MONITORING GROUNDWATER STORAGE BASINS AND HYDROLOGICAL CHANGES USING THE GRACE SATELLITE AND SENTINEL-1 FOR THE GANGA RIVER BASIN

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ABSTRACT:

Groundwater depletion-related subsidence is a significant issue in many parts of the world. It can permanently reduce the amount of groundwater stored in an aquifer and even cause structural damage to the Earth's surface. The Ganga Basin in the northwestern region of India is no exception, with around a meter of subsidence occurring between 2018 and 2023. However, understanding the connection between variations in groundwater quantities and ground deformation has been challenging. We used surface displacement measurements from InSAR and gravimetric terrestrial water storage estimates from the GRACE satellite pair to characterize the hydrological dynamics within the Ganga Basin. Sentinel-1 was used to map the entire Ganga River basin in the inundated zone. The InSAR time series shows coherent short-term changes that coincide with hydrological features when the long-term aquifer compaction is removed. For instance, an uplift is seen at the confluence of multiple rivers and streams that drain into the southeastern margin of the basin in the winters of 2018–2019 and 2021–2022. Imaging the monthly spatial variations in water volumes is based on these data and calculations of mass changes from the orbiting of Sentinel-1 and GRACE satellites. We even employ machine learning techniques as evaluative methods to make it simple to combine InSAR quickly and convincingly with gravimetric datasets, which will help advance global efforts to understand better and manage groundwater resources.

1. INTRODUCTION

1.1 Background and General Introduction

With 3% of all freshwater on Earth, groundwater is the largest freshwater resource. Approximately 69% of Earth's freshwater is locked away in ice in glaciers and polar ice caps, and another 30% of Earth's freshwater is under the surface in the form of groundwater. It is a crucial resource for irrigation in agriculture, balancing the global food security challenges. This groundwater resource provides over 75% of the domestic water needs in the world while also serving as a major supplier of industrial water. In addition, groundwater successfully maintains river flows during droughts and acts as a buffer against changes in precipitation. Due to population growth and water constraints, groundwater zones have become the primary freshwater supply. Some regions rely on it too much and utilise groundwater much more quickly than it replenishes itself, which causes water tables to fall constantly.

The middle and lower Gangetic River basin aquifer system sustains essential agribusiness, industrial inputs, and the tanning industry (leather-based) and supplies drinking water. The Ganges River basin is home to more than 650 million people. Thus, becoming vital surface water and groundwater resource for many. Although it results in long-term storage loss and infrastructure damage, subsidence brought on by groundwater depletion has been challenging to assess and anticipate. The Indo-Gangetic Basin's hydrodynamics are varied in complexity, and the fundamental elements of the geology are not well characterised. Furthermore, the complex hydrology of the basin, with multiple sources and sinks, can cause substantial changes over periods as short as a few months. Thus, orbiting satellite-based systems are well suited for monitoring variations within the Indo-Gangetic Basin at various timescales. Here, we take into account Sentinel-1's interferometric synthetic aperture radar (InSAR) observations, which offer estimates of line-of-sight (LOS) displacements of the Earth's changes in terrestrial water storage (TWS), as determined by NASA - GRACE and GRACE Follow-On (FO) missions. Both data sets have unique characteristics that make any study challenging, and are both vulnerable to hydrologic changes in the Indo-Gangetic Basin. For instance, differences in the water table, earth movement, soil moisture, groundwater level mapping and snow cover can all be linked to changes in the gravity field measured by GRACE and GRACE-FO. As a result, using gravity data alone, it is challenging, if not impossible, to discern between water mass variations in shallow aquifers. Thus, it is difficult, if not impossible, to distinguish between water mass changes in the shallow aquifers and in the underlying confined aquifer using gravitational observations alone. Observations of surface deformation have their own issues, primarily due to the complicated relationship between ground motion and hydrological changes [Gido et al., 2020].

The main hydrological drivers of deformation in a porous medium are changes in the total stress minus the fluid pressure within a given aquifer, a quantity known as the effective stress. In an unconfined aquifer, the fluid pressure is moderated by the possible upward movement of the water table and the coupling to the atmosphere.

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2. STUDY AREA AND DATA-SETS

The Indo-Gangetic Plain, also known as the North Indian River Plain, is a 700-thousand sq. kilometres (172-million-acre) fertile plain encompassing northern regions of the Indian subcontinent, including most of northern and eastern India, most of east Pakistan, virtually all of Bangladesh and southern plains of Nepal. Also known as the Indus–Ganga Plain, the region is named after the Indus and the Ganges rivers and encompasses a number of large urban areas. The plain is bound on the north by the Himalayas, which feed its numerous rivers and are the source of the fertile alluvium deposited across the region by the two river systems. The Deccan Plateau marks the southern edge of the plain. On the west rises the Iranian Plateau. Many developed cities like Delhi, Dhaka, Kolkata, Lahore and Karachi are located in the Indo-Gangetic Plain. The Indo-Gangetic Plain (IGP) region of India, covering about 15% of the total area of the country, is one of the most intensively cultivated regions of the world (Yadav, 1998; Singh et al., 2015). The study area lies between 21°N 35′ - 32°N 28′ latitude and 73°E 50′ - 89° E 49′ longitude with a geographical area of 5.72 lakh sq. kilometres [Ojha et al., 2020]. This study used GRACE satellites to utilise satellite gravimeters to measure Earth's gravity field variations. These variations are primarily caused by changes in water distribution, including groundwater. By monitoring gravity anomalies over time, GRACE can estimate changes in groundwater storage at regional scales. This information is particularly valuable for assessing long-term trends in groundwater availability and tracking large-scale groundwater depletion or recharge patterns.

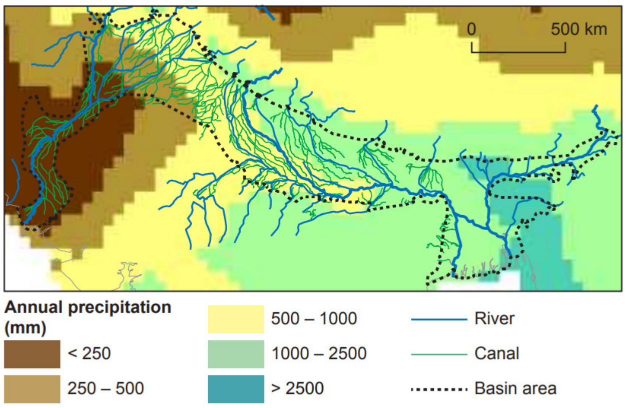

Figure 1: Catchment Area of Indo- Gangetic Basin

Sentinel-1 InSAR datasets, on the other hand, employ radar technology to measure ground surface displacements with high precision. By analyzing the interference patterns of radar waves reflected from the Earth's surface, InSAR can detect subtle changes in ground elevation. This capability makes it suitable for monitoring localized variations in groundwater levels and identifying areas of land subsidence or uplift associated with groundwater extraction or recharge.

The GRACE and Sentinel-1 InSAR datasets offer significant advantages for groundwater level mapping. GRACE provides a broader view of regional-scale groundwater changes, while Sentinel-1 InSAR offers finer spatial resolution to detect localized variations. By integrating these datasets, researchers can comprehensively understand groundwater dynamics, ranging from large-scale trends to localized effects [Taneja et al., 2019].

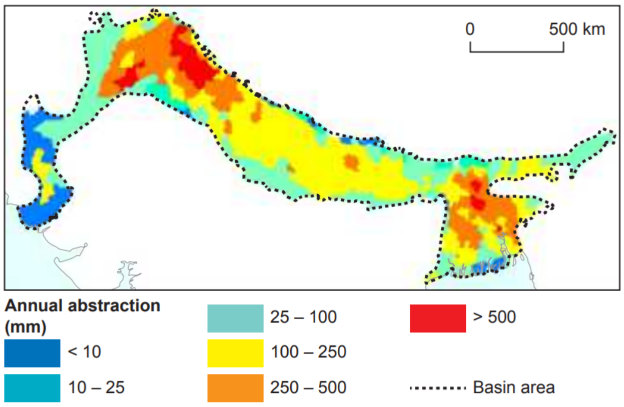

Figure 2: Annual changes in Groundwater water level limit in catchment sites

3. METHODOLOGY

3.1 Data Compilation and Preprocessing:

In order to accurately estimate hydrological variations, a comprehensive dataset was carefully curated and specifically designed to meet the needs of our study. This section provides an overview of the dataset compilation process, encompassing groundwater-level data collection, interpolation techniques, and the integration of satellite datasets. Groundwater Level Data Compilation: A comprehensive dataset encompassed groundwater level measurements from approximately 80,000 stations across India. These measurements were collected during various time periods, specifically May 2016, Aug 2016, Nov 2016, and Jan 2017.

3.1.1 Interpolation Techniques: The collected groundwater level data points were subjected to interpolation using the Inverse Distance Weighting (IDW) method to obtain a spatial representation of groundwater levels throughout India. This method enabled the generation of a raster file that effectively depicts the distribution of groundwater levels across the study area. The raster file derived from the interpolation is the target date for training our deep learning model.

3.1.2 Integration of Satellite Data: Our methodology incorporates the combined band information extracted from two essential satellite datasets: Gravity Recovery and Climate Experiment (GRACE) and SENTINEL-1. The integration of the combined information from GRACE and SENTINEL-1 datasets yields superior performance compared to utilizing the information from each dataset in isolation. Below, we elucidate the significance of the information derived from each dataset in our final prediction:

GRACE Satellite Data : The GRACE satellite data provides valuable insights into terrestrial water storage (TWS) changes through gravitational measurements. By analyzing variations in the gravity field, we can infer changes in water mass, including ground movement, soil moisture, water table fluctuations, and snow cover. Integrating GRACE data enhances our understanding of hydrological dynamics and facilitates the estimation of groundwater levels. However, it is important to note that accurately predicting groundwater levels based solely on GRACE data can be challenging. This is because variations in the gravity field are influenced by a combination of factors, including changes in snow cover, soil moisture levels, and water table fluctuations and ground movement [Liu et al., 2019].

SENTINEL-1 Satellite Data : The SENTINEL-1 satellite data offers invaluable Interferometric Synthetic Aperture Radar (InSAR) observations through phase shifts between the radar signals during the successive passes of the orbiting satellite. These observations enable the detection of surface deformations associated with hydrological changes. Incorporating SENTINEL-1 data allows us to capture localised surface deformations and further refine our analysis of hydrological variations. However, it is important to note that the relationship between ground deformations detected by SENTINEL-1 and changes in groundwater levels is complex and not directly proportional. Due to the influence of various factors, such as subsurface geological properties and hydrological dynamics, SENTINEL-1 data alone does not offer a reliable means to estimate groundwater levels [Massoud et al., 2022].

By combining the data from both the GRACE and SENTINEL-1 satellites, we have successfully avoided the limitations inherent in individual datasets and achieved a more comprehensive understanding of hydrological variations. GRACE data offers a broader perspective on water mass changes, while SENTINEL-1 data enables the detection of localised surface deformations. This integration of satellite datasets empowers us to accurately estimate groundwater levels and create detailed maps illustrating variations across India [Ramjeawon et al., 2022].

3.2 Deep Learning Model:

In our study, we leveraged convolutional neural networks (CNNs), a class of deep learning models widely recognized for their exceptional performance in various image analysis tasks. Estimating groundwater levels from satellite images involves a similar paradigm to image segmentation, where the objective is to accurately delineate specific objects or regions of interest within an image. While image segmentation often focuses on classification tasks, in the context of groundwater level estimation, we perform regression analysis to predict the continuous groundwater levels [Rateb and Kuo, 2019].

To address this challenge, we employed the U-Net model [Vasco et al., 2022]., widely regarded as the gold standard in image segmentation. The U-Net architecture excels at capturing contextual information and preserving high-resolution details throughout the segmentation process. n the following section, we delve into the specifics of the U-Net model and its adaptation for estimating groundwater levels from satellite imagery. We discuss its architectural details, training process, and the incorporation of the combined information from GRACE and SENTINEL-1 datasets.

3.2.1 U-Net Architecture: To estimate groundwater levels from satellite images, we employed the U-Net model, a widely acclaimed architecture renowned for its effectiveness in image segmentation tasks. The U-Net architecture offers a powerful solution by combining an encoding path, which captures contextual information from the input image, and a decoding path that generates an output segmentation map. What sets U-Net apart is its ability to preserve high-resolution features throughout the encoding and decoding process through the strategic use of skip connections. This architectural design facilitates the accurate delineation of groundwater features, ensuring that subtle variations and intricate patterns essential for groundwater level estimation are captured. By leveraging the U-Net model, we enhance our ability to extract meaningful information from satellite images and achieve precise estimations of groundwater levels in geospatial analysis and remote sensing applications. Figure 3 illustrates the U-Net architecture, showcasing the flow of information and the skip connections that facilitate the preservation of fine-grained features [Vasco et al., 2022].

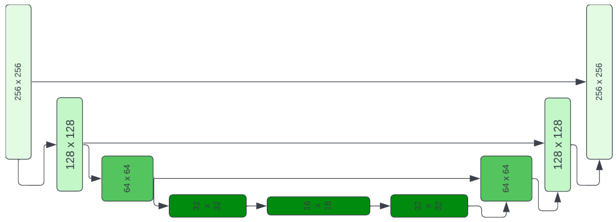

Figure 3: U-net architecture.

3.2.2 Model Training Process: The training process for our U-Net model involves several steps to optimize its performance in estimating groundwater levels. The model takes as input an image containing combined band information from both GRACE and SENTINEL-1 satellites, encompassing a (256 x 256) pixel neighborhood centered around each query point. This neighborhood context enables the model to capture essential features for estimating groundwater levels with local precision. The model then produces an output map representing the estimated groundwater levels in the pixel neighborhood of the query point. It is important to note that the input satellite images and the output estimation map may have different resolutions, these difference in resolution can significantly impact the model's performance [Tripathi et al., 2022].

We hypothesize that aligning the resolutions of the input and output images will maximize the model's performance. One of the key benefits of aligning the resolutions of the input image and the output map is that they represent the same area in a physical sense. This consistency in resolution ensures that the input image and the output map capture groundwater dynamics within the exact spatial extent. By representing the same area, the model can accurately associate the localized features in the input image with the corresponding groundwater level estimation in the output map.

However, achieving the same resolution for the input image and the output map can be challenging especially when it comes to collecting ground-water level data with a resolution as high as the SENTINEL-1 or GRACE satellites. Collecting ground truth data at such fine resolutions would require extensive field measurements or monitoring stations, which can be impractical and costly, especially for large-scale studies. Consequently, the availability of high-resolution ground water level data that directly corresponds to the satellite observations is often limited.

Interpolation methods, although commonly used to increase the resolution of ground water level data, present their own challenges. Applying interpolation techniques to achieve a matching resolution can incur high computational costs and introduce potential issues such as inaccuracies and artifacts in the interpolated data. Striking the right balance between resolution and computational efficiency is essential in achieving accurate and efficient groundwater level estimations

In the subsequent section, we describe the data ingestion pipeline, where we address the resolution considerations and outline the steps taken to prepare the satellite data for training the U-Net model

3.2.3 Dataset Preparation : In this section, we will discuss the process of Data Acquisition and Preparation, which plays a vital role in generating the training and evaluation datasets utilized in our study. To construct the training dataset, a subset of approximately 10,000 points was randomly selected from the states of Uttar Pradesh, Madhya Pradesh, Rajasthan, and Haryana. For

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each sampled point, satellite data (inputs) and corresponding groundwater level data (targets) within a (256 x 256) pixel neighborhood centered around the point were collected, forming the training dataset. The selection of these states and the random sampling approach ensures representation from diverse geographical regions within the Ganga River Basin.

Similarly, for the creation of the evaluation dataset, around 5,000 points were randomly sampled from the states of Delhi, Chattisgarh, and West Bengal. The evaluation dataset follows the same data collection and processing methodology as the training dataset, ensuring consistency in the evaluation process.

Figure 4 illustrates the regions from which the points were sampled to create the training and evaluation datasets. The regions used for creating the training dataset are depicted in red, while the regions for the evaluation dataset are highlighted in blue.

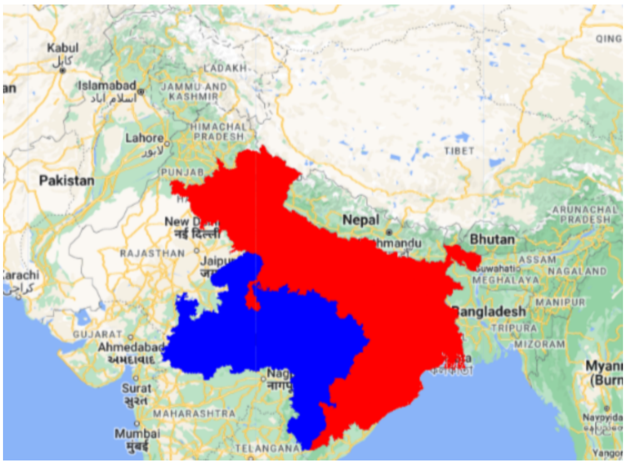

Figure 4: Sampling Regions for Training and Evaluation Datasets in the Ganga River Basin.

3.3 Training and Evaluation Results:

The U-Net model was trained on an NVIDIA A100 GPU for a total of 20 hours using the curated training dataset. An adaptive learning rate strategy was employed to optimize the model's convergence. Following training, the model was evaluated using standard regression metrics. The evaluation results demonstrated promising performance, with a mean absolute error (MAE) of 6.3 meters, a root mean squared error (RMSE) of 8.3 meters. These metrics indicate the accuracy and reliability of the model's predictions on unseen data, highlighting the effectiveness of our approach.

By implementing this methodology, we achieved precise and robust estimations of groundwater levels by leveraging the U-Net model's ability to extract relevant features from combined satellite images. The interpolating groundwater level data using the IDW method allowed for comprehensive estimates across India. This research contributes to improved understanding and monitoring of groundwater resources [Gido et al., 2020].

4. RESULTS AND DISCUSSION

In this section, we present the results and observations derived from our study on estimating groundwater levels using integrated satellite datasets and ground truth data within the Ganga River Basin. Through comprehensive analysis of our dataset, we have gained valuable insights into the temporal trends of groundwater

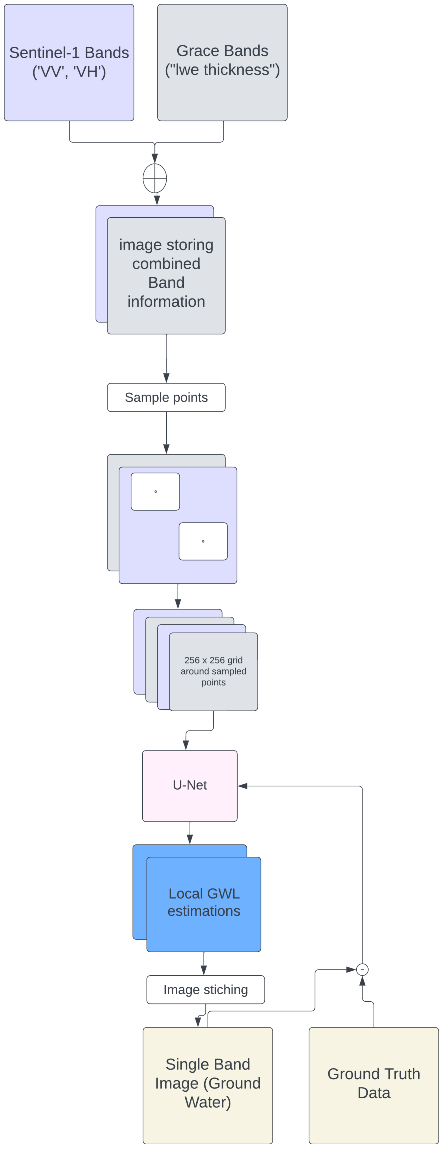

Figure 5: Training Pipeline

levels in the study area. These findings contribute to a deeper understanding of the hydrological dynamics and provide crucial information for effective water resource management and planning.

4.1 Spatial and Temporal Variations

In our study, we examined the groundwater levels recorded during specific periods: May 2016, Aug 2016, Nov 2016, and Jan 2017. These time intervals were chosen to capture seasonal variations in the data. Figure 4 illustrates the spatial distribution of groundwater levels during these months, providing insights into the observed values across the study area. From the spatial distribution of groundwater levels in the study area during these time periods, we made several notable observations. Firstly, we observed that the region near Delhi exhibited the highest groundwater levels among the sampled months. This finding can be attributed to the data collection methodology, which primarily relied on well data. Wells in the Delhi region recorded comparatively higher groundwater levels, contributing to this observation.

Furthermore, an important observation was made regarding the groundwater levels in Assam during May. It became apparent

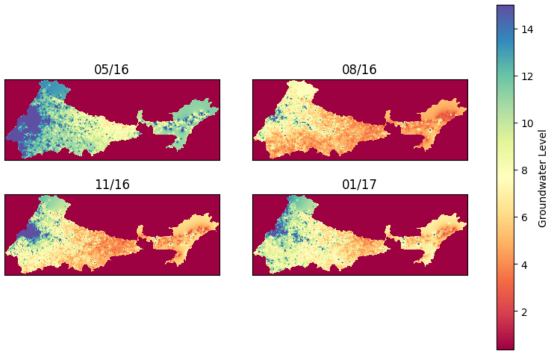

Figure 6: Spatial Distribution of Groundwater Levels in the Study Area: May 2016, Aug 2016, Nov 2016, and Jan 2017

that groundwater levels in Assam were notably higher during this month, which can be explained by the heavy rainfall experienced in the region during the monsoon season of 2016.

In addition to the spatial variations observed in the dataset, distinct seasonal trends in groundwater levels were identified. The month of May consistently showed higher recorded groundwater levels compared to the other sampled months. Following May, there was a sharp decline in groundwater levels during August. However, from November to January, there was a gradual increase in groundwater levels.

These observed variations in groundwater levels align with the temporal patterns of precipitation. The higher recorded groundwater levels in May follows the peak of the precipitation season, which typically occurs in April. During this time, increased rainfall contributes to enhanced recharge of the aquifers, resulting in higher groundwater levels in following months.

Conversely, the decline in groundwater levels during August an be attributed to higher evaporation rates and reduced recharge from precipitation. The subsequent gradual increase in groundwater levels from November to January may be attributed to the rising precipitation levels during this period.

These observations highlight the dynamic nature of groundwater fluctuations, influenced by the interplay between precipitation and evaporation. The findings underscore the importance of considering both factors when assessing and managing groundwater resources.

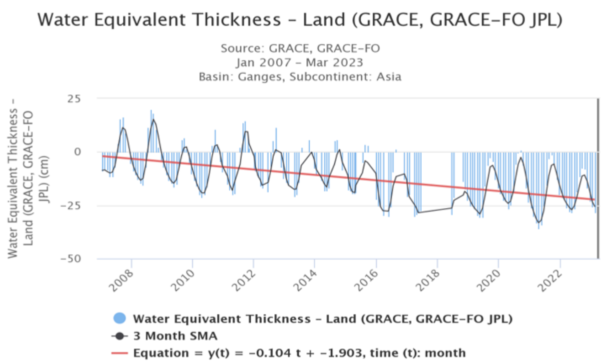

Figure 7: Water Equivalent Thickness- Land (GRACE, GRACE-FO JPL)

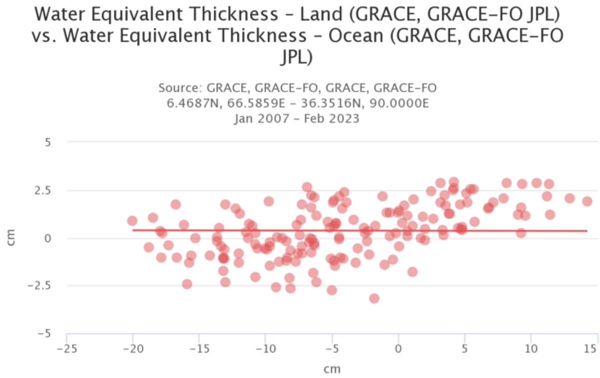

Figure 8: Water Equivalent Thickness- Land vs Water Equivalent Thickness- Ocean (GRACE, GRACE-FO JPL)

4.2 Water Equivalent Thickness Land - Ocean using GRACE, GRACE - FO JPL

To estimate the Water Equivalent Thickness over land, the GRACE and GRACE-FO missions use mathematical algorithms and models to process the gravity data and convert them into water storage variations. These variations are then represented in terms of equivalent thickness of water, usually in centimeters or millimeters.

Groundwater monitoring and hydrological basin mapping are two essential applications of GRACE and GRACE-FO data. By tracking changes in water storage over time, these missions provide valuable information for understanding groundwater depletion or replenishment rates, hydrological cycle dynamics, and water resource management.

When it comes to comparing Water Equivalent Thickness between land and ocean, there are some key differences:

Land Water Equivalent Thickness: This represents the mass of water stored in various land regions, including soil moisture, snow, and groundwater. Changes in land WET can be influenced by factors such as precipitation, evapotranspiration, and human activities like irrigation and dam construction.

Ocean Water Equivalent Thickness: This refers to the mass of water stored in the oceans. It includes variations in ocean mass due to processes like thermal expansion, melting glaciers and ice sheets, and ocean currents. Changes in ocean WET are particularly relevant for studying sea level rise and its contribution to climate change.

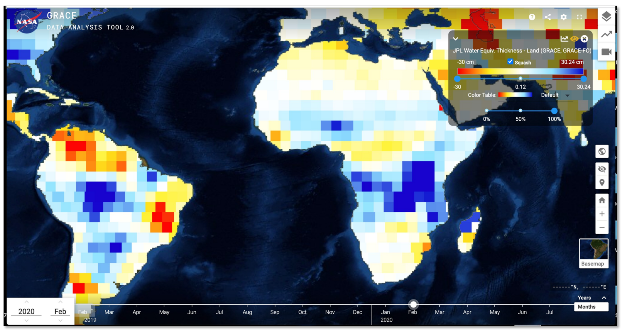

Figure 9: JPL GRACE Data Analysis Tool

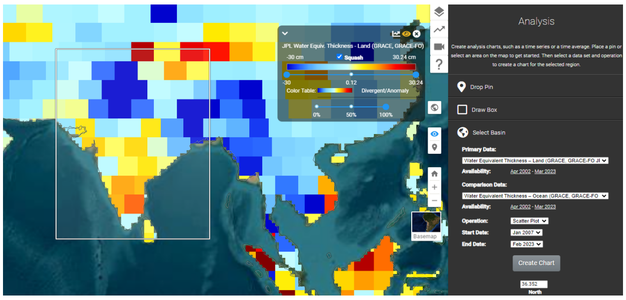

Figure 10: JPL GRACE Data Analysis Tool

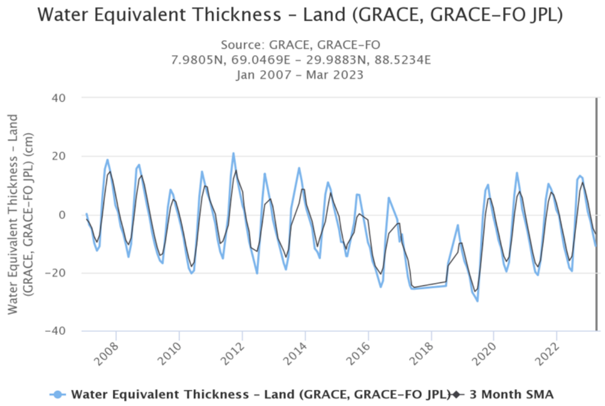

Figure 11: Water Equivalent Thickness- Land (GRACE, GRACE-FO JPL)

5. CONCLUSION

In conclusion, from using satellite datasets Sentinel-1, GRACE and GRACE-FO, it is possible to compare time-series and spatio-temporal changes in groundwater storage over time.

By utilizing WET data from GRACE and GRACE-FO, it is possible to quantify changes in water storage, including groundwater, across the Ganga River Basin. WET provides a valuable measure of the overall water availability and can help identify areas experiencing significant groundwater depletion or replenishment.

In the context of groundwater monitoring, U-Net can be utilized to process satellite imagery, such as SAR data from Sentinel-1, and extract relevant information related to groundwater extent and dynamics. By training the U-Net model on labeled data, it can learn to accurately segment and analyze the groundwater features, enabling more automated and efficient groundwater monitoring. By integrating WET data from GRACE and GRACE-FO, Sentinel-1 SAR data, and utilizing the U-Net deep learning architecture, scientists and water resource managers can benefit from a multi-faceted approach to groundwater monitoring in the Ganga River Basin. This integrated approach allows for a comprehensive assessment of both large-scale and localized variations in groundwater storage, facilitating sustainable groundwater management and decision-making process [Vasco et al., 2022].

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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REFERENCES

Gido, N. A., Amin, H., Bagherbandi, M. and Nilfouroushan, F., 2020. Satellite monitoring of mass changes and ground subsidence in sudan's oil fields using grace and sentinel-1 data. Remote Sensing 12(11), pp. 1792.

Liu, Z., Liu, P.-W., Massoud, E., Farr, T. G., Lundgren, P. and Famiglietti, J. S., 2019. Monitoring groundwater change in california's central valley using sentinel-1 and grace observations. Geosciences 9(10), pp. 436.

Massoud, E., Shaban, A., Liu, Z. and Hage, M. E., 2022. Using information from remote sensing to estimate groundwater: Grace and sentinel-1 satellites. In: Satellite Monitoring of Water Resources in the Middle East, Springer, pp. 273–286.

Ojha, N., Sharma, A., Kumar, M., Girach, I., Ansari, T. U., Sharma, S. K., Singh, N., Pozzer, A. and Gunthe, S. S., 2020. On the widespread enhancement in fine particulate matter across the indo-gangetic plain towards winter. Scientific reports 10(1), pp. 5862.

Ramjeawon, M., Demlie, M. and Toucher, M., 2022. Analyses of groundwater storage change using grace satellite data in the usutu-mhlatuze drainage region, north-eastern south africa. Journal of Hydrology: Regional Studies 42, pp. 101118.

Rateb, A. and Kuo, C.-Y., 2019. Quantifying vertical deformation in the tigris–euphrates basin due to the groundwater abstraction: Insights from grace and sentinel-1 satellites. Water 11(8), pp. 1658.

Taneja, G., Pal, B. D., Joshi, P. K., Aggarwal, P. K. and Tyagi, N. K., 2019. Farmers' preferences for climate-smart agriculture—an assessment in the Indo-Gangetic Plain. Springer.

Tripathi, A., Reshi, A. R., Moniruzzaman, M., Rahaman, K. R., Tiwari, R. K. and Malik, K., 2022. Interoperability of-band sentinel-1 sar and grace satellite sensors on psinsar-based urban surface subsidence mapping of varanasi, india. IEEE Sensors Journal 22(21), pp. 21071–21081.

Vasco, D. W., Kim, K. H., Farr, T. G., Reager, J., Bekaert, D., Sangha, S. S., Rutqvist, J. and Beaudoing, H. K., 2022. Using sentinel-1 and grace satellite data to monitor the hydrological variations within the tulare basin, california. Scientific reports 12(1), pp. 1–14.