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The Role of Geospatial Data in Data Economy

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Abstract

This work is a pre-study, and it is intended to produce a report under the guidance of the Ministry of Agriculture and Forestry (MAF) about the role of geospatial data in data economy, especially in a Finnish context. The aim was to review the state-of-the-art and needs regarding geospatial data and positioning in today's data economy as well as the impact of geospatial data and positioning.

Geospatial data has an important role in data economy. The report delves into the technical aspects of data, unveiling the untapped potential of its value and the cross-disciplinary role it serves in multiple industries. Furthermore, the report emphasizes the synergistic-sustainability potential geospatial data has for addressing climate impacts and facilitating more precise environmental monitoring.

The subject is multidisciplinary, and therefore it was logical to include a wide variety of perspectives in the report.

According to the review of literature and an illustrating case study, there is a need for many kinds of further research related to geospatial data connected to more precise Earth observation, pervasive positioning solutions, value and use of geospatial data in decision-making and resource allocation, measuring the value as well as customizing services and products related to it. The research related to competences needed to use the data, improvement of the use of data as well as the use of environmental performance indicators is needed too.

Keywords	geospatial data, positioning, Earth Observation, coordinate reference systems, value of geospatial data, industries, environmental monitoring, data economy		
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Paikkatiedon rooli datataloudessa

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Tekijä/t	Ville Tuomi, Kannan Selvan, Tayyab Warraich, Mikko Ranta, Elina Huculak, Hafiz Haq, Marko Kohtamäki, Petri Välisuo, Essi Nousiainen, Johanna Haveri, Heidi Kuusniemi, Mari Laakso		
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Tiivistelmä

Tämän esiselvityksen tarkoituksena on tuottaa Maa- ja metsätalousministeriön (MMM) ohjauksessa raportti paikkatiedon roolista datataloudessa erityisesti Suomessa. Tavoitteena on ollut tarkastella paikkatiedon ja paikannuksen nykytilaa ja tarpeita tämän päivän datataloudessa ja -liiketoiminnassa sekä paikkatiedon ja paikannuksen vaikutuksia.

Paikkatiedolla on tärkeä rooli datataloudessa. Tässä raportissa käsitellään paikkadataa teknisestä näkökulmasta, tuodaan esiin datan arvon hyödyntämätön potentiaali ja monitieteinen rooli eri toimialoilla, sekä pohditaan paikkadatan roolia ilmastovaikutusten ja ympäristön seurannan mahdollistajana. Monialainen aihe vaati monenlaisia näkökulmia.

Kirjallisuuskatsauksen ja havainnollistavan tapaustutkimuksen mukaan tarvitaan monenlaista paikkatietodataan liittyvää lisätutkimusta. Se voi liittyä tarkempaan Maan havainnointiin, joka paikassa toimiviin paikannusratkaisuihin, paikkatiedon arvoon, datan käyttöön päätöksenteossa ja resurssien allokoinnissa, arvon mittaamiseen, sekä dataan liittyvien palveluiden ja tuotteiden räätälöimiseen. Datan hyödyntämisosaamiseen, käytön parantamiseen ja ympäristövaikutusten mittaamiseen liittyvää tutkimusta tarvitaan myös.

Asiasanat	paikkatieto, paikannus, kaukokartoitus, koordinaattijärjestelmät, paikkatiedon arvo, toimialat, ympäristön seuranta, datatalous		
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Geospatiala datas roll i dataekonomi

Jord- och skogsbruksministeriets publikationer 2023:18

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Författare	Ville Tuomi, Kannan Selvan, Tayyab Warraich, Mikko Ranta, Elina Huculak, Hafiz Haq, Marko Kohtamäki, Petri Välisuo, Essi Nousiainen, Johanna Haveri, Heidi Kuusniemi, Mari Laakso		
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Referat

Denna förstudie är avsedd att producera en rapport under ledning av Jord- och skogsbruksministeriet (JSM) angående geospatiala datas roll i dataekonomin, särskilt i ett finskt sammanhang. Syftet var att presentera nuvarande läge och behov gällande geospatiala data och positionering i dagens dataekonomi samt påverkan av geospatial data och positionering.

Geospatial data har en viktig roll i dataekonomi. I denna rapport diskuteras tekniska aspekter av data, värde av data, datas roll i olika branscher samt klimatpåverkan och miljöövervakning med hjälp av data. Ämnet är multidisciplinärt och därför var det logiskt att ta med många olika perspektiv i rapporten.

Enligt litteraturöversikten och en illustrerande fallstudie finns det ett behov av många typer av ytterligare forskning kopplat till mer exakt jordobservation, genomgripande positioneringslösningar, värde och användning av geospatiala data i beslutsfattande och resursallokering, för att mäta värdet av tjänster och produkter samt anpassa dom. Forskningen relaterad till kompetens som behövs för att använda data, förbättring av användningen av data samt användning av miljöprestandaindikatorer behövs.

Nyckelord	geospatial data, positionering, jordobservation, koordinatreferenssystem, värde av geospatial data, industrier, miljöövervakning, dataekonomi		
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Contents

1 Introduction

This work is a pre-study, and it is intended to produce a report under the guidance of the Ministry of Agriculture and Forestry (MAF) regarding the role of geospatial data in data economy, especially in a Finnish context.

Within the fusion of digital technologies and human-centric approaches to production processes, Industry 5.0 leverages the synergies of smart machines and humans to reach greater targets while prioritizing sustainability and social responsibility. Key cutting-edge technologies driving the big data production of Industry 5.0 include geospatial data such as GIS, remote sensing, Earth Observation, and GNSS (such as Galileo and GPS), among other location information technologies. Geospatial data serves as location-based data, which is foundational to understanding the data economy. It offers economic growth opportunities when positively impacting the competitiveness and productivity of companies. Both open and commercial geospatial data are used in many industries. In many cases the location data is the link between the physical and the digital world.

Geospatial data can be defined as "an expansive source of information that is useful for a broad spectrum of researchers across disciplines" (Goodman et al., 2019). Geospatial data contains information about objects, places, events, and other features that can be located geographically. This location may be static in the short run, like the location of a building or dynamic, like moving people. The data normally combine location information, like coordinates, attribute information, like location characteristics as well as sometimes even temporal information, like time or life span of the located object and its attributes (Wichmann et al., 2023). Geospatial data is characterized by high volume, high velocity as well as open geospatial datasets from various sources with high degree of variety. Sometimes geospatial big data is seen as a subset of big data and therefore there are opportunities to use big data techniques to handle geospatial data (Sveen, 2019).

Data economy is an umbrella term, which includes digital business models independent of a particular industry, for example, data products and services and digital technologies. Data economy refers to the part of the economy in which a business model is based on utilization and use of knowledge in different ways (Ahvonen et al., 2023). It can also refer to the overall impact of the data market on the economy as a whole. "Moreover, the data economy has far-reaching implications for the overall economic landscape, encompassing the generation, collection, storage, processing, distribution, analysis, elaboration, delivery, and exploitation of data facilitated by digital technologies" (Azkan et al., 2019). In data economy, mass data flows like never before, circulating at lightning speed, as every individual, including ordinary citizens, contributes to the massive-scale data collection (Lammi & Pantzar, 2019).

Data economy refers to the digital economy with a continuous production and fast circulation of data masses, and where digital technologies generate, collect and store data to be analyzed, processed and distributed (Knaapi-Junnila et al., 2022). In the former research, it is more common to use the term digital economy, but the meaning is essentially the same. Both terms are multidisciplinary, and there is research in the fields of social sciences, computer sciences, business, management and accounting, and engineering as well as economics, econometrics and finance (see appendix 1 and 2).

Kruse et al. (2017) aptly describe that in assessing the value of geospatial data, and its hyponym geospatial information, it is not the action per se that is of ultimate interest, it is the outcome of the action - value can be expressed, for example, as measurable improvement in a social context (e.g. reduction in mortality and morbidity, reduced damage to capital assets, improved profit, improved community well-being, and other social or economic benefit) (Kruse et al., 2017). The value of geospatial data can additionally address critical global challenges such as the Sustainable Development Goals and responsive natural- and human-built environments at the local, national, and global scales (Kruse et al., 2017). With these in mind, this pre-study report assesses the overall role of geospatial data in the data economy context.

1.1 Objectives and Scope of the Research

Our research presented in this report sets forth two ambitious objectives that shape its core:

1. Review the state-of-art and needs regarding geospatial data and positioning
2. Review the impact of geospatial data and positioning

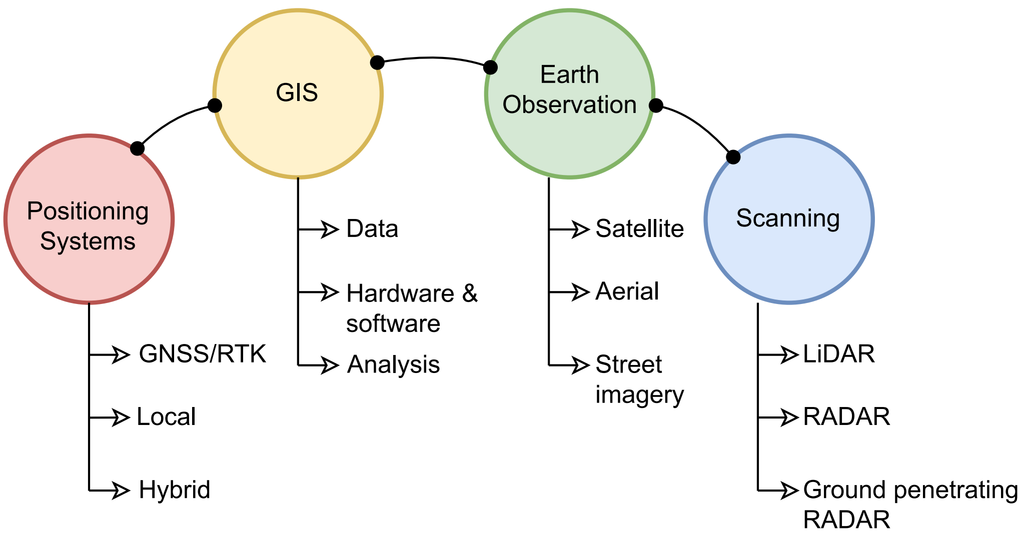
Drawing on the literature review and case study the University of Vaasa conducted, the research strives to craft a framework with potential application use for empirical studies connected to geospatial data in data economy. Both review and case study should be further developed, if they are to be published in academic journals, but due to time constraints this could not have been done in this report. The research is focusing on positive impacts, as emphasized by the MAF.

After the report is finalized, there is intention to continue the research via journal articles in the research groups of the University of Vaasa and beyond. The value of this report is that it reveals key issues and further research ideas related to geospatial data in a wider data economy context and areas where Finland could focus on.

2 Review and Assessment of Geospatial Information and Positioning – Technical Part

According to Geospatial (2021), geospatial technology refers to various technologies and tools used for mapping the Earth's surface and providing context to the spatial data collected through analytics. It is defined as any technology that creates, stores, analyses, and visualizes geospatial data. It is a complex entity that includes geospatial data sourced from different technologies which are then categorized into four segments being positioning systems, Geographic Information Systems (GIS), Earth observation, and scanning tools and technologies as shown in Figure 1. The geospatial information obtained from these different categories are in many forms including but not limited to digital elevation maps, remote sensing imagery products, point clouds, GNSS navigation and timing data.

Figure 1. Categories of Geospatial Technology.



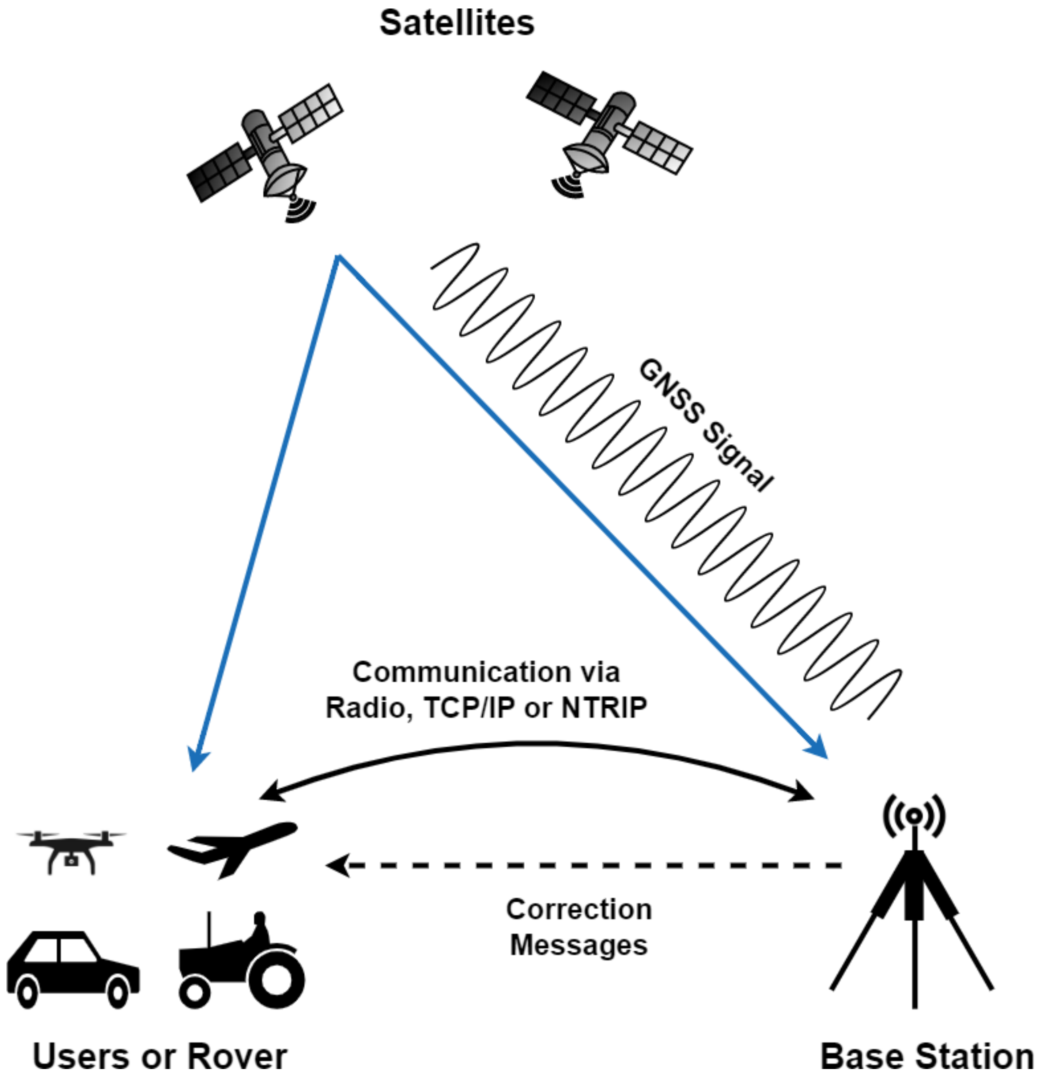
2.1 Positioning Systems

The positioning systems are classified into several categories being precision positioning systems, local positioning systems, and hybrid positioning systems used widely in both outdoor and indoor environments. Precision positioning systems are based on combining the Global Navigation Satellite Systems (GNSS) with real-time kinematic (RTK) technology. Local positioning systems (LPS) are positioning technologies that offer position or location information within a limited geographic area. Hybrid positioning systems are systems used for finding the position based on the fusion of different positioning technologies. The limitations of existing stand-alone positioning systems are compensated by combining several positioning technologies to produce fusion information for more accurate positioning (Guo et al., 2020; Hasan et al., 2018).

2.1.1 Precision Positioning Systems

GNSS consists of multiple constellations of satellites such as Global Positioning System (GPS), Galileo, GLONASS, and BeiDou which provide positioning and timing information. GNSS is the most widely used positioning system for outdoor localization due to its high accuracy and global coverage. It cannot be used in indoor environments due to strong signal attenuation, multipath, and interference issues. Other positioning systems that can be used for indoor localization include radio communication technology-based Wi-Fi, Bluetooth, ZigBee, RFID, and Ultra-Wideband (UWB) or others such as visible light and acoustic-based technologies (Pascacio et al., 2021; Zafari et al., 2019). Meter level accuracy is obtained based on standalone GNSS and local positioning systems. However, there are many applications that require decimeter-level or even higher positioning accuracy. The RTK technique utilizes the phase of GNSS satellites' carrier signal along with correction sources to achieve highly accurate and precise positioning. Correction sources are obtained either locally or virtually from a base station, or through networked transport of RTCM via internet protocol (NTRIP) from a third-party service via the internet. Precision agriculture and surveying are among the applications that benefit from this method. Although RTK has been a widely adopted solution, it has been considered expensive traditionally for a long time, despite its continued effectiveness and reliability. However, the recent developments in low-cost GNSS receivers and correction services paved the way for precision positioning in many applications (Jackson et al., 2018). A schematic diagram of the GNSS and RTK technologies is provided in Figure 2.

Figure 2. GNSS and RTK Technologies.



2.1.2 Local Positioning Systems

The non-line-of-sight (NLOS) constraints of GNSS in indoor environments has helped in developing alternative positioning systems which are independent of GNSS. These positioning systems have become necessary in estimating position in indoor environments. Hence, these positioning systems are designed to obtain a position in relation to a local field or area known as an LPS (Hasan et al., 2018). Significant growth in LPS has been observed in recent years with technologies such as Wi-Fi (Liu et al., 2007), UWB (Elsanhoury et al., 2022), Bluetooth direction finding (Sambu & Won, 2022), ZigBee (Baronti et al., 2007), RFID (Holm, 2009), 5G (Dwivedi et al., 2021), visible light (Kuo et al., 2014), acoustic signal (Huang et al., 2015), and ultrasound (Ijaz et al., 2013). Table 1 provides a summary of different local positioning systems from a localization standpoint. The quality and efficiency of LPS depend on various metrics such as accuracy, precision, costs, power consumption, and coverage. LPS is application dependent, i.e., they are designed to operate in a certain environment, hence a trade-off between metrics should be considered to choose the best LPS technology for the situation (Hasan et al., 2018).

Table 1. Summary on Different Local Positioning Systems.

Technology	Accuracy (m)	Power Consumption	Technique	Remarks
Wi-Fi	1-5	Moderate	Proximity, Trilateration, Fingerprinting, RSS-propagation model	High accuracy, Available widely, RF interference at 2.4 GHz, susceptible to multipath
Bluetooth	2-5	Low	Proximity, Trilateration, Fingerprinting	High throughput, Limited coverage and prone to noise
UWB	0.01-1	Moderate	Trilateration, Angulation	Limited coverage, high cost, performance degrades in NLOS
RFID	1-2	Low	Proximity, Trilateration, Fingerprinting, RSS-propagation model	Real-time location, proximity-based positioning, short range
ZigBee	3-5	Low	Proximity, Trilateration, Fingerprinting, RSS-propagation model	Low cost, data transmission rate is low
Infrared	1-2	Low	Proximity, Trilateration	Low cost, short-range, no effect of multipath
Ultrasound	0.03-1	Low	Trilateration	No effect of multipath, depends on sensor placement
5G mmWave	0.2-0.5	Low	Fingerprinting	High accuracy, operator costs and multipath effect

2.1.3 Hybrid Positioning Systems

The precision and local positioning systems-based technologies such as GNSS, Wi-Fi, Bluetooth, UWB, RFID, etc. are discussed above. Other technologies based on laser and visual sensor-based positioning such as LiDARs (Light Detection And Ranging) and cameras can be used independently or concurrently with other positioning systems. A satisfactory positioning solution in terms of accuracy, availability, continuity, and reliability cannot be offered solely by any of these technologies. For example, inertial navigation systems (INS) are unaffected by interferences; however, due to drifting, they perform only for a short period in time which degrades their usability. On the other hand, multipath and NLOS situations degrade the performance when UWB is used alone. By fusing or combining, the weakness of both systems can be overcome by so-called hybrid positioning systems (HPS) (Gakne & O'Keefe, 2018). This way, the drifting of INS is compensated for by the absolute positioning offered by UWB and the multipath effects are mitigated in UWB by INS. Each technology has its limitations that can be mitigated by using HPS. However, integrating various technologies using HPS depends on the case, requirements, and sensors. Not all technologies or sensors are compatible with each other in HPS applications. The integration of these technologies is done by using loose coupling or tight coupling methods. Loose coupling combines the positioning solution obtained by different techniques, while tight coupling uses the combined information obtained from sensors and solves the positioning solution. Thus, HPS integrates different technologies and provides seamless positioning solutions in contrast to individual positioning systems (Jiang et al., 2021).

2.2 Geospatial Information System

Geospatial Information Systems (GIS) are systems used in analysing and interpreting geospatial data. The primary function includes data acquisition, mapping, spatial database management, and analysis. GIS allows the user to view, understand, interpret and visualize the data, which reveals relationships, patterns and trends in various formats such as maps and charts. GIS integrates different components such as hardware, software, data and users. Hardware refers to a wide range of devices, such as computers on which GIS operates. GIS software consists of functions and tools that are used to store, analyse and display geospatial information. GIS integrates different types of data layers using spatial location. Thus, geospatial data refers to the dataset that has geographic or location information. The next component of GIS is the technical users designing and maintaining the system, complementary, there are the users who use GIS in their everyday work (Burrough et al., 2015; Liu & Cheng, 2020).

Geospatial data is divided into several types depending on the data being measured and how it is being utilized. The two primary types are vector data and raster data. Vector data consists of geometric shapes such as points, lines, and polygons to represent the location and shape of geographic features. It is ideal for representing properties, cities, roads, waterways and boundaries. In contrast, raster data uses grid cells or cell-based formats to record data as pixels. It represents data through an image, such as aerial photography, satellite imagery and painted map. Though geospatial data is essentially based on one of these two data types, geospatial analysis depends heavily on raster datasets (Decker, 2001).

2.3 Earth Observation

Earth observation gathers information about Earth's characteristics using remote sensing technologies. Maps and imagery datasets used in GIS are obtained from space-borne and airborne sensors using remote sensing techniques. Remote sensing refers to acquiring data from a distance i.e., observing objects using platforms that are distant from the object being observed. Remote sensing platforms such as space-borne, near-space, airborne, and ground observe the Earth from a range of several meters to 40 thousand kilometres. It includes data from satellites, aerial images, uncrewed aerial vehicles, and ground-based sensors. Traditional imaging devices and modern innovative sensors such as infrared radiometers, multispectral scanners, microwave radiometers, laser altimeters, linear scanners and LiDAR are also used in the acquisition of Earth observation data. Imagery data is offered at multi-scale levels ranging from coarse to acceptable resolution, depending on the sensors used. Spatial resolution of various satellite sensors is given as follows: NOAA AVHRR (1.1 km per pixel), MODIS (250 m per pixel), Landsat TM (30 m per pixel), IKONOS, Quickbird and GeoEye-1 with 1 m, 0.61 m and 0.4 m respectively. A centimetre-level spatial resolution is achieved using airborne and ground-based sensors. Space-based Earth observation offers data acquisition using multi-platforms, multi-sensors, and multi-scale capabilities with high spatial and temporal resolution. The recent investments in the satellite capabilities, open access data and tools, advanced algorithms and data processing enabled the community to utilise geospatial information for numerous applications (D. Li et al., 2009). Copernicus, with its Sentinel spacecrafts, is the Earth observation component of the European Union's Space programme, offering data that draw from satellite Earth Observation and in-situ (non-space) data. The information services provided by Copernicus are free and openly accessible to users.

2.4 Scanning

The demand for 3-dimensional information is increasing at a rapid rate. 3D geospatial information is used in areas such as architecture, urban planning, environmental monitoring, telecommunications, cartography, rescue operations and landscape planning. The use of 3D GIS replaced 2D maps and databases. It is necessary to consider the type of measurement methods and algorithms used for creating a 3D model. High-speed measurement methods are required for collecting data about terrain, while fast and reliable algorithms are essential for modelling. Thus, 3D scanning maps the object, structure or area in the three-dimensional coordinates called point cloud (Wieczorek et al., 2013). The scanning segment comprises of three types being LiDAR, radar and ground penetrating radar.

2.4.1 Laser Scanning

Laser scanning uses a laser source to emit a laser pulse to the target objects. The sensor observes the laser pulse reflected from the target. The signal travel time is computed and then used in estimating the distance. This type of laser sensor is referred to as light detection and ranging (LiDAR). The collection of the pulsed laser measurements is called as point cloud, and it can be further processed to form a 3D visualization. Geospatial information obtained by laser scanning is well-established in engineering and geodetic surveys. LiDAR data is used to map entire cities as well as features and objects such as road networks, bridges vegetation can be classified and extracted. Thus, using LiDAR method, high-quality visualization of the scanned object is possible and can create a 3D model of complex objects or structures. Laser scanning uses different methods, such as satellite laser scanning, airborne laser scanning, mobile laser scanning and terrestrial laser scanning (Shishkina et al., 2019; Wieczorek et al., 2013).

2.4.2 Radar

In comparison to LiDAR, radar application of active sensors directly provides 3D information and ranges via radio or electromagnetic waves instead of light waves from a laser. The radar system detects the reflected radio waves from the objects. The frequency of the radio wave depends on the radar application. Radar technology is not widely used due to its manufacturing costs. The introduction of mm-wave radars has not only reduced production costs but is also a promising alternative to high-resolution scanners. Passive sensors deliver image data from which 3D information is processed using mathematical formulations (Álvarez et al., 2021; Remondino, 2011).

2.4.3 Ground Penetrating Radar

Ground penetrating radar (GPR) is one of the survey methods which uses electromagnetic waves to image beneath the Earth's surface. It is primarily used for locating materials under the ground, for example, concrete, asphalt, etc. The GPR emits pulses of electromagnetic waves into the subsurface. The change in the subsurface is identified when the electromagnetic energy is reflected back to the surface. Surveying based on GPR can effectively locate and distinguish different materials and substances. Most of the GPR systems are used in close proximity to the surface. In addition, airborne systems are useful in mapping ice formations, glaciers, and penetrates forest canopy. GPR is a highly cost-effective, non-disruptive technique used in obtaining subsurface information rapidly (Daniels, 2007).

2.5 Geospatial Analysis

Geospatial analysis is a process involved in applying statistical analysis and other techniques to data which have geospatial information. The geospatial information obtained by various categories such as positioning systems, Earth observation and scanning are discussed in the previous sections. Geospatial analysis employs software to process and apply analytical methods to manipulate and visualize GIS data. Geospatial analysis using GIS is useful for various applications in the field of environmental and life sciences and other areas such as defence, intelligence, utilities, social sciences, medicine and public safety, disaster management, natural resource management, etc.

2.6 Challenges in Positioning Systems

GNSS is the most widely used technology for acquiring location information. It plays a crucial role in various applications by providing reliable outdoor positioning information. The performance of GNSS is limited to the outdoor environment due to inherently weak GNSS signals. The weak signals are caused by obstacles, multipath effects, atmospheric conditions, interference, and receiver limitations. In addition, the indoor environments are complex in nature causing the signal and noise levels to fluctuate due to the dense and varying conditions, NLOS conditions, reflective materials, and obstacles. Therefore, positioning technologies based on GNSS are suitable only for outdoor environments, while research and development on their usability indoors is highly limited, but still being investigated (Subedi & Pyun, 2020).

GNSS precision positioning techniques such as RTK positioning use a fixed base station and a rover to reduce the rover's position error. The correction service is obtained with the use of the base station as discussed earlier in the positioning systems section. However, the main limitation of RTK-based positioning technology is the limited range available with respect to the base station. Precision accuracy is obtained only for the baseline of less than 20 kilometres using conventional RTK positioning methods. This constraint can be overcome with the use of network RTK (NRTK) method. NRTK consists of a network of permanent stations which send the data to the control centre which interpolates optimal correction data to be transmitted to the user in real time. Though NRTK has gained popularity by providing correction information for a long baseline, the cost of a subscription with NRTK provider is higher. (El-Mowafy, 2012) In addition, Precise Point Positioning (PPP) technique is a common method to improve the accuracy by delivering correction information without the need for a base station. It is a widely used technique in many applications, but it also has some limitations. The long convergence time and certain GNSS correction services offer only satellite orbit and clock errors and not atmospheric errors limiting the positioning accuracy level. Furthermore, the PPP technique is expensive due to the commercial paid GNSS correction services. (Alkan et al., 2016) However, affordable solutions are offered by new players such as e.g. PointPerfect. High-precision services are provided in order to achieve centimetre-level accuracy and reliable positioning with shorter convergence time (u-blox, 2023). There is a positioning method that combines PPP and RTK and overcomes the limitations of both techniques known as the PPP-RTK method. PPP based on RTK networks achieves centimetre-level accuracy in 1 to 10 minutes with the help of ionospheric and tropospheric delay corrections derived from the local or regional network. This enables fast single-receiver ambiguity resolution with absolute positioning. However, PPP-RTK performance is affected in GNSS-challenged or denied environments (X. Li et al., 2022). Other GNSS positioning methods such as differential GNSS (DGNSS) and standard point positioning (SPP) has limitations and their performance is lower than the PPP, RTK and PPP-RTK methods. Thus, there are a variety of different GNSS position estimation approaches called positioning methods or modes with different levels of complexity, accuracy, and price.

Applications such as precision forestry requires accurate positioning in addition to remote sensing data and GIS. Positioning errors are higher under canopy conditions, broadleaved forests, and mountain areas. Though developments in the GNSS segment have improved the static accuracy, research on mitigating multipath and cycle slip in forest environments are still being conducted. Sub-centimetre-level positioning accuracy is still challenging in forest environments (Abdi et al., 2022; Brach, 2022). With rapid development in the New Space industry, low Earth orbit (LEO) constellation of satellites have the potential to provide stronger signals compared to GNSS systems with less path loss. This makes LEO satellites to be more resilient to jamming and effectively solve the need for precise positioning in challenging environments such as indoors, forests and canyons. However, for large LEO constellations to be deployed, cost reduction across the value chain, from satellite manufacturing through launch and operations needs to be considered (Reid et al., 2018).

2.7 Correction Services

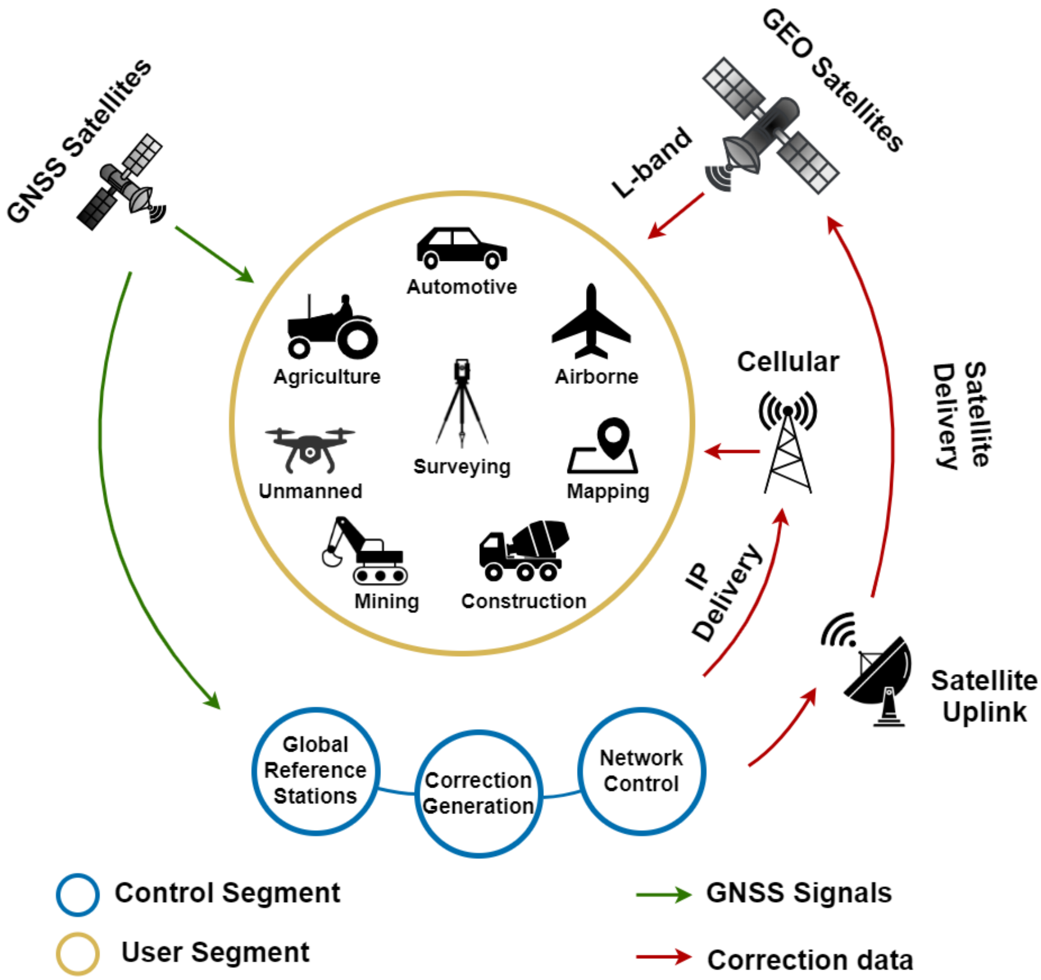
At present, GNSS systems and receivers are accurate and highly reliable. However, only a limited accuracy is offered by the GNSS constellation. The accuracies can be improved using correction services provided by the GNSS agencies and commercial entities. The accuracy and reliability of GNSS information are improved by using the Space Based Augmentation System (SBAS) that corrects the signal measurement errors and provides information on the integrity, continuity, and availability of the signals. SBAS consists of accurately located reference stations distributed across the world. Several countries have their own SBAS called regional SBAS, for example, European Geostationary Navigation Overlay Service (EGNOS) is operated by European Space Agency (ESA) covering the majority of the European Union. Other national SBASs include Wide Area Augmentation System (WAAS) by the USA, System for Differential Corrections and Monitoring (SDCM) by Russia, GPS-aided GEO-Augmented Navigation (GAGAN) by India, and so on. SBAS uses the GNSS measurements observed by the reference stations from which differential corrections and integrity messages are calculated and broadcasted using geostationary (GEO) satellites. SBAS are free regional correction services that can be used by the GNSS receivers that support them. SBAS improves the position calculations by providing ionospheric corrections since it is the largest source of errors that affects the GNSS satellite position accuracy. A meter-level accuracy for the aviation industry and a few centimetre-level accuracies for other sectors such as agriculture, mining, freight, defence and national security are obtained with the help of SBAS (EUSPA, 2023b; Johnson, 2023).

Similar to SBAS, Galileo High Accuracy Service (HAS) uses the satellite link to deliver the correction data. It is a free-of-charge high-accuracy positioning service providing corrections for PPP positioning mode. At present, Galileo HAS transmits precise orbits, clocks, and biases for Galileo and GPS through the E6-B signal in space and the Internet. The full-service phase will be complemented additionally with precise ionosphere corrections and HAS data authentication. It enables precise real-time positioning with an accuracy of less than 0.2 meters (EUSPA, 2023a).

NTRIP correction services on the other hand provide corrections to the users in real time for an accurate RTK survey. The user receives the corrections over the internet without the need for an additional receiver acting as a base station. NTRIP includes three components namely the base, caster and the user. The network of continuously operating reference stations (CORS) measures the code and carrier phases and estimate the corrections. NTRIP transfers the corrections computed in the CORS network to the users through the Internet. Examples of CORS networks are the European EUREF and International GNSS Service (IGS) networks. The density of CORS varies from place to place and when the user is far away from any of them, a virtual reference station (VRS) is used. NTRIP models a VRS next to the user to eliminate long baseline and provide the correction data. A precise solution is accordingly obtained by using local networks and internet connectivity (Johnson, 2023).

There are many commercial platforms offering correction services for highly accurate precision positioning needed in several applications. However, a general overview of how the correction data is generated by the control centre using the GNSS signals obtained by the reference stations is transmitted via Internet or L-band communication through satellite is shown in Figure 3.

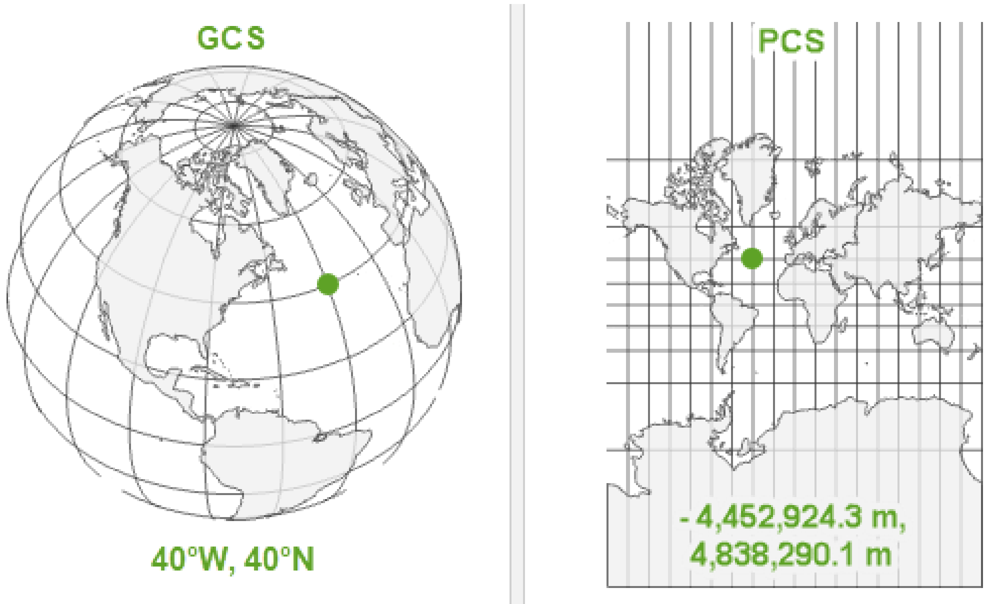
Figure 3. Overview of correction services.



2.8 Role of Coordinate Reference System

All geospatial data has a coordinate system that locates the data either in a two or three-dimensional space. It is a reference system that represents the locations of geographic features, imagery, and observations such as GNSS locations, within a common geographic framework. The role of a coordinate reference system is to identify and unambiguously describe any point in space. Most of the geospatial data is in a geographic or projected coordinate system. In the geographic coordinate system, locations are identified on the curved surface of the Earth. It is measured in angular units from the center of the Earth relative to two planes: the plane defined by the equator and the plane defined by the prime meridian (which crosses Greenwich, England). Therefore, a location is given by using two values namely, latitude and longitude value. On the other hand, a projected coordinate system (PCS) is a reference system for identifying locations and measuring features on a flat (map) surface. It consists of a grid structure made through lines that intersect at right angles. Projected coordinate systems (which are based on Cartesian coordinates) have an origin, an x-axis, a y-axis, and a linear unit of measure. The difference between GCS and PCS is shown in Figure 4 (Gimond, 2023).

Figure 4. Difference between Geographic Coordinate System (GCS) and Projected Coordinate System (PCS), from (Smith, 2020).



The most precise global reference system available is the International Terrestrial Reference System (ITRS). Based on ITRS, EUREF (Regional Reference Frame Sub-Commission for Europe) has established European Geodetic Reference Systems known as European Terrestrial Reference System 89 (ETRS89). Coordinates in ETRS89 are expressed as three-dimensional cartesian coordinates or ellipsoidal coordinates. The reference system is widely accepted by civil aviation, industries, and national and regional agencies as the backbone of georeferencing (Bosy, 2014). The Finnish Geodetic Institute has created national reference systems such as the National Grid Coordinate KKJ (kansallinen koordinaattijärjestelmä), EUREF-FIN, N60, and N2000. KKJ coordinates are presented in geographical (latitude, longitude) or in rectangular grid coordinates (northing, easting). KKJ is a two-dimensional coordinate system that does not contain any definition of the height system. In order to create the vertical coordinate (height) reference systems N60 and N2000, both nationwide levellings and gravity observations were needed. The current national coordinate system EUREF-FIN is the three-dimensional realization of the ETRS89 that replaced Finland's old national coordinate system KKJ. EUREF-FIN was created and tied to a global coordinate reference system using satellite positioning. Thus, EUREF-FIN coincides with WGS84 at the meter level. Therefore, in many purposes not requiring high accuracies EUREF-FIN and WGS84 are considered the same. In addition, for countrywide use, it is recommended to use pan-European ETRS89-TMnn -projection (UTM, nn = zone number). In Finland projection, ETRS-TM35 is used countrywide and is therefore called ETRS-TM35FIN, where FIN is for the non-standard zone width. ETRS-TM35 is recommended for public administration use. There are some distortions based on the projection. It is not completely accurate in every part of Finland. ETRS-TMzn, where zn indicates the UTM band code, Gauss-Krüger projection ETRS-GKn, where n is the (closest) central meridian. These systems cover a small area, typically municipalities have their own systems, for example, Helsinki has a system named ETRS-GK25 (Uikkanen, 2021).

In summary, a coordinate reference system is essential when working with geospatial data. It will help in identifying where data is located. It is a standard approach that uses numbers to describe a location. Geospatial data comes with certain numbers attached to the data which specify the location depending on the type of coordinate system used. Therefore, a coordinate reference system allows geospatial data to use common locations for integration. At the same time, it is also essential to keep the reference systems accurate and up to date by re-measuring systematically or otherwise maintained. Globalization and the increased accuracy of present observation techniques require that changes and motions of the Earth need to be observed more precisely than before.

2.9 Availability and Usability of Geospatial Data

Geospatial data has become more accessible than ever due to the significant spatial data provided by governmental and space agencies and meteorological organizations. Open data is available in order to improve accessibility and promote the re-use of public sector information. The open data is offered at international, European Union, national and regional levels. Depending on the type of spatial data, there exists several portals that offer valuable and significant data to the public. Table 2 will provide lists of Finnish spatial data services that are available for users.

Table 2. List of different Finnish spatial data services.

S.No	Providers	Service Description
1.	National Land Survey's geodata portal Paikkatietoikkuna	Various datasets such as maps and spatial data
2.	National Land Survey of Finland open data service	Basic map, topographic database, topographic, background and general maps, orthoimages, laser scanning data, DEMs, place names, administrative borders, etc.
3.	Biomass Atlas	Biomass from forest and field as well as manure and waste biomasses
4.	Finnish environmental administration (SYKE) Open data service	Datasets on Finnish environment including land cover, nature protection areas, lakes, rivers, ground water, floods, satellite mosaic image.
5.	GeoPortti GeoCubes Finland	Multi-resolution raster geodata like DEM, superficial deposits, land cover and forestry
6.	Paituli	Data from governmental organization and Finnish researchers
7.	Metsäkeskus forest datasets	Privately owned forests and 1 meter canopy height model
8.	National resources institute	National forest inventory thematic datasets
9.	Statistics Finland	Population, educational institutions, production and industrial facilities, traffic accidents.
10.	Finnish Transport Agency	Digiroad roads for routing and geocoding, railways, sea depth
11.	Finnish meteorological institute's open data service	Real-time weather observations, time series and forecasts

Apart from the Finnish spatial data services offered at national and regional levels, there are many international spatial data services offered by various organizations. The table is categorized based on the products and services offered. Table 3 will highlight the different international spatial data services available.

Table 3. Lists of International spatial data services.

S.No	Products & Services	Providers	Description
1.	General vector data	OpenStreetMap	Data on physical features on the ground e.g., roads, buildings.
		Natural Earth	Coast lines, contours, rivers, lakes, glaciers, country borders.
2.	Satellite images	ESA	Sentinel data from Copernicus Open Access Hub. Sentinel 2 images, resolution 10-60m.
			Proba-V – multispectral imagery products for analyzing vegetation cover.
		NASA/USGS	Landsat, resolution 15-120m.
			MODIS, continuous global coverage, data from 36 bands, resolution 250-1000m.
			ASTER, resolution 15, 30, 90m.
		AWS Public Data Sets	Open access datasets from earth observing Sentinel, Landsat, MODIS and other satellites.
3.	Digital Elevation Models	ESA	Copernicus DEM, 90m available as open-access data, 30m global and 10m European DEM with restricted access.
			EU-DEM, only Europe, 25m.
		JAXA	ALOS DEM, 30m.
		NASA and NGA	SRTM, resolution 30m.
		USGS	GMTED2010
		ASTER	GDEM, resolution 30m.

S.No	Products & Services	Providers	Description
4.	Land cover/ vegetation	ESRI	10-Meter Land Cover, resolution: 10m.
		EEA	CORINE Land Cover products for Europe, resolution: 100m and 250m.
		FAO	Global Land Cover-SHARE, 2014, resolution: 1km.
		ESA	GlobCover, 2005-06 and 2009, resolution: 300m.
		JRC	Global Land Cover 2000, resolution: 1km.
		GLAD	Forest change, surface water dynamics, humid tropical forests, tree cover, bare ground, land change (1982-2016), forest monitoring, etc.
		VITO	SPOT Vegetation Programme, products with resolution of 1km. Updated continuously, 1998-2014.
5.	Population	NASA	SEDAC (Socioeconomic Data and Applications Center) socioeconomic datasets.
		Eurostat	Population Distribution, inc. European population, resolution: 1x1km and densely populated areas, 2006, 2011.

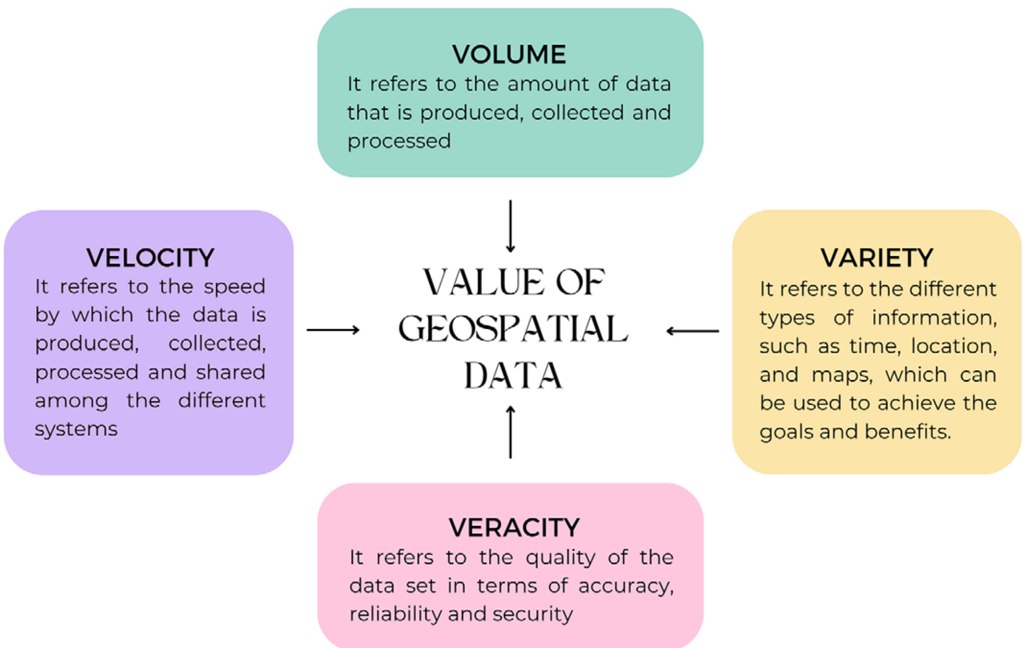
The geospatial data services are offered both on national and international levels as provided in Table 2 and Table 3 and are used by a significant number of users for various applications. These different geospatial data and tools are used by the users in retrieving, analysing, and visualizing geospatial information. Large and diverse sets of geospatial data are collected by various organizations for the past several decades. The data is easily available and accessible to the users through the portals. Such vast and different geospatial data not only benefits the users but also meets the current trends such as 3D analysis, digital twins, real-time data and big data and analytics, artificial intelligence (AI) and machine learning, and Web GIS. The usability of geospatial data continues to grow every day. Governments, businesses, and the public use geospatial data widely for mapping, navigation, telecommunication services, urban planning, public health, agriculture, disaster management, risk assessment, environmental impact analysis, surveying, military, banking, etc. (MGISS, 2023)

3 Value and Valuation of Geospatial Data

3.1 Value of Data

What is value? Value is generally defined as something against which customers are willing to pay. Several views of value are expressed across literature. In a business studies context, value is often defined either from customer perspective, or from manufacturer's perspective (Kohtamäki & Rajala, 2016). The escalating trend of digitalization and ever-increasing data production, optimization and storage among companies has raised the debate: "What is the Value of Data?". For valuing data, it and its monetizing approaches need to be defined precisely. Generally, data is any kind of processed or unprocessed information which can be interpreted to gain benefits. In literature, it is coined as the combination of symbols holding the properties of objects (Ackoff, 1989), or as unprocessed records, numbers and information, labelled as data (Leidner and Alavi, 2001). However, Thomas and Leiponen (2016) termed data non-rivalrous information, meaning it can be used by multiple actors simultaneously. Also, data sharing does not completely destroy the value of data, but decreases it significantly (Ofulue & Benyoucef, 2022). In this study, we refer data to a set of information that entails any kind of location or boundary of Earth details, as known as geospatial data.

Figure 5. Characteristics of the Value of Geospatial Data.



Based on geospatial data characteristics, it could be considered as a specific type of big data. According to Yin & Kaynak (2015) from IBM, along with Goes (2014), Big Data is defined by four distinctive characteristics often referred to as the Four V's. These include Volume, which pertains to the sheer quantity of data being generated, collected, and processed; Variety, which encapsulates the diverse types of information handled, such as timestamps, geographical locations, and maps; Veracity, a term indicating the information's quality in terms of its accuracy, reliability, and security; and finally, Velocity, representing the rapid pace at which data is created, collected, processed, and distributed across various systems. Some researchers, such as Hadi et al. (2015), have proposed 'Value' as a fifth characteristic of Big Data. However, we posit that the measurement and determination of geospatial data's value heavily depends on the Four V's of Big Data (as illustrated in Figure 4). Therefore, we advocate that these Four V's - Volume, Variety, Veracity, and Velocity - should be viewed as the defining factors of geospatial data and any assessment of value should be grounded in these parameters."

3.2 Valuation i.e. Measuring the Value of Geospatial Data

3.2.1 Data Monetization and Monetary Value of Data

Data monetization is evolved from the concept of business intelligence (BI) (Ofulue & Benyoucef, 2022), which involves extracting valuable insights through the analysis of business information. As advanced technologies continue to proliferate at an unprecedented rate among the manufacturing business, monetization of data and data insights of advanced technologies is increasingly becoming a strategic instrument for businesses to leverage for their advantage (Gebauer et al., 2020). Gartner defines data monetization as the process of "using data to achieve quantifiable economic benefit". More recently, Woroch and Strobel (2022) expanded upon this concept, describing it as an innovative value-creation process that captures value by designing and implementing data-based revenue models. For the purposes of this study, we have adopted the definition posited by Parvinen et al. (2020), which considers data monetization as 'an approach to leveraging the unique properties of data as an intangible asset, creating and capturing value by exploiting collected and organized data in novel ways.

To gain a competitive advantage and open distinctive revenue avenues, businesses are developing multiple tactics for data monetization (DM). According to Moore (2015), there are two paths to monetize data; (1) Direct DM and (2) Indirect DM. Direct DM refers to gaining economic benefits directly through the provision, sale and giving rights to use the data or data insights. Indirect DM refers to the opening of new revenue avenues and gaining economic benefits by creating and improving new products, services, processes or business models but without the data or data insights sale or even their rights. Through a systematic literature review, Baecker et al (2020) discovers twelve data monetization tactics which firms are employing, presented in Table 4. Through the content analysis, we divide the twelve DM tactics into two main categories; direct monetization and indirect monetization. Direct monetization involves direct selling which employs two tactics; (1) Data Asset Sale and (2) Data Insights Sale. However, by using the Wixom (2014) approach, we have further divided indirect DM into two methods; (1) Bartering and (2) Wrapping. Bartering is a practice involving the trading and sharing of goods or services among participants without any monetary exchange. In parallel, 'wrapping' pertains to the optimization of data to instigate internal business innovation and improvement. Drawing from the concept of bartering, 'data bartering' is an emerging tactic. This strategy can be described as an exchange process, where information (raw data) or knowledge (processed data) is swapped among networks in exchange for valuable assets, such as data from partners' operations. On a similar note, 'wrapping' stands as a commonly employed technique in data monetization. It involves leveraging data for internal benefits such as enhancing business models, fostering product innovation, or improving processes. Thus, it involves nine DM tactics. All monetization tactics play a role in enhancing and opening new revenue streams. However, in the realm of indirect monetization, companies often encounter scarcity in terms of skills, technology and resources, that are significant barriers in revenue growth. Similarly, direct monetization can be impeded by stringent laws, regulations, and the nature of the data itself. Given these data opportunities, assessing the value of data proves to be a complex and time-consuming process. The subsequent section delves into the methods of valuation, their applicability, and the steps involved in measuring the value of data assets.

Table 4. Tactics to Monetize Data (Baecker et al., 2020. p. 979).

Monetization Type	Sales Tactics	Data Monetization Tactics	Definition	
Direct Monetization	**Direct Selling**	Data Asset sale	Utilizing data to generate additional streams of revenue by either selling or giving rights to use the data assets.	p. 979
		Data insights sale	Generating revenue through the sale of informative/knowledgeable insights acquired by stepwise processing of data for insights generation such as analytics or visualization based on data.	p. 979
Indirect Monetization	**Bartering**	Data bartering	Exchanging data against the non-monetary but valuable benefits such as data, equipment, services, softwares or tools.	p. 979
	Wrapping	Contextualization	Employing contextual data to produce monetary profits	p. 979
		Individualization	Employing client's data to individualize the organizational value proposition to some extent for individual customers.	p. 979
		Build & strengthen customer relationship	Developing and sustaining the long-term relationships with customers through the use of data	p. 979
		Strategically opening data	Providing access to internal data to business partners and other parties in pursuit of value co-creation, marketing and branding, or for some other advantages.	p. 979
		Data enrichment	Obtaining monetary benefits by incorporating different data sources such as internal and external in the data processes (storing, conversion and cleansing).	p. 979
		Data privacy and control guarantee	Monetization of data by assuring the customers that their data will not be used and in addition, giving them rights to control the data.	p. 979
		Business process improvement	Generating value based on the data by enhancing the internal business process.	p. 979
		Product/service innovation	Employing data to add new offerings such as new products or services for customers.	p. 979
		Product/Service optimization	Bringing improvement into the existing product or service portfolio by employing data.	p. 979

3.2.2 Valuation from the Perspective of Accounting

From an accounting viewpoint, geospatial data can be construed as a form of intangible asset within an organizational context. In the contemporary business landscape, these non-physical assets encompassing intellectual abilities, operational processes, branding, organizational culture, and data resources have emerged as vital strategic constituents. The role of such intangible elements as catalysts for economic expansion is being progressively highlighted by governmental bodies, who concurrently advocate for increased corporate focus on the management and exploitation of these assets. The allocation of resources towards the non-tangible aspects of business operations is indispensable for corporations aiming to generate value-added goods and services. In line with the industry's transition from manufacturing-centric to service-oriented practices, powered by knowledge-based professionals in developed nations globally, intellectual capital, typified by resources such as geospatial data, has gained prominence as a dominant asset.

Thus, accounting scholars and regulatory authorities around the world necessitate firms to capitalize the cost and value of intangible assets and amortize it over a period that approximates the economic life of the assets (Powell, 2010). These accounting stipulations have long been a subject of contention (Wyatt, 2005). The crux of the controversy revolves around whether the reported value of intangible assets on the balance sheet accurately reflects the value of their future economic benefits. Contemporary measurement systems inadequately address the accounting of intangible assets in a manner that is both transparent and comprehensive. A related query pertains to whether the recorded amortization of intangible assets indicates the decline in their economic value and to which degree the reported value of intangible assets and their corresponding amortization expense are manifested in the market value of firms' equity. This correct valuation of intangible assets, like geospatial data, is of utmost significance for users of financial statements in decision-making processes, for accounting regulators in formulating financial reporting policies, as well as for companies themselves.

In a wider context, prevalent criticism has been leveled against the corporate disclosure of financial metrics, primarily due to its inability to accurately represent the variances in uncertainty associated with future economic benefits and costs related to diverse assets. The balance sheet fails to allocate differential weight to assets embodying disparate levels of uncertainty pertaining to their associated future economic gains and expenditures. Paradoxically, a plethora of valuation models underscore the notion that an asset's value is inversely proportional to the uncertainty enveloping future benefits derivable from the said asset (Robichek & Myers, 1966; Rubinstein, 1973; Epstein & Turnbull, 1980). The relationship between uncertainty and asset value is overlooked in most balance sheet and income statement measures and constitutes the primary rationale for the critique of financial statements. This concern gains added relevance in the context of intangible assets, such as geospatial data, due to their inherent characteristics and the significantly elevated uncertainty encompassing the quantity and timing of their prospective economic benefits.

Regulatory accounting authorities suggest that an intangible asset should be recorded at historical cost and amortized over the period during which the firm anticipates benefiting from its utilization. Nonetheless, in contrast to fixed assets, the uncertainty concerning the magnitude and timing of future benefits expected from intangible assets is substantially greater. Owing to the elevated levels of uncertainty associated with future benefits derived from intangible assets, numerous practitioners and academics have proposed that such expenditures be expensed in the period in which they are incurred. This proposition aligns with valuation models, which imply that the value of an asset will approach zero as the uncertainty of its future economic benefits approach infinity. Egginton (1990) and Hodgson et al. (1993) posited several challenges for the amortization of a specific type of intangible asset, consequently resulting in the decline in the value of the intangible asset being reported in the income statement with substantial error. The use of an intangible asset is contingent upon the nature of the asset, its economic life, and the pattern of consumption of its future economic benefits. Unlike tangible assets, the determination of the lifetime duration during which the asset's economic benefit will be consumed and the reduction pattern of the asset's service potential entail considerably greater uncertainty, as the specific benefit remains unclear. This heightened degree of uncertainty leads to a decrease in the accuracy of the reported value of the intangible asset in the income statement. Whether the heightened level of uncertainty related to the benefits from intangible assets is significant enough to prompt the market to discount those benefits more than it does for other asset benefit streams is a matter of continuous debate among accounting researchers.

3.2.3 Valuation Methods and Geospatial Data

Geospatial data embodies numerous characteristics inherent to intangible assets, including intangibility, exchangeability, and variability, leading to considerable complexities in their valuation process (Li, 2016). Furthermore, the intrinsic nature of geospatial data implies that its value is temporal and is influenced by factors such as prevailing market conditions, usage circumstances, and data categorization. Ordinarily, recent geospatial data holds superior value in decision-making processes, with its value projected to diminish over time. Consequently, the acquisition of timely high-resolution geospatial data is typically associated with a higher cost, entailing escalated expenses related to transfer, exchange, and trading processes (Abbasi et al., 2016).

In the context of accounting valuation for geospatial data, it becomes paramount to consider their implications on the overall corporate value and bridge the information chasm that exists between geospatial specialists and accounting professionals (Li, 2016). Past scholarly work has delved into various asset accounting valuation models, some of which are apt for the valuation of geospatial data. Loukis et al. (2012) put forth a tri-layered value model for data valuation, while Shi et al. (2017) recommended a data asset valuation model predicated on three facets, namely collection, processing, and maintenance. An algorithm for data asset evaluation, considering data attributes such as data category, data validity duration, data application range, and data complexity, was suggested by Wang (2016). Further, Zou (2017) advocates for the categorization of data assets as either internally collected/processed or externally procured, and the evaluation to be done either on the basis of associated costs (like labour, computing, and electrical costs) or the historical cost of procurement, respectively. These methodologies can also be employed to ascertain the value of geospatial data.

Aligning these approaches for geospatial data, we suggest some solutions. Hares and Royle (1994) proposed a method for converting intangible benefits into cash flow for cost-benefit analysis. Their approach involved three stages: identifying and measuring benefits, predicting outcomes in physical terms, and evaluating the resulting cash flow from these intangible benefits. Anandarajan and Wen (1999) endorsed a similar technique for achieving the financial quantification of intangible advantages. Murphy and Simon (2002) underscored the significance of intangibles in IT projects, like geospatial data, and illustrated the implementation of a framework through which they could be integrated into conventional evaluation methodologies. Reilly (1998) introduced three approaches for valuing proprietary technology, namely the market approach, the cost approach, and the income approach, while Stewart (1997) suggested the Calculated Intangible Value (CIV) approach. The suitability of each valuation method varies depending on the asset type, available data, and the unique circumstances of distinct industries. We introduce these methods in more detail in the following and discuss how they can be used to value geospatial data assets.

The cost method endeavours to approximate the benefits and costs associated with attaining equivalent functionality through disparate technologies, processes, or human resources, that is, by evaluating the replacement cost of the asset or employing benchmarking techniques. Thus, the cost approach for evaluating geospatial data assets is rooted in the method of data acquisition, specifically self-collection or external procurement. In the case of self-collected data assets, the cost evaluation process should commence by considering the initial construction costs associated with data collection and the ongoing operational costs. The construction costs encompass the expenses incurred in acquiring and storing raw data, as well as the costs of constructing an information system, including labour and storage equipment fees. The ongoing operational costs consist of the technical expenses incurred during the data pre-processing phase, such as data cleaning, masking, correlation, and, as well as expenses associated with data mining to generate business value (Moody & Walsh, 1999).

The net present value (NPV) approach, which stems from capital budgeting theory (Mao, 1970), is a method of estimating the future benefits that a company can derive from geospatial data assets, which is then discounted using the prevailing market rate. This approach diverges from the cost approach in that it acknowledges the potential profitability of intangible assets that may emerge in the future. The future benefits generated by geospatial data can vary significantly depending on how a company employs them. To apply the NPV approach, a company must consider the historical utilization of similar intangible assets and their intended use of geospatial data in the future to estimate their potential future cash inflows.

The market value approach is deemed suitable for data assets that are comparable to other items in the active market or when estimating the value of a data asset using the net present value or cost approaches proves challenging (Dainienė & Dagilienė, 2014). Within the context of geospatial data assets, the market value approach involves analysing comparable transactions concerning similar data assets, which can provide an indication of the market value for such assets. This approach may be suitable when external data on transactions involving geospatial data assets are available, as it allows for the assessment of the value of the assets based on actual market participants' behaviour.

Calculated Intangible Value (CIV) approach (Stewart, 1997) posits that the valuation of intangible assets is grounded in the residual operating income model, which serves as a variant of the fundamental equity value model. When valuing geospatial data, the steps to be followed under this approach include:

1. Determining the book value of the assets and the discounted flow of residual operating income to ascertain the company's value.
2. Determining the book value of tangible assets and intangible assets other than geospatial data, and the discounted flow of residual earnings utilizing the average industrial rate of return.
3. Calculating the difference between the total book value of the company and the value of assets in Phase 2 to determine the value of geospatial data.

Several other valuation approaches for intangible assets, like geospatial data, have been suggested by other disciplines. For instance, based on a practitioner's perspective, Jia (2019) categorized them into three valuation methods: Query-based pricing, data attribute-based pricing, and auction-based pricing. However, many of these approaches fail to consider three essential aspects of valuation: task-specificness, fairness, and efficiency.

According to InfoComm Media Development Authority report, three of the above-mentioned valuation approaches can be employed to estimate the value of data: the market approach, the cost approach, and the Income approach. Furthermore, the report suggests considering the data characteristics, circumstances of transactions and data availability while employing the valuation approach. In a similar vein, Deloitte suggested a 4-stage comprehensive framework for valuing data. In the first and second stages, businesses should compile and analyze data assets and their attributes such as the identification of key factors that make the data set unique. In the third and fourth stages, businesses should evaluate the use case of data and its attributes through a valuation lens: growth, returns and risk. For each use case, the appropriate valuation approach should be adopted based on these attributes. The recommended valuation approaches include the market approach, multi-period excess earnings method, with and without method, relief from royalty method and the cost approach. The report also recommends employing alternative evaluation methods to add robustness to the valuation. Table 5. provides a comprehensive summary of our discussion and offers a holistic overview of methodologies available for valuing geospatial data.

Table 5. Monetary value of data in literature.

Document	Methods used/presented	Comments	Source
Existing Approach to Data Valuation	Query-based pricing, Data attribute-based pricing, Auction-based pricing	Do not consider task specificness, fairness or efficiency	https://bair.berkeley.edu/blog/2019/12/16/data-worth/
Data Monetization - What It Is & How It's Done	1) Selling or licensing your data to third parties. 2) Driving internal optimization and innovation. 3) Open exchange or sharing of data with partners	Provides a comprehensive list of references.	https://www.anmut.co.uk/data-monetization-what-it-is-how-its-done/
Data Valuation | Why It Matters & How It's Done	1) The cost value method, 2) The market value approach, 3) The economic value approach (a) income or utility valuation, b) use case valuation (business model maturity index (Internet of Water) or decision-based valuation)) 4) The stakeholder value approach	Stakeholder approach is recommended	https://www.anmut.co.uk/an-introduction-to-data-valuation/
Methods for valuing data	For producers: modified historical cost, market value. For users: Business Model Maturity Index, decision-based valuation. For hubs: consumption-based	Includes references to additional literature.	https://internetofwater.org/wp-content/uploads/2018/12/01-Options-to-Value-Data.pdf
Guide to Data Valuation for Sharing Data	1) Market approach, 2) Cost approach, 3) Income approach	Significant differences between approaches. The cost approach provides the smallest value and the income approach provides the largest value (see page 36).	https://www.imda.gov.sg/-/media/Imda/Files/Programme/AI-Data-Innovation/Guide-to-Data-Valuation-for-Data-Sharing.pdf
Transforming Highways England's approach to data. An Anmut Case Study,	Provides return on investment for 50 data projects	On average, "£ 1 investment in data by Highways England produces £ 2,7 in economic value for the logistics companies, commuters and other groups that depend on its roads".	https://www.anmut.co.uk/successful-cdo-cs/

Document	Methods used/presented	Comments	Source
Data valuation: Understanding the value of your data assets	1) The market approach, 2) Multi-period excess earnings method (MPEEM), 3) With-and-without method, 4) Relief from royalty method, 5) The cost approach	Before valuation, identify current data assets and their attributes. After valuation identify current and alternative use cases. See examples, p. 8-9 (also agriculture)	https://www2.deloitte.com/content/dam/Deloitte/global/Documents/Finance/Valuation-Data-Digital.pdf
EO and GNSS Market Report, European Space Program Agency, 2022	Revenue from data/services sales in a given year. Earth Observation and GNSS are evaluated in 17 industry value chains.	Includes agriculture	https://www.euspa.europa.eu/sites/default/files/uploads/euspa_market_report_2022.pdf
A Review of Data Valuation Approaches and Building and Scoring a Data Valuation Model	market-based valuation, economic models, and applying dimensions to data	Includes also a geospatial data example, HDSR, Issues 5, 1, 2023	https://hdsr.mitpress.mit.edu/pub/1qxkrnig/release/1?readingCollection=49a3a635
Putting Value on Data	1) Income approach, 2) market approach, 3) cost approach	Includes good illustrations of value drivers and use cases	https://www.pwc.co.uk/data-analytics/documents/putting-value-on-data.pdf

In summary, the cost, net present value, and market value approaches offer distinct and the most promising methods for evaluating geospatial data assets. The selection of an appropriate method depends on factors such as the method of data acquisition, the availability of historical utilization data for similar assets, and the existence of comparable transactions in the active market. By considering these factors, companies can adopt a suitable approach to accurately estimate the value of their geospatial data assets, ultimately informing strategic decision-making and resource allocation processes.

4 The Role of Geospatial Data in Different Industries and Cases

As discussed in the previous section, measuring the value of geospatial data is complex. Presumably, the existing empirical research on the topic is limited and based on case studies or conceptual discussions (European Commission, 2022). In the report by the EUSPA, the value of geospatial data (EO & GNSS) is measured across value chains in 14 out of 17 industries in Europe and compared to other areas globally. Value was measured as data revenues (MEUR) and value-added service revenues (MEUR) (European Union Agency for the Space Programme, 2022). Also, the market value of different industries in Europe is being monitored and the development of marketing predicted (Datalandscape, n.d.).

The aim of the research was to determine the impact of geospatial data. Evidently, one of the methods to evaluate the impact is with revenues. The objectives of this work were to assess the role of geospatial data in an economic sense, the growth benefits of geospatial data, the profitability/productivity benefits, export opportunities, and climate impact. The industries which were chosen for this report were industries where the use of geospatial data may be increasing. According to the report of ETLA (2023), the biggest industry in Finland is services (retail industry, tourism, logistics, finance and facilities and business services, 67 %) and the second biggest is industrial production (metal industry, forestry chemistry and food; 25 %), followed by construction (6.8 %). Information and communication were the most growing part of facility and business services, but it was not chosen for this report as an industry, because it was not clear what kinds of companies might be growing. The demand for facility services is decreasing, but the telecommunication, and especially software and consulting business is growing. In the market report of European Union Agency for the Space Programme (2022) there was not such an industry as software and consulting highlighted, but software was seen as a measure of size of market generating revenues.

4.1 Industries

4.1.1 Agriculture and Forestry

According to Zhang et al. (2021), the total profit of agricultural production consists of "total net economic benefit (TNEB) of agricultural products and ecosystem service value (ESV) of the ecosystem." The market price of crops, cost of inputs, and ecosystem service value are economic factors that show complex uncertainties as well as influence the decision-making. The collection and processing of spatial data is a difficult aspect of agricultural production planning.

The benefits of the use of geospatial data in agriculture can be defined for instance in the following ways: "Satellite-based high-spectral remote sensing is a fast and low-cost operation, hence making it feasible for monitoring in a large spatial domain and a long-term period" (Dai et al., 2022). Risk of fertilizer residual in rice paddies can be lowered with the help of UAV-based spraying and it is efficient as well (Xu et al., 2021). "Pairing GPS with yield monitors or soil testing allows farm operators to create yield maps or soil maps that inform crop production decisions. Farm machines like combine harvesters and tractors can be guided or autosteered via GPS, which may reduce input costs and give the operator more time to focus on other tasks" (Hanson et al., 2022).

Climate change impacts the productivity of farming. GIS can be used, at least indirectly, to evaluate economic loss (Singh & Dhadse, 2021; Xian et al., 2022) and with the help of GIS software, to calculate total emissions directly (Ding et al., 2020). According to Jayarathna et al. (2021) GIS can be used to plan eco-efficiency of biomass production supply chains too.

To achieve sustainable water-use efficiency (WUE) and water-efficient practices, like irrigation systems or administrative water allocation, we should consider the economic benefits and environmental burdens. These systems should be included in a knowledge-exchange system to enable farmers to improve their water use (Liu & Song, 2020; Tang et al., 2020). According to Luo et.al (2021), it is possible to use remote sensing to make predictions, and thereby ensure economic benefits as well as to increase food production under limited water resources.

Europe's intention to become the first carbon neutral continent by 2050 is ambitious and demands the management of primary forests. Unfortunately, there are no scalable assessment methods which can be applied to the full international scale of primary forests to characterize their biodiversity traits. Finland is estimated to host approximately 2,817.36*ha of primary forests (Sabatini et al., 2021). Currently LUKE produces the "Valtakunnan metsien inventointi (VMI)," or "National Forest Inventory (NFI)" initially once every 10 years and in the 21st century, once every 5 years (Korhonen et al., 2021). Remote sensing and geospatial data can host a real-time data forest inventory of Finland's primary forests as well as provide forest health monitoring. Remote sensing technology can be used to create detailed forest inventories, identifying the location, type, and density of trees. This data can be used to make informed decisions about forest management, including the timing of harvesting and replanting, and the use of pesticides or other interventions to prevent further damage. Geospatial data can be used to monitor the health of forests, identifying any areas that may be affected by pests, invasive species, disease, or other environmental factors. Pilot studies regarding the rise and success of volunteered geographic information (VGI) activities have had positive results in supporting national mapping agencies (NMA) in data collection by both citizens and NMA (Rönneberg et al., 2019). Similar volunteering schemes could be useful in facilitating a national forest inventory.

As a conclusion, the benefits of the use of geospatial data are cost reduction, increasing eco-efficiency, water use efficiency as well as the reduction of risks. Revenues from Earth Observation data and agricultural services are supposed to grow evenly in the next decade, from a combined total across all applications of 377 million € to 652 million € in 2031. EU market share of EO is 46 % in agriculture, 60 % in forestry and 89 % in fisheries and aquaculture (European Union Agency for the Space Programme, 2022).

4.1.2 Energy

Geospatial data has been used to optimize and reduce environmental impacts and costs in the oil & gas industry (Skretas et al., 2022). GIS based multi-criteria decision support system can be used to analyze economic sustainability in the case of biogas production (Yalcinkaya, 2020) as well as to find the best locations for solar farms (Mokarram et al., 2020), or in decision-making support in development projects (Elsayed & Ismaeel, 2019). GIS has also been used to help investments the planning of biomass utilization, in which potential and location should be known (Danzì et al., 2020; Furubayashi & Nakata, 2018). GIS have also been used in techno-economic analysis, which provided potential water production maps, levelized water cost as well as energy consumption and solar input data (Pimentel da Silva & Sharqawy, 2020).

GIS has been used as a part of a tool for assessment of risks, costs and the reliability of electricity distribution (Sánchez Muñoz & Dominguez García, 2021), geothermal sites (Coro & Trumpy, 2020) as well as a part of a planning tool aimed at increasing the use of bioenergy, for instance (Valente et al., 2018).

Precise time is an integral part of certain advanced measurements that are increasingly used for grid operations and planning applications (Dagle et al., 2021). Power grid systems rely thus on GNSS as a time reference source and atomic clocks as a backup in case of outages. GNSS is used primarily to the synchronisation of energy networks and smart grids, particularly in helping to distribute the produced energy (European Union Agency for the Space Programme, 2022, p. 81), therefore playing a key role in the industry.

Sustainability, cost reduction, and environmental impact are key benefits in the energy industry. According to the EUSPA report (European Union Agency for the Space Programme, 2022, p. 89-92), the revenues from the sales of EO data and services to the energy and raw materials sector in 2021 amounted to 305 million €, and are expected to grow to 402 million € by 2031. Revenues from GNSS may decrease in the same period.

4.1.3 Manufacturing

In the Osterrieder et al. (2020) literature review regarding smart factories, perspectives of research are fragmented, and in most cases, there is only low generalizability. The studies "often rely upon machine data, typically have a technical nature and seldom incorporate impact estimations." The review concluded that there are eight thematic perspectives on smart factory: decision making, cyber-physical systems, data handling, IT infrastructure, digital transformation, human machine interaction, IoT, and cloud manufacturing and services. In general, there is a need to communicate and show the profitability of investment in Industry 4.0 related things (Lundgren et al., 2022). In the construction industry, the GIS supply chain model present an overview of supply-demand dynamics in a virtual environment with geographical traffic information (Yu et al., 2021).

Manufacturing firms can optimize their operations as well as make them more efficient by utilizing geospatial data. Examples of technologies are Building Information Modeling, drones, indoor positioning systems as well as IoT sensors. For example, General Electric was able to improve one customer's reliability from 93% to 99.49% in less than two years as well as cut reactive maintenance by 40% in one year (Geospatial 2021, p. 21).

4.1.4 Logistics

There are many positive impacts of the use of geospatial data in logistics. The value of data can be estimated in the case of Earth observation in the EU region. The EU has the biggest market share in aviation and drones (93%), maritime and inland waterways (81 %), but smaller market shares in rail (35%) and road & automotive (12%) (European Union Agency for the Space Programme, 2022). In the following part, drones and autonomous vehicles are used as examples with great market potential in the area of logistics.

4.1.4.1 Drones in Transportation and Logistics

Drones are classified as a kind of autonomous technology. Lemardelé et al. (2021) claimed that autonomous technologies have the potential to reduce last-mile operations costs and externalities. "The most optimal use of these technologies and, consequently, the major operations costs and externalities reductions, depend on the considered service regions and their characteristics. In a large and low-density service region (as in the Paris suburb use case), truck-launched delivery drones could help cut the total operations costs by almost 25%. In more dense urban environments (Barcelona historical center use case), GADDs (ground autonomous delivery devices) show more economic potentialities than truck-launched delivery drones." In short, population density is important, and drones are connected to some other means of transportation, like trucks.

There are many benefits in using drones according to research. The drone sector in the EU region will employ more than 100,000 people, and the economic impact will annually be 10 billion €. Approximately 20% of flight time is expected to be remotely or optionally piloted by 2050 (Jane Fox, 2022). New features in technology improve flexibility and the total profit (Amine Masmoudi et al., 2022). According to Rodrigues Dias et al. (2022), the use of Industry 4.0 (I4.0) technologies, like artificial intelligence, virtual reality, drones and additive manufacturing drive circular economy in the aerospace industry. I4.0 technologies can be used to increase productivity.

Reasons for perceived risks and usefulness of drones have been studied. According to Lamb et al. (2022), the higher the perceived risk there is, the weaker the perceived usefulness of the UAS is. The use of drones with long battery endurance to perform the assessment task may not be necessary from an economic perspective. The efficiency of the truck-and-drone system is very sensitive to drone speed (Zhang et al., 2021). Drones can perform high volume and high-speed delivery, they help reduce traffic congestion (important in cities), but require infrastructure changes, involve high investment costs, and the delivery costs are dependent on the level of automation (Doole et al., 2020). A decision support has been improved for e-commerce companies to construct an efficient drone delivery system with minimal operating costs and investments (Shen et al., 2021).

The most acceptable use of drones is rescue operations (Del-Real & Díaz-Fernández, 2021; Komasová et al., 2020), traffic monitoring, and monitoring of people to ensure state security (Komasová et al., 2020). Using drones for fire handling and disaster recovery are the most beneficial for firefighting in high-rise buildings. The urban planning, municipal works and infrastructure inspection utilities of drones are the most beneficial for providing logistics support at personal and community levels (Zhang et al., 2021), whereas medical drones will revolutionize health care delivery, particularly in rural areas. The initial costs of implementation of drones are high, hence, the benefits of technology should be communicated to improve general acceptance (Nyaaba & Ayamga, 2021). According to Sabino et al. (2022), the main perceived risks included "drone misuse, privacy disrespect, malfunction, damage, safety, noise and legal liability". The main benefits expected were "application flexibility, emergency response and monitoring, cost reduction and safety".

Drone videos could also be seen positively. According to Vujičić et al. (2022), destination management organizations should see vacation drone videos as a new kind of user-generated content for their destinations, which could be used in marketing.

The legitimacy of drone technology and the overcoming of technology transfer barriers depends on communication. Technology is supposed to benefit the consumers' self-image. UAV firms emphasize the UAV's functional capabilities to counter the perceived technical barrier (Mendoza et al., 2021). The public is tentatively ready for extensive drone application. Perceived potential benefits lie mainly in the benefits for consumers for the economy as well as improvement of workplace safety (Lin Tan et al., 2021; see also Yaprak et al., 2021). According to Kim (2020), price and type of goods influence consumer preference, which also depends on socio-demographic characteristics like gender, age as well as household income (Kim, 2020).

To conclude, the benefits of the use of geospatial data were cost reduction, profitability and productivity in organizations, and employment on a societal level. Other benefits that emerged were safety and security.

4.1.4.2 Autonomous Vehicles in Transportation and Logistics

According to the Marletto (2019), the future diffusion of autonomous vehicles (AVs) in urban areas and their impacts depend on how technology is incorporated into the urban mobility. Impacts of AVs on other dimensions of mobility, such as traffic jams, emissions and energy consumption, will depend on the following things: the mode of transport (car, bus, train etc.), level of automation, connections (vehicle-to-vehicle and/or vehicle-to-infrastructure), used propulsion (internal combustion, hybrid electric, or full electric), transport business model (owned, rented/shared or scheduled, individual/household or collective, passengers or freight, integrated with other transport modes or not etc.), use domain (long haul, suburban, urban, commuting) as well as regulations (speed limits, restricted area of use etc.). According to Marletto (2019), automation can reduce transportation costs. Travel costs as also supposed to be reduced in general (Merkert & Bushell, 2020). A near-total transition to automated ride services is highly unlikely, because ownership of vehicles continues to be usually the least-cost option, which is true especially in rural areas (Wadud & Mattioli, 2021). Perceived usefulness is an important latent determinant of the intentions to use AVs. According to Gurumurthy & Kockelman (2020), the use of shared autonomous vehicle (SAV) will be particularly popular for long-distance business travel, and privacy may not be an important concern for that kind of travel. Hyland & Mahmassani (2020) claimed, that allowing shared rides significantly improves the operational efficiency of the AV fleet (water traffic), where the efficiency gains stem from economies of demand density and network effects. Also, an increase in efficiency lowers costs. According to Kolarova et.al (2019), using SAV is perceived as a less attractive option than using a privately owned autonomous vehicle.

There is a need for a wider public discourse on automated vehicle technology and for moving beyond the technocratic and expert-centered logic in order to find a wider range of automated mobility futures (Hopkins & Schwanen, 2021). Perceived usefulness is seen as an important latent determinant of the intentions to use AVs. The maturity of technology does not guarantee the wide adoption of AVs, and public acceptance is needed (Xiao & Goulias, 2022). Users of AVs perceive the usefulness of an AV in various ways. The users can be enthusiasts or highly resist AVs, or something in between (Kim et al., 2019). As an example, according to Cunningham et al. (2019), most Australians are currently not willing to pay more for a fully autonomous vehicle than for a manually operated one. Several sample demographic and characteristic variables (e.g. gender or self-classification as an early vs. late adopter of technology) have unique associations with the aspects of AV acceptability.

According to Gu and Wallace (2021), there are benefits related to increased efficiency in water transportation and ports by using AVs. Besides the labor cost reduction, significant savings on travelling distance can be gained if autonomous water-taxis are introduced. Anyway, these results are approximate and demonstrate only potential benefits, because the initial investment cost of the water-taxi fleet and the terminals are not involved in the evaluation. Filom et al. (2022) state that ports use machine learning (ML) for business analytics. Artificial Intelligence could outperform humans and decrease the overall port cost. ML could be used, for example, in port demand forecast.

According to Abe (2019), more substantial cost reductions in rail or bus trips with taxi access could occur in the case of shorter trip distances or in residential areas far from stations. Larger reductions in rail trips with bus access could occur in low-density metropolitan areas. Vehicle automation in public road transit could primarily benefit the transit industry and government by improving labor productivity and reducing subsidies. Vehicle automation in more flexible modes could cause benefits for both metropolitan residents and transit industry. As transportation technology matures, examining people's behaviors and intentions in mixed traffic can lead to better preparation for the future roads and maximize the safety benefits of AVs (Lee et al., 2021, see also Xing et al., 2022).

Costs, labor productivity, and operational efficiency could be improved by using AVs. This applies for road, rail, and water transportation. However, concrete values for savings and increased productivity were not found in the studies incorporated in this subsection, and further research in the area would be required.

4.1.5 Other Services

Geospatial data can be utilized also in other services than transportation and logistics. Liu et al. (2020) built a model for an IoT based laundry service, which utilizes big data analytics, intelligent logistics management as well as machine learning techniques. Using GNSS and real-time big data, the model calculated the best transportation path and updated and re-routed the logistic terminals quickly and simultaneously. E-cycling is another application area for GNSS data. In general, priorities in service development are location (Kabak et al., 2018) and cost reduction (Prajapati et al., 2022), but the use of big data, for instance in the banking and financial sector, call for skilled workforce, financial support, readiness of infrastructure as well as appropriate big data technologies that have significant impacts on other enablers (Hajiheydari et al., 2021).

The geospatial technologies and data were in the front row in the fight against the Covid-19 pandemic. According to Mir et al. (2022) pandemic countering strategies such as extensive area lockdowns, mapping of critical coordinates, location-based quarantines, and managing the tests of the population based on geospatial analytics along with other multidimensional data were developed in China. In the United States, city governments are using geospatial-based google flu trends which has 97% accuracy to forecast influenza outbreaks. Some other public applications of location data include preparedness for aid in the case of a disaster, mitigation strategy planning and prompt response (Mir et al., 2022).

In the retail industry, the trend of organic or fresh farming from farm to table needs evidential support. These processes are hard to keep track of, but using geospatial data -based apps, these retailers can monitor the progression of the supply chain. The HarvestMark (Moser and Thilmany, 2011) and Trace Genomics (Khatun et al., 2020) systems are mapped in such a way that retailers also have access to it and can monitor the progression of the produce in real time and plan the selling of the upcoming products in a timely manner. This keeps the integrity of the product intact with the location of the product being always shared and enabling quality monitoring.

To conclude, the benefits achieved by using geospatial data found in the review were increased efficiency and cost reduction, as well as health benefits. Lower costs and increased efficiency were also mentioned in the subsections of transportation and logistics services.

4.1.6 Construction and Infrastructure

It is estimated that adoption of digital technology has direct effects on economic, environmental, and social performance in the construction industry (Li et al., 2021), but on the other hand successful implementation of technologies calls for "leadership, technology awareness, suitable company size, usability of proposed solution, acceptable cost of implementation and interoperability" (Silverio-Fernandez et al., 2019). According to the Chen et al. (2022) literature review concerning the years 2001-2020, there are a total of 26 technologies, which can be categorized into five groups in terms of their functionality in construction process, which are data acquisition, analytics, visualization, communication and design and construction automation. Digital technologies, especially for data acquisition (including for instance IoT) and visualization, enhance and enable innovation in the construction industry. Many of these crucial technologies are geospatially driven. The most important benefits of these technologies refer to the improvements in efficiency, health and safety, productivity, quality as well as sustainability. Drones have been used in the construction industry for safety purposes (Hassandokht Mashhadi et al., 2022; Umar, 2021), as well as reducing variation (Noruwa et al., 2022), but the most important positive impacts of multirotor drones in construction are safety, cost-effectiveness and carbon emission reduction (Li & Liu, 2019).

Building information modelling (BIM) is supposed to be the single most widely used technology thus far. It has been used together with other technologies such as unmanned aerial vehicles, as well as geographic information systems (GIS) (Chen et al., 2022). GIS can be connected to Life Cycle Assessment (LCA) in the construction industry and there are tools called GIS-LCA tools (Revelo Cáceres et al., 2023). IoT has been used for monitoring construction sites (Guo et al., 2022), as a part of smart product service systems in housing construction (Li et al., 2021), to make projects more successful (Xing et al., 2021), to reduce project delays (Rajadurai & Vilventhan, 2022) and as a part of project risk management (Rane et al., 2021).

IoT is seen as one of the most important technologies for safety management in the construction industry (Yap et al., 2022), but it is estimated that an increase in efficiency and productivity are the primary impact of the IoT (Oke et al., 2022). According to former studies, IoT has a positive impact in the construction industry related to many aspects, such as business process improvement and business performance (Jonny et al., 2021) and quality control (Yao, 2022). The challenge in the estimations is that even though they are empirical studies, there are no clear numbers showing the magnitude of the impact. According to the Wang et al. (2020), IoT-based shop floor material management in construction project leads to cost reduction and improved efficiency. On the other hand, predicted benefits strongly affect the users' willingness to adopt IoT (Chen et al., 2020).

Revenues in the construction and infrastructure industries in the EU coming from EO data & service sales during the years 2020 was 192 million € and a slight global increase is expected, but revenues from GNSS will increase until the year 2026 and after that slowly decrease (European Union Agency for the Space Programme, 2022). Unclear benefits and gains and cost of implementation of I4.0 such as IoT are the most important challenges in terms of adoption of I4.0 in construction industry (Demirkesen & Algan, 2021). According to the former studies, there are many kinds of benefits from geospatial data in the industry, such as positive impacts on economic, environmental and social performance (sustainability), efficiency, health and safety, quality, productivity, and even innovations. There is a clear demand for new studies in which the benefits are described in a concrete manner ("in euros").

Figure 6. Benefits of geospatial data in different industries.

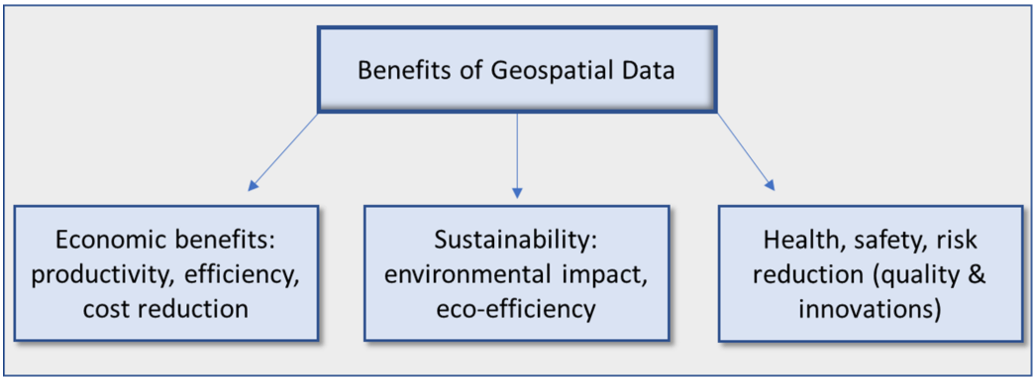


Figure 6. presents three different kinds of benefits from geospatial data according to the former research. The main benefits can be divided into economic benefits, sustainability, and health, safety and risks reduction categories. The benefits are clearly interrelated, because economic issues are also included in sustainability, which consists of economic, environmental and social issues, which in turn are related to health and safety issues. Health and safety are ordinarily connected to quality, for instance in integrated management systems, which usually include environmental issues too. Widely used quality management frameworks, like EFQM (European Foundation for Quality Management), are made to produce innovations. Thus, health, safety and risk reduction are traditional management in a way. They were mentioned in the construction and infrastructure industry as well.

4.1.7 A Short Case Example – The Role of Geospatial Data in Ponsse Product-Service Systems

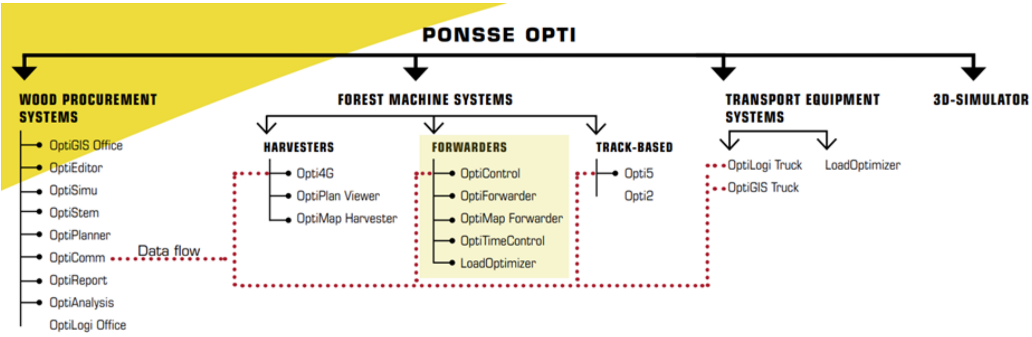
Studying the role of geospatial data in product-service systems will certainly bring crucial insights in examining the value of geospatial data and its emerging importance for manufacturers and solution providers, thus the researcher suggests Ponsse PSS (Product Service Systems) as a futuristic avenue for the case study. Ponsse Plc is a family-owned

Finnish multinational company, established in Vieremä in 1970. It specializes in the manufacturing, sales and maintenance of forest machinery and is the world's leading producer of cut-to-length method equipment. The journey of Ponsse toward Product-service systems is spanned over 50 years. Ponsse started as a product-oriented company, developing cut-to-length machinery for the forest industry, which gradually transitioned itself into a service provider and later into a solution provider. Ponsse operation portfolio includes three areas, Forest Machinery, Services, and Information Systems. The forest machinery includes seven harvester models, eight forwarder models, 11 harvester head models, four types of simulators, and some crane models. In addition, they sell used machinery from different brands including John Deere, Komatsu, and Tigercat, which provides a wide range of options to their customers. Moreover, Ponsse offers a wide range of digital solutions to its clients. For instance, the Ponsse Manager service helps entrepreneurs improve efficiency, productivity, and information through an Operations Management System which includes machine management, real-time management of productivity, remote management, transportation, and machines' service management and reports. Another ground-breaking digital service is Ponsse Data API, which offers real-time and accurate data, including different types of geospatial data that plays a crucial role in reporting, follow-up, and resource planning of the forest machinery fleet. Some other digital services include different levels of service contracts including full maintenance contracts and training through Ponsse Academy. All of the Ponsse machinery is equipped with state-of-the-art information systems, such as wood procurement systems, forest machine systems, and transport equipment systems, which are generating, storing, and processing multidimensional data. For instance, Harvesters are equipped with Opti 5G, Opti 4G, Opti PlanViewer, and Opti MapHarvester, whereas forwarders are equipped with Opti Control, Opti Forwarder, Opti MapForwarder, Opti TimeControl, and Load Optimizer. Based on the multidimensional Ponsse provides a variety of solutions to clients. All systems are interlinked with each other in a cloud environment, see Figure 7 to see the data flow, offering a complete fleet solution to the clients.

Figure 7. Ponsse Product-Service Systems (Ponsse, n.d.).

The role of geospatial data is very crucial for Ponsse services and solutions. For instance, for cut-to-length machines, it is very important to know the boundaries, terrain, surroundings, and weather conditions accurately to improve cost and time efficiency, planning of routes and tasks, and effective management, which is now possible due to location data and satellite imagery. The location data also entails real-time weather forecasting. Geospatial data is also pivotal for semi-automation and complete automation. Recently, harvesters and forwarders are equipped with real-time geospatial location technology which aids customers in tracking the operations of the fleet. Another advantage is that instead of steering the cranes, operators can locate the area and the crane can move automatically following the coordinates and perform the functions through GNSS data, making it semi-automated (from our interviews). According to Ponsse, the GNSS data has the capability to develop new products based on geospatial technology. In addition, Ponsse already has a product that is based on geospatial technology, and it is currently in the testing phase. Although we presume that this technology has the potential to revolutionize the forestry industry, the costs linked to the data may form a barrier to achieving its full potential for some time.

Figure 8. Ponsse solution for wood procurement (Ponsse, Wood Procurement, n.d.).



4.1.8 Concluding Remarks of Geospatial Data in Different Industries

In summary, value of geospatial data in the afore-mentioned industries is based on cost reduction and increased efficiency. The other important issues are benefits related to sustainability as well as traditional business and production measures, such as productivity, profitability and quality. Other benefits mentioned were safety and security, employment, and innovations. In the majority of the studies there were only situation-specific evaluations for the value of data. Clear figures were found mainly in the macro level, like value of GNSS or EO in the EU. Business opportunities in logistics, drones or autonomous vehicles depend on the acceptance of technology as well as perceived benefits and risks. The benefits are described in Table 6.

Table 6. A conclusion of the benefits of geospatial data in different industries.

Industry	Benefits of the use of geospatial data	Some numerical descriptions/comments of benefits
Agriculture and forestry	• cost reduction • increasing of eco-efficiency • water use efficiency • reduction of risks.	Revenues from Earth Observation (EO) data and services sales in agriculture are expected to steadily grow in the coming decade, from combined total across all applications of 377 million € to 652 million € in 2031. EU market share of EU of EO is 46 % in agriculture, 60 % in forestry and 89 % in fisheries and aquaculture
Energy	• sustainability • reduction of costs • environmental impact	The revenues from the sale of both EO data and services to the energy and raw materials sector in 2021 amounted to €305 m, and it is supposed to grow to revenues of €402 by 2031. Revenues from GNSS may decrease at the same time period
Manufacturing	• optimization of operations • increasing efficiency	As an example, General Electrics was enable to improve one customer's reliability from 93 % to 99, 49 % in less than two years as well as cut reactive maintenance by 40 % in one year
Transportation and logistics	Drones: • cost reduction • profitability & productivity • employment in society • safety and security. AVs: • costs, • labour productivity, • operational efficiency	The value of data can be estimated in the case of Earth observation in the EU region. Eu has biggest market share in aviation and drones (93 %), maritime and inland waterways (81 %), but smaller market shares in rail (35 %) and road and automotive (12%) Comment: concrete numbers of savings and productivity were not so clearly presented in the studies used in this sub chapter.
Other services	• increasing of efficiency • reducing costs • health benefits achieved	Comment: efficiency and cost might be studied in many service industries, but health benefits is industry specific and maybe a more complex issue
Construction and infrastructure	• economic, environmental and social performance (sustainability) • efficiency • health and safety • quality • productivity • innovations.	Revenues in the construction and infrastructure industry in the EU coming from EO data & service sales during the years 2020 was 192 million € and it will increase slightly globally, but revenues from GNSS will increase till the year 2026 and after that slowly decrease. Comment: There is a clear need for new studies in which the benefits are described in a concrete way ("in euros").

It was seen in the case of Ponsse too that costs, time efficiency and productivity were important positive impacts from the use of geospatial data, as well as innovations. By the interlinking of systems, the company could offer better solutions for customers.

Export trade could be made to those regions with growing markets. The products or services should be "customized" in a way that a buyer sees the product or service beneficial; how much costs can be saved, what are the positive impacts of the data and underlying technology, how to handle risks connected to the product or service. The value of data should be measured on company-level too – new kinds of research is required to create a framework for this.

4.2 Climate Impact and Use in Environmental Monitoring

4.2.1 Brief Overview of Geospatial Data in the Context of the Environment

Geospatial data is an extraordinary source to prevent environmental impact on the planet (United Nations, 2023). Geospatial data can used to conduct risk assessment of business operations and local communities impacted by climate related activities including preventing loss of biodiversity, ensuring water supply for businesses and communities, monitoring carbon emissions, analyzing the damage caused by flooding and natural disasters, droughts, and improving the quality of wildlife. Furthermore, geospatial data can lower the cost of production, improve community engagement, help align business strategy with national policies, and monitor the progress of net zero carbon emissions (WEF, 2022). Geospatial data provides a platform to investigate socio-economic vulnerabilities of local communities (Bera et al., 2021). The data also allows for identifying the water yield affected by climate change in addition to agricultural droughts, hazards, exposure, and mitigation capacity by combining geospatial information with conventional ground data (Ma et al., 2022; Hoque et al., 2021).

4.2.2 Applications of Geospatial Data for the Climate

Geospatial data can be used in various climate change applications be it forecasting temperature, wind direction and speed, and other phenomena that influence local communities and businesses, or developing mitigation strategies. The benefits of geospatial data are as follows:

- Predicting the climate change effects on local communities. According to Panda et al. (2022), geospatial data can be used to identify hazards and vulnerability risks in road crossings and it can be used to construct models and better decision-making tools for safeguarding the road stream. The data also provides information on weather-affected terrains to support the decision-making in hydrological modelling applications (Eylander et al., 2023). Geospatial data helps analyze the damage caused by cyclonic storms on ecology and the shoreline (Mishra et al., 2021).
- Mapping the vulnerable areas affected by the climate change. Geospatial data can be used to map the pattern of Zn in urban top soil and it helps in the field of peacebuilding and environmental conservation (Shi et al., 2021; Young et al., 2023).
- Evaluating the impact of mitigation strategies. Geospatial data helps investigate the forest loss due to the climate change or the impact of human urbanization activities in various regions (Pramudya et al., 2023). This analysis can improve decision making regarding quantifiable actions needed to compensate the damage caused by human activities. Furthermore, the social and economic policy considerations on the communities affected by flooding and the rise of the sea level can significantly benefit from geospatial data analysis (Becerra et al., 2020). In addition, the sociological constraint of geospatial literacy can be mitigated by allowing access to information that shows the temporal effects of climate change.
- Assessing the criticality of biodiversity conservation and carbon sequestration in various regions. Geospatial data allows for identifying the loss of biodiversity as well as monitoring the environmental impact of agricultural practices (Kross et al., 2022). By considering the geospatial assessment of agricultural areas, carbon neutrality can be achieved sooner. Moreover, the geospatial data enables mapping polluted water bodies such as lakes and rivers and helps identify the cause of potential damage to the ecosystems and biodiversity (Oliva et al., 2023).

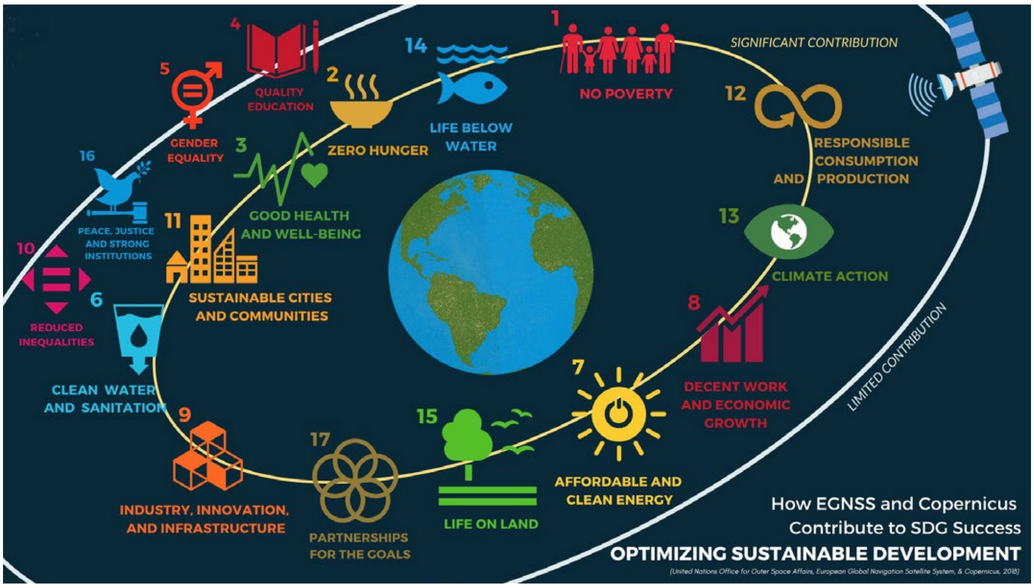
4.2.3 Decarbonization Potential of Geospatial Data

Geospatial data plays a significant role in decarbonization of transportation sector by identifying an optimal infrastructure for fuel production and distribution with cost effective solutions. This includes the production and distribution of future hydrogen fuel through various transportation methods, net-zero emissions, and expansion of carbon handprint (Reed et al., 2022). Geospatial data is also used for identifying the geographical potential and the most favorable conditions for wind and solar farms that include grid reliability, availability of land, feasible capacity and land appropriateness, which allows the decision makers to classify the suitability of land for constructing power plants (Doorga et al., 2022; Elkadeem et al., 2022; Harrucksteiner et al., 2023). The global carbon emissions of the construction sector are considerably high. Geospatial data can be used to reduce the carbon emissions from buildings by estimating the rooftop energy production on commercial and residential scales (Molner et al., 2022). Waste management is another challenging area that improved management infrastructure with limited land space. Geospatial data could be used in waste management infrastructure to create value from waste (Doorga et al., 2022a). Recently, agrivoltaic systems (photovoltaic and crop production on same land) where design, policy and economic level are the major challenges solvable by adopting geospatial methodology and resulting in reduced water consumption for crops (less evaporation) and efficient land use, have gained attention (Willockx et al., 2022). Similarly, solar canopy rooftops for parking lots are an area where geospatial data can be used for accurate design (Rudge, 2022). Geospatial data also helps articulate policies to achieve carbon neutrality by creating infrastructure for energy service stations for electric vehicles and gas (Zhou et al., 2022).

4.2.4 Environmental Monitoring, Geospatial Data, and SDG Applications

A joint study on Earth observation and GNSS with a special focus on Copernicus and European GNSS (EGNSS) revealed that the use of both geospatial systems opens up a variety of synergistic possibilities, resulting in substantial progress potential for sustainable development (United Nations Office for Outer Space Affairs, European Global Navigation Satellite System, & Copernicus, 2018). Furthermore, the study detailed nearly 40 case studies describing how Copernicus and EGNSS offer concrete contributions to achieving SDG targets.

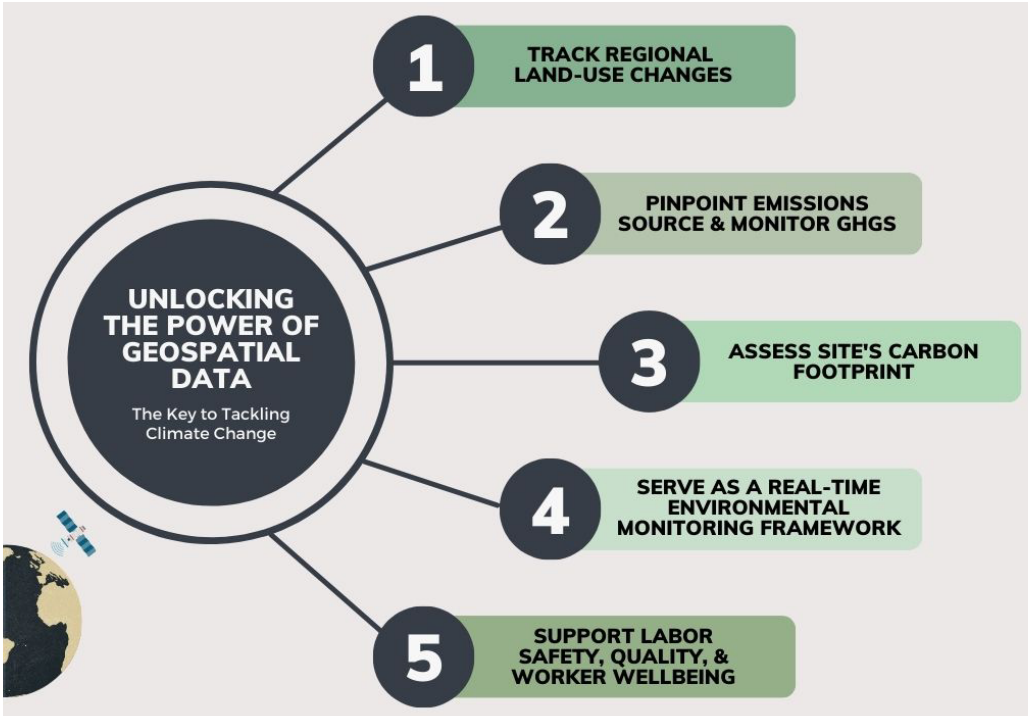
Figure 9. Contribution of Geospatial Data to the SDGs.



Per Figure 9, we can see that geospatial data provides significant contribution to 13 out of the 17 SDG targets, and limited contribution to the remaining four in indirect applications (United Nations Office for Outer Space Affairs, European Global Navigation Satellite System, & Copernicus, 2018, p. 2). In particular, SDGS 13 Climate Action, 11 Sustainable Cities and Communities, and 9 Industry Innovation and Infrastructure were found to benefit the most. In 2021 the UN published 'The SDGs Geospatial Roadmap' report to further emphasize the application potential of geospatial data, earth observations, and related data sources and tools to measure and monitor the SDGs and their global indicators. The report highlighted that geospatial and location-based data can be used as official data for the SDGs and their global indicators vis-à-vis leveraging a nation's geospatial information system to serve as a blueprint of what happens where and to integrate a wide variety of government services that contribute to economic growth, national security, sustainable and equitable social development, sustainability, and national prosperity (United Nations, Global Geospatial Information Management, 2021, p. 2 & 5). Furthermore, the United Nations has emphasized the importance of addressing the gap in foundational geospatial data and leadership, knowledge, and innovation, which are needed by all countries (p.5). Overall, geospatial data can provide critical information for decision-making and planning processes to promote sustainable forest management and equitable agriculture.

A comprehensive, harmonized monitoring of natural habitats and green spaces is a necessary next step to address current industry-environmental monitoring roadblocks. The predominant trend in ecosystem classification relies on expert-based fieldwork which is labor-intensive and time-consuming in nature. In response, remote sensing provides promising data for classification and monitoring of habitats (Iglseder, 2023). As presented in Figure 10, the advent of satellite and remote sensing technology is advantageous in its environmental monitoring capacities due to the high frequency of data collection, global availability of remote sensing data, the data itself being suitable for digital analysis and classification, in addition to the low costs of acquisition (Suratman et al., 2023). The Sentinel observations of the open EU satellite remote sensing infrastructure Copernicus have been identified to have the potential to assist in promoting forest resilience, multifunctionality, and biodiversity (Barredo et al., 2021). Furthermore, remote sensing technologies provide real-time data monitoring to provide more effective, faster intervention responses to climate-induced natural disasters such as forest fires (Alaria et al., 2023).

Figure 10. Application of Geospatial Data to Climate Change and Environmental Issues.

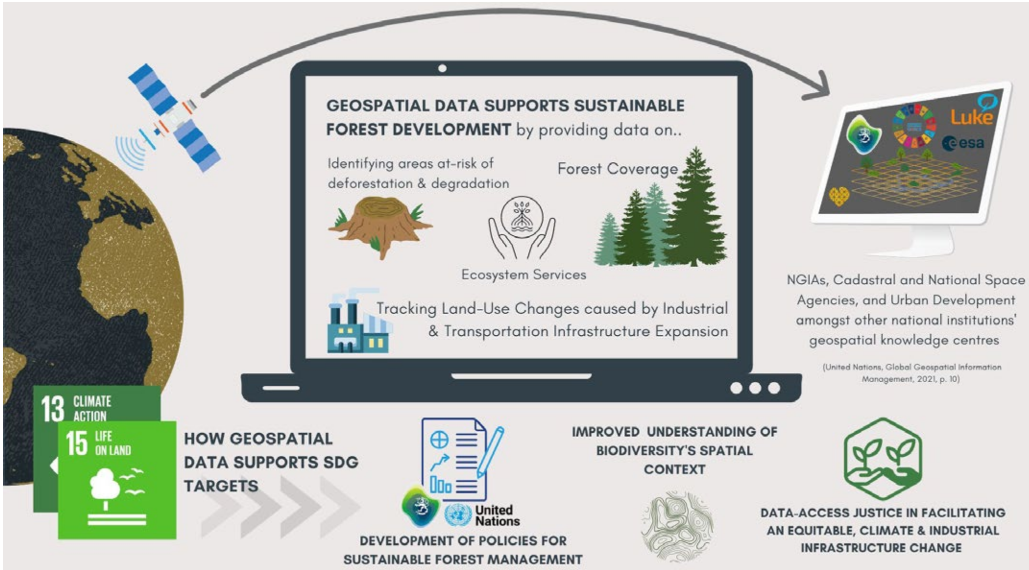


Concurrently with the rise of sensors like LiDAR, RGB camera and multispectral, massive datasets have been gathered for virtual modelling and monitoring of the agroforestry-relevant environmental and vegetation parameters necessary for cross-sector optimization (Jurado et al., 2022). Despite the rising precision of sensors, the industry must still address sources of disagreement regarding data products. With such a range in data products to conduct environmental monitoring and mapping land use change, the majority of data products report classification accuracies of 70 to 80%, depending on location (Bowers et al., 2017). Complementary, as remote sensing has been used to advance traditional fieldwork monitoring, fieldwork in turn can be used to supplement gaps in natural habitat datasets. Satellite and remote sensing data have the opportunity to assist in maintaining national forest inventory data, which is key for habitat conservation in areas hosting high-conservation-value forests (HCVFs) which are critical for continued biodiversity and ecosystem service provisioning (Munteanu et al., 2022). The preservation of HCVFs and primary forests has become a high-priority objective within the European Union (Sabatini et al., 2020).

4.2.4.1 Geospatial Data for SDGs – Case Examples

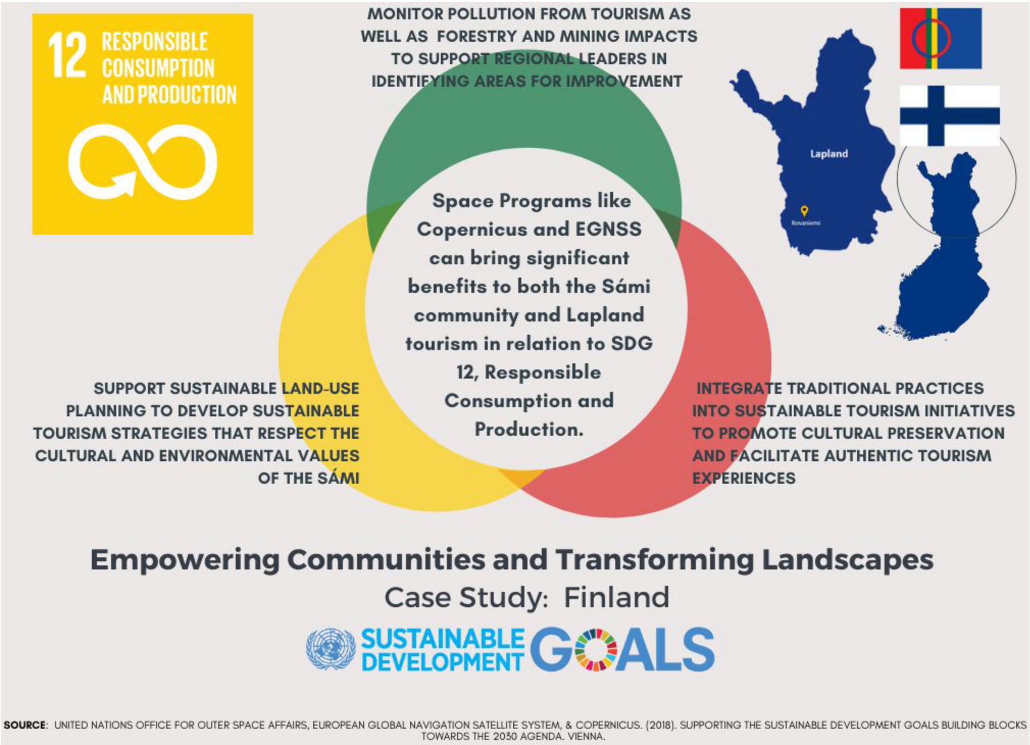
As seen in Figure 11, geospatial data can be used to sustainably manage forests by providing data on forest cover and land use to ecosystem services. This data can help identify areas at risk of deforestation and degradation and facilitate the development of policies and interventions for sustainable forest management. For example, the SDGs Geospatial Roadmap highlights the use of Earth observations and related data sources to measure and monitor SDG 15, which focuses on protecting, restoring, and promoting sustainable use of terrestrial ecosystems, including forests (United Nations, Global Geospatial Information Management, 2021, p. 31). According to Tognetti et al. (2022), the concept of climate-smart forestry (CSF) has risen in popularity with the increasing demand for forest management practices that facilitate successful forest and societal adaption to climate-induced changes. CSF is an approach that promotes forest management practices that target strategic greenhouse gas removal to increase forest productivity and incomes as well as with the overall objective of establishing more resilient forests. The application of satellite-platform-based observations to ecological monitoring frameworks to improve understanding of biodiversity's spatial context will support monitoring endeavors, such as those outlined in the EU Forest Strategy for 2030. As we continue to develop new technologies, we create new opportunities. By adopting a forward-thinking approach to using geospatial data for achieving sustainability targets, as those again, encompassed by the SDGs and the Forest Strategy for 2030, countries can benefit from these emerging data sources, even if they are not necessarily innovative. The Landsat program, which began in 1972, is an example of this evolution. Over time, Landsat's sensors have improved, providing increasingly accurate data. Today, privately-owned and state-run constellations offer a wide range of data, including orthoimagery (United Nations, Global Geospatial Information Management, 2021, p. 25). Currently and problematically, there are no scalable assessment methods which can be applied to the full transboundary-scale of forests to characterize its biodiversity traits. The real time produced datasets by remote sensing and satellite technologies serves as a solution to facilitate more effective and centralized planning to better promote resilient forest ecosystems. This, in turn, allows for the green transition to successfully integrate itself into Europe's agroforestry industries.

Figure 11. How Geospatial Data Supports SDG 15 Life on Land.



What benefits does geospatial and satellite data offer from a Finnish perspective? If Finland intends to be carbon neutral by 2035, geospatial data and satellite data can contribute significantly towards achieving carbon neutrality as well as sustainable development goals as described in Figure 12. For instance, satellite data applications, such as precision agriculture and food security monitoring, can aid in crop health assessment and early warning systems for natural disasters (United Nations Office for Outer Space Affairs, European Global Navigation Satellite System, & Copernicus, 2018, p. 85). In terms of sustainable development, the European Union space programs like Copernicus and EGNSS can contribute by providing cost-effective tools for poverty mapping and identifying human settlements, leading to job creation and economic growth. Specifically, SDG 12, Responsible Consumption and Production, receives significant support from EGNSS and Copernicus initiatives (United Nations Office for Outer Space Affairs, European Global Navigation Satellite System, & Copernicus, 2018, p. 77). Furthermore, these geospatial technologies have been recognized for their substantial contributions in developing and implementing tools to monitor sustainable development impacts in the context of sustainable tourism, job creation, and the promotion of local culture and products (United Nations Office for Outer Space Affairs, European Global Navigation Satellite System, & Copernicus, 2018, p. 77). Lapland, in particular, would stand to benefit the most from EGNSS and Copernicus, as their downstream satellite data can support sustainable and inclusive land-use development, aligning with Sámi needs alongside winter tourism and infrastructure development.

Figure 12. Empowering Communities and Transforming Landscapes, A Finnish Case Study.



Geospatial technology, the rise of Industry 5.0, and advancing smart technology exists as a positive driver for social change and environmental justice, but they can also create a perceived complexity. While geospatial is one of the most efficient and precise ways to provide evidence for SDG statistics and data science, there is a significant lack of geospatial information management skills, analysis, and methodologies (United Nations, Global Geospatial Information Management, 2021, p. 10). How can we address this skills gap as a society? Similarly, issues of climate change and pollution know no boundaries, SDGs should not be considered exclusively from a national-perspective. The data needs of the SDGs are the same data needs that empower national and transboundary decision-making or progress towards other environmental global agendas. Leveraging the potential of geospatial information requires bringing together different national institutions such as NGIAs, Cadastral and National Space Agencies, and Urban Development amongst other national institutions.

In summary, risk management and cost reduction related things were important in the use of environmental monitoring too. Climate change applications could improve predicting the climate change impacts, which might help in mitigation of the impacts. Environmental monitoring helps in decarbonization of transportation, identifying best locations for solar energy production and reduction of water consumption and efficiency of land use.

Decision making and planning in agriculture and forest industries can be improved with the help of low cost and efficient monitoring. In the long run and in the level of society, biodiversity and preservation of valuable forests can be easier. Monitoring helps also to get evidence for achievement of SDGs. To achieve the goals, competences related to the use of geospatial data as well as cooperation between institutions are needed.

5 Summary and Conclusions

The objectives of this research were to review the state-of-the-art applications and needs regarding geospatial data and positioning from the technical point of view as well as to review the impact of geospatial data and positioning from the point of view of business administration and social sciences within today's data economy. Responding to the first objective, a review of available technologies crucial for geospatial data production was presented. Additionally, it was concluded that understanding the role of coordinate reference systems is essential when working with geospatial data. A coordinate reference system is elementary to identify where the data is located. Geospatial data comes with certain numbers attached to the data specifying the location based on the type of coordinate system used. Therefore, a coordinate reference system allows geospatial data to use common location for integration. At the same time, it is essential to keep the reference systems precise and up to date by re-measuring regularly. Globalization and the increased accuracy of current observation techniques require that changes and motions of the Earth need to be observed more precisely than before. Knowledge of different reference systems is essential when combining data from various sources and understanding the difference between coordinates in different reference systems is vital. In addition, with the current positioning and observation systems, various geospatial data and positioning solutions were developed that help in numerous applications. However, the rapid development in such geospatial data requires more analytical solutions based on emerging technologies to efficiently monitor the Earth. Future research focusing on building resilient and versatile infrastructures can help in developing seamless and reliable positioning systems that will extensively benefit the geospatial community.

Value and valuation of geospatial data were discussed as a response to the second objective, reviewing the impact of geospatial data and positioning for data economy. It was concluded that the cost, net present value, and market value approaches each offer distinct methods for evaluating geospatial data assets. The selection of an appropriate method depends on factors such as the method of data acquisition, the availability of historical utilization data for similar assets, and the existence of comparable transactions in the active market. By considering these factors, companies can adopt a suitable approach to accurately estimate the value of their geospatial data assets, ultimately informing strategic decision-making and resource allocation processes.

The value of geospatial data and its positive impact on some industries were based on cost reduction and increased efficiency. Other main concerns were benefits related to sustainability, productivity, profitability, quality, safety and security, employment, and innovations. In most of the studies there were only situation-specific evaluations of the value of data. Specific numbers were found mostly at the macro level, like the value of GNSS or EO in the EU. Business opportunities depend on the acceptance of technology as well as perceived usefulness of data and the relationship between benefits and risks. Export trade could be engaged in with those regions with growing markets. For successful trade, the products and services should be customized in a way that a buyer sees it beneficial: how much cost savings can be achieved, what are the positive impacts of data and technology, how to handle risks connected to the product or service. The value of data should be measured at company level as well – new research is required to create a framework for this.

Risk management and cost reduction related issues were significant in environmental monitoring as well. Climate change applications could improve climate change impact prediction to mitigate negative impacts. Environmental monitoring helps in decarbonization of transportation, identifying the best locations for solar energy production and reduction of water consumption, and efficiency of land use. Decision-making and planning in agriculture and forest industries can be improved with the help of efficient and low-cost monitoring. In the long run, biodiversity preservation of valuable forests could become easier. Monitoring also helps gather evidence for the achievement of SDGs and carbon neutrality. To achieve the goals, competences related to the use of data as well as cooperation between institutions are needed.

Our research focuses on data economy, which is an umbrella term including digital business models independent of a particular industry, for example, data products and services and digital technologies. Opportunities for both new businesses connected to geospatial data and future export trade exist.

A concluding list of the open questions to be studied further is presented in Table 7. By doing the empirical research suggested in the Table, it is possible to build a framework of value and positive impacts of geospatial data in the data economy consisting of technical and business-related aspects (monetary value etc.), industry-specific factors, and sustainability monitoring related methods. Climate change, biodiversity protection, and matters of sustainable development are best addressed with holistic, collaborative approaches; geospatial data serves as a tool and a framework to address previous regional development gaps and facilitate a more sustainable future.

Table 7. What kind of research is needed in the future?

Research gap	Future research (aim of empirical studies)
Changes and motions of the Earth need to be observed more precisely than before.	How to apply data analytics with the emerging AI, ML, Big data, Cloud and IoT technologies to the Earth observation data and efficiently monitor the Earth?
The lack of pervasive/ubiquitous positioning solutions (outdoor/indoor) for geospatial data	How to develop more resilient and versatile infrastructures and produce seamless and reliable positioning solutions for geospatial data?
Autonomous vehicles, precision farming, forestry, and similar new use cases demand more accurate and trustworthy positioning solutions, which are commonly available.	Study the possibilities of forthcoming LEO positioning satellites and authenticated high accuracy satellite positioning solutions. Develop robust positioning algorithms with sensor fusion, seamless positioning, and built-in fault detection capabilities.
The global warming, deforestation, and nature loss require accurate monitoring.	Develop new algorithms to monitor the state of the Earth from multi- and hyperspectral satellite images, to quantify the consequences of human activities.
In principle, companies can adopt a suitable approach to accurately estimate the value of their geospatial data assets, ultimately informing strategic decision-making and resource allocation processes, but there is a lack of concrete (especially numerical) research.	What are the suitable approaches to accurately estimate the value of their geospatial data assets in different companies as well as how to use the data in strategic decision-making and resource allocation processes? (broader research)
To make the trade, products/services should be “customized” in a way, that a buyer sees the product/service beneficial: how much costs can be saved, what are the positive impacts of data and technology, how to handle risks connected to a product or service. The value of data should be measured at a company-level too – new research is needed to create a framework for this.	How to customize geospatial data related services and products? What kind of framework could be used in companies to measure the value of geospatial data? What kinds of geospatial data related business opportunities are there in telecommunications as well as software and consulting services in Finland? (series of case studies)
To achieve the goals of environmental monitoring as well as Sustainable Development Goal targets, competences related to the use of data as well as cooperation between institutions are required.	What kinds of competences are needed to improve the generation of geospatial data, the use of geospatial data and how to get these competences? How to improve the use of data with the help of enhancing co-operation between institutions? How can the environmental performance indicators be fulfilled by using geospatial data?

Appendices

Appendix 1. Definitions of Data Economy

Definition	Journal/ publication	Research or other document
Data economy refers to the digital economy with a constant production and fast circulation of data masses and where digital technologies generate, collect and store data to be analyzed, processed and distributed (Knaapi-Junnila et al., 2022)	Information Technology and People	Research
data economy is seen as "an umbrella term, which includes digital business models independent of a particular industry, for example, data products and services, digital technologies, data value chains, and their technical implications for data creation, processing, provision, and use to gain benefits for an organization"(Azkan et al., 2019)	Technology Innovation Management Review	Research
European Commission: "data economy measures the overall impacts of the data market on the economy as a whole. It involves the generation, collection, storage, processing, distribution, analysis elaboration, delivery, and exploitation of data enabled by digital technologies" (Azkan et al., 2019)	Technology Innovation Management Review	Research (& EU)
Data economy refers to the development of a digital economy where massive scale data is collected by everyone, also ordinary citizens, and where data circulates faster than ever. (Lammi & Pantzar, 2019)	Technology in society	Research
Data economy refers to the part economy in which a business model is based on utilization and use of knowledge in different ways (Ahvonen et al., 2023)	Report of Sitra	Applied research
Data economy consists of data value, data management and data literacy (*Deloitte Data Economy.Pdf*, n.d.)	Web page of Deloitte	Web page

Appendix 2. Additional Literature

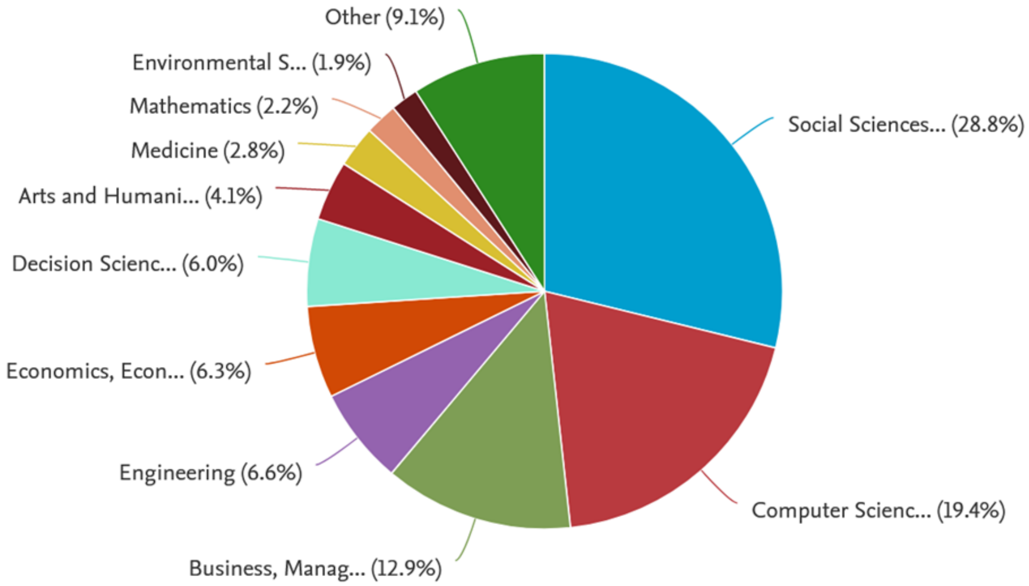
Research on data economy and digital economy

Digital economy is more widely used word in the literature compared to the data economy, but both terms are multidisciplinary. This is easy to see, when we compare literature search from Scopus database, when we made a search between the years 2013-2023.

Search string in data economy was the following: TITLE-ABS-KEY("data economy") AND PUBYEAR > 2012 AND PUBYEAR < 2024 AND (LIMIT-TO(LANGUAGE, "English")) AND (LIMIT-TO(DOCTYPE, "ar")). As a result, we found 164 articles. Search string in digital economy was the following:TITLE-ABS-KEY ("digital economy") AND PUBYEAR > 2012 AND PUBYEAR < 2024 AND (LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (SRCTYPE , "j")). As a result, there was 3127 journal articles. To sum up, data economy (and digital economy) is multidisciplinary subject area, which is studies most in the field of social sciences, but also in many other areas listed in the table below.

Subject area	Data Economy, f	%	Digital economy, f	%
Social sciences	92	28,8,	1374	21,6
Computer sciences	62	19,4	788	12,4
Business, Management and Accounting	41	12,9	1005	15,8
Engineering	21	6,6	609	9,6
Economics, Econometrics and Finance	20	6,3	782	12,3
Decision Sciences	19	6,0	255	4,0
Arts and Humanities	13	4,1	160	2,5

Data economy subject area:



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