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Understanding Volume Estimation Uncertainty of Lakes and Wetlands Using Satellites and Citizen Science

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Abstract

Understanding Volume Estimation Uncertainty of Lakes and Wetlands Using Satellites and Citizen Science

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Chair of the Supervisory Committee:
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Civil and Environmental Engineering

Despite lakes and wetlands being critical indicators of climate change, there is limited knowledge of their volumetric change around the world. We studied the variations in the volume of water stored in small lakes and wetlands using satellite remote sensing and lake water height data contributed by citizen scientists. A total of 106 water bodies across the globe were studied using satellite data in the optical and microwave wavelengths from Landsat 8, Sentinel-1 and Sentinel-2. The uncertainty in volume estimation as a function of geography and geophysical factors such as cloud cover, precipitation and water surface temperature, was studied. The key

finding that emerged from this global study is that uncertainty is highest in regions with a distinct precipitation season such as in the monsoon dominated South Asia or the Pacific Northwestern region of the US. This uncertainty is further compounded when small lakes and wetlands are seasonal with alternating land use as a water body and agricultural land, such as the wetlands of Northeastern Bangladesh. On an average, 45% of studied lakes could be estimated of their volume change with an uncertainty less than the expected volume in South Asia. In North America, uncertainty in volume estimation was to found to be around 50% in lakes eastward of the 108th meridian with lowest uncertainty found in lakes along the East coast of the US. The study provides a baseline for understanding the current state of the art in estimating volumetric change of lakes and wetlands using citizen science in anticipation of the planned Surface Water Ocean Topography (SWOT) Mission.

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Note: This thesis is a slightly modified version of a journal paper I submitted in IEEE JSTARS:

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I would like to thank Professor Tamlin Pavelsky and Grant Parkins and the entire Lake Observation by Citizen Scientists and Satellites (LOCSS) team for collecting water elevation data and providing invaluable insights on my research. I am also grateful to my peers Pritam Das, Sanchit Minocha in the SASWE Research Group and my friends Eric Gagliano, Shashank Bhushan, Bareera Mirza, Carina Thompson, Abduselam Shaltu, Rohan Mewada and Shahryar Ahmad for their support and cooperation.

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I would like to emphasize the immense appreciation and gratefulness I have for those I do not personally know but have helped me indirectly through the maintenance of infrastructure that’s allowed me to focus on my research.

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DEDICATION

This thesis is dedicated to my parents, Mr. Shakeel Khan Pathan and Mrs. Tabassum, and my sisters, Dr. Aayaisha Khan and Alveena Khan.

Chapter 1. INTRODUCTION

1.1 MOTIVATION

Water bodies such as small lakes (i.e. those smaller than 100 km^2) and wetlands provide vital functions for ecosystems and sustain biodiversity. Globally, wetlands cover an area of 1.2 billion hectares, which is equivalent to the area of Canada [1]. Downing et al. [2] claimed that the total surface area of natural and artificial lakes is over 4.6 million km^2 which translates to about 117 million [3]. These water bodies act as biological supermarkets and groundwater recharge and discharge points, and they provide both water and nutrients necessary for crop production. Wetlands and small lakes also help in flood control and support eco-tourism. According to Global Wetland Outlook (Ramsar Convention, 2021), wetlands have been rapidly declining. Approximately 35% of the world's wetlands have disappeared since 1970 [1]. While there are various physical drivers that affect the behavior of wetlands and small lakes, the most critical among them, other than perhaps direct human management, is likely changing patterns of weather, hydrology and climate [1].

In recent years, our ability to track the extent of small lakes and wetlands has increased manifold. Lehner and Döll [4] developed the Global Lakes and Wetlands Database (GLWD), which provides the maps and water surface area of the lake, wetlands, reservoirs and rivers. For lakes, GLWD was superseded by the HydroLAKES database [5], which mapped about 1.4 million lakes larger than 0.1 km2 (see Figure 1.1). A study by Sheng et al. [6] mapped 7.7 million lakes that are larger than 0.004km2. Meanwhile, Verpoorter et al. [3] used satellite imagery to identify more than 117 million lakes globally. Hu et al. [7] studied the areal extent of the wetlands and lakes by developing a new index (Precipitation Topographic Wetness Index). However, despite this improved understanding of the location and extent of small lakes and wetlands, understanding of the physical behavior of wetlands and lakes around the world remains limited, especially in developing regions. Specifically, we understand very little about how volumetric changes of lakes and wetlands modulate over time and as a function of climate, season or geographic region. A primary reason for this gap is the paucity of in-situ lake and wetland gauges relative to the widespread presence of lakes and wetlands around the globe. Unlike for rivers, there are no major national or international repositories dedicated to storing in situ lake level data. Even in developed countries, such data is limited—for example, the US Geological Survey gauges more than ten thousand rivers but only a few hundred lakes.

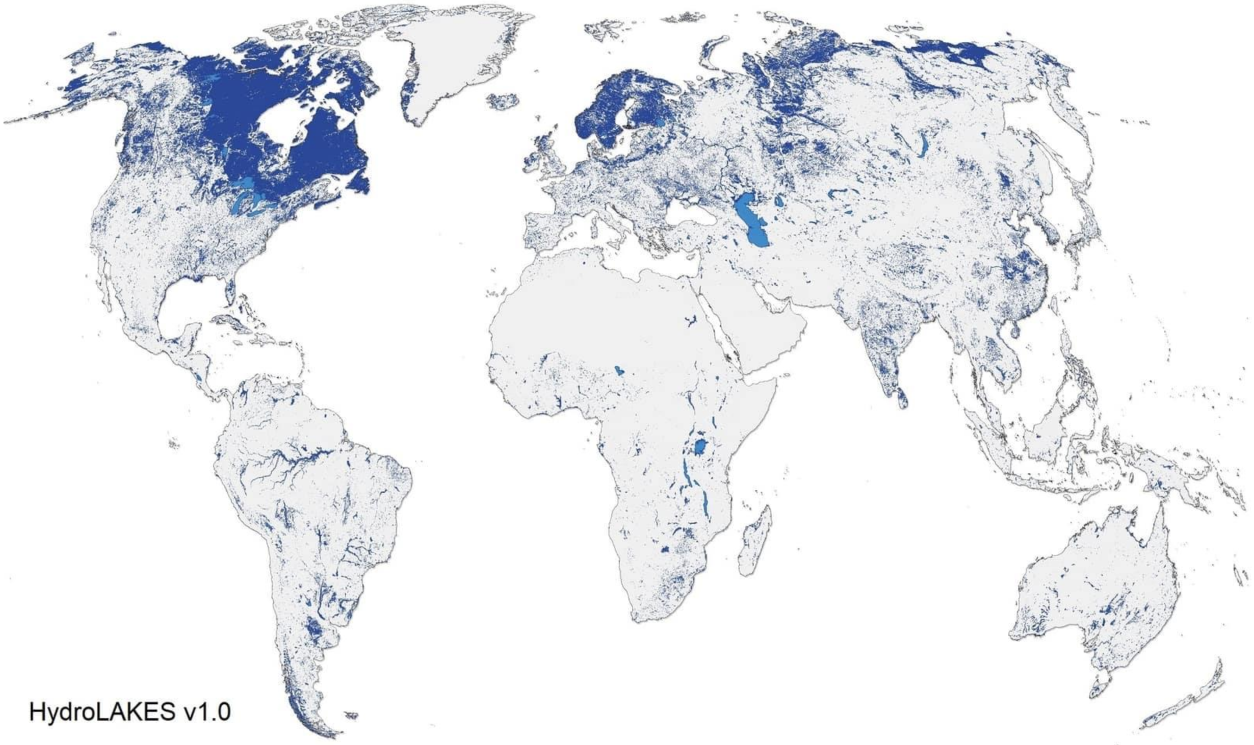

Figure 1.1: HydroLAKES Database Depiction of Global Lakes and Wetlands

Studying volumetric changes at a global scale is therefore not feasible using limited in-situ gauges given the remoteness of numerous water bodies and lack of economic or institutional resources to maintain an in-situ measurement network. Studying wetlands and small lakes using satellite remote sensing is a cost-effective and feasible way to understand the volumetric change of water bodies on a global scale [8], [9]. Most studies that aim to do so use different sensors to study surface water extent and water surface elevation, which, in combination, allow estimation of volume change. Detection of the surface water extent and elevation can be performed with sensors of different resolutions and electromagnetic wavelengths. Coarser spatial resolution sensors such as NOAA/AVHRR and Moderate Resolution Imaging Spectroradiometer (MODIS) have low spatial accuracy but high temporal resolution and coverage and are often used to study large lakes [10]. Medium spatial resolution sensors, with a resolution of around 10m - 30m and are widely used in studies of smaller lakes [3]. A few examples for medium resolution are the Landsat series, Sentinel 2 and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER). High spatial resolution sensors such as Planet, RapidEye, IKONOS have a resolution around 1m - 5m, but they are not freely available. The type and nature of water bodies that can be studied with reasonable accuracy usually depend on the pertinent resolution and sampling frequency of sensor data that is available.

1.2 RESEARCH QUESTION

Our study explores uncertainty in volume estimation, which can provide valuable information to the decision-makers or stakeholders to make more robust decisions based on estimation uncertainty. There are various factors that affect the uncertainty in volume estimation. For example, in South Asia, a key source of uncertainty is likely to be cloud cover during monsoon for the optical sensors and inundated vegetation for SAR microwave sensors. At higher latitudes or mountainous regions where lakes freeze, the area estimation may be more challenging due to the limitations of detecting inundation variations due to ice cover or due to the shadow effect of the high topography.

In this study, we have explored four different techniques that monitor inundation extent, and thus estimate volume (Table 1.1). The key research question being addressed is - ***what is the range of uncertainty associated with estimating the volume of lakes and wetlands using current sensors, and how does this uncertainty vary as a function of geography, season and average environmental conditions?*** We used data from 106 lakes and wetlands, in which water level changes were monitored by LOCSS citizen scientists. Validation of water levels collected by citizen scientists against automated water level gauges shows that they are highly accurate, with uncertainties of less than 2 cm [11]. Such high performance in lake level estimation can be achieved only for very large lakes using satellite altimetry. We have also used data from non-citizen programs (such as automatic gauging) when necessary to fill in gaps in our lake water height database.

Table 1.1: Summary of Sensors And Techniques Used For Lake Area Estimation

Sensor	**Revisit Time**	**Technique**	**Band**	**Threshold**
L8	16 days	Dynamic Surface Water Extent (DSWE)	Multiple	N/A
		Modified Normalized Difference Water Index (MNDWI)	Green band, short-wave infrared	0.3
S1	10 days	Backscattering thresholding	–	< -13 db
S2	5 days	Dynamic Surface Water Extent (DSWE)	Multiple	N/A

1.3 THESIS OUTLINE

The structure of the thesis is as follows. In chapter 2, we discuss the background of different kinds of sensors used in the contemporary world as well as their merits and demerits, and the diversity in water classification techniques. In chapter 3, we discuss the methodology we followed in detail, and in chapter 4, we discuss the results. Finally, in chapter 5, we discuss the implications of our results and present conclusions.

Chapter 2. BACKGROUND

In recent years, studies have shown that multi-sensor approaches combining optical and SAR data to measure inundation extent are often more robust [12]. Researchers have come up with various indices like Modified Normalized Difference Water Index (MNDWI) [13], Normalized Difference Water Index (NDWI) [14], and techniques like Dynamic Surface Water Extent (DSWE) [15] and angle looking Synthetic Aperture Radar (SAR). Optical satellites like the Landsat series [15]–[17] MODIS sensors onboard the National Aeronautics and Space Administration (NASA) Terra and Aqua satellites [18], and Visible Infrared Imaging Radiometer Suite onboard Suomi National Polar-orbiting Partnership (NPP VIIRS) [19] can be used to study water surface area and volume of water stored. However, a major drawback of optical satellites is that they cannot penetrate clouds. To overcome the issue of cloud cover, SAR can be used with an understanding of the proper threshold on backscattering to detect water surfaces [20]. However, SAR may not always be accurate because other smooth surfaces and shadowed areas share almost identical scattering properties with water surfaces. For example, bare soils can sometimes create false-positive cases [21]. Despite such a wide range of available techniques, the uncertainty of surface water area and hence volume estimation due to the choice of methods has not been rigorously studied for lakes and wetlands. Understanding these uncertainties is challenging yet important. It is challenging due to cloud cover and seasonally contrasting environments. For example, freezing/thawing of lakes in higher latitudes can make detection of variations in volume impossible [21], [22]. Similarly, lake area cannot be regularly detected due to extensive cloud cover, for example during months-long monsoon seasons.

Both optical and microwave angle-looking sensors can only estimate the area of the water bodies. On the other hand, satellite altimeters such as Jason 3, Sentinel 3, SARAL/AltiKa, provide water surface elevation [23] . Baup et al. [24] developed three independent approaches to estimate lake volume: high-resolution image-based volume, altimetry-based volume, and altimetry and high resolution-based volume changes. Duan and Bastiaanssen [25] and Cretaux et al. [26] have used a combination of lake extent and water level at different dates in order to build hypsometry relationship which were then used to calculate lake extent and level simultaneously using satellite altimetry measurements. The uncertainty in elevations from altimeters can vary from a few centimeters for large water bodies to tens of centimeters for small water bodies [27]. The limitation of altimeters is the limited spatial sampling due to the narrow width of the sampling track. On the other hand, lidar missions with very high spatial coverage like IceSat-1 or IceSat-2, have the proven potential to measure water level at very high accuracy over a large number of lakes worldwide [28] due to their long revisit times that however lead to missing sub-seasonal variabilities and rapid changes of lake levels.

To overcome the combined challenges of the current fleet of sensors and the limitations of existing in situ gauge networks, one possible solution to monitoring lake water level is the application of citizen science in monitoring water bodies [11], [29], [30]. Citizen science is an emerging science where the public participates and collaborates in scientific research to increase knowledge. One example of the use of citizen science is the Lake Observation by Citizen Scientists and Satellites (LOCSS) (https://www.locss.org/) program, where citizen scientists report the water height elevation of lakes or wetlands by reading staff gauges [11]. Hereafter, we use the terms height and elevation interchangeably to refer essentially to the vertical dimension of lakes reported by citizen scientists to estimate volume change. The objective of the LOCSS project is to work with stakeholders and local communities, who are responsible for understanding and documenting the physical behavior of lakes or depend on lake information for decision-making activities. The purpose of this study is to understand how different methods for estimating lake volume change combining satellite measurements of inundation extent with LOCSS measurements of water surface elevation, impact our ability to accurately detect variations in lake volume. By exploring an ensemble of methods and sensors to estimate area and consequently volume changes, we can derive a robust understanding of estimation uncertainty for lake volume changes. This understanding can be further nuanced for a given region that is unique to the season and other geophysical drivers such as cloud cover, rainfall, topography and water surface temperature in regions where lakes freeze.

Our study explores uncertainty in volume estimation, which can provide valuable information to the decision-makers or stakeholders to make more robust decisions based on estimation uncertainty. There are various factors that affect the uncertainty in volume estimation. For example, in South Asia, a key source of uncertainty is likely to be cloud cover during monsoon for the optical sensors and inundated vegetation for SAR microwave sensors. At higher latitudes or mountainous regions where lakes freeze, the area estimation may become more challenging due to the limitations of detecting inundation variations due to ice cover or due to the shadow effect of the high topography.

Chapter 3. METHODOLOGY

The flowchart for the methodology followed is shown in Figure 3.1. The methodology has four key components as follows: i. extracting water surface area of lakes and wetlands; ii. estimating the volume stored for all the water bodies; iii. repeating steps i) and ii) using other methods (see Table 1.1) to create an ensemble of estimates; iv. comparing the uncertainty in estimated volume as a function of region, nominal lake area and geophysical factors such as cloud cover, precipitation and water surface temperature. From here onwards we will use uncertainty and uncertainty in volume estimate interchangeably.

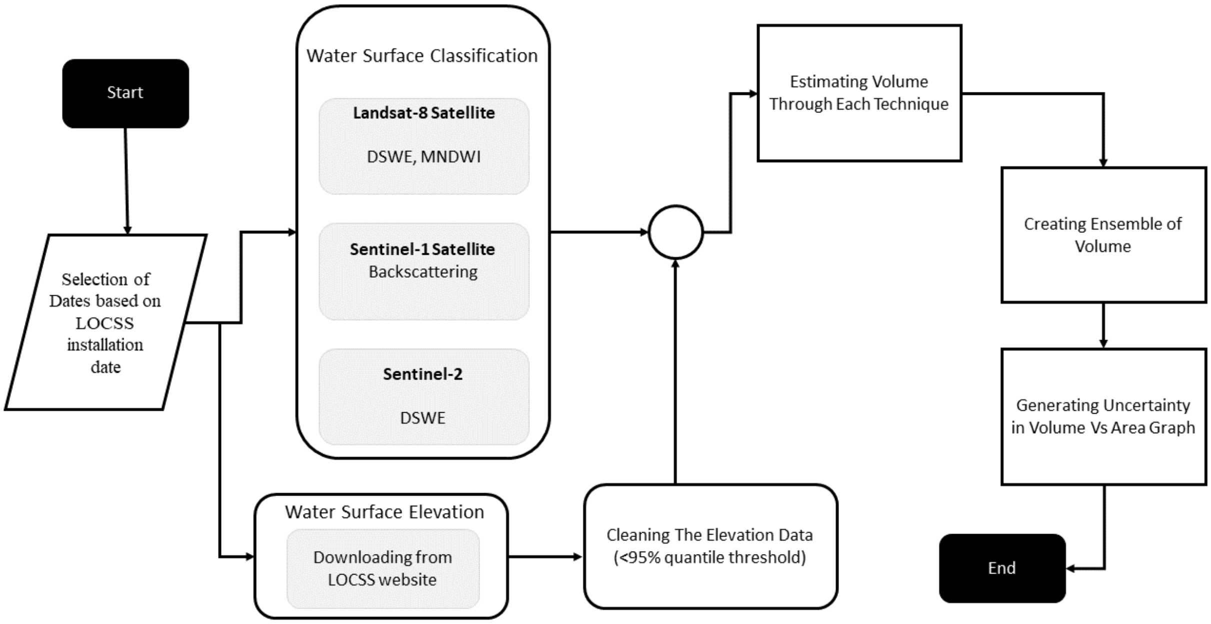

Figure 3.1: Flowchart for methodology used for exploring uncertainty of satellite-based lake volume estimation

3.1 STUDY SITE

To better understand the complex nature of uncertainty in volume estimation and how it varies at different locations, we monitored 106 lakes and wetlands globally from the LOCSS program

(Figure 3.2). We focused on water bodies from the South Asian region (Bangladesh, Nepal and India). For North America, LOCSS lake height data was obtained from water bodies located in Illinois, Massachusetts, New Hampshire, North Carolina, New York and Washington (Figure 3.3). In Europe, we had LOCSS lake height data located in the South of France in the Pyrénées mountain.

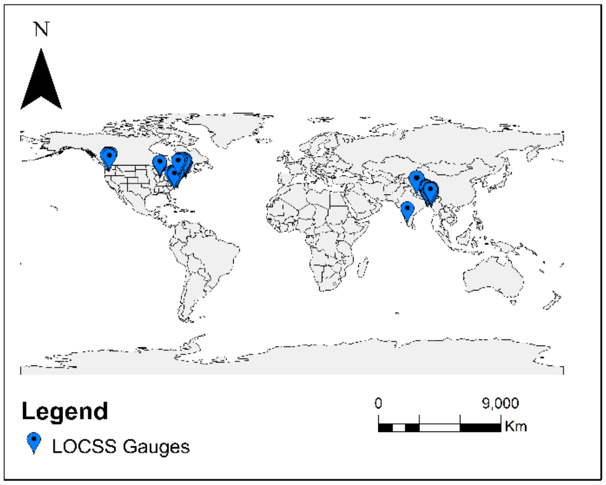

Figure 3.2: Location of LOCSS sites for the citizen science monitoring of lakes and wetlands.

The lakes in the USA and France are perennial, with some that freeze during winter. On the other hand, most of the lakes and wetlands in Bangladesh are seasonal, where water accumulates during the months of the monsoon (May to November).

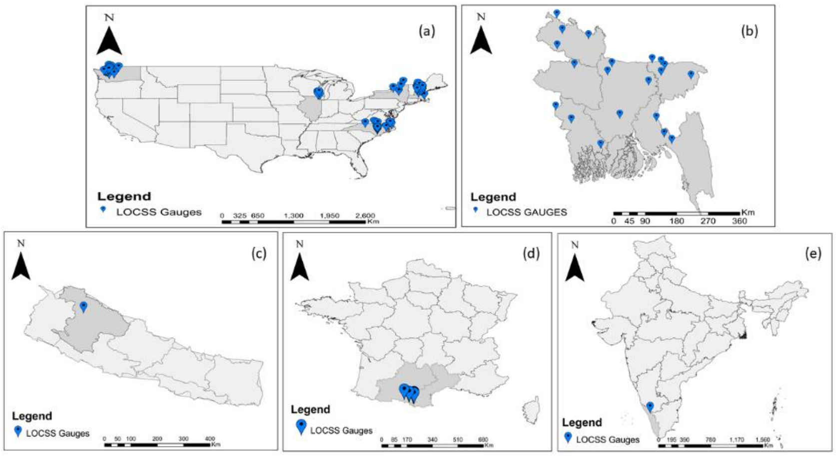

Figure 3.3: Location of LOCSS gauges in a) USA (71 lakes), b) Bangladesh (20 lakes), c) Nepal (1 lake), d) France (13 lakes), e) India (1 lake)

3.2 DATASET

For estimating the surface water area, satellite missions Sentinel 1, Sentinel 2 and Landsat 8 were used. Sentinel 1 has C-band synthetic aperture radar imaging that can penetrate the clouds and has a spatial resolution of 10 m and revisit time of 6 days. Images from the Sentinel 2 Multispectral Instrument (MSI) were used with a spatial resolution of 10 m and revisit time of 5 days. Landsat 8 Operational Land Imager (OLI) Tier-1 Surface Reflectance with a spatial resolution of 30m and revisit time of 16 days was used. These sensors were chosen as they were publicly available and have shown skill in detecting water surfaces [31]–[34]. The satellite data is freely available on Google Earth Engine, a cloud-based computing platform ideally suited for a global study of lakes [35].

The water elevation data were collected from the citizen scientists engaged or partnered via the LOCSS program. For example, lake water height data from South Asia were obtained from citizens engaged with the relevant state or national government water agencies, such as Bangladesh Water Development Board for Bangladesh, Centre for Water Resources Development and

Management for Kerala (India),and Nepal Department of Hydrology and Meteorology for Nepal. Similarly, most lake height data over the US were obtained from citizen scientists in the area with gauges maintained by local partnering organizations (such as US Fish and Wildlife Service, City of Sammamish Parks and Recreation, Lake County Forest Preserve District etc.) A detailed list of local partnering agencies can be found on LOCSS website (www.locss.org). In France, the lake heights were collected by hikers who had sent photos of the gauges via smartphone. For more details, the reader is referred to Little et al. (2021) and www.locss.org. A previous study on LOCSS had shown the water elevation data from citizen scientists are reliable and accurate when compared to automated gauges (Little et al., 2021). Nevertheless, all LOCSS data were subject to a quality control to filter out human errors that represented clear outliers. A clear outlier is one where the lake water height data is found to be a random anomaly from the underlying trend observed before and after. Such outliers were replaced with a 95% percentile threshold shown in Figure 3.4 below. For the case of France, some photos sent may also be grainy and not readable. The presence of such outliers occurred in less than 0.1% of the data. LOCSS gauges were installed in 2017 in the USA and France, 2019 in Bangladesh, 2021 in Nepal.

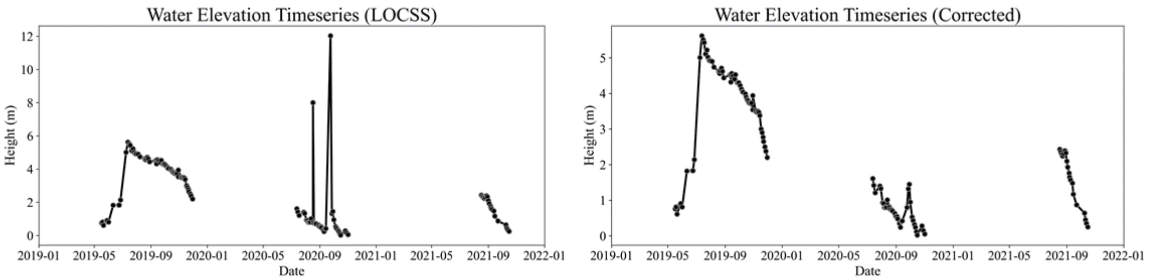

Figure 3.4: Example of water surface elevation before and after correction of outliers

3.3 EXTRACTING WATER SURFACE AREA

3.3.1 *Landsat 8*

The Landsat 8 OLI/TIRS (L8) sensor was used to estimate the water surface area through a variety of water classification techniques. Atmospherically corrected L8 data using the (Land Surface Reflectance Code) LaSRC [36] was used for the study. Two water classification techniques were used. The first was the Dynamic Surface Water Extraction (DSWE, [15]). DSWE has the ability to extract the water surface where the pixel is partially covered with vegetation and water. In addition to Landsat imagery, DSWE uses a digital elevation model, slope, hill and cloud shade. These parameters are calculated using the Fmask function [37]. The output of the DSWE consists of six possible classes: Not water, water - high confidence, water - moderate confidence, potential - wetland/ partial surface water conservative, and masked out due to the cloud, cloud shadow, or snow. The second technique used to extract the water surface area is the Modified Normalized Difference Water Index (MNDWI). Xu [13] developed the definition using the NIR band with (Short Wave Infrared) SWIR band to detect the water feature in built-up areas where a threshold of 0.3 for the MNDWI was found to be a robust choice [38], [39].

3.3.2 *Sentinel 2*

Optical imagery from Sentinel 2 (S2) sensor has a spatial resolution of 10 m, which is an improvement over the Landsat 8 spatial resolution of 30m. The DSWE technique was also applied to Sentinel 2 images. As the DSWE algorithm was designed specifically for the L8 images, scaling of S2 reflectance data is required to make DSWE work for S2 data. Surface reflectance transformation functions between S2 and L8 can be used to transform the S2 bands to L8 bands. In the study, we used the transformation function developed by Zhang et al. [39] to linearly map the S2 bands to L8 bands and use the DSWE algorithm. For the MNDWI technique on S2 imagery, no transformation is required according to the study conducted by Du et al. [40].

3.3.3 *Sentinel 1*

Sentinel 1 is an angle looking C-band SAR that sends radar signals which can penetrate clouds. Water classification using the Sentinel 1 imagery was accomplished with the help of the backscattering thresholding technique. Non-water surfaces usually have high roughness and thus, they have high backscattered energy as compared to the water-like surface. The water-like surfaces appear dark in the imagery because of their smooth surface. Hence, this phenomenon can be used to extract the water surface extent by putting a threshold on the backscatter values. However, one of the drawbacks of the SAR is speckle noise, which degrades the quality of the image and causes information loss. Over the years, various techniques have been used to reduce the speckle noise such as wavelet transform [41] mean-median filters [42]. We used a focal median filter with a 30 m × 30 m window. Incidence angle also plays an important role in the image pre-processing; for the water surface classification, we considered look angles from 31.7^{o} to 45.4^{o}. More details on this choice are described by Ahmad et al. [29]. With the pre-processed image, a backscatter threshold of -13db was selected to identify the water body, as suggested by Liu [43].

3.4 EXTRACTING WATER SURFACE ELEVATION

The water surface elevations were gathered with the help of citizen scientists. The data for all the water bodies were downloaded from the LOCSS website where they are publicly available.

3.5 ESTIMATING THE VOLUME STORED AND GENERATING UNCERTAINTY ENSEMBLE

After estimating the water surface area and extracting the water surface elevation, volume of water stored above the minimum observed level was estimated for each of the techniques and sensors. Satellite water extent data were used for days that matched or were within 3 days of the measurement date of citizen scientists from LOCSS. To estimate the volume variation, we linearly interpolated the water surface area data, so that the timestamps of both water elevation and water surface area are the same, which makes it easy to calculate the volume change. The information of the exact bathymetry of the water bodies was not available, so we estimated the volume stored with respect to the lowest observed water surface elevation in the time series, similar to Ahmad et al. [29] who had earlier applied citizen scientist height data for northeastern wetlands of Bangladesh. The lowest water elevation observation was obtained from the LOCSS website over the period of the study. For simplicity, many studies in the past have assumed trapezoidal bathymetry [11], [29], so we also assumed trapezoidal bathymetry as shown in Figure 3.5.

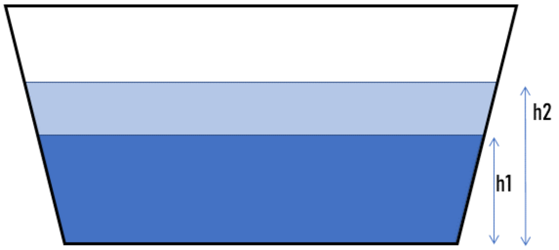

Figure 3.5: Trapezoidal Bathymetry

Pyramidal bathymetry of lakes can also be assumed as proposed in Cretaux et al. [26] but internal comparisons done between both hypotheses have usually yielded very similar results. In Figure 3.5, assume h1 and h2 are water surface elevations reported by citizen scientists at different instances of time. We then apply the corrections in water surface elevation (if needed) and try to estimate the water surface area A1 and A2 at the elevation reported timestamps through the satellite as shown in Figure 3.6.

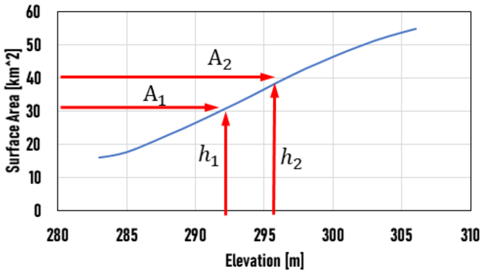

Figure 3.6: Getting Satellite Imagery on/ at nearest timestamp of water surface elevation

The volume of water stored between two such timestamps is estimated as per trapezoidal rule as shown in Equation 3.1.

$$\Delta S = A_{avg.} * \Delta \mathrm{h} = \frac{(A_2+A_1)}{2} * (\mathrm{h}_2 - \mathrm{h}_1) \qquad (3.1)$$

Hence volume stored by the water body at a given time can be calculated as:

$$V_t = \frac{(h_t - h_{min})(A_t + A_{min})}{2} \qquad [L3] \qquad (3.2)$$

Here in Equation 3.2, h_t is the water elevation at time t, h_{min} is the lowest water elevation of the time series at each lake. A_t is the area of the lake at time t and A_{min} is the minimum area of the lake. The volume estimated in this fashion using equation 3.2 yields the volume that can be estimated from the lowest level observed in the satellite record. Understandably, this approach may yield large errors when the difference between h_t and h_{min} is large enough to disqualify the assumption of trapezoidal bathymetry between those two heights. In our scrutiny of bathymetries above the minimum observed level, lakes that experience large height differences of many meters, such as in Bangladesh (South Asia), follow a very flat and steady trapezoidal bathymetry. In regions where bathymetry shape may be irregular over large heights, such as in the studied lakes of Europe, USA, India and Nepal, the height differences reported by citizens are usually not large enough. Figure 3.7 and Figure 3.8 shows the topography of the surrounding area of the water body and the water surface elevation.

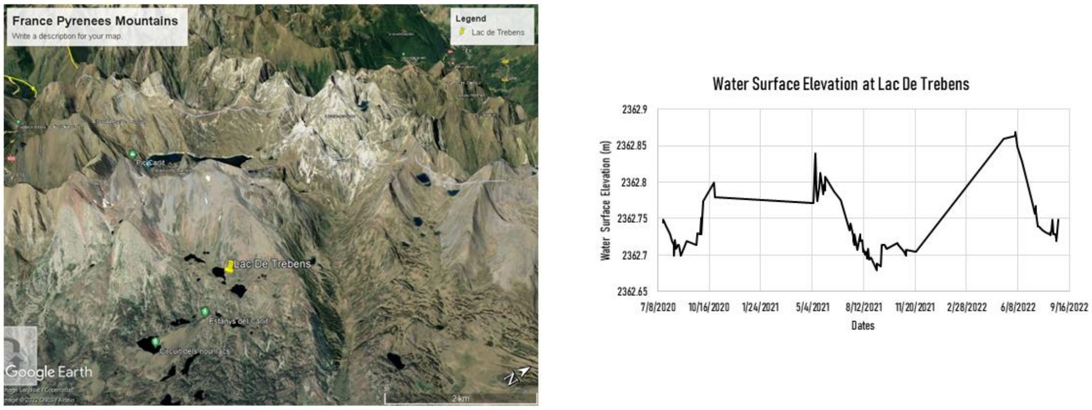

Figure 3.7: Topography and Water Surface Elevation of a Lake in France

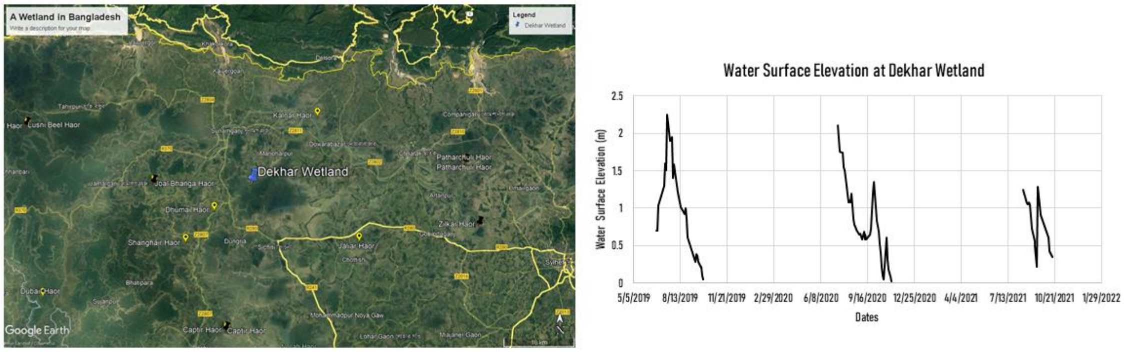

Figure 3.8: Topography and Water Surface Elevation of a Wetland in Bangladesh

The volume stored was estimated for all four techniques used in the study (Table 1.1), and an ensemble of the volume estimates was generated. Figure 3.9 shows an example of the ensemble of estimated volumes.

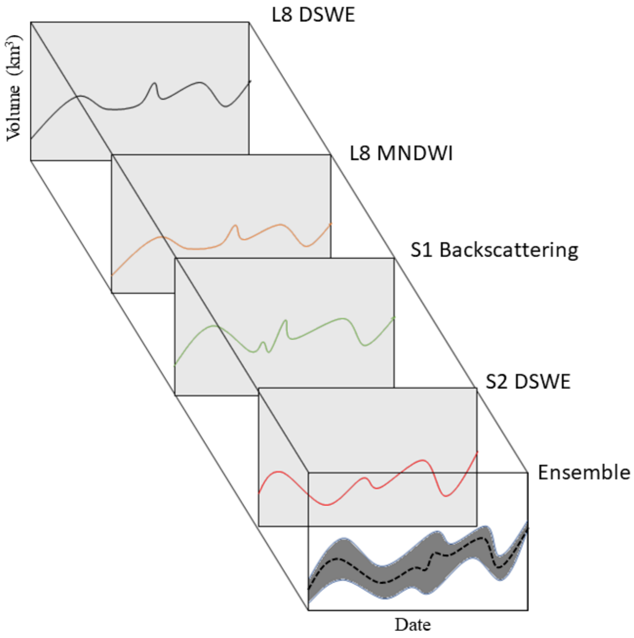

Figure 3.9: Generating the ensemble of estimates on volume stored

3.6 STUDIED FACTORS AFFECTING UNCERTAINTY

3.6.1 South Asia:

To understand the complexity of uncertainty in estimating volume, various factors contributing to the uncertainty were studied. Countries such as Bangladesh, India, and Nepal have a monsoonal climate, which brings extensive cloud cover and a high amount of rainfall for 3-5 months. Hence precipitation patterns and cloud cover were compared with uncertainty. Optical sensors have a limitation that they cannot penetrate the clouds. The complementary nature of optical and radar sensors with unique strengths and weaknesses collectively give rise to estimation uncertainty. Gridded precipitation data for Bangladesh was downloaded from the ERA5 hourly precipitation and Bangladesh Meteorological Department data library and gridded precipitation data for India was downloaded from Indian Meteorological Department. The cloud cover data was collected from information provided in the Landsat 8 satellite data product.

3.6.2 North America

In the regions of North America studied here, the monsoon is not as dominant, unlike South Asia. We therefore studied the uncertainty in volume estimation as a function of temperature and cloud cover. The water surface temperature of lakes was estimated using the Landsat 7 Collection 1 Tier 1 (L7). Low-gain Thermal Infrared 1 Band (B6_VCID_1) was used to estimate the temperature. While the cloud cover over the water bodies was estimated using L8.

3.6.3 Europe

In Europe, we studied the water bodies in France. All of the lakes in France were in highly mountainous areas of the Pyrenees. Thus, with the exception of Nepal, these lakes were located in the most topographically variable landscape of any LOCSS lakes. These lakes also freeze in the winter. We ran the same analysis on France as we did on North America.

3.7 ESTIMATING THE UNCERTAINTY IN VOLUME ESTIMATION

We chose a metric for uncertainty in volume estimation that provides us with an idea for average spread of the estimated volumes over time relative to the statistically expected volume of a water body (also over time). Here the expected volume is assumed to be the arithmetic mean of the volumes estimated by the four methods. We call this metric the "time-averaged uncertainty metric." This time-averaged uncertainty metric is calculated using equation 3.2. Here we use the time-averaged uncertainty metric in relative terms normalized by the mean volume, to allow comparison across all lakes and regions. A time-averaged uncertainty metric value of less than one means that the current suite of sensors and methods is generally able to estimate volume variations with a spread that is less than the mean value, and hence the uncertainty may be considered acceptable at any given time. Vice versa, an uncertainty metric value of more than 1 means the spread of uncertainty is significantly larger than the mean value itself, and hence the volume uncertainty may be considered unacceptable at any time. **Error! Reference source not found.** illustrates how the time-specific uncertainty in the volume varies for the Korchar wetland in Bangladesh over time to yield the time-averaged uncertainty metric defined in Equation 3.2.

$$Time\ averaged\ Uncertainty\ = \frac{\sum_{0}^{n}\left[\frac{Max\ Volume_t - Min\ Volume_t}{Mean\ Volume_t}\right]}{\sum_{0}^{n} t} \qquad (3.2)$$

The time-specific behavior of uncertainty is particularly suited for developing a temporal understanding of seasonal water bodies, such as wetlands in South Asia. During the development of a wetland in the monsoon season, the spread of the ensemble may be smaller yet the uncertainty metric for that specific time can be higher because of time-specific low mean for estimated volumes. Such a high time-specific uncertainty can be indicative of the limitation of the sensors for water bodies with very small volumes and variations at that time. As these wetlands develop and the volume stored increases, the time-specific uncertainty metric can decrease if the collective precision of the sensors hold. Conversely, the opposite can happen with time-specific uncertainty rising as volume increases. We show one such example in Figure 3.10**Error! Reference source not found.** (a) and (b). A red line is shown to demonstrate the case for a wetland in Bangladesh where the time specific uncertainty rises despite increase in volume after the height of the monsoon in August. This corroborates the fact that uncertainty of volume estimation can be dependent on many factors, many of which are time-specific (such as cloud cover, land temperature, growth of vegetation, and irregular/non-trapezoidal bathymetry).

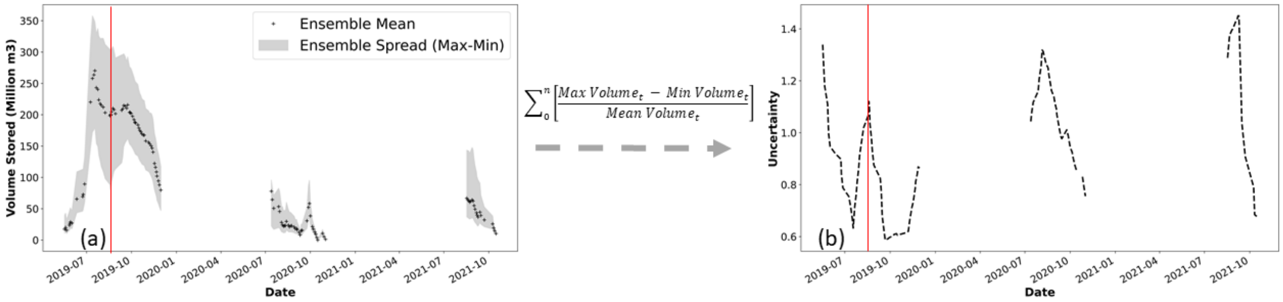

Figure 3.10: Volume stored and Uncertainty time-series for Korchar wetland in Bangladesh.

Chapter 4. RESULTS

4.1 RESULTS

In this chapter we demonstrate a few examples of time varying uncertainty (not the time averaged uncertainty) that are representative of lakes and wetlands for their regions. Figure 4.1 shows the volume estimation uncertainty of a wetland in Bangladesh. In general, the wetlands in Bangladesh are fully inundated during May to December, while and from January to April, they are often dry. It is seen that during higher cloud cover and precipitation, the uncertainty spread is high. Figure 4.2 shows the ensemble of Pookode lake in Kerala, India. Kerala in general receives two monsoons. One is the southwest monsoon (June - September) and the other is the northeast monsoon (October to December). Essentially, the entire period of June to December is characterized by extensive cloud cover. We observe that volume stored and uncertainty in volume are both higher as the monsoons retreat in December with gradual decrease as cloud cover and precipitation decreases in April. The pattern repeats itself from June to December again as the two monsoon seasons complete their cycle.

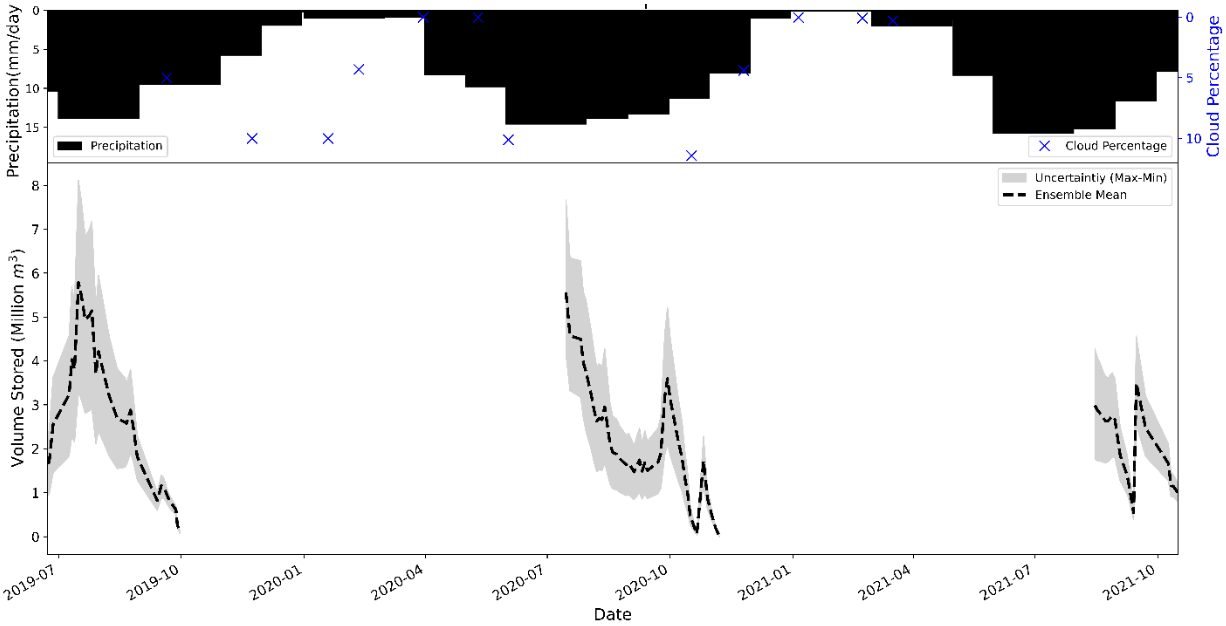

Figure 4.1: Time series of uncertainty of volume estimation of Dekhar Haor wetland in Bangladesh

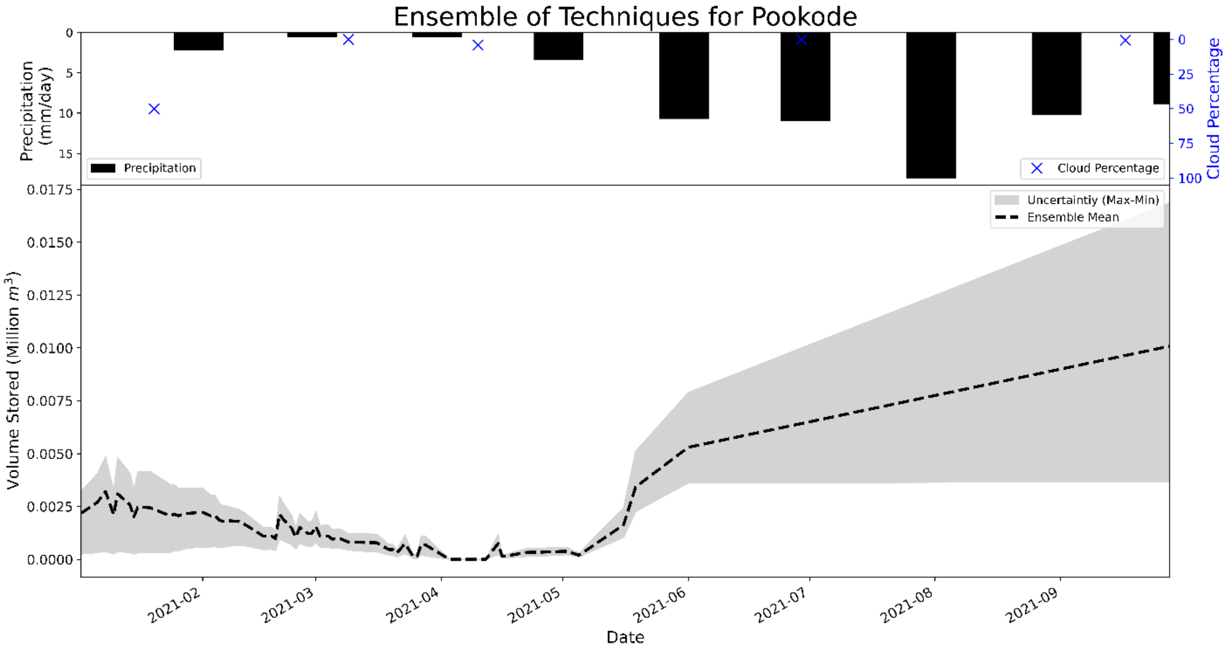

Figure 4.2: Time series of uncertainty of volume estimation in Pookode lake in Kerala (India).

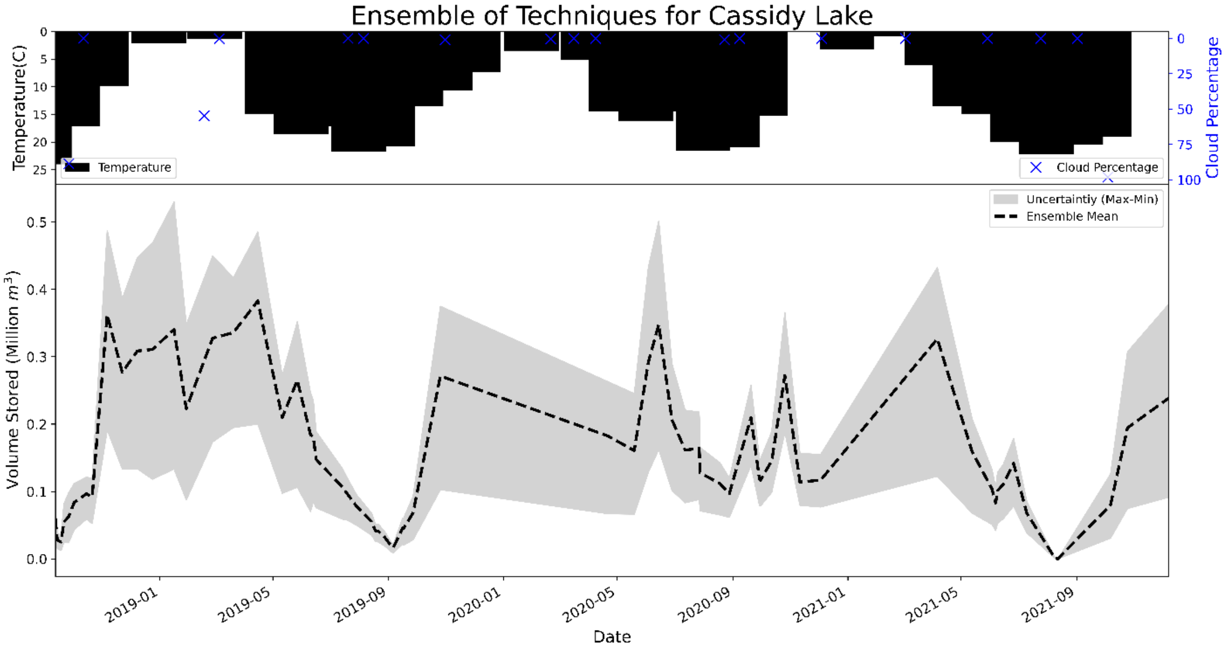

Figure 4.3: Ensemble of Cassidy Lake in Washington state.

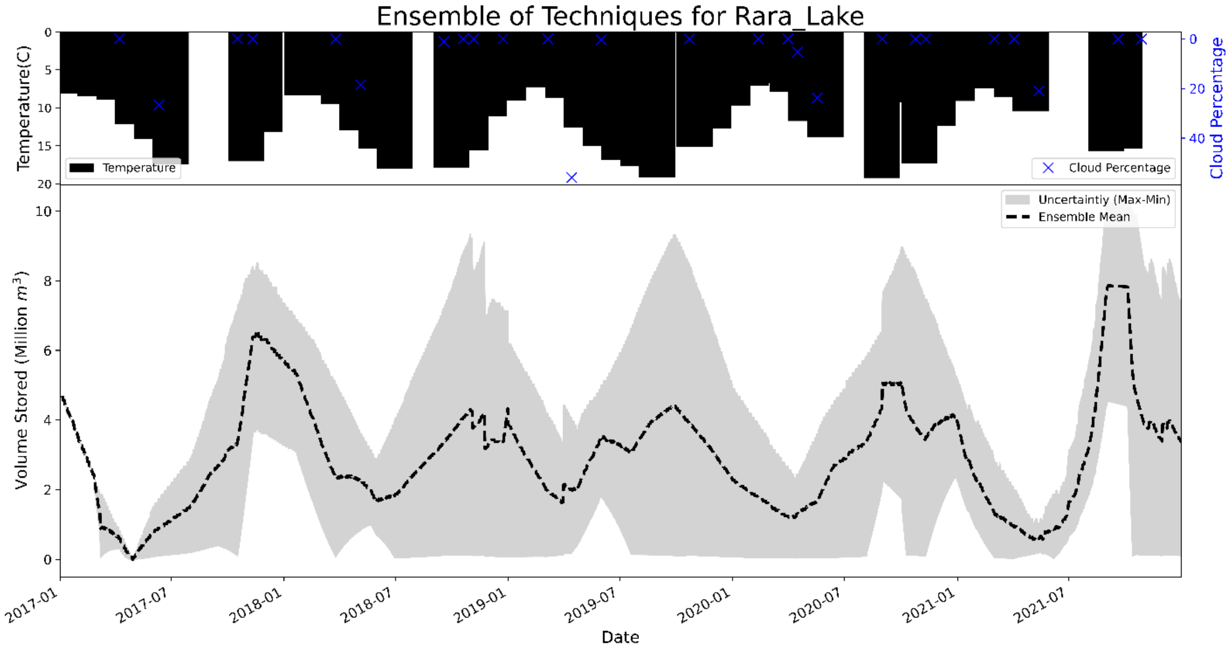

Figure 4.4: Ensemble of Rara Lake in Nepal.

For US lakes, we studied volume uncertainty as a function of cloud cover and water surface temperature given the tendency of some lakes in upper latitudes to freeze during winter. In Figure 4.3, we show the uncertainty spread for Cassidy Lake (Washington State), which is found to be high during freezing conditions. When volume stored is low, the uncertainty spread is also found to be quite high. As there are likely many other controlling factors, water temperature provides only a partial explanation of the temporal behavior of uncertainty.

Figure 4.5 shows the time-averaged uncertainty metric (Equation 2) for all the water bodies as a function of the nominal lake area. This is a plot showing the aggregate behavior volume estimation uncertainty for each region as lake area changes. The idea is to understand if there is a threshold area for a lake size below which the time averaged uncertainty metric is high (> 1). From Figure 4.5 the percentage of water bodies having uncertainty metric less than 1 in Washington, South East Asia (Bangladesh, India and Nepal), Illinois, East Coast USA (New York, Massachusetts, North Carolina) and France was found to be 56%, 45%, 75%, 71% and 62% respectively.

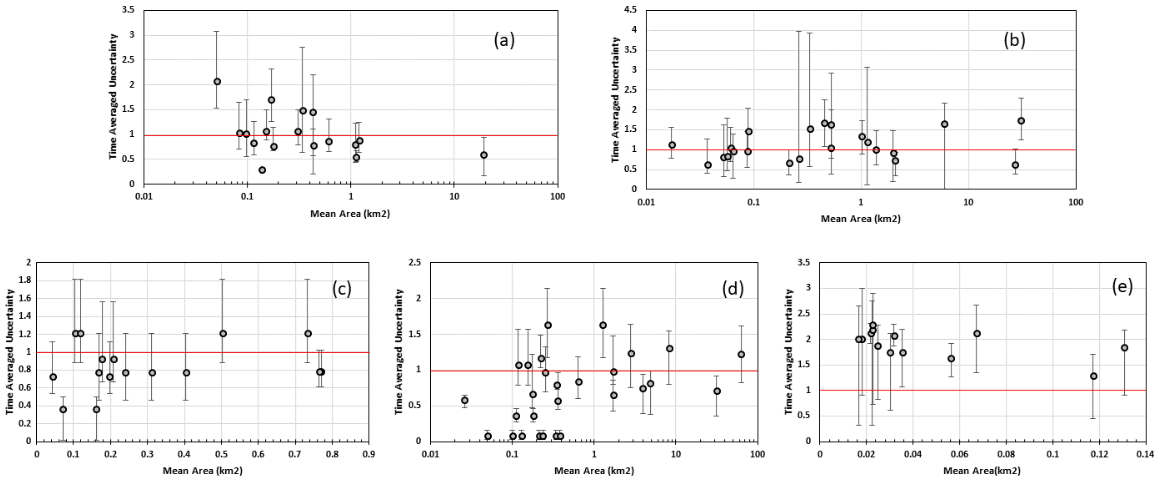

Figure 4.5: Time-averaged Uncertainty in volume Vs Nominal lake area for- (a): Washington (USA), (b): Bangladesh, India and Nepal, (c): Illinois, (d): New York, Massachusetts, North Carolina, (e): France

To understand the role played by individual area estimation methods in volume estimation uncertainty, we ranked each of the four methods from highest to lowest average volume estimates for a given lake. In Figure 4.6, we show in a four panel plot the methods for each lake with highest volume (uppermost panel), second-highest volume (middle panel), second-lowest volume (2nd panel from bottom) and lowest volume (bottommost panel). The idea is to see if performance of methods is consistent across lakes or if other geophysical factors pertaining to the lake and the ambient environment control the tendency to estimate the highest or lowest value in the ensemble. In general, the DSWE method using Sentinel-2 and backscattering method using Sentinel-1both have a tendency to yield higher volume estimates. However, when looked at as a whole, there does not seem to be a single method that is found to consistently estimate the highest, lowest volume or median volume. This indicates that in our study of lake volume estimation uncertainty, there is no single method that can be filtered out to minimize uncertainty and that all methods should be considered collectively to improve our understanding of uncertainty.

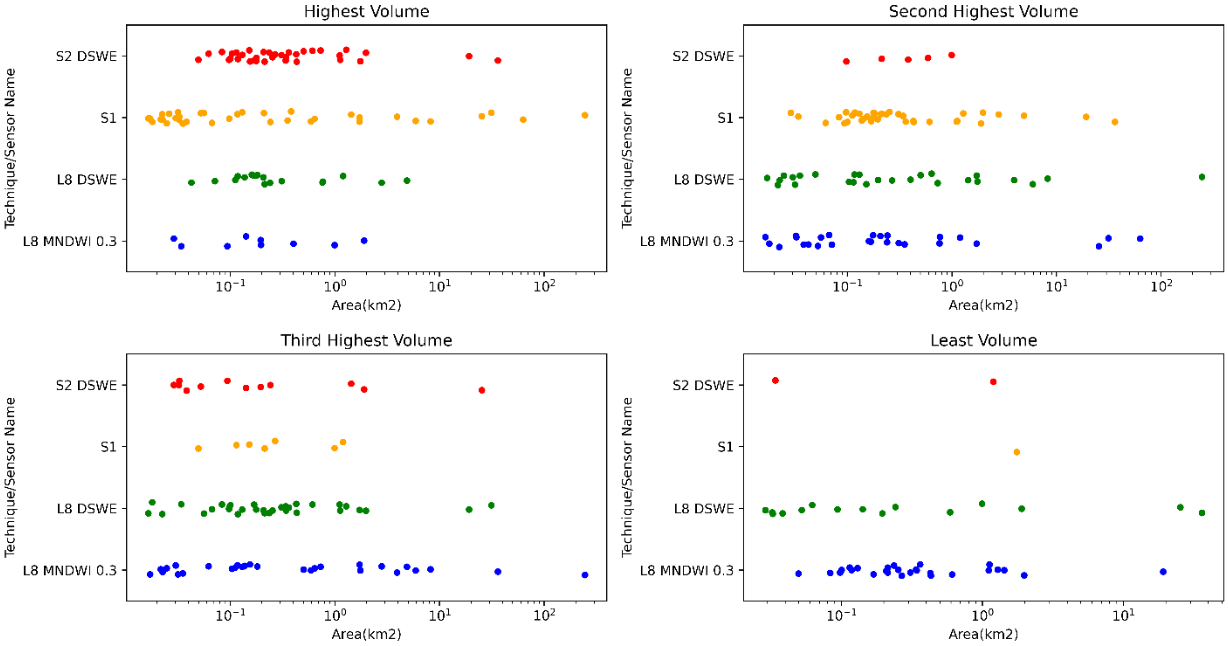

Figure 4.6: Ranking of the four methods

Chapter 5. CONCLUSIONS

5.1 CONCLUSION

We studied 106 lakes and wetlands around the world where LOCSS gauges were installed to record water elevations measured by citizen scientists. We define a time-averaged uncertainty metric where the threshold value 1 will be used as the cutoff for acceptable uncertainty (< 1) or unacceptable uncertainty (> 1). When considering all the lakes studied, there is no clear pattern in our findings where lakes larger than a certain threshold can claim to experience higher skill in estimation of volume. However, at individual regions, there are some nuanced patterns. For example, lakes in Washington and France show a clear dependency of uncertainty as a function of area where the time-averaged uncertainty metric decreases as nominal lake area increases. In South Asia, lakes larger than 0.5 km2 experience an uncertainty metric of less than 1 near-consistently. This trend is driven mostly by lakes in Bangladesh where lakes larger than 10 km2 yield acceptable uncertainty. This implies that the flat terrain nature of Bangladesh topography combined with more dynamic hydro-meteorological and land use patterns compared to other regions studied pose a significant challenge to lake volume estimation. In the US, what is interesting is that lakes east of the 108th meridian (Colorado Rockies) exhibit considerably lower uncertainty in volume estimation. This uncertainty decreases gradually for lakes located further eastwards, starting from Illinois to Eastern US (Massachusetts, New York and North Carolina). For example, in Washington state, the average time-averaged uncertainty appears to be around 20% higher than lakes in Illinois which are about 50% higher than lakes in the eastern US. It is clear that much smaller-sized lakes in the eastern US can be estimated with considerably less uncertainty. In France, we saw that the spread of uncertainty is high. One of the plausible reasons for this can be the shadow of the mountains. The LOCSS gauges are installed in the South of France, near the

Pyrenees mountains. While digitizing the lakes in France, mountains projecting the shadow on water bodies were observed. Ji et al. [44] discussed how mountain shadows can be misclassified as water pixels. We should however exercise caution in interpreting the volume estimation uncertainty pattern for each region (e.g., USA, France and South Asia) given that samples of lakes studied here may not necessarily be a statistically representative sample of all lakes in those regions.

5.2 BROADER IMPACTS

Our lake height data were obtained from the citizen science program of LOCSS, which has the additional objective of validating and improving lake products anticipated from the planned Surface Water and Ocean Topography (SWOT) mission. The SWOT satellite mission is a joint mission of the National Aeronautics and Space Administration (NASA) and Centre National d'Etudes Spatiales (CNES) with contributions from the Canada Space Agency and the United Kingdom Space Agency. SWOT is planned for launch in November 2022 [45]. It will be the first satellite of its kind that will report water surface elevation and water surface area simultaneously with a revisit time of 21 days or less at a given location. The primary instrument on SWOT is Ka-band Radar Interferometer (KaRIn), which uses radar interferometry and synthetic-aperture radar (SAR), which gives high-resolution water elevation and inundation extent [45]. Currently, as noted in this study, to estimate the volume, water surface area is derived from satellite sensors while the elevations are obtained either from concurrently-flying altimeters or from the in-situ data. SWOT, with its simultaneous measurement of area and elevation, will improve our ability to estimate volume more consistently. Moreover, SWOT is a swath interferometer which will cover the whole Earth and monitor lakes larger than 250 X 250 meters. This will be an unprecedented global view of the lake storage change dynamics at global scale.

Our findings therefore have implications for the SWOT mission. First of all, the availability of LOCSS gauge data from citizens can be expected to provide valuable validation data to compare SWOT-estimated volume changes once SWOT starts to provide lake area and elevation simultaneously. Secondly, SWOT observables could be combined with pre-SWOT satellite data to create higher frequency estimates of lake volume with lower estimation uncertainty. Armed with a general idea of what regions, specific factors and the minimum lake size matter in achieving an acceptable uncertainty, LOCSS gauges can be strategically expanded or the data quality for lake storage change can be flagged accordingly.

The estimation of uncertainty for volume is useful for practical applications at ungauged regions lacking historical records, such as sizing of surface water storage facilities or flood control structures. For example, if an urban settlement is planned in the ungauged region with no historical records, where lakes are the only source of surface water, then the freshwater storage and distribution system size would need to be based on the minimum (worst case) scenario of lake volume experienced over a sufficiently long period. Similarly, a flood protection facility in the same ungauged region would have to be designed based on the maximum (worst case) scenario of lake volume observed over a long record. The range of estimation uncertainty gleaned from an ensemble of satellite sensors and techniques facilitates such societally relevant application in the design of water management facilities at regions lacking historical in-situ records. In a previous effort based on LOCSS [29], the estimation of total volume stored in northeastern Bangladesh with uncertainty has already triggered a conversation by the Bangladesh Government to exploit any excess surface water for commercial revenue-generating purposes (personal communication with Director General of Bangladesh Water Development Board).

Our study is not without limitations. One key limitation is the short period of LOCSS data for many regions, such as South Asia. Another limitation is the absence of high-resolution optical imagery at the meter scale, such as Planetscope data, that can provide a better reference for lake volume under clear sky conditions [46]. For example, volume estimated by an optical sensor at 1 m resolution could provide a much better understanding of the expected volume. We hope these limitations can be addressed in a future study as the LOCSS data continue to grow with more participation from citizen scientists around the world.

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