionary Algorithms (EA)

Evolutionary Algorithms belong to the nature- or, specifically, biology-inspired computation algorithms. As the name implies, their optimization capacity is

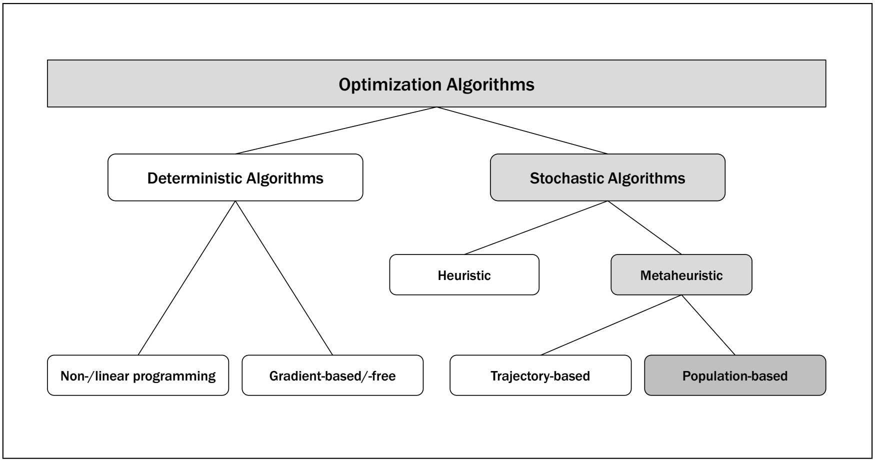

Figure 4.6: A classification schema for optimization algorithms.
Source: Modified after Yang (2010, p. 21), © 2010 John Wiley & Sons.

based on the rules of natural optimization through adaption, such as found in the biological evolution. In literature, EA are frequently classified as Artificial Intelligence (AI). However, due to some concerns from the philosophical perspective, here the more intuitive classification to the nature-inspired algorithms is followed. EA have been "invented" parallel in Germany by Rechenberg (1973) (referred to as Evolutionary Strategies) and in the US by John Holland (typically referred to as Genetic Algorithms). Since, a wide range of variants has been developed. However, all variants share a fundamental principle: a collective learning process within a population of individuals, where each individual "represents a search point in the space of potential solutions to a given problem. The population is arbitrarily initialized and it evolves toward better and better regions of the search space by means of randomized processes of selection (which is deterministic in some algorithms) and mutation" (Bäck & Schwefel, 1993, p. 1). Recombination, however, is not inherent to all algorithms, such as found in particular types of Evolutionary Strategies (ES).

Disadvantageous of all EA are their non-deterministic nature (through the stochastic component) and hence not guarantee convergence to the optimal solution. However, these metaheuristic approaches to optimization have demonstrated to solve complex problems with large search spaces (cf. Nguyen et al., 2012; Boussaïd et al., 2013). Thus far, only few studies have used EA in the context of image analysis. A variant, namely Genetic Algorithms (GA), have been demonstrated suitable for adaptive segmentation of natural (color) images (Bhanu et al., 1995; Bhandarkar, 1999) as well as for multi-source remote sensing imagery (Costa et al., 2008; Sumer & Turker, 2013). In this work, a metaheuristic evolutionary optimization algorithm, namely an Evolutionary Strategy (as firstly proposed by Rechenberg, 1973, and who's notation is followed here), is to be developed and evaluated for the given optimization problem in the field of image segmentation.

4.3.3 Adaptive Segmentation Using a $(\mu + \lambda)$-ES

For the given challenge outlined in section 4.1 the optimization problem comprises the algorithm and parameter adaption for image segmentation. The parameter search is formalized as an objective function using empirical discrepancy (cf. Zhang, 1996) as evaluation criterion. Hence, the given optimization problem consists in finding the global minimum of this typically non-linear objective function. Algorithm 1 gives the pseudocode of the proposed approach.

This $(\mu + \lambda)$-ES algorithm is implemented, tested and evaluated in section 6.2.

4.4 Adaptive Segment-Based Classification

4.4.1 Design of an Adaptable Strategy

As described in section 3.1.3, image segmentation is a crucial but not the final step in the image analysis chain. The potentially meaningful object candidates (segments) may have to be further classified. For the classification (or in this context also referred to as visual pattern recognition, cf. section 3.1.3) the same challenges apply as for the image segmentation.

As discussed earlier, there are basically two strategies, top-down (model-driven) and bottom-up (data-driven) approaches to object recognition. Model-driven algorithms such as Template Matching (TM) yield typically high recognition rates but are too inflexible concerning heterogeneous lay-

Algorithm 1 : A $(\mu+\lambda)$-Evolutionary Strategy Algorithm for Adaptive Map Image Segmentation

$\mu \leftarrow$ parents, $\lambda \leftarrow$ offspring, $p \leftarrow$ initial population, $f_t \leftarrow$ target fitness, $m_r \leftarrow$ mutation rate
$P \leftarrow []$ # generate initial population
for $i := 1$ to p **do**
    $P_i \leftarrow$ [generate random gene expressions as coded image segmentation parameters]
end for
$\forall\ P_i \rightarrow$ decode + evaluate using fitness function $f(x) = \frac{1}{n}\sum_{i=1}^{n}\frac{AS_i^p(x)}{AR_i^p}\ \forall\ AS_i^p(AR_i^p) \neq \oslash$
select best fitting P_i
# start evolutionary cycle
while $f(P_i) > f_t$ **do**
    $Q \leftarrow P_i$ # copy parent genes to offspring (new generation)
    for $i := \mu$ to $\mu + \lambda$ **do**
        $Q_i \leftarrow$ [mutate genetic copy of P_i using Gaussian distributed random numbers with rate m_r]
    end for
    $\forall\ Q_i \rightarrow$ decode + evaluate using fitness function $f(x)$
    $P_i \leftarrow$ select the μ best fitting individual(s) from Q_i
end while
return best individual $P_i \rightarrow$ decode genetic code and apply for map image segmentation

outs. Knowledge-based approaches, which represent the knowledge about the objects in a rule-set (typically a decision tree classifier) require a considerable amount of problem knowledge to be adapted. On the other hand, data-driven approaches may adapt very well but typically require higher training efforts regarding the amount of training samples.

4.4.2 A Hybrid Model- and Data-driven Strategy

In conclusion of the theoretical considerations outlined in section 3.1 and 4.1, a hybrid model- and data-driven strategy is suggested. The hybrid approach aims at making use of the advantages of both strategies while reducing the disadvantages for the given problem. For the practical implementation of an adaptable classification/object recognition strategy, the following configuration is suggested: a knowledge-based strategy (such as a hierarchical rule set) pre-classifies the segments into a set of certain objects (e.g., according to typical characteristics such as size) and a set of uncertain segments, i.e., candidate objects. This reduced set of candidate objects is subsequently further classified using an inductive, data-driven strategy such as represented by an artificial neural net (ANN, cf. figure 4.7).

The author recognizes the great variety of state-of-the-art classification algorithms for high-dimensional pattern recognition problems (such as Support-Vector Machines and Random Forests, cf. section 3.1.3). Here, the neural net approach is chosen for both theoretical and practical considerations. First of all, artificial neural nets mimic best the human recognition process at the fundamental level. Future research achievements in computational neuroscience may directly contribute to advancements in the field of ANN. On the other hand, neural net implementations are known to be computationally expensive, in particular regarding their training process. However, this poses no relevant issue for the application in the context of this work as no real-time implementation nor an on-the-fly training is required (see the conceptual considerations outlined in section 4.1).

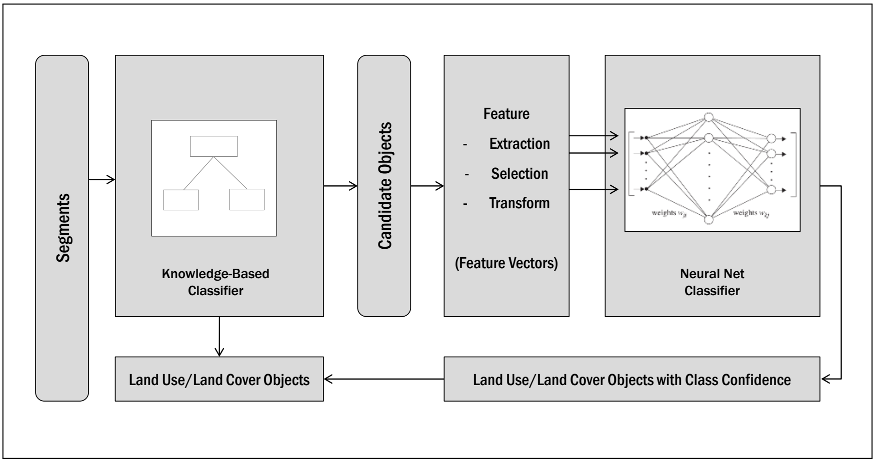

Figure 4.7: Schema of the proposed hybrid classification approach.
Source: Author's own

The major advantage of this approach is the yielded probabilistic class assignment. In the suggested feed-forward neural network architecture, specifically a three-layered multilayer perceptron using the *back-propagation* learning algorithm (e.g., cf. Steger et al., 2008), a logistic function:

$$f(x) = \frac{1}{1 + e^{-x}} \tag{4.15}$$

with first derivative $f'(x) = f(x) - f^2(x)$ is used as sigmoidal neuronal activation function (cf. Blackwell & Chen, 2009, p. 80), yielding soft class membership predictions ϵ_j for each object. These probabilistic class assignments can be subsequently used to address and model the thematic uncertainty inherent to the data and the recognition process (cf. section 5.3.2).

4.4.3 A Cascading Neural Network Architecture

To further increase the flexibility and adaptability of the object recognition approach, a cascading neural network architecture is suggested. Figure 4.8 shows a graphical outline of the proposed model. The concept is inspired from the reverse case, suggested in Marpu et al. (2009), using one neural net to summarize the classification output of various (class-depended) neural nets. The advantage of this hierarchical cascading architecture is that the third layer classifiers (ANN-2 and ANN-3 in figure 4.8) can be separately and hence very specifically be trained to a recognition task such as Optical Character Recognition (OCR). Thus, the approach can be modularly set up and combined, depending on the level of accuracy and information required by the respective research question (cf. conceptual outline in figure 4.2).

Another advantage over using only a single classifier is the minimization of the problem or "*curse of dimensionality*" (cf. Bishop, 2006, pp. 33-35; Duda et al., 2000, p. 44), while adapting the object recognition algorithm to new object classes. That is, extending an existing classifier with new input features for the adaption requires an increasing number of training samples as the corresponding feature space increases exponentially.

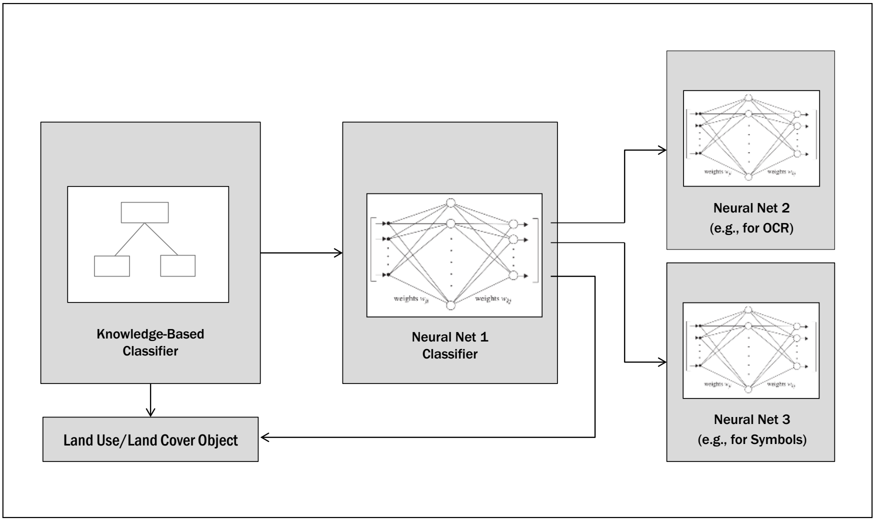

Figure 4.8: A cascading neural network architecture for modular adaptive segment classification.
Source: Author's own, class-dependent concept based on Marpu et al. (2009).

4.5 Synopsis of the Methodology

Figure 4.9 provides a graphical synopsis of the methodology for the adaptive image analysis, which has been developed in this chapter. The figure extends the conceptual workflow developed in section 4.1 for the adaptive acquisition of LULC information from heterogeneous image sources. The upper part refers to the data acquisition, i.e., the acquisition of digital image data from paper map sources. The central part refers to the information acquisition, i.e., the extraction of LULC information from the digital images. The lower part refers to the information processing and application aiming to extract new knowledge and insights from the retrieved retrospective information.

In the following chapter, a conceptual framework is proposed for modeling the uncertainty, which is inherent to both the data sources and the image analysis process.

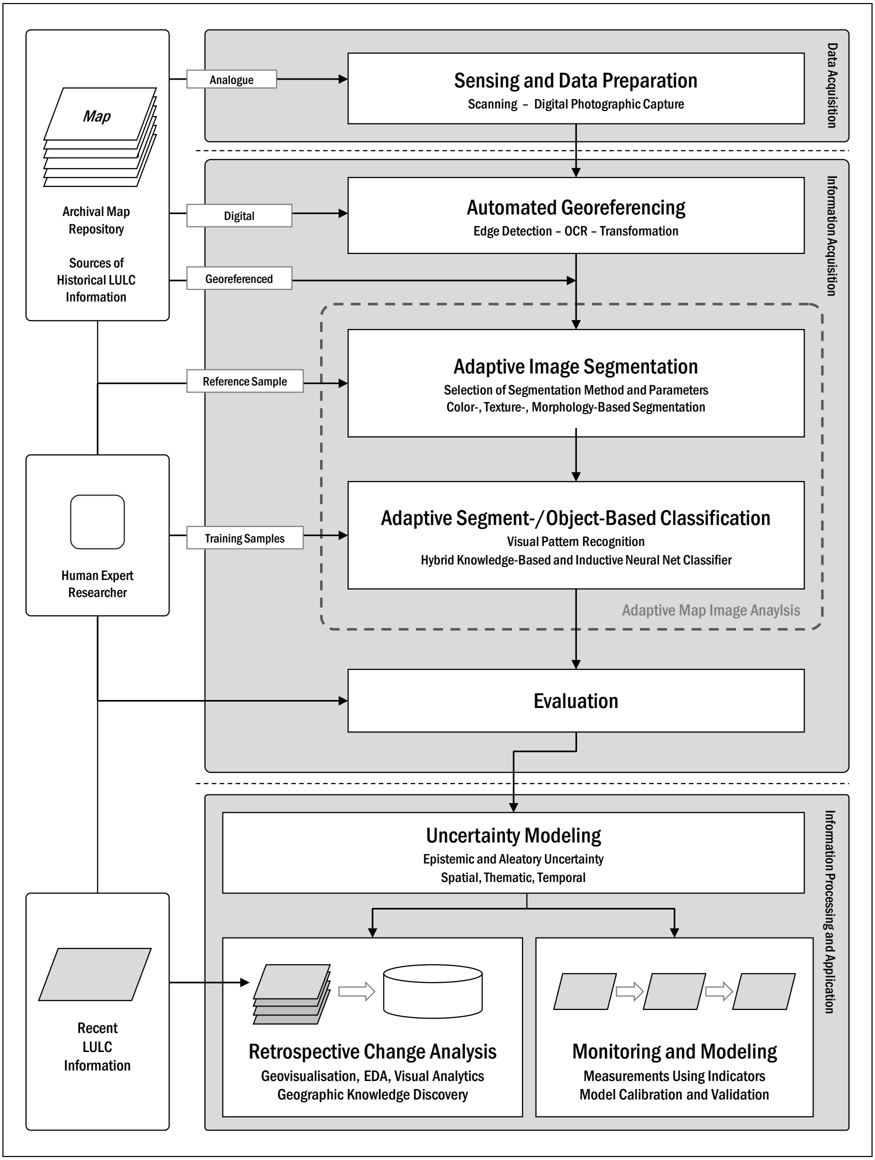

Figure 4.9: A graphical synopsis of the herein proposed methodology for adaptive map image analysis.
Source: Author's own.

5 Modeling Uncertainty for Change Analysis

Uncertainty is inherent to all data, experiments, and measurements. This holds also true for observations conducted using the most precise instrument as well as at the smallest, subatomic scale. The latter is known as the Principle of Uncertainty of quantum mechanics formulated by Werner Heisenberg (Heisenberg, 1927; for English, cf. Heisenberg, 1949, pp. 20-22). To the current state of knowledge, this fundamental physical principle defines by its nature the ultimate limit of human cognitive faculty. All scientific efforts to study, model, quantify, and visualize uncertainties in data and information can be summarized to a short dictum: "It is better to be vaguely right than exactly wrong", stated by Read (1920, p. 351). To address the fourth research question, this chapter introduces some fundamental concepts, sources, and implications of uncertainties in spatial data for map-based information extraction and spatiotemporal change analysis (section 5.1). Building upon the theoretical concept, three modeling approaches for the predominant categories, the spatial (section 5.2), the thematic (section 5.3), and the temporal uncertainty (section 5.4), are suggested. In conclusion, a combined probabilistic multi-temporal and an equi-temporal modeling approach using the Dempster-Shafer Theory of Evidence (section 5.5), is proposed.

5.1 Conceptualizing Uncertainty in Geoinformation

In contrast to philosophy (e.g., *Sorites* paradox, cf. Williamson, 1994), natural sciences and engineering have traditionally either largely ignored or focused on avoiding and eliminating uncertainty (Klir & Smith, 2001, pp. 6). Some of the 20th century discoveries, however, such as the above mentioned *Heisenberg* principle, have challenged this paradigm fundamentally. In mathematics, according to Klir & Smith (2001), the consequent emergence of two major theoretical generalizations finally gave rise to a broader formalization and a dealing with uncertainty beyond probability: First, the fuzzy set theory by Zadeh (1965) as a generalization of the set theory and second, the generalization of classical measure theory to the theory of monotone

H. Herold, *Geoinformation from the Past*,
https://doi.org/10.1007/978-3-658-20570-6_5

measures by Choquet (1954). In particular the former concept has found wide adoption and application within the Geographic Information Science (e.g., Altman, 1994; Usery, 1996; Fisher, 2000; Tang et al., 2007).

Understanding uncertainty has been a research challenge in GIScience for more than two decades (Goodchild, 2010, p. 9). The way uncertainty is discussed in literature changed from being merely perceived as a flaw into being accepted as an ***intrinsic property*** of geographic information (cf. Longley et al., 2005; Goodchild, 2010; Wallentin & Car, 2012, p. 2). Recent contributions to conceptualize uncertainty in the geospatial domain have been given through Gahegan & Ehlers (2000), Winter (2000), Crosetto & Tarantola (2001), Zhang & Goodchild (2002), Plewe (2002), Couclelis (2003), Duckham & Sharp (2005), Leyk et al. (2005), Shi & Liu (2007), Heuvelink et al. (2007), Winter & Yin (2010), and Wallentin & Car (2012).

In summary, uncertainty can be seen as an ***umbrella term*** (cf. Longley et al., 2005, p. 148; Leyk et al., 2005, p. 294) for three basic concepts, namely error, vagueness, and ambiguity. Based on this terminology, figure 5.1 depicts one possibility of conceptualizing uncertainty in geospatial data. It also provides suitable modeling approaches, suggested in Fisher et al. (2006b, p. 45): the probability theory, the fuzzy set theory, and the evidence theory. For a comprehensive discussion of the concept as well as the varying aspects of vagueness from different scientific and philosophical perspectives, the reader is referred to Williamson (1994), Fisher (1999), Regan et al. (2002), and Leyk et al. (2005).

Another, partially complementary, categorization of uncertainty suggested in Ayyub & Klir (2006, pp. 56-57) is primarily used in physics, metrology, engineering, and risk analysis: ***Aleatory uncertainty*** is caused by random errors. Events, representations, and modeling variables are perceived to be inherently random and, thus, have to be treated as non-deterministic in nature. ***Epistemic uncertainty***, in contrast, is caused by systematic imperfections inherent to the model, the measuring instrument, or the representation itself. It is present as a result of the lack of complete knowledge and understanding of a system. The *Comité International des Poids et Mesures* (CIPM) suggested in 1981 the use of "*Type A*" and "*Type B*" as identifiers for the respective components of uncertainty.

Geographical change analysis implies the spatiotemporal component. Understanding and modeling uncertainty in the spatiotemporal domain requires a concept of the logical relations between the geographical entities in space

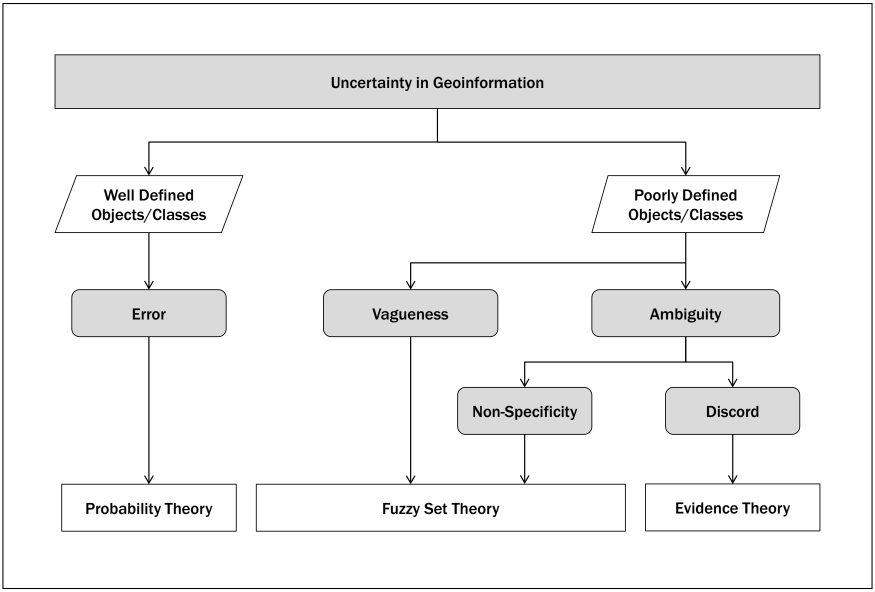

Figure 5.1: Conceptualization and suggested modeling theories for uncertainty in geoinformation.
Source: Modified after Fisher et al. (2006b), © 2006 ISTE, John Wiley & Sons.

and time. Thus, in the following a brief overview of these spatiotemporal relations from set-theoretical perspective is given.

5.1.1 Spatiotemporal Relations of Geospatial Entities

For a formal definition of binary topological relations between spatial entities in one and higher dimensions, Egenhofer (1989) suggested the 4-intersection-model. The topological relation of two regions A and B is characterized by the content of four intersection sets, $\oslash$ or $\neg\oslash$, between the interiors ($^\circ$) and the boundaries (δ) of the regions (cf. Egenhofer, 1989; Mysiak, 2000; Winter, 2000):

$$I_4(A,B) = \begin{pmatrix} A^\circ \cap B^\circ & A^\circ \cap \delta B \\ \delta A \cap B^\circ & \delta A \cap \delta B \end{pmatrix}. \tag{5.1}$$

The eight binary topological relations of regions that are distinguished by the model I_4 are shown in table 5.1. The 2 x 2 intersection matrix has been extended by Egenhofer & Franzoza (1991) including the exterior ($^-$) additionally to the interior and the boundary to a 9-intersection-model I_9:

$$I_9(A,B) = \begin{pmatrix} A^\circ \cap B^\circ & A^\circ \cap \delta B & A^\circ \cap B^- \\ \delta A \cap B^\circ & \delta A \cap \delta B & \delta A \cap B^- \\ A^- \cap B^\circ & A^- \cap \delta B & A^- \cap B^- \end{pmatrix}. \tag{5.2}$$

Egenhofer & Herring (1990) formalized the extension to point and line intersection sets. Winter (2000) extended the intersection set to model uncertainty within topological relations.

Table 5.1: The eight topological relations of two spatial entities that are distinguishable by the intersection model.
Source: Modified after Winter (2000, p. 414) and based on Egenhofer & Herring (1990), © 2000 Taylor & Francis.

$I_4(A,B)$	$I_4(A,B)$	$I_4(A,B)$	$I_4(A,B)$
$\begin{pmatrix} \emptyset & \emptyset \\ \emptyset & \emptyset \end{pmatrix}$	$\begin{pmatrix} \emptyset & \emptyset \\ \emptyset & \neg\emptyset \end{pmatrix}$	$\begin{pmatrix} \neg\emptyset & \neg\emptyset \\ \neg\emptyset & \neg\emptyset \end{pmatrix}$	$\begin{pmatrix} \neg\emptyset & \emptyset \\ \emptyset & \neg\emptyset \end{pmatrix}$
Disjoint	Touch	Overlap	Equal
$\begin{pmatrix} \neg\emptyset & \neg\emptyset \\ \emptyset & \neg\emptyset \end{pmatrix}$	$\begin{pmatrix} \neg\emptyset & \emptyset \\ \neg\emptyset & \neg\emptyset \end{pmatrix}$	$\begin{pmatrix} \neg\emptyset & \neg\emptyset \\ \emptyset & \emptyset \end{pmatrix}$	$\begin{pmatrix} \neg\emptyset & \emptyset \\ \neg\emptyset & \emptyset \end{pmatrix}$
Covers	Covered	Contains	Contained

To formalize the temporal component of topological relations, Allen (1983) suggested a twelve-tiered typology of linear temporal relations, and Worboys (1994), on the other hand, suggested a unified model for spatial and temporal information. Claramunt & Thériault (1996) and Claramunt et al. (1998) extended the model with a comprehensive typology of spatiotemporal processes. Figure 5.2 shows the basic elements of the three-tiered typology: changes of a single entity over time (1), the functional change relationships between entities (2), and the restructuring processes (3). A generalized framework and taxonomy for spatiotemporal representations of geographical entities, suggested by Goodchild et al. (2007), is shown in figure 5.3.

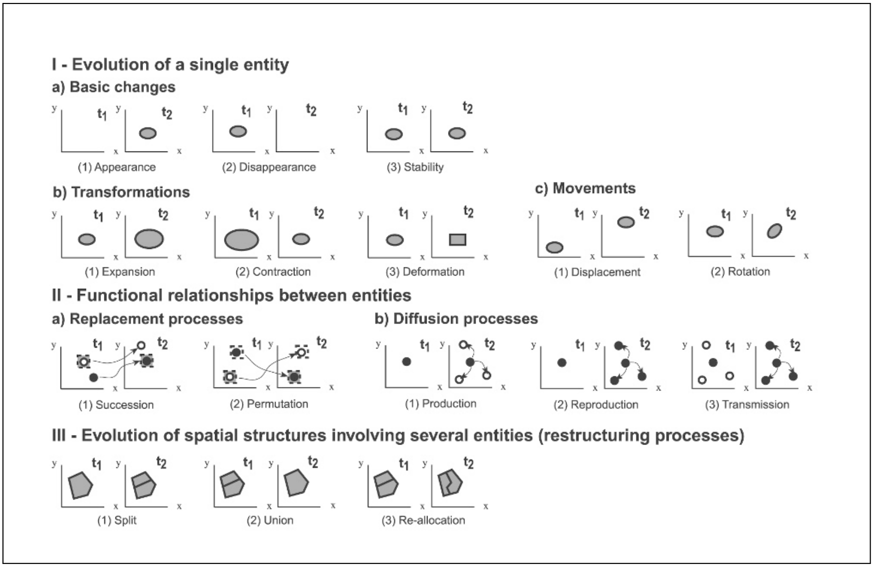

Figure 5.2: A typology of temporal relations and spatiotemporal processes.
Source: Adapted from Claramunt & Thériault (1996, p. 31)

Hornsby & Egenhofer (1997) and Hornsby & Egenhofer (2000) develop an identity-based spatiotemporal change model combining the primitives relating to existence, non-existence, and transition to nine change operations: (1) *continue non-existence without history*, (2) *create*, (3) *recall*, (4) *destroy*, (5) *continue existence*, (6) *eliminate*, (7) *forget*, (8) *reincarnate*, and (9) *continue non-existence with history*. Plumejeaud et al. (2011) extend the concept for multi-scale applications.

In particular, the identity-based model plays an essential role for the change analysis of map-based geoinformation that is discussed in this work (cf. section 5.1.3).

5.1.2 Sources of Uncertainty in Map-Based Geoinformation

The general conceptualizations of uncertainty inherent to both the computational representation of geospatial entities and their spatiotemporal relations outlined so far, do not comprehensively solve the complex problem of uncertainty investigation in map-based change analysis (cf. Leyk, 2005, p. 27). Therefore, Leyk et al. (2005) suggest a framework that acknowledges the specific characteristics of the problem under consideration. According to the three basic elements of GIS, namley data acquisition, handling, and use, uncertainty in map-based investigations is categorized in three source domains (cf. Leyk et al., 2005, p. 298):

Production-oriented uncertainty is defined as the amount of uncertainty inherent in the historical map. It can be perceived as the difference between the entity or cartographic model and the geographical truth which it represents. The difference is also termed *source error* (Goodchild, 1989, p. 108) and is inherent to the cartographic design and map making process, described in section 2.1.3 of this work.

Transformation-oriented uncertainty is defined as the amount of uncertainty caused by data processing and editing. It can be perceived as the difference between the explicit digital information and the analogue source which implicitly contains this information. The difference is also termed *processing error* (Goodchild, 1989, p. 108) and is inherent to the processes of digitization (scanning), georeferencing, and object extraction (field-to-object model transformation), described in the section 4.1 to 4.5 of this work.

Application-oriented uncertainty is defined as the amount of uncertainty inherent to the use and application of map-based information. It can be perceived as the difference between the entity change model and the changing geographical reality it represents over time.

The difference is introduced as the *use error* (by Beard, 1989, p. 108) and is inherent to the non-indented application of analogue representations, exclusively designed for human interpretation, in the computational information extraction and change analysis, investigated in this work. The three uncertainty source domains can, following Leyk's framework, be linked to the quality characteristics of geospatial data.
indexdata quality

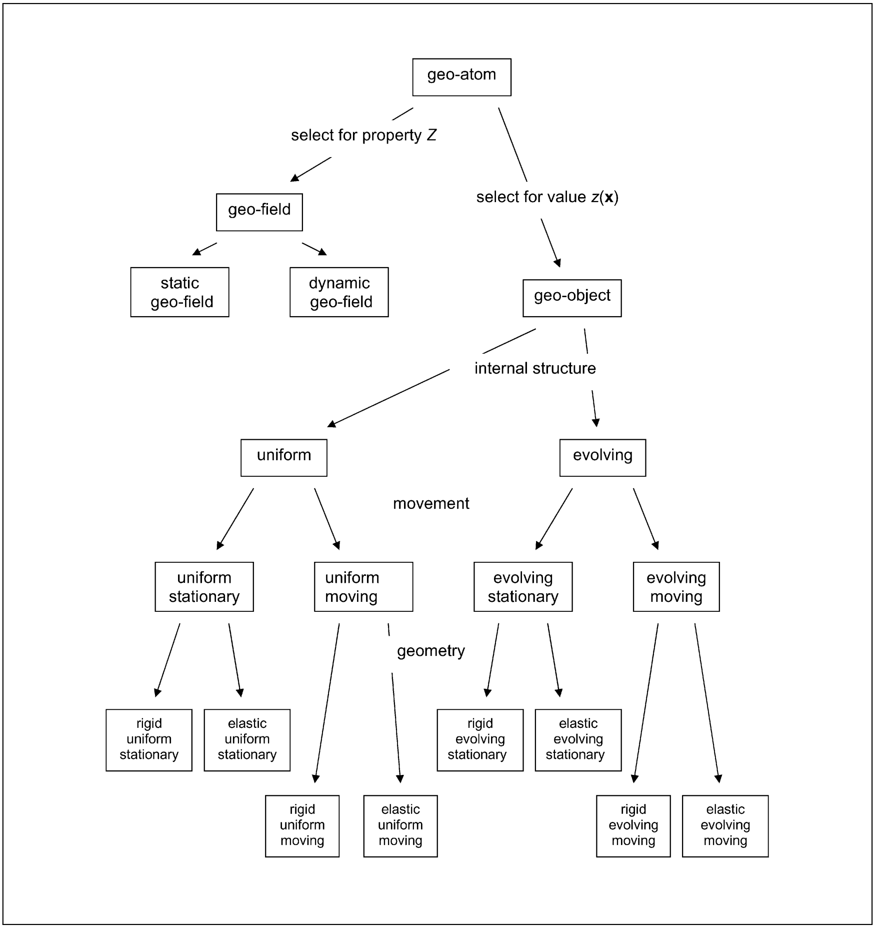

Figure 5.3: A general framework and taxonomy of the spatiotemporal representations of geographical entities.
Source: Adapted from Goodchild et al. (2007, p. 256), © 2007 Taylor & Francis.

The elements of data quality are internationally standardized by the technical committee for geographic information and geomatics of the International Organization for Standardization (ISO) and defined in ISO/TC211 (2009, p. 50): ***completeness*** as the presence and absence of features, their attributes, and relationships; ***logical consistency*** as the degree of adherence to logical rules of data structure, attribution and relationships while the data structure can be of conceptual, logical, or physical nature; ***positional accuracy*** as the accuracy of the position of features; ***thematic accuracy*** as the accuracy of quantitative attributes and the correctness of non-quantitative attributes and of the classifications of features and their relationships; and ***temporal accuracy*** as the accuracy of the temporal attributes and temporal relationships of features.

Positional, thematic, and temporal inaccuracies in the geospatial data are perceived as the respective uncertainties and are referred to as positional or spatial, thematic or attributive, and temporal uncertainty, consequently (e.g., in Bolstad et al., 1990; Gahegan & Ehlers, 2000; Heuvelink et al., 2007). According to Plewe (2002, p. 436), the three aspects or categories of spatiotemporal uncertainty are referred to as the dimensions of uncertainty.

5.1.3 Uncertainty Dimensions in Retrospective Change Analysis

The state-of-the-art standard methodology for retrospective map-based land change analysis has been introduced to the international literature by Kienast (1993). The concept, also referred to as *backward editing*, has found widespread acceptance and application in land change analysis and landscape ecology. Numerous examples of use have been shown in section 2.1.3. The application-oriented concept, originally developed for visual map interpretation and change analysis, can be transferred to a computational concept using the theoretical identity-based spatiotemporal change model suggested by Hornsby & Egenhofer (2000) that is described section 5.1.1.

By linking the considerations on spatiotemporal representations, uncertainty sources, and data quality (discussed in the preceding sections) with the requirements of a computational identity-based change model, three dominating uncertainty categories can be identified: ***spatial***, ***thematic***, and ***temporal uncertainty***, in the following denoted as μ_δ, μ_ϵ, and μ_ζ. Figure 5.4 visualizes the concept of the backward identity-based change model including the three uncertainty dimensions.

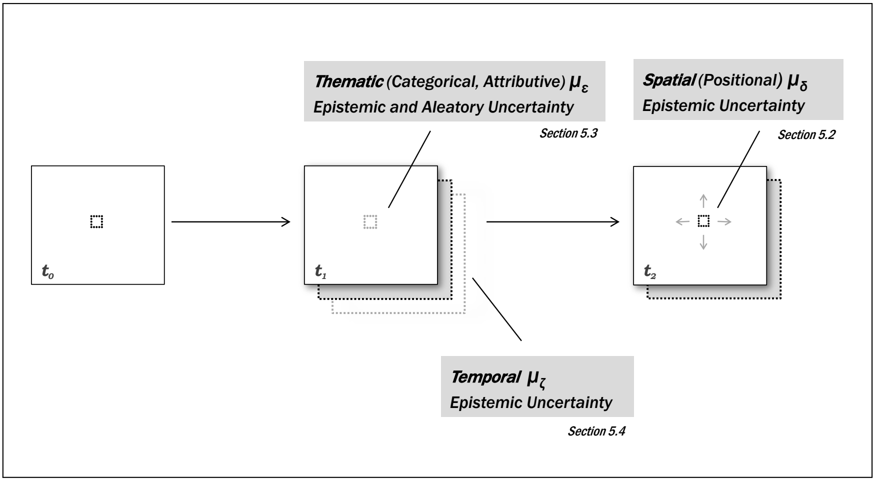

Figure 5.4: Visualization of the backward identity-based change model and the relevant uncertainty dimensions.
Source: Author's own; concept of the backward editing change model based on Kienast (1993).

It becomes obvious, that the inherent epistemic uncertainties cause both *false positive* (FP) and *false negative* (FN) entity identifications in the change model, i.e., falsely and falsely not detected change, and hence have crucial implications on the change results and the findings derived from them.

Therefore, three probabilistic modeling approaches for the identified spatial, thematic, and temporal uncertainties, using the terminological source-oriented framework suggested in Leyk et al. (2005), have been developed in this work and are described in the following.

5.2 Modeling Spatial Uncertainty

5.2.1 Sources and Implications

Spatial (or also termed as positional) uncertainty in map-based information predominately arises from the map making (generalization and cartographic modeling) and map transformation (georeferencing and image analysis) process. According to the topographic mapping and cartographic design process described in section 2.1.3, any two-dimensional representation of the real world inherently underlies abstraction and generalization. In addition, the digitization as well as the transformation of coordinates and entity representations contribute distortions. Figure 5.5 visualizes the sources of the production-oriented and the transformation-oriented spatial uncertainty, respectively.

The absolute positional differences between the geographical and cartographic entities are negligible or even not recognizable when using the map document in the intended manner, namely the interpretation by human beings for spatial cognition and orientation. However, when overlaying multi-temporal cartographic representations of the same geographical subset at the same scale, spatial inaccuracies and distortions become apparent and pose a severe challenge for automated change detection (application-oriented spatial uncertainty).

A commonly used metric for assessing the two-dimensional spatial inaccuracy is the root mean square error (RMSE):

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (p_i - \hat{p_i})^2} \ , \tag{5.3}$$

where p_i denotes the map position of an entity, $\hat{p_i}$ its true or reference location, and n the number of observations. Studies on the quantification of the spatial uncertainty in historical map documents of various scales (e.g., Bolstad et al., 1990; Bolstad & Smith, 1992; Podobnikar, 2007; Tucci & Giordano, 2011) using tools such as *MapAnalyst* (Jenny & Hurni, 2011) reveal typical spatial RMSE that correspond to 5 to 12 meters in real world. Local planimetric distortions may thus be significantly greater.

That is, identity-based comparisons of objects with spatial extents smaller than the spatial uncertainty using the standard methodology after Kienast (1993) and Hornsby & Egenhofer (2000), may lead to the following unfavorable implications for the change analysis:

(a) *false negative* change detection, i.e., the absolute amount of change is underestimated:

$$\Theta_{1(t_0)} \ \cap \ \Theta_{1(t_1)} \ = \ \emptyset; \tag{5.4}$$

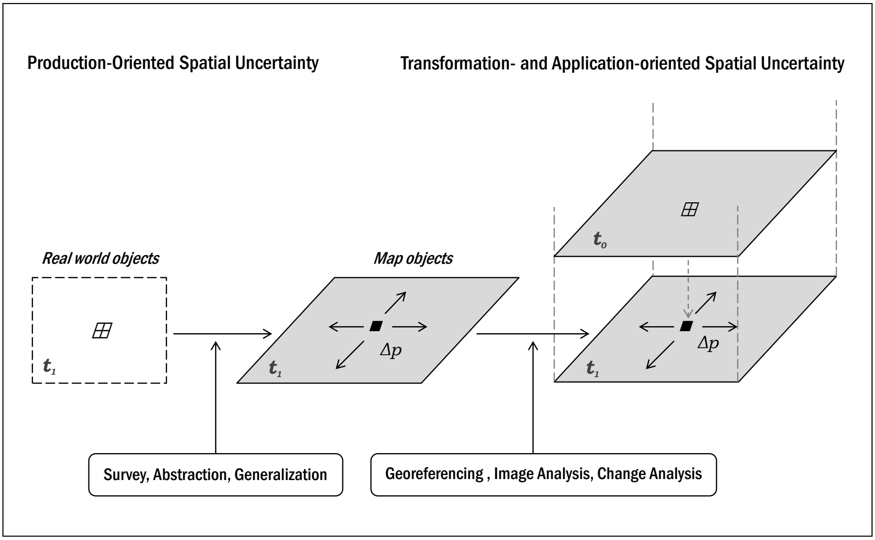

Figure 5.5: Sources of spatial uncertainty in the map production, the map transformation, and the application for change detection.
Source: Author's own.

(b) *false positive* change detection, i.e., the absolute amount of change is overestimated:

$$\Theta_{1(t_0)} \quad \cap \quad \Theta_{2(t_1)} \quad \neq \quad \emptyset, \tag{5.5}$$

where $\Theta_{1(t_0)}$ and $\Theta_{1(t_1)}$ represent identical, i.e., homologue, objects at different point in time t (equation 5.4), while $\Theta_{1(t_0)}$ and $\Theta_{2(t_1)}$ denote two temporally non-identical objects (equation 5.5), respectively. There are two basic strategies to cope with spatial uncertainty of in automated change analysis:

1. reducing the resolution of the change model, e.g., by aggregating the entities of interest to a lower geometric level (down-scaling, e.g., used in Meinel et al., 2009), or,

2. defining non-Boolean memberships to the entities of interest (e.g., Kiiveri, 1997; Fisher et al., 2006a; Heuvelink et al., 2007).

In particular the latter emphasizes the local dependency of spatial uncertainties which is in turn based on the assumption of Tobler's *First Law* *of Geography* (Tobler, 1970, p. 236). In the following, two non-Boolean, probabilistic field- and object-based approaches are developed.

5.2.2 Probabilistic Field-Based Approach

The assignment of non-Boolean characteristics to discrete entities can be achieved by an object-to-field transformation. An appropriate method to create geofields from geoobjects is the density estimation (cf. Goodchild et al., 2007, p. 249). Figure 5.6 shows the basic principle of the field-based approach to model and cope with spatial uncertainty.

Accordingly, the object centroids are converted into a continuous field using a *Gaussian* kernel representing an approximation of the displacement from their true position Δp (fuzzification). The resulting spatial predictor $\delta_{(field)}$ can be used as a probability measure of the object's existence at some point in time t. The probability P of the incident that an arbitrary map object Θ_i in t_0 has an homologous counterpart at a certain point in time t_j can thus be formalized as a function of $\delta_{j_{(field)}}$:

$$P(\Theta_i)_0 = f(\delta_{j_{(field)}}) \in \mathbb{R}\,\{0...1\}\,. \tag{5.6}$$

Hence, temporally homologous but spatially non-overlapping entities can be probabilistically linked. The width of the kernel has to be chosen according to the estimated amount of spatial uncertainty, usually estimated by the RMSE of sample observations. The defuzzification of the fuzzy entity links can be achieved according to the method described in section 5.5.1.

5.2.3 Probabilistic Object-Based Approach

An object-based approach using Boolean logic can be preferably applied over a fuzzy field-based approach where unambiguous object mappings between datasets are possible. This is the case, if homologous objects in different datasets fully or at least partially overlap, i.e., if the local spatial distortions are smaller than the object sizes. Advantageous are a more straightforward implementation and more accurate change results. In literature, examples of Boolean object-based change models for remote sensing and map-based applications are manifold (cf. section 3.3).

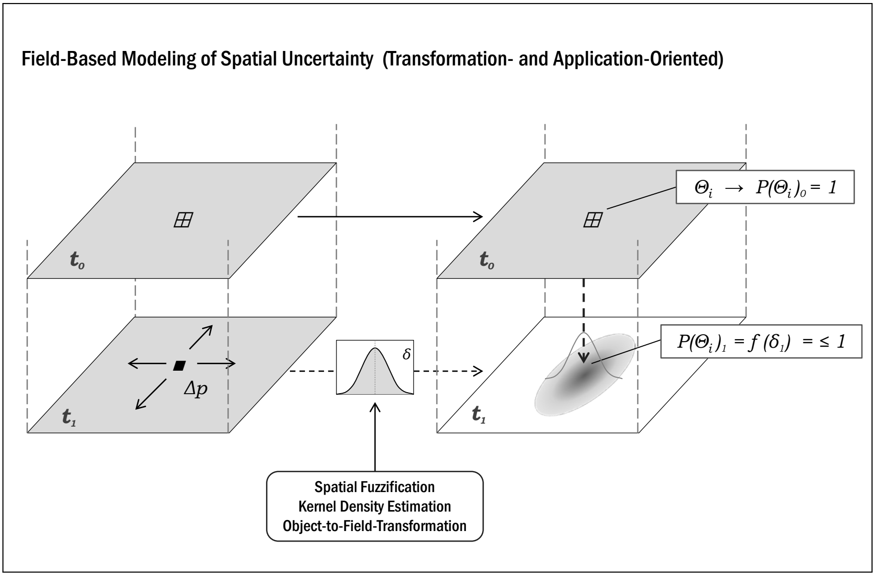

Figure 5.6: A field-based modeling approach of spatial uncertainty for identity-based backward change analysis.
Source: Author's own.

However, in long-term and high-resolution retrospective monitoring applications, the local spatial displacements are frequently greater than the size of the objects of interest. Alternatively to the field-based approach described above, a non-Boolean probabilistic object-based approach may be considered if the local distortions are moderate and spatially homogeneous (affine map). Revell & Antoine (2009) applied a probabilistic object-based approach using a conflation framework described in Blasby et al. (2003) and Davis & Aquino (2003) for matching two equi-temporal datasets of different source, scale, and level of detail. Herold et al. (2012) applied the model for multi-temporal probabilistic object-based matching.

The probabilistic object-based approach is based on similarities regarding the position of the object's gravitational center (centroid) and the object's morphological properties. According to Blasby et al. (2003), Revell & Antoine (2009), and Herold et al. (2012), the set of features used for shape-based matching may include: the ***centroid distance*** as the distance between the centroids of the two objects; the ***Hausdorff distance*** as the greatest local deviation between two geometries; the ***symmetric difference*** as the total area of the non-overlapping portions of the two geometries; the ***symmetric difference (centroids aligned)*** as the distance between the centroids of the two objects that have been shifted such that their centroids are coincident; the ***compactness*** as the ratio of object area to object perimeter, and the ***angle histogram*** as the histogram of the angles that the objects outline segments have with the positive x-axis, weighted by segment length.

High morphological similarity rates are assumed as indicators for temporal homologue objects. Analogously to the field-based approach, the resulting spatial predictor $\delta_{(obj)}$ is used as a measure for the object's existence at some point in time t. Figure 5.7 shows the principle of the methodology. The probability P of the incident that an arbitrary object Θ_i in t_0 has an homologous counterpart at a certain point in time t_j can be formalized as a function of $\delta_{j_{(obj)}}$:

$$P(\Theta_i)_0 = f(\delta_{j_{(obj)}}) \in \mathbb{R}\{0...1\}\,. \tag{5.7}$$

That is, objects with low similarity rates, i.e., without representation in the older data set, are marked as new objects within the respective time period. Hence, the approach is, compared to a Boolean approach, less sensitive to distorted and temporally non-overlapping objects.

5.3 Modeling Thematic Uncertainty

5.3.1 Sources and Implications

Thematic (or also termed attribute or categorical) uncertainty in map-based information arises from the map making (cartographic modeling) as well as the map transformation (image analysis) process. According to the topographic mapping and cartographic design process described in section 2.1.3, any real world representation inherently underlies abstraction and generalization. That is, real world entities are either not recorded or morphologically changed, respectively. In addition, the rules for abstraction and generalization change over time and space, mainly due to varying cultural importance of some entities. This effect is by some authors (e.g., Leyk, 2005) referred to as semantic uncertainty.

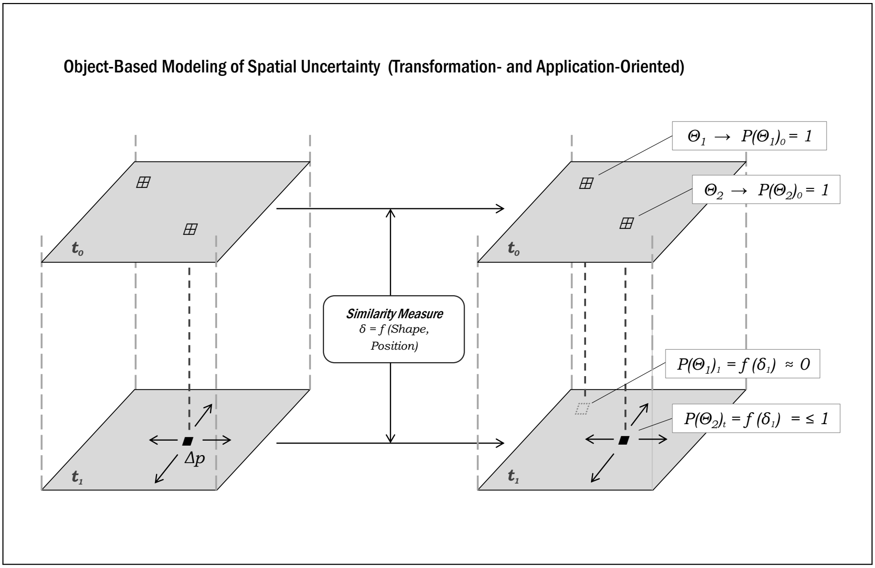

Figure 5.7: An object-based modeling approach of spatial uncertainty for identity-based backward change analysis.
Source: Author's own.

The second source of thematic uncertainty is the map image analysis process, introducing imperfectly segmented or incorrectly classified digital representations of the map content. Figure 5.8 visualizes the sources of the production-oriented and the transformation-oriented thematic uncertainty, respectively. Implications of thematic uncertainty for change analysis can be described analogously to spatial uncertainty (cf. section 5.2.1). Here, imperfectly segmented and incorrectly classified entities lead to *false negative* change detection, where the absolute amount of change is underestimated, and to *false positive* change detection, i.e., where the absolute amount of change is overestimated, respectively.

Depending on the data sources used, the ratio of the production- and the transformation-oriented uncertainty contributing to these errors can differ greatly. Assuming a similar cartographic model over time, the result of the change analysis may heavily or solely depend on the transformation-oriented uncertainty. In the following, an approach to reduce the substantial

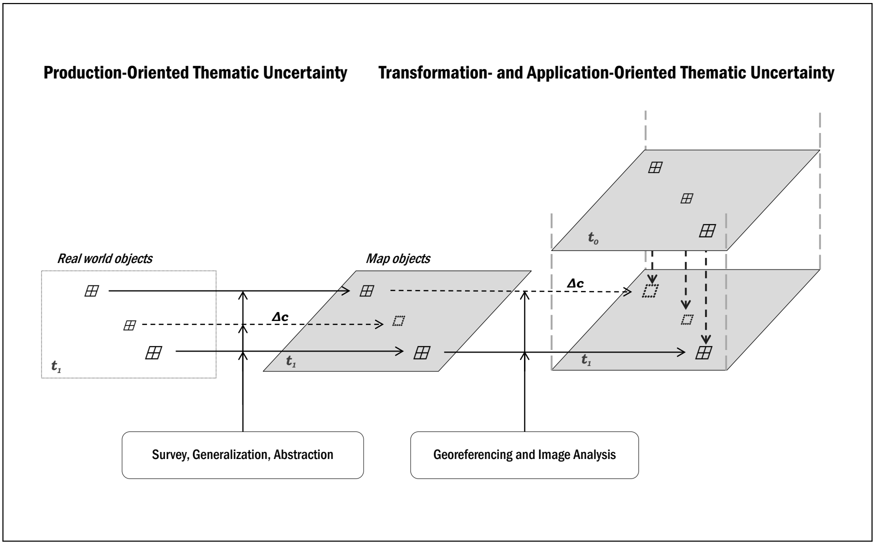

Figure 5.8: Sources of thematic uncertainty in map production, the transformation process and application.
Source: Author's own.

implications of the transformation-oriented thematic uncertainty on the retrospective change analysis is presented.

5.3.2 Probabilistic Recognition Approach

A common solution to address thematic uncertainty is the assignment of probabilistic class memberships through fuzzy or soft classifiers; a concept widely used in remote sensing applications (e.g., Schowengerdt, 2007, and Blaschke, 2010). In contrast to crisp classifications, the resulting objects may belong, to a certain degree, to more than one thematic class.

The methodology proposed in chapter three enables probabilistic class assignments through a soft classifier. In the artificial neural network architecture suggested in section 4.4, a logistic function:

$$f(x) = \frac{1}{1 + e^{-x}} \tag{5.8}$$

with first derivative $f'(x) = f(x) - f^2(x)$ is used as sigmoidal activation function (cf. Blackwell & Chen, 2009), yielding soft class membership predictions ϵ_j for each object. Thus, the probability P of the incident that an arbitrary map object Θ_i in t_0 has an homologous counterpart at a certain point in time t_j can be formalized as a function of ϵ_j:

$$P(\Theta_i)_0 = f(\epsilon_j) \; \in \mathbb{R}\,\{0...1\}\,. \tag{5.9}$$

That is, high values of the thematic predictor ϵ are used as indicator for object existence. Figure 5.9 shows the principle of the probabilistic recognition approach to model and cope with thematic uncertainty.

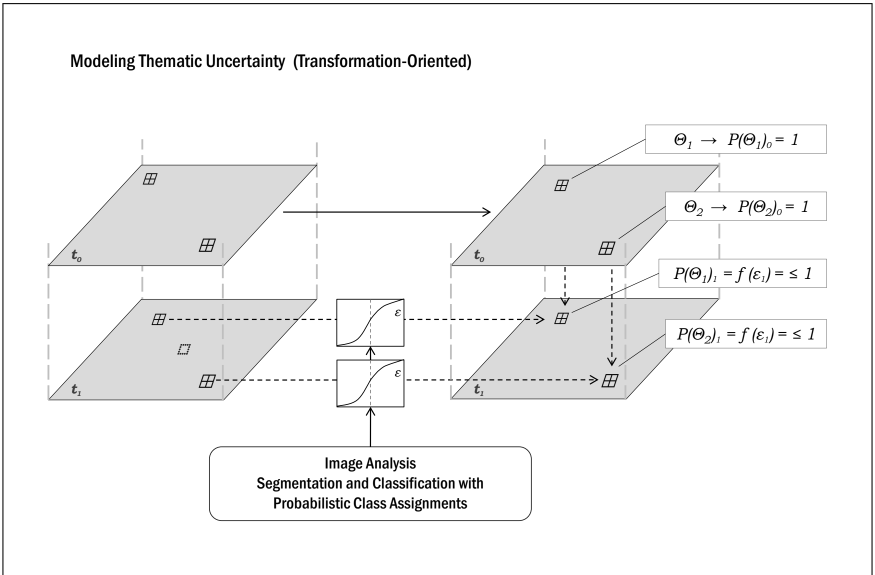

Figure 5.9: A probabilistic approach for thematic uncertainty in identity-based backward change analysis.
Source: Author's own.

Another approach capable of reducing both production- and transformation-oriented thematic uncertainty is the integration of *a-priori*-knowledge into the classification process. Ancillary information might be available through archival remote sensing imagery or another, smaller-scale historical maps. However, such information is also inherently subject to uncertainty. Therefore, a combinatorial modeling approach for information from uncertain sources as suggested in section 5.5.2 has to be used.

5.4 Modeling Temporal Uncertainty

5.4.1 Sources and Implications

Temporal uncertainty in map-based information arises from the map making process and map use for change analysis. According to the topographic surveying and mapping process described in section 2.1.3, there is an immanent time delay between real world changes, the topographic survey and the map publishing. To distinguish between the date of change and its recording Langran & Chrisman (1988) introduce the terms *world time* and *database time* for modern surveys. Especially when referring to historical maps, the temporal difference can not be assumed as equal for a map sheet, in this work denoted as ***intra-data set variability***.

The second source of temporal uncertainty is the application of the maps for change analysis (application-oriented uncertainty), i.e., restoring a continuous process solely from discrete snapshots in time. Depending on the spatial coverage and scale of a study, the historical coverage usually contains more than one data set, i.e. map sheet, per time period. In case these data sets are of different survey date, ***inter-data set variability*** occurs. Figure 5.10 visualizes the sources of the production- and the application-oriented temporal uncertainty, respectively.

Implications of temporal uncertainty cause that entity change events such as appearance, morphological alterations (mutations), and disappearance are not correctly represented in the change model. In contrast to spatial and thematic uncertainty, the implications of temporal uncertainties are usually less substantial for long-term change analysis. However, for some high-resolution monitoring applications the temporal accuracy of the change result might be of great importance (e.g., Meinel et al., 2009). In the following, a probabilistic backdating approach addressing the inter-data source variability is suggested.

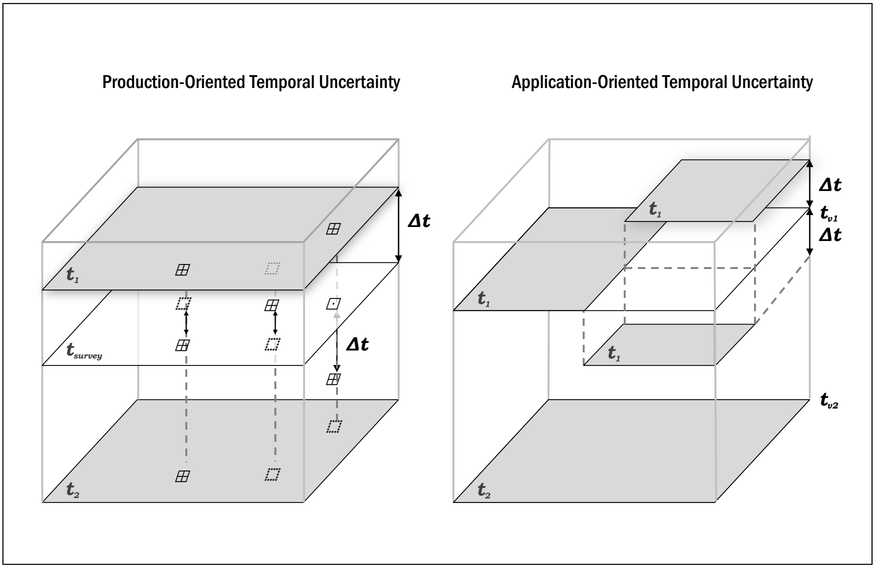

Figure 5.10: Sources of temporal uncertainty in map production and the application.
Source: Author's own.

5.4.2 Probabilistic Backdating Approach

An approach to cope with temporal uncertainty is the introduction of virtual time or event layers. Here, virtual time layers t_{v_i} are introduced and set to the oldest data set in the respective time period under investigation. Assuming that entity appearance (or creation), existence, and disappearance (or destruction) events represent continuous natural or anthropogenic processes, the events in the newer dataset can be backdated according to the time difference Δt between the data t_{j+x} and the virtual t_{v_j} layer. A normalized temporal predictor ζ can be introduced through relating Δt to the difference between the time layer t_{j+x} and the next older virtual time layer:

$$\zeta_j = \frac{t_{j+x} - t_{v_j}}{t_{j+x} - t_{v_{j\text{-}1}}} \quad \in \mathbb{R}\{0...1\}\,. \tag{5.10}$$

Thus, the probability P of the incident that an arbitrary new map object Θ_i in t_{j+x} has already been existing at the virtual point in time $t_j = t_{v_j}$ can be formalized as a function of ζ_j:

$$P(\Theta_i)_{j(=vj)} = f(\zeta_j) \quad \in \mathbb{R}\,\{0...1\}\,. \tag{5.11}$$

That is, the temporal predictor is used as indicator for object existence at the time of virtual layer. Low values of ζ indicate that the entity change has occurred between the virtual layers. Figure 5.11 shows the principle of the probabilistic backdating approach to model and cope with temporal uncertainty.

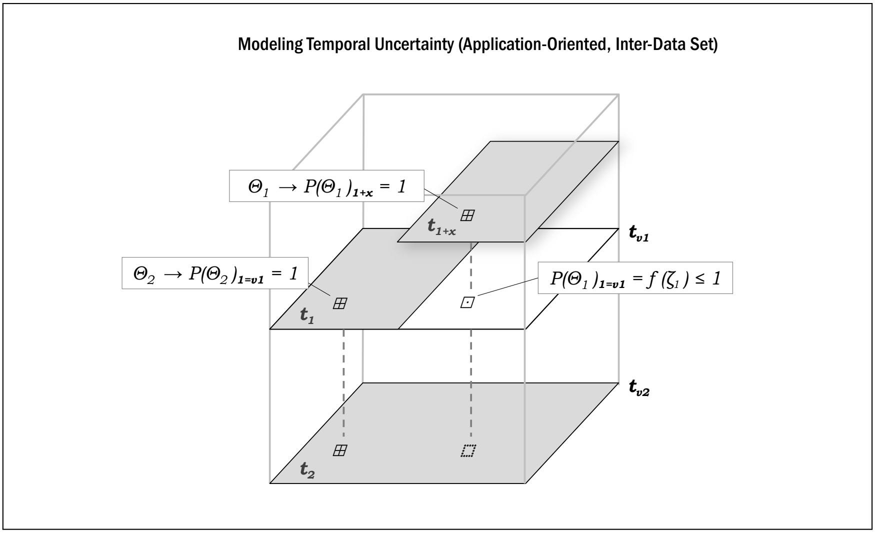

Figure 5.11: A probabilistic approach for temporal uncertainty in identity-based backward change analysis.
Source: Author's own.

5.5 Combinations and Extension by the DS-Theory of Evidence

For a comprehensive investigation and modeling of all uncertainty dimensions, the previously separately reviewed and independently modeled spatial, thematic, and temporal uncertainties have to be combined. Figure 5.12 illustrates a combinatorial approach for a probabilistic retrospective change analysis.

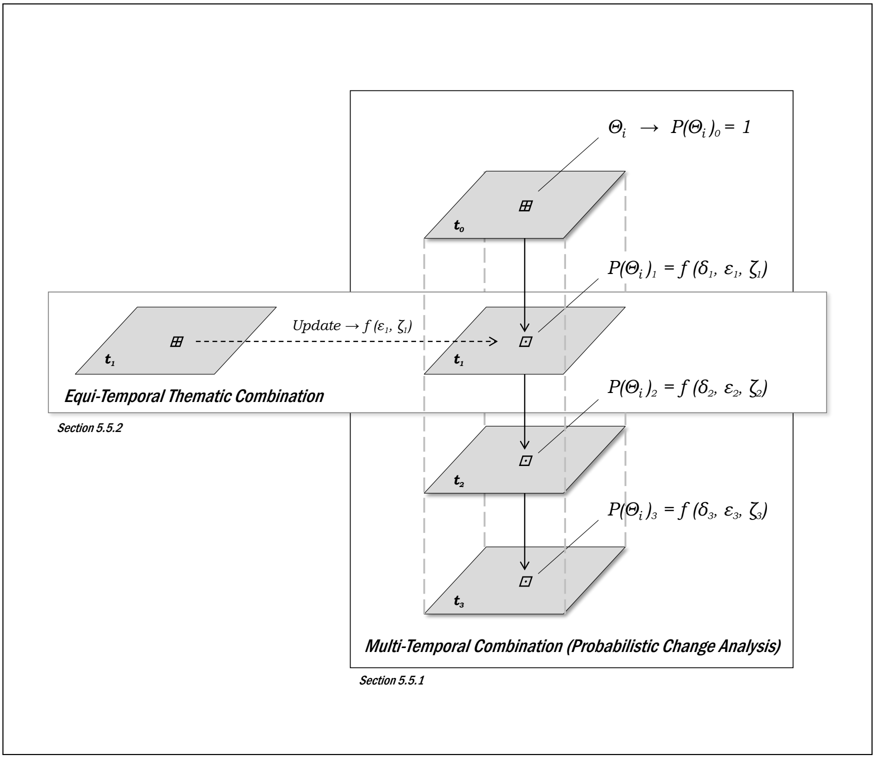

Figure 5.12: Combinatorial modeling of spatial, thematic, and temporal uncertainties for change analysis.
Source: Author's own.

The multi-temporal component is outlined in the following section 5.5.1. As suggested in the preceding sections 5.3.2 and 5.4.2, the amount of thematic and temporal uncertainty can be reduced by integrating *a-priori*-knowledge for each respective point in time. However, such information may also be subject to a certain degree of uncertainty. Therefore, an equi-temporal combination approach for incorporating uncertain *a-priori*-knowledge is subsequently described.

5.5.1 Multi-Temporal Combinations for Retrospective Change Analysis

Following the standard methodology of backward editing for retrospective land change analysis described in section 5.1.3, the previously independently modeled spatial μ_δ, thematic μ_ϵ and, temporal μ_ζ uncertainties can be combined in the following way. For each presently existing object Θ_i the probability $P(\Theta_i)$ of its existences at a time t can be described as:

$$P(\Theta_i)_t = \omega_\delta \cdot f(\delta_t) \,\cap\, \omega_\epsilon \cdot f(\epsilon_t) \,\cap\, \omega_\zeta \cdot f(\zeta_t) \quad \in \mathbb{R}\,\{0...1\} \tag{5.12}$$

where δ_t denotes the spatial, ϵ_t the thematic, and ζ_t the temporal predictor, as previously defined in the sections 5.2, 5.3, and 5.4. The weighting factors $\omega_\delta, \omega_\epsilon$, and ω_ζ ($\forall\ \omega \in \{0..1\}$) are introduced to enable balancing the importance of each uncertainty dimension. The change vector $\vec{\theta_i}$ that contains all evidence for the existence of Θ_i over a retrospective time period t_0 to t_n can accordingly be formulated as:

$$\vec{\theta_i} = (P(\Theta_i)_0, P(\Theta_i)_1, P(\Theta_i)_2, \ldots, P(\Theta_i)_n). \tag{5.13}$$

The probabilistic formulation of the object existence and thus its change over time can be discretized to $E(\Theta_i)_t$ using a threshold T_θ:

$$E(\Theta_i)_t = \begin{cases} 0 & \text{for } P(\Theta_i)_t \leq T_\theta, \\ 1 & \text{for } P(\Theta_i)_t > T_\theta, \end{cases} \tag{5.14}$$

yielding binary values for the object existence hypotheses at each point in time within the change vector $\vec{\hat{\theta}_i}$ of object Θ_i:

$$\vec{\hat{\theta}_i} = (E(\Theta_i)_0, E(\Theta_i)_1, E(\Theta_i)_2, \ldots, E(\Theta_i)_n). \tag{5.15}$$

Example: Considering an arbitrary object Θ_i with the following hypothetical spatial (δ_t), thematic (ϵ_t) and temporal (ζ_t) predictors in four points $t_0, t_1, t_2,$ and t_3 in time:

$$\begin{array}{l} P(\Theta_i)_0 = \omega_\delta \cdot 0.99 \;\cap\; \omega_\epsilon \cdot 1.00 \;\cap\; \omega_\zeta \cdot 0.95 \\ P(\Theta_i)_1 = \omega_\delta \cdot 0.89 \;\cap\; \omega_\epsilon \cdot 0.91 \;\cap\; \omega_\zeta \cdot 0.86 \\ P(\Theta_i)_2 = \omega_\delta \cdot 0.17 \;\cap\; \omega_\epsilon \cdot 0.31 \;\cap\; \omega_\zeta \cdot 0.78 \\ P(\Theta_i)_3 = \omega_\delta \cdot 0.55 \;\cap\; \omega_\epsilon \cdot 0.76 \;\cap\; \omega_\zeta \cdot 0.28 \end{array} \tag{5.16}$$

where, for the sake of clarity, equal weighting factors $\omega_\delta = \omega_\epsilon = \omega_\zeta = 1.0$ are assigned. As the predicting functions of each dimension are modeled as independent variables (X_i) in the preceding sections, the joint probabilities can be obtained by the product rule:

$$P\left(\bigcap_{i=1}^{n} X_i\right) = \prod_{i=1}^{n} \mathrm{P}(X_i). \tag{5.17}$$

Hence, the resulting change vector for object Θ_i, i.e., the object's retrieved history, can be calculated according to equation 5.13:

$$\vec{\theta_i} = (0.94, 0.69, 0.04, 0.12). \tag{5.18}$$

By discretizing $\vec{\theta_i}$ using equation 5.14 and $T_\theta = 0.5$, the evidence for object's existence can be formulated as:

$$\vec{\hat{\theta}_i} = (1, 1, 0, 0). \tag{5.19}$$

That is, the object under consideration started existing between t_2 and t_1 and is existing to present, while the accepted level of the overall uncertainty μ_σ is less than 50%. Based on this discrete formulation of object existence, basic consistency checks can be applied (e.g., as in Hecht et al., 2008), using entity-specific knowledge about typical entities' life cycle or temporal behavior.

5.5.2 Equi-Temporal Combinations for Incorporating *a-priori*-Knowledge

As previously suggested in the sections 5.3.2 and 5.4.2, in particular the amount of thematic and temporal uncertainty can be reduced by integrating *a-priori*-knowledge (cf. figure 5.10). Ancillary information might be available through archival remote sensing imagery, historical maps, or even non-spatially explicit statistical data. However, such information is, by its nature, also subject to a certain degree of uncertainty.

As an example one might assume a land cover mask of the urban extent derived from either archival remote sensing imagery, or, considering a “pre-satellite” point in time, a small-scale nationwide topographic or thematic map. The former, as a primary data source, is capable of significantly reducing the temporal uncertainty but still contains thematic uncertainty, which is introduced by the visual or computational image interpretation. In contrast, the latter as secondary data source might be capable of reducing the thematic uncertainty while containing a higher amount of temporal production-oriented uncertainty.

Thus, a combinatorial modeling approach has to offer the possibility to rate different uncertain sources according to their perceived confidence or plausibility. As discussed and applied in the preceding sections, inferring knowledge under uncertainty is generally addressed by a probability theoretical approach, for conditional probabilities formalized as the *Bayes’ theorem* (cf. O’Sullivan & Unwin, 2003, p. 306).

A major shortcoming of Bayesian probabilistic and fuzzy set-based approaches is that incomplete knowledge about a system cannot be comprehensively modeled. For instance, the absence of evidence about a hypothesis is not just treated as a lack of evidence, but as constituting evidence against that hypothesis (cf. Lein, 2003, p. 64).

A solution to that problem has been suggested by Dempster (1967, 1968) through the generalization of the Bayesian probability theory. Shafer (1976) refined and extended the work to a comprehensive ***Mathematical Theory of Evidence*** as a framework for the description of incomplete knowledge. Therefore, the joint theoretical concept is in literature also referred to as the *Dempster-Shafer Evidence Theory (DST)*. Since its publication, the concept has been widely adopted for information fusion in artificial intelligence (AI, e.g., Barnett, 1981) but has mainly recently also been taken up in other scientific disciplines such as remote sensing (multi-sensor data fusion and classification, e.g., Lein, 2003; Rottensteiner et al., 2007), risk analysis and geology (e.g., Tangestani, 2009; He et al., 2011; Park, 2011; Mousavi, 2012), and medical image analysis (e.g., Shoyaib et al., 2012). The terminology and definitions used in the following are based on Dempster (1967), Klir (1990), and Klir & Yuan (1995).

The basic element of the Evidence Theory is a set of unique and mutually exclusive hypotheses (A_n, called singletons) that forms the *Frame of Discernment*, in this work denoted as Ω. The power set of this frame $\mathcal{P}(\Omega)$ represents all sub-sets of Ω, including the empty set:

$$\mathcal{P}(\Omega) = \{\varnothing, A, \neg A, \Omega\}\,. \tag{5.20}$$

For the problem given in this work, the frame of discernment Ω could contain, as in the simple case in the example given above, the mutually exclusive hypotheses regarding the land use of an area under investigation:

$$\Omega = \{urban, non\text{-}urban\} \tag{5.21}$$

For each hypothesis in $\mathcal{P}(\Omega)$ a *Basic Probability Assignment (BPA)*, referred to as the mass function m, is assigned $m : \mathcal{P}(\Omega) \to [0,1]$, such that the mass function of an empty set is zero and the sum of all mass functions is one:

$$m(\varnothing) = 0, \tag{5.22}$$

$$\sum_{A \in \mathcal{P}(\Omega)} m(A) = 1. \tag{5.23}$$

For each basic mass function m, a pair of measures (or evidential functions) is associated: (1) the *belief measure* (bel) represents the sum of the evidence supporting a hypothesis:

$$\mathrm{bel}(A) = \sum_{B|B \subseteq A} m(B), \tag{5.24}$$

while (2) the *plausibility measure* (pl) represents the sum of the evidence that does not contradict to a hypothesis:

$$\mathrm{pl}(A) = \sum_{B|B \cap A \neq \varnothing} m(B). \tag{5.25}$$

The *belief* and the *plausibility* measure are linked through:

$$\mathrm{pl}(A) = 1 - \mathrm{bel}(\neg A), \tag{5.26}$$

$$\mathrm{pl}(\neg A) = 1 - \mathrm{bel}(A), \tag{5.27}$$

respectively, where $\neg A$ denotes the complementary set of A. The two measures form the upper and lower probabilities for the hypothesis support (cf. Dempster, 1967):

$$\mathrm{bel}(A) \leq P(A) \leq \mathrm{pl}(A), \tag{5.28}$$

and thus allow to model the ignorance about a system or the support of an hypothesis by an *belief* interval (cf. figure **??**).

To combine the evidence of two or more mass functions, i.e., the information from two or more independent uncertain sources, *Dempster's rule of combination* (cf. Klir & Yuan, 1995, p. 183) can be used. The combined mass of two mass functions m_1 and m_2 is thereby given via:

$$(m_1 \oplus m_2)(A) = \frac{1}{z} \sum_{B_1 \cap B_2 = A} m_1(B_1) \cdot m_2(B_2), \tag{5.29}$$

for all $A \neq \varnothing$ and $m_{1,2}(\varnothing) = 0$, where the normalizing factor z is:

$$z = 1 - \sum_{B_1 \cap B_2 \neq \varnothing} m_1(B_1) \cdot m_2(B_2). \tag{5.30}$$

Accordingly, the combination of three and more sources can be calculated using the formula given in Rottensteiner et al. (2007, p. 289). Further rules of combination such as *Inagaki's* and *Yager's* rule can be found in Ayyub & Klir (2006, pp. 140-147).

Hence, an evidence theoretical approach such as DST allows to integrate evidence from uncertain and possibly contradicting sources such as the equi-temporal combination of historical map-based land use information, while explicitly and independently modeling uncertainty and the lack of evidence. The methodology can be perceived as the attempt to mimic "the natural behavior of reasoning by narrowing the hypothesis set down to a smaller number of possibilities as the evidence increases" (Lein, 2003, p. 63). Difficulties of the approach encompass the exponential computational complexity (cf. Khaleghi et al., 2013, p. 33) and the quantitative definition of the mass functions (cf. Park, 2011, p. 368).

In conclusion, the probabilistic fuzzy approach suggested in sections 5.2 to 5.5.1 is suitable for modeling spatial, thematic, and temporal uncertainties and their (multi-temporal) combination for retrospective change analyses, while the evidence theoretical approach is to be preferred for integrating *a-priori* knowledge by (equi-temporal) combinations of uncertain information sources. In the following chapter, implementations of the proposed methodology for retrieving historical land use information from heterogeneous and inherently uncertain data sources are evaluated and discussed based on experimental results.

6 Evaluation and Discussion

In order to evaluate the methodology presented in the preceding chapters four and five, the proposed adaptive image analysis algorithm has been implemented as software prototype. This chapter introduces the implementation and evaluation strategy, describes the experiments conducted using real world data and concludes with a discussion of the results.

6.1 Implementation

Figure 6.1 shows the conceptual outline of the implementation approach for the methodology, which can be characterized as loosely coupled (Longley et al., 2005, p. 377). That is, the geospatial data management and the image analysis part are coupled using parameter files.

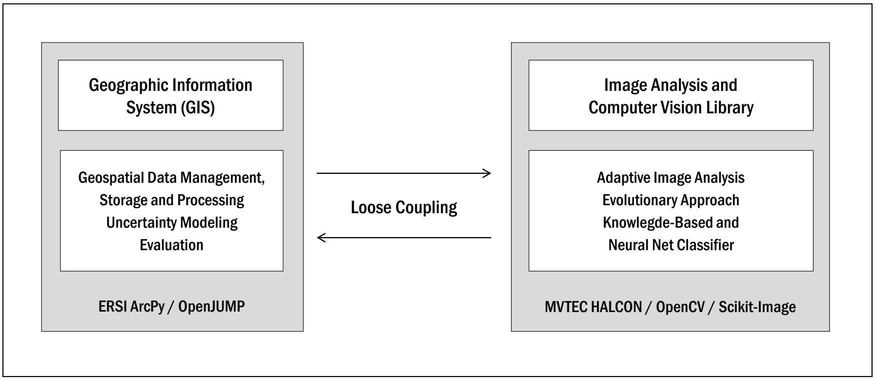

Figure 6.1: Implementation using loose coupling between geospatial data management and image analysis.
Source: Author's own.

For the evaluating of the implementation of the methodical approach, binary evaluation measures such as *precision (correctness)* and *recall (com-*

H. Herold, *Geoinformation from the Past*,
https://doi.org/10.1007/978-3-658-20570-6_6

pleteness) - typically applied for (visual) pattern recognition problems - are used (cf. Leyk et al., 2006, p. 964; Herold et al., 2012, p. 254). Precision refers to the *true positive / (true positives + false positives)* $\in [0;1]$, while the recall rate refers to the *true positives / (true positives + false negatives)* $\in [0;1]$. The F_β-measure using $\beta = 1$ refers to the harmonic mean of precision and recall.

6.2 Experiments

Various experiments are conducted to evaluate the hypotheses three, five, and six (H3, H5, H6) and hence the suitability of the proposed methodology using real world data. The evaluation follows the measures introduced in the preceding section. The descriptions of the experiments are organized as follows: statement of the objective, outline of the experimental design, and presentation of the results. The results are discussed in section 6.3.

6.2.1 E-1. Color, Textural, and Morphological Segmentation

The objective of the first experiment is to evaluate hypothesis three (H3), which states that methods of digital image analysis such as color-, texture-, morphology-based segmentation can be used to acquire spatially explicit LULC information from the archival map sources.

Experimental Design

To test the suitability of the three fundamental segmentation algorithms described in sections 4.2.1 to 4.2.3, archived maps of three points in time, namely 1785, 1910, and 2010, are selected. The maps have purposely been selected to cover both the same area (Dresden, Germany) as well as all three basic image segmentation algorithms. As reference, urban land use and land cover such as built-up space or single buildings are visually delineated and contrasted to the segmentation results. Figure 6.2 shows an outline of the experimental design.

Experimental Results

Table 6.1 shows the segmentation criterion, the segmentation algorithm and segmentation parameters used, as well as the best result which could be achieved by manual parametrization. In the last row, the time for manual adaption using expert knowledge is given.

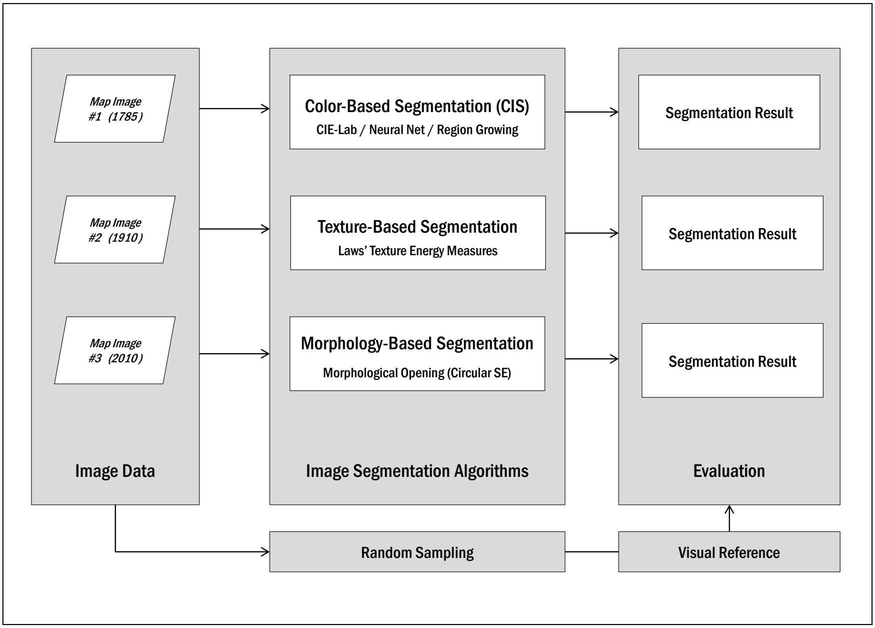

Figure 6.2: Experimental design E-1. Color-, texture-, and morphology-based map image segmentation.
Source: Author's own.

6.2.2 E-2. Segmentation Using a $(\mu + \lambda)$-Evolutionary Strategy

Objective

The objective of the second experiment is to evaluate hypothesis five (H5), which states that image segmentation can be considered a non-linear optimization problem. Hence, a stochastic search algorithm may be used to

Table 6.1: Experimental results E-1. Evaluation results for the three input maps applying three different image segmentation algorithms (color-, texture-, morphology-based segmentation). The optimal parameter values used for map image segmentation are given for each method.
Source: Author's own

Homogeneity criterion	**Color**	**Texture**	**Morphology**
Method	Neural Net (MLP)	Texture Laws	Mathematical M.
Parameter I	Space = *CIE*-Lab	FILTYP = 4.0 ('OS')	OTHRL = 0
Parameter II	Error Tolerance = 0.01	SHIFT = 0.5	OTHRU = 10
Parameter III	Hidden Units = 1	MEDIAN = 0.5	MSE = 2 ('circ')
Parameter IV	Activation = sigmodial	Median = 0.5	ORAD = 3.50
Parameter V	Max. Iterations = 300	-	-
Results			
Recall	0.834	0.891	0.942
Precision	0.742	0.912	0.961
Adaption (min)	10	25	5

find a (quasi-)optimal segmentation parametrization. The metaheuristic evolutionary approach to adaptive segmentation – developed and described in section 4.3 – is tested and evaluated here. Primary evaluation criteria are both the convergence and stability characteristics of the algorithm, which are crucial for practical applicability.

Experimental Design

In order to evaluate the suitability and adaptive capacities of the developed evolutionary segmentation algorithm, three subsets of two historical maps from 1885 and 1910, respectively, are used. To segment the wanted LULC information from these maps, texture- and/or morphology-based segmentation (cf. section 6.2.1) with numerous parameter settings and their combinations have to be applied. To automatically adapt the parameters, an evolutionary approach is proposed. As described in section 4.3, the following fitness function (*Area Fit Index*, AFI) was used in the EA:

$$f(x) = AFI = \frac{1}{n} \sum_{i=1}^{n} \frac{AS_i^p(x)}{AR_i^p} \quad \forall \ AS_i^p(AR_i^p) \neq \oslash, \tag{6.1}$$

where x denotes the set of segmentation parameters, $AS_i^p(x)$ denotes the area of the i-th segment retrieved by using the set of segmentation parameters x, and AR_i^p the area of the i-th reference segment. For the evaluation of the stability of the approach, repetitions of the experiment (i.e., repeated evolutionary cycles) are conducted. Subsequently, the outcomes of each evolutionary cycles are compared. As evaluation criterion the shape agreement (fitness) over all reference segments is used. The segment shape is described by the *Shape Index* (SI, cf. Neubert et al., 2008, p. 775):

$$SI = \frac{P}{4\sqrt{A}}, \tag{6.2}$$

where P is the perimeter and A the area of the segment. From (6.2) the *Shape Fitness Index* (SFI) is derived:

$$SFI = 100 \cdot \frac{SI_S - SI_R}{SI_R}, \tag{6.3}$$

where SI_S refers to the shape fitness index of the segmented and SI_R of the reference segment. Figure 6.3 shows an outline of the design of the experiment.

As reference segments, urban land use and land cover such as built-up space and single buildings are visually delineated and contrasted to the automatically adapted segmentation results.

Experimental Results

As EAs show inherently non-deterministic characteristics, i.e., the time to optimum finding can not be predicted, a convergence test as well as a stability test have been carried out. Figures 6.4 and 6.5 show the convergence characteristics of two evolutionary cycles. Low AFI values indicate a high fitness of the genetic individual for the segmentation problem. In the first case, convergence (i.e., complete adaption, $AFI = 0$) is achieved after 121 generations, in the latter after 448 generations.

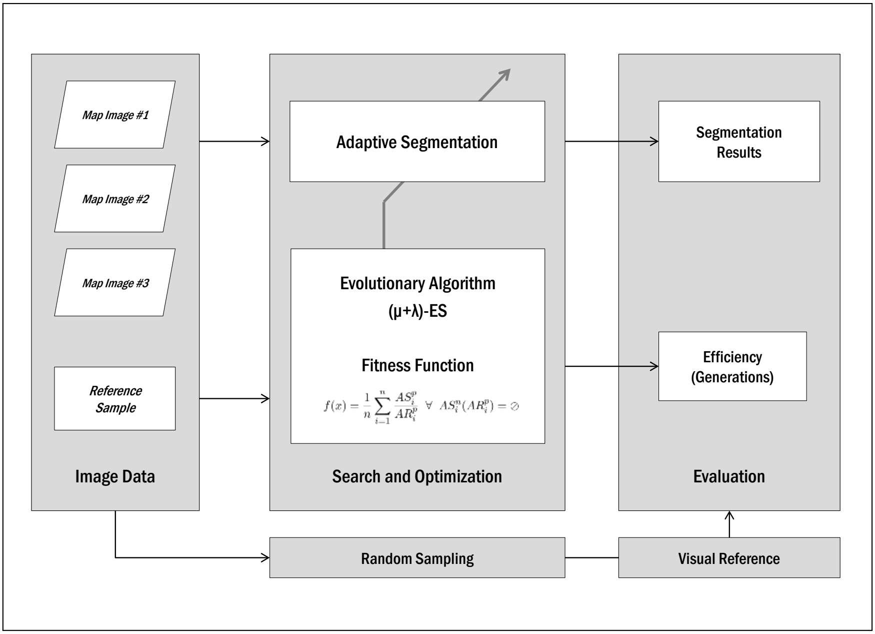

Figure 6.3: Experimental design E-2. Adaptive image segmentation using a $(\mu + \lambda)$-Evolutionary Strategy.
Source: Author's own.

Figure 6.6 shows the result of the stability test. The maximum number of generations was set to 1,000. SFI values close to 100 indicate convergence. There was only one evolutionary cycle (cycle 6), in which the algorithm has not converged to the optimum within the given limit of 1,000 evolutionary generations. The mean number of generations to converge was 237.

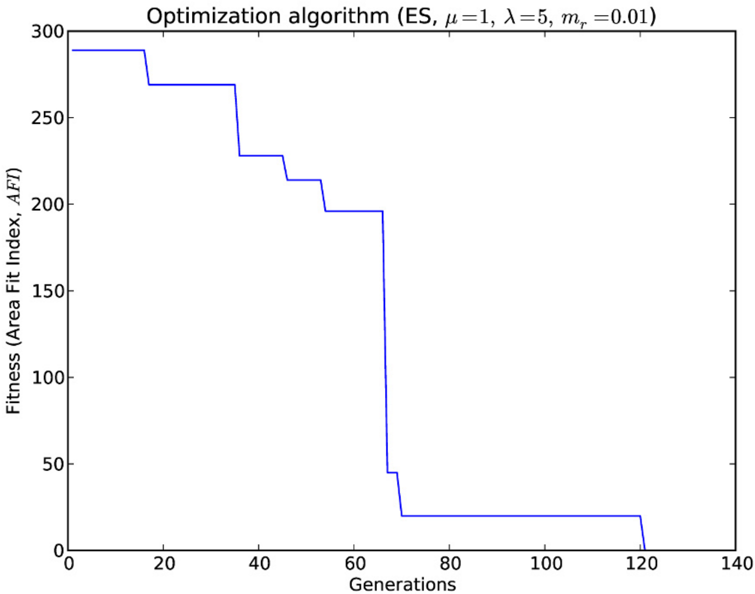

Figure 6.4: Result E-2. Convergence characteristics of the ES (2nd evolutionary cycle, 121 generations).
Source: Author's own.

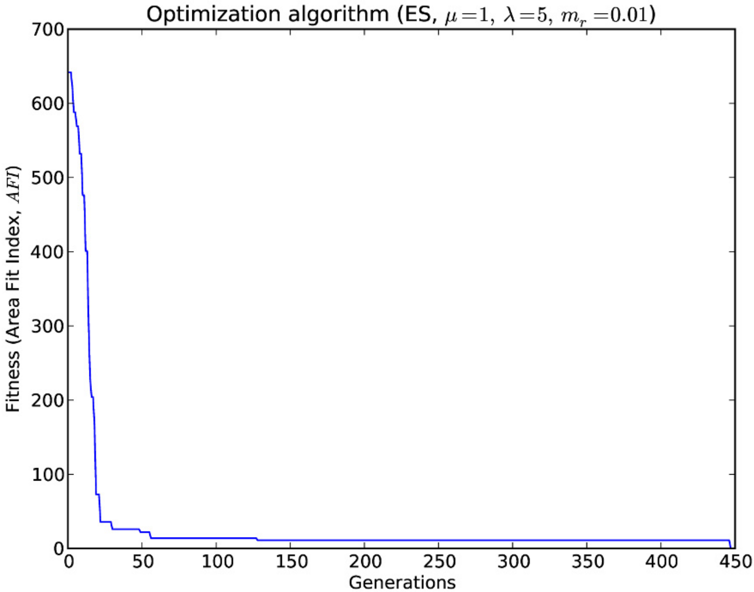

Figure 6.5: Result E-2. Convergence characteristics of the ES (3rd evolutionary cycle, 448 generations).
Source: Author's own.

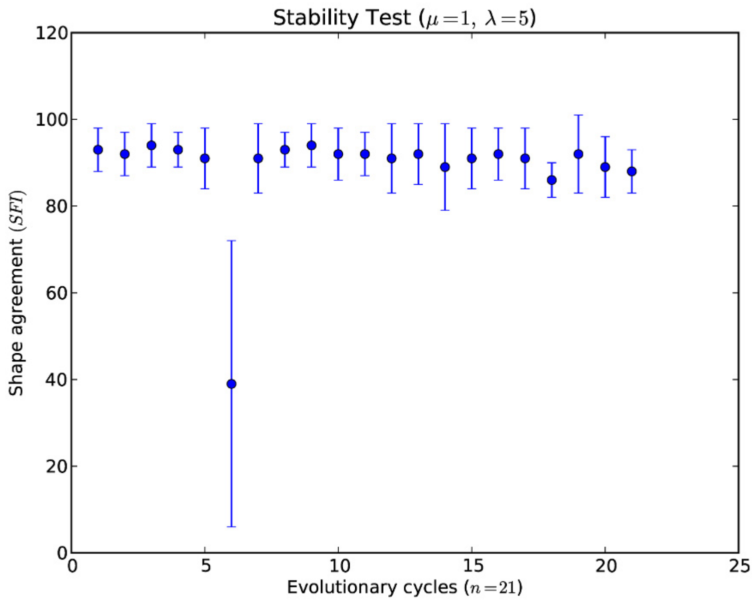

Figure 6.6: Result E-2. Stability of the $(\mu + \lambda)$-ES (maximum number of generations = 1,000).
Source: Author's own.

6.2.3 E-3. Computational Scalability of the Evolutionary Approach

Evolutionary approaches to numerical optimization are known to be computational expensive. For practical consideration, it may take a long time until the algorithm converges to the optimal solution. On the other hand, EA are, inherently, highly parallelizable. Therefore, the objective of the third experiment is to investigate the parallelization characteristics of the proposed approach in order to evaluate its scalability for practical applications.

Experimental Design

To test the computational scalability of the proposed evolutionary approach described in 4.3, experiments using a varying number of processing units, i.e., Central Processing Unit (CPU) cores, are conducted. Because of the stochastic, non-deterministic nature of evolutionary approaches, the number of generations is set to a fixed number (n = 10,000). For the same reason, the same input image as well as reference samples are used. The number of CPU cores used, is increased (doubled at each time) from 1 up to 8 cores. Measurements of the computation time are tenfold repeated in order to minimize random effects such as the computational load of the operation system. Figure 6.7 shows the experimental design.

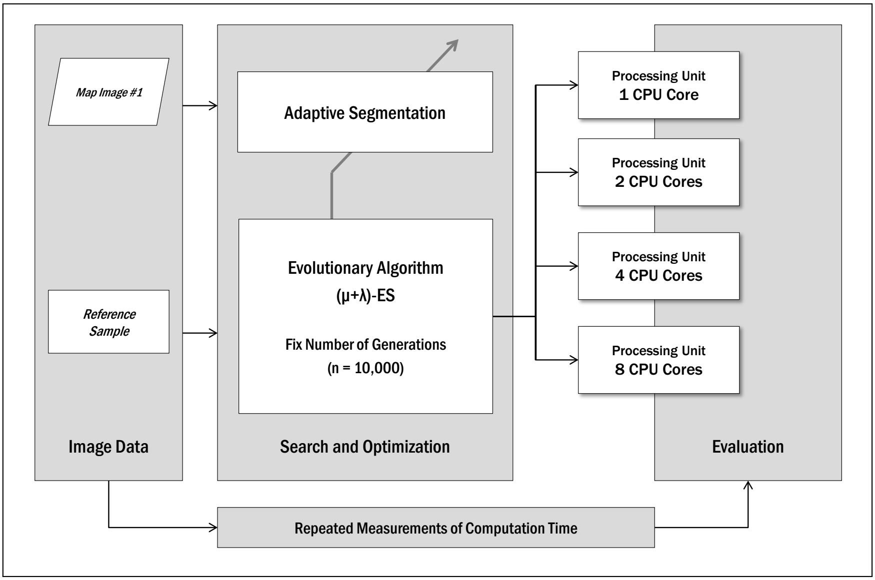

Figure 6.7: Experimental design E-3. Computational scalability of the evolutionary approach.
Source: Author's own.

To generalize the evidence to arbitrary computing environments, the computation time C_t is normalized to the number of CPU cores n, such that the *Normalized Computation Time* (NC_t) is given by:

$$NC_t = \frac{n \cdot C_{t_{(n)}}}{C_{t_{(1)}}}, \tag{6.4}$$

while the number of computed generations is fixed to 10,000 per core. That is, the NC_t of 1 CPU core is 1 and should ideally be also 1 for any number of cores, i.e., a perfect scaling.

Experimental Results

Figure 6.8 shows the result of the computational scalability test. It depicts that NC_t is greater than 1 but increases slowly, indicating both that the EA scales well and that there arises only relatively little computational parallelization overhead.

6.2.4 E-4. Adaptive Classification using the Neural Net Approach

The objective of the fourth experiment is to evaluate hypothesis six (H6) and to test the hybrid model- and data-driven approach suggested in section 4.4. The performance of an adapted classifier should be evaluated across the objects' scale space and across different test sites and layouts.

Experimental Design

Figure 6.9 shows the experimental setup for the evaluation of the classification approach. For the second part of the experiment, the classifier is adapted and applied to different test sites.

Experimental Results

The tables 6.2 and 6.3 give the recognition rates for different object sizes and test sites. In contrast to the recall rate, the precision rate gradually varies

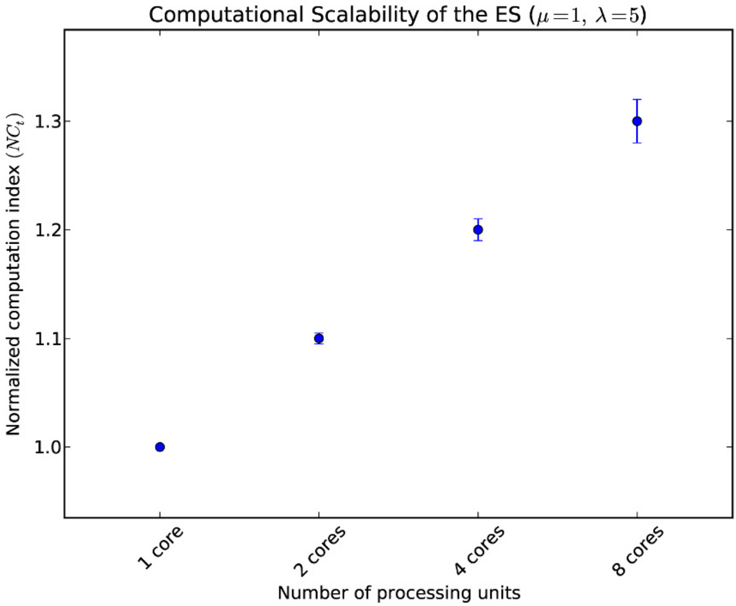

Figure 6.8: Result E-3. Computational scalability of the proposed evolutionary approach.
Source: Author's own.

across different object sizes. This is because the amount of areal objects differs across the classes and thus yields varying commission errors (false positives) within the respective size ranges.

The recognition rates for different test sites and layouts show only minor variations (cf. table 6.3), indicating the methodology capable for the adaption to various map layouts, which is crucial for the general spatial and temporal scalability.

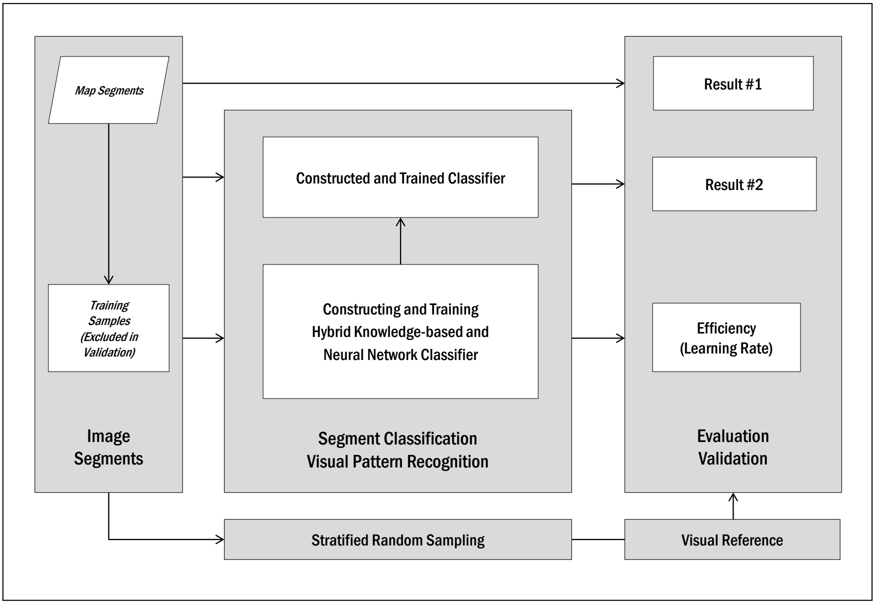

Figure 6.9: Experimental design E-4. Classification (object recognition) using the hybrid neural net approach.
Source: Author's own.

Table 6.2: Result E-4. Recognition rates across the objects' scale space (n = 4,452).
Source: Author's own, partially presented in Herold et al. (2012, p. 255).

Object size OS in sqm	Precision	Recall	F_1-measure
$50 < OS \leq 200$	0.8429	0.997	0.1783
$200 < OS \leq 300$	0.9667	0.997	0.1808
$300 < OS \leq 400$	0.9623	0.997	0.1807
$400 < OS \leq 500$	0.9905	0.997	0.1812
$500 < OS \leq 600$	0.9425	0.997	0.1803
$600 < OS \leq 700$	0.9741	0.997	0.1809
$700 < OS \leq 800$	0.9831	0.997	0.1810
$800 < OS \leq 900$	0.9902	0.997	0.1812
$900 < OS \leq 1{,}000$	0.9772	0.997	0.1809
$1{,}000 < OS \leq 10{,}000$	0.9859	0.997	0.1811

Table 6.3: Result E-4. Recognition rates across different test sites and layouts.
Source: Author's own.

Test site (ID)	Coverage (sqkm)	Objects	Precision	Recall	F_1-measure
1	100	19,543	0.987	0.999	0.993
2	48	11,539	0.939	0.994	0.966
3	80	17,011	0.943	0.995	0.969

6.3 Discussion

The discussion encompasses a concise summary of strengths and limitations of the methodology as well as some resulting potentials of its application.

6.3.1 Strengths

The major strength and advancement over other approaches to the retrieval of historical land use information is the adaptability to heterogeneous map sources, which are typically found in long-term retrospective LULCC studies (and are in the focus of this thesis research). The adaptability includes both the mid-level image segmentation as well as the high-level image analysis (visual pattern recognition, cf. the experiments E-2, E-3, and E-4). This is achieved by a non-linear optimization algorithm and a combined model- and data-driven recognition strategy. Hereby, the required problem knowledge and efforts to built a new or adapt an existing approach to a new map source can significantly be reduced. Furthermore, the methodology is readily and arbitrary extensible to other segmentation algorithms. In contrast to previous approaches, the resultant LULC information contains a class assignment probability, which allows non-Boolean change detection and thus reasoning under uncertainty.

Depending on the quality of the input data sources, the retrieved LULC information allows meso- and even microscale retrospective investigations on the land cover object level. Figure 6.10 shows a sample visualization of building-based, intra-urban change detection solely inferred from a multi-temporal series of topographic maps. However, this resolution can only be achieved using a relatively homogeneous map series. For older and more heterogeneous data sets, a field-based approach such as suggested in section 5.2.2 is more appropriate.

6.3.2 Limitations

Limitations of the methodology regard both the adaptive image analysis approach as well as the uncertainty modeling framework. Concerning the former aspect, the presented methodology is still focused primarily on the most prevalent visual variables as well as areal objects. There are still no

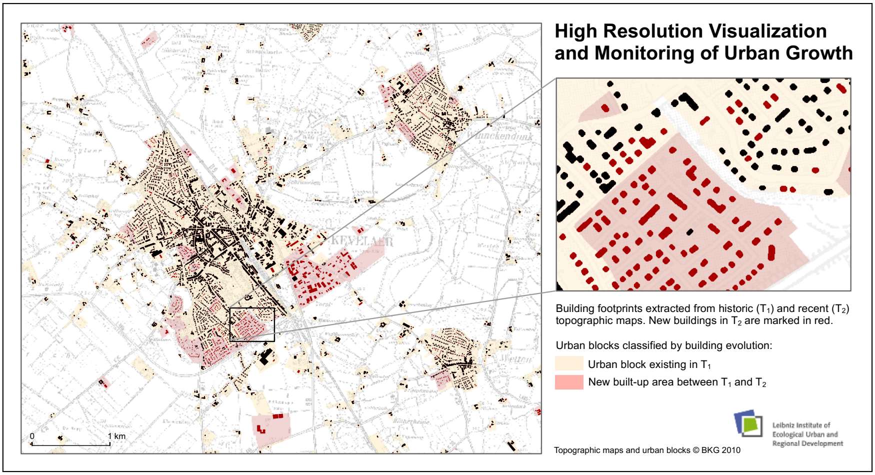

Figure 6.10: Long-term high-resolution monitoring of urban land use and land cover change.
Source: Herold et al. (2011, p. 4, updated).

complete structural recognition (cf. section 3.1.3) nor the recognition of linear objects such as street lines implemented yet. This has to be integrated to access all of the contained historical LULC information. In contrast to texture- and morphology-based segmentation, color-based segmentation is implemented separately, but can readily be integrated using the suggested evolutionary heuristic optimization approach. As discussed, the adaptability of the approach is certainly limited to the evaluated trigonometry-based maps of the past two centuries. Investigations of "pre-Anthropocene" LULC changes using earlier maps still require human intelligence and knowledge.

Concerning the latter, namely the uncertainty modeling framework for change detection, a major limitation poses the necessary simplification within the change analysis model (cf. section 5.1). As the field- as well as the object-based model are based on the most recent data set, morphological changes of entities over time are not traced.

A general limitation concerns the retrospective evaluation of the retrieved information. As there is no or only very little reference data (historical, geospatial, unbiased) available, the evaluation is limited to the abstracted graphical model of reality. The real word situation of some point in time may not be reconstructed by other sources and may thus not be used for evaluation. Hence, both the methodology and the retrieved historical LULC information are primarily suitable for exploratory research on long-term land use and land cover changes.

6.3.3 Applicability and Potentials

The experimental results and the discussion of strengths and limitations of the proposed approach indicate some potential fields of application, which have been theoretically addressed in section 2.4 and are illustrated in the following.

Figure 6.11 depicts the potentials of long-term observational data for artificially accelerated geospatial process visualizations. These visualizations may help to communicate and to raise awareness for – in terms of human perception – slowly and hence almost indiscernible proceeding processes such as land change.

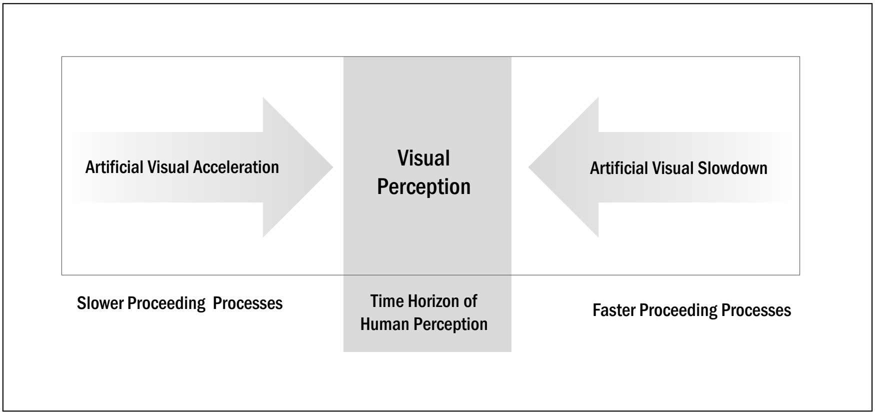

Figure 6.11: Artificial visual acceleration and slowdown of (geo-)processes in terms of the time horizon of human perception.
Source: Author's own.

Figure 6.12 shows the potential of “up-scaling” the retrieved geoinformation for the coupling with the Earth System Sciences and the typically lower resolution Earth System Models (ESM). This addresses the fourth objective of Land Change Science (cf. section 2.2.1). Figure 6.13 presents another field of application, namely knowledge discovery for a deeper process understanding. Long-term retrospective observations may support this data-driven science approach by providing a wider temporal scope for hypotheses generation, testing, and the investigation of driving forces.

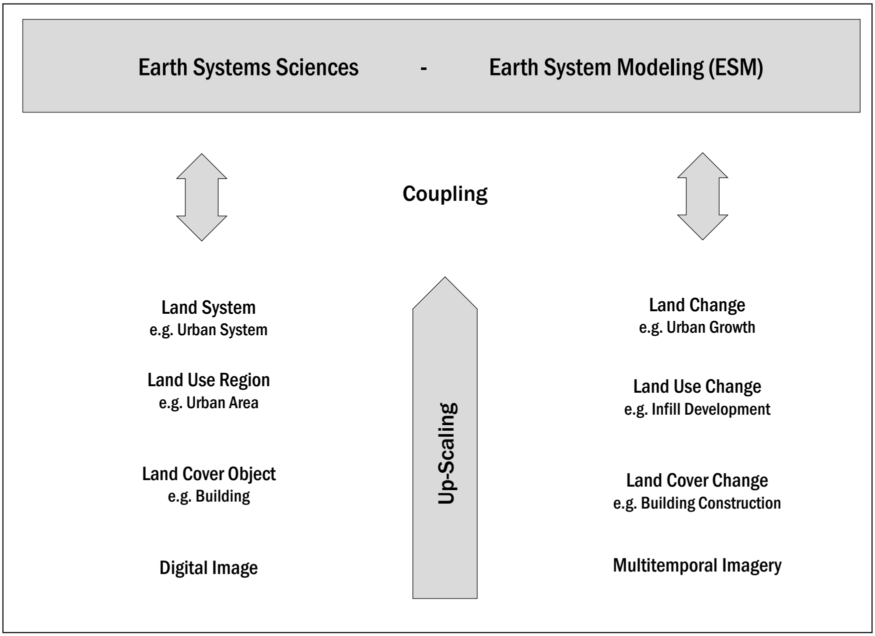

Figure 6.12: From image to land change and the coupling to Earth System Models. Source: Author’s own.

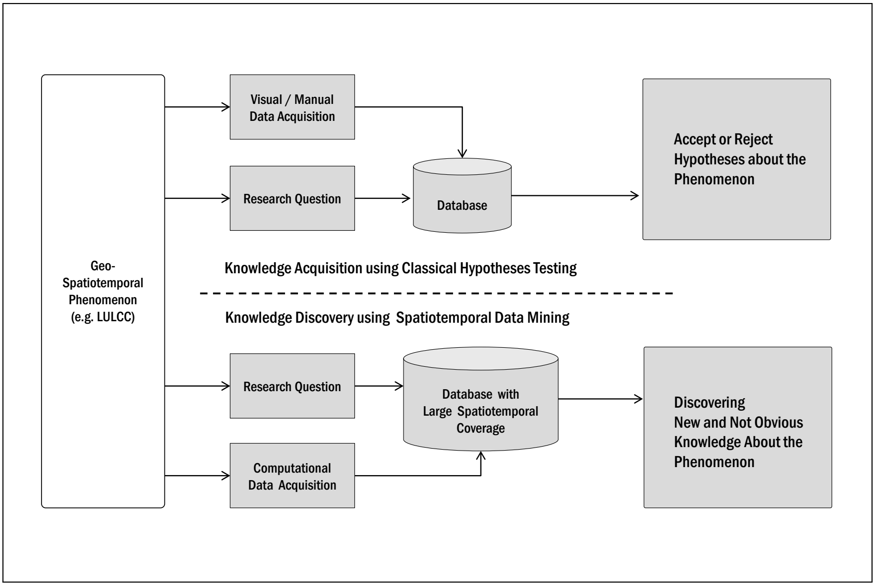

Figure 6.13: Potentials of computationally acquired geoinformation for Geographical Knowledge Discovery and Big Data Analytics.
Source: Author's own.

7 Conclusions and Future Research

The concluding chapter sums up the thesis work by revisiting the research questions, by evaluating the initially stated hypothesis and summarizing the major contributions of the work. In conclusion, research perspectives are given for the various aspects discussed in this work.

7.1 Revisiting the Research Questions and Hypotheses

RQ 1: *What potentials offer long-term retrospective and spatially explicit observational data for a better understanding and prediction of land use and land cover changes?*

The potentials can, according to the considerations elaborated in sections 2.2, 2.3, and 2.4, be summarized to the following answers. Long-term retrospective observations may:

1. *contribute to the objectives of Land Change Science (LCS), in particular the ones aiming to improve: first, the monitoring of land change patterns and dynamics; second, the understanding of these changes as a coupled human-environment system; third, the disentangling of the complex suite of biophysical and socioeconomic forces; and fourth, the spatially explicit land change modeling compatible with Earth System Models (cf. Rindfuss et al., 2004; Verburg et al., 2004; Turner et al., 2007).*
2. *support the retrospective monitoring and change detection using spatial metrics. That is, spatially explicit indicators such as suggested in McGarigal & Marks (1994) or Jaeger et al. (2010), for example, may be applied to quantitatively track changes over long periods of time (e.g., pre-industrial landscapes, cf. Antrop, 2005).*
3. *support the long-term calibration and validation of spatially explicit numerical land change models such as cellular automata (CA) and agent-based models (ABM/MAS). This may improve both the understanding of proximate and underlying causes of change (cf. Lambin et al., 2003, pp. 216-217) as*

H. Herold, *Geoinformation from the Past*,
https://doi.org/10.1007/978-3-658-20570-6_7

well as the prediction of uncertainties in simulations of future developments (cf. Goldstein et al., 2004, and section 2.3.2). Although spatial modeling has experienced a revival since the "Requiem for Large-Scale Models" announced by Lee (1973), there are still challenges in both validation (as a neglected aspect, cf. Wu, 2002) and process understanding: "Despite a century of effort, our understanding of how cities evolve is still woefully inadequate." (Batty, 2008, p. 769). However, the latter may follow rather simple laws of physics (e.g., cf. Bettencourt et al., 2007; Bettencourt, 2013).

4. *support the implementation of spatially explicit management tools such as regional information and monitoring systems as well as spatial planning/decision support systems (SPSS/SDSS). These systems may assist planners and decision-makers with the ex-post evaluation of spatial planning paradigms (also during "pre-planning" times), the development of sustainable land management strategies (e.g., Siedentop, 2006; Bock et al., 2011), and the analysis of the resilience of cities and ecosystems against perturbations (e.g., Müller, 2011).*

5. *support the visualization and communication of long-term LULCC process by means of web-based visualization systems (e.g., Meinel & Neumann, 2003), 3D Virtual Reality (VR) models (e.g., Walz, 2008), or Historical GIS (HGIS, e.g., Bretagnolle et al., 2000; Knowles, 2013).*

6. *support spatiotemporal data mining and geographical knowledge discovery by providing a wider temporal scope for hypotheses generation and the investigation of driving forces (e.g., Miller & Han, 2001; Behnisch, 2007; Mennis & Guo, 2009).*

Evaluating H1: The initially stated hypothesis can be largely confirmed. As it has been elaborated in section 1.1 and 2.2, spatiotemporal observational data at appropriate spatial and temporal scales and scopes are fundamental to environmental monitoring and modeling. Anthropogenic impacts such as the human-induced components of land and climate change are – in terms of human perception – gradually proceeding long-term processes.

Analogously to climatology (ice cores), biology (fossil record), or geology (lithostratigraphy), direct short-term observations have to be extended by (indirect) measurements of the past. As it has been outlined in section 2.3.2, long-term retrospective information is of particular value for the calibration and validation of spatial models. Additionally, it has been shown that these observational data have also great value for perceiving and communicating the gradually proceeding phenomenon of land change. Thus, the first hypothesis can be reformulated to the following thesis: Long-term and spatially explicit monitoring is essential to perceive, quantify, communicate, model, forecast, and eventually understand complex and gradually proceeding geospatial processes such as the land use and land cover change.

RQ 2: *What data sources enable long-term retrospective land change monitoring and what challenges and approaches exist to access the geoinformation contained in these sources?*

Regarding the **data sources** for a long-term retrospective monitoring, the following answers– according to the research elaborated in sections 2.1.1 to 2.1.3, and 3.4 – are given:

1. *The primary and most efficient source for recent and retrospective land change monitoring is remote sensing. In particular, spaceborne remote sensing imagery from civilian and formerly military platforms provide a high spatial temporal coverage. Airborne imagery may regionally provide a valuable data source prior to the space era. However, either way the availability of this data source is limited to the 20th century.*
2. *Another important source are thematic land use and land cover maps. These digital maps explicitly describe the LULC at a defined cartographic scale. That is, the information has not to be extracted but is ready-to-use for computational analysis. A further advantage over remote sensing data, which basically detects the land cover as the biophysical manifestations, the land use is derived by in situ measurements and socio-economic statistics; a process termed as "socializing the pixel" (Geoghegan et al., 1998, pp. 51-52). Existing data sets are temporally limited to some decades before present (cf. section 2.1.2). However, there exist some long-term approaches to reconstruct historical information on certain land use classes such as for the past 12,000 years (Holocene, cf. Klein Goldewijk et al., 2010, 2011) or the past 6,000 years (Mid to Late Holocene, Olofsson & Hickler, 2007). These long-term retrospective land use maps are typically of low resolution (0.5 degrees) and are based on assumptions of the historical population and land use of Homo sapiens.*
3. *A third important source – and for studies covering the Anthropocene a conditio sine qua non – are cartographic records such as historical cadastral and, in particular, topographic map series. For centuries, cartographic documents have been unique and efficient "storages devices" (Roberts, 1962, p. 12) for geospatial information. While the evidence of earliest cartography*

reaches back more than 4,000 years to the prehistoric and historical civilizations of the Near and Middle East, the Anthropocene is largely covered by trigonometry-based maps. The era of trigonometric land surveys started in 1744 in France with Cassini de Thury's new projection and surveying (Carte géométrique de la France). Numerous land surveys followed all across Europe such as the Austro-Hungarian surveys (e.g., Josephine military survey, 1763-1787), the Ordnance (1791-1850), the Saxonian (1780-1806), the Prussian (1830-1865), and the Gaussian survey (1821-1825); later also in the spheres of the colonial powers.

Referring to the **challenges** historical data sources pose for the computational acquisition of the contained geoinformation, the following answers are given (cf. sections 3.3, 3.4, and 4.1):

1. *Cartographic representations are designed for the interpretation by human beings. Thus, the density, variation, and complexity of the contained information is remarkably high. Additional graphical deviations and artefacts caused by the production and transformation process pose no issue to the extraordinary recognition capabilities of the human visual system (HSV) but to any computational approach.*
2. *There is a degraded and reduced graphical quality due to the document age, the material aging, or/and the digitization process (i.e., scanning or photographing considering the Nyquist-Shannon sampling theorem).*
3. *There exists an enormous diversity in the representations of geographical entities over time and space, caused and driven by technological, historical, and cultural differences, changes and advancements.*
4. *The varying representational scales of contemporary (e.g., remote sensing) and historical data sources require a multi-scale concept for spatiotemporal data conflation.*
5. *Neither the information contained in the historical documents nor the historical real world situation, which is abstractly represented in the data source, can be retrieved perfectly. Thus, uncertainty has to be perceived as an inevitable and inherent property of the retrieved historical land use information and, therefore, has to be adequately modeled for retrospective land change analyses.*

Regarding **existing approaches** the following answers are given (cf. sections 3.3.1 to 3.4):

1. *There exists a multitude of approaches to the automated extraction and vectorization of specific geographical features, symbols, and toponyms from various map types.*
2. *Although the capabilities of human interpreters are not – and typically not even nearly – achieved, some algorithms, which are specifically adapted to a certain map type or geographical entity, yield sufficient recognition rates for operational use.*
3. *Only few approaches aim to the analysis of different types or multitemporal versions of maps. Thus, the challenge of the varying graphical representations over space and time has been rarely addressed yet.*
4. *The adaption to varying representations of geographical entities is typically laborious and requires a great deal of problem knowledge in most approaches.*
5. *So far, only a few approaches are explicitly developed for historical maps and thus address the problem of degraded quality of the cartographic representation.*
6. *Only very few studies (e.g., Bolstad et al., 1990; Leyk et al., 2005) address the uncertainty in both the retrieved information and the retrospective change analysis.*

Evaluating H2, H3, H4: The second research question implied three hypotheses to be investigated in this work. The first hypothesis referred to the combination of archival remote sensing imagery and trigonometry-based geotopographic maps to document the land change during the past 200 years. This could be confirmed, however, the period can be extended by 50 years. As it can be concluded from section 2.1, geotopographic maps are the major – and to a large extend even the only – sources of LULC information since the proposed onset of the Anthropocene. Thus, the second hypothesis can be reformulated to the thesis: By preserving spatial landscape and settlement patterns at discrete points in time, archival data sources such as remote sensing imagery and geotopographic maps, in particular, give evidence of the land change during the past 250 years, proposed as the onset of the Anthropocene.

Considering the vast amount and diversity of approaches to cartographic image analysis reviewed in sections 3.3, the third hypothesis referring to the color-, texture-, and morphology-based segmentation and pattern recognition methods can be confirmed. As the reduction of visual interpretation efforts mainly supports research aiming to the understanding of land change, the third hypothesis can be reformulated to the thesis: Methods of image analysis such as image segmentation and visual pattern recognition are suitable to acquire spatially explicit information from these historical map sources. Reducing the efforts of visual interpretation may increase the spatiotemporal scope and resolution of the land use component in long-term studies and Earth system modeling.

The forth hypothesis referred to challenges that the utilization and processing of map sources pose for long-term retrospective land change detection. Considering the research outlined in section 2.1 and chapter 3, the hypothesis is strongly supported. Moreover, both challenges have to be treated with the same priority and have always to be jointly considered. The fourth hypothesis can hence be reformulated to the thesis: There are two fundamental challenges adherent to retrospective information acquisition and long-term change detection: first, the spatiotemporal heterogeneity of geographical entity representations, and second, the uncertainty inherent to both the data source itself and its non-intended computational processing and utilization for land change detection. Both challenges have not yet been adequately addressed in literature and existing approaches.

RQ 3: *How can the historical geoinformation be retrieved considering the spatiotemporal heterogeneous representation of geographical entities caused by the long-term coverage?*

Based on the findings of the sections 4.1 to 4.4 and 6.2 the following answers are given:

1. *Considering both the abstracted representation as well as the fact that a user or the map key could readily provide a minimal set of entity reference samples, image segmentation can be mathematically conceptualized as an optimization problem.*
2. *Metaheuristics such as Evolutionary Algorithms (EA) can be used for optimization.*
3. *Despite their computational and stochastic characteristics, the tested ES proofed suitable for practical application to image segmentation optimization.*
4. *For preserving adaptability in higher-level image analysis, a hybrid model- and data-driven strategy has been shown suitable.*

Evaluating H5 and H6: While H5 is fully supported by the experiments the sixth hypothesis has to be reformulated in such a way that the combination of both strategies indicates to be the best approach. The fifth and sixth hypotheses can hence be combined to the thesis: Metaheuristics such as Evolutionary Algorithms (EA) can be used to cope with the spatiotemporal heterogeneity, considering image segmentation and its parameterization a global, non-linear optimization problem. For preserving adaptability in higher-level image analysis, a hybrid model- and data-driven strategy, combining a knowledge-based with an inductive Artificial Neural Net (ANN) classifier, is suggested.

RQ 4: *How can the uncertainty inherent to the data source itself as well as the information acquisition and change detection process be modeled to build time series?*

Based on the research and findings of the sections 5.1 to 5.4 the following answers are given:

1. *Uncertainty has to be perceived as an inevitable and inherent property of the retrieved historical land use information comprising a aleatory and epistemic dimension.*
2. *There are three sources of uncertainty, namely, the production-oriented, the transformation-oriented, and the application-oriented uncertainty, which ought to be modeled separately.*
3. *There are spatial, thematic and temporal uncertainties, which can be modeled using a probabilistic field- or object-based approach.*

Evaluating H7: Besides the addressed positional (spatial) uncertainty there are thematic and temporal uncertainties, which may be equally important. Thus, the seventh hypotheses can be reformulated to the thesis: To model the spatial, thematic, and temporal uncertainties for change detection, a probabilistic field- and object-based approach is suggested. For equi-temporal reasoning from various uncertain sources, the potentials of Dempster-Shafer Theory of Evidence (DST) are to be further explored.

RQ 5: *What potentials indicates the evaluation of the proposed methodology and what perspectives for further research can hence be identified?*

Based on the research and findings of the sections 6.2 and 6.3 the following answers are given:

1. *The experimental evaluation using real world data indicates the suitability of the methodical concept in support of an Anthropocene land change monitoring.*
2. *The potentials correspond to the general potentials of long-term retrospective information given to answer the first question (see p. 135), such as high-resolution visualizations, spatiotemporal monitoring and modeling as well as hypotheses generation.*

There was no research hypothesis formulated for this exploratory question. The last aspect of the research question regarding the future research needs will be answered in section 7.3 at the end of this chapter.

7.2 Scientific Contributions

Concluding from both the answers given to the research questions and the evaluation of the initially stated hypotheses, the contributions of the thesis can be distilled to:

- an in-depth investigation of potentials of long-term and spatially explicit observational data for land use and land cover change research,
- a synoptical analysis of the major data sources for retrospective land change research, covering a period from *"pre-Anthropocene"* times to the recent age of remote sensing,
- a comprehensive survey of the state-of-the-art in the computational map interpretation for the acquisition of geoinformation form both a methodical and an application-oriented perspective,
- a methodical approach to adaptive image analysis to address the spatiotemporal heterogeneity of entity representations in historical data sources,
- a conceptual framework for modeling the spatial, thematic, and temporal uncertainties inherent to the retrieved information caused by the long-term coverage, and
- finally, a critical review and experimental evaluation of the proposed methodology identifying strengths and limitations in order to derive further research needs.

In the following section research needs are identified and some final conclusions are drawn.

7.3 Future Research Perspectives

Future research should clearly focus on both the further development of the proposed approach as well as, more generally, the potentials of its application. Concerning the former, the approach to information acquisition could be improved and extended in many ways. As stated earlier in section 7.1, this approach as well as other proposed approaches to map image analysis are still far behind the capabilities of the human visual system. Thus, despite the adaptability the application is certainly restricted to the mentioned trigonometry-based maps of the past two centuries. Investigations of “pre-Anthropocene” landscape changes using earlier maps such as conducted in Csaplovics (2005) are bound to a human interpreter, i.e., human intelligence and knowledge. However, these early maps could be used as supplementary information, as suggested by Haase et al. (2007, p. 250), for instance.

Methodically there is a wide range of extensions conceivable, for example, the test of other metaheuristic optimization algorithms (although limited by the “no free lunch theorems”, cf. Wolpert & Macready, 1997), the utilization of a more complex fitness function, the optimizing of the feature learning, the investigation of the spatial scalability (cf. Schinke et al., 2013), or the test of unsupervised classification strategies such as self-organizing maps (SOM, cf. Kohonen & Somervuo, 1998; Walter, 2011). Last not least, the methodology could be extended to further geographical and map features such as compound and linear objects (e.g., cf. Gamba & Mecocci, 1999; Muhs et al., 2013). This extension could also improve the georeferencing and change detection capabilities through reducing map distortion effects between different points in time using automatically derived ground control points.

To further evaluate the spatial scalability, the approach is to be implemented in the existing SEMENTA®- CHANGE workflow (Meinel et al., 2009; Herold et al., 2010) in order to allow operational use for large area coverage. Concerning the further development of the uncertainty modeling framework, methods of multicriteria decision analysis (Malczewski, 2006) or Markov Random Fields, for instance, could be evaluated for the multi-temporal change analysis. For equi-temporal reasoning from various uncertain sources, the potentials of Dempster-Shafer Theory of Evidence should to be further explored.

Besides the above mentioned methodical advancements, one of the most important future research needs is the investigation of the potentials of retrieved historical information. This includes – but is not limited to – methods of Geovisualization, Visual Analytics (VA), Exploratory Data Analysis (EDA), Geospatial Data Mining and Geographic Knowledge Discovery (GKD, cf. Miller & Han, 2001; Mennis & Guo, 2009). Practical applications of the retrieved information may include the indicator-based retrospective monitoring in a web-enabled system (e.g., Meinel, 2010), the further semantic enrichment of the retrieved information (e.g., Walter, 2011; Hecht, 2014), to test spatial model calibration and validation (e.g., Thinh & Vogel, 2006; Stanilov & Batty, 2011), the comparison with historical land use databases (e.g., Hurtt et al., 2006; Klein Goldewijk et al., 2011), the georeferencing (allocation) and disaggregation of historical census data, or the inference of historical statistical data, for example through the "historization" of contemporary geospatial databases.

In conclusion, the quantitative description may represent an essential, but certainly only an initial step towards process understanding, prediction, and management. The computational access to geoinformation of former times since the onset of the *Anthropocene* and the associated spatiotemporal analysis and visualization capabilities may indisputably help to raise awareness for – in terms of human perception – slowly and hence almost indiscernible proceeding change processes. Research towards the understanding of the underlying drivers and process dynamics has to be based on a synthesis of physical, formal, engineering, social and life sciences forming an interdisciplinary body of knowledge.

However, in the midst of the ubiquity and exponential growth of knowledge in the alleged information age, the more fundamental question remains: does an ever deeper understanding of the Earth's system dynamics also induce wiser human and societal decision making, imperative to cope with mankind's facing global challenges? The future will prove.

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