Stakeholder perceptions of digitalisation and automation in geospatial planning and data production workflows

Christian Koski

Aalto University

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Christian Koski

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ABSTRACT

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The successful adoption of information systems depends on stakeholders' perceptions of their usefulness, reliability, and understandability. These perceptions are particularly important when technologies are introduced to workflows that transition from manual or analogue methods to digital or automated systems. The research presented in this thesis examined stakeholders' perceptions of two emerging geospatial technologies operating in different contexts: 1) collaborative geographic information systems (CGIS) used in maritime spatial planning (MSP) workshops, and 2) artificial intelligence (AI) used in the production of data for topographic databases (TDBs).

The research examined system characteristics that influence MSP stakeholders' perceptions of the utility, ease of use, and understandability of CGIS in MSP workshops and Finnish TDB users' perceptions of trust, risks, transparency, and understandability of AI used in geospatial data production. Furthermore, the research identified challenges and limitations that may hinder successful adoption of the two technologies in the given context. The research used mixed methods, including prototype implementation, workshop observations, questionnaires, and analysis of AI-generated spatial outputs. In three of the four studies, research data were collected from real-world MSP stakeholders or TDB users. Understanding stakeholder perceptions is crucial for designing geospatial technologies that are both technically effective and socially acceptable.

The results show that CGIS tools that support exploration, visual analysis, and creation of geospatial data are perceived as useful for various tasks in collaborative MSP settings. They also suggest that automated spatial analysis adds complexity and introduces issues with comprehension and ease of use. The integration of spatial analysis tools into CGIS can mitigate some challenges with using spatial analysis tools in collaborative settings by increasing methodological flexibility and offering additional support tools. Commonly reported machine learning metrics do not adequately explain spatial data quality metrics, which challenges the interpretation of data quality in AI-based TDB data production. Stakeholders generally perceive AI-based automation as trustworthy in producing high-quality data for TDBs if validating outcomes is done manually. However, stakeholders have many concerns about the security, privacy, and potential misuse of AI models. The results further indicate that a lack of transparency and comprehension can be barriers to the acceptance of systems in geospatial data production workflows.

Overall, the findings in this thesis highlight the key factors shaping stakeholders' trust, perceived utility, and acceptance of CGIS and AI technologies that are used in the digitalisation and automation of geospatial workflows. The research also identifies challenges that can be barriers to the technologies' adoption. The thesis contributes new knowledge by addressing a gap in research on the adoption of geospatial technologies, particularly regarding stakeholder perceptions of CGIS and AI-based geospatial data production.

Aalto-universitetet

SAMMANDRAG

Författare Christian Koski

Namnet på doktorsavhandlingen Intressenters uppfattningar om digitalisering och automatisering i geospatiala planering och dataproduktionsarbetsflöden

Artikelavhandling

Samarbetspartner – Geodatacentralen FGI vid Lantmäteriverket

Sidantal 69

Nyckelord samverkande geografiska informationssystem, artificiell intelligens, havsplanering

Ett framgångsrikt införande av informationssystem beror på intressenters uppfattningar om systemens användbarhet, tillförlitlighet och begriplighet. Dessa uppfattningar är särskilt viktiga när teknologier introduceras i arbetsflöden som övergår från manuella eller analoga processer till digitala eller automatiserade. Forskningen som presenteras i denna avhandling undersöker intressenters uppfattningar om två framväxande geospatiala teknologier som verkar i olika sammanhang: 1) samverkande geografiska informationssystem (Collaborative Geographic Information Systems, CGIS) som används i havsplanerings workshops och 2) artificiell intelligens (AI) som används i automatisering av produktionen av geodata för topografiska databaser.

Forskningen studerade systemegenskaper som påverkar intressenters uppfattningar om nyttan, användarvänligheten, och begripligheten av CGIS i workshops för havsplanering och finländska topografiska databasanvändares uppfattningar om förtroende, risker, transparens, och begriplighet av AI som används i dataproduktionen för topografiska databaser. Den identifierade även utmaningar och begränsningar som kunde hindra framgångsrikt införande av de två teknologier i dessa geospatiala arbetsflöden. I undersökningen tillämpades blandade metoder, inklusive prototypimplementering, observationer av arbetsmöten, enkäter och analys av utdata som genererats av AI. Forskningsdata samlades i två av delstudierna in från intressenter inom havsplanering och i en delstudie från användare av topografiska databaser. Att förstå intressentuppfattningar är avgörande för utformningen av geospatiala tekniska lösningar som är både tekniskt effektiva och socialt accepterade.

Resultaten visar att verktyg i CGIS som stödjer utforskning, visuell analys och skapandet av geodata uppfattas som användbara för olika uppgifter i samarbetsbaserade sammanhang för havsplanering. De indikerar också att automatiserad analys tillför komplexitet och medför utmaningar gällande begriplighet och användarvänlighet. Integrering av spatiala analysverktyg i CGIS kan mildra vissa utmaningar i användningen av rumsliga analysverktyg i samarbetsmiljöer genom att öka den metodologiska flexibiliteten och erbjuda kompletterande stödverktyg. Vanligt förekommande maskininlärningsmetrik förklarar i begränsad utsträckning kvalitet av geodata, vilket försvårar tolkningen av datakvaliteten på utdata från AI-baserade modeller inom produktion av topografiska databaser. Generellt uppfattar intressenter AI-baserad automatisering som tillförlitlig för produktion av högkvalitativa data för topografiska databaser, förutsatt att granskning och validering av resultaten görs manuellt. Samtidigt uttrycker intressenter flera orosmoment relaterade till säkerhet, integritet och potentiellt missbruk av AI-modeller. Resultaten indikerar dessutom att bristande transparens eller förståelse är centrala faktorer som kan hindra ett framgångsrikt införande av systemen i arbetsflödena.

Sammanfattningsvis lyfter resultaten i denna avhandling fram centrala faktorer som formar intressenters förtroende, upplevda nytta och acceptans av CGIS och AI-teknologier som används vid digitalisering och automatisering av arbetsflöden med geodata. Forskningen identifierar också utmaningar som kan utgöra hinder för införande av systemen. Avhandlingen bidrar med ny kunskap inom dessa områden och fyller en kunskapslucka i den befintliga forskningen om införande av teknik, särskilt när det gäller intressenters uppfattningar om CGIS och AI-baserad automatisering av geodataproduktion.

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Christian Koski

Table of contents

List of publications

This thesis consists of an overview and of the following four publications which are referred to in the text by their Roman numerals.

I Koski, C., Rönneberg, M., Kettunen, P., Eliasen, S., Hansen, H. S., & Oksanen, J. (2021). Utility of collaborative GIS for maritime spatial planning: Design and evaluation of Baltic Explorer. Transactions in GIS, 25(3), 1347-1365. DOI: 10.1111/tgis.12732

II Koski, C., Rönneberg, M., Kettunen, P., Armoškaitė, A., Strake, S., & Oksanen, J. (2021). User experiences of using a spatial analysis tool in collaborative GIS for maritime spatial planning. Transactions in GIS, 25(4), 1809-1824. DOI: 10.1111/tgis.12827

III Koski, C., Kettunen, P., Poutanen, J., Zhu, L., & Oksanen, J. (2023). Mapping small watercourses from DEMs with deep learning—exploring the causes of false predictions. Remote Sensing, 15(11), 2776. DOI: 10.3390/rs15112776

IV Koski, C., Kettunen, P., Tenkanen, H., & Oksanen, J., "Trust in artificial intelligence to extract geospatial features for topographic databases", 35 pages, in press (August 2026), International Journal of Geographical Information Science. DOI: 10.1080/13658816.2026.2716279

Authors´ Contribution

I: **Utility of collaborative GIS for maritime spatial planning: Design and evaluation of Baltic Explorer**
Conceptualisation, C.K., M.R., P.K., H.S.H. and J.O.; methodology, C.K, M.R, P.K. and J.O.; software, C.K. and M.R.; validation, C.K., M.R. and P.K.; formal analysis, C.K.; investigation: literature review, C.K., questionnaires, C.K., M.R., P.K., S.E. and J.O., Umeå workshop, M.R., P.K. and S.E., controlled environment test C.K. and M.R.; resources, S.E., H.S.H. and J.O.; data curation, C.K., M.R. and P.K.; writing—original draft preparation, C.K.; writing—review and editing, M.R., P.K., S.E., H.S.H. and J.O.; visualisation, C.K., M.R. and P.K.; supervision, P.K., and J.O.; project administration, P.K., H.S.H. and J.O.; funding acquisition, H.S.H. and J.O.

II: **User experiences of using a spatial analysis tool in collaborative GIS for maritime spatial planning**
Conceptualisation, C.K., M.R., P.K., A.A., S.S. and J.O.; methodology, C.K, M.R, P.K., A.A., S.S. and J.O.; software, C.K. and M.R.; validation, C.K., M.R. and P.K.; formal analysis, C.K.; investigation, C.K., M.R., P.K., A.A. and S.S.; resources, S.S. and J.O.; data curation, C.K., M.R., A.A., S.S. and P.K.; writing—original draft preparation, C.K.; writing—review and editing, M.R., P.K., A.A., S.S. and J.O.; visualisation, C.K., M.R. and P.K.; supervision, P.K., and J.O.; project administration, P.K., S.S. and J.O.; funding acquisition, S.S. and J.O.

III: **Mapping small watercourses from DEMs with deep learning—exploring the causes of false predictions**
Conceptualisation, C.K., P.K., L.Z. and J.O.; methodology, C.K, P.K, L.Z. and J.O.; software, C.K.; validation, C.K., P.K. and J.O.; formal analysis, C.K.; investigation, C.K. and P.K.; resources, P.K., L.Z. and J.O.; data curation, C.K. and J.P.; writing—original draft preparation, C.K. and J.P.; writing—review and editing, P.K., J.P., L.Z. and J.O.; visualisation, C.K. and J.P.; supervision, P.K., L.Z. and J.O.; project administration, L.Z. and P.K.; funding acquisition, P.K., L.Z. and J.O.

IV: **Trust in artificial intelligence to extract geospatial features for topographic databases**

Conceptualisation, C.K., P.K., H.T. and J.O.; methodology, C.K, P.K, H.T. and J.O.; validation, C.K., P.K., H.T. and J.O.; formal analysis, C.K. and P.K.; investigation, C.K. and P.K.; resources, P.K., H.T. and J.O.; data curation, C.K.; writing—original draft preparation, C.K.; writing—review and editing, P.K., H.T. and J.O.; visualisation, C.K.; supervision, P.K., H.T. and J.O.; project administration, P.K. and J.O.; funding acquisition, C.K., P.K., H.T. and J.O.

List of Abbreviations

AI	artificial intelligence
CGIS	collaborative geographic information system
CNN	convolutional neural network
DEM	digital elevation model
DL	deep learning
GIS	geographic information system
IT	information technology
MSP	maritime spatial planning
NMA	national mapping agency
OGC	Open Geospatial Consortium
SDSS	spatial decision support system
SMCA	spatial multi-criteria analysis
TAM	Technology Acceptance Model
TDB	topographic database
UTAUT	Unified Theory of Acceptance and Use of Technology
WMS	OGC's Web Map Service
WMTS	OGC's Web Map Tile Service

1 Introduction

Various global trends, including increased competition for maritime space and the growing complexity of environmental monitoring, are driving the demand for innovative approaches to geospatial data use and production. Maritime spatial planning (MSP) and the production of data for topographic databases (TDBs) are two areas where the digitalisation and automation of workflows could have a significant positive impact.

MSP has emerged as a key method for managing marine resources effectively, aiming to promote sustainable growth and reduce conflicts among maritime activities. The participatory, cross-border, and multidisciplinary nature of MSP requires collaboration between stakeholders (Kull et al., 2021; Zaucha, 2014). Participatory sessions in MSP have often relied on analogue paper maps. However, the need for the effective use of digital geospatial data in these sessions has created a demand for innovative applications that can facilitate data-driven discussions among stakeholder groups with diverse interests and backgrounds (Pınarbaşı et al., 2017). Traditional geographic information systems (GIS) and spatial decision support systems (SDSS) are established in planning and decision-making practices but can be too complex for novice users, inflexible, and often lack collaborative features (MacEachren, 2000; Merrifield et al., 2013; Ramsey, 2009). Collaborative geographic information systems (CGIS) aim to address these limitations by providing tools for effective geospatial data management in group settings (Armstrong, 1994; Balram & Dragicevic, 2006). CGIS could therefore potentially offer the interactivity and efficiency required for collaborative geospatial data management in MSP, beyond what can typically be achieved with paper maps.

These developments in MSP reflect a broader shift towards the digitalisation and automation of geospatial workflows, driven by increasing demands for more efficient use of geospatial data. Beyond participatory planning, new use cases for TDB data are driving the need for more efficient geospatial data production methods. For decades, TDB data have been manually digitised from remote sensing images, as few automated solutions have been able to support such work (Usery et al., 2018). However, the rapid advancement of artificial intelligence (AI), particularly deep learning (DL), coupled with the increased accuracy of remote sensing data, has attracted the interest of national mapping agencies (NMAs) in applying DL to TDB production workflows (Murray et al., 2020; Usery et al., 2022;

Zhu et al., 2024). In particular, convolutional neural networks (CNNs) have demonstrated high accuracy in segmenting geospatial features (Hoeser et al., 2020; Hoeser & Kuenzer, 2020; Mai et al., 2025), including small watercourses such as ditches and streams (Busarello et al., 2025; Lidberg et al., 2023; Stanislawski et al., 2021; Xu et al., 2021).

Across both participatory planning and automated geospatial data production workflows, the successful adoption of new systems depends not only on their technical performance and robustness but also on stakeholder perceptions. Stakeholders' perceptions of system properties, such as perceived usefulness and ease of use, as well as their trust in systems, are key factors affecting acceptance of various information technology (IT) systems (Choung et al., 2023; Davis, 1989; Rane et al., 2024; Venkatesh et al., 2003). There is a substantial knowledge gap regarding stakeholder perceptions of CGIS in participatory decision-making contexts and of AI-based workflows in geospatial data production. The use of GIS in MSP workshops differs from conventional GIS applications because there are multiple users working together on the same task, at the same time, and in the same location. Tasks may not be pre-defined, many participants have limited experience working with GIS, and there is limited time for both collaboration and preparation. Previous studies have identified mainly high-level requirements for tools used in MSP, such as being multi-functional, free to use, financially and technically stable, and providing communication and participation support (see Pınarbaşı et al., 2017). There is limited knowledge of which specific CGIS functionalities and features support collaborative geospatial data-driven planning in MSP workshops. Similarly, although trust in AI has been studied in a range of application domains, studies addressing data users' trust and perceptions of AI-based geospatial data production workflows remain limited. This thesis aims to contribute to addressing these gaps by investigating MSP stakeholders' perceptions of CGIS utility, their understanding of complex CGIS functionalities, and TDB data users' perceptions of trust, risk, and understandability of AI-based systems and their outputs in geospatial data production.

1.1 Objectives and research questions

This study's main objective is to provide an insight into stakeholder perceptions of CGIS and AI technologies in the digitalisation and automation of previously analogue or manual geospatial planning and data production workflows. The thesis aims to answer the following three research questions:

1. **How do stakeholders perceive CGIS and AI systems introduced to previously analogue or manual geospatial planning or data production workflows?**
   Technological transitions, whether through digitalisation or automation, in established workflows can improve process effectiveness and create new opportunities and possibilities for enhanced outcomes. However, the successful adoption of new systems depends on stakeholder acceptance. Understanding how stakeholders perceive these technologies is therefore essential for designing and developing systems that are likely to be accepted.

2. **Which system design features and quality attributes of CGIS and AI-based geospatial data production systems influence stakeholders' perceptions of utility, trust, and understanding of the systems and their outputs?**
   Acceptance of IT systems is often attributed to stakeholders' perceptions of their usefulness and ease of use, while trust has been identified as a key factor for acceptance of AI-based systems. Therefore, in designing and implementing successful CGIS and AI-based data production systems, it is important to understand which system design features (e.g. functionalities, user interface design, and documentation) and system quality attributes (e.g. utility, transparency, understandability) are perceived as being central for utility and understanding of, and trust in, the systems and their outputs.

3. **What challenges or limitations may hinder the effective adoption of CGIS and AI systems in geospatial workflows?**
   Technical and non-technical issues, such as stakeholder concerns, can result in the rejection of new technologies. Identifying and understanding the challenges and limitations in designing and implementing CGIS and AI systems for the digitalisation and automation of geospatial workflows may help to avoid this, or guide future research and development resources to finding appropriate solutions.

The research presented in this thesis can enhance the future design and development of CGIS and AI-based geospatial data production systems, enabling them to better serve stakeholder needs and increasing the likelihood that they will be accepted and adopted. Furthermore, this research contributes to knowledge on these topics, providing a stronger foundation for future research in the adoption of geospatial technologies.

1.2 Scope

The research in this thesis addresses selected aspects of stakeholder perceptions of geospatial technologies in the digitalisation and automation of geospatial workflows. It focuses on utility, transparency, understandability, and trust in CGIS for MSP and AI-based TDB data production. Although not a primary focus of the study due to the explorative nature of some of the research, stakeholder perceptions of other system quality attributes, such as ease of use, were also captured in the studies. CGIS and AI-based geospatial data production systems were selected due to their alignment with the objectives of research and piloting projects of the Finnish Geospatial Research Institute (FGI) in the National Land Survey of Finland. Target stakeholders for the study included stakeholders of MSP in the Baltic Sea region and users of TDB data in Finland. Data on stakeholder perceptions of CGIS in Articles I and II were primarily collected from MSP stakeholder meetings in Sweden and Latvia, involving stakeholders such as planners, decision-makers, industry representatives, experts, and researchers from Latvia, Sweden, and Finland. In Article IV, data on stakeholder perceptions of AI-based TDB data production were collected from users of TDBs working for Finnish government organisations and municipalities.

1.3 Articles

The research in this thesis is based on four articles that support the broader research questions of this thesis, each with its own aims and research questions. Articles I and II focus on stakeholder perceptions of CGIS utility and understandability in MSP workshop settings, especially regarding data management functionalities and spatial analysis. Article III complements the other studies by analysing the behaviour of CNN-based geospatial data production methods, with a focus on exploring the causes of false predictions from CNN-based watercourse extraction. It provides a technical basis through which users in Article IV evaluate trust, highlighting the challenge of interpreting outputs from geospatial DL methods. Article IV focuses on TDB data users' trust in, and concerns about, AI-based geospatial data production systems and their outputs, as well as their perceptions of the transparency and understandability of the data and systems in such workflows.

1.3.1 Article I

Article I presents the problem explication, requirement setting, design, demonstration, and assessment phases of developing a new prototype CGIS, Baltic Explorer, using a design science research approach. The system provides a digital platform for collaborative planning in MSP workshops, where paper maps have commonly been used. The central focus of the assessment is Baltic Explorer's perceived utility in supporting and facilitating collaborative tasks in MSP workshops. Although not a central theme of the study, some stakeholders' perceptions and observations of the system's usability were also captured. Part of the assessment was conducted with real-world MSP stakeholders in a workshop session, during which they used the system to facilitate discussion among planners, decision-makers, experts, and scientists.

1.3.2 Article II

The research in Article II continues the exploration of the perceived utility of tools in CGIS, this time focusing on a spatial multi-criteria analysis (SMCA) tool that introduces an element of automation into the setting. A new SMCA tool was designed, developed, and integrated into Baltic Explorer, in which stakeholders could modify the analysis parameters, similar to many standalone SDSS developed for MSP. The tool utilises pre-determined biodiversity datasets within a pre-defined workflow for analysing suitable locations for a new wind farm in waters under Latvian jurisdiction. In addition to the tool's utility, its perceived functional and operational understandability and ease of use, as well as its synergy with Baltic Explorer, were examined. As in Article I, the assessment was conducted in a real-world MSP workshop.

1.3.3 Article III

Article III presents the application of a CNN-based method for segmenting watercourse features in remote sensing datasets and explores the causes of errors in the outputs. The article also discusses the challenge of interpreting geospatial data quality using machine learning metrics, which do not directly align with typical geospatial data quality metrics, and may therefore be difficult for geospatial data users to understand. Article III does not directly study stakeholder perceptions. Rather, it provides technical insight and perspective on the behaviour, limitations, and evaluation of AI-based geospatial data production systems, particularly in relation to error characteristics, uncertainty, and human influence on the process, which may shape stakeholder perceptions of the trustworthiness and understandability of such systems. Stakeholder perceptions of similar systems are examined directly in Article IV. The research presented in Article III was conducted as part of the National Land Survey of Finland's efforts to pilot AI-based methods in TDB data production.

1.3.4 Article IV

Article IV explores TDB data users' perceptions of trust, risks, understandability across three dimensions (mechanistic, risk, and output), and transparency in the use of AI for producing data for TDBs. Stakeholders' perceptions were collected through a questionnaire sent to users of TDB data working in public organisations in Finland. Because the extraction of TDB features from remote sensing images has been primarily a manual process in Finland, a transition to the use of CNNs for feature extraction would represent a significant step towards the automation of the data production process. The study was conducted as part of the National Land Survey of Finland's efforts to understand the perceptions of its data's users.

1.3.5 Relationship between articles and research questions

The four articles address the three research questions from complementary perspectives, as is summarised in Table 1.

Table 1. Relationship between research questions (RQs) and the articles.

	Article I	*Article II*	*Article III*	*Article IV*
RQ1	Explores MSP stakeholders' perceptions of CGIS functionalities that provide digital data management tools for the exploration of geospatial data in MSP workshops.	Explores MSP stakeholders' perceptions of the introduction of a spatial analysis tool within a CGIS-supported MSP workflow.	Reveals AI behaviour that can be relevant to shaping perceptions and provides a technical foundation for Article IV.	Examines TDB data users' perceptions of trust, risk, understandability, and transparency in AI-based automation of data production workflows.
RQ2	Identifies specific system design features, in particular functionalities, that influence the perceived utility of CGIS.	Provides insight into the perceived utility, ease of use, and understandability of a spatial analysis tool integrated within a CGIS.	Explains data characteristics and model behaviour that affect the interpretability of outcome predictions from AI models and their trustworthiness.	Identifies specific factors that influence trust and contribute to a sufficient level of transparency in AI-based automation of TDB data production.
RQ3	Identifies barriers that may limit the perceived usefulness of CGIS.	Identifies challenges in using geospatial analysis tools in MSP stakeholder workshops.	Explains challenges in developing and interpreting the outcomes of AI models in TDB data production.	Identifies TDB data users' concerns about the use of AI-based methods for TDB data production.

2 Contextual background

In this chapter, I present the contextual background of the core elements of this thesis, including maritime spatial planning, collaborative geographic information systems, the production of data for topographic databases, and deep learning methods for geospatial feature extraction.

2.1 Core context of the research

Stakeholder perceptions of geospatial IT systems and data are context-dependent. This thesis examines stakeholder perceptions of two technologies and their outputs: CGIS and CNNs. Both cases are studied in the context of being introduced as new technologies to workflows that are largely analogue or manual (Figure 1). These two workflows are: 1) the collaborative use of geospatial data in MSP workshops, and 2) the production of data for TDBs.

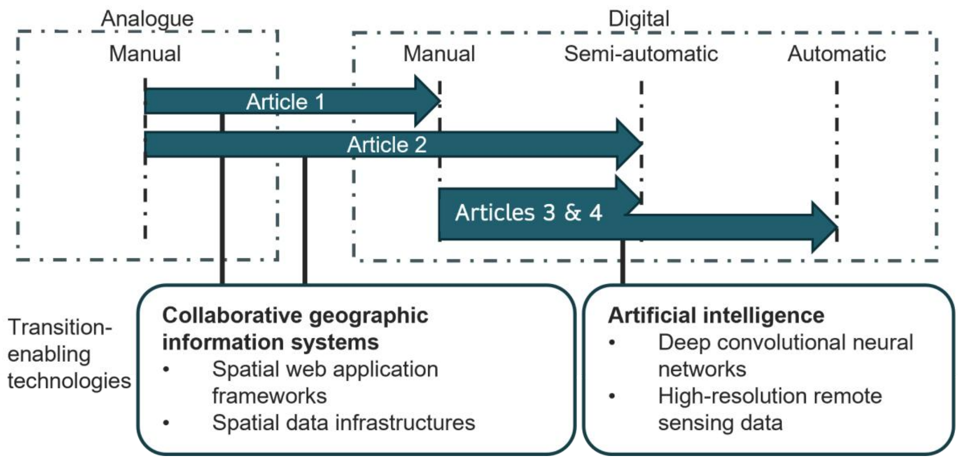

Figure 1. The articles present stakeholder perceptions of technologies that enable the transition of previously analogue and manual workflows to digital and automated workflows. The level of automation in AI-based geospatial data production workflows may vary from semi-automatic to fully automated. Data user perceptions of trust in workflows with alternative levels of AI-based automation are studied in Article IV.

The two workflows have distinct characteristics. The use of geospatial data in MSP stakeholder workshops represents a socio-technical workflow with recurring patterns of interaction between participants, facilitators, and geospatial data. These workflows are often exploratory, whereas geospatial data production workflows typically follow a fixed, procedural sequence of steps. In Article I, the participatory MSP workflow, that previously relied on paper maps and other analogue tools, is enhanced through a CGIS, Baltic Explorer. This transitions the workflow from analogue to digital and enables more efficient data management and idea sharing through the CGIS features (Figure 2). In Article II, a SMCA tool is integrated into Baltic Explorer, introducing an element of automation to the workflow. Articles III and IV focus on scenarios in which geospatial data production workflows, where features are manually digitised (drawn in vector format using remote sensing reference layers), are automated through CNN-based feature extraction. In such data production workflows, the level of automation of other phases, for example data quality assessment, may vary, and can influence data users' trust in the process.

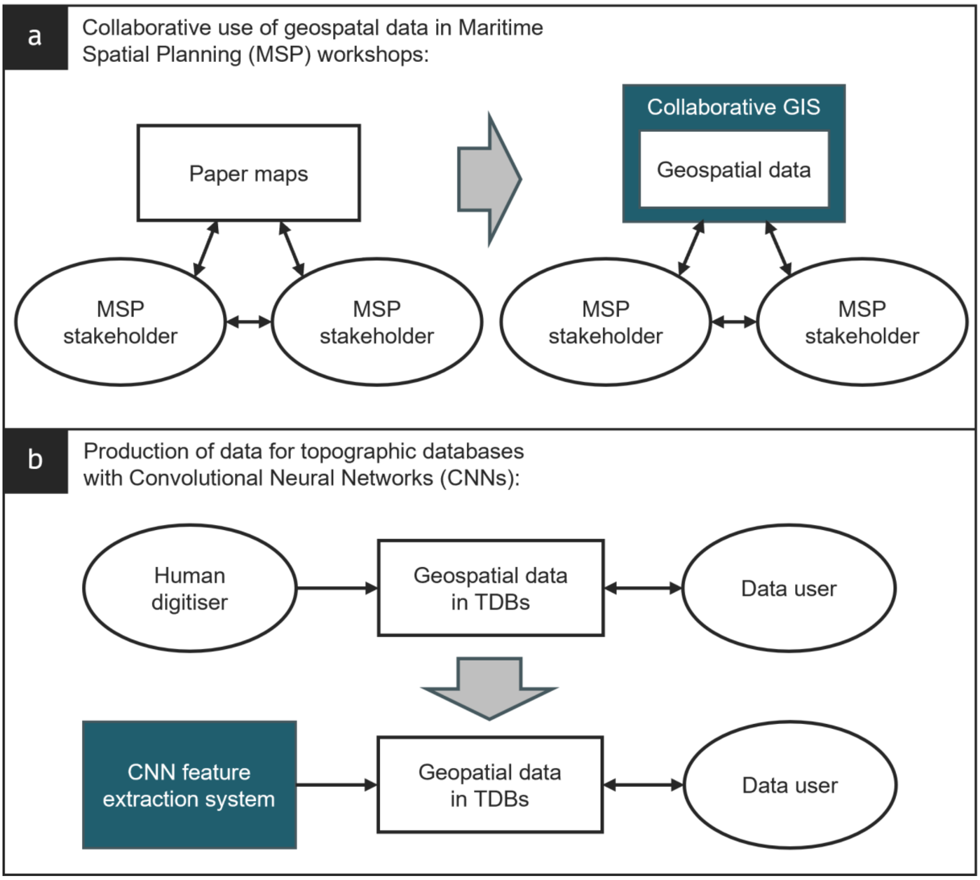

Figure 2. The studies in this thesis are based on two types of digitalisation and automation scenarios. (a) In collaborative MSP workflows, CGIS are used to digitalise the previously analogue planning environment, paper maps. (b) In TDB data production workflows, CNN-based feature extraction systems are used to automate the extraction of features from remote sensing data, previously done by human digitisers. In this scenario, data users do not interact directly with the system, but are indirectly affected by the transition through the data.

2.2 Maritime spatial planning

Maritime spatial planning has emerged as a key method for managing marine resources effectively that aims to promote sustainable growth and reduce conflicts among maritime activities. A key development for promoting MSP in Europe was the issuing of the European Union's MSP Directive (Directive 2014/89/EU, 2014). It mandated the European Union's member states to establish maritime spatial plans by 2021 to facilitate the coordinated and sustainable use of marine resources (Friess & Grémaud-Colombier, 2021). The plans need to be maintained and updated regularly (Directive 2014/89/EU, 2014). The MSP Directive further mandates participatory planning and cross-border collaboration between relevant nation-states and MSP stakeholders (Kull et al., 2021; Zaucha, 2014). This collaboration addresses the unique characteristics of the sea, where the absence of physical borders enables human activities to affect ecosystems across vast distances. Collaboration in MSP is also important for understanding planning problems and developing robust planning practices (Morf et al., 2019).

In practice, stakeholder involvement often varies in interactivity (Pomeroy & Douvere, 2008). However, in-person interaction has been found to produce beneficial outcomes, including building trust and understanding between collaborators, which are not necessarily achieved through less interactive processes (Flannery & Ó Cinnéide, 2012; Pelzer et al., 2014). Morf et al. (2019) argue that practical benefits for stakeholders and decision-makers can be gained from collaborative creation and sharing of knowledge and information. However, collaboration at state and transboundary levels is challenging. Stakeholders in MSP are a diverse group of people with different goals, motivation, expertise, and skills (Pomeroy & Douvere, 2008). To enhance collaboration in MSP, tools that can support the use of geospatial data in groups, and account for the skills and experience of its stakeholders, are required (Pınarbaşı et al., 2017).

Geospatial data are at the core of the MSP process to enable informed decisions. MSP requires data from a wide variety of sources beyond traditional government data. For example, local knowledge can be of great importance (Gopnik et al., 2012). Although users with limited experience of IT systems may prefer traditional tools, such as paper maps (Rose et al., 2016), GIS can provide effective methods to contextualise discussion and the expression of issues and preferences when they have a spatial context (Talen, 2000). Traditional desktop GIS have often been used to manage spatial data in MSP (Merrifield et al., 2013). Geospatial tools developed specifically for MSP tend to be model-based SDSS that support planners in analysing spatial relations, conditions, and phenomena. However, both desktop GIS and SDSS have been shown to adapt poorly to collaborative settings as they lack tools to support collaboration and decision-making directly (MacEachren, 2000). SDSS also often pre-define tasks and data making them adapt poorly to different use cases and problem-solving methods (Pınarbaşı et al., 2017; Ramsey, 2009). Desktop GIS are also poorly suitable for collaborative decision-making due to their complexity (Jing et al., 2019; Merrifield et al., 2013). Although previous studies highlight some adoption and acceptance-related challenges of geospatial systems, understanding MSP stakeholders' perceptions of the utility of CGIS functionalities and system design features for collaborative MSP work, and other similar decision-making processes, has received limited attention in scientific literature.

2.3 Collaborative geographic information systems

The need for GIS that can support group decision-making processes has been acknowledged for several decades (e.g. Armstrong, 1993, 1994). However, research on these systems remains limited. CGIS is not a well-established term (Sun & Li, 2016), and as a consequence, it has been used to describe various types of systems or approaches. Armstrong (1994) describes GIS that supports group decision-making as group SDSS. Balram and Dragicevic (2006) provide a thorough definition of CGIS, describing it as an integration of theories, tools, and technologies that structure human participation in group spatial decision processes. In their view, CGIS and public participatory GIS are two subsets of participatory GIS (Balram & Dragicevic, 2006). Ramsey (2009, p. 1972) adds to this view: "CGIS is a model in which diverse collaboration participants share information and create knowledge that can help serve the purpose of collective environmental and resource management". Sun and Li (2016) describe CGIS in a more technical sense, defining it as a system that integrates certain types of tools and properties. For example, they argue that, due to their role in supporting group work, the seamless integration of communication and workflow coordination tools greatly improves the collaborative process, and these tools are therefore important in CGIS (Sun & Li, 2016). Armstrong (1993) argued that groupware can be classified into four subgroups based on the users' locations and time of use and later he expanded this idea to collaborative group GIS (Figure 3) (Armstrong, 1994). The study presented by Sun and Li (2016) focuses on a web-based CGIS, with users working from different locations at the same time. The CGIS studied in this thesis is designed to operate in the same-time, same-location settings, as most MSP stakeholder meetings at the time of conducting the studies were on-site.

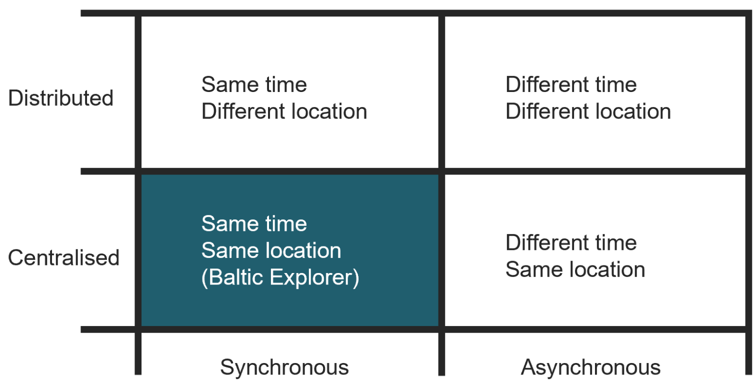

Figure 3. Groupware systems can be allocated into four categories based on their locational and temporal modes of operation. Articles I and II focus on studying the utility of properties of Baltic Explorer, a CGIS operating in same-time, same-location settings. (Adapted from Armstrong, 1993)

CGIS has been demonstrated to help non-expert users better understand geospatial data and analysis (Guerlain et al., 2016). Some researchers have argued that the objective of CGIS is to support exploration rather than pre-determined workflows designed to achieve specific outcomes. For example, Balram and Dragicevic (2006) argue that results achieved using CGIS come from a joint and structured exploration of ill-defined problems rather than a task-oriented approach. According to Ramsey (2009), CGIS has two objectives: 1) to support group problem-solving activities, and 2) to support the exploration of diverse problem understandings by collaborators. This dual objective is a challenge, as a system designed to support one objective is often ineffective at supporting the other (Ramsey, 2009). Ramsey (2009) makes three recommendations for designing CGIS for decision-making processes involving environmental or natural resource management: 1) to "have a neutral facilitator"; 2) to "avoid pre-defining the problem"; and 3) to "support problem exploration with flexible GIS applications".

2.4 Topographic database production and updating

Topographic databases of NMAs were originally created by digitising the contents of topographic maps (see review by Usery et al., 2018). TDBs typically provide nationwide geospatial data on a wide variety of human-made and natural features in structured, seamless digital databases, which enable their use in other applications such as spatial analysis and modelling (Kent & Hopfstock, 2018). TDB data and topographic maps are often considered of high quality and highly reliable (Kent & Hopfstock, 2018). In many countries, including Finland, TDB data is today shared and distributed for free, which has increased the range of users that now include governmental institutions, municipalities, private organisations, and individuals. As new applications for the data have rapidly increased and diversified, its quality requirements have become more demanding. Issues with manually digitised features such as unsystematic variations in interpretation, delineation, and classification have proved problematic in some use cases (Sliuzas & Brussel, 2000). In recent decades, TDB data have been updated using stereoplotting and other digitising methods, with high-resolution remote sensing data as reference (Usery et al., 2018). During this time, the availability and quality of reference data have improved significantly. For example, laser scanning point clouds have become available and are constantly being produced at higher density. This development has enabled TDB features and their borders to be identified and mapped at higher accuracy than ever before. However, manual digitising remains laborious, and several NMAs are now exploring DL methods as a potential solution to further increase automation of data production workflows (Kausika & van Altena, 2025; Murray et al., 2020; Usery et al., 2022; Zhu et al., 2024). Although the potential of these methods has been demonstrated from a technical perspective, introducing AI methods to TDB production raises questions about trust and ethics (Kausika & van Altena, 2025; Lin & Zhao, 2025). Yet, research examining these concerns in the context of AI-based geospatial data production remains scarce.

2.5 Deep learning methods for geospatial feature extraction

Deep learning has advanced many remote sensing image-processing tasks, including classification, segmentation, and object detection (Hoeser et al., 2020; Hoeser & Kuenzer, 2020; Mai et al., 2025). In recent years, DL has been applied to the segmentation of several features typically associated with TDBs, including land use and land cover features (Pradhan et al., 2020), buildings (Maltezos et al., 2019; Nahhas et al., 2018; Zhang et al., 2022), roads (Abdollahi et al., 2020, 2021), and hydrographic features (Busarello et al., 2025; Lidberg et al., 2023; Stanislawski et al., 2021; Xu et al., 2021). However, there are still many technical challenges in applying DL to geospatial feature extraction. Researchers have pointed out that architectures being used with remote sensing data are often designed for generic image data, and optimal architectures for different tasks may not yet have been discovered (Ball et al., 2017; Usery et al., 2022; Yang et al., 2018). Recently, some researchers have modified existing architectures to optimise them for the extraction of spatial features (e.g. Abdollahi et al., 2021; Xu et al., 2021), while others have created new architectures that are tailored for the segmentation of specific spatial features (Mai et al., 2025).

Another challenge in adopting DL methods for geospatial feature extraction is the need for large, high-accuracy training sets from different terrain types and the need for relatively high computational resources required (Yang et al., 2018). High-quality datasets for training networks for segmenting geospatial features are not widely available (Usery et al., 2022). Some methods have been developed to reduce the amount of required training data, such as augmentation, unsupervised learning, self-supervised learning, and transfer learning (Ball et al., 2017; Wang et al., 2022). However, producing new datasets for training is not straightforward, as it is often difficult to define the object and its spatial extent, particularly for natural features (Usery et al., 2022).

Nevertheless, applied research demonstrating DL technology's ability to segment TDB features from remote sensing images at high accuracy has shown its potential to replace manual labour and increase efficiency in TDB production workflows. Several NMAs have been experimenting with such approaches in their TDB data production workflows (Kausika & van Altena, 2025; Murray et al., 2020; Usery et al., 2022; Zhu et al., 2024).

2.5.1 Watercourse extraction with deep learning

Research on automated methods for extracting watercourses from remote sensing datasets has been ongoing for decades, and several methods, most prominently flow accumulation (O'Callaghan & Mark, 1984), have become well-established. However, due to the complexity of water flow networks and their physical traits, flow accumulation-based methods often fail to provide high-quality results at high resolution, particularly in flat areas (Mao et al., 2021; Martz & Garbrecht, 1998). Other methods for extracting watercourses use elevation characteristics such as elevation profiles, classification, curvature (Bailly et al., 2008; Passalacqua et al., 2010), relative elevation calculated from a digital elevation model (DEM) (Cazorzi et al., 2013), or voids in the laser scanning point clouds caused by water reflection (Broersen et al., 2017). Roelens et al. (2018) present another approach to ditch extraction that is based on the use of a random forest classifier applied to radiometric, geometric, and intensity density features to create vector ditch features. Other methods also include the use of random forest, BayesNet, k-nearest neighbours, or support vector machines to detect watercourses from multitemporal red-green-blue orthomosaics, or Sentinel-2 imagery (La Salandra et al., 2023; Thanh Noi & Kappas, 2018).

In recent years, researchers have experimented with using DL, particularly CNNs, for watercourse segmentation (Lidberg et al., 2023; Stanislawski et al., 2021; Xu et al., 2021). CNNs have been shown to significantly outperform flow accumulation for detecting ditches from high-resolution remote sensing data (Busarello et al., 2025). Xu et al. (2021) developed a new architecture for the segmentation of streams and waterbodies from high-resolution remote sensing datasets, based on U-Net (see Ronneberger et al., 2015). They demonstrate that the new network outperforms the original U-Net, a support vector machine, and an artificial neural network model. Stanislawski et al. (2021) apply a U-Net-based model for waterbody and watercourse extraction, with a 5 metre resolution DEM as input data. They augment the results with D-8 flow accumulation, demonstrating how the mixed method approach improves the outcomes of model predictions. Article III of this thesis focuses on understanding errors in CNN-based segmentation of ditches and streams, which are common features in TDBs, and whose digitising process could potentially be automated based on promising research results.

3 Theoretical background

This chapter presents the theoretical foundation of the stakeholder perceptions that are central in this thesis, with a particular focus on their implications for geospatial systems and data. The research in this thesis is transdisciplinary, combining elements of stakeholder perceptions of utility, human-computer interaction, the acceptance of information technology, geographic information science, and trust in AI. It also draws on remote sensing, DL, spatial data quality, and collaborative spatial planning. The central stakeholder perceptions of this thesis are the utility of CGIS functionalities in MSP workshops, perceptions of understandability of automated spatial analysis tools in decision-making processes, and trust in, concerns about, and perceptions of transparency and understandability of AI-based systems used to automate the production of TDB data.

3.1 Stakeholder perceptions of geospatial systems and data

Stakeholder perceptions of technologies significantly influence the acceptance, adoption, and effective use of technology and data. Stakeholder perceptions of geospatial technologies and data are a broad subject that is often studied through more specific, but often overlapping, research concepts.

IT acceptance models, such as the Technology Acceptance Model (TAM) (Davis, 1989) and Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) measure and model relationships between user perceptions and the acceptance and adoption of IT systems. Both TAM and UTAUT highlight the central role of perceived usefulness and ease of use for acceptance of IT (Davis, 1989; Venkatesh et al., 2003). Other key constructs in UTAUT and its later iteration UTAUT2, also include social influence, facilitating conditions, hedonic motivation, price value, and habit (Venkatesh et al., 2003, 2012). Furthermore, UTAUT2 introduces moderators, user characteristics such as age, gender, and cultural background, that affect the strength of relationships between perceptions and acceptance (Sun & Zhang, 2006; Venkatesh et al., 2012). Recent studies applying TAM and UTAUT to DL systems have extended the models to include trust as an additional construct (Choung et al., 2023; Kelly et al., 2023).

Both TAM and UTAUT provide useful explanatory frameworks for studying perceptions of geospatial systems. Previous studies have identified usefulness, ease of use, and habit as central constructs for acceptance of geospatial systems as well as experience as a central moderating factor between the constructs and acceptance (Castanha et al., 2023; Gupta & Dogra, 2017; Henrico et al., 2021, 2022). In the case studies of this thesis, the focus is on digitalisation and automation of workflows where new tools differ substantially from previous practices. In such context, acceptance is likely to depend less on established habits and experiences and more on user perceptions of usefulness, ease of use, and trust.

Other relevant theories and frameworks for understanding stakeholder perceptions of IT systems include human-computer interaction (see Dix, 2017), Task-Technology Fit (Goodhue & Thompson, 1995), and the Information Systems Success Model (DeLone & McLean, 1992). These models, theories, and frameworks have been modified and applied in studying various types of geospatial systems (e.g. Eldrandaly et al., 2015; Man et al., 2022). Rather than focusing primarily on which constructs directly influence acceptance, these frameworks and theories help to identify factors that shape users' perceptions of usefulness and ease of use.

Stakeholders' perceptions of and trust in systems are influenced by their understanding of the system. This understanding is shaped by system design features (e.g. functionalities and user interface design), system quality attributes (e.g. understandability, transparency, utility, and usability), as well as stakeholders' capabilities (e.g. GIS expertise and AI literacy) (Figure 4). Perceptions of and trust in systems can also be influenced by perceptions of the characteristics of the system provider, for example competence, reputation, and trustworthiness. Stakeholders' characteristics may moderate the strengths of the relationships between perceptions and acceptance of systems.

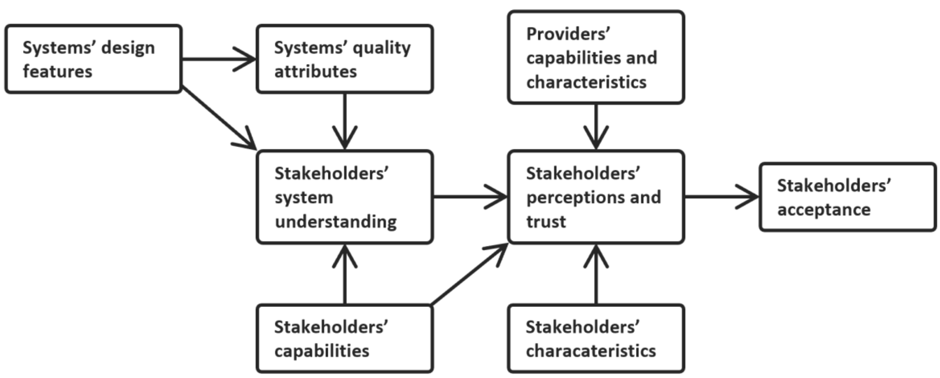

Figure 4. Stakeholders' perceptions predict their acceptance of systems. Stakeholder characteristics may moderate the relationship between perceptions and acceptance. Stakeholders' perceptions are influenced by their system understanding, capabilities, and perceptions of system provider characteristics. System understanding is shaped by system design features, system quality attributes, and stakeholder capabilities.

3.2 Utility and usability of information technology

A central perception examined in Articles I and II is stakeholders' perception of the utility of CGIS. Utility in IT is closely related to other, more established concepts of perceived usefulness, perceived usability, and perceived ease of use. Perceived usefulness and ease of use are two central constructs that directly affect the acceptance of technologies (Davis, 1989; Venkatesh et al., 2003). In TAM, perceived usefulness is defined as "the degree to which an individual believes that using a particular system would enhance his or her job performance", and perceived ease of use as "the degree to which an individual believes that using a particular system would be free of physical and mental effort" (Davis, 1989, pp. 10 –12). Subsequent models have reworded these two constructs. For example, UTAUT conceptualises perceived usefulness as performance expectancy and perceived ease of use as effort expectancy, maintaining the same underlying meanings (Venkatesh et al., 2003). Several studies have demonstrated the relevance of perceived usefulness and ease of use for the acceptance of various geospatial (Alzahrani et al., 2024; Castanha et al., 2023; Henrico et al., 2021) and AI systems (Ali et al., 2025; Kelly et al., 2023). Nevertheless, the TAM has been criticised for including only these two constructs, which are argued to be insufficient for explaining users' intention to use systems. Therefore, several complementary constructs, including social influence, facilitating conditions, hedonic motivation, habit (Venkatesh et al., 2012), trust (Choung et al., 2023; Jain et al., 2022; Ramirez Aranda et al., 2023; Rane et al., 2024), and peer influence (Cheung & Vogel, 2013) have been proposed by researchers to enhance acceptance models. Other researchers have developed their own acceptance models for AI systems, such as the AI Device Use Acceptance model (Gursoy et al., 2019).

Usability is a central concept in the field of human-computer interaction. The ISO 9241-11:2018 standard defines usability as "the extent to which a system, product, or service can be used by specified users to achieve specified goals with effectiveness, efficiency, and satisfaction in a specified context of use" (International Organization for Standardization, 2018). Although this definition may imply objective usability, human-computer interaction is often concerned with perceived usability, which refers to a subjective assessment of how usable a system is. Human-computer interaction is fundamentally about user experience and therefore perception-driven. Usability and perceived ease of use are sometimes used interchangeably, but usability can also be understood as a wider concept that includes effectiveness and satisfaction in addition to effort (see International Organization for Standardization, 2018).

Utility as a concept is not widely established in the field of IT, unlike usefulness, ease of use, and usability. Nielsen (1994) defines utility as whether a system provides the functionalities required to perform the user's task. Therefore, users' perception of utility can be understood as whether users believe that the system provides the necessary functionalities for their tasks. Pelzer (2017) extends Nielsen's definition by adding that utility is the outcome of the fit between task and technology, a view which is also shared by the Task-Technology Fit theory (Goodhue & Thompson, 1995). Nielsen (1994) further argues that usefulness is a function of a system's usability and utility, and that a system requires both to be useful. Nevertheless, the term utility is often used interchangeably with usefulness (e.g. Pelzer et al., 2015). A negative correlation between usability and utility has also been identified. Roth et al. (2015) argue that increasing utility by adding more complex functionalities reduces usability for non-expert users.

3.2.1 Utility of geospatial data

Conceptually, the usefulness of IT systems resembles data's fitness for use. Petutschnig et al. (2024) define the fitness for use of data as a function of their suitability (quality in terms of data properties such as spatial resolution and raster cell size) and reliability (data quality attributes such as accuracy, timeliness, and completeness) in relation to a specific use case. Suitability in this case refers to a concept similar to the utility of IT systems. The term utility has also been used in relation to geospatial tasks. Frank et al. (2004) argued that the utility of geospatial datasets depends on whether the dataset leads to better outcomes in decision-making or the execution of tasks. Meeks and Dasgupta (2004) propose a Geospatial Information Utility metric that models geospatial information utility as the sum of the quality of individual information components and user-defined needs for information. Both the model by Petutschnig et al. (2024) and the model by Meeks and Dasgupta (2004) draw parallels with Nielsen's (1994) equation for the usefulness of IT systems. In these models the terms data fitness for purpose and information utility are used for usefulness, while data suitability and information needs (that is, fitness for the purpose or the task for which it is required) are used for utility. Like data reliability and data quality, usability is a quality attribute, although other system quality attributes such as reliability are ignored in Nielsen's equation.

Other researchers have described fitness for use as an element of data quality (Radosevic et al., 2023). Fitness for use relies heavily on data quality, which can be subjective, depending on the users and the task for which the data are used (Lush et al., 2018; Meeks & Dasgupta, 2004). The 7th edition of the *Geographic information – Data quality* standard (International Organization for Standardization, 2023) defines the components for describing geospatial data quality, data quality measures, and procedures for their evaluation, and how they should be reported. However, Radosevic et al. (2023) argue that such a descriptive approach to spatial data quality is not always helpful for assessing fitness for use.

Furthermore, perceptions of fitness for use depend on the user's domain expertise, and expertise with geospatial tools and data (Grira et al., 2013).

3.2.2 Utility assessment of geospatial systems and data

Assessing utility is important, not only to validate systems, but also to enable developers to understand what makes systems useful. A lack of useful functionalities has been identified as a barrier to the adoption of geospatial systems in real-world MSP efforts (Pınarbaşı et al., 2017). Utility assessments are often conducted and reported in the scientific literature with the introduction of new systems. For example, Arciniegas and Janssen (2012) introduce a new system for land-use planning workshops and assess some features of the system based on participants' perceptions of their usefulness and ease of use. Studies focusing on utility assessment alone are rare. Sidlar and Rinner (2009) evaluate the objective utility of the Argumentation Map prototype (Keßler et al., 2005) based on a method they developed, which uses the usage ratios of individual system functions as a proxy for utility.

Because of the size of geospatial datasets, they are typically assessed through heuristic methods, by comparing them to authoritative datasets or analysing their provenance information (Fogliaroni et al., 2018), for example. Assessing the fitness for use of geospatial data has proved challenging. Several researchers have proposed new methods for assessing the fitness for use of geospatial data based on metadata (e.g. Meeks & Dasgupta, 2004; Pôças et al., 2014). However, these methods rely on metadata that are accurate and complete, and in some cases, on metadata that goes beyond the mandatory elements of the ISO 19115 metadata series (International Organization for Standardization, 2014). In practice, many metadata records are incomplete, and evidence of the practical application of the proposed methods is limited (Lush et al., 2018). Quarati (2021) finds a weak correlation between the use of open spatial data from government bodies and the quality of their metadata. Moreover, reference datasets may have their own quality issues, and this uncertainty is often not reported (Nightingale et al., 2019). Emerging data capture and production methods such as crowdsourcing and AI have caused concerns about the quality of outputs, and how it should be evaluated (Fogliaroni et al., 2018; Moreri et al., 2018; Petutschnig et al., 2024).

3.3 Trust

Trust can be framed, defined, and categorised in many ways, depending on the context in which it applies and the nature of the relationships (Lush et al., 2018). It is also context-sensitive, influenced by factors such as the trusted act, the trustee, the trustor, and the environment (Tamò-Larrieux et al., 2024). When the trust in a system aligns with its actual trustworthiness, trust is said to be warranted (Jacovi et al., 2021). Trust can be directed at individual system properties such as confidence in a system's ability to produce reliable outcomes, assurance that models will not be misused for harmful purposes, or the belief that the use of AI will not cause unintended negative consequences (Steimers & Schneider, 2022).

3.3.1 Trust in artificial intelligence systems

Trust is a key predictor of an AI system's acceptance (Choung et al., 2023; Kelly et al., 2023; Rane et al., 2024). Trust in AI systems can be built extrinsically by observing external behaviour and outcomes, or intrinsically, by building an understanding of the model's reasoning process (Jacovi et al., 2021). The trustor can gain trust in AI through their own observations, or through the documentation and reputation of others (Afroogh et al., 2024).

Many factors can affect trust in AI, including the performance, explainability, and transparency of AI systems (Jiang et al., 2024), as well as characteristics of the operator and developer, such as their integrity and ability (Vössing et al., 2022). Trust in AI can further be moderated by the characteristics of the trustor. For example, digital affinity, a person's natural attraction to, interest in, and pleasure in learning to use digital methods, has been found to affect trust in AI systems (Saßmannshausen et al., 2021). Furthermore, cultural factors, including the level of trust in government and regional regulatory requirements such as the recently issued European Union AI Act (Regulation (EU) 2024/1689, 2024) which regulates high-risk AI systems developed, operated, or used in the EU can promote trust in AI systems and their operators (Dang & Li, 2025; Middleton et al., 2022). Other external factors such as the increased coverage of AI in the media, although generally balanced between positive and negative societal impacts (Ouchchy et al., 2020), can influence trust in AI systems.

3.3.2 Trust in geospatial data and systems

Although trust is a widely researched topic in many IT fields, research on trust in geospatial systems and data is relatively limited (Lush et al., 2018). Building trust through stakeholder involvement is a key requirement for geospatial AI systems, ensuring that solutions fit stakeholders' interests and requirements (Wang et al., 2024). Skarlatidou et al. (2011) point out that trust is central to the acceptance of web-GIS by novice users. They argued that non-expert interaction further establishes risks and uncertainty because of web-GIS interface complexity, context of the applications, geospatial data, and spatial analysis (Skarlatidou et al., 2011). Paolanti et al. (2024) develop and demonstrate a framework that enables a quantitative assessment of the risks and trustworthiness of DL systems for remote sensing based on five factors: 1) technical and social robustness; 2) fairness; 3) transparency and explainability; 4) accessibility; and 5) sustainability.

Lush et al. (2018) argue that trust is vital in geospatial data selection and use, and that it is important for assessing its trustworthiness, alongside its fitness for use and quality. Trust in the production of geospatial data has mostly been researched from the perspective of volunteered geographic information, for which researchers have developed several evaluation methods, such as assessment based on creator reputation and trust (see Fogliaroni et al., 2018; Moreri et al., 2018). The relatively low number of studies on trust in the production of other types of geospatial data limits our current understanding of trust in data produced by AI-based automation. As with collecting volunteered geographic information, moving from a manual process to AI-based automation reduces the producer's control over the data production and introduces a new trustee, the AI model. While many AI systems produce recommendations that can be validated by the user directly, in CNN-based geospatial data extraction for TDBs, assessment of output quality is challenging because of the size and complexity of geospatial datasets. Such assessments require reference data or in-depth knowledge about the area, which data users outside the data producer's organisation may not possess. Therefore, TDB data users must often trust the data based on assessment of small samples or information provided by others. Several researchers have highlighted the importance of metadata for trust in geospatial data. Provenance is central to user trust in geospatial data. Because such information documents the data production process, including AI-based methods, it enhances transparency and reproducibility of geospatial workflows (Tullis & Kar, 2021). Nevertheless, it is unclear what specific details about the AI-based workflows are relevant to data users. These factors highlight the importance of future research on stakeholders' trust in AI-based geospatial data production.

3.4 Transparency and understandability

The exact definition of transparency in IT systems varies (Vorm & Combs, 2022). Ofem et al. (2022) argue that the transparency of IT systems is generally regarded as a non-functional system requirement that is best studied through the concept of requirements engineering activities. It is argued that the transparency of decision-support tools increases both trust in the tools and the likelihood that they will be used (Rose et al., 2016). Balram and Dragicevic (2006) argue that the acceptance of planning outcomes also depends on transparency. When designed correctly, GIS can also increase the transparency of decision-making processes for novice users (Merrifield et al., 2013).

3.4.1 Understanding and understandability

Transparency is closely connected with system understandability, but transparency alone is not comprehension (Vössing et al., 2022). In this thesis, system understanding is conceptualised as a cognitive state that reflects how well the user understands different aspects of the system and influences trust (see Lee & See, 2004) and user perceptions of system characteristics (see Whyte et al., 1997). Users' system understanding is shaped by users' capabilities, system design features, and system quality attributes, particularly transparency and understandability.

Users' system understanding is multi-dimensional, concerned with various aspects of the system. To support clarity in discussion, this thesis distinguishes between seven descriptive dimensions of system understanding, derived from distinct epistemic aspects of how users comprehend IT systems (Table 2). System understanding develops through experience, experimentation, and education, which may be supported by transparency. A lack of system understanding can have a direct negative impact on the effective use of systems. For example, insufficient experience with geospatial data has been shown to challenge the process of finding relevant data (Wells et al., 2021). Stakeholders' mechanistic understanding of spatial analyses in SDSS is important to avoid the conception that decisions are made by software (Collie et al., 2013).

Table 2. Aspects of system understandability and their relation to user perceptions.

Dimension	*Meaning*	*Impact*	*Theoretical grounding*
Operational	How to use the system	Ease of use	HCI usability research (e.g. Nielsen, 1994)
Functional	What can be done with the system	Usefulness	TAM (Davis, 1989) / UTAUT (Venkatesh et al., 2003)
Mechanistic	How the system processes inputs to outputs	Trust through predictability	Explainable systems (e.g. Lim et al., 2009)
Structural	How the system is built (for example, system architecture and code)	Trust through reliability and robustness	Information system success / system quality research (Delone & McLean, 2003)
Output	How the outputs of the system should be interpreted, evaluated, and used	Outputs' usefulness + calibrates trust	Explainable systems (e.g. Lim et al., 2009)
Risk	What limitations and negative impact the system may have	Calibrates trust	Trust in automation (e.g. Lee & See, 2004)
Contextual	How the system fits the intended use case	Usefulness through task-technology fit	Task-technology fit (Goodhue & Thompson, 1995)

3.4.2 Transparency and explainability of deep learning systems

Transparency is an important factor for building trust in a human-centred AI system (Shevtsova et al., 2024; Tucci et al., 2022; Wang et al., 2024). As the performance and accuracy of DL models improve, they are becoming increasingly complex and difficult to understand (Roussel & Böhm, 2023). Although transparency and openness promote trust, most DL models today are considered "black-box" systems because their decision-making reasoning is too difficult to understand, even by AI experts (Ali et al., 2023; Ball et al., 2017; Xing & Sieber, 2023). To enable true transparency, there needs to be an understanding of DL models' inner workings, enabling stakeholders to meaningfully interpret how they produce their outputs (Vössing et al., 2022).

To increase understanding of the inner workings of AI systems, researchers have increasingly been studying methods for enhancing the explainability of existing models and developing new explainable ones to enhance the transparency of their decision-making (Ali et al., 2023). Explainable models, generally referred to as explainable AI, can reveal various aspects of how models arrive at their conclusions, increasing the mechanistic understanding of the system, which ideally leads to desirable outcomes such as the acceptance of the model (Langer et al., 2021). However, most explainable AI models are designed for experts (Ali et al., 2023). The outputs of explainable AI models require interpretation, which can be demanding for novice users, as many explainable AI models themselves can be complex and difficult to understand (Heimerl et al., 2022; Xing & Sieber, 2023; Yang et al., 2020). Moreover, few models have been developed in the context of geospatial AI (Roussel & Böhm, 2023).

3.5 Risks with the use of geospatial artificial intelligence

Risks associated with the use of AI are widely recognised, but they vary depending on the context (Zeng et al., 2024). A variety of risks have been identified as potential barriers to the adoption of geospatial AI systems and data, including privacy and security issues, the reliability of outputs, misuse of data, and lack of transparency and explainability (Alzahrani et al., 2024; Devillers et al., 2007; Paolanti et al., 2024; Rane et al., 2024; Xu et al., 2023). Despite the growing number of studies on risks with different types of AI systems, there is still limited research about risks with AI systems being used for geospatial data production.

Privacy and security issues have been recognised as risks for both AI systems and geospatial data (Curzon et al., 2021; Radosevic et al., 2023). The emergence of smartphones and location-based technologies that enable the sharing of private location-based data has sparked research under the term geoprivacy (Keßler & McKenzie, 2018). The mapping of large geospatial datasets also presents a risk of accidentally publishing data containing sensitive information (Kounadi & Leitner, 2014). Researchers have developed a variety of methods to protect and anonymise geospatial data (Brauer et al., 2022, 2023; Kounadi & Leitner, 2014). However, there is still widespread concern about these issues and the various ways in which they can present themselves. For example, Kang et al. (2024) argue that although laws and regulations may protect sensitive information in published datasets, government institutions are not prevented from training AI models with the data. Additionally, the integration of spatial analysis with AI has raised concerns about privacy violations and deepening inequalities, where bias can lead to the marginalisation of groups of people (Oluoch, 2024; Wang et al., 2024).

Another concern for the use of AI systems, especially DL, is vulnerability to the potential misuse of models for malicious purposes and attacks on models (Liu et al., 2021). For example, input images can be manipulated to change the outcome of models, or models can be used to create highly realistic synthetic content that can be used for malicious purposes (Chen et al., 2021; Zhao et al., 2020). Such approaches utilise models and methods that have been developed for good purposes such as efficient remote sensing data processing, obscuring sensitive information in geospatial datasets, and generating synthetic training data for improving model accuracy (Shin & Lee, 2021; Tjio et al., 2022; Yin & Yang, 2018). Malicious intent may also be unintentionally enabled by providing too much transparency to AI systems, making them vulnerable to exploitation (Afroogh et al., 2024). Therefore, careful consideration is required when deciding which details of AI systems are provided to the public.

4 Methods and data

In this thesis, a variety of methods and data were used to research stakeholder perceptions in introducing new technologies to digitalise and automate geospatial workflows (Table 3). Overall, the research focused on two cases in which a new system was first developed for a geospatial data workflow (Articles I, II, and III). The system, method, or workflow was then assessed primarily through stakeholder and user perceptions (Articles I, II, and IV), observations of its use in real-world settings (Articles I and II), or the quantitative analysis of outputs (Article III).

4.1 Overview of research methods

The study in Article I followed a five-step design science research methodology consisting of: 1) "problem explication"; 2) "specification of requirements"; 3) "design and development"; 4) "demonstration"; and 5) "evaluation". Design science research is a methodological approach that makes prescriptive scientific contributions that present knowledge about artefacts such as prototype systems through identifying real-world problems, designing and developing solutions for the problems, and then studying the solutions (Dresch et al., 2015; Johannesson & Perjons, 2021). Design science research was adopted as the methodological framework as the development of Baltic Explorer progressed, as its stages aligned closely with the methods and activities already undertaken during the BONUS BASMATI project. Steps 1 to 3 of our approach in Article I were based on a literature review and the development of a prototype CGIS, with each step utilising results from the previous step. Step 4 was carried out by demonstrating the developed prototype CGIS in a real-world stakeholder workshop. Step 5 was conducted by assessing the CGIS based on observations of its use in the workshop, as well as a questionnaire for the workshop participants. The assessment aimed to collect data on stakeholders' perceptions of the utility of CGIS properties. An additional user test was also conducted in a controlled environment to collect user perceptions of the utility of alternative hardware options for CGIS.

Article II aimed to develop knowledge of stakeholders' perceptions of the utility and operational and functional understandability of spatial analysis tools in participatory MSP workshops. The methods included the design and development of a SMCA tool, the preparation of input data, integration-enabling modifications to the CGIS developed in Article I, the development of a user-friendly interface, and the demonstration of the system in a real-world workshop setting. Research data were collected through observations and a questionnaire for workshop participants.

Article III introduced a CNN-based watercourse feature extraction system and explored its outputs, assessing them using a variety of quantitative and qualitative methods. The study aimed to provide an insight into what types of errors were present in the outputs and reflect on how the watercourse feature extraction system performed with various input data, and how errors in the outputs affected the segmentation at a feature level. Quantitative and visual analyses were used as the primary methods in the study.

Article IV collected insights into stakeholders' trust in and concerns about the AI-based automation of geospatial feature extraction (the type of AI system developed in Article III) through a questionnaire. The questionnaire was sent to users of TDB data in Finnish public organisations. The responses to the questionnaire were then analysed using both quantitative and qualitative methods.

Table 3. Summary of research methods used in the thesis.

Method:	*Article I*	*Article II*	*Article III*	*Article IV*
Literature review	X	X	X	X
System development	X	X	X	
User test in controlled environment	X			
Real-world stakeholder assessment	X	X		X
Observations at real-world event	X	X		
Questionnaires	X	X		X
Correlation analysis				X
Experiments with alternative parameters			X	
Quantitative analysis of model predictions			X	
Visual analysis of model predictions			X	

4.2 Systems and data

Two system implementations were central to the studies in this thesis: 1) the Baltic Explorer prototype, including an integrated SMCA tool (Articles I and II); and 2) a watercourse segmentation system based on a deep CNN architecture (Article III). The CNN system in Article III is also representative of the type of AI system focused on in Article IV. A range of geospatial datasets was also central to the research.

These included: 1) OGC Web Map Service (WMS) and Web Map Tile Service (WMTS) datasets by third-party data providers that were made easy to access through Baltic Explorer (Articles I and II); 2) vector datasets in Baltic Explorer created by workshop participants with the Baltic Explorer's drawing and editing tools (Articles I and II); 3) raster datasets of ecosystem components for the SMCA tool (Article II); 4) the input and training datasets for segmentation of small watercourses, as well as the model predictions (Article III).

4.2.1 Baltic Explorer

The Baltic Explorer prototype (commonly referred to as Baltic Explorer) is a cross-platform CGIS designed for facilitating discussions in groups through geospatial data. The Baltic Explorer offers an alternative to using paper maps in participatory MSP planning sessions by providing simple, flexible, and easy-to-use digital tools for geospatial data management and visualisation. One of its core concepts is shared workspaces that enable multiple users to work within the same map interface at the same time, from any number of devices, with changes synchronised between them (Figure 5). Its flexible interface design allows it to adapt to different screen sizes and input devices, enabling its use on various hardware platforms, including large touchscreens and mobile phones. Baltic Explorer has two main functionalities for interacting with geospatial data. These are: 1) an "overlay data on map" tool that enables WMS datasets from internal and external sources to be easily accessed and displayed on the map interface, and 2) a "draw and edit features" tool that enables the editing and creation of vector data. The information for retrieving WMS data layers is stored in the Baltic Explorer's database, where users can add access information for additional layers. The layers then appear in the overlay data menu, from where users can add them to the map interface with a single click (Figure 6b).

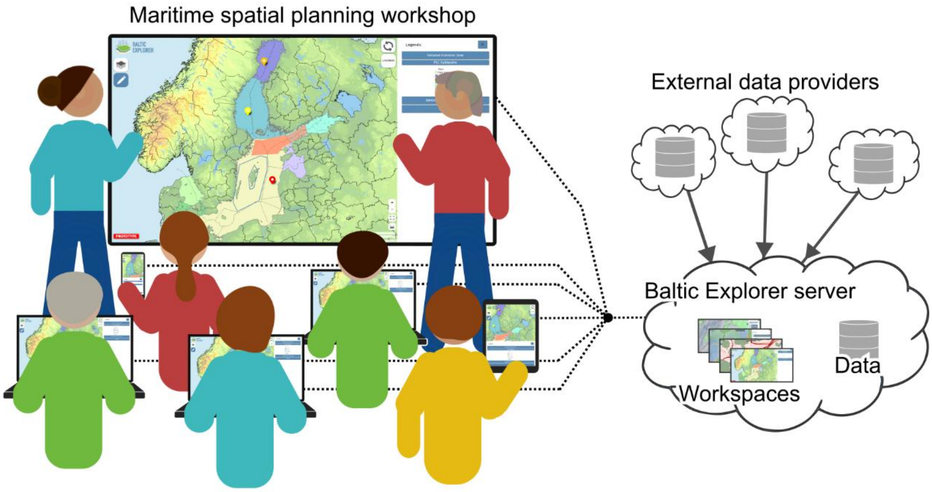

Figure 5. Baltic Explorer was designed to facilitate discussions through geospatial data in MSP workshop settings, enabling virtually any number of participants to simultaneously interact with the system. The user interface adapts to different devices. WMS datasets from external providers can be accessed through Baltic Explorer and visualised in its map interface. (Figure adapted and modified from Article II)

The technical implementation of Baltic Explorer was developed by forking the code of the open-source online map creation tool uMap[1]. The development included: 1) adding support for changing the coordinate reference system, 2) redesigning the user interface, 3) removing redundant functionalities, and 4) adding new functionalities, such as the "overlay data on map" tool. The system is based on the Django Python web framework[2], the PostgreSQL database management system[3] with PostGIS extension[4], and the Leaflet JavaScript library[5] for interactive maps. Vector features are stored as .json[6] files.

For the research in Article II, Baltic Explorer was modified to enable the integration of a SMCA tool as a separate module that could be accessed within the Baltic Explorer's map interface (Figure 6d). The tool analysed areas where one or more of up to five pre-defined ecosystem components were present. Each ecosystem component could be given a threshold value corresponding to the minimum coverage required for it to be considered in the analysis. A new user interface

[1] https://umap.openstreetmap.fr/en
[2] https://www.djangoproject.com
[3] https://www.postgresql.org
[4] https://postgis.net
[5] https://leafletjs.com
[6] https://www.json.org

module was designed and developed that included tools to adjust the parameters of the analysis, perform the analysis on the server, and view the results in the map interface. To provide transparency and support the tool users' comprehension, the user interface visualised the process in a stepwise manner, with tooltips providing additional help at each step. The data-processing backend scripts were developed using GDAL[7] with Python[8].

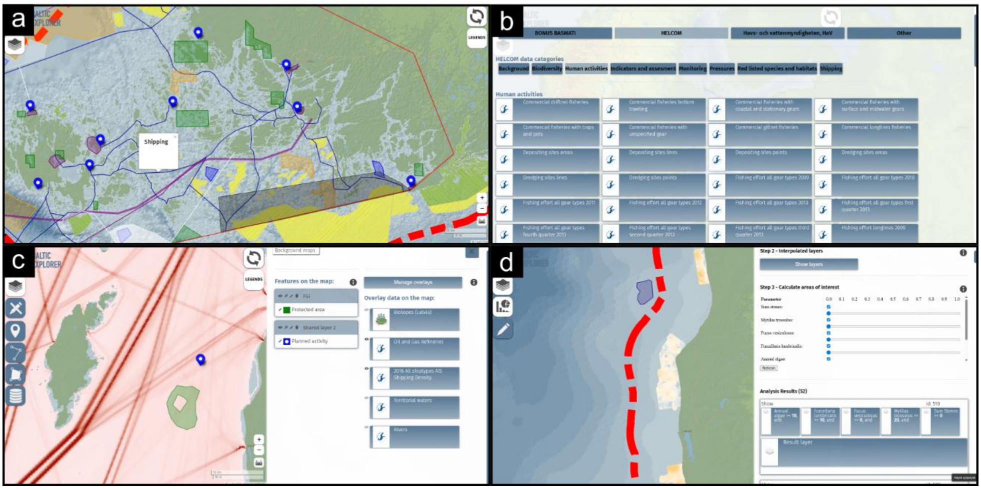

Figure 6. The main view in Baltic Explorer's user interface is a full-screen map (a) on which new geospatial features can be drawn and where WMS datasets from external providers can be visualised. Additional WMS layers can be searched for and added through an overlay data menu (b). Additional data management tools are located within a "pop-up" sidebar menu (c). The user interface for the integrated SMCA tool (d) was also implemented in a sidebar.

4.2.2 Geospatial data in Baltic Explorer

Baltic Explorer's main background map layer is an unnamed WMTS layer from the Baltic Marine Environment Protection Commission. A key function of Baltic Explorer is its "overlay data on map" tool, which allows third-party WMS layers to be displayed on top of the background map. Roughly 800 WMS layers were initially made available in the system during the main development phase. Baltic Explorer has tools for system administrators to enable access to additional layers from any compatible spatial data infrastructure through a graphical interface, while developers can enable access to additional layers by adding their access information

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7 https://gdal.org/
8 https://www.python.org/

directly to the database. Once the required information has been added to the database, the layers become accessible from all workspaces. Baltic Explorer also enables vector data to be added, used, stored, and exported. Unlike raster data, vector data are workspace-specific and can be included in two ways: 1) they can be drawn on the map using the "draw and edit features" tool; or 2) they can be uploaded to the system from a file. During the study presented in Article II, case-specific geospatial data for the analysis tool were added to Baltic Explorer. The source data for the tool consisted of 3,189 points where divers had mapped the coverage of various ecosystem components. Before being added to the Baltic Explorer server, the data were pre-processed by interpolating five raster layers from the point data using GDAL's inverse distance-weighted interpolation. Each resulting layer contained one of the components, stones, mussels, annual algae, or one of two types of perennial algae.

4.2.3 U-Net-based watercourse segmentation system

The system for segmenting small watercourses (less than five-metre-wide ditches and streams) with CNNs was developed with the open-source machine learning framework PyTorch[9]. The CNN architecture was heavily based on U-Net, with double convolutions and skip-connections as in the original U-Net (see Ronneberger et al., 2015). Modifications were made to optimise the speed and quality of outputs, by testing alternative model architectures, depths, and hyperparameters. The modifications included: reducing the depth of the architecture, reducing the size of tiles, increasing padding size, and using oversized tiles, which were later cropped to reduce issues at the borders of the tiles. The reduced depth increased speed significantly without a notable decrease in f1-score. The testing of optimal architecture was not extensive because the architecture was not the focus of the study. The same architecture was used for all models. The system uses the cross-entropy loss function and the AdamOptimiser optimisation algorithm (Kingma & Ba, 2015). For a detailed description of the final architecture and other features of the system that were used to study the causes of false predictions in small watercourse segmentation, see Article III.

4.2.4 Input and label datasets for watercourse segmentation

In Article III, because of the insufficient quality of the existing watercourse datasets from Finland, a new training dataset was produced for the CNN model. The dataset

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[9] https://pytorch.org/

required significant manual digitising efforts and some automated pre-processing. First, a five-points-per-square-metre laser scanning point cloud was used to generate a 0.5 metre resolution DEM. The main reference dataset, a topographic position index raster layer, was then generated from the DEM. Other reference datasets included a hillshading layer and a flow accumulation layer that were derived from the DEM, as well as 0.25 metre resolution orthophotos. All datasets were provided by the National Land Survey of Finland. The reference datasets were used to detect and digitise the centrelines of all ditches and small streams less than five-metre-wide in a six-by-six square kilometre training data area. A key feature of the dataset was the clarity class attribute, a number ranging from 1 to 5 (with 1 being the clearest features, and 5 the most obscure), given to each watercourse feature (Figure 7). This attribute reflects how clearly the digitiser could see and determine the centreline of the feature from the reference datasets. The original purpose of the clarity class was to make it easier for the digitiser to determine which features would be included in the dataset, enabling unclear features to be filtered out later. However, the clarity classes later became central in assessing the causes of false predictions, as they enabled an analysis of the impact of including or omitting features of various clarity from the training set. The CNN watercourse segmentation system used two sources for input datasets, the earlier mentioned five-points-per-square-metre point cloud, and 0.25 metre resolution orthophotos from the National Land Survey of Finland.

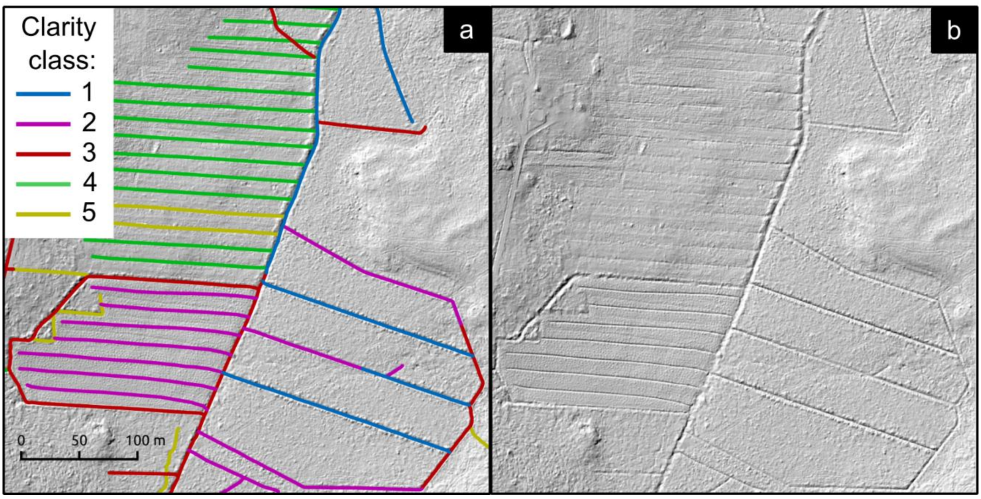

Figure 7. (a) The clarity classes of the digitised training dataset were central to analysing causes of false predictions in Article III. (b) The clarity classes were designed to capture the level of uncertainty in the background layers, as perceived by the digitiser. (Figure adapted from Article III)

4.3 Workflow definitions

A general workflow description for Baltic Explorer was defined in Article I. This structure is intended to clarify the rationale and purpose behind the different functionalities and features of the system. The workflow description consisted of three phases: 1) the pre-workflow phase, where workspaces are set up; 2) a workshop phase where the system is used; and 3) a post-workflow phase, where the results and data are reviewed, processed, and stored. In Article II, the analysis tool workflow was explained to users in two ways: 1) by demonstrating it before the interactive session; and 2) by designing the user interface so that the tool's use was presented as a stepwise process.

In Article IV, the questionnaire included a visual explanation that broadly described the steps of CNN-based feature extraction (see Figure 8) and the model's training workflows (following the same procedure for training presented in Article III). In addition, descriptions of manual, semi-automatic, and fully automatic production workflows were included. The purpose of these descriptions was to clarify what type of AI system the questionnaire concerned, and the intended use of the AI system. Furthermore, the feature extraction and model training examples provided a simplified explanation of the core concept of how CNN-based models are trained and used.

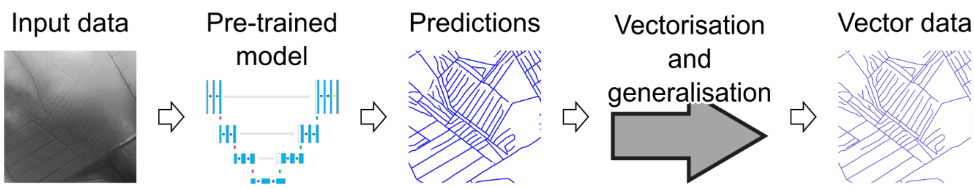

Figure 8. The core stages of an example process for the automatic extraction of geospatial vector features with CNNs. Input data, for example DEMs, are fed into a pre-trained CNN model that makes predictions of the locations of small watercourses. The predictions are then vectorised, generalised, and refined in a post-processing step, resulting in data that can be used to update TDBs. In a manual process, vector features are digitised directly from the input data, or its derivatives.

4.4 Research data collection and system assessments

The assessments in Articles I, II, and IV focused on stakeholder and user perceptions, while Article III assessed the CNN-based system, and its outputs based on quantitative and visual analyses. Each of Articles I, II, and IV focused on a different combination of perceptions (Table 4). Articles I and II focused on the perceived utility of Baltic Explorer and the integrated SMCA tool. Unlike Article I, Article II also focused on the users' operational and functional understanding of the SMCA tool and its ease of use. Article IV focused on stakeholders' trust, concerns, and perceptions of transparency and need of mechanistic and output understanding. Article III provided a technical foundation for Article IV and informed about challenges with output understanding of current AI-based geospatial data extraction solutions. Although the focus of these studies was on specific perceptions, in some cases they provided information about additional stakeholder perceptions, as well as observations about objective system and data properties.

Table 4. Perceptions covered by Articles I, II, and IV.

Perception:	*Article I*	*Article II*	*Article IV*
Utility	X	X	-
Understandability	-	X	X
Transparency	Not a major focus of assessment, but present in results	Not a major focus of assessment, but present in results	X
Usability	Not a major focus in the assessment, but present in results	Not a major focus in the assessment, but present in results	-
Trust	Minor focus	Minor focus	X

4.4.1 The Umeå workshop

The Umeå workshop (Article I) was a real-world MSP event organised by the Pan Baltic Scope project in March 2019 (Figure 9a). The workshop included planners, industry representatives, scientists, and experts from Finland (including the Åland Islands) and Sweden. Baltic Explorer was used in a planning session during the workshop, where the tasks were open-ended. During the session, participants discussed planning objectives, available data, and other issues. The participants were divided into two groups of roughly 15 participants each. Each group had a large, shared screen available (personal computer and projector), as well as various personal devices. The research data for the study in Article I were collected through naturalistic observations during the session and a short questionnaire (Appendix 1) available in English and Latvian about the utility of CGIS functionalities that was handed to participants after the session. The questionnaire received 16 valid responses. Based on their own assessment, respondents were relatively experienced in MSP (3.44/5) compared with SDSS (2.31/5).

The questionnaire was kept short and included a single main question about the utility of five tools implemented in or planned for Baltic Explorer: draw and edit; data overlay; a feature commenting tool; a voting tool; and a chatbox. Respondents evaluated whether they perceived each tool to be helpful for six tasks: 1) understanding the collaborative planning task; 2) "expressing interests of one's sector"; 3) "gaining insight into interests of other sectors"; 4) "promoting constructive discussion across sectors"; 5) "reaching decisions among collaborators"; and 6) "building trust among collaborators". The questionnaire also included an open-ended question allowing respondents to leave additional comments about the system, which aimed to provide additional insight into the stakeholders' perceptions of the system's utility and usability.

4.4.2 The Riga workshop

The Riga workshop (Article II) was a real-world MSP event that was organised by the Latvian Institute of Aquatic Ecology and the Latvian Ministry of Environmental Protection and Regional Development on the 20th of February 2020 (Figure 9b). The aim of the workshop was to engage stakeholders and inform them about the national MSP process in Latvia. The workshop was attended by 55 individuals representing 26 institutions. The workshop participants were high-level stakeholders, including regional planning authorities, representatives from Latvian ministries, the Latvian Nature Conservation Agency, and non-governmental organisations with a prior involvement with MSP in Latvia. The interactive session where Baltic Explorer and the integrated SMCA tool were used was attended by 24 people, who were divided into two groups. The participants were asked to "identify a new wind farm site in marine waters under the Latvian jurisdiction" using Baltic Explorer and its analysis tool. Research data on stakeholder perceptions and objective system properties were collected through naturalistic observations during the session and a questionnaire in English (Appendix 3) handed to the participants after the session. The questionnaire repeated the same item about the helpfulness of tools as in Article I, this time including the "overlay data on map", "draw and edit features", and the SMCA tools. In addition, it included questions about the operational and functional understanding of the tool, as well as the general utility and usability of the SMCA tool and of analysis tools in general for MSP. The questionnaire received 21 responses, some of which were partial. Eight respondents self-identified as sector representatives, three as planners, three as scientists, three as decision-makers, and seven as "other". Two participants had dual roles: scientist-planner and scientist-decision-maker. Observations about usefulness and usability of the CGIS were collected by four researchers, with two observing each group.

Figure 9. The interactive sessions of the Umeå and Riga MSP workshops had real-world stakeholders use Baltic Explorer to advance planning efforts and to assess the system's utility. (a) In the Umeå workshop, Baltic Explorer included its core functionalities. (b) In the Riga workshop a SMCA tool that was central to the planning task and had been integrated into Baltic Explorer. (Adapted and modified from Article II)

4.4.3 Hardware usefulness assessment

Although not often mentioned in research on stakeholder perceptions, the acceptance of software systems may be affected by the hardware platform on which they are used (Lin et al., 2014). Baltic Explorer was designed to adapt to different screen sizes and input methods (mouse and keyboard, and touchscreens), which would allow it to be used on various types of devices, such as large, shared touchscreens, and personal computers, and provide flexibility for its use. The controlled environment user test in Article I aimed to build an understanding of the role of two device types (computers with small displays for personal use and devices with large displays visible to all participants) in the use of Baltic Explorer. The participants were nine doctoral students and nine GIS professionals performing pre-defined, stepwise tasks in a gamified scenario, where they collaborated to find an optimal solution to the use of maritime space. Given the objectives and nature of the test, it was not viewed as necessary that the participants were real-world stakeholders. The participants were divided into six groups of three. Two groups were given both personal devices (one each) and a shared device, two groups only a shared device, and two groups only personal devices. The participants assumed the roles of MSP actors, each with different goals. Their goal was to present their interests, listen to the interests of others, and collaborate in finding a compromise that minimised conflicts of interest and led to the most optimised use of maritime areas. After the test, the participants replied to a questionnaire about their perceptions of the utility of the available hardware devices for the various tasks performed during the test (Appendix 2). All 18 participants responded to the questionnaire.

4.4.4 Artificial intelligence questionnaire

In Article IV, a semi-structured questionnaire with 14 questions (Appendix 4), was sent in April and May of 2024 to 326 e-mail addresses of employees who were believed to work with TDB data in governmental institutions and municipalities in Finland. The questionnaire aimed to collect data users' perceptions of the use of AI, especially DL, in the production of TDB data. It was conducted with Google Forms with a link provided in the e-mail. The questionnaire received 59 valid responses. Most respondents were proficient in both digital and spatial tools, while skills in using AI varied, and most respondents had no skills in developing AI solutions. All respondents were familiar with TDB data to some degree and thus belonged to the study's intended target group. A set of different bar plots was used to visualise the results of the questionnaire. In addition, Spearman rank correlation was calculated for pairs of questions with the SciPy Python library[10] to provide additional insights into related perceptions.

4.4.5 Assessment of watercourse segmentation and false predictions

Article III used quantitative and qualitative assessments to explore and identify the causes of false predictions in the outputs of a CNN trained to detect small watercourses from remote sensing data (see section 4.2.3 and 4.2.4). Throughout Article III, recall, precision, and F1-score were used for validating output quality quantitatively. In addition, relaxed recall and precision, where false predictions are considered true if they are within one metre of a true prediction, were calculated for several output layers. Five-fold k-fold cross-validation was used to provide an additional insight into the results, such as the variation in results between different areas. Ten different input data layers were used in training models, after which the best-performing layer was combined with other layers to determine if adding additional data improved the results. In this test, the labelled data, which included features from all five clarity classes, were used. However, additional models were trained that only included features from clarity classes one to three and one to four. The results from various models were compared to quantitatively assess the impact of individual clarity classes on recall, and variation in results when omitting obscure features from the training data. Visual analysis was used to determine the types of watercourse features that were commonly causing false predictions.

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[10] https://scipy.org/

5 Results and discussion

In this chapter, I summarise the results of this thesis and discuss their significance for designing, developing, and adopting collaborative geographic information systems and artificial intelligence technologies in the digitalisation and automation of geospatial workflows. I also discuss the challenges and limitations of the research, provide recommendations for developing useful and acceptable systems, and suggest directions for future research.

5.1 Stakeholders' general perceptions of the technological transition

Overall, stakeholders perceived the introduction of CGIS and AI-based technologies into existing analogue and manual workflows as useful and trustworthy, although these perceptions were conditional.

The results of Articles I and II demonstrated that the set of functionalities and other features implemented in the Baltic Explorer CGIS prototype were generally perceived as helpful by the participants in the MSP workshops. These results were supported by observations during the real-world workshops, which confirmed that MSP stakeholders could use the tools to advance discussions and planning tasks. Furthermore, following the Umeå and Riga workshops, Baltic Explorer has been used in another MSP stakeholder workshop, at which participants expressed a preference for the system's overlay tool for map visualisations, compared with paper maps (Bonnevie et al., 2023). However, stakeholders also perceived the Baltic Explorer prototype as having several weaknesses that should be addressed when designing and developing similar systems. For example, metadata were absent from the overlay data, which created issues with trust in the data's timeliness. Furthermore, some stakeholders did not fully understand how to use the SMCA tool or what it does.

Results of Article IV further showed that Finnish TDB users trusted AI-based automation of data production workflows. However, this trust is conditional, requiring manual assessment of outputs, and the data users had various concerns related to the use of AI. The concerns addressed in the questionnaire, which were related to degradation of data quality, security and privacy issues, understandability issues, malicious attacks against models, and models being misused, were all extremely concerning to at least some respondents. In addition, respondents highlighted additional concerns when answering an open-ended question. These included degradation of professional competence, changes in the nature of data, and job losses. Issues with data quality, including systematic errors, were one of the most prevalent concerns for most respondents. Respondents also questioned whether it was really necessary to accelerate data production. These concerns align with previously identified risks and concerns associated with the use of AI (see Paolanti et al., 2024; Rane et al., 2024; Xu et al., 2023).

5.2 Utility

The studies in Articles I and II were concerned with the utility of CGIS properties, including MSP stakeholders' perceptions of the utility of functionalities, the utility of alternative hardware platforms, and the utility of SMCA tool that was integrated into Baltic Explorer. The results also included some observations and stakeholder perceptions about the ease of use of the tools.

5.2.1 Utility challenges of geospatial systems in collaborative settings

The results of the problem explication phase in Article I showed that one barrier to adopting existing tools in real-world MSP efforts is their limited flexibility, which prevents them from adapting to different use cases. This issue is particularly apparent in model-based SDSS, which are often designed for a specific problem, with pre-defined methods and, in many cases, fixed source data, geographic areas, and scales (Pınarbaşı et al., 2017; Ramsey, 2009; Stelzenmüller et al., 2013). These tools implicitly assume that stakeholders have already agreed on the problem definition, methods, and data, which is not necessarily the case (Ramsey, 2009). Spatial decision problems are often ill-defined (Andrienko et al., 2007), which makes it difficult to specify tasks in MSP workshops. Nevertheless, some helpful functionalities have been previously identified for similar use cases, including tools that enable the collection of local knowledge (Alexander et al., 2012); efficient data access, integration, and management tools, as well as tools that support the outcomes of collaboration (Sun & Li, 2016); tools for exploring planning problems (Ramsey, 2009); tools for commenting on map features (Keßler et al., 2005); and interactive visualisations (Andrienko et al., 2007; Rose et al., 2016).

5.2.2 Perceived utility of collaborative GIS functionalities

The results from the questionnaires in Articles I and II showed that the main tools in Baltic Explorer, the "draw and edit features" and "overlay data on map", were perceived as helpful for several different tasks. Observations during the workshops further identified scenarios where the tools proved useful. Responses to the Umeå workshop questionnaire in Article I showed that the data overlay tool, which enables access to geospatial datasets from multiple providers and to overlay them all together on a map, was perceived as helpful by the greatest number of respondents for four out of six tasks. This highlighted the importance of the tool for the overall utility of Baltic Explorer in the workshop. However, in the Riga workshop in Article II, on average, the "draw and edit features" tool was perceived as helpful by more respondents than the "overlay data on map" tool. A possible explanation for the variation in the perception of tool helpfulness is the limited number of respondents and the context-sensitivity of tool utility. The tasks between the workshops varied. Whereas in the Umeå workshop, the task was open-ended without clear goals, in the Riga workshop, the task was linear and clearly defined for the participants, and it included the use of the integrated SMCA tool, which was not available in the Umeå workshop. The results of Article II show that compared with the overlay tool, more participants felt that the "draw and edit features" tool complemented the analysis tool, which implies that the feature drawing and editing tool fit the purpose of the workshop task better than the overlay tool. However, observations showed that the "overlay data on map" tool was shown to increase flexibility to the problem solution, as in the Riga workshop, one subgroup of stakeholders used the overlay tool as the primary tool for solving the planning task, with the analysis tool only functioning as a means for validating the planning results.

The results of Articles I and II further demonstrated how the perceived utility of Baltic Explorer is directly connected with the geospatial data that is accessed from and visualised within the system. Furthermore, as the data were mostly provided by third-party organisations, the results demonstrated how the perceived utility of a system could be influenced by the availability and quality of external services. The reliance on third-party data poses a risk, as changes in the services of the third-party data providers can reduce utility. This risk is to some degree mitigated in Baltic Explorer, as it is not tied to any single data provider.

Based on the results of Article I, communication aids such as a "chatbox", and especially a "voting tool", were not generally perceived as helpful by MSP stakeholders. It is noteworthy that these tools were not implemented in the system, and despite them being somewhat generic, assessing their usefulness may have been more challenging for participants. In the controlled environment user test in Article I, one participant suggested adding communication tools to the system, but there were no requests for such tools in the open-response section of the questionnaires in the real-world workshops. Only a single non-planner in the Umeå workshop perceived a "voting tool" as helpful for a single task, and the "chatbox" was also perceived as significantly less helpful on average than the remaining tools.

The results further indicated that the roles of actors are a moderating factor in the perceived utility of CGIS functionalities. In Article I, except for the "overlay data on map" tool, a greater percentage of planners found functionalities in CGIS to be on average helpful, compared with non-planners. The difference was particularly large for a "chatbox" and a "voting tool". The reasons for the results were not investigated in the study, leaving them open to speculation. With many actors in MSP having different goals, tools could be more useful for certain types of actors. For example, a planner might view voting as a method of obtaining tangible evidence to support their plans. However, a decision-maker might not wish to risk voting on matters on which they have the power to decide on their own. Meanwhile sector representatives might see voting in the presence of competing sectors as an unfavourable method for advancing their interests.

5.2.3 Utility of spatial analysis in collaborative decision-making

The results in Article II showed that spatial analysis tools in general were perceived as useful in MSP workshops by 16 out of 21 respondents, while the remaining five respondents were undecided. However, only eight respondents agreed that the SMCA tool introduced in the workshop had the required functionalities for solving the workshop task, and six agreed that it was appropriate for the task. This highlights a known limitation of SDSS, that pre-defined methods and data may be problematic in collaborative settings, as previously argued by Ramsey (2009). Nevertheless, the results of Article II further showed that many respondents considered the analysis tool to be helpful for various tasks in MSP workshops, although it was considered helpful by fewer respondents for expressing interests of their sector and gaining insight into interests of other sectors, compared to both the "draw and edit features" and "overlay data on map" tools. The results also indicated that stakeholders perceived the integration of the SMCA tool with Baltic Explorer beneficial, as the drawing and editing and data overlay tools were considered to work well together with the SMCA tool. The research in Article II further showed that there was a consensus among workshop participants that in general SDSS results are useful in MSP workshops. This result supports the notion proposed by several researchers that computational and analytical methods are important in supporting collaborative planning (e.g. Rassweiler et al., 2014; Ruiz-Frau et al., 2015).

5.2.4 Missing features of Baltic Explorer

The observations in the Umeå and Riga workshops highlighted the absence of some potentially useful functionalities, and that existing functionalities might not be known or understood by stakeholders during the workshop. Participants in the

Umeå workshop specifically noted the lack of metadata in the system, which caused issues such as uncertainty about the data’s timeliness. Time of creation has been identified as a critical factor in the trustworthiness of geospatial data (Fogliaroni et al., 2018; Tessarolo et al., 2017). Therefore, the results highlighted the importance of metadata for users’ trust in system content (see Lush et al., 2018). Although it would have been technically possible to make metadata visible to users within the system, no methods were implemented in Baltic Explorer for automatically retrieving the metadata. However, even if such methods were available, in practice, metadata records are often incomplete (Lush et al., 2018), which raises questions about accountability. The developer must provide functionalities that enable metadata, while the data provider needs to make the metadata retrievable.

Another type of missing functionality was revealed in one instance during the Umeå workshop, when users were interested in visualising the sizes of wind turbines and assessing from how far the turbines would be visible. However, they found no functionalities in Baltic Explorer to support such an assessment. Such a line-of-sight tool has potential to see some use in the specific case of MSP, where the view of offshore constructions and ships can be critical for assessing their impact on the recreational use of coastal areas, for example. At sea, the view can be blocked by both obstacles above sea level and the curvature of the Earth.

5.2.5 Utility of hardware platforms

The results from the problem explication phase in Article I highlighted the potential impact of hardware options on the utility of CGIS in workshop settings. The controlled environment test further showed that users perceived the suitability of a personal device for presenting their interests, and a shared device for preparing to present their interests, to be higher when the alternative device was unavailable. In addition, the results showed that the overall preference for devices varied between GIS professionals and doctoral students for two out of four tasks, with students preferring personal devices, and GIS professionals preferring shared devices for the tasks. Observations from the Umeå and Riga workshops provided further insight into the usefulness of different hardware devices. Poor usability led to users abandoning the use of mobile phones and tablets in the Umeå workshop. In the Riga workshop, one group used the Baltic Explorer only through a large touchscreen display, while the other group split into three subgroups, with two subgroups using only their personal devices. The third subgroup used a large touchscreen display. The results from the controlled environment user test further showed that users were relatively satisfied with the shared device in the three-person groups where it was the only device available, showing that in small groups, the use of large, shared screens or personal computers on their own can be effective. These results highlighted the benefits of implementing Baltic Explorer as a web application, as it requires no installation, provides flexibility in hardware choice, and enables simultaneous access to shared workspaces from virtually any number of devices, addressing some known weaknesses of designing CGIS for use on devices such as touch tables (see Arciniegas & Janssen, 2012).

5.2.6 Usability and its impact on utility

Articles I and II highlighted how usability, despite not being the primary focus of the studies, could not be ignored when considering the utility of CGIS. The results of the problem explication phase in Article I revealed that the limited technical skills and lack of experience with GIS among typical participants in an MSP workshop mean that usability and simplicity are key system quality attributes of CGIS in such settings (as pointed out by Arciniegas & Janssen, 2012, and Pınarbaşı et al., 2017). Therefore, these factors had to be accounted for in the design and implementation of Baltic Explorer. During the Umeå workshop, some usability issues were observed that might have affected final outcomes. For example, usability issues prevented the system's use with mobile phones and tablets. Workshop participants also perceived that the overlay data menu and search functionalities needed improvements to make finding datasets easier. These issues could have directly impacted how users performed different tasks and the functionalities they could access. For example, overlay datasets that were perceived as critical for advancing discussions are not helpful if users do not know that they can be accessed through the system, or if they are unable to find them. More than half of the participants in the Riga workshop were either undecided or disagreed that the SMCA tool was easy to use.

5.3 Trust

Article IV focused on stakeholders' perceptions of trust in the use of AI to automate the production of data for TDBs. Some additional perceptions of trust in workflows involving the use of CGIS were also explored in Articles I and II.

5.3.1 Trust in AI-based automation to produce high quality outputs

Article IV's results suggested that TDB users in Finland view data quality issues as the most prevalent concern with AI-based data production. Furthermore, the results of the questionnaire showed that most users distrusted the output data quality of fully automated AI-based data production workflows. Most respondents also perceived manual quality assessment as a significant factor influencing their trust in the produced data. The semi-automatic workflow with a manual data quality assessment phase was trusted to a similar degree as production processes based on manual digitising. This aligns with the general view that human oversight of AI increases trust in it (Holzinger et al., 2025; Laux, 2024). However, Laux (2024) also points out that human oversight can also give a false sense of accuracy and security in AI systems as humans may lack competence and may have harmful incentives. The results of Article IV further showed that data users viewed quality metrics provided by the data producer as more impactful on their trust than their own assessments. This also indicates that the data users had a high level of trust in the producer and their workflows. The results also showed that users with a better mechanistic understanding (i.e. how CNN-based systems produce the data) had more trust in both fully and semi-automated AI-based workflows to produce high-quality data.

The results of Article III demonstrated that in CNN-based geospatial data production, there are multiple probable causes for false predictions, that make validation of spatial data quality based on interpretation of machine learning metrics alone challenging. In Article IV, respondents raised concerns about issues in input and labelled data that are used in development and operation of AI models for TDB data production. The results of Article III provide evidence that these concerns are valid, as issues in both input and labelled datasets were common in the context of watercourse segmentation. A likely contributing factor to false negative predictions, which resulted in gaps in watercourse sections, was small areas in the point cloud with low point density, which affected the quality of the input DEM. Furthermore, the visual analysis showed that many false predictions were likely caused by human errors in the digitising of the training dataset. This highlighted how human factors can continue to impact the quality of outputs in CNN-based automation of TDB data production.

5.3.2 Concerns beyond data quality

Article IV's results showed that TDB data users in Finland had several concerns about transitioning to AI-based automation of TDB data production, extending beyond data quality. Malicious attacks on models, the use of models to generate falsified information, security issues, and privacy issues were perceived as extreme concerns by more data users than reduced data quality and understandability of production methods. However, the same issues were also of no concern to more users than data quality-related issues. The results also provided some indication that more experienced AI users were less concerned with non-data-related concerns, except for mechanistic understandability of AI models.

Although the explanatory factors for these results were not studied in more detail in this thesis, the spread in the level of concern could reflect a poor risk understanding. The types of risks present will ultimately depend on contextual information that was missing from the questionnaire, such as how these systems are implemented and managed. For example, malicious attacks and the misuse of the model may be related to how much transparency is offered and whether the models are open for public use. As Afroog et al. (2024) point out, too much transparency can make the system more vulnerable to malicious attacks. However, unlike many well-known AI applications, such as chat-bots, AI systems that produce data for TDBs are likely to be used internally by NMAs, and therefore, such attacks would have to originate from within the organisation. Nevertheless, opening the models for public use could enable their misuse by external individuals and organisations.

Privacy and sensitive data-related issues could arise at various stages of data collection and processing. If sensitive data were not replaced before manual digitising, the digitiser could identify such features and choose not to digitise them. However, in an automated solution, such features would have to be recognised by the system, or the data could be assessed after extraction. Both approaches could be riskier, as features could be missed. Furthermore, there is a concern that models are trained with sensitive data, which could pose a risk for privacy and security (Kang et al., 2024).

Article IV's results revealed that stakeholders also had concerns about the nature of the data changing when automating TDB data production with AI. This concern is valid, as it is unlikely that the decision-making of AI-solutions perfectly match that of human digitisers. However, different AI-solutions could produce data with different characteristics, and the nature of manually digitised TDB datasets also varies between countries, and sometimes between digitisers. Some respondents also expressed concerns about job loss, and the loss of professional competence in the data producing organisations, should TDB data production be automated. The results further showed that data users had concerns about the maintenance of AI models and the systems breaking down or malfunctioning. It was noted that AI models might degrade with time and therefore need updating. Similarly, in Article I's problem explication phase, maintenance, licensing, and costs were also identified as challenges with adopting tools in real-world MSP.

5.3.3 Factors affecting trust in artificial intelligence

The factors that most affected data users' trust in AI-based TDB data production were the data producer's reputation and trustworthiness, quality measurements provided by the data producer, and openness about production methods. This further demonstrates the importance of data quality and transparency but also shows that the data producer's characteristics matter. In particular, the producer being a public organisation, having a reputation as a known geospatial data producer, and sharing information about data production methods were perceived as increasing trust in data quality. The data producer being a private organisation or person was perceived to reduce trust for most respondents. However, the public sector might have been viewed more positively, as the respondents were TDB users working in the public sector, either in Finnish government institutions or municipalities. Nevertheless, the results suggested that stakeholders prefer TDB data production to remain within NMAs.

5.3.4 Collaborative geographic information systems and trust

Although Articles I and II did not explicitly aim to study stakeholder trust, the results indicated that trust in the system's data could be a factor in the perceived utility of a CGIS, and that some functionalities could support trust-relations between collaborators. Although not explicitly stated to the Umeå workshop participants, most of the data for the "overlay data on map" tool was provided by third-party sources (the provider of the data was indicated in the data selection menu). The high perceived utility of the tool in the workshop therefore implies that users trusted such data sufficiently to consider the tool and its data useful, at least conditionally, as stakeholders requested metadata to be accessible from the system. This aligns with previous research that has highlighted the importance of metadata for trust in geospatial data (see Prestby, 2025; Skarlatidou et al., 2011, 2013).

Article I's results further showed that there was a relatively large difference between respondents' perception of the utility of the data overlay tool and the drawing and editing tool for two tasks, "gaining insight into interests of other sectors" (81.3% compared with 31.3%) and "building trust among collaborators" (62.5% compared with 25%). This might imply that the stakeholders perceived third-party data as more trustworthy than data drawn by others within the workshop setting. However, similar results were not observed in the Riga workshop questionnaire in Article II. Perhaps surprisingly, the highest number of respondents perceived the SMCA tool as building trust among collaborators.

5.4 Transparency and understandability

The results of Articles I and II showed that when Baltic Explorer and the SMCA tool were introduced as new technologies in geospatial workflows, their complexity challenged stakeholders' operational and functional understanding of the systems. The results of Articles III and IV demonstrated the challenges related to mechanistic and output understanding of AI systems, and stakeholder perceptions of transparency in CNN-based production of TDB data.

5.4.1 Understanding of tools in collaborative geographic information systems

The results of the problem explication phase in Article I showed that one of the main barriers to the use of existing SDSS and GIS in participatory MSP is that they are designed as expert systems. Many MSP stakeholders are novice GIS users, making these existing systems complex for them to use and understand. Previous research has identified complexity as a key factor in rejection of IT systems (Rama Murthy & Mani, 2013). CGIS must therefore be designed to be simple and easy to use, as was one of the core principles of the Baltic Explorer's design.

The results of Article II showed that it was challenging for some stakeholders to understand the SMCA tool. Despite the demonstration and the step-by-step tooltips in the interface that aimed to increase workshop participants' operational, functional, and mechanistic understanding of the tool, several respondents that took part in the interactive session in Riga did not understand how to use it, and two respondents did not understand what it did. Therefore, while transparency was provided through tooltips, demonstration, and user guidance, the transparency did not translate to comprehension for all users. This shows that it can be difficult for MSP stakeholders to grasp even relatively straightforward spatial analysis, when there is limited time available to demonstrate and use such tools. A lack of comprehension can therefore become a barrier for providing equal opportunities for stakeholders to influence plans, risking that those with more expertise in GIS and analysis have an advantage in advancing their goals.

Issues were also observed with MSP stakeholders' understanding of some of Baltic Explorer's more discrete functionalities and features. In the Umeå workshop, some users did not understand how to zoom in and out on the map. In the Riga workshop, it was observed that some users struggled with understanding Baltic Explorer's workspace feature. One group split into three subgroups, which created issues when changes were made in the workspace by one subgroup that affected the view of all subgroups. Although the issue with the system could have been solved by creating additional copies of the workspace, the participants were probably unaware of such an option, and the limited experience with the system also meant that they were probably unable to foresee the software-related issues arising from splitting the main group.

Education is frequently raised as a solution for overcoming issues with usability and understandability (e.g. Ramsey, 2009). However, for CGIS used in stakeholder decision-making workshops, except for brief explanations, stakeholders cannot be expected to invest the time and effort required to learn to use and understand the systems. Despite these challenges, the stakeholders viewed analysis tools as useful for MSP workshops. These results highlight the challenge of designing systems that are both useful and usable, also known as the usability-utility trade-off (Roth et al., 2015).

5.4.2 Transparency and understanding of deep learning systems

Article IV's results demonstrated that transparency is a key factor in trust in the quality of data produced by AI-based geospatial feature extraction. The results showed that TDB data users want to understand models' decision-making logic, in addition to other details about the AI systems used in geospatial data production. Nevertheless, most respondents considered the accuracy of models to be more important than their understandability. Furthermore, data users' ranking of concerns showed that more than a third of respondents perceived understanding models' decision-making reasoning as the smallest concern, the highest number for any concern. Along with privacy issues, the concern was also the one with the least number of respondents who were moderately or more concerned about it. The results therefore suggested that most respondents might not be too concerned about lack of mechanistic understanding of models producing TDB data, despite wanting to understand how the systems work. However, given how important transparency was perceived for trust, the results suggest that transparency alone without comprehension can increase trust in AI systems.

In practice, building understanding of AI decision-making is challenging. The results of Article III also demonstrated how outputs of CNN models for geospatial data extraction can be challenging to understand, interpret, and analyse. The results of Article III showed that false predictions in segmentation of small watercourses with CNNs were caused by various types of errors, with the two most prevalent being centreline offset between labelled and predicted watercourses, and errors in unclear features (Figure 10). Other causes for false predictions that were identified included voids in the point cloud, errors in the labelled data, and underrepresentation of feature types in the training data.

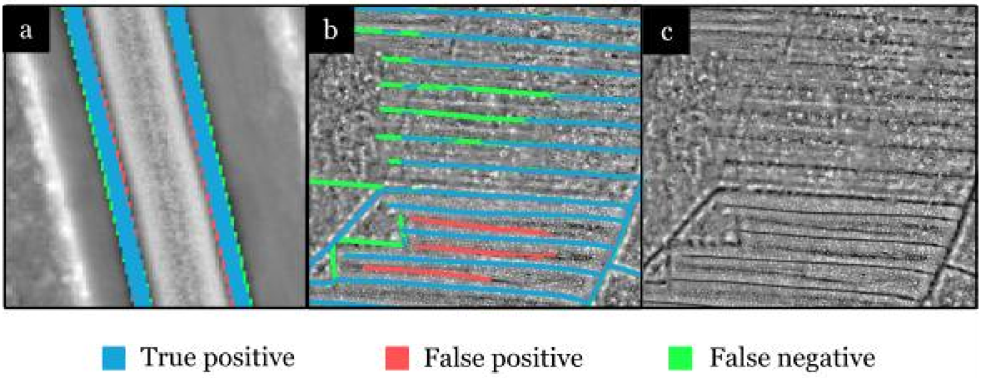

Figure 10. Typical machine learning metrics (F1-score, recall, precision) do not differentiate between various types of spatial data quality issues. (a) Article III demonstrated that in CNN-based watercourse segmentation, labels and predictions are unlikely to align perfectly, which causes false predictions on both sides of watercourse features. (b, c) On the other hand, unclear source data often results in omission or commission of full or partial features. From a spatial data quality perspective, the former issue reduces positional accuracy, while the latter affects completeness.

The F1-score is commonly used as a proxy measure for reporting the quality of outputs. It is also often used in training feature extraction models to determine the best model based on intermediate validation. Although it may be suitable in some use cases or as a universal metric for the validation and comparison of CNN outputs, its indication of quality depends on context, and it has significant weaknesses in geospatial feature extraction. These weaknesses were highlighted in the results of Article III. Although the purpose of the output data was not explicitly defined in Article III, watercourse datasets in TDBs have many use cases where the connectivity of the network is critical in modelling waterflow, for example. Other use cases require the best possible coverage of features, when mapping watercourses for the restoration of wetlands to their natural state, for example. The F1-score is the harmonic mean of recall and precision, which are often reported alongside the F1-score in CNN output assessments. Like the F1-score, they are used as global pixel-level metrics of omission and commission, rather than feature-level metrics. Article III's results demonstrated that in watercourse segmentation with DL, some false predictions contributed to errors that would slightly reduce positional accuracy of extracted vector features, rather than feature omission or commission. Such errors represented a significant portion of all false predictions. Recall and precision could potentially give insight into data quality. A higher recall would probably be correlated with fewer gaps in watercourse features, for example. However, there is limited research on the relationships between machine learning metrics and spatial data quality metrics.

Article III's results further showed that there were many uncertainties related to input data, labelled data, and the CNN approach that could cause false predictions. These uncertainties make interpretation of outputs even more complex. Based on visual analysis, a probable cause of some missing watercourse sections was poor local point density in the source point cloud data. Further visual analysis showed that many false positive predictions were also caused by features being missed by the digitiser when producing the training data. Furthermore, false negative predictions strongly correlated with the clarity score of watercourses, showing that uncertainties perceived by the digitiser also caused uncertainty in the predictions. Interestingly, however, the input dataset leading to the best results (based on the F1-score) was the DEM on its own, from which it was significantly harder to identify watercourses for the human eye compared with other layers like the topographic position index. Digitising natural features such as watercourses with fuzzy borders and varying depth and width requires significant interpretation and decisions about what counts as a watercourse. Although the training dataset was produced for the specific use case presented in Article III, and the digitising precision greatly exceeded that of typical TDB watercourse digitising at the National Land Survey of Finland, errors in the training dataset were not avoided. It is therefore possible that a significant portion of false predictions were in fact issues with the labelled data, where they should be labelled as watercourses. However, the extent of this issue cannot be easily verified, as the training data used for labels is the most accurate dataset available. These issues further challenge the interpretation of F1-scores, recall, and precision in geospatial feature extraction.

5.4.3 Accountability for understanding the technologies

Although the results of this thesis highlighted issues with stakeholders' understanding of CGIS tools, spatial analysis, and DL methods for geospatial data production, the solutions for overcoming these issues remain largely unknown. These issues also raise the question of who is accountable for stakeholders' understanding. Article IV's results suggested that much of the information that supports the understanding of the methods and data are expected from the data producer, including method descriptions, quality assessments, and explanations about the decision-making logic of DL models. Although system developers and data producers can provide the means and support for stakeholders' understanding without any commitment from stakeholders to learn, these means may be insufficient. Nevertheless, given that, more than half of TDB data users responding to the questionnaire in Article IV perceived that they needed to understand the AI methods used in data production, they might be motivated and willing to invest time in doing so.

5.5 Link between perceptions of geospatial systems and data

The results of Articles I and II demonstrated that the usefulness of the data provided through Baltic Explorer was related to its perceived utility (see Section 5.2.2). Although the connection between the utility of the geospatial data production system and its data was evident, the results of Article IV showed that for most respondents, the quality of the output data alone was insufficient to determine acceptance. Many risks associated with using AI in the production of geospatial data, beyond data quality issues, were perceived as concerning by the data users, even though in such cases there is no direct interaction between the user and the system.

Together, these results reflect the connection between geospatial systems and data, and how the perceived properties of one can affect the acceptance of the other. The most prominent models of IT acceptance do not explicitly recognise perceptions of data-related factors, such as data quality, security, and privacy (Davis, 1989; Venkatesh et al., 2003). However, some models such as the Information Systems Success Model (DeLone & McLean, 1992) explicitly include data quality as a construct. Other data-related factors, such as data security and privacy, are generally not addressed in these foundational models. It may be valuable to extend acceptance models for geospatial systems to explicitly include data-related factors.

5.6 Challenges with determining true performance and trustworthiness

It can be valuable to understand the true trustworthiness and properties of systems because it enables the validation of whether trust in the systems' abilities is warranted. However, such assessments can be challenging for CGIS and CNN-based geospatial feature extraction systems.

The requirements, and design and development phases in Article I highlighted the challenges of determining the purpose, specific capabilities, and other properties of CGIS. Therefore, measuring the system quality by means other than stakeholder perceptions is challenging, although some insight into the objective quality of Baltic Explorer and the SMCA tool was provided by the results of Articles I and II. Frank et al. (2004) argue that a decision-support system's utility is based on whether it leads to better decision-making outcomes. While this sets a clear goal for such systems, it could be challenging to objectively determine the impact of the system's features on decision-making outcomes and to separate them from other factors. As the results of Article I demonstrated, perceived utility also depends on the user's role, for example. Similarly, stakeholders may view the objective of using CGIS differently depending on their role.

As discussed in Article III, typical machine learning metrics poorly explain the quality of data in terms of spatial data quality metrics. Developers of AI-based geospatial data production methods should therefore aim to also develop methods for assessing the results based on metrics that are relevant in a geospatial context. Furthermore, integrating these data quality metrics into AI-based methods, for example, by accounting for them in loss functions, could improve the quality of the datasets produced. The fitness for use of geospatial data requires an assessment of not only their quality and suitability for use cases, but also their trustworthiness (Lush et al., 2018). Assessments of AI-based geospatial data production should therefore also include assessing issues such as security and privacy. Together, these measures would lead to a more comprehensive understanding of the quality and trustworthiness of AI-based geospatial data production.

5.7 Synthesis of results in relation to research questions

5.7.1 Research question 1

The findings of this thesis indicate that stakeholders generally perceive the introduction of digital CGIS features into MSP planning positively, while the use of AI in automation of topographic data production is perceived cautiously. However, in both cases, acceptance of these systems is conditional.

CGIS was perceived as particularly valuable for enabling easy access to large volumes of geospatial data and supporting collaboration through methods that are only possible through digitalisation. Therefore, the results suggest that MSP stakeholders recognise clear benefits in digitalisation of geospatial workflows in the MSP context. The availability of metadata was important for the perceived utility of tools that relied on external data sources. Spatial analysis tools and their outputs were in general perceived as useful for MSP, although the SMCA tool integrated with Baltic Explorer did not receive the same level of support. Some stakeholders experienced difficulties understanding some Baltic Explorer features, as well as how to use the SMCA tool and interpret its outputs, which may have limited their ability to evaluate the tool's utility and trustworthiness.

Data users trusted the output quality of AI-based automation of TDB data production to a similar degree as in workflows with manual digitising, if data quality assessment remained manual. This shows that AI and at least some automation of the production workflow can be trusted in terms of data quality. However, other concerns about the use of AI expressed by TDB data users related to transparency, security, privacy, and institutional characteristics of the producer, indicate additional conditions for trust in AI and automation.

5.7.2 Research question 2

The studies identified several system design features and quality attributes that can support stakeholders' perceptions of utility, trust, and understanding of both CGIS and AI-based geospatial data production workflows. The results from Articles I and II indicated that the utility of Baltic Explorer in MSP workshops was influenced primarily by system flexibility, data access functionality, usability, and contextual factors. The "overlay data on map" and "draw and edit features" tools were consistently perceived as useful for various workshop tasks. Furthermore, the utility of the SMCA tool was perceived to be supported by the data overlay and feature drawing and editing tools, which are simple and flexible tools that support problem exploration and alternative problem-solving methods. Because third-party data availability strongly influenced perception of utility, metadata availability also became important for establishing confidence in the data quality, provenance, and timeliness. In addition, usability and understandability, as well as locational and temporal modes of operation, influenced stakeholders' perception of tools. Roles of actors in the MSP process further moderated utility perceptions. Finally, utility perceptions were context-dependent, influenced by workshop design, actor roles, and hardware. These findings indicate that utility of CGIS emerges from the interaction between users, tasks, and technological environments.

The results suggest that TDB users' trust in AI-based data production is influenced by the level of human oversight in data quality validation, data quality, provenance reporting, transparency, and institutional reputation of the producer. Key factors influencing data users' trust include users' understanding of model behaviour, experience with AI solutions, experience with spatial tools, producer characteristics, as well as use cases for the produced data. The results also demonstrate that although data quality is a major factor in building trust for AI-based data production, security, privacy and ethical factors are also relevant for data users' trust perceptions. In addition to system design features and data-related attributes, the results further indicate that trust and acceptance are also influenced by institutional factors. These include the perceived reliability of the data producer, transparency of organisational processes, and the availability of documentation and explanations of methods. The results also suggest that stakeholders prefer data providers to take responsibility for communicating how systems and AI-based methods function, including limitations and uncertainties.

The findings further suggest that stakeholders' perceptions of geospatial systems are closely linked to their perceptions of the data used or produced by those systems. Data quality, provenance, timeliness, security, and privacy influence not only trust in the data itself, but also perceptions of the systems responsible for producing or managing it. In both cases, data and transparency in regard to their quality and provenance are key factors to enable trust in the data.

5.7.3 Research question 3

Outcomes from automated geospatial workflows may not be perceived as useful or trustworthy by stakeholders if they do not agree on the problem-solving method, problem definition, the level of automation, or data.

Poor CGIS user interface design that fails to inform users of relevant functionalities can lead to unintended behaviour of the system that is making the system difficult to use, disrupting and prolonging work, thus reducing the usefulness and ease of use of the system. Stakeholders have various concerns about risks of using AI that extend beyond quality into security, privacy, misuse, competence loss, organisational dependence, malicious attacks, model degradation, and maintenance burdens. Limited understanding of these risks may hinder adoption of AI-based geospatial data production systems.

Geospatial systems and data are connected, and issues with one may influence the rejection of the other. Stakeholders may reject data, including systems relying on the data, if the data is inadequately documented or missing important metadata such as date-of-creation. Although human in the loop is a pre-requisite for trust in AI-based automation of geospatial data production, human oversight may also lead to unwarranted trust. Transparency of methods can increase trust in AI-based TDB data production, but mechanistic, risk, and output understanding of such systems may be challenging to achieve. Classical machine learning metrics relate to multiple spatial data quality issues simultaneously, making meaningful interpretations of data quality based on them difficult. Furthermore, AI-based geospatial feature extraction methods rely on input data, labelled training data, and complex DL models that each have many uncertainties.

5.8 Limitations and challenges of research

The research in this thesis has some limitations, and many challenges were faced when conducting the studies. Stakeholder perceptions are highly context-sensitive, and how the results of this thesis apply to other technologies, geographic areas, groups of stakeholders, and other moderating factors is unclear. Even in the context of CGIS for MSP and AI in TDB data production, specific factors such as workshop tasks and use cases for TDB data, which were not defined in detail in this research, may affect the results' relevance. Use cases for TDB data also influence which spatial data quality metrics are most relevant. Respondents may have answered the questionnaire based on use cases that they frequently encountered, which was not considered when analysing the results of the questionnaires. The studies were also limited by the technological maturity of the developed systems. The studies were conducted with prototype systems that suffered from usability and stability issues. These issues highlighted the challenge of developing prototype software with sufficient usability to conduct studies with, and whether utility and usability should be studied separately. Furthermore, in Article IV, the respondents were unlikely to have prior experience of TDB data produced using AI-based feature extraction, as such data had not been produced for the TDB of the National Land Survey of Finland. Their understanding of the quality of AI-produced TDB data was therefore limited. Finally, the questionnaire in Article I was administered in English, while in Article II participants could choose between English and Latvian. English was likely not the mother tongue of most respondents. Therefore, misunderstandings due to language may have occurred and may have contributed to some participants not responding to the questionnaires in the Riga and Umeå workshops.

Another limitation of the studies was the small sample sizes. The results of Articles I and II are based on observations and questionnaires from a single real-world event each, where the questionnaires received a limited number of responses. This may have caused, for example, the variation between the results in Articles I and II concerning the perceived utility of Baltic Explorer's tools. As previous studies of these topics are limited, especially studies involving user tests with real-world stakeholders, the existing literature cannot provide a sufficient insight into verifying the results. Furthermore, the limited number of respondents prevented in-depth statistical analysis, for example, how participants' backgrounds influenced their perceptions. Further studies should therefore be conducted to gain a better understanding of the results' generalisability. However, this is unlikely to be easy. The studies in this thesis showed that it was challenging to collect data from real-world stakeholders in MSP. Workshop organisers are often not keen on using experimental prototype systems in sessions where they have limited time to collaborate with stakeholders. It was therefore challenging to get stakeholders to interact with Baltic Explorer in workshops. The time slots in the workshops for demonstration and interaction with the system were also limited. Furthermore, not all participants were keen on responding to the questionnaires, which were kept short to improve the chances of receiving responses. Many possible moderating factors, such as age and digital affinity, were therefore not considered. In both real-world workshops, some stakeholders who participated in the interactive sessions did not respond to the questionnaire. Furthermore, the Covid-19 pandemic coincided with the study in Article II. With travel restrictions in multiple countries in the Baltic Sea region, including Finland, there were few onsite MSP stakeholder meetings, and travel to meetings abroad from Finland was impossible. Opportunities to collect data about Baltic Explorer and the analysis tool were therefore severely limited.

5.9 Recommendations and future research

Based on the findings of this thesis, participatory MSP workshops and similar collaborative planning settings can benefit from transparent digital data management tools, like those implemented in Baltic Explorer. However, these tools need further improvement regarding their usability and transparency; for example, ensuring that metadata are available for external datasets and that datasets are easy to find. An option is also to store third-party datasets locally to ensure that they can always be accessed. However, the trade-off is that the data then require maintenance and updates. In contrast to same-time, different-location CGIS (see Sun & Li, 2016), communication tools are not perceived as critical in same-time, same-location CGIS. Tools in CGIS should be simple because of time constraints, the lack of experience with GIS tools, and the relatively large number of participants in MSP meetings. Tools also need to provide flexibility to remain useful in various use cases and for problem-solving methods. Utilising complex automated tools, such as model-based SDSS, needs to be approached with discretion. Stakeholders need to agree on the problem-solving methods and be given time to develop sufficient understanding of the tools before their use. Integrating the tools into explorative systems, such as CGIS, can provide flexibility for users to come up with alternative problem-solving methods. Further research is needed to better understand stakeholder perceptions and the usability–utility trade-off in the context of spatial analysis tools in collaborative settings that include novice users and operate under time constraints. Further research is also required to identify metrics that adequately describe the quality of CNN predictions in automated production of geospatial data. Developing such metrics could enable data quality and uncertainties to be communicated more accurately, thereby increasing transparency and trust in the data production process. In addition, further studies should investigate whether these metrics can be incorporated into the training of CNN models to optimise outputs for geospatial data quality. NMAs seeking to automate their TDB data production with AI-based methods need to allocate resources for understanding the decision-making of their models and the risks involved with their use. Transparency regarding the reliability of their AI-based systems, including data quality, security, and privacy risks, is essential for responsible automation and AI use, and ensuring that the TDB data are trusted. Assessment of data quality should be manual to increase trust in the data production workflow among data users. Future research should also aim to understand what type of explanatory information best supports data users' mechanistic understanding of model behaviour, understanding of associated risks, and understanding of system outputs. To produce such information, there may be a need to develop new explainable geospatial AI solutions designed for novice AI users. Finally, to better assess the generalisability of the results presented in this thesis, broader studies with larger and more diverse groups of stakeholders from various geographic areas should be conducted.

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Appendix

Appendix 1. Umeå workshop questionnaire.

Baltic Explorer questionnaire

BONUS BASMATI
Baltic Sea Maritime Spatial Planning for Sustainable Ecosystem Services

MSP = Maritime Spatial Planning
SDSS = Spatial Decision Support System

1. Your role in MSP?

You can pick more than one option

- ☐ Sector representative
- ☐ Planner
- ☐ Scientist
- ☐ Decision maker
- ☐ Other, ______________________

2. Your experience with:

	No experience				Expert
MSP?	○	○	○	○	○
SDSS?	○	○	○	○	○

3. The following functionality in collaborative SDSS

You can pick more than one option

	Overlay data on map	Draw & edit features	*Feature commenting tool	*Voting tool	*Chat box
helps in understanding the collaborative planning task	☐	☐	☐	☐	☐
helps in expressing interests of your sector	☐	☐	☐	☐	☐
helps in gaining insight into interests of other sectors	☐	☐	☐	☐	☐
helps in promoting constructive discussion across sectors	☐	☐	☐	☐	☐
helps in reaching decisions among collaborators	☐	☐	☐	☐	☐
helps in building trust among collaborators	☐	☐	☐	☐	☐

* Not yet implemented in Baltic Explorer

Please turn the page!

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Baltic Explorer questionnaire

BONUS BASMATI
Baltic Sea Maritime Spatial Planning for Sustainable Ecosystem Services

5. Feedback, questions, ideas about Baltic Explorer:

Thank you!

Appendix 2. Hardware usefulness questionnaire.

Baltic Explorer questionnaire

BONUS BASMATI
Baltic Sea Maritime Spatial Planning for Sustainable Ecosystem Services

1. What sector did you represent in the game?

- ☐ Energy
- ☐ Environment
- ☐ Tourism

2. How well did each device type support the task 1:
"Prepare to present your interests"? 1: very weakly - 5: very well

	1	2	3	4	5	I did not use the device
personal display	○	○	○	○	○	○
large display	○	○	○	○	○	○

3. How well did each device type support the task 2:
"Present your sectors interests"? 1: very weakly - 5: very well

	1	2	3	4	5	I did not use the device
personal display	○	○	○	○	○	○
large display	○	○	○	○	○	○

Please turn the page!

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Baltic Explorer questionnaire

BONUS BASMATI
Baltic Sea Maritime Spatial Planning
for Sustainable Ecosystem Services

4. How well did each device type support the task 3:
"Gain insight on other sectors interests"? 1: very weakly - 5: very well

	1	2	3	4	5	I did not use the device
personal display	○	○	○	○	○	○
large display	○	○	○	○	○	○

5. How well did each device type support the task 4:
"Collaborate to resolve conflicts"? 1: very weakly - 5: very well

	1	2	3	4	5	I did not use the device
personal display	○	○	○	○	○	○
large display	○	○	○	○	○	○

6. Feedback, questions, ideas about the game and Baltic Explorer:

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Thank you!

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Appendix 3. Riga workshop questionnaire.

Baltic Explorer questionnaire

BONUS BASMATI
Baltic Sea Maritime Spatial Planning for Sustainable Ecosystem Services

You can pick more than one option

1. Your role(s) in Maritime Spatial Planning (MSP)?

☐ Sector representative ☐ Planner ☐ Scientist ☐ Decision maker

☐ Other, ______________________

You can pick more than one option

3. The following tool in Baltic Explorer	Overlay data	Draw & edit features	Analysis
helps in understanding the collaborative planning task	☐	☐	☐
helps in expressing your interests to others	☐	☐	☐
helps in gaining insight into interests of other	☐	☐	☐
helps in promoting constructive discussion across sectors	☐	☐	☐
helps in reaching decisions among collaborators	☐	☐	☐
helps in building trust among collaborators	☐	☐	☐

4 Regarding the **Analysis tool**, how well did you understand:

1: Very poorly 2: Poorly 3: Fairly 4: Well 5: Very well

	1	2	3	4	5
What the tool does?	○	○	○	○	○
How to use the tool?	○	○	○	○	○

Please turn the page!

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5. Regarding the **Analysis tool**:

1: Strongly disagree 2: Disagree 3: Undecided 4: Agree 5: Strongly agree

	1	2	3	4	5
It was easy to use the tool	○	○	○	○	○
Analysis tool provided the needed functionality for solving the task	○	○	○	○	○
Analysis was appropriate for solving the task	○	○	○	○	○
Analysis tool results are useful for MSP work	○	○	○	○	○
Analysis tools are useful for MSP workshops	○	○	○	○	○

6. How well did the following tools work together with the **Analysis tool**?

1: Very poorly 2: Poorly 3: Fairly 4: Well 5: Very well

	1	2	3	4	5
Draw and edit features	○	○	○	○	○
Overlay data	○	○	○	○	○
Measurement tool	○	○	○	○	○

8. Feedback about the workshop:

____

____

____

Thank you!

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Appendix 4. Trust in artificial intelligence questionnaire.

Tekoäly maastotiedon tuotannossa - luottamus, tiedon laatu, ja avoimuus

* Pakollinen kysymys

Suostumus osallistua tutkimukseen

Tarkoitus: Sinua pyydetään osallistumaan tutkimukseen. Tutkimuksessa selvitetään loppukäyttäjien näkökulmia tiedon laatuun, luottamukseen ja avoimuuteen, kun tekoälyä käytetään osana maastotietojen (Maanmittauslaitoksen maastotietokannan sisältö esim. maastokohteet, tiestö, rakennukset, vesistöt ym.) tuottamisprosessia.

Menettelyt: Jos päätät osallistua, pyydämme sinua vastaamaan tähän verkkokyselyyn. Esitetyn kyselylomakkeen täyttäminen kestää noin 20-25 minuuttia.

Hyödyt: Tämän tutkimuksen avulla odotamme tuottavamme uutta tietoa loppukäyttäjien näkökulmista tiedon laatuun, luottamukseen ja avoimuuteen, kun tekoälymenetelmiä käytetään maastotietojen tuottamiseen. Vastaukset auttavat Maanmittauslaitosta ja muita tiedontuottajia ymmärtämään, kuinka tällainen tuotantomenetelmän muutos vaikuttaa loppukäyttäjiin. Kyselyn tekijä saa tietoa maastotiedon tuotannosta.

Riskit: Tutkimus ei aiheuta merkittäviä riskejä osallistujille.

Luottamuksellisuus: Keräämiämme tietoja ei yhdistetä millään tavoin henkilöllisyyteenne. Tietoja käytetään ainoastaan yleistettyihin analyyseihin.

Tietojen jakaminen: Tutkimuksen päätyttyä saatamme haluta esitellä tuloksia konferensseissa ja artikkeleissa sekä jakaa tämän tutkimuksen yhteydessä kerättyjä tietoja muiden yliopistojen tai tutkijoiden kanssa tulevia tutkimustarkoituksia varten. Lisäksi haluaisimme säilyttää tiedot mahdollista myöhempää tutkimuskäyttöä varten. Suojaamme kuitenkin yksityisyyttäsi tulevaisuudessa samalla tavalla kuin tässä tutkimuksessa, ja tietoja käytetään vain akateemisiin tarkoituksiin. Kyselyyn vastaaminen osoittaa, että annat luvan käyttää kerättyjä tietoja tuleviin tutkimustarkoituksiin. Kyselyyn vastataan anonyymisti. Emme kerää vastaajien nimiä tai yhteystietoja talteen.

Oikeus kieltäytyä tai peruuttaa kysely: Voit kieltäytyä osallistumasta tähän tutkimukseen ja voit lopettaa osallistumisen milloin tahansa.

Tutkimukseen osallistuminen on vapaaehtoista. Kyselylomakkeeseen vastaaminen tarkoittaa, että olet päättänyt osallistua tutkimushenkilönä edellä kuvattuun tutkimukseen. Voit tulostaa tämän suostumuksen arkistoosi heti verkkoselaimesi tulostustoiminnolla.

1 Taustakysymyksiä

1.1 Arvioi osaamisesi taso seuraavissa: *

Merkitse vain yksi soikio riviä kohden.

	Ei osaamista	Perehtynyt	Perustason osaaminen	Hyvä osaaminen	Erittäin hyvä osaaminen
Digitaaliset työkalut	◯	◯	◯	◯	◯
Paikkatietotyökalujen käyttö	◯	◯	◯	◯	◯
Tekoälyratkaisujen käyttö	◯	◯	◯	◯	◯
Tekoälyratkaisujen kehittäminen	◯	◯	◯	◯	◯

1.2 Kuinka hyvin tunnet maastotietoja (Maanmittauslaitoksen maastotietokannan sisältö esim. maastokohteet, tiestö, rakennukset, vesistöt ym.)? *

Merkitse vain yksi soikio.

- ◯ En lainkaan
- ◯ Hieman
- ◯ Jokseenkin hyvin
- ◯ Kohtalaisen hyvin
- ◯ Erittäin hyvin
- ◯ En osaa sanoa

1.3 Kuinka hyvin tunnet maastotietojen tuotantomenetelmiä? *

Merkitse vain yksi soikio.

- ◯ En lainkaan
- ◯ Hieman
- ◯ Jokseenkin hyvin
- ◯ Kohtalaisen hyvin
- ◯ Erittäin hyvin
- ◯ En osaa sanoa

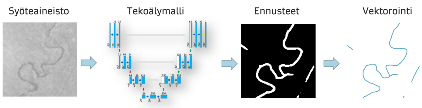
2 Tekoäly maastotiedon tuotannossa.

Alla on kuvattu esimerkki siitä, miten tekoälyä voi hyödyntää maastotietojen tuotannossa.

Käytämme tehokasta tekoälyteknologiaa, konvoluutioneuroverkkoa (CNN), automatisoidaksemme tuotantoprosessin, jossa digitoidaan ja tunnistetaan maastokohteita kaukokartoitusaineistosta kuten ilmakuvista ja korkeusmalleista. Viimeiset vuosikymmenet kohteita on digitoitu kaukokartoitusaineistoista manuaalisesti.

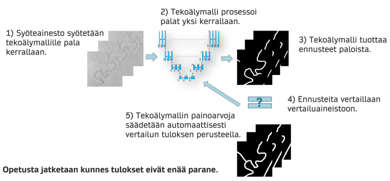
Opetetun tekoälyn käyttäminen kohteiden tunnistamiseen.
Valmiiksi opetetulle tekoälymallille annetaan syötteenä kuvia (esimerkiksi ilmakuvia tai korkeusmalleja), joita se käsittelee erilaisin menetelmin. Tekoälymalli tuottaa syötteistä kuvia, joissa on ennuste siitä, mitkä pikselit kuuluvat kartoitettavaan kohteeseen (Kuva 1). Tuloskuvassa kunkin pikselin ennustetaan olevan joko positiivinen (kuuluu kartoitettavaan kohteeseen) tai negatiivinen (ei kuulu kartoitettavaan kohteeseen). Ennustekuva voidaan vektoroida jatkokäsittelyn avulla, jossa voidaan myös korjata virheitä ja täydentää aineistoa.

Kuva 1. Kohteiden tunnistaminen tekoälyllä.



Miten tekoälymalli on opetettu?
Ennen tuotantokäyttöä CNN:n miljoonat painoarvot (muunnettavien parametrien arvot) optimoidaan automaattisesti opetusvaiheessa. Tässä vaiheessa mallin tuotoksia (ennusteita) verrataan laadukkaisiin manuaalisesti digitoituihin vertailutietoihin, jotka vastaavat ihanteellisia ennusteita (Kuva 2). Vertailun perusteella, tekoälymallin painoarvoja säädetään automaattisesti. Tätä toistetaan jopa miljoonia kertoja. Koulutuksen aikana mallin oppimista seurataan säännöllisin väliajoin arvioimalla sen tuottamia tuloksia alueilta, joita ei ole käytetty opetuksessa. Näin voidaan päätellä missä vaiheessa tekoälymallin tuottamat tulokset eivät enää parane. Kun opetus on saatu päätökseen, CNN:n painoarvot on hienosäädetty, ja malli on valmis tekemään tarkkoja ennusteita miltä tahansa alueelta, josta löytyy vastaavaa syöteaineistoa kuin mitä on käytetty opetuksessa.

Kuva 2. Tekoälymallin opettaminen.



2.1 Kuinka hyvin koet nyt ymmärtäväsi tekoälymenetelmän toiminnan? *

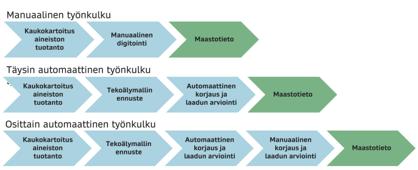
Merkitse vain yksi soikio.

	1	2	3	4	5	
En ollenkaan	◯	◯	◯	◯	◯	Erittäin hyvin

3 Tekoälymallien integrointi tiedontuotannon työnkulkuun.

Tällä hetkellä iso osa Maanmittauslaitoksen maastotiedoista tuotetaan manuaalisesti digitoimalla. Käsin digitointia voi pyrkiä automatisoimaan tekoälyä hyödyntämällä kuten edellisessä osiossa on kuvattu. Alla on kuvattu kolme vaihtoehtoista työnkulkua, joissa automaation aste vaihtelee (Kuva 3).

Kuva 3. Vaihtoehtoiset työnkulut



3.1 Miten paljon luotat kunkin vaihtoehtoisen työnkulun kykyyn tuottaa korkealaatuisia maastotietoja? *

Merkitse vain yksi soikio riviä kohden.

	Erittäin epäluotettava	Epäluotettava	Neutraali	Luotettava	Erittäin luotettava	En osaa sanoa
Manuaalinen työnkulku						
Täysin automaattinen työnkulku						
Osittain automaattinen työnkulku						

3.2 Oletko samaa mieltä seuraavista väittämistä? *

Merkitse vain yksi soikio riviä kohden.

	Täysin eri mieltä	Eri mieltä	Ei samaa eikä eri mieltä	Samaa mieltä	Täysin samaa mieltä	En osaa sanoa
Täysin manuaalinen työnkulku on välttämätön, jotta saavutetaan riittävä maastotiedon laatutaso.						
Täysin automaattiseen työnkulkuun ei voi luottaa.						
Täysin automaattinen työnkulku on perusteltu, kun tuotettujen tietojen laatu on keskimäärin parempi kuin ihmisen tekemän digitoinnin laatu.						
On hyväksyttävää, että tekoälymalli tuottaa hieman heikompaa laatua kuin manuaalinen digitointi, koska automatisointi säästää resursseja ja voi nopeuttaa tiedon tuotantoa.						

3.3 Kuinka huolestunut olet sueraavista asioista, jos maastotietoa tuotetaan tekoälyä hyödyntäen? *

Merkitse vain yksi soikio riviä kohden.

	En ollenkaan huolestunut	Jonkin verran huolestunut	Kohtalaisen huolestunut	Suuresti huolestunut	Erittäin suuresti huolestunut	En osaa sanoa
Menetelmää tai mallin päätöksenteon perusteluja ei pystytä ymmärtämään	◯	◯	◯	◯	◯	◯
Tietojen laadun heikkeneminen	◯	◯	◯	◯	◯	◯
Turvallisuuskysymykset, kuten arkaluonteisten tietojen paljastuminen	◯	◯	◯	◯	◯	◯
Yksityisyyden suojaan liittyvät kysymykset, kuten henkilötietojen paljastuminen	◯	◯	◯	◯	◯	◯
Systemaattiset virheet (virheet jotka toistuvat läpi aineiston)	◯	◯	◯	◯	◯	◯
Ilkivaltainen hyökkäys tekoälymallia vastaan, esimerkiksi mallin painoarvojen manipuloiminen, joka jää huomaamatta	◯	◯	◯	◯	◯	◯
Tekoälymallia käytetään väärennettyjen tietojen tuottamiseen	◯	◯	◯	◯	◯	◯

3.4 Järjestä seuraavat asiat pienimmästä huolenaiheesta suurimpaa huolenaiheeseen, jos maastotietoa tuotetaan tekoälyä hyödyntäen. *

HUOM! Jokaiselta sarakkeelta ja riviltä voi valita vain yhden vastausvaihtoehdon.

Merkitse vain yksi soikio riviä kohden.

	1 Pienin huolenaihe	2	3	4	5	6	7 Suurin huolenaihe
Menetelmää tai mallin päätöksenteon perusteluja ei pystytä ymmärtämään	◯	◯	◯	◯	◯	◯	◯
Tietojen laadun heikkeneminen	◯	◯	◯	◯	◯	◯	◯
Turvallisuuskysymykset, kuten arkaluonteisten tietojen paljastuminen	◯	◯	◯	◯	◯	◯	◯
Yksityisyyden suojaan liittyvät kysymykset, kuten henkilötietojen paljastuminen	◯	◯	◯	◯	◯	◯	◯
Systemaattiset virheet (virheet jotka toistuvat läpi aineiston)	◯	◯	◯	◯	◯	◯	◯
Ilkivaltainen hyökkäys tekoälymallia vastaan, esimerkiksi mallin painoarvojen manipuloiminen, joka jää huomaamatta	◯	◯	◯	◯	◯	◯	◯
Tekoälymallia käytetään väärennettyjen tietojen tuottamiseen	◯	◯	◯	◯	◯	◯	◯

3.5 Onko sinulla muita huolenaiheita tekoälyn käytöstä maastotietojen tuottamisessa? Kuvaile huolenaiheesi ja niiden suuruusluokka (asteikolla 1-5)?

4 Luottamus tekoälyllä tuotetun tiedon laatuun

4.1 Miten seuraavat tiedontuottajan ominaisuudet vaikuttavat luottamukseesi tekoälyä hyödyntämällä tuotetun maastotiedon laatuun? *

Merkitse vain yksi soikio riviä kohden.

	Vähentää voimakkaasti luottamusta	Vähentää luottamusta	Ei vaikutusta	Lisää luottamusta	Lisää vahvasti luottamusta	En osaa sanoa
Tiedon tuottaja on julkinen organisaatio	⬭	⬭	⬭	⬭	⬭	⬭
Tietojen tuottaja on yksityinen organisaatio.	⬭	⬭	⬭	⬭	⬭	⬭
Tiedontuottaja on paikkatietoaktiivien yhteisö	⬭	⬭	⬭	⬭	⬭	⬭
Tietojen tuottaja on yksityishenkilö	⬭	⬭	⬭	⬭	⬭	⬭
Tiedontuottaja on tunnettu tekoälyratkaisujen kehittäjänä	⬭	⬭	⬭	⬭	⬭	⬭
Tiedontuotttaja on tunnettu paikkatietojen tuottajana	⬭	⬭	⬭	⬭	⬭	⬭
Tiedontuottaja jakaa avoimesti tietoa tuotantomenetelmistä	⬭	⬭	⬭	⬭	⬭	⬭

4.2 Kuinka paljon seuraavat seikat vaikuttavat luottamukseesi tekoälyä hyödyntämällä tuotetun maastotiedon laatuun? *

Merkitse vain yksi soikio riviä kohden.

	Ei lainkaan	Hieman	Jonkin verran	Kohtalaiseseti	Erittäin paljon	En osaa sanoa
Tiedontuottajan maine ja luotettavuus	⬭	⬭	⬭	⬭	⬭	⬭
Tietojen mukana toimitetut laatutiedot	⬭	⬭	⬭	⬭	⬭	⬭
Tuotantomenetelmän avoimuus	⬭	⬭	⬭	⬭	⬭	⬭
Tietojen laadun maine (kolmansien osapuolten näkemykset laadusta)	⬭	⬭	⬭	⬭	⬭	⬭
Oma arviosi tietojen laadusta	⬭	⬭	⬭	⬭	⬭	⬭
Tiedon laatu on tarkastettu manuaalisesti	⬭	⬭	⬭	⬭	⬭	⬭
Tiedon laatu on tarkastettu automaattisilla menetelmillä	⬭	⬭	⬭	⬭	⬭	⬭

5 Tekoälymenetelmän ja sillä tuotetun maastotiedon avoimuus ja läpinäkyvyys.

5.1 Oletko samaa mieltä seuraavista väittämistä? *

Merkitse vain yksi soikio riviä kohden.

	Täysin eri mieltä	Eri mieltä	Ei samaa eikä eri mieltä	Samaa mieltä	Täysin samaa mieltä	En osaa sanoa
Maastotiedon tuotannossa käytettävän tekoälymenetelmän kaikki yksityiskohdat tulee olla avointa tietoa	○	○	○	○	○	○
Minun on ymmärrettävä tekoälymallien päätöksenteon logiikkaa luottaakseni sen tuottamiin tietoihin	○	○	○	○	○	○
Tiedon tuottajan on ymmärrettävä tekoälymallien päätöksenteon logiikka ja pystyttävä selittämään se muille, jos häneltä kysytään siitä	○	○	○	○	○	○
Ei ole tärkeää, miten tekoälymalli tekee johtopäätöksensä, ainoastaan lopullisen aineiston laadulla on merkitystä	○	○	○	○	○	○

5.2 Jos maastotietoa tuotetaan tekoälymenetelmillä, mitkä seuraavista tekoälymenetelmään liittyvistä tiedoista on jaettava aineiston loppukäyttäjille? *

HUOM! Voit valita useamman vastausvaihtoehdon jokaiselta riviltä.

Valitse kaikki sopivat vaihtoehdot.

	Pitää jakaa. Jakaminen on tärkeää aineiston laadun arvioimiseen	Pitää jakaa. Jakaminen lisää luottamusta aineiston laatuun.	Ei ole tarvetta jakaa.
Tekoälymallin opettamiseen käytettyjen aineistojen laatutiedot	☐	☐	☐
Kuvaesimerkkejä tekoälymallin opettamiseen käytetyistä aineistoista	☐	☐	☐
Yksityiskohtaiset tiedot toiminnoista, joita tekoälymenetelmässä käytetään (tekoälyarkkitehtuuri)	☐	☐	☐
Helposti ymmärrettävä kuvaus tekoälymallin päätöksenteon logiikasta	☐	☐	☐

5.3 Monimutkaisemmat tekoälymallit tekevät yleensä tarkempia ennusteita, mutta niiden päätöksentekoa on vaikeampi ymmärtää.

Kumpi on tärkeämpää, mallin tarkkuus vai mallin ymmärrettävyys? *

Merkitse vain yksi soikio.

- Tekoälymallin tarkkuus on paljon tärkeämpää
- Teokoäly mallin tarkkuus on jokseenkin tärkeämpää
- Molemmat ovat yhtä tärkeitä
- Tekoälymallin ymmärrettävyys on jokseenkin tärkeämpää
- Tekoälymallin ymmärrettävyys on paljon tärkeämpää
- En osaa sanoa

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