DEEP AND MACHINE LEARNING FOR MONITORING GROUNDWATER STORAGE BASINS AND HYDROLOGICAL CHANGES USING THE GRAVITY RECOVERY AND CLIMATE EXPERIMENT (GRACE) SATELLITE MISSION AND SENTINEL-1 DATA FOR THE GANGA RIVER BASIN IN THE INDIAN REGION.

Kayithi Naga Sai[a], Abhinav Galodha[b*], Parnika Jain[c], Deepak Sharma[d]

[a] Department of Mechanical Engineering, IIT Delhi, @nagasaikayithi@gmail.com
[b] School of Interdisciplinary Studies, Indian Institute of Technology, IIT Delhi, @abhinavgalohda@gmail.com
[c] The Neerja Modi School, Jaipur, Rajasthan, India, @per.pan472@gmail.com
[d] Department of Biochemical Engineering and Biotechnology, IIT Delhi, @deepak30821@gmail.com

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KEY WORDS: Visual Transformers (ViT); VGG (Very Deep Convolutional Networks); U-Net; ground water level mapping; groundwater level variations; groundwater monitoring; spatio-temporal analysis; geophysics; Indo-Gangetic basin; Sentinel-1; Gravity Recovery and Climate Experiment (GRACE).

ABSTRACT:

Accurate estimation of groundwater levels in river basins is paramount for hydro-geological research and sustainable water resource management. In this paper, we introduce a deep learning framework explicitly developed for precise groundwater level estimation in the Ganga River Basin. Leveraging the combined band information of Sentinel-1 synthetic aperture radar (SAR) and GRACE satellite data, our approach capitalizes on the trans-formative capabilities of Vision Transformers (ViT) and their variants, with a particular focus on Swin-Transformer variant enriched with Normalization Attention Modules (NAMs).To address the unique challenges of the Ganga River Basin, we curated a comprehensive dataset, forming a robust foundation for training computer vision models tailored to this distinct geographical region. Through rigorous experiments, our state-of-the-art Vision Transformers demonstrated significant potential in groundwater level estimation, with the Swin-Transformer NAM-based model achieving an outstanding Mean Absolute Error (MAE) of 1.2. These remarkable results surpass conventional methodologies and underscore the substantial advancements achieved through advanced transformer-based architectures in this domain. Moreover, this research contributes a robust dataset for future endeavours, fostering further advancements in groundwater estimation and related fields. This study represents a substantial step towards advancing sustainable groundwater utilization practices in the Ganga River Basin and beyond.

1. INTRODUCTION

1.1 Background and General Introduction

The Ganga River Basin, spanning over 700 thousand square kilometres, represents a critical groundwater resource in the Indian subcontinent. With the Ganges River as its lifeline, this vast river system plays a pivotal role in sustaining ecosystems and supporting the livelihoods of millions of people. Groundwater in the Ganga River Basin is a vital freshwater source, fulfilling agricultural, domestic, and industrial needs while nurturing the region's diverse flora and fauna.

However, recent studies have sounded an alarm over the declining groundwater levels in this region, necessitating immediate attention and effective management strategies. Studies conducted by [Janardhanan et al., 2023] and [Chinnasamy, 2017] have reported a concerning decrease in groundwater levels in various parts of the Ganga River Basin. These findings highlight the impacts of human activities, such as excessive groundwater extraction for irrigation and urbanization, leading to an imbalance in the basin's water budget. Moreover, [Dangar and Mishra, 2021] demonstrated that climate change is also contributing to the declining groundwater levels in the region. Changing precipitation patterns and rising temperatures affect surface water availability, altering the dynamics of groundwater recharge and discharge processes.

Such a substantial decline in groundwater levels calls for innovative and comprehensive approaches to monitor and manage this vital resource effectively. Conventional groundwater level estimation methods, often reliant on localized measurements, may not suffice to capture the complex spatial and temporal variations within the basin. As a result, there is a growing interest in exploring advanced data-driven approaches that harness the wealth of satellite data to provide a more holistic understanding of groundwater dynamics.

Here, we propose a deep learning framework to estimate the groundwater levels from Sentinel-1 Interferometric Synthetic Aperture Radar (InSAR) observations and terrestrial water storage (TWS) changes measured from NASA's Gravity Recovery and Climate Experiment (GRACE) and GRACE Follow-on (FO) missions, all of which are sensitive to hydrologic variations in the study area. Our approach harnesses the trans-formative capabilities of Vision Transformers (ViT) [Wang et al., 2022] and their variants, Particularly focusing on enhancing the Swin-Transformer variant [Gong et al., 2022] with the integration of Normalization Attention Modules (NAMs) [Liu et al., 2021].

As part of our methodology, we curated a comprehensive dataset comprising the combined information of Sentinel-1 and GRACE satellite data and the ground truth data for the groundwater levels at various locations across the study area. This dataset forms a robust foundation for training and validating our models, tailored to the distinct characteristics and challenges of the Ganga River Basin.

* Corresponding author
The authors Sai and Galodha are equal contributors.

Through rigorous experimentation and analysis, we present in-depth results of our model development and training in the following sections. Our approach seeks to deliver accurate and efficient estimates of groundwater levels, allowing us to gain deeper insights into groundwater dynamics through advanced data-driven techniques. By doing so, we strive to significantly contribute to the sustainable management of this invaluable natural resource in the Ganga River Basin and extend our findings to benefit beyond its boundaries.

2. STUDY AREA AND DATA-SETS

2.1 Study area:

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 several 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].

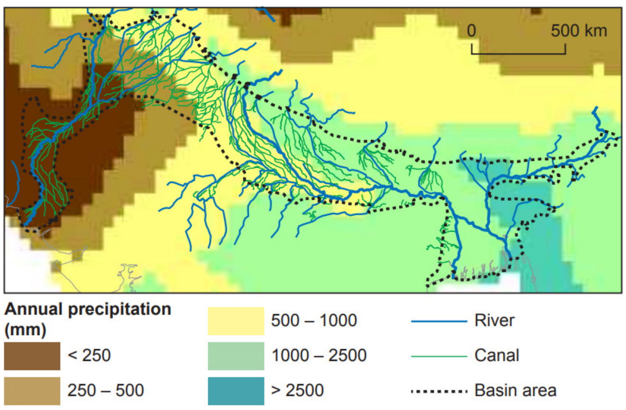

Figure 1: Catchment Area of Indo- Gangetic Basin

2.2 Datasets

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.

- Gravity Field Mapping: The GRACE and GRACE-FO satellites use a twin-satellite system to measure tiny variations in Earth's gravity field. As groundwater changes result in mass re-distributions, they cause minute alterations in the gravity field, which these satellites can detect.
- Terrestrial Water Storage Changes: The data from GRACE and GRACE-FO are used to estimate changes in terrestrial water storage, which include groundwater variations. Scientists can infer groundwater changes in large basins over regional and global scales.
- Complementary to InSAR: GRACE and GRACE-FO data offer a broader perspective on groundwater variations across extensive regions. Combining both datasets enhances the accuracy and coverage of groundwater estimation.
- Long-Term Monitoring: GRACE and GRACE-FO provide long-term time series data, allowing for observing groundwater trends and seasonal variations over several years.

Sentinel-1 for Groundwater Estimation: Sentinel-1, equipped with synthetic aperture radar (SAR) instruments, plays a crucial role in groundwater estimation and monitoring. The satellite's SAR data offers several advantages for this purpose:

- All-Weather and Day-Night Observations: Sentinel-1 can acquire data regardless of weather conditions, both during the day and at night. This is essential for groundwater estimation, as clouds and darkness do not affect data acquisition.
- Repeatability and Frequent Coverage: Sentinel-1 has a short revisit time, providing frequent coverage of the same area. This characteristic is valuable for tracking temporal variations in groundwater levels and detecting short-term changes.
- Interferometric Synthetic Aperture Radar (InSAR): InSAR, a technique utilized by Sentinel-1, enables the precise measurement of ground surface displacements. It can detect changes in the Earth's surface with high accuracy, including subsidence and uplift, which are often associated with groundwater depletion or recharge.
- Surface Deformation Monitoring: By comparing SAR images acquired at different times, InSAR can detect and quantify ground surface deformations caused by changes in groundwater levels. This information is crucial for assessing the aquifer's response to pumping and natural recharge.
- Groundwater Mapping: SAR data can also be used for mapping surface water bodies and monitoring their extent and variations, which is essential for understanding interactions.
- Thus, Sentinel-1 The ground surface displacements in InSAR datasets are precisely measured using radar technology. 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.

Combining the data from Sentinel-1 and GRACE/GRACE-FO provides a powerful and complementary approach to groundwater estimation. The high-resolution surface deformation data from Sentinel-1, along with the regional-scale groundwater variations inferred from GRACE/GRACE-FO, offer a comprehensive understanding of groundwater dynamics in large basins like the Indo-Gangetic Basin, enabling better water resource management and

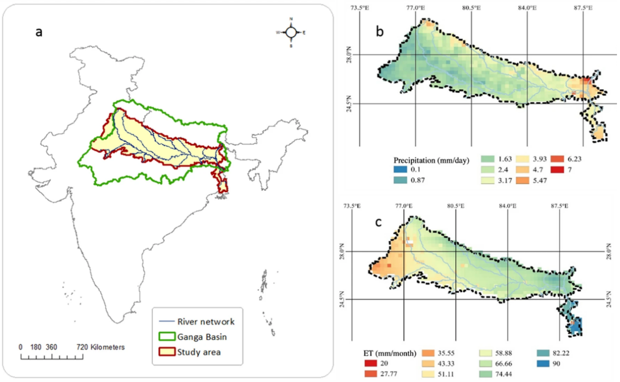

Figure 2: (a) Location of the study area within the Ganga Basin. (b) Mean precipitation during a period of 14 years from 2003 to 2016. (c) Mean evapotranspiration during a period of 14 years from 2003 to 2016.

sustainable planning. Researchers can comprehensively understand groundwater dynamics, ranging from large-scale trends to localized effects.

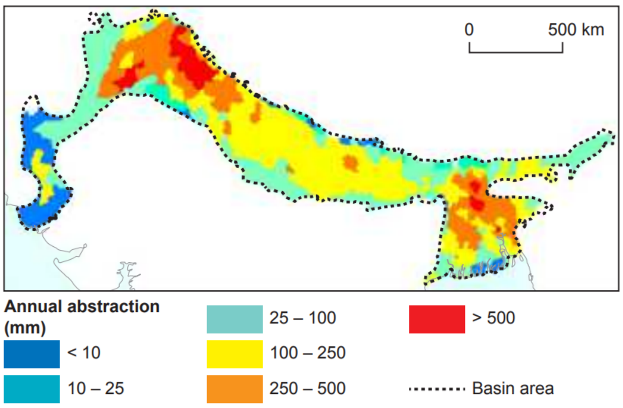

Figure 3: Annual changes in Groundwater water level limit in catchment sites

3. METHODOLOGY

3.1 Data Compilation and Preprocessing:

Accurate estimation of groundwater levels is of paramount importance for understanding hydrological dynamics and making informed decisions in geospatial applications. In this section, we detail the rigorous process of compiling a comprehensive dataset tailored to meet the specific requirements of our study. The dataset is curated to encompass groundwater level observations, spanning a vast network of nearly 45,000 sites across India, and captured at different time intervals from May 2016 to May 2017.

3.1.1 Integration of Satellite Data: Our methodology incorporates two important satellite datasets, Gravity Recovery and Climate Experiment (GRACE) and SENTINEL-1, to augment the groundwater level estimation process. Combining data from these sources has shown improved predictive performance compared to using each dataset separately. Below, we elucidate the significance of the data derived from each satellite dataset and its contribution to our final predictions

GRACE Satellite Data : The GRACE satellite data provides valuable insights into changes in terrestrial water storage (TWS) through gravimetric observations. By examining variations in the gravity field, we can infer changes in water mass, including groundwater, soil moisture, fluctuations in the water table, and snow cover. The integration of GRACE data enhances our comprehension of hydrological dynamics, facilitating a more accurate estimation of groundwater levels. It is important to note, however, that predicting groundwater levels solely based on GRACE data can be challenging. Many factors, such as changes in snow cover, soil moisture levels, water table fluctuations, and ground movement, influence gravity field variations [Liu et al., 2019].

SENTINEL-1 Satellite Data: The utilization of Interferometric Synthetic Aperture Radar (InSAR) data from the SENTINEL-1 satellite, proficient in estimating ground deformations with high precision [Raspini et al., 2018], presents a robust and valuable resource in isolation. The InSAR technology enables the observation and monitoring of localized surface deformations over time, providing essential insights into hydrological changes, including fluctuations in groundwater levels. When integrated with gravimetric observations, using SENTINEL-1 and GRACE datasets offers a robust and comprehensive approach to assess, understand, and estimate ground-water fluctuations with improved accuracy and resolution. However, it is crucial to acknowledge that despite the benefits, the intricate relationship between surface deformations and ground-water level changes, influenced by diverse factors such as subsurface geological features and complex hydrological dynamics, necessitates the integration of complementary data sources and models to achieve reliable and precise ground-water level estimation. [Castellazzi et al., 2016].

By combining these two datasets, We have effectively avoided any constraints encountered in individual datasets and attained a more thorough understanding of hydrological fluctuations [Vasco et al., 2022]. While SENTINEL-1 data permits the detection of localized surface deformations, GRACE data provides a broader perspective on changes in water mass. Our ability to correctly estimate groundwater levels and produce geo-spatial maps representing changes along the study area is made possible by interlinking identified satellite datasets [Ramjeawon et al., 2022].

3.2 Deep Learning Model:

In this section, we outline our approach to groundwater level estimation using Vision Transformers, a class of deep-learning models known for their remarkable performance in computer vision tasks. Building upon the comprehensive dataset compiled from various sources, including GRACE and SENTINEL-1 satellite datasets, we integrate multi-modal information and leverage the power of Vision Transformers to achieve accurate and continuous groundwater level predictions.

3.2.1 Vision Transformers for Geo-Spatial Data: The Vision Transformers (ViTs) are advanced deep-learning models for image-related tasks. Unlike traditional Convolutional Neural Networks (CNNs), ViTs leverage self-attention mechanisms to efficiently capture spatial relationships and dependencies within images. By dividing the input satellite image into smaller patches and applying self-attention across all patches, ViTs can effectively learn complex patterns and contextually relevant information. Their ability to efficiently capture global contextual information makes them well suited for processing satellite imagery which is essential for understanding large-scale scenes and complex patterns in remote sensing data. [Dosovitskiy et al., 2020], [Liu et al., 2019], [Gong et al., 2022] and [Wang et al., 2022].

The ViT model begins by dividing the input satellite image into smaller non-overlapping patches, each representing a local region of the image. These patches are then linearly embedded into a lower-dimensional feature space, reducing computational complexity while retaining essential visual information. To maintain spatial context, positional embeddings are added to the feature vectors, ensuring the model can differentiate between different regions in the image. The core of the ViT model consists of multiple Transformer encoder layers. Each encoder layer incorporates multi-head self-attention mechanisms, enabling the model to attend to various image patches simultaneously. In Figure 4, we provide a visual representation of the internal workings of the Transformer architecture.

Although Vision Transformers performed exceptionally well on the validation dataset. They were not good enough to be used in industrial applications. To further enhance the performance of our models, we incorporate a variant of Vision Transformers known as Swin Transformers (Swin-T). We also had a few modifications to the attention mechanism by using Normalization Attention Modules (NAMs). In the following sections, we will delve into the details of model training and dataset preparation.

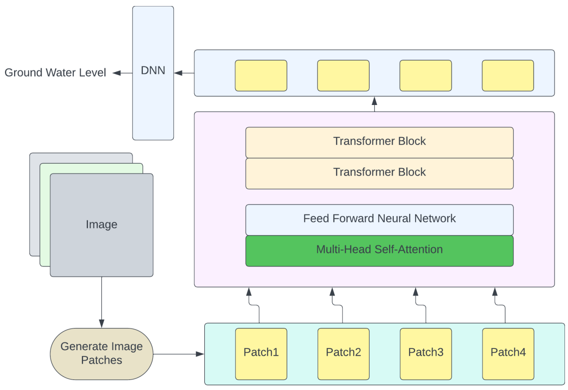

Figure 4: ViT architecture.

3.2.2 Dataset Preparation : The data acquisition and preparation process is a crucial step in generating the training and evaluation datasets used in our study. We randomly selected a subset of approximately 45000 points from the Ganga river basin region to construct the training dataset. For each sampled point, the model peeks into a 256 x 256 window around the sample point and tries to predict the groundwater level at the sampled point. This dataset defines an image regression task which forms the foundation for training our ViT model. We collected the ground truth data from the WRIS, and after careful analysis of the ground truth data, we were able to detect some seasonal patterns in the variations in the groundwater levels.

3.2.3 Model Training Process: In this section, we outline the model training process. Our training involved multiple models, including variations based on ResNet [He et al., 2016], ViT, and Swin-ViT architectures, each undergoing 30 epochs of training on NVIDIA P100 GPUs, taking approximately 20 - 25 hours per model. Through this rigorous training and evaluation, we aimed to identify the most suitable approach for accurate groundwater level estimation from satellite imagery. The results obtained from our trained models will be presented and discussed in the following sections. [Tripathi et al., 2022].

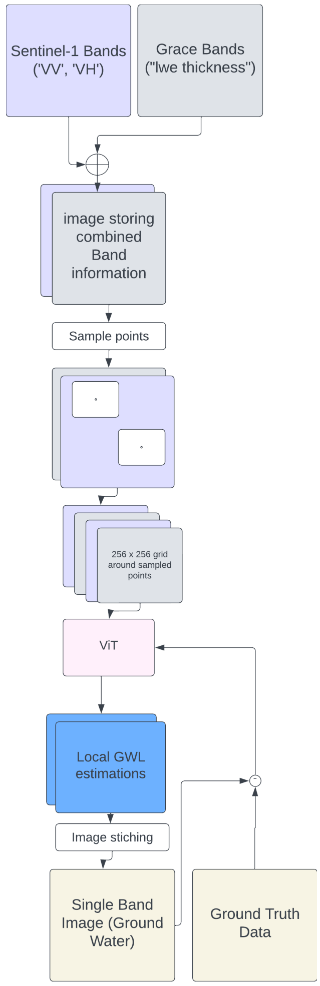

Figure 5: Training Pipeline

3.3 Training Pipeline:

In this section, we provide an overview of our deep-learning models' training pipeline used in the study. The training process involved rigorous dataset preparation, data collection, and pre-processing steps, as described in previous sections. Leveraging this dataset, several models were trained on an NVIDIA TESLA P100 GPU, optimizing model parameters by minimizing Mean Squared Error (MSE) as the loss function. The training spanned 20 epochs to ensure ample exposure to the dataset and facilitate the learning of intricate patterns and relationships. For a comprehensive evaluation, we employed Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) as performance metrics. Figure 5 illustrates the comprehensive training pipeline, covering data preprocessing, model training, and evaluation. [Gido et al., 2020].

4. RESULTS AND DISCUSSION

4.1 Spatial and Temporal Variations

The analysis of the compiled dataset reveals intriguing spatial and temporal variations in groundwater levels across diverse regions and time-frames. Spatially, we observe distinct patterns of groundwater fluctuations, with some areas exhibiting higher groundwater levels than others. These variations can be attributed to geological differences, land use practices, and local hydrological conditions.

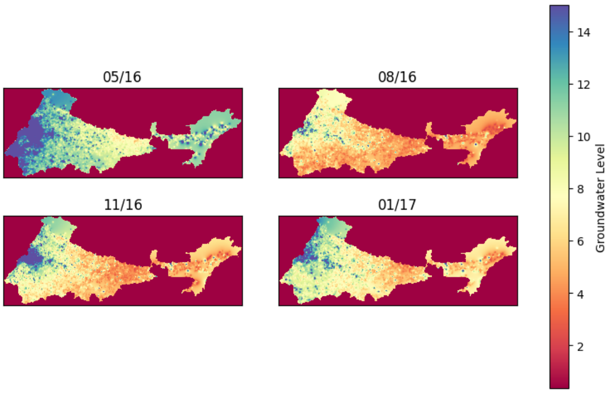

Figure 6: Spatial Variation of Groundwater Levels

Figure 6 provides a visual representation of the spatial distribution of groundwater levels during the months 05/16, 08/16, 11/16, and 01/17. For visualization purposes, the groundwater levels have been clipped to 0 - 14, while the original dataset used for training contains levels in a broader range of 0 - 192.8. Notably, the data highlights that groundwater levels in Delhi exhibit significantly lower values than in other regions, indicating potential water scarcity challenges in the area. Additionally, from August 2016 to November 2016, specific regions, including parts of Assam and most of Bihar and Jharkhand, had sustained their groundwater levels despite the steep drop in the other regions. This observation can be attributed to the impact of the massive flood of the Ganga River that occurred between 18 and 31 August 2016.

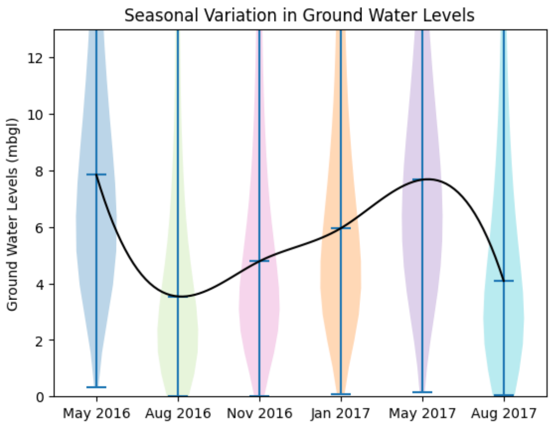

Figure 7: Temporal Variation of Groundwater levels.

Temporally, a clear seasonal pattern is observed for groundwater levels across the different months used in this study, reflecting the influence of climatic and hydrological factors on groundwater dynamics. Furthermore, to gain a comprehensive understanding of the temporal variations, Figure 7 presents violin plots of groundwater levels across different months. From the figure, we can observe the distinct seasonal pattern closely resembling the sinusoidal variation underlying the dynamics of groundwater levels, further validating the impact of climatic changes on the groundwater system.

4.2 Groundwater Level Estimation Results

We present the results of groundwater level estimation using our deep learning models based on ViT, Swin-ViT, and ResNet architectures. Each model underwent rigorous training on the NVIDIA P100 GPU, utilising its computational capabilities. To assess the performance of our models, we employed RMSE and Mean Absolute Error (MAE) as evaluation metrics, while MSE was used as the loss function during the training process.

Figure 8 illustrates the MAE values achieved by each model on the validation dataset. From the figure, we can observe the different model's performance in capturing the discrepancies between the predicted and actual groundwater levels. Lower RMSE values indicate better performance.

In Figure 8, The ResNet and ViT are trained to estimate the groundwater levels by relying on the sentinel-1 images. The ViT* model is trained using Sentinel-1 and GRACE satellite images. To leverage the distribution of the groundwater levels in the dataset (where more than 90% of the data points have a groundwater level not more than 25.), We trained a ViT and Swin-T on a restricted dataset with groundwater levels under 25, denoted as ViTˆ and SwinT in Figure 7. The results demonstrate the model's competence in accurately estimating groundwater levels within this range.

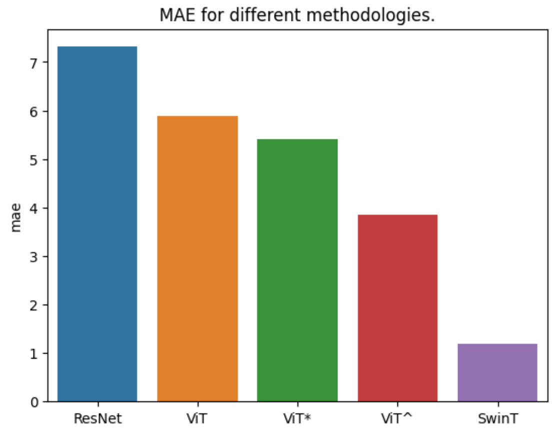

Figure 8: Mean Absolute Error of Different Models for Ground Water Level Estimation.

The analysis reveals that the ViT architecture, trained solely on Sentinel-1 images, and the ViT* model, incorporating both Sentinel-1 and GRACE satellite images, perform well in estimating groundwater levels compared to ResNet, trained solely on Sentinel-1 images. The band information from the GRACE images proved to be valuable in enhancing the accuracy of the predictions. Additionally, we observed a significant improvement in performance with the integration of the Swin-T architecture and NAMs, underscoring the power of these innovations in groundwater level estimation.

4.3 Discussion

In this section, we evaluate the strengths and limitations of each deep learning model for groundwater level estimation. The remarkable performance of ViT and Swin-ViT models demonstrates the efficacy of self-attention mechanisms in handling spatial dependencies within satellite imagery, surpassing traditional CNN-based approaches like ResNet.

Furthermore, the integration of Swin-ViT and NAMs showcases the potential of innovative transformer-based architectures and feature normalization techniques to enhance model performance, paving the way for further advancements in geospatial analysis and hydrological modelling. Our findings, along with spatial-temporal visualizations, provide valuable insights into applying deep learning models for accurate groundwater level estimation from satellite imagery. These contributions advance geospatial analysis and hydrological research, with implications for sustainable water resource management and environmental studies.

5. CONCLUSION

In conclusion, our research presents a specialized deep-learning framework for precise groundwater level estimation in the Ganga River Basin, leveraging Sentinel-1 SAR and GRACE satellite data. Our approach demonstrates significant potential for addressing declining groundwater levels. Future research can explore temporal dynamics, climate change impacts, and additional datasets to enhance accuracy. Collaborative efforts between geospatial analysis and hydro-geology communities will further advance sustainable groundwater management. Together, we can secure the future of this invaluable resource and support communities and ecosystems reliant on it.

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

Castellazzi, P., Martel, R., Galloway, D. L., Longuevergne, L. and Rivera, A., 2016. Assessing groundwater depletion and dynamics using grace and insar: Potential and limitations. Groundwater 54(6), pp. 768–780.

Chinnasamy, P., 2017. Depleting groundwater–an opportunity for flood storage? a case study from part of the ganges river basin, india. Hydrology Research 48(2), pp. 431–441.

Dangar, S. and Mishra, V., 2021. Natural and anthropogenic drivers of the lost groundwater from the ganga river basin. Environmental Research Letters 16(11), pp. 114009.

Dosovitskiy, A., Beyer, L., Kolesnikov, A., Weissenborn, D., Zhai, X., Unterthiner, T., Dehghani, M., Minderer, M., Heigold, G., Gelly, S. et al., 2020. An image is worth 16x16 words: Transformers for image recognition at scale. arXiv preprint arXiv:2010.11929.

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.

Gong, H., Mu, T., Li, Q., Dai, H., Li, C., He, Z., Wang, W., Han, F., Tuniyazi, A., Li, H. et al., 2022. Swin-transformer-enabled yolov5 with attention mechanism for small object detection on satellite images. Remote Sensing 14(12), pp. 2861.

He, K., Zhang, X., Ren, S. and Sun, J., 2016. Deep residual learning for image recognition. In: Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 770–778.

Janardhanan, S., Nair, A. S., Indu, J., Pagendam, D. and Kaushika, G., 2023. Estimation of groundwater storage loss for the indian ganga basin using multiple lines of evidence. Scientific Reports 13(1), pp. 1797.

Liu, Y., Shao, Z., Teng, Y. and Hoffmann, N., 2021. Nam: Normalization-based attention module. arxiv. arXiv preprint arXiv:2111.12419.

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.

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.

Raspini, F., Bianchini, S., Ciampalini, A., Del Soldato, M., Solari, L., Novali, F., Del Conte, S., Rucci, A., Ferretti, A. and Casagli, N., 2018. Continuous, semi-automatic monitoring of ground deformation using sentinel-1 satellites. Scientific reports 8(1), pp. 7253.

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.

Wang, H., Xing, C., Yin, J. and Yang, J., 2022. Land cover classification for polarimetric sar images based on vision transformer. Remote Sensing 14(18), pp. 4656.