A framework for determining remote sensing capabilities for ecosystem services valuation

by
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Ph.D.
Purdue University, 2010

Submitted to the System Design and Management Program
in partial fulfillment of the requirements for the degree of

Master of Science in Engineering and Management

at the
Massachusetts Institute of Technology

February 2025

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ABSTRACT

Nature provides vital services—clean water, air purification, and climate regulation—to human societies thanks to the "natural capital" like forests and lakes on our planet. Accurately measuring and valuing these ecosystem services is crucial for informed economic and development decisions. Remote sensing (RS) technology offers a powerful way to monitor natural capital (e.g., mapping forest cover, assessing water quality). However, current data lack the accuracy and precision needed for robustly monitoring the value of these services. This deficiency has impeded the use of natural capital assessment data in economic decision-making. This research partly addresses this challenge by developing a new framework to investigate the necessary sensor characteristics (spectral, radiometric, temporal, spatial) for effectively monitoring natural capital and quantifying ecosystem services. The framework first identifies the different types of services provided by an ecosystem, then uses a physics-based approach to identify crucial physical parameters and determines the necessary measurements that need to be made from a sensor for their quantification. The sources of uncertainty impacting quantification and value estimation are also analyzed in detail. The approach is integrated to formulate a system utility function that is used to compare performance of existing and proposed RS systems, and the overall results are subsequently used in proposing required capabilities for future remote sensing systems for natural capital monitoring. The framework is demonstrated on a case study focused on the flood attenuation function (service) provided by wetlands. Water budget models are utilized to identify essential parameters for monitoring water storage by wetlands. Using a study area encompassing the Fall Lake Creek reservoir (Oregon, USA), water storage capacity is measured and monitored by integrating USGS digital elevation models with Sentinel-1 synthetic aperture radar, Sentinel-2 optical data, and Planet Scope optical data. Results are validated against USGS published ground truth measurements. A strong correlation (r^2 of 0.95) was observed with all three datasets. An uncertainty analysis was conducted, using the random fields method, in which synthetic spatially autocorrelated errors were added to the RS datasets. Radiometric uncertainties were studied through addition of gaussian noise as a percentage of reflectance values, and results showed effects of < 2.5% on estimated water volume. Elevation data uncertainties (which were approximated to simulate uncertainties in globally available DEMs) showed higher effects, and errors in estimated storage volumes increased proportionally. A study of inundation (for a case study over Miami, FL) revealed that as the root mean square error of the DEMs increased from 2m to 7 m, the risk of flooding (defined as water depth accumulation of greater than 90 cm) increased more than 3 times. A utility function was developed to evaluate sensors based on their ability to estimate wetland water volumes. This function considers sensor characteristics like spatial, radiometric, and temporal resolution. Notably, the function estimates that a future optical system with 2x improved spatial and 4x improved temporal resolution (compared to Sentinel-2) can increase utility 7-fold.

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Acknowledgments

This thesis would not have been possible without the support and guidance of many individuals. First, I would like to express my gratitude to my advisor, Dr. Afreen Siddiqi, for her unwavering support, encouragement, and mentorship throughout this journey. Her expertise, insights, and feedback were invaluable in shaping my research and helping me to achieve my academic goals.

I would also like to extend my sincere thanks to the faculty and students of the System Design and Management program at MIT. Their dedication to teaching and their commitment to fostering a stimulating intellectual environment have been instrumental in my academic development.

To my parents and sister, thank you for your unconditional love, support, and belief in me. You have always encouraged me to pursue my dreams and have instilled in me the values of hard work, perseverance, and dedication. I am eternally grateful for your sacrifices and for providing me with the foundation upon which I have built my academic career.

To my wonderful children, Meera and Siddharth, thank you for your patience, understanding, and unwavering love. You have been my constant source of joy and inspiration, and your presence in my life has given me the strength and motivation to overcome any challenges.

Finally, to my beloved wife, Divya, thank you for your unwavering love, support, and encouragement throughout this challenging but rewarding journey. Your patience, understanding, and sacrifices have allowed me to focus on my studies and complete this thesis. I am eternally grateful for your partnership and for sharing this journey with me.

This thesis is dedicated to all of you.

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Acronyms, Terms, and Definitions

AOI – Area of Interest

CEOS – Committee on Earth Observation Satellites

DEM – Digital Elevation Model

EESV – Essential Ecosystem Service Variables

ESA – European Space Agency

ET – Evapotranspiration

FWHM – Full Width at Half Maximum

GDAL – Geospatial Data Abstraction Language

GEE – Google Earth Engine

GeoTIFF – Geographic Tagged Image File Format

GSD – Ground Sample Distance

GWI – Groundwater Inflow

GWO – Groundwater Outflow

IPBES – Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services

Lidar – Light Detection and Ranging

LLM – Large Language Model

MA – Millennium Ecosystem Assessment

MNDWI – Modified Normalized Difference Water Index

MODIS – Moderate Resolution Imaging Spectroradiometer

NASA – National Aeronautics and Space Administration

NC – Natural Capital

NCA – Natural Capital Accounting

NDVI – Normalized Difference Vegetation Index

NIR – Near Infrared

RMSE – Root Mean Square Error

RS – Remote Sensing

SAR – Synthetic Aperture Radar

SEEA – System of Environmental Economic Accounting

SNR - Signal-to-Noise Ratio

SRTM – Shuttle Radar Topography Mission

SWI – Surface Water Inflow

SWIR – Short Wave Infrared

SWO – Surface Water Outflow

TEEB – The Economics of Ecosystems and Biodiversity

UAS – Uncrewed Aircraft System

UN – United Nations

USGS – United States Geological Survey

UTM – Universal Transverse Mercator

VV – Vertical Transmit and Vertical Receive

WGS84 – World Geodetic System 1984

1. Introduction

1.1 Introduction to Natural Capital

Natural Capital (NC) is the world's stock of natural resources, which includes geology, soils, air, water, and all living organisms. These NC assets provide people with free goods and services, often called ecosystem services, which underpin our economy and society, making human life possible (IPDES 2019). Figure 1-1 Illustrates the importance of NC to the society. These services (de Groot, 2002) are categorized into four main types:

1. Provisioning Services: These include the products obtained from ecosystems, such as food, water, timber, and fiber.
2. Regulating Services: These are the benefits obtained from the regulation of ecosystem processes, including climate regulation, disease control, and water purification.
3. Cultural Services: These encompass non-material benefits people obtain from ecosystems through spiritual enrichment, cognitive development, reflection, recreation, and aesthetic experiences.
4. Supporting Services: These are services that are necessary to produce all other ecosystem services, such as soil formation, nutrient cycling, and primary production

There has been a decline in the quality and quantity of the benefits that ecosystems provide due to human activities in many regions. This includes habitat destruction, overexploitation of species, pollution, and climate change. The main drivers of biodiversity and ecosystem degradation are land-use change (Foley et al, 2005), direct exploitation of organisms, climate change, pollution, and invasive species. For e.g., Wetlands are often drained and converted for agricultural purposes, urban development, and other land uses. This leads to Increased flooding, habitat loss, and a decrease in water quality (IPDES 2019).

To address this degradation, policies and regulations are required. However, effective policy making regarding conservation and ecosystem services is often hindered by a lack of relevant information. According to Daily et al. (2009) this lack of information can stem from several factors, including:

- Poor understanding of ecosystem complexity
- Insufficient monitoring of ecosystems
- Rapid degradation of ecosystems leading to loss of necessary information needed to develop effective protective policies

This lack of data has been increasingly recognized and has stimulated research in developing frameworks for quantifying and monitoring NC. These frameworks (Hein at al., 2016) include the Millennium Ecosystem Assessment (MA), the Economics of Ecosystems and Biodiversity (TEEB), the Intergovernmental Platform on Biodiversity and Ecosystem Services (IPBES), and the System of Environmental-Economic Accounting-Experimental Ecosystem Accounting (SEEA EEA). The Executive Office of the President (2023) emphasizes the need for a natural capital accounting (NCA) framework for organizing and reporting information about NC, which includes ecosystems, biodiversity, and natural resources. NCA tracks changes in natural capital over time and links these changes to economic and social activities. It provides a way to measure and value ecosystem services (figure 1-2), assess the condition of ecosystems, and inform decision-making about sustainable ecosystem management. NCA is still under development, but it has the potential to be a valuable tool for supporting future sustainable development.

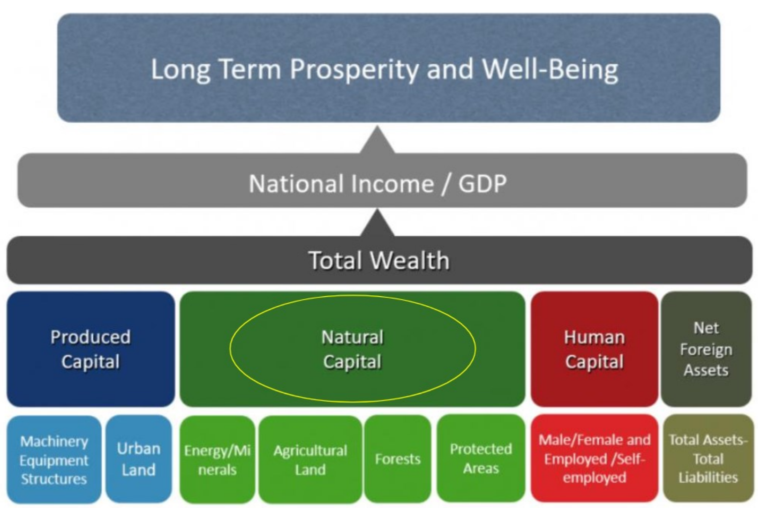

Figure 1-1 - NC as a part of the total wealth of nations (source: https://www.doi.gov/sites/doi.gov/files/nca-ppa-seminar-presentation-apr2023-508.pdf)

The NCA framework recognizes that natural capital is an important part of the total wealth of a nation. By integrating this information into decision-making processes like policy formulation, land-use planning, and investment decisions, NCA ensures that the benefits provided by NC are acknowledged and considered, promoting sustainable practices that support both the economy and the environment. The NCA framework considers the environment's role in economic and social well-being (Bateman and Mace, 2020). The three cornerstones of the framework are efficiency, sustainability and equity. Efficiency analysis ensures that resources are used optimally, while sustainability analysis considers the long-term impacts on NC stocks. Equity analysis examines the distribution of benefits and costs across society.

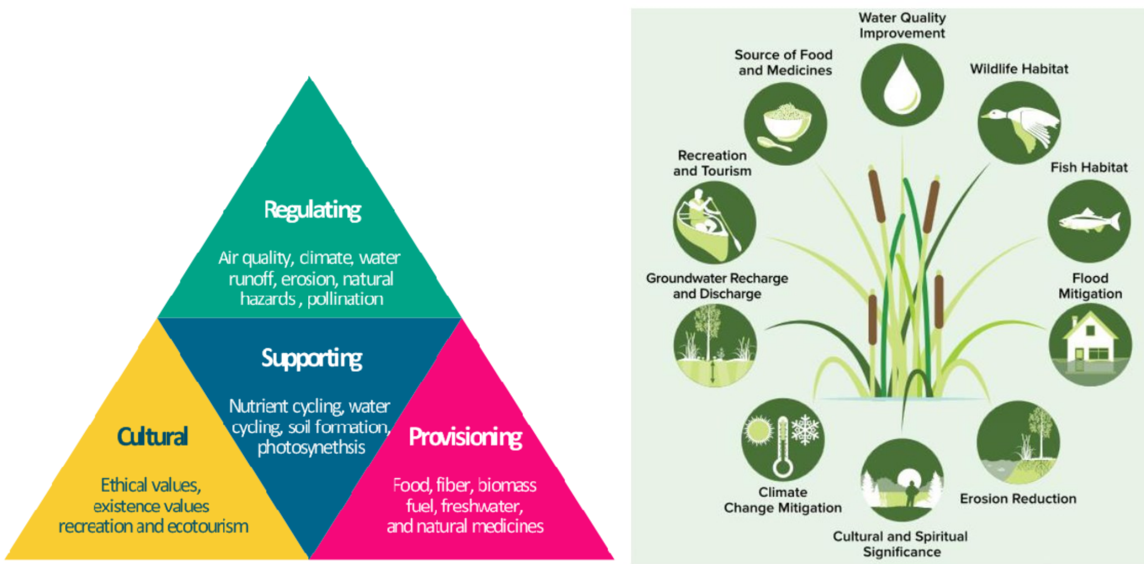

Figure 1-2 - Ecosystem services (left) and (right) example of services provided by wetlands (Source: Ontario Ministry of Natural Resources and Forestry. 2017 A Wetland Conservation Strategy for Ontario)

Table 1-1 - Examples of NC, their categorization, and the ecosystem services offered by them.

Natural Capital	**Ecosystem Service Category**	**Ecosystem Services**
Wetlands	Provisioning	Food production, raw materials, freshwater, fish, aquatic vegetation, wood
Wetlands	Regulating	Water regulation, disturbance regulation, nutrient cycling, erosion control, water treatment, carbon sequestration, gas regulation, flood attenuation, sediment flushing, nutrient uptake, moderation of water regimes, groundwater recharge, erosion prevention, pollution control and detoxification
Wetlands	Cultural	Recreation, tourism, cultural heritage
Wetlands	Supporting	Habitat/biodiversity
Forests	Provisioning	Wood, fuel
Forests	Regulating	Clean air, carbon sequestration
Forests	Supporting	Productive soils
Coral Reefs	Provisioning	Fisheries
Coral Reefs	Regulating	Coastal protection
Coral Reefs	Cultural	Tourism
Mangroves	Provisioning	Fisheries
Mangroves	Regulating	Coastal protection, erosion protection
Rivers	Provisioning	Sand, fish
Rivers	Supporting	Species habitat

1.2 Monitoring Natural Capital Using Remote Sensing

Monitoring NC is essential for several reasons (Foley 2005; European Environment Agency 2015):

- Understanding Ecosystem Health: Monitoring provides insights into the health and condition of ecosystems, allowing for the identification of areas experiencing degradation or improvement.
- Sustainable Resource Management: By tracking the status and trends of NC, decision-makers can implement sustainable management practices that ensure the long-term availability of essential resources.
- Economic Risk Assessment: Monitoring helps assess the risks associated with NC depletion and degradation, enabling informed decision-making.
- Environmental Sustainability: Monitoring NC is crucial for tracking progress towards

environmental sustainability goals and identifying areas where interventions are needed.

- Economic Valuation: Monitoring helps quantify the economic value of NC and ecosystem services, enabling their integration into economic accounting and decision-making.

Remote sensing (RS) has emerged as a valuable tool for monitoring NC due to its ability to provide comprehensive and timely data on a variety of environmental parameters (NASA ARSET 2022). Some key reasons why RS is valuable for this purpose are:

1. Large-Scale Monitoring: RS allows for the observation and monitoring of large and remote areas that are difficult to access. This is particularly useful for tracking changes in ecosystems over time.
2. Temporal Analysis: RS enables the analysis of temporal changes, helping to identify trends and patterns in ecosystem services over time (NASA ARSET 2022).
3. Cost-Effective: Compared to traditional field-based methods, RS is often more cost-effective and efficient, allowing for the collection of data over large areas with minimal physical presence (Foster et al., 2024).
4. Integration with Other Data: RS data can be integrated with other types of data, such as socio-economic and climate data.
5. Support for Decision-Making: The insights gained from RS can inform policy and management decisions, helping to prioritize conservation efforts and sustainable resource management (Siddiqi et al., 2023).

Researchers have explored the potential of RS to assess and quantify various aspects of NC, including forest cover, water resources, biodiversity, and ecosystem services (Magliarditi et al., 2019; Mashala et al., 2023). Over 80% (NASA ARSET 2022) of the inputs to NCA are spatial in nature and RS is the best method to collect data at large scales.

However, RS technologies vary in their capabilities (Avtar et al., 2024) because of various stakeholder concerns. Designing RS systems to effectively monitor the benefits provided by NC requires a focus on the benefits offered by NC. It involves considering the ecological, social, and economic benefits of NC and incorporating these into the system requirements. Value-focused thinking (Keeny, 2008) directs attention toward the desired outcomes throughout the decision-making process. There are three main ways that value-focused thinking improves decision-making. First, it often leads to a focused set of objectives for evaluating alternatives, as generating objectives is a central focus. Second, it helps create new alternatives, some of which may be better than those previously considered. Third, it proactively identifies decision opportunities that are more favorable than those imposed upon us.

By prioritizing the monitoring of NC benefits, RS systems can be designed to play a significant role in supporting sustainable development and ensuring the long-term health of ecosystems.

1.3 Research Objectives

RS systems, whose capabilities have been designed with explicit considerations for needs of NC benefits, can enhance data acquisition, quality, and reduce uncertainties in quantitative evaluation of NC accounts. Motivated by this need, the primary goal of this research is to establish a framework for identifying RS capabilities for monitoring the value of ecosystem services as defined in the NC framework.

1.4 Research Approach

The thesis accomplishes its objectives by developing a framework (shown in figure 1-3) that systematically identifies ecosystem functions that deliver benefits, quantitatively defines them by modeling the biophysical processes that govern these functions, determines specific parameters that are used in these models, and determines the RS capabilities needed to measure those parameters. Finally, a system utility function is derived to evaluate the effectiveness of RS systems to monitor NC. To demonstrate the framework, the approach includes a case study of wetlands and specifically develops a utility function that investigates gaps in the ability of current and planned RS systems to monitor wetland flood attenuation functions. The analysis is then used to propose new sensor requirements to address these gaps. The thesis explores sensor resolution, spectral bands, and data acquisition, as well as the uncertainties in measurements, and their impacts on estimating NC. The thesis emphasizes the importance of maintaining traceability of the required capabilities to well-accepted frameworks, ensuring that the recommendations are grounded in established principles and guidelines, and ensure their utility in monitoring specific NC value. By identifying gaps and recommending sensor improvements, the report aims to drive advancements in RS technology and contribute to enhanced NC monitoring.

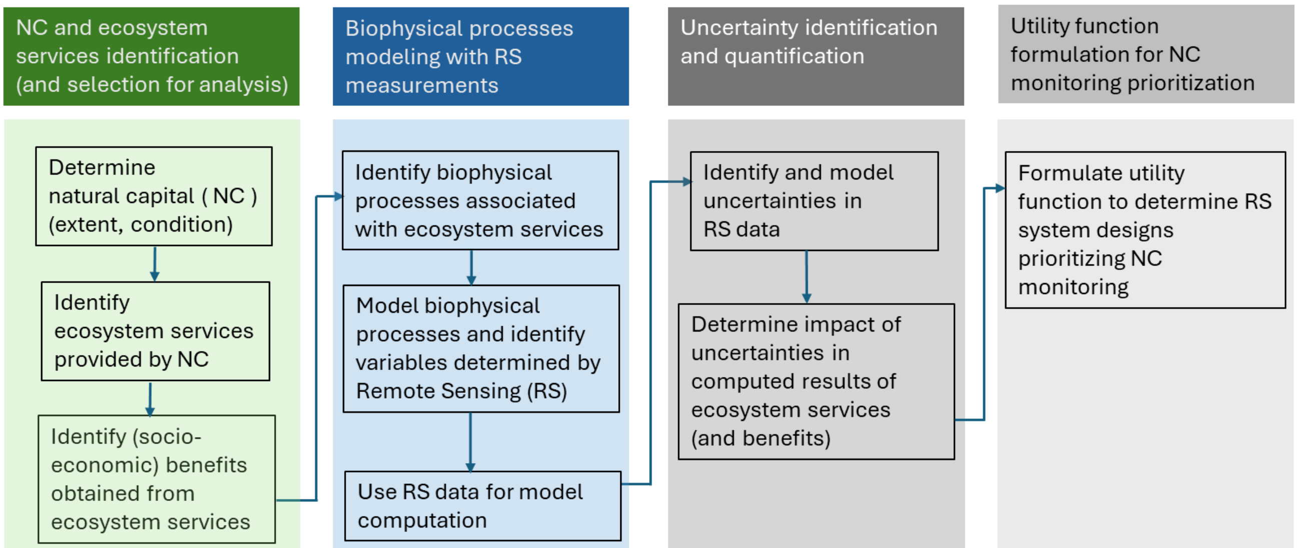

Figure 1-3 - Framework to identify remote sensing needs for ecosystem services.

1.5 Thesis Structure

The thesis starts with an introduction to natural capital, the need for monitoring its extent, condition, and functions, and the emerging NC accounting frameworks. Next, a rationale for using RS as a technological tool to monitor NC is discussed, and capabilities of RS for quantifying value of ecosystem services derived from NC are highlighted.

Chapter 2 reviews and explores the use of RS for monitoring NC, particularly focusing on wetlands. It discusses various monitoring methods, highlighting RS's advantages in providing comprehensive and timely data. Wetlands are emphasized for their crucial ecosystem services, especially water storage and flood attenuation. Different RS technologies, including optical, SAR, and Lidar, are reviewed as valuable tools for wetland assessment.

In Chapter 3, wetland functions towards water storage and flood control are studied in detail. Hydrological models are explored and the variables necessary for modeling the water storage capacity are developed. Key variables include precipitation, topography, and evapotranspiration, which are measured using various RS techniques. This data informs the water budget of wetlands, and the topographic information is used to study and estimate the volume of water stored in wetlands, against available capacity.

Chapter 4 demonstrates methods to integrate RS data with high-resolution Digital Elevation Models (DEMs) to estimate water volume in wetland environments. The study uses Sentinel-1, Sentinel-2, and PlanetScope satellite imagery, along with a 1-meter resolution DEM derived from aerial photogrammetry. The methodology involves image preprocessing, water extent extraction using various spectral indices (MNDWI, NDWI, and VV backscatter), and volumetric calculations. The analysis was performed using Google Earth Engine (GEE) and Python libraries for geospatial analysis.

The results show a strong correlation between the estimated water elevation and USGS measured elevation, particularly when the reservoir has sufficient water. The chapter also discusses the challenges of accurately delineating water extent in shallow areas and the need for more sophisticated data processing techniques to improve water detection in complex wetland environments

Chapter 5 delves into uncertainty analysis of the methods and data used in chapter 4 and directly informs the system utility function by highlighting the factors that contribute to uncertainty in wetland water volume estimation. The analysis investigates uncertainties and their impacts on NC estimates by using random fields methods to introduce errors in the input data (radiometric and elevation measurements). Water volume was estimated using multiple digital elevation models. This process helped in understanding the impact of reflectance and elevation measurement variability on water level and volume calculations. Understanding these sources of uncertainty informs the system utility function to better evaluate different RS systems for water monitoring applications.

Chapter 6 provides an overall summary, discusses key findings, and suggests further research directions.

2. Literature Review

2.1 Natural Capital and Ecosystem Services

The concept of "natural capital" has emerged as a critical framework for understanding the value of the natural world and its contributions to human well-being and economic prosperity. This section reviews key definitions of NC from influential organizations and academic literature, highlighting the diverse perspectives and common threads that shape this evolving concept.

The Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) provides a comprehensive definition that encompasses both renewable and non-renewable resources: "Natural capital refers to the Earth's stock of renewable and non-renewable natural resources, including ecosystems, species, freshwater, land, minerals, the air and oceans, as well as natural processes and functions" (IPBES, 2019). This definition underscores the interconnectedness of various natural elements and the importance of ecological processes.

The work of The Economics of Ecosystems and Biodiversity (TEEB) emphasizes the dynamic nature of NC, defining it as "the stock of natural ecosystems that yields a flow of valuable ecosystem goods or services into the future" (UNEP, 2010). This definition highlights the capacity of natural systems to generate a continuous stream of benefits for human societies. Daily et al. (2009) reiterate the comprehensive nature of NC as "the Earth's stock of natural assets, including geology, soil, air, water, and all living things," and stress the importance of integrating this concept into decision-making processes.

The United Nations Environment Programme (UNEP) broadly defines NC as "the natural resources and ecosystem services that underpin human well-being and economic activity" (UNEP, 2021), highlighting the link between the environment and human societies.

The World Bank, focusing on the economic aspects, defines NC as "natural resources (e.g., minerals, energy, timber, fish) and ecosystems (e.g., forests, wetlands, oceans)" (World Bank, 2016), acknowledging both the extractive and functional value of nature. Other organizations have played a pivotal role in defining and promoting the concept of NC.

2.2 Natural Capital Accounting

The System of Environmental Economic Accounting (SEEA) Ecosystem Accounting, adopted by the United Nations Statistical Commission in 2021, is a commonly used approach for NCA (Vallecillo et al., 2019). SEEA provides a standardized framework for organizing and presenting statistics on the environment and its relationship with the economy. The Natural Capital Protocol is another valuable framework that enables organizations to identify, measure, and value their direct and indirect impacts and dependencies on natural capital (Steele, Paul, et al., 2021). This protocol helps businesses integrate natural capital considerations into their decision-making processes, promoting sustainable practices and reducing environmental impacts. Monitoring Essential Ecosystem Service Variables (EESVs) provides a comprehensive picture of how the links between nature and people are changing (Balvanera et al., 2022). EESVs represent key attributes of ecosystem services that can be monitored across space and time, providing valuable insights into the dynamics of human-environment interactions.

Recognizing the importance of NC, the US government has launched an initiative to establish natural capital accounts (Executive Office of The White House, 2022). This initiative aims to measure the economic value that natural assets provide to society and connect changes in nature with changes in economic performance, further highlighting the growing recognition of the importance of NC in national accounting and policymaking.

2.3 Monitoring Natural Capital and Ecosystem Services

Effective management of NC and ecosystem services requires ongoing monitoring to track their status and trends. Various methods are employed for this purpose, including:

- Field surveys: These involve on-the-ground observations and measurements of ecological parameters, such as species abundance, vegetation cover, and water quality. While valuable for detailed information, field surveys can be time-consuming, costly, and impractical especially for large or remote areas such as at national and continental scales (NASA ARSET, 2022).

- Remote sensing (RS): This technology utilizes satellite or airborne sensors to collect data on Earth's surface, providing information on land cover, vegetation health, and other environmental variables. RS offers a powerful means of monitoring NC and ecosystem services over large areas and at regular intervals (Meyer, 2022). For example, Landsat is the oldest archive of earth observation data, going back to 1971 (Wulder et al., 2016)
- Modeling: Mathematical models are used to simulate ecosystem processes and predict changes in NC and ecosystem services. These models can help assess the potential impacts of different management scenarios and inform decision-making (Neugarten et al., 2019).
- Citizen science: Engaging the public in data collection can significantly expand the spatial and temporal coverage of monitoring efforts. Citizen science initiatives empower individuals to contribute to scientific research and environmental monitoring, enhancing data collection and raising awareness about environmental issues (Raymond et al., 2009).

2.4 Physical Models of Natural Capital Value

NC value refers to the economic worth of a natural resource, encompassing the present value of its future ecosystem service flows (Fenichel et al., 2016). These services, such as clean water provision or storm surge protection, contribute to human well-being and economic activities (Fenichel et al., 2016). A key challenge in valuing NC is the absence of a market for many natural assets, making it difficult to assign a price (Fenichel et al., 2016). Hence, the valuation of NC often involves complex economic and biophysical modeling to determine the present value of its future economic benefits (Fenichel et al., 2016).

There are various methods used to value NC, each with its own strengths and limitations, often limiting its use to a select range of ecosystem goods and services within a given landscape (Costanza et al., 2006). The Replacement Cost (RC) method is based on the price of the cheapest alternative way of obtaining a service (Costanza et al., 2006). For example, the value of a wetland in the treatment of wastewater might be estimated using the cost of chemical or mechanical alternatives (Costanza et al., 2006). The Avoided Cost (AC) method can be used to estimate value based on the cost of damage due to lost services (Costanza et al., 2006). For instance, the value of a wetland in providing storm surge protection might be estimated using the cost of damage incurred when a coastal storm strikes an area with and without a wetland.

Other methods for valuing NC include Travel Cost (TC), Hedonic Pricing (HP), and Contingent Valuation (CV). Travel Cost (TC) is used to estimate the economic value of recreational benefits provided by a natural resource. It is based on the idea that the value of a natural area for recreation can be estimated using people's willingness to pay to travel to that area (Costanza et al., 2006). Hedonic Pricing (HP) is used to estimate the economic value of natural resources based on their impact on market prices. For example, the value of a forest for recreation might be estimated using the impact of proximity to the forest on housing prices (Costanza et al., 2006). Contingent Valuation (CV) is used to estimate the economic value of non-market goods and services. It is based on asking people how much they would be willing to pay for a good or service if it were available in a market (Costanza et al., 2006).

Lee and Nepf (2024) used a physical proxy to value NC. They determined the relationship between NC and the physical processes by which ecosystem services are delivered. Lee and Nepf incorporated a predictive model for wave attenuation that considers species-specific plant morphology and structural stiffness. This model was validated with field measurements and then applied to a real-world marsh-fronted seawall design at Juniper Cove, Massachusetts. The economic benefits of the marsh were evaluated by considering its environmental services value and the avoided cost of seawall heightening that would be required to achieve the same overtopping rate without the marsh. The study found that the benefit-cost ratio was sensitive to the discount rate but remained greater than one, suggesting that marsh-fronted seawalls are an economically justified nature-based solution.

2.5 Remote Sensing: A Powerful Tool for Natural Capital Monitoring

A key challenge in applying the NC framework is in understanding the relationships between NC stocks and ecosystem services these stocks provide. This includes developing consistent approaches to measurement and understanding the dynamics of ecosystem processes (Whitehouse, 2020; United

Nations 2021; Bateman and Mace, 2020). Existing methods for measurements include ground-based referencing, as well as RS-based monitoring and measuring NC. RS offers significant value in this context by providing comprehensive, accurate, and timely data on various ecosystem attributes (Chirici et al., 2016). It enables mapping the extents of ecosystems, large-scale monitoring of changes in land cover, vegetation health, and other critical indicators of ecosystem services. The technological advancements in satellite RS, geospatial data storage and processing allow for more precise assessments and support informed decision-making for ecosystem management and policy development. This technology offers spatially explicit (i.e., the data is geographically referenced and can be visualized on a map), repeatable, and readily accessible environmental information, which is vital for integrating environmental and economic data in ecosystem accounting (ARSET NASA, 2022). In the context of ecosystem services, spatially explicit data is important because the value of a service often depends on where it is produced and who benefits from it. For example, the flood protection provided by a wetland is most valuable to people and property located downstream.

RS data is instrumental in evaluating the capacity of ecosystems to provide various services (figure 2-1). By using RS, researchers can track changes in ecosystems' service supply capacity over time and across different regions (Chirici et al., 2016; Pettorelli et al., 2018). RS enables continuous observation of ecosystems, delivering essential information on changes in ecosystem conditions and productivity. This capability is particularly valuable for large-scale and remote areas where direct measurement is challenging (Turner et al., 2015).

The integration of RS data with biophysical models and other data sources allows for comprehensive assessments of ecosystem services. This combination helps develop models that link ecosystem capacity with actual service supply, enhancing the accuracy and sustainability of ecosystem management practices (Nelson et al., 2009).

Detailed and spatially explicit information on ecosystem services provided by RS supports policymaking for sustainable ecosystem management. The data aids in designing and monitoring policies that aim to mitigate the adverse effects of economic development on ecosystems (Costanza et al., 1997;

Daily et al., 2009).

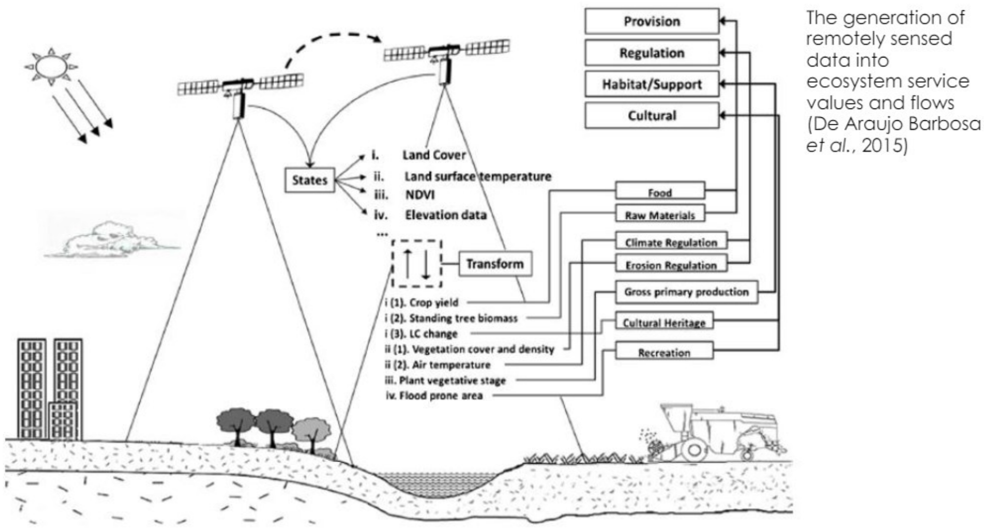

Figure 2-1 - Role of RS in evaluating ecosystem services (De Araujo Barbosa and others, 2015)

Specifically, RS offers several distinct advantages for monitoring NC and ecosystem services:

- **Broad spatial coverage:** Satellites can capture data over extensive areas, providing a synoptic view of ecosystems and enabling the assessment of regional and global trends (NASA ARSET, 2022). This broad perspective is crucial for understanding large-scale environmental changes and their impacts on human societies.
- **Temporal frequency:** Satellites revisit the same location at regular intervals, allowing for the detection of changes in ecosystem conditions over time (NASA ARSET, 2022). This temporal dimension is essential for monitoring trends, identifying anomalies, and assessing the effectiveness of management interventions.
- **Cost-effectiveness:** RS can be more cost-effective than traditional field surveys, especially for monitoring large or remote areas (NASA ARSET, 2022; Foster et al., 2024). This cost-efficiency makes it a valuable tool for resource-constrained organizations and countries.

- **Access to inaccessible areas:** RS can provide data on areas that are difficult or dangerous to access, such as dense forests or mountainous terrain (NASA, 2022; Foster et al., 2024). This capability expands the reach of monitoring efforts and enables data collection in challenging environments.

- **Variety of data:** RS sensors capture data across different parts of the electromagnetic spectrum, providing information on various aspects of ecosystems, including vegetation health, water quality, and land cover (Meyer, 2022). This versatility allows for a comprehensive assessment of ecosystem conditions and processes.

Furthermore, RS data is becoming increasingly accessible through various platforms, making it a more readily available tool for a wider range of users (NASA, 2022). This increased accessibility is empowering researchers, policymakers, and communities with the information they need to make informed decisions about natural resource management (Lombardo et al., 2023). RS also offers specific advantages for monitoring ecosystem services, such as:

- **Understanding service delivery:** RS can help track the delivery of ecosystem services and their connection to the management of NC, enhancing our understanding and capacity to act (NASA ARSET, 2022).

- **Improving predictive models:** RS data can be used to improve predictive models of habitat distribution and help capture changes in ecosystems more effectively (NASA ARSET, 2022).

- **Developing indicators:** RS can be used to construct indicators to assess the seasonality and productivity of grasslands, document the evolution of snow cover, and monitor "sentinel" environments that are particularly sensitive to climate change, such as peatlands and salt marshes (NASA ARSET, 2022).

These factors have positioned RS as the technology of choice in monitoring NC and valuing assessments. NC needs to be evaluated in a consistent manner using earth observation satellites (Magliarditi et al., 2019). While remote sensing data offers valuable insights for understanding natural capital, there remains a disconnect between the specific needs of natural capital assessments and the capabilities of current remote sensing technologies. Enthekhabi et al., (2010) introduced a framework for defining requirements for soil moisture measurements using RS based on specific application needs. The authors argued that traditional metrics like the root-mean-square error (RMSE) and correlation coefficient (r) have limitations when evaluating soil moisture retrievals due to potential biases in the mean and amplitude of fluctuations. They proposed a shift towards application-specific metrics that consider the relationship between soil moisture and the quantity of interest for a particular application. The framework involves defining application-specific requirements, establishing the relationship between soil moisture and the application quantity, characterizing soil moisture variability, converting application requirements into soil moisture accuracy, and expressing soil moisture accuracy in traditional metrics. This approach allows users to define their own requirements for a given application's quantity, which are then transformed into traditional RMSE and r metrics for soil moisture accuracy. By considering the specific needs of different applications, this framework provides more meaningful and relevant evaluations of soil moisture data.

In this thesis, the NC value tracked for generating RS requirements is along the lines of its physical proxy based NC valuation model suggested by Lee and Nepf (2024). The relationship between this physical proxy and the ecosystem functions that govern NC is studied. Entekhabi et al. (2010) sought to define sensor system requirements as a function of application requirements. However, this thesis tracks the physical proxy (rather than application requirements) of NC all the way to RS sensor requirements.

Despite the significant progress made, several gaps remain. These include RS data availability, the connection between RS data its use in biophysical modeling and quantifying ecosystem functions, economic valuation methodologies, integration with policy, social and cultural values. This thesis looks closely at the RS data availability, data quality and their impact on quantification.

3. Case Study: Wetlands and Flood Prevention

3.1 Wetlands' Role in NC

Wetlands are defined as ecosystems that arise when inundation by water produces soils dominated by anaerobic processes, which, in turn, forces the biota, particularly rooted plants, to adapt to flooding (Mitsch et al., 2009). Wetlands provide a wide range of services to humans and the environment. These services include water storage, flood attenuation, water quality improvement, carbon sequestration, and habitat provision for diverse plant and animal species. Wetlands are important for food production, providing habitat for fish, shellfish, and other aquatic organisms. They also play a role in crop production, as they can be used for growing rice and other crops. Additionally, wetlands provide raw materials such as timber, fuel, and peat. Wetlands act as natural sponges, absorbing and storing excess water during floods and releasing it slowly during dry periods. They also help to protect shorelines from erosion and buffer against storms. Wetlands play a crucial role in filtering pollutants and improving water quality.

Table 3-1 - Ecosystem services provided by wetlands (Maltby 2009)

Ecosystem Service	Description	Service Type
Water Purification	Wetlands act as natural filters, removing pollutants and excess nutrients from the water.	Regulating
Carbon Sequestration	Wetlands store large amounts of carbon, helping to mitigate climate change.	Regulating
Habitat Provision	Wetlands provide critical habitat for a wide variety of plant and animal species.	Supporting
Flood Control	Wetlands act as natural buffers, absorbing excess rainfall and reducing peak flows.	Regulating
Food Production	Wetlands provide habitat for fish, shellfish, and other aquatic organisms. They can also be used for growing rice and other crops.	Provisioning
Raw Materials	Wetlands provide timber, fuel, and peat.	Provisioning
Recreation and Tourism	Wetlands offer opportunities for activities such as birdwatching, boating, and fishing.	Cultural
Aesthetic and Spiritual Value	Wetlands provide beautiful and unique landscapes that have cultural and spiritual significance for many communities.	Cultural

Although wetlands only receive about 1% of global terrestrial rainfall, they yield significantly higher ecosystem goods and services (Costanza et al., 2014). In economic terms, a study on wetland ecosystem benefits in developing countries by Chaikumbung et al., (2016) suggests wetland ecosystems provide $2192 per hectare per annum. Costanza at al., (1997) suggest they are valued at over and $14 trillion.

Among the regulating services provided by wetlands, flood control is particularly significant, especially in the context of increasing climate variability and extreme weather events. Wetlands play a vital role in flood prevention by storing excess water during floods (figure 3-1) and reducing flow velocity, which helps mitigate flood peaks and minimize potential downstream damage (Perosa et al., 2021). Accurately quantifying the water-holding capacity of wetlands is essential for assessing the risk of inundation in surrounding areas during rainfall or other extreme events.

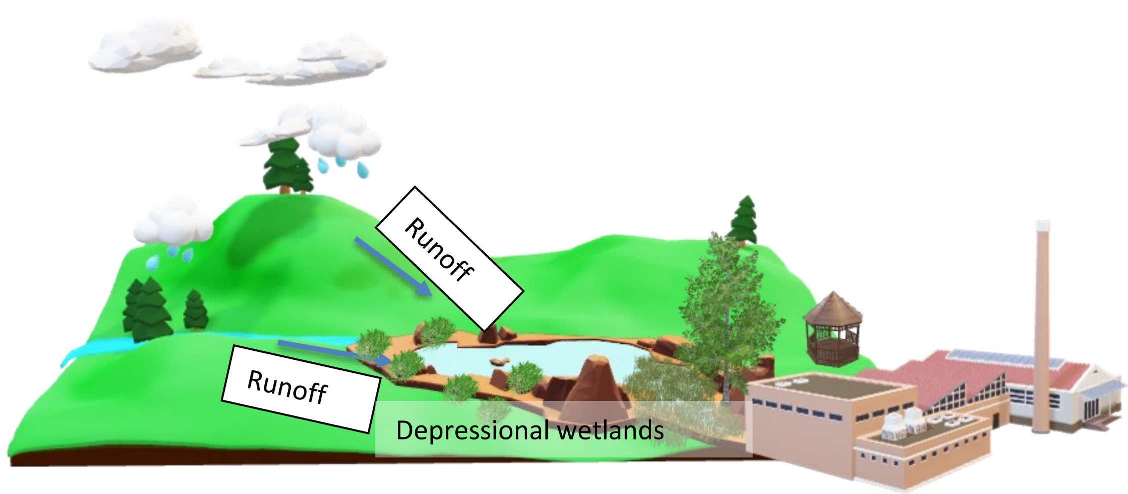

Figure 3-1 - Role of wetland in flood attenuation: Wetlands serve as temporary store of excess water after precipitation and other events

This research provides a prescriptive framework for tracking this critical ecosystem service. It focuses on evaluating the ability of wetlands to store excess water that would otherwise contribute to flooding in nearby communities. By modeling and identifying key parameters based on the hydrological water budget, the study emphasizes the factors necessary for determining water storage volumes. Additionally, it highlights the RS measurements and technologies required for parameter estimation and assesses the uncertainties in the measurement process. The analysis considers the effects of these uncertainties on estimates of water storage capacity. Finally, the research integrates these measurements and uncertainties into a system utility function that can guide the design of new RS systems and evaluate the performance of existing RS systems.

3.2 Hydrological Modeling for Wetland Water Budget

Hydrological modeling of wetlands has evolved significantly, transitioning from simplistic lumped models to more complex, spatially distributed models (Gleeson et al., 2007). The early models often treated wetlands as mere storage components, neglecting the dynamic interplay of various hydrological processes. However, recent advances in RS and GIS technologies have enabled the development of sophisticated models that capture the spatial heterogeneity and temporal variability of wetlands. These models incorporate a wide range of parameters, including topography, soil type, vegetation cover, and climate data, to simulate wetland hydrology more accurately.

Table 3-2 - The components of water budget in a wetland (Mitsch et al., 2009)

Water Budget Components	**Description**
Inflows	Water entering the wetland through precipitation, surface runoff, and groundwater.
Outflows	Water leaving the wetland through evapotranspiration, surface outflow, and groundwater outflow.
Storage	The balance between inflows and outflows, determining the amount of water stored in the wetland.

Understanding the water budget of a wetland is fundamental to constructing a robust hydrological model. The water budget accounts for all the inflows and outflows of water within a wetland system, providing insights into its storage capacity and overall hydrological function. Key parameters that influence the water budget include precipitation, evapotranspiration, surface runoff, and groundwater flow (Table 3-2).

The key variables (Mitsch et al., 2009) in hydrological modeling and water budget are

- Precipitation: The primary input of water into a wetland, precipitation can vary significantly in intensity, duration, and temporal distribution, influencing the wetland's water storage and overall hydrology.
- Topography: The shape and slope of the wetland basin and its surrounding catchment area influence the direction and rate of surface water flow, affecting water storage and runoff patterns.
- Surface Area: The surface area of the wetland determines the volume of water it can hold and the rate of evaporation. Larger surface areas generally lead to greater water storage and evaporation.
- Evapotranspiration: The combined process of evaporation and transpiration, evapotranspiration represents a significant loss of water from wetlands, influenced by factors such as temperature, humidity, and wind speed.

The water balance/budget equation is a fundamental equation governing wetland hydrology. It is a conservative equation that states that the change in water storage within a wetland is equal to the difference between inflows and outflows. Adapting from Mitsch et al., (2009),

- $S = S_0 + \Delta S$ (3.1)

  where S is the absolute storage at a given time, S_0 is the initial storage and ΔS is the change in storage

- $\Delta S = P + SWI + GWI - ET - SWO - GWO - \Delta Vol$ (3.2)

  where ΔS is the change in water storage (cubic meters), P is the spatially averaged precipitation (in cubic meters), SWI is the volume of surface water inflow, GWI is the groundwater inflow, ET is evapotranspiration, SWO is surface water outflow, GWO is groundwater outflow, and ΔVol is change in volume of the land surface due to compaction or subsidence, (Mitsch et al., 2009). Compaction can result from loss of water from the soil, and subsidence can result from sinking due to ground water extraction or other natural processes.

Apart from these, water flow across terrain is characterized by surface roughness, which is a function of vegetation, debris, and micro topography, affects the rate of water infiltration. A rougher surface slows down water flow, promoting infiltration. Water flow is also affected by the area and slope of the wetland's channels (figure 3-2).

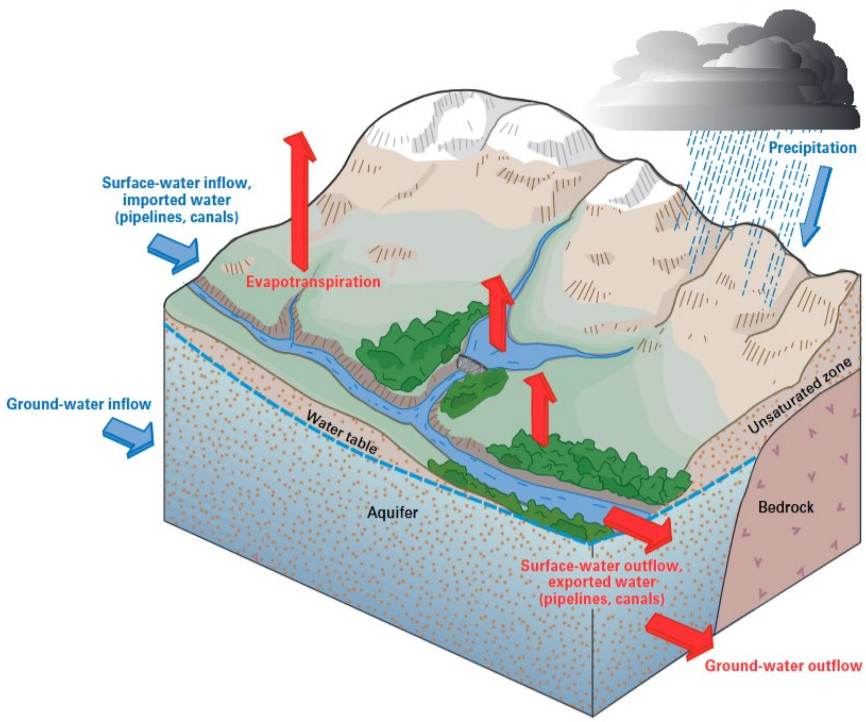

Figure 3-2 - The hydrologic cycle for watersheds and wetlands (Source: "Water Budgets: Foundations for Effective Water-Resources and Environmental Management." Geological Survey (U.S.), 2007. https://doi.org/10.3133/cir1308

3.3 Remote Sensing Measurements to Quantify Wetland Water Budget

RS technologies offer powerful tools for monitoring and assessing wetland water storage capacity. These technologies involve the use of sensors to collect data about the Earth's surface from a distance, typically from aircraft or satellites. Different types of RS technologies, such as optical imagery, Synthetic

Aperture Radar (SAR), and Light Detection and Ranging (Lidar), provide unique information about wetland characteristics. The choice of RS technology depends on the specific research question and the characteristics of the wetland being studied (Ozemi and Bauer, 2002). Optical RS uses sensors that detect, and record reflected sunlight. This technology is widely used for wetland mapping and classification, as different wetland types and vegetation communities have distinct spectral signatures. Optical imagery can be used to assess wetland extent, vegetation health, and water quality (Ozemi and Bauer, 2002). Hyperspectral imagery, with its high spectral resolution, can even be used to identify specific wetland species (Klemas, V. 2005). However, the use of optical sensors in identifying wetlands can be limited by factors such as water depth, mixed pixels, and dense vegetation cover (Mahdavi et al., 2022). SAR is an active RS technology that emits microwave signals and measures the backscattered energy. SAR data can be used to map wetland extent, identify inundated areas, and estimate soil moisture. SAR has the advantage of being able to penetrate cloud cover and vegetation, making it useful for monitoring wetlands in all weather conditions (Mahdavi et al., 2022). Different SAR sensors operate in various bands, with longer wavelengths (e.g., L-band) being more appropriate for the separation of forested or densely vegetated wetlands from non-flooded ones (Huang et al., 2018).

Lidar is another active RS technology that uses laser pulses to measure distances and create high-resolution elevation models. Lidar data can be used to map wetland topography, vegetation structure, and water depth. Lidar is particularly useful for mapping forested wetlands, as it can penetrate the canopy and provide detailed information about the ground surface (Lane, and D'Amico,2010). Lidar data can be combined with optical imagery to improve the accuracy of wetland mapping and assessment, as well as delineating the extents of water and estimating storage. Thermal infrared RS provides valuable insights into both groundwater and evapotranspiration processes. Thermal infrared sensors measure the surface temperature of the Earth, revealing variations that can indicate groundwater inflow and outflow zones. For example, cooler areas might suggest groundwater discharge, while warmer areas could point to recharge zones. Moreover, thermal infrared data helps estimate evapotranspiration rates by capturing the cooling effect of evaporation on the land surface. To accurately quantify evapotranspiration, shortwave infrared and visible/near-infrared RS techniques are also essential. Shortwave infrared is particularly sensitive to water content in vegetation and soil, allowing for the detection of changes in plant water stress, a key indicator of evapotranspiration. Meanwhile, visible and near-infrared data are used to calculate vegetation indices like NDVI (Normalized Difference Vegetation Index). These indices reflect plant health and greenness, providing valuable information for estimating evapotranspiration and assessing the overall productivity of ecosystems. Table 3-3 summarizes relevant hydrological parameters and the RS systems with the ability to measure these parameters

Table 3-3 - Compilation of the hydrological parameters important for flood assessment and the RS sensors used to measure them

Parameter	Wavelengths	RS Sensors
S/ S_0/ ΔS (Storage Current/Initial/Change in storage)	Microwave (SAR, InSAR), Topographic data	Sentinel-1 (5-40 m; 6-12 days) ALOS-2 Palsar 2 (3-100 m; 14 - 46 days) TerraSAR-X (1 - 16 m; 11 days) ICESAT-1,2 (70m, 91 days)
P (Precipitation)	Microwave, Infrared	GPM, (5 km, 3 hrs) TRMM (5 km, 3 days) CloudSat (1.4 km, 16 days GOES (500m to 2 km, 15 minutes) Meteosat (500m to 3 km, 15 minutes)
Surface Water Inflow/Outflow (SWI/SWO)	Topographic data, Microwave	Landsat (30m, 8-16 days) Sentinel-2 (10- 20 m, 5-10 days) MODIS(250 m - 1 km, 1-2 days NISAR (3-10 m, 12 days)
Groundwater Inflow/Outflow (GWI/GWO)	Primarily inferred indirectly from other parameters. Thermal Infrared can be used to detect areas of groundwater discharge Gravity measurements from GRACE can provide information on changes in groundwater storage	Landsat (30 m), ASTER (15 - 90m, 16 days) GRACE (300 km, 30 days)
ET (Evapotranspiration)	Thermal Infrared, Shortwave Infrared	Landsat MODIS Sentinel-3(300 m - 1 km) ECOSTRESS (~70 m)

3.4 Discussion and Outlook

In this chapter, an overview of the crucial nature of wetlands towards flood prevention, water purification, and biodiversity support was presented. The chapter explored RS methods to monitor these benefits, focusing on flood management. It discussed parameters like water storage, evapotranspiration, and groundwater recharge, and how RS technologies like SAR and InSAR can monitor them. The relationship between NC services/benefits (e.g. flood attenuation) to a physical quantity (i.e. water storage capacity) was established.

The next chapter discusses RS methods used to assess water volume by using an example of water stored in an open reservoir. Understanding how the data from the RS sensors are used to estimate storage and the uncertainties in the computed water storage (which is the proxy for value of wetlands as it relates to flood control mechanism) is crucial for understanding uncertainties.

4. Estimating Water Storage Capacity from RS Data

4.1 Estimating Wetland Water Extent and Volume

The primary methods for estimating wetland storage volumes involve:

- Topographic Surveys: Topographic surveys capture detailed elevation data of a wetland and its surrounding areas. By identifying the maximum elevation or spill point of the wetland, one can delineate the wetland basin and calculate its volume.
- Surface Area to Volume Relationships: By establishing a relationship between the surface area of a wetland and its volume, one can estimate the volume of a wetland by measuring its surface area, which can be obtained from aerial imagery or field surveys.
- Elevation data collection: Lidar (Light Detection and Ranging) data provides fine-scale elevation data, eliminating the need for on-site surveys. Lidar data can be used to create a digital elevation model (DEM) of the wetland, which can then be used to calculate the volume of the wetland basin.
- Mathematical Modeling: Mathematical equations can be used to relate area and volume to depth in shallow wetland depressions. These equations often incorporate variables such as maximum depth and a coefficient representing the basin shape to improve accuracy.

In this chapter, satellite-acquired data (Sentinel-1, 2 and Planetscope) is used to identify the aerial extents of water. Then a digital elevation model (DEM) is used to determine water elevation and water volumes present at the time of data (imagery) collection. Figure 4-1 provides an illustration of a depressional wetland, including a top view of water extent with a grid indicating pixels of a remotely sensed satellite image and a cross-sectional view of depths measured by DEM.

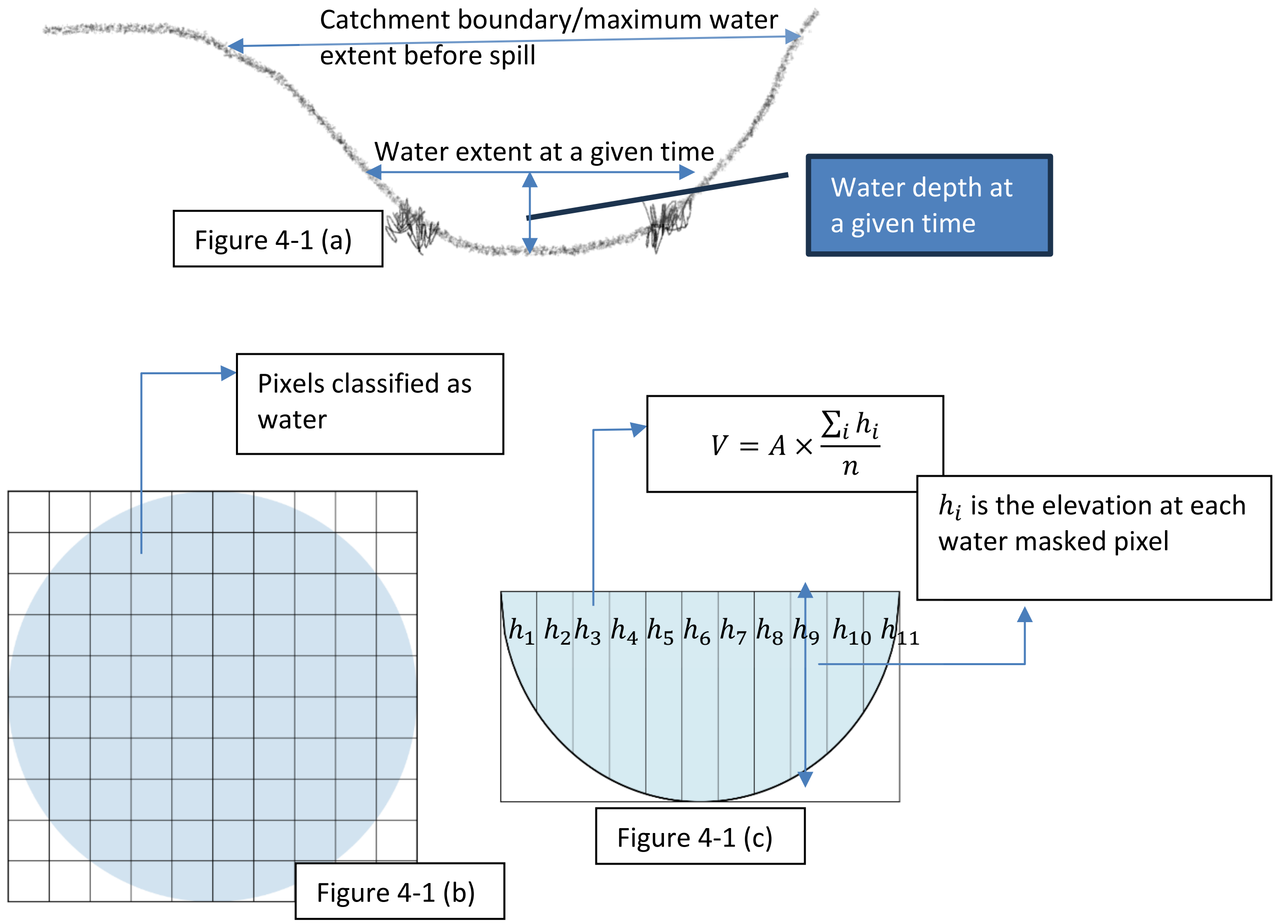

Figure 4-1 - 1 Illustration of a depressional wetland. The top view of water extent is illustrated in figure 4-1(b) with the uniform grid indicating the pixels of a remotely sensed satellite image. Figure 4-1 (c) represents the cross-sectional depths measured by DEM

Sentinel-1 and Sentinel -2 are SAR and optical remote sensing sensors under the European Space Agency's Copernicus program(https://www.esa.int/Applications/Observing_the_Earth/Copernicus). Sentinel-2 (Spoto et al., 2012) Is a two satellite constellation with a 5-day revisit time, 10-60 meter spatial resolution across 13 spectral bands (visible to shortwave infrared), and a 290 km swath width. Sentinel-1 (Torres et al., 2017), also was a two satellite program, Intending to provide SAR data with a 6-

day revisit time, flexible spatial resolution (5-100 meters) depending on the imaging mode, and a wider swath width of up to 400 km. Both Sentinel missions offer high radiometric and geometric accuracy and various data products ranging from raw to ortho-rectified data, contributing significantly to Copernicus services like land monitoring, emergency response, and maritime surveillance.

Planet SuperDove (Lavender 2024) prioritizes very high spatial resolution (3 meters) and a daily revisit rate, capturing data in 8 spectral bands (visible and near-infrared) with a 24-kilometer swath width. Its high radiometric performance and rapid revisit cycle make it ideal for applications demanding frequent and detailed observations, such as precision agriculture and urban mapping. Each system offers unique strengths depending on the specific application: Sentinel-2 for its wide spectral range, Sentinel-1 for its SAR capabilities, and SuperDove for its high spatial resolution and frequent coverage.

The next section demonstrates the extraction of water extents from both optical (Sentinel-2, PlanetScope) and SAR (Sentinel-1) data. Different spectral bands and indices were employed to achieve this:

- Sentinel-2: The green (Band 3) and shortwave infrared 1 (Band 11) bands were used to calculate the Modified Normalized Difference Water Index (MWI).
- PlanetScope: The green and near-infrared bands were used to calculate the Normalized Difference Water Index (NDWI).
- Sentinel-1: The 'VV' polarization backscatter was used to identify water bodies, which typically exhibit low backscatter due to their smooth surface (Huang et al., 2017). However, when the water levels are low, both VH and VV can be used.

Water pixels are mapped by thresholding the MNDWI, NDWI, and 'VV' backscatter, respectively. Once mapped, a vector mask boundary of the mask of the water pixels are spatially intersected with the digital elevation data. In this study, water elevation is taken to be the 95th percentile of the elevation values obtained from the intersection of the water boundary and the DEM.

4.1.1. Study Area

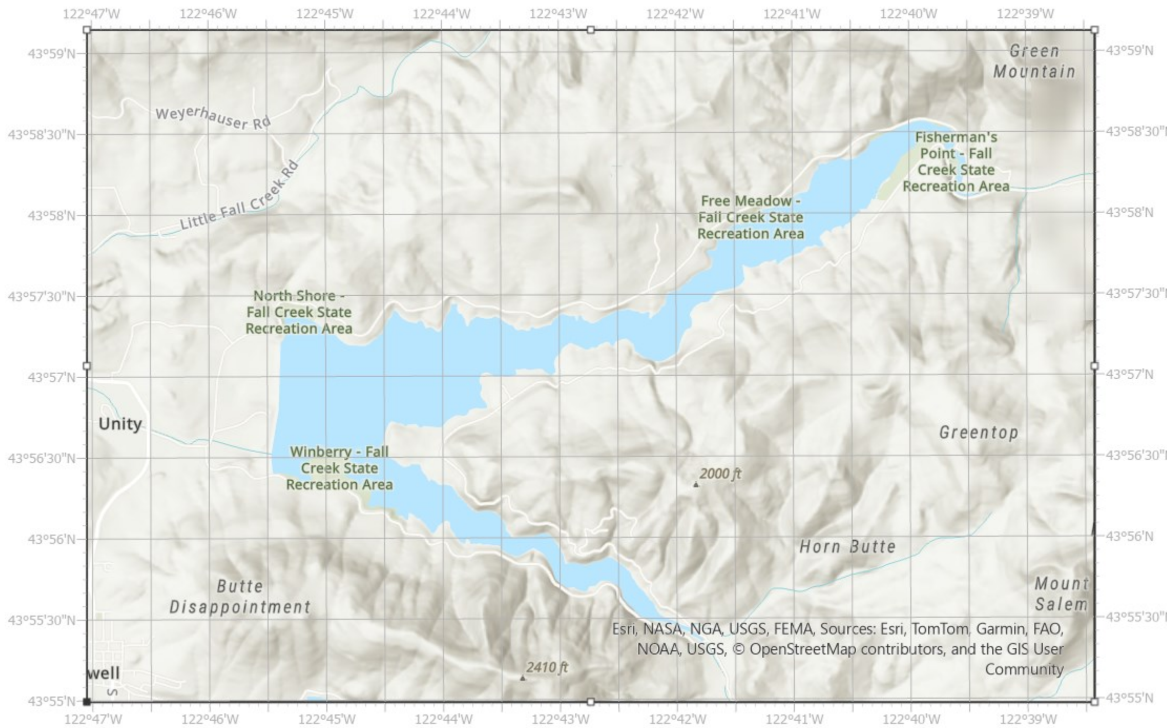

Figure 4-2 - Map and location of Fall Creek Lake reservoir study area (Source ESRI/ArcGIS pro 3.3)

The Fall Creek Lake study area (figure 4-2), located in west-central Oregon, encompasses a diverse landscape ranging from the Willamette Valley Foothills to the High Cascades. This area is characterized by a significant elevation gradient, with altitudes ranging from 454 feet in Springfield to approximately 6,500 feet in the High Cascades. The watershed is predominantly forested, with forests covering 91% of the total acreage, while the remaining areas include developed lands, pasture, and rangelands (Logan and others, 2014). Fall Creek Lake, a 1,820-acre flood control reservoir, is a central feature of the study area. The lake is fed by two main tributaries, Winberry Creek and upper Fall Creek, which drain the lower elevations of the Western Cascades. The outflow of the lake flows westward for approximately 7 miles before joining the Middle Fork Willamette River. The study area also includes Little Fall Creek, an unregulated tributary to lower Fall Creek, and Dexter Reservoir, which impounds the upper Middle Fork

Willamette River (Logan et al., 2014).

The hydrology of the study area is influenced by both natural and artificial factors. While most of the watershed is forested, impacting water quality and sediment dynamics, the presence of Fall Creek Lake and Dexter Reservoir indicates significant human intervention in the river system. This intervention likely affects the natural flow patterns and sediment transport within the watershed (Logan et al., 2014).

Fall Creek Reservoir was selected as the study area due to the availability of both reliable ground truth data and a high-resolution DEM. The reservoir's operational characteristics, including periodic drawdowns for maintenance and flood control, provided an opportunity to acquire a DEM that accurately captures the terrain beneath the water surface. This DEM, acquired in 2016 during a drawdown period, has a 1-meter spatial resolution and minimizes potential errors in volume calculations compared to DEMs that rely on interpolation to represent the reservoir bed. Additionally, the availability of water elevation measurements from the United States Geological Survey (USGS) offers a valuable source of ground truth data for validating the accuracy of the RS-based water volume estimations. This combination of high-quality DEM and reliable ground truth data makes Fall Creek Reservoir an ideal study area for evaluating the effectiveness of the proposed methodology.

4.1.2. Datasets

A 1-meter spatial resolution DEM derived from aerial photogrammetry was acquired for the study area. The U.S. Geological Survey studied how yearly drawdowns of Fall Creek Lake in Oregon affect the downstream river system. They used aerial photographs taken by drones and a Cessna aircraft to create 3D models of the lakebed during a drawdown (Mangano and Keith, 2016). These models helped them analyze how sediment moves from the reservoir downstream and understand the changes in the river channel. The data collected included aerial photographs, 3D point clouds, elevation models, and orthophotographs, providing detailed information about the lakebed and the impact of the drawdowns.

This test site provided a useful case with redundant data available (multiple elevation models) for testing the ability of satellite RS-based datasets to determine water volumes and water elevation. For example, the availability of lakebed digital elevation data allows for the estimation of water volumes as discussed earlier. The availability of independent ground measurements of water elevation multiple times a day allows for testing the satellite data estimated water surface elevation with ground truth.

Sentinel-1 Ground Range Detected (GRD) data was accessed from the Google Earth Engine (GEE; Gorelick et al., 2017) public data catalog (COPERNICUS/S1_GRD). This collection includes data from Sentinel-1 satellite. Sentinel-2 imagery was accessed from the GEE public data catalog (COPERNICUS/S2_SR_HARMONIZED). PlanetScope satellite imagery was also acquired using Planet’s data archives for research. Planet's SuperDove satellites, with their 8-band sensors, capture high-resolution imagery (3.7 m GSD) across a 20 km swath, providing comprehensive spectral information in coastal blue, blue, green I, green, yellow, red, red-edge, and NIR bands (Frazier and Hemingway, 2017). This data is delivered in 16-bit orthorectified GeoTIFF format, radiometrically calibrated to Top-of-Atmosphere reflectance, and geometrically corrected to an accuracy of <10 meters RMSE. In this work, the green and the NIR bands were used, and the data was upsampled to 3 m. Table 4-1 summarizes the data used in this study.

Table 4-1 - Summary of Data Sources Used in Water Volume Estimation and Validation

Data Source	Data Type	Spatial Resolution	Temporal Resolution	Spectral/Polarimetric Bands	Purpose
Sentinel-1 (COPERNICUS/S1_GRD)	SAR (GRD)	10m	6 days (revisit time)	VV polarization	Water body extraction, leveraging low backscatter of water
Sentinel-2 (COPERNICUS/S2_SR_HARMONIZED)	Optical (Surface Reflectance)	10m, 20m, 60m	5 days (revisit time)	B3 (Green), B11 (SWIR)	Water body extraction using MNDWI
PlanetScope	Optical (Surface Reflectance)	3m (native), upsampled to 0.3m	Daily	Green, Near-infrared	Water body extraction using NDWI
Aerial Photogrammetry	DEM	1m (resampled from 4-5cm)	Single acquisition (2016)	Elevation	Terrain model, water level and volume estimation
USGS Water elevation data	Water level measurements	N/A	Hourly	N/A	Ground truth data for validation

4.1.3. Data Processing

The data processing workflow for estimating water surface elevation and water storage volume are illustrated in figure 4-3. The digital elevation model (originally collected at 4.5 cm ground sample distance) was resampled to 1 m and uploaded to google earth engine accessible data drives. The DEM was resampled using cubic convolution using the Geospatial Data Abstraction Language (GDAL) software. This not only decreases the data processing requirements, but since the other data sets are of much coarser spatial resolution (Table 4.1), a high-resolution elevation data (finer than 1 m) is not necessary. The Sentinel-1 image was preprocessed in GEE. This involved clipping the image to the area of interest and applying a speckle filter to reduce noise. Water bodies were identified using the backscatter characteristics of SAR data. A water mask was generated by thresholding the 'VV' backscatter values of the Sentinel-1 image. VV polarization is considered better for detecting clear water. In the case of shallow water, “VH” polarization may also be considered. The water mask provides the two-dimensional extents of water present in the area of interest (AOI). The Sentinel-2 image was also preprocessed in GEE to minimize the influence of clouds and enhance water features. This involved:

1. Clipping: The image was clipped to the AOI to focus the analysis on the relevant region.
2. Cloud Masking: The QA60 band of the Sentinel-2 image was used to identify and mask out cloud-affected pixels, ensuring that only clear-sky observations were used. Sentinel-1 SAR images can “see” through clouds and do not have this problem.
3. Modified Normalized Difference Water Index (MNDWI) Calculation: For Sentinel-2 data, the MNDWI (Xu, 2006), a spectral index sensitive to water bodies, was calculated using the green (B3) and shortwave infrared 1 (B11) bands.
    1. MNDWI = (B3 -B11) / (B3 + B11). --(4.1)
4. Water Masking: A binary water mask was generated by thresholding the MNDWI values above 0.1 in the case of Sentinel-2 data.
5. Water masks from Sentinel-1 pixels were generated using pixels with backscatter values greater than -0.18 in the VV polarization (Huang 2017).

The PlanetScope imagery has a ground sample distance of 3 m, The Normalized Difference Water Index (NDWI) was calculated from the green and near-infrared bands of the PlanetScope image using the following formula (Xu, 2006):

NDWI = (Green - NIR) / (Green + NIR). --(4.2)

A binary water mask was created by thresholding the NDWI image. Pixels with NDWI values greater than -0.5 were classified as water. To eliminate small, isolated pixels and smooth the water body boundaries, a majority filter with a window size of 9 pixels was applied to the water mask.

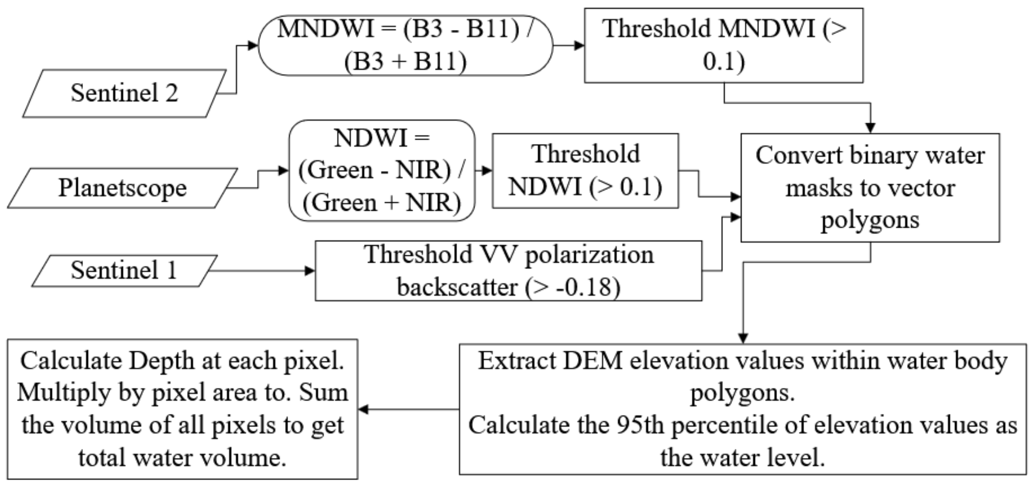

Figure 4-3 - Data processing workflow for estimation of water volume. The processing flows are slightly different for the three sensors, until the water masks are extracted.

Vector polygons representing the water bodies were extracted from the binary water mask using the rasterio.features.shapes function (figure 4-4). These polygons were initially in the same coordinate system as the PlanetScope imagery (WGS84). To ensure accurate spatial alignment with the DEM, the polygons were reprojected to the UTM zone of the DEM using the geopandas library. The water level was estimated by analyzing the elevation values in the DEM that intersected with the water body polygons(figure 4-4). In this research, the 95th percentile of the corresponding elevation values was taken as the representative water level.

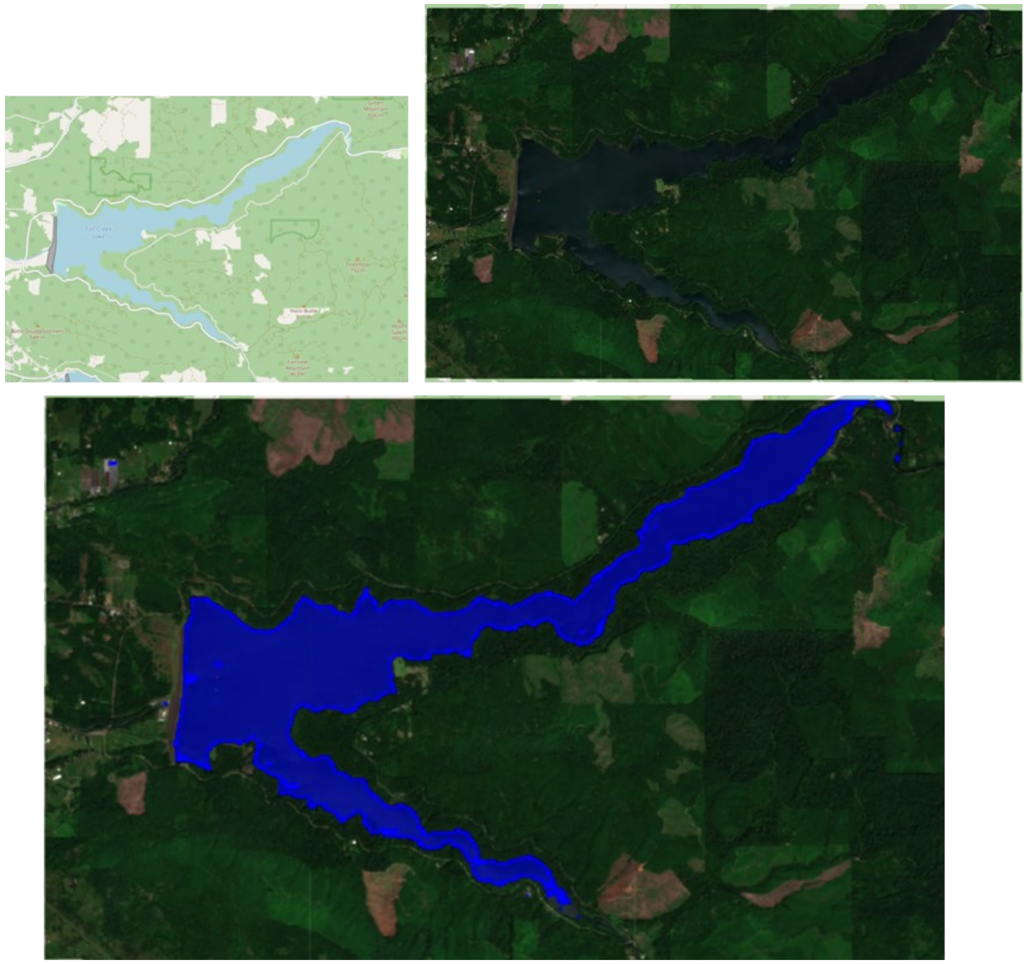

Figure 4-4 - An illustration of the reservoir, a Sentinel 2B image over the area, and the water mask

The volume of water in the reservoir was calculated by subtracting the DEM elevation from the estimated water level for each pixel within the water body polygon (figure 4-5). The pixel area was calculated as the square of the GSD. The average water depth of the masked pixels was multiplied by the masked pixel area to obtain the total water volume.

$$V = A \times \frac{\sum_i h_i}{n} \quad \text{-- (4.3)}$$

$$h_i = H_{95th\ percentile} - H_{DEM\ at\ i} \quad \text{--(4.4)}$$

where h_i is the depth of the water masked pixel

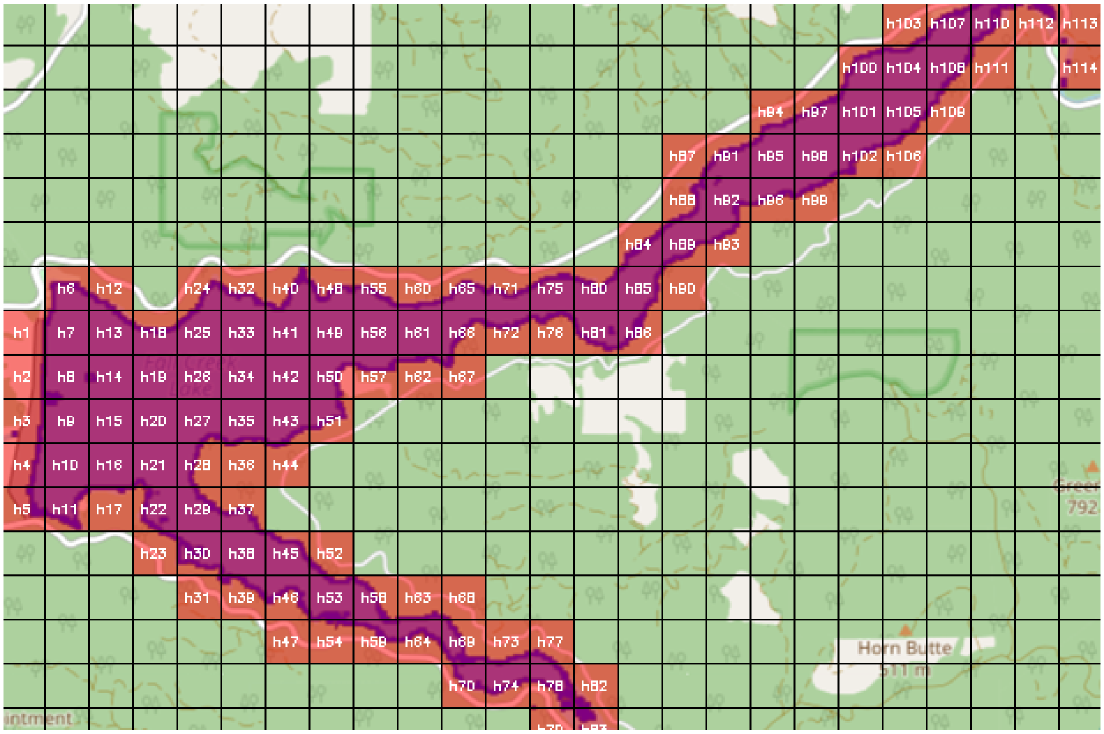

Figure 4-5 - Estimation of water volume: The grid represents the Image pixels. Water pixels (In red) are masked, and water depth at each pixel is extracted. The volume is the sum of the water masked pixel area times the water depth. The orange pixels are to ensure that pixels outside of this region are not considered for analysis

Since ground truth on the volume of water in the lake is not available, the comparisons between the USGS measurements (ground truth of water elevation) and the RS-based measurements were limited to water elevation estimates (Mangano and Keith, 2016).

This approach is similar to the study by (Zhang et al., 2014). In that study, water surface area was derived from MODIS NDVI imagery (2000-2012) and enhanced using unsupervised classification. ICESat/GLAS satellite altimetry provided water surface elevation data, with daily reservoir elevation estimated as the average of all measurements within each overpass. By pairing coincident area and elevation data, reservoir-specific area-elevation relationships were established, enabling the estimation of water surface elevation during periods lacking ICESat/GLAS coverage. Finally, reservoir storage was calculated from the combined time series of water surface area and elevation. The method used in this study differs because the water elevation is not derived from satellite lidar data.

The analysis integrated the capabilities of GEE with Python libraries, including geemap for GEE interaction, rasterio for raster data handling, pyproj for coordinate transformations, and shapely and Geopandas for geospatial vector processing. The Sentinel data was processed in Google Colaboratory environment using Python 3.10 and using the calibrated reflectance and backscatter data (Sentinel 2 and Sentinel 1 respectively) available in GEE.

4.2 Results

The estimated water elevation (figure 4-6 and Table 4-2) and USGS measured elevation show a strong correlation, particularly when the reservoir has sufficient water. It shows that the concurrent use of 3D and image-based RS data can estimate water elevation and water volumes and shows that the equations and algorithms used in the method described above provides an accurate way (with r^2 of 0.95) to estimate volume.

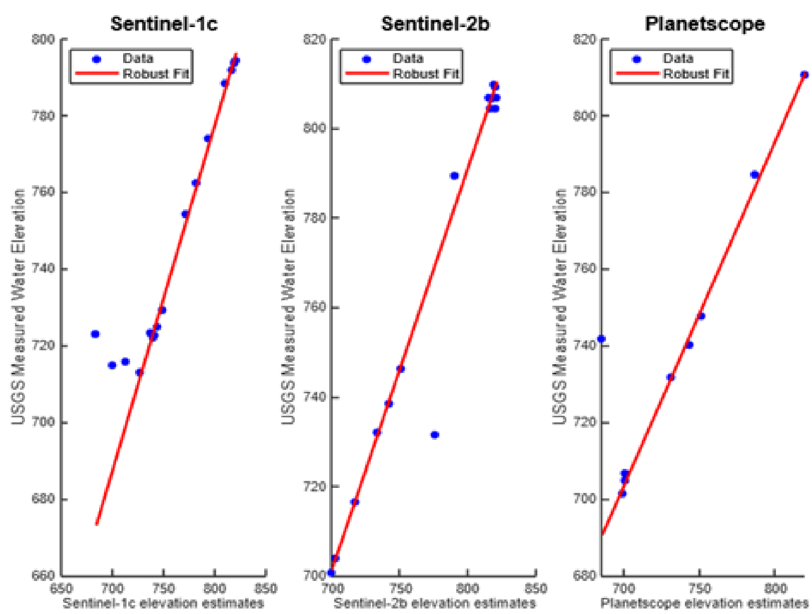

Figure 4-6 - Results of estimation of water elevation and their comparison with USGS measurements

Table 4-2 - Results of estimation of water elevation and their comparison with USGS measurements. The equations represent a robust regression value (Random Sample Consensus method)

Data sets	Robust regression line equation	r^2	r^2 (robust)	Number of scenes
Sentinel 1	y = 0.89c + 57.35	.77	0.95	30
Sentinel 2	y = 0.89x + 72.45	.75	0.99	10
Planet Superdove	y = 0.90x + 72.645	.79	.94	10

Figure 4-6 and Table 4-2 illustrate the relationship between water elevation measurements obtained from different satellite sensors (Sentinel-1, Sentinel-2, and Planet) and corresponding USGS ground truth measurements. The analysis reveals that there is sufficient information present in both the imagery (Sentinel-2 and Planet) and radar data (Sentinel-1) to effectively identify water, even when employing simple index-based thresholding methods. The outlying points observed in the graphs predominantly correspond to instances when the water levels in the reservoir drop. This decrease in water level can lead to misidentified pixels, which tend to underestimate the actual water levels, particularly noticeable in the radar and Planet data.

It is important to acknowledge that the methods employed in this analysis are relatively simple, relying on index-based thresholding. The presence of outlying data points highlights the limitations of these basic methods, especially when dealing with fluctuating water levels. Despite these limitations, there is ample signal present in the data to accurately demarcate water pixels, even with lower water levels in the reservoir. By employing more sophisticated algorithms, such as those combining SWIR (MNDWI), NIR (NDWI), and RGB-based water indices, or by leveraging machine learning (Lopez-Tapia et al., 2021) or deep learning-based methods (Cao et al., 2024), the accuracy of water pixel identification can be further enhanced.

4.3 Discussion

It is acknowledged that most of the data used for generating the regression lines in figure 4-6 and Table 4-2 represent ideal conditions. The choice of Fall Creek Reservoir was made due to the availability of reliable ground truth data and a high-resolution DEM, which could have increased the likelihood of obtaining favorable results. While this does not necessarily invalidate the study's findings, they should be considered when interpreting the results, as it is very hard to determine high accuracy DEMs for wetlands. The satellite imagery was carefully selected to ensure minimal cloud cover (less than 10% according to the Sentinel QA bands) or obstructions, allowing for clear and unobstructed views of the water body. Additionally, the Sentinel and Planet data have undergone rigorous calibration procedures to ensure accurate reflectance and backscatter measurements.

Furthermore, the availability of a highly accurate digital elevation model derived from UAS based aerial photogrammetry significantly contributes to the precision of the water level and volume estimations. This high-resolution DEM, with a 1-meter spatial resolution (and derived from a 4.5 cm spatial resolution DEM), captures the terrain beneath the water surface with exceptional detail, minimizing potential errors in volume calculations. The

However, it's crucial to recognize that such high-quality DEMs may not be readily available for all wetland areas. The acquisition of a suitable DEM should be considered an integral part of the system design when applying this methodology to different wetlands. The Zhang et al., 2014 paper discussed earlier uses GLAS/ICESAT-1 measurements to obtain the water elevation at an uncertainty of 10 cm. Their uncertainty analysis may lead to the conclusion that image and radiometric RS data may be the source of higher uncertainty in estimating water volumes. It should therefore be pointed out that ICESAT-1's point spacing is low, and its temporal cadence may not be enough to reliably obtain elevations to monitor water storage anywhere other than the cryosphere (Abdalati et al., 2010). However, GLAS/ICESAT-1 and ICESAT-2 data can be used as the gold standard to calibrate and validate other missions, and methods to estimate water elevation. Most of the digital elevation models available in the world have higher errors than 10 cm (Liu et al., 2020). Therefore, in the next chapter, we Introduce errors in the digital elevation data available and focus on uncertainty in water volume estimation arising out of errors in the elevation data.

This chapter demonstrates the viability of integrating RS data with high-resolution DEMs for water volume estimation. The results highlight the potential of this approach for monitoring and managing water resources, particularly in regions with limited ground-based observations. The use of more sophisticated data processing techniques and robust uncertainty analysis frameworks will further enhance the accuracy and reliability of water volume estimations in diverse wetland settings.

5. Estimating Uncertainties and Computing Utility

5.1 Sources of Uncertainty

Since the flood attenuation benefit provided by wetlands is related to their ability to store water, the uncertainty in economic value is directly related to the uncertainty in measuring the volumes of water stored in wetlands. This volume is a function of the extents of water, the depth, and the slope of the terrain. Therefore, uncertainty in the volume of water is considered a reasonable proxy for uncertainty in the benefits. The uncertainty in estimation of volume can be due several reasons. The ability to capture and monitor any given wetland is dependent on the orbital revisit period, which is the frequency with which the same orbit is repeated, and the swath width of the sensor. Together, these two parameters influence the frequency with which a given spot on the earth can be observed by the sensor. Landsat, for example, can capture a given location on earth once in 16 days and Sentinel can do so once every 8 days. The absence of observed data over the area between the two revisits is one of the biggest causes of uncertainty.

Sensor and data characteristics including spatial/temporal resolution limits, calibration errors, atmospheric distortions during data acquisition, and noise can affect accuracy of measured reflectances, which can in turn affect the water indices (MNDWI, NDWI etc.). In the case of SAR data, ripples on the water surface due to wave action can cause backscatter thresholds needed to identify water pixels tricky to use. Another example is that a coarse resolution (e.g., Landsat 30m) might miss small water features or the boundaries may not be captured well. However, the presence of high-quality satellites (Markham et al., 2019; Gascon et al., 2017), validation data such as Radcalnet(Bouvet et al., 2019), etc. can significantly reduce these uncertainties.

Low-resolution DEMs can misrepresent topography. This is quantified and studied in the next section as vertical inaccuracies can significantly distort depth estimates in flat wetlands. Cloud and canopy present the most significant sources of uncertainty. These are unrelated to sensors, and as such cannot be "processed out" of the data. While SAR data can "see through" clouds, as seen in table 2, this can be debilitating for an optical sensor. Dense canopies or emergent vegetation obscure water detection and completely occlude observations. Seasonal changes complicate reflectance interpretation. Surface Characteristics: Water depth, turbidity, and algal blooms alter spectral signatures. Wind affects reflectance, particularly for SAR scenes. Table 5.1. lists some significant sources of uncertainty.

Table 5-1 - Comprehensive categories and sources of uncertainty in optical earth observation based water volume determination

Category	**Source of Uncertainty**	**Key Points**	**Example**
Sensor-Specific Uncertainties	Resolution, Noise, Calibration,	coarse resolution, low signal-to-noise ratio, Calibration errors,	Landsat 30m resolution missing small water channels
	Atmospheric Effects	Distortion from atmospheric scattering/absorption	Water vapor affecting certain spectral bands
Platform-Related Uncertainties	Orbital/Flight Path Variations	Geometric distortions affecting image alignment	Misaligned pixels between different acquisition dates
Terrain and Elevation	DEM Accuracy and Vertical Errors	Low-resolution DEMs misrepresent topography; vertical errors affect depth	Inaccurate microtopography in wetlands
	Terrain Shadows	Shadows can obscure or	Steep slope shadows

		distort water reflectance	mistaken for water
Environmental Factors	Vegetation Interference	Dense canopy/emergent vegetation obscuring water	Forested wetlands hiding water under the canopy
	Seasonal Changes	Phenology affecting reflectance, e.g., leaf-on/leaf-off conditions	Emergent vegetation appearing similar to water in some bands
Surface Water Characteristics	Depth, Turbidity, Algal Blooms	Shallow water appearing bright; sediment altering reflectance	High sediment load making water appear murky
Classification Issues	Algorithm Choice and Thresholds	Selection of algorithms and thresholds impacting accuracy	NDWI threshold variations impacting water detection
	Training Data Quality	Limited, biased, or poorly timed training data affecting classification	Biased training points skewing results
	Mixed Pixels	Pixels with both water and land cover causing under/overestimation	Edge pixels containing both water and vegetation
Validation and Assessment	Field Data and Temporal Mismatches	Limited, inconsistent, or non-concurrent field data	Field measurements not matching the timing of satellite images

5.2 Quantitative Uncertainty Analysis

Table 5-2 captures the observation statistics for Landsat and Sentinel 2 combination over Fall Creek Lake, near Lowell OR. While there are many sources of uncertainty (Povey et al., 2015) in RS data, three are considered in this discussion: temporal, radiometric and elevation related uncertainties. Temporal uncertainty is perhaps the most significant in terms of the ability to monitor water storage. Between '2022-01-01' and '2024-12-31 ' or a total of 1096 days, only 411 combined Landsat (8/9) and Sentinel (2A and 2B) data are available for analyses over the study area. This reduces to 209 when only cloud free scenes are filtered. The Sentinel 1 SAR satellite constellation has a lower revisit of 3.4 days (1096/320), but the actual useful datasets available for analysis are still higher (320). Therefore, we have large periods of potentially unobservable events. This is a limitation of sensors operating in the optical spectrum unless interoperability is adopted.

Table 5-2- The temporal capability associated with water volume monitoring using optical (Landsat 8 and Landsat 9, as well as Sentinel 2A and Sentinel 2B) and Synthetic Aperture Radar (SAR) based sensors

Sensor	Time period and days	Number of observations	Number of valuable observations (Defined as imagery with less than 20% cloud cover)	Value factor (assuming 20% or less cloud cover provides perfect value)
Landsat + Sentinel 2A and Sentinel 2B	'2022-01-01' to '2024-12-31 '/1096 days	445	204	204/1096 = 0.186
Sentinel 1 (SAR)	‘2022-01-01' to '2024-12-31 '/1096 days	320	320	320/1096 = 0.290

To study the uncertainty in water volume estimates due to error in digital elevation models (figure 5-1), a random fields based method (Hristopulos 2020) was combined with Monte Carlo based assessment. A random field in this context can be thought of as a region where error values are spatially correlated, meaning that data points closer together tend to be more similar than those further apart. When analyzing spatial data for uncertainty, spatial autocorrelation needs to be accounted for. Ignoring this can lead to biased and inefficient estimates of the relationships within the data, as well as misleading conclusions. To address this, spatial econometric techniques are used to account for the spatial autocorrelation of errors, leading to more accurate and reliable results.

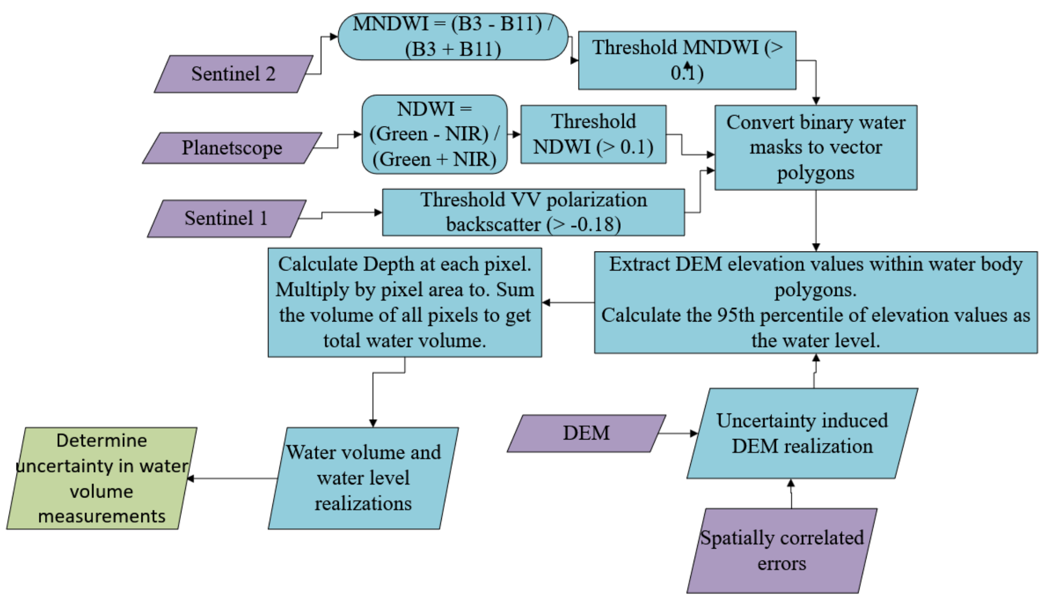

Figure 5-1 - Uncertainty estimation of water volumes as a function of DEM uncertainty

The random fields method used for DEM uncertainty analysis creates multiple (in this case thirty), slightly different DEMs to account for the fact that the DEM might have errors. It works by:

1. Focusing on Slopes: It assumes that steeper slopes in the terrain are more likely to have larger errors in the DEM.
2. Adding Errors: Pixels are randomly chosen from high and low slopes of DEM separately (50 pixels each). Errors are simulated based on the input root mean square error estimated for the elevation

models (5 m standard deviation) for higher slopes (greater than 10 degrees) and 2 m (standard deviation) for lesser slopes.

3. Kriging: In the next step, Kriging technique is used to spread these errors smoothly across the entire area of interest. Kriging ensures that the errors are spatially correlated, meaning that errors close to each other are more likely to be similar. This creates a more realistic "error map."
4. Creating Variations: Steps 2 and 3 are repeated by introducing random errors (up to 5m). It combines the original DEM with the error map to generate many different versions (realizations) of what the true terrain might look like. Each version reflects a possible realization given the uncertainty in the original DEM.
5. Analysis of Water Volumes: Each of these versions is saved as a separate file, and water volume is estimated by keeping the Sentinel 2 images constant and using these multiple realizations of DEMs as input.

A similar process is repeated for radiometric errors in the data. In this case, errors were introduced only in the short-wave infrared band (SWIR) in a semi-controlled manner. The analysis is performed across different ranges of the imagery, and Gaussian smoothing is applied to reflect realistic environmental changes. This process involves adding Gaussian noise as a percentage of the reflectance values in satellite imagery. The rationale behind this approach is that lower reflectance values, typically representing darker areas or water bodies, tend to have higher inherent noise due to weaker signal strength and atmospheric effects. By scaling the noise to be proportional to reflectance, we model a more realistic scenario where darker regions exhibit greater variability.

Specifically, the noise percentage is defined relative to the mean reflectance within specified ranges, ensuring that lower reflectance bands are affected more significantly. This simulates real sensor behavior where the signal-to-noise ratio decreases with lower reflectance. The process helps to better understand the impact of reflectance variability on key outputs, such as water level and volume calculations, highlighting the reliability of the analysis under different conditions and potential errors.

Table 5-3 shows the result of noisy data on the volume of water estimated in the reservoir.

Table 5-3 - Results of random fields-based uncertainty analyses

12499090.0 cu. M H: 732.06 feet or 223.13 m	**Noise levels as**	**Summary of Volume deviation from "Truth"**
Sentinel 2 Uncertainty	For reflectance ranges: 0-0.1: 30% 0.3-0.6: 15% 0.6-1: 7.5%	Underestimation in estimates of volume by 2.5% on average
DEM Uncertainty	5m standard deviation for slopes greater than 10 degrees	Variations in estimates of water volume by 14% on an average

The uncertainty evaluation reveals that the greatest source of uncertainty in water volume estimation is the quality of elevation data. While in countries like the US, high-resolution Digital Elevation Models (DEMs) may be readily available, this is not the case globally. In many regions, water volumes must be estimated based on sparse ground-truth analysis, which becomes the most dominant uncertainty factor

It's important to note that uncertainty in mapping the extents appears to be biased towards underestimating the water volume in the reservoir. This has significant implications because it suggests a higher flood risk for a given precipitation level. Reservoir managers might believe they can store more water than is realistically possible, leading to a false sense of security during a precipitation event. However, the availability of free and high-quality satellite data, such as Landsat and Sentinel, coupled with the accessibility of well-maintained test sites, has led to a significant reduction in radiometric uncertainty. The Committee on Earth Observation Satellites (CEOS) operates RadCalNet (Bouvet et al.,

2019) sites, and other test sites (Cal/Val Portal, https://calvalportal.ceos.org/calvalsites Accessed 1-19-2025; Test Sites Catalog | EROS CalVal Center of Excellence, Accessed January 19, 2025. https://calval.cr.usgs.gov/apps/test_sites_catalog) are maintained by the United States Geological Survey (USGS) and the European Space Agency (ESA). These test sites offer well-characterized ground measurements and atmospheric data, enabling rigorous calibration and validation of satellite data. Smaller satellites can leverage these resources to ensure their data quality is comparable to that of established missions.

5.3 Simulating Areas Inundated by Water Overflow

3D hydraulic simulation functionality in ArcGIS Pro 3.3 is used to model a hypothetical flooding scenario. This scenario assumed a partial reservoir breach (from the location indicated in figure 5-2), with water volume equivalent to half the reservoir's capacity, originating from a point source at the dam crest (figure 5-2).

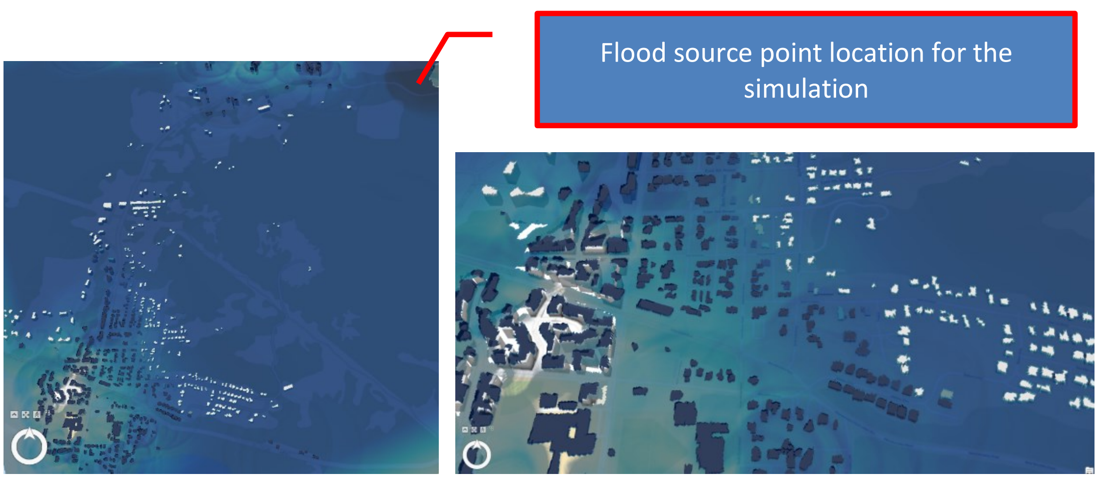

Figure 5-2 - Simulation of water overflow from Fall Creek Lake

A 30m resolution Shuttle Radar Topography Mission (SRTM; Earth Resources Observation and Science (EROS) Center, 2017) DEM served as the topographic base for the simulation. Preprocessing of the DEM ensured the removal of any anomalies that could hinder accurate water flow modeling.

Utilizing default hydraulic parameters, the simulation calculated water flow dynamics, considering the defined water source and terrain. The simulation output, a series of raster layers representing water depth at various time intervals, was used to generate a flood extent and water depth map (figure 5-1). This methodology allowed for the visualization and analysis of potential flood impacts under the specified conditions, despite limitations in data resolution and the simplified breach scenario. This map shows the area of land protected from flooding by the reservoir. The darker the blue, the greater the impact of the reservoir at that location. While this is a human built reservoir, it performs the same function as a wetland, when it comes to capturing excess water. This highlights the important role these ecosystems play in mitigating flood risk.

5.4 Impact of Data Uncertainty

To study DEM uncertainty and flood attenuation functions and benefits provided by wetlands, a more realistic example of the Everglades and adjoining city of Miami was chosen as a test area (Simons et al., 2024). High quality DEMs are available for both sites from the USGS. Multiple sets of uncertainty induced DEMs were generated from the original DEM by adding random errors with different standard deviations. Kriging was used to create spatially correlated errors.

To perform the uncertainty analysis, rainfall was assumed to occur uniformly over the wetlands area marked in figure 5-3.

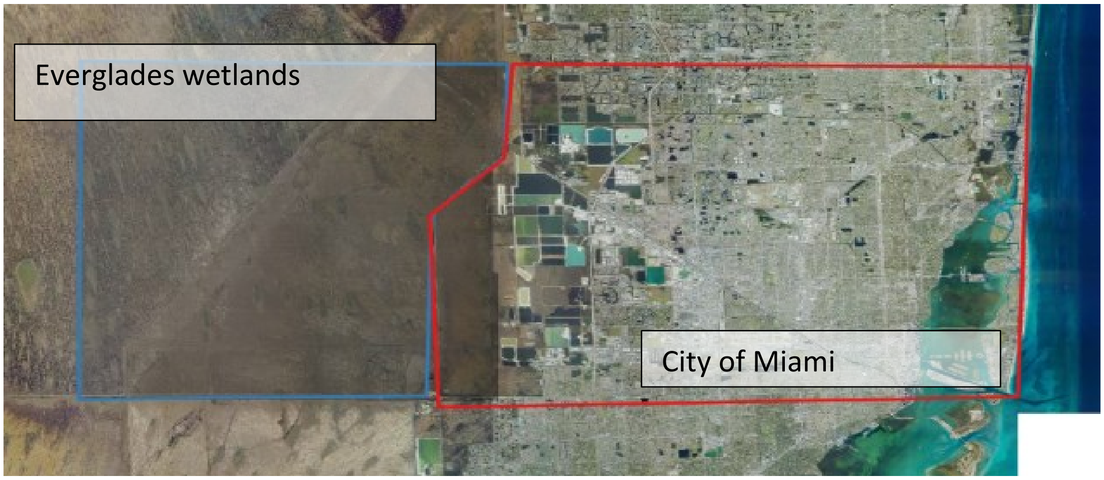

Figure 5-3 - Everglades wetlands adjoining Miami

The data processing flow is shown in figure 5-4. Based on a water level at 90th percentile of the

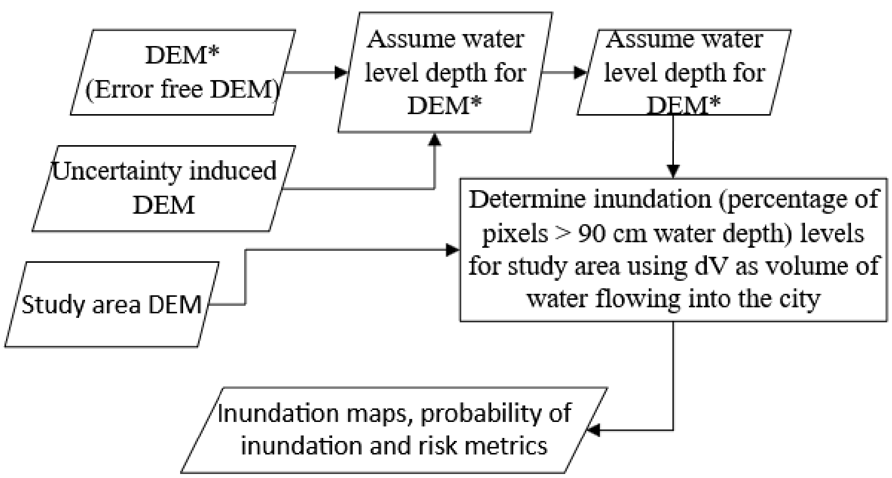

Figure 5-4 - Uncertainty analysis process; DEM* is considered the error free data and DEMi refers to uncertainty induced data

elevation of the wetlands DEM, water volumes were estimated for the wetlands using error free DEM and for each simulated DEM using topographic analysis (Gesch, 2007) only. FEMA considers inundation to be a low flood event if an area accumulates more than 90 cm of water depth.

$$\%\ of\ Area\ inundate = \frac{Number\ of\ pixels\ with\ water\ depth > 90\ cm}{Total\ number\ of\ pixels\ in\ study\ area} \text{ ------------------------------------ } (5.1)$$

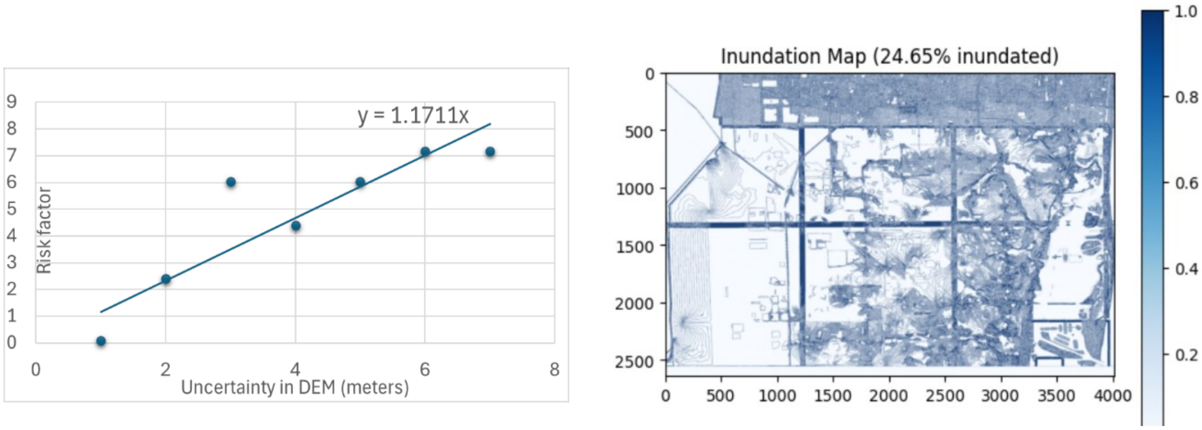

Figure 5-5 - Inundation risk factor trend as a function of DEM Uncertainty and inundation map of Miami. The X and the Y axis are in pixels (10 m GSD) and the blue depth as a fraction of 90 cm (to be considered inundated).

Assuming 90 cm water depth to be the threshold, figure 5-5 (left) provides a trend on the inundation patterns (percent of areas inundated) as a function of DEM uncertainty. The first graph shown in figure 5-5 indicates that the uncertainty in risk of inundation increases with uncertainty in DEM. The risk factor of flooding is proportional to probability of water spill and the percentage of pixels being inundated with higher than 90 cm. Figure 5-6 shows the observed relationship between the fraction of error in estimated volumes ($\frac{dV = V_i - V_{DEM}^*}{V_{DEM}^*}$) vs. the areas inundated. The step wise linear relationship suggests that flooding does not increase gradually with uncertainty. Instead, it changes in discrete steps, suggesting that certain areas are predicted to become inundated relatively suddenly once the uncertainty exceeds a certain level. While the city of Miami is generally flat, there are some variations in elevation, with the western regions at elevated levels. This, along with the canals (seen as dark blue linear features in figure 5-5) could lead to more localized flooding patterns, with some areas experiencing sudden inundation while others flood more gradually.

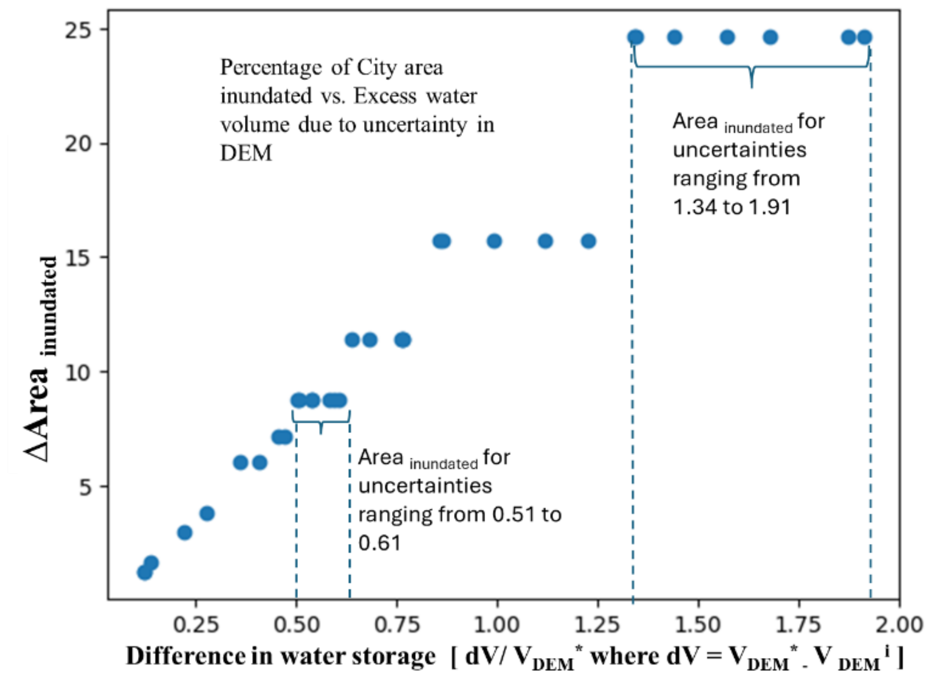

Figure 5-6 - Inundation risk factor trend as a function of DEM Uncertainty

This simulation not only emphasizes the value of the wetlands in flood prevention, but it also emphasizes that the integration of RS data of higher quality (and less uncertainty) enhances the capability of decision makers to make informed choices about actions that need to be taken in expected rainfall and other events.

5.5 System Utility Function

To ensure that any future RS design can effectively capture and quantify the flood attenuation benefits of wetlands, the insights gained from the preceding uncertainty analysis are now utilized to develop a RS system utility function. The utility function defined in this section a way to quantify the usefulness or utility of a RS system for monitoring the value provided by wetlands through water volume storage.

The utility function considers several important factors and combines them into a single "total utility" score. The breakdown of the heuristic process is given below:

3D Data availability:

- Importance: Having 3D data (elevation) is crucial for accurate water volume calculations.
- Spatial Utility $3DU = \frac{5}{GSD}$
    - Penalty: If no 3D data is available, the system loses 50% of the maximum possible utility (0.25), resulting in a deduction of 0.125. This is because there are methods to estimate volume from aerial extents of water. However, those are often site-specific and require field work (Gleeson et al., 2007).
    - Currently the best DEM available for the public is the WorldDEM (https://space-solutions.airbus.com/imagery/reference-layers/worlddem-neo/, accessed 1-19-2025) which is at 5 m GSD. Hence, 5 is chosen as the factor in the numerator.

Spectral Data availability:

- Importance: Different wavelengths of light (bands) reveal different information about water.
- Scoring: The utility depends on which bands are available and the signal-to-noise ratio (SNR) of the sensor:
    - $SRU = \begin{cases} \text{SWIR and NIR? } 1 * W_{SNR} \\ Only\ NIR?: 0.75 * W_{SNR} \\ Only\ RGB?: 0.25 * W_{SNR} \end{cases}$
- Resolution matters: For high-resolution images, RGB might be sufficient. Low-resolution images benefit from the information provided by SWIR and/or NIR bands.
- The weight associated with spectral and radiometric factor, W_{SNR}, is not just dependent on random noise in the signals, but a combination of radiometric and spectral uncertainties of the data. The signal-to-noise ratio of Sentinel and Landsat data can be taken as reference. While many commercial data providers do not release their system SNR, the USGS and European Space Agency have been performing a comprehensive comparison of RS data sets, both commercial and

governmental. Commercial data sets often have an r^2 value ranging from 0.7-0.9 when their top of atmosphere reflectance values is radiometrically against Sentinel or Landsat data using simultaneous near observation methods (Vrabel and others, 2024).

- $W_{SNR} = 1\ for\ Landsat\ and\ Sentinel$
- $W_{SNR} = average\ of\ (0.7, 0.9)\ for\ Planet$

Revisit Utility

- Importance: How often the satellite revisits the same location is key for monitoring changes.
- RU = $\frac{1}{Revisit\ time(days)}$
- This is probably one of the most important factors, along with cloud cover (and canopy cover). These factors affect the frequency of data capture over a given area of interest.

Spatial Resolution (GSD):

- Spatial Utility is assessed as:
  - $SU = \begin{cases} \frac{5}{GSD} \text{ for optical data with GSD} > 5 \text{ m} \\ 1\ otherwise \end{cases}$

- Finer spatial resolution (smaller GSD) allows for more detailed observations. The 5 m comes from the assumption that resolution is enough for estimating the extents of wetlands. Usually wetlands are in flat regions, and any reduction in uncertainty due to higher resolution may not be significant as the volume of water estimated will not change significantly.

Revisit utility and Cloud Cover:

- Importance: Clouds obstruct the view of optical sensors (those that use visible and infrared light).
- Scoring:
  - Optical Systems: On average, the cloud cover over land is 55% (King et al., 2013). However, this may vary seasonally. A weight of 0.45 (1 - 55/100) is added (representing

the fraction of cloud-free days) and multiplied by the revisit utility. For example, a 1-day revisit system gets a cloud weight of 0.81 (0.18 * 45). This means more frequent revisits are penalized less by cloud cover.

- SAR Systems: SAR uses radar, which penetrates clouds. These systems get a cloud utility of 1.
- $CU = \begin{cases} 0.45 \text{ for optical data} \\ 1 \; for\ SAR\ data \end{cases}$

The final utility is calculated by multiplying the values from each category:

$$System\ utility\ score = \frac{RU\ *\ CU\ *\ (\mathrm{W}_{DEMuncertainty} \times 3\mathrm{DU}\ +\ \mathrm{W}_{spatial\ uncertainty} \times SU\ +\ \mathrm{W}_{SNR} \times SRU)}{\mathrm{W}_{DEMuncertainty} +\ \mathrm{W}_{spatial\ uncertainty} + \mathrm{W}_{SNR}}$$

where RU is revisit utility, CU is cloud utility, 3DU is 3D utility, SU is spatial utility and SRU is spectral/radiometric utility. $\mathrm{W}_{DEMuncertainty}$ is inversely proportional to the uncertainty in DEM, $\mathrm{W}_{spatial\ uncertainty}$ is inversely proportional to spatial resolution uncertainty of the sensor which is defined as the full width at half maximum of the optical system or FWHM (Helder et al., 2004; Cantrell and Christopherson, 2024), and W_{SNR} is the weight given to uncertainty in radiometric quality of data.

$$\mathrm{W}_{DEMuncertainty} = \frac{2\ m}{DEM\ uncertainty\ in\ meters}$$

$$\mathrm{W}_{spatial\ uncertainty} = \frac{1}{FWHM}$$

$$\mathrm{W}_{SNR} = \frac{100}{Radiometric\ uncertainty\ (as\ a\ percentage)}$$

This system utility function is an attempt to evaluate different RS systems for water monitoring applications, considering their strengths and weaknesses in terms of 3D data, spectral capabilities, revisit frequency, spatial resolution, and cloud cover impacts. It is assumed that revisit utility and cloud utility are nonnegotiable. In a thought experiment, if the revisit period is infinite, the utility will be zero.

Similarly, if an area of interest is always cloudy, the cloud utility of any optical sensor will be zero. On the other hand, in case of spectral utility, any visible- SWIR data will have some utility, as it may still be possible to delineate water pixels, even if the appropriate wavelength bands are not available through visual interpretation, etc.

Table 5-4 provides a worked example of the system utility for Landsat 8/9 constellation, Sentinel 1 sensor, Sentinel 2 constellation, a combined Sentinel 2 and Landsat constellation, as well as Planet constellation. The SAR based Iceye and Capella space systems constellation are also evaluated. Both Iceye and Capella are high resolution constellations with higher than daily revisit capability. However their backscatter variations are higher, as compared to Sentinel 1(Ruiz and Ruval, 2024 ; Fioretti 2022).

Table 5-4 - System utility analysis for the sensors analyzed in this thesis

	Revisit utility	Cloud cover coefficient	(3d utility, 3D uncertainty Weight	Spatial resolution utility, spatial uncertainty Weight	Spectral utility, spectral uncertainty Weight	Total utility Score
Landsat 8\9	0.125	0.45	0,0.16	0.17, 1	1,1	0.049
2A/2B	0.2	0.45	0,0.16	0.50, 1	1, 1	0.067
Landsat/Sentinel Harmonized constellation	0.33	0.45	0,0.16	0.50,1	1,1	0.111
Sentinel 1	0.06	1	0,0.16	0.17, 1	1, 1	0.050
Planet	1	0.45	0,0.16	1, 0.25	0.5, 0.7	0.144
ICEYE Constellation	1	1	0,0.16	20, 1	0.5, 0.68	0.720
Capella constellation	1	1	0,0.16	5, 1	0.5, 0.68	0.750
Notional Optical system	1	0.45	1,1	1, 1	1, 1	0.450
Notional SAR based system	1	1	1 ,1	1, 1	0.7,1	1

Two notional systems have been included in the utility analysis table also. The proposed optical system has a revisit period of 1 day, and a spatial resolution of 5 m. The radiometric fidelity is assumed to be of the standard of Landsat or Sentinel 2. The notional SAR based system is assumed to have a revisit period of 1 day, and a spatial resolution of 1 m, with the same radiometric precision as Sentinel 1. Figure 5-7 provides a bar plot of log-scaled utility scores of the systems discussed above.

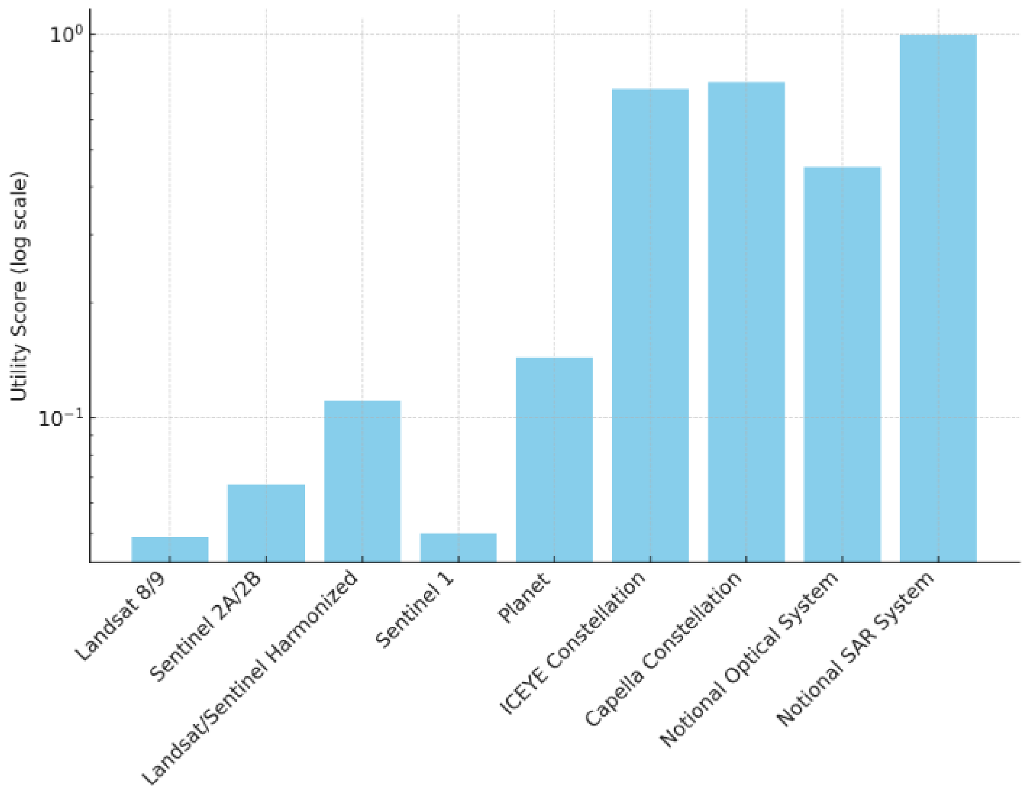

Figure 5-7 - System Utility Scores of RS systems from Table 5-4

The system utility function aims to quantify the usefulness of RS systems for monitoring water volume storage in wetlands. The higher the score, the more useful the system is for this purpose. Landsat 8/9 has a total utility score of 0.049 due to its longer revisit time, the influence of cloud cover, and lower spatial resolution (30 m). Its spectral utility is high because Landsat is considered the gold standard in terms of radiometric data quality, but the other limitations (in terms of revisit and lower spatial resolution) result in a low overall score. Sentinel-2A/2B has a slightly better score of 0.067 due to its more frequent revisit time and higher spatial resolution (10 m and 20 m) utility. The combined

Landsat/Sentinel Harmonized constellation has a higher score of 0.111 due to the improved revisit time. The table also considers the spatial resolution of the combined system to be the same as Sentinel 2 (10 m).

Sentinel-1 has a score of 0.050. Its cloud cover utility is high because it uses radar, which can "see" through clouds, but the long revisit time limits the overall score. Its spectral utility is also slightly diminished because the water mask extraction depends on the values of a single channel, that can be affected by waves on the surface and other noise. The score will be higher once Sentinel 1C becomes operational. Planet has a score of 0.144 due to its very frequent revisit time, negating the effects of cloud cover, and better spatial resolution. However, the lack of 3D data and lower spectral utility limit the score from reaching close to the theoretical maximum of 1. The Iceye (Ruiz and Cohen, 2024) and Capella space systems (Fioretti, 2022) score high when they are considered as a constellation, due to their vastly superior spatial resolution and temporal revisit. These systems are also not dependent on lack of cloud cover.

The notional optical system achieves a utility score of 0.45, reflecting its relatively lower performance, primarily due to the persistent limitation imposed by cloud cover. In contrast, the notional SAR-based system attains the highest utility score of 1.0. This superior performance is attributed to its ability to negate cloud cover effects through a rapid revisit time of one day, enhanced spatial resolution of 5 meters, and high spectral utility. However, it is important to acknowledge the significant costs associated with implementing such systems. For instance, the combined cost of Landsat 8 and 9 exceeds $850 million (Harwood, 2013). Despite these high costs, a combination of existing national and private sector satellites can collectively provide the required data (Lewis et al., 2018).

5.6 Discussion

This chapter investigates the impacts of the radiometric, temporal and elevation uncertainties in

RS data on the ability to estimate water volumes and storage capacity of wetlands. It was shown that elevation data uncertainties, as compared to radiometric data uncertainties lead to more errors in estimating water capacity. This is primarily due to the availability of high quality radiometrically calibrated RS data, whereas high quality elevation data is not available globally. This highlights a critical challenge in accurate water volume estimation, especially in regions where detailed DEMs are lacking. The analysis revealed a strong correlation between satellite-derived and ground-based water level measurements, highlighting the potential of Earth observation for efficient wetland monitoring. Uncertainty analysis in the Everglades emphasized the importance of DEM accuracy for flood risk assessment. The analysis indicated that the more uncertain the elevation data, the more chances that decision makers will be caught off guard in predicting inundation and its impacts. This finding poses a challenge in regions lacking detailed elevation data. Future RS systems should prioritize 3D data, spectral capabilities, revisit frequency, and spatial resolution.

To address these uncertainties and inform the design of future RS systems, the chapter proposes a system utility function. This utility function follows from research on developing quantitative metrics for conducting trade studies and evaluating architectures for RS systems (Siddiqi et al., 2019). The utility function formulated here serves to evaluate the usefulness of different RS systems for monitoring water volume storage in wetlands, considering factors like 3D data availability, spectral capabilities, revisit frequency, spatial resolution, and cloud cover impacts. The higher the score in this utility function, the more useful the system is deemed for estimating water volume. It aggregates multiple factors crucial for accurate water volume estimation into a single score, providing a comprehensive evaluation of system capabilities. These factors include the temporal availability and quality of 3D data (DEMs), spectral capabilities of the sensor, revisit frequency, spatial resolution, and cloud cover management strategies. The function prioritizes systems with high-resolution DEMs, appropriate spectral capabilities, frequent revisits, aligning with the technical requirements of accurate and reliable water volume estimation in wetlands. The system utility function uses weighting factors to account for uncertainties in data, with weights determined by the level of uncertainty. For example, the weight for DEM uncertainty is inversely proportional to the uncertainty in the DEM. Specific uncertainties, such as those related to DEM, spatial resolution, and radiometric quality, are factored in using weights. Quantitatively, the utility analysis results show that a notional optical RS system with 2 times increase in spatial resolution (as compared to Sentinel 2) and 4 times increase in temporal resolution can lead to a 7 times enhancement in utility (comparing Sentinel 2's utility of 0.67 vs. the notional system's utility of 0.45 to Sentinel 2 constellation in Table 5-4). This highlights the importance of prioritizing these technical specifications in the design of future systems for monitoring wetland ecosystem services. The improvements in the notional SAR based system is not as dramatic (compared to a utility of Capella and Iceye's 0.7 vs. the proposed system's 1, an almost 40% improvement).

The upcoming NASA-ISRO Synthetic Aperture Radar (NISAR), scheduled for launch in March 2025, offers significant improvements. NISAR (Chapman et al., 2024) will map the globe systematically every 12 days, with a pixel size of 7 m and 2–8 m cross-track resolution. Using dual-frequency radar (L-band with a 24 cm wavelength and S-band with a 12 cm wavelength), NISAR is designed to monitor surface deformation and environmental changes. Its L-band capability is particularly promising for wetland mapping under canopy. McDonald et al. (2024) outline plans to validate NISAR's ability to detect water inundation beneath vegetation. Applying the utility rubric in this thesis to specifications of NISAR, the sensor has a relatively low utility score of 0.1 due to its lower revisit rate. The score is still double the free and open Sentinel-1 data. Therefore, together with Sentinel 1 constellation (considering the recently launched Sentinel 1-C), the availability of free and open data will have a temporal revisit of once in 4 days. That combination improves the utility score to 0.25. Additionally, NISAR's canopy penetration capabilities and anticipated high-quality data make it a critical reference sensor for providing unprecedented information about wetlands and other NC, as well as validating other RS systems.

The availability of free and high-quality satellite data, such as Landsat and Sentinel, coupled with the accessibility of well-maintained test sites, has been instrumental in improving the capacity of smaller satellites to acquire and provide high-quality data for various applications. The utility function has not made any special provision for free and open data. However, free and open data is essential for accessibility, innovation, transparency, collaboration, efficiency, and economic growth. The Landsat program is a prime example of the benefits of free and open data. Since the USGS adopted an open data policy in 2008, the use of Landsat data has increased dramatically, enabling detailed and consistent monitoring of Earth's surface over time (Wulder et al., 2012). This has led to significant advancements in scientific research, environmental monitoring, and resource management, demonstrating the transformative power of accessible data. Free and open data ensures that data is available to everyone, fostering innovation by providing the raw materials needed for new ideas and solutions. Open data promotes transparency and accountability, allowing citizens to see how decisions are made, and resources are allocated. It encourages collaboration across different sectors and disciplines, reducing duplication of effort and driving economic growth by enabling new business opportunities and improving the efficiency of existing industries. Access to free and high-quality benchmark data like Landsat, MODIS and Sentinel, along with well-maintained test sites, has created a more level playing field for smaller satellite operators, fostering innovation and competition in the Earth observation sector. This, in turn, has led to a wider availability of high-quality satellite data, benefiting various applications and research areas.

6. Conclusions and Future Research

6.1 Research Limitations

This thesis investigated the RS data needed to effectively monitor NC for quantifying ecosystem services. Specifically, the thesis studied methods to estimate water volumes and water storage capacity of wetlands. The thesis emphasized the importance of measuring these services to understand the benefits provided by nature and make informed decisions about natural resource management, recognizing RS as a key technology for monitoring ecosystem services at scale.

The thesis developed an analytical framework to systematically identify limitations in current RS capabilities and directly inform the design of future systems by establishing traceability to societal benefits. This framework first identified the benefits of the ecosystem services provided by the NC, employed a physics-based approach to identify parameters crucial to that value, and determined the necessary measurements for their quantification. The thesis investigated the available RS sensors and future capabilities needed to monitor the value of ecosystem services, including an analysis of sources of uncertainty impacting value estimation. A system utility function was formulated to assess the performance of existing and proposed RS systems in monitoring and quantifying specific ecosystem services.

The thesis applied the framework to a case study focused on the flood attenuation function of wetlands. Hydrological models were utilized to identify essential parameters for monitoring floodwater storage by wetlands. Using a study area encompassing the Fall Lake Creek reservoir in Oregon, they measured and monitored water storage capacity by integrating USGS digital elevation models with Sentinel-1 synthetic aperture radar, Sentinel-2 optical data, and Planet Scope optical data. The results were validated against USGS-published ground truth measurements. Uncertainty analysis on the data was performed by introducing spatially autocorrelated synthetic errors into input datasets to assess their impact on estimated water elevation and storage volumes.

The analysis revealed a strong correlation between satellite-derived and ground-based water level measurements, highlighting the potential of Earth observation for efficient wetland monitoring. Uncertainty analysis in the Everglades emphasized the importance of DEM accuracy for flood risk assessment. The analysis indicated that the more uncertain elevation data, the more chances that decision makers will be caught off guard in predicting inundation and its impacts. This finding poses a challenge in regions lacking accurate elevation data. Therefore, efforts must be made to increase the availability of accurate and high-resolution elevation data globally. Noting that change in topography is generally smooth and predictable, in the event of a tradeoff between accurate elevation data (i.e. the elevation values are highly accurate) and greater resolution (the GSD), the choice may lean towards accuracy.

The utility function developed in this thesis offers a solid framework for assessing RS systems for monitoring water storage in wetlands. The current weighting scheme, which prioritizes factors such as spatial resolution, temporal resolution, and spectral capabilities, relies on reasonable assumptions but may not fully capture the complexity of various wetland environments or stakeholder priorities. Incorporating expert insights from ecologists, hydrologists, and RS specialists can help refine these weights to better reflect real-world needs.

The thesis discussed two proposed systems that scored high system utility scores. These sensors, if implemented and combined with high quality elevation data, can monitor wetlands all around the world with every day, and provide real time information in water levels to the communities that live around them. Quantitatively, the results show that a future optical RS system with a 2 times improvement in spatial resolution (as compared to Sentinel 2) and a 4 times improvement in temporal resolution can lead to a 7 times enhancement in utility (comparing Sentinel 2's utility of 0.67 vs. the notional system's utility of 0.45 to Sentinel 2 constellation). This highlights the importance of prioritizing these technical specifications in the design of future systems for monitoring wetland ecosystem services. The improvements in the notional SAR-based system is not as dramatic (compared to a utility of Capella and Iceye's 0.7 vs. the proposed system's 1, an almost 40% improvement). However, it must be noted that Capella space systems and Iceye's data are not free and are not available to all communities.

Despite this, these sensors face limitations in areas with dense or tall vegetation, requiring careful consideration of their applicability in such environments. The thesis primarily focuses on open water wetlands and does not adequately address the challenges of monitoring wetlands under dense canopy cover. Current RS capabilities are limited in their ability to "see through" vegetation canopies. Sensors such as ALOS PALSAR and JERS-1, equipped with L-band SAR technology, have wavelengths capable of penetrating canopies. While effective for mapping wetlands under forest cover, these sensors have revisit intervals exceeding 44 days, limiting their temporal resolution.

This framework, linking key biophysical parameters to RS measurements and their uncertainties, provides a blueprint for assessing other ecosystem services, contributing to informed NC management. This framework can be further integrated with EO value frameworks, along with errors and uncertainty considerations and inclusion of effective calibration, to advance quality of data for NC monitoring and related decisions. Based on these findings, the thesis proposed methods to evaluate new sensor requirements, including advancements in resolution, spectral bands, and data acquisition techniques, aimed at maximizing the utility function.

6.2 Future Research

Several promising avenues for future research emerge from this thesis. One potential direction involves exploring the use of Large Language Models (LLMs) to refine the concept of "natural value."

Rather than solely analyzing academic literature, LLMs could be trained on a broader range of texts, including scientific publications, policy documents, economic reports, indigenous knowledge systems, and artistic expressions related to nature. This expanded dataset could facilitate a more nuanced and comprehensive understanding of natural value, moving beyond purely economic or ecological definitions. Relevant research questions could investigate how different cultural perspectives and disciplines define natural value, whether LLMs can identify common themes and discrepancies among these definitions, and if they can generate integrated frameworks for quantifying this value in ways that are relevant to RS. Key considerations include ensuring the training data is representative and unbiased, mitigating potential biases within the LLMs themselves, and validating the LLM-generated value frameworks. However, the challenges of using large language models (LLMs) in generating requirements or value is enormous. It must be remembered that LLMs are still in their infancy. These challenges include limited requirements-specific data especially for hardware requirements that limit the ability to train and fine-tune LLMs effectively (Norheim et al., 2024).

Quantifying the monetary benefits of ecosystem services involves assigning monetary value to the various benefits the ecosystem services provide (Fenichel et al., 2016). This can be accomplished through market-based approaches, contingent valuation, hedonic pricing etc. Market-based approaches utilize market prices of goods and services that are directly or indirectly linked to ecosystem services to estimate their value. Contingent valuation involves surveying people to determine their willingness to pay for ecosystem services. Hedonic pricing uses the relationship between the price of a good or service and its associated ecosystem service benefits to estimate the value of the ecosystem service.   While progress has been made in quantifying the monetary benefits of ecosystem services, several areas need further research. One such area is the development of more robust valuation techniques that can better capture the full range of benefits provided by ecosystem services (Babí Almenar et al., 2022). This requires a full understanding of the biophysical functions that deliver these benefits and how these should be quantified. Another area is about better methods for integrating the monetary benefits of ecosystem services into decision-making processes. For example, how can the value of wetlands water storage capacity be used to prioritize evacuation, infrastructure building and other strategies that may save existing infrastructure, lives and property. Finally, there is a need for more research on the distributional impacts of ecosystem services and their associated monetary benefits.

While the utility function is informed by physical modeling and uncertainty analysis, other expert opinions may be different. So future research could incorporate expert stakeholder opinions in developing the utility function further. However, a shareholder expert may also be biased towards existing system capabilities, as they are quite used to them. So, a balance between analysis driven and expert opinion driven parameters for the utility function. The thesis also does not include a sensitivity analysis to evaluate the impact of varying weights on utility scores.

Another important research area is the application of tradespace and Pareto frontier analyses using multiple utility functions (Siddiqi 2024). Given that ecosystem management often involves balancing competing objectives, such as carbon sequestration and timber production, utilizing multiple utility functions allows for a more realistic assessment of trade-offs and the identification of potential solutions. Future research could focus on mathematically formulating and integrating utility functions derived from multiple utility functions (e.g., flood attenuation, carbon sequestration, biodiversity) into a tradespace analysis. This would involve evaluating the performance of different RS system designs across these multiple utility functions, identifying Pareto optimal solutions that optimize overall utility while minimizing trade-offs, and incorporating uncertainty in RS data and utility function estimations into the analysis. This approach would likely benefit from multi-objective optimization algorithms and visualization techniques for high-dimensional datasets.

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