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Downscaling GRACE Data for Improved Groundwater Forecasting Using Artificial Neural Networks

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Abstract

This study introduces a dual-phase approach utilizing Artificial Neural Networks (ANNs) to overcome the challenges of groundwater monitoring at regional scales. Traditional well-based methods provide limited spatial coverage, while GRACE satellite data, despite its value for large-scale hydrological analysis, suffers from low spatial resolution (~300 km), limiting its application for local-scale assessments. Existing downscaling methods such as geographically weighted regression and Random Forests are computationally intensive and often lack adaptability to complex groundwater systems. In this study, Phase 1 refines GRACE data using ANNs to achieve a 4×4 km spatial resolution, addressing the resolution challenge for regional applications. Phase 2 integrates the downscaled GRACE data with groundwater well observations and climatic factors to predict groundwater levels with high accuracy (R^2 = 0.9885). This dual-phase framework demonstrates significant improvements over existing methods, providing an efficient and scalable solution for groundwater monitoring in hydrologically complex regions. The findings highlight the potential of machine learning to enhance groundwater resource management, particularly in addressing water scarcity and climate variability challenges.

Keywords: Artificial Neural Networks; GRACE Data; Downscaling; Groundwater Level.

1. Introduction

The water composition of the Earth consists of approximately 97.5% seawater and 2.5% freshwater. A substantial amount of this freshwater is found in subsurface aquifers, holding approximately 100 times more freshwater than that found in rivers and lakes [1]. Mississippi is one of the most dependent states for groundwater, and even then, management is essential for sustaining communities globally [2]. Groundwater management is essential for sustaining communities globally. It serves as the primary water source for agriculture, domestic consumption, and industrial use. [3, 4]. In recent decades, the reliance on groundwater has increased due to climate change, population growth, and factors like energy cost and socio-environmental issues, leading to a doubling of groundwater depletion [5-7]. In the southwest of the United States (US), factors like population increase, urbanization, agricultural growth, and drought has negatively affected the groundwater supplies [8]. Therefore, it is important to monitor groundwater continuously in order to manage this limited supply of fresh water.

In the United States, traditionally, groundwater levels have been tracked through well monitoring or on-site measurements. The United States Geological Survey (USGS) plays a significant role in this process. They reported that

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there were more than 850,000 active monitoring wells in the United States, which aids this purpose [9, 10]. Despite the large number of monitoring wells distributed throughout the US, which provide information about long- and short-term groundwater levels, there remains a need for more monitoring wells to better understand underground water level trends [9, 11, 12]. In contrast, many regions outside the United States face even greater challenges due to a lack of adequate monitoring infrastructure. Existing monitoring wells in these areas often suffer from unreliable data caused by inadequate spatial and temporal coverage, making it difficult to obtain a comprehensive understanding of groundwater dynamics [12, 13]. These limitations highlight the need for alternative methods, such as satellite-based observations, to complement well monitoring and provide continuous, large-scale groundwater data [12, 13].

Continuous, top-notch hydrological data is vital for the efficient and sustainable administration of water resources, as well as for predicting water trends affected by climate change and human actions. The Gravity Recovery and Climate Experiment (GRACE) has played a key role in gathering data on five critical components of the Earth's hydrological cycle: polar ice, soil moisture, storage of surface and groundwater, and the distribution of ocean mass. This satellite program monitors shifts in the Earth's mass, mainly due to water, and converts these observations into Total Water Storage Change (TWSC) data, which indicates anomalies in water mass both on and beneath the Earth's surface. GRACE's capacity to identify gravitational differences caused by water layers as thin as one centimeter over a 300-km area marks a major technological breakthrough. Although initially limited to a spatial resolution of around 300 km, the data from the GRACE program has been essential in researching groundwater storage changes, providing vital insights into the dynamics of groundwater. GRACE allows for the observation of monthly variations in Earth's gravitational potential and provides a unique view of terrestrial water storage variations at a large scale after removing the effects of the ocean and atmosphere [14]. This data is particularly important for evaluating the long-term effectiveness of water management strategies designed to reconcile the differences in water availability and demand across various regions and times [4].

Satellite remote sensing platforms, notably NASA's GRACE program, have been widely utilized to overcome the limitations of inadequate groundwater monitoring data. Many studies have demonstrated that GRACE data, when combined with other data sources, is reliable for monitoring groundwater changes on a large scale [15-19]. However, despite its utility, GRACE data suffers from a low spatial resolution, covering more than 150,000 km² per pixel, which restricts its applicability for small-scale and local hydrological studies [20]. This limitation poses a significant challenge for regions requiring high-resolution groundwater monitoring to address localized water management issues. To address the low spatial resolution issue in GRACE data, various downscaling methods have been explored to enhance its spatial accuracy, enabling its use in regional and local applications. These methods aim to "densify" the satellite-based data and improve its applicability for detailed groundwater assessments.

Recent advancements have expanded the capabilities of GRACE data through various downscaling approaches. Studies such as Arshad et al. [21] have utilized mixed geographically weighted regression models to improve spatial resolution, although these methods can be computationally intensive and region-specific. Techniques involving machine learning frameworks, like in Zuo et al. [22], offer enhanced resolution but may require extensive training datasets and careful calibration to avoid overfitting. Innovations in spatio-temporal assessment and the application of spectral combination methods [23] provide detailed local-scale insights but can be complex to implement and validate, limiting their widespread application. Furthermore, the integration of land surface model outputs [24] and the application of statistical techniques to fill data gaps [25] have shown promising results but require careful handling of error propagation, which may reduce accuracy in complex hydrological settings.

Recent scholarly works have focused on the application of sophisticated machine learning models to downscale GRACE data in the field of study [3, 4, 26-33]. Recent studies, including [34-37], have demonstrated innovative downscaling techniques, underscoring the growing importance of machine learning approaches for addressing groundwater challenges. The downscaling methodologies have been enhanced with the incorporation of approaches like cluster-based extreme gradient boosting [25], which show high accuracy but also highlight the need for careful calibration to prevent overfitting. A noteworthy study conducted by Pulla et al. [38] has shown the capability of machine learning to overcome the challenge of GRACE's limited spatial resolution. The research not only utilized a suite of machine learning models, including Deep Learning, Multi-layer Perceptron, Gradient Boosting Regressor, and k-Nearest Neighbors, but also performed a rigorous statistical and visual analysis of their results. They validated their results against regional water level data [29], providing insights into model accuracy and offering a comprehensive workflow for rapid model development and evaluation. Miro & Famiglietti [39] is one of the first research studies that use Artificial Neural Networks (ANNs) to develop a model to downscale GRACE data to 4 km spatial resolution dataset of groundwater storage change from 2002 to 2010 over a portion of California's Central Valley. Verma & Katpatal [40] also use ANNs model to downscale GRACE to a finer spatial resolution (0.125°) to analyze the groundwater storage anomalies over the Ballistic aquifer system, India, from 2002 to 2016. They report a satisfying regression coefficient as 0.696 to 0.818.

Despite advancements in downscaling methods such as Random Forests, and hybrid machine learning techniques, existing approaches face significant limitations. These include computational inefficiency, limited adaptability to complex hydrological systems, and an inability to achieve the fine spatial resolution needed for local groundwater assessments. GRACE data, while invaluable for large-scale groundwater monitoring, suffers from coarse spatial resolution (~300 km), which restricts its practical use in regions like the Mississippi Delta, where groundwater systems are dynamic and heavily utilized.

To overcome these challenges, this study introduces a dual-phase Artificial Neural Network (ANN) framework. Phase 1 downscales GRACE data to a 4x4 km resolution, addressing the resolution limitation and enabling its application for local-scale monitoring. Phase 2 integrates the downscaled GRACE data with climatic predictors and well observations to predict groundwater levels with high accuracy ($R^2 = 0.9885$). ANNs demonstrate distinct advantages, including adaptability, efficiency in modeling non-linear systems, accuracy, and user-friendliness. Furthermore, due to the large volume of data, the simplicity and reduced computational cost of ANNs offer substantial benefits [41]. This novel approach bridges the gap between global satellite observations and local groundwater management needs, offering an efficient, adaptable, and accurate solution to support sustainable water resource management.

2. Research Methodology

We selected data reflecting key factors influencing groundwater levels, such as precipitation, evapotranspiration, runoff, and soil moisture [42-44]. Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) was chosen for its detailed precipitation data, with its 5 km spatial resolution, and frequent updates (daily to decadal). To capture the full scope of influences on groundwater, we also integrated data from TerraClimate, which provided monthly metrics on additional variables at a high spatial resolution of 4 km. Further details on CHIRPS and TerraClimate data and their integration into our study are provided in the following paragraph. We enhanced GRACE data resolution to create a finer product essential for our ANN's second phase, which predicts the Mississippi Delta's water levels. Below are the datasets we used:

2.1. Data

2.1.1. Study Area

The Mississippi Delta region (hereinafter, the Delta), located in the northwest part of the state of Mississippi (shown in Figure 1) and covering approximately 18,100 km^2, holds the essential lower Mississippi River alluvial aquifer and features a complex hydrological system where the Mississippi River and surrounding bays interact significantly with groundwater, especially during floods and storms. The area is primarily agricultural, with extensive irrigation relying on the Mississippi River Valley alluvial aquifer. Groundwater depletion and surface water decline are critical issues due to over-extraction for irrigation, affecting streamflow and leading to concerns about future water availability [45]. The region's subsurface is characterized by sandy and clayey deposits, providing pathways for groundwater-surface water exchange, which can lead to increased land subsidence and erosion under high pore-water pressure conditions [46].

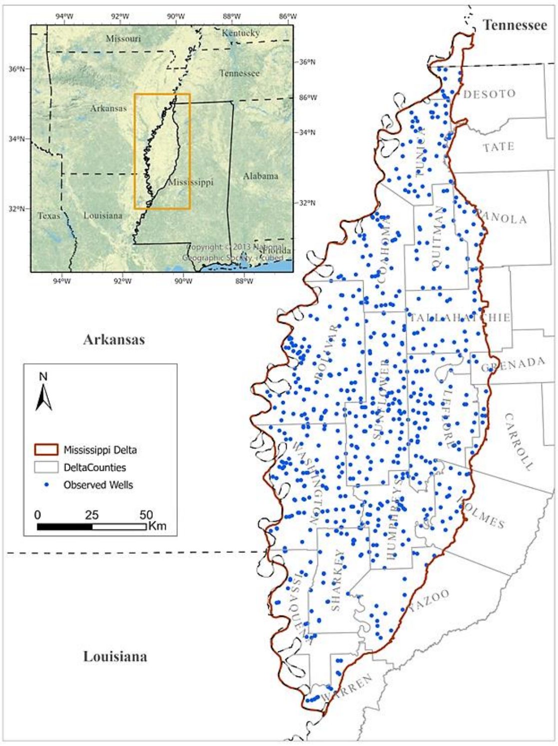


Figure 1. A map showing the Mississippi Delta region with the distribution of the water wells used in this study

2.1.2. GRACE Data

Launched in 2002, the Gravity Recovery and Climate Experiment (GRACE) is a twin satellite system capable of measuring temporal variations in Earth's gravity. These measurements can detect changes in terrestrial water storage after removing oceanic and atmospheric effects [14]. It is essential to note that this study specifically utilized the GRACE mascon monthly products, chosen for their finer spatial resolution compared to standard GRACE data. While the spatial resolution of GRACE mascon data is approximately 56 km, standard GRACE data possesses a spatial resolution of approximately 300 km. The first-order downscaling of the GRACE mascon data was achieved using statistical downscaling approaches. These methods incorporate additional high-resolution information to enhance the spatial accuracy of the GRACE products [29].

2.1.3. Climate Hazards Group Infrared Precipitation with Stations (CHIRPS)

CHIRPS is a near real-time, quasi-global precipitation product. Its high spatial and temporal resolution data (5 km and monthly, respectively) has been available since 1981, making it a valuable resource for long-term precipitation patterns [47]. CHIRPS data serves as an input dataset for the ANNs model, contributing to our efforts in downscaling GRACE data.

2.1.4. TerraClimate

TerraClimate offered a dataset of climate and climatic water balance for global terrestrial surfaces. It included data from 1958 to 2020 (updated annually), with a monthly temporal resolution and a spatial resolution of 4 km [48]. The dataset incorporated several variables that impacted water table levels, such as evapotranspiration and runoff. We utilize different variables listed below in our model: latitude (lat), longitude (lon), time, actual evapotranspiration (aet), climate water deficit (def), palmer drought severity index (pdsi), reference evapotranspiration (pet), precipitation accumulation (pr), downward surface shortwave radiation (srad), runoff (ro), soil moisture (soil), snow water equivalent (swe), and precipitation (prep).

2.2. Methods Approach

In this research, we implemented a two-step approach to predict variations in groundwater levels in the Delta. In Phase 1, we applied an ANNs model to downscale GRACE mascon data enabling us to work with higher-resolution data. For Phase 2, this downscaled data was used with other geographical and climatic variables in a second ANNs model to make groundwater level predictions. We provide a detailed description of each stage, corresponding to the steps shown in Figure 2, in the subsequent sections of this paper.

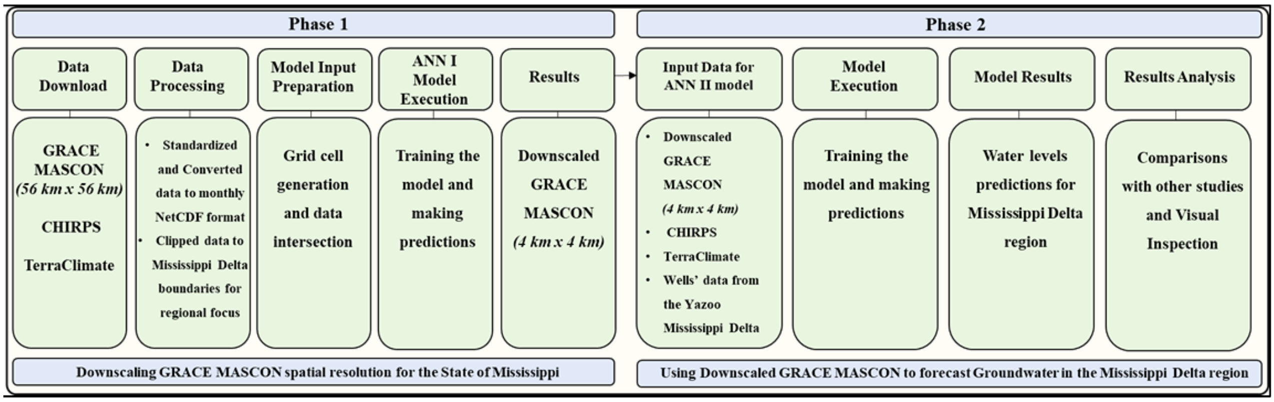


Figure 2. Two-step approach for groundwater prediction in the Mississippi Delta [17]

2.2.1. Data Processing

We matched the monthly averages of climatic variables from the TerraClimate and CHIRPS datasets with the temporal resolution of GRACE data, ensuring coherence across datasets. The harmonization involved refining grid cells to the highest spatial resolution and clipping the data to specifically focus on the Delta boundaries. Data normalization was performed using Python's scikit-learn 'StandardScaler', which standardized our datasets to a mean of zero and a standard deviation of one, tailoring the data for effective assimilation by the ANNs model and enhancing its predictive precision [49]. To validate the model's efficacy, the data was partitioned into training (60%) and testing (40%) sets, in accordance with established machine learning practices [38, 50, 51]. This division supports a robust assessment of the ANNs model's predictive reliability on unseen data.

2.2.2. Development of the First Phase ANNs model

In the first phase of this study, we developed a feed-forward back-propagation ANNs approach to downscale GRACE data. This type of ANNs model employed an algorithm that calculates the output error during forward propagation. Subsequently, this error is distributed to each weight during backward propagation [39, 52]. The structure of the ANNs model was determined according to the guidelines proposed by Najjar [53], which suggested setting the number of nodes in the input layer equal to the number of inputs and the same criteria for the nodes in the output layer. Given the extensive data used in this study and the computing resources required, one hidden layer was selected. This decision was made not only to manage computation but also to make the model better at understanding patterns in the data rather than just memorizing it. We determined the right number of hidden nodes by evaluating the R^2 values, a measure that helps us see how well the model fits the data. We compiled a table incorporating this data, which was subsequently employed in the construction of the first ANNs model presented as follows:

- Date, X-Lon (Longitude), Y-Lat (Latitude), Water Level: Observed wells data provided by YMD.
- TerraClimate Variables (aet, def, pdsi, pet, srad, ro, soil, swe): Actual evapotranspiration (aet), climate water deficit (def), Palmer Drought Severity Index (pdsi), potential evapotranspiration (pet), surface shortwave radiation (srad), runoff (ro), soil moisture (soil), and snow water equivalent (swe).
- precip: Precipitation data from CHIRPS.

2.2.3. Development of the Second Phase ANNs model

In the second phase of our study, we used the downscaled GRACE obtained from the first-phase ANNs model as input to further predict water table levels in the Mississippi Delta. For this purpose, we utilized wells' water level data from the Yazoo Mississippi Delta Joint Water Management District (YMD). These measurements, hereinafter referred to as "Observed wells" included recordings from 643 wells in the region, spanning from 2000 to 2022. Distributed across the Delta, the observed wells offer a comprehensive geographic representation, as illustrated in the map in Figure 1.

To align the observed wells' data with the timeframe of the downscaled GRACE model outputs, we focused on measurements taken between 2002 and 2020. For each observed well, we located its corresponding output from the first ANNs model using the well's latitude, longitude, and collection date.

2.2.4. Model Assessment

To validate the first phase of our study, we calculated the R^2 for our model outputs and visually validated the results by comparing maps of the original GRACE data with the downscaled GRACE data. For the second phase, we reserved a randomly selected subset of 50 wells out of 643 for validation. We then used our model to predict these values and obtained the R^2. For visual validation, we compared the observed water level variations over time with the predicted water levels. Additionally, we visually assessed the model's output in estimating groundwater in the Delta by selecting several years with significant hydrological events, such as floods and droughts, and mapping the observed versus predicted data. We also compared our model's output with USGS potentiometric data for select years. This approach helped validate the spatial and temporal predictions of the model.

To assess the significance of downscaled GRACE data in our predictive model, we built another ANNs model using the same inputs as before, but this time we excluded the downscaled GRACE data. And lastly, to evaluate the individual contributions of each input feature to the prediction of groundwater levels, we employed the permutation importance method. This approach measured the decrease in model performance (e.g., accuracy) when the values of a specific feature were randomly shuffled, thereby simulating the removal of the feature's relationship with the target variable [54].

3. Results

After running the first phase of the ANNs model, we downscaled GRACA data for the entire State of Mississippi for 18 years to a 4X4 km spatial resolution. After testing various configurations, a neural network with 13 input nodes, one hidden layer of 26 hidden nodes, and one output node emerged as the best configuration. This ANN model achieved an R^2 of 0.853, which underscores the model's downscaling power. This value exceeds the typical R^2 range reported in similar studies (e.g., [39, 40]), where R^2 values ranged from 0.69 to 0.82 for groundwater modeling. The higher R^2 achieved here reflects the added benefit of integrating high-resolution climatic data and ANN-based downscaling. A direct comparison of our ANN-based downscaling results with those of Wang et al. [34] reveals similarities and key distinctions. While Wang et al. [34] achieved a resolution of 0.25° using Random Forests, our ANN model downscaled GRACE data to a 4×4 km resolution. This finer resolution is crucial for regional applications like the Mississippi Delta. Additionally, our model demonstrated higher predictive accuracy ($R^2 = 0.9885$) compared to Wang et al. [34], who reported RMSE values of 3.94 cm for similar datasets. Figure 3 illustrates a sample output of the first ANN model.

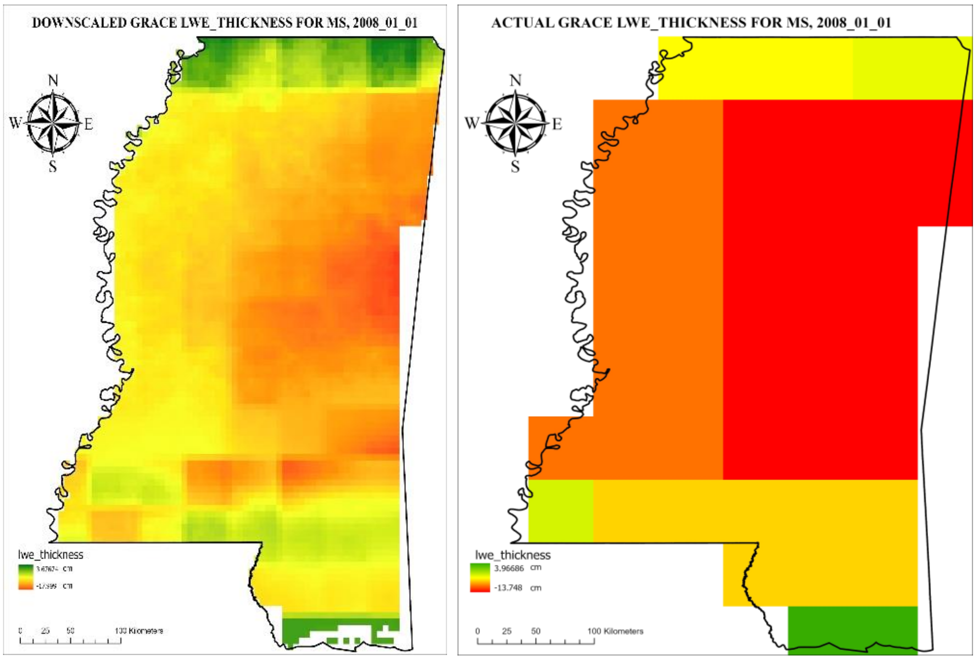
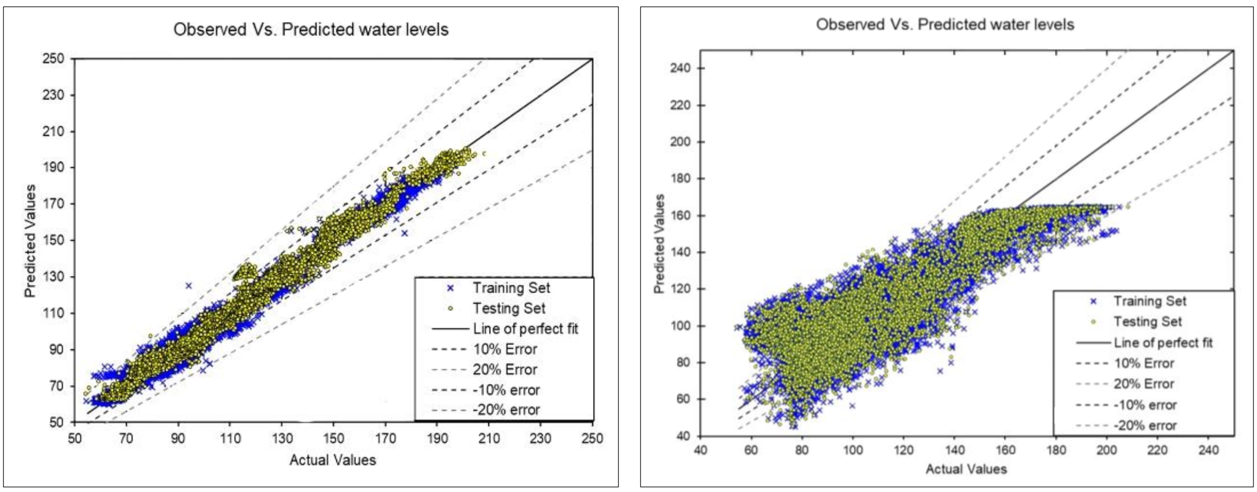


Figure 3. Model downscaled GRACE (left) vs. the original GRACE (right) for the State of Mississippi, January 2008

Building on the first ANNs model results, the second ANNs model was developed, and the training process achieved an R^2 of 0.9885. This model has 14 inputs, one hidden layer with 17 hidden nodes, and one output. We compared the outputs of this model with the observed wells. Figure 4a presents a scatter plot comparing the observed and predicted groundwater levels for all wells using our ANNs model that included downscaled GRACE from the first phase. Each point represents a single well measurement. The diagonal line on the plot indicated a perfect fit, where the actual and predicted values align. The closer the points are to this line, the more accurate the predictions. To provide additional clarity, ±10% and ±20% error lines are included in the figure, showing the percentage difference between the actual and predicted values. The scatter plots (Figure 4-a) reveal that most of the data points fall within the ±10% error margin, indicating a high level of accuracy for the model's predictions. Ali et al. [37] employed a geographically weighted regression (GWR) model to downscale GRACE data for the North China Plain, achieving strong correlations with in-situ data (R = 0.83). However, our study's R^2 of 0.9885 significantly outperformed their results, likely due to our integration of climatic predictors and the ANN's ability to model complex non-linear relationships. Similarly, Xue et al. [35] utilized a semi-supervised variational autoencoder, which, while computationally demanding, demonstrated high consistency in spatial-temporal trends. Our ANN approach offers a simpler yet equally effective alternative. This result demonstrates the model's reliability in capturing the observed variability in groundwater levels. Notably, when the downscaled GRACE data was excluded (Figure 4-b), a significant reduction in accuracy was observed, highlighting the critical role of this dataset in improving predictions.



(a) (b)

Figure 4. (a) Actual vs. predicted groundwater levels with the ANNs model, including downscaled GRACE data, with most data within ±10% error. (b) Actual vs. predicted groundwater levels without downscaled GRACE data, showing decreased accuracy.

For further assessment, Figure 5 presents the comparison between the timeseries of the water level measurements from the observed wells and the predictions obtained from the developed ANNs model between 2002 and 2018 for two randomly selected wells. The plot illustrated the agreement between the observed and predicted values over time. While the agreement was strong, the lines in the plot might appear irregular due to the limited data available. Nevertheless, this plot provided a valuable visual representation of the model's performance over a long period of time and highlighted its ability to capture the overall trends and variations in the groundwater levels.

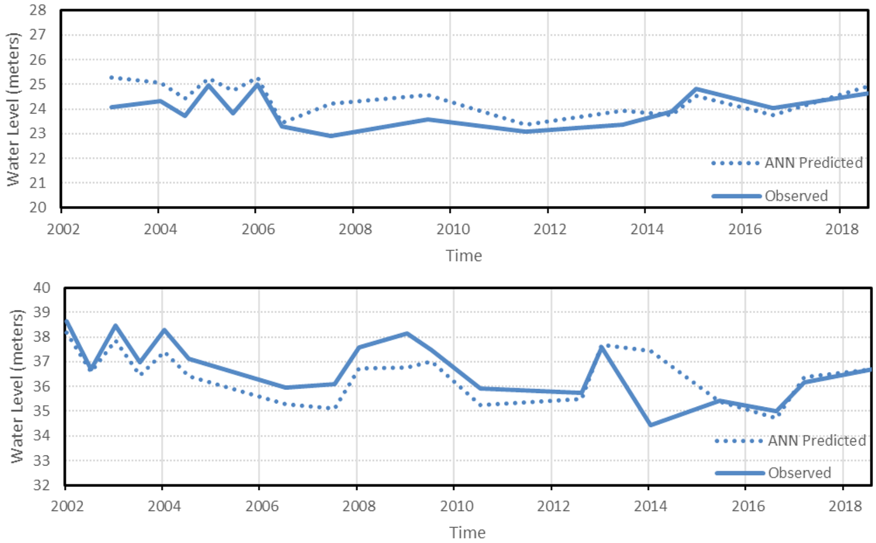


Figure 5. Time series comparison of Observed vs. ANNs-Predicted Well Measurements for Two Wells: (Top) Well 1 (lon: -90.5750, lat: 33.1250), (bottom) Well 2 (lon: -90.1250, lat: 33.5250)

Feature importance analysis for the ANNs model, which incorporated downscaled GRACE data as an input, was conducted, and the results are presented in Figure 6. This figure illustrates the importance of each input to the model. It's crucial to understand the limitations of the permutation importance method. Firstly, when several features are closely correlated, this method may exaggerate the significance of one feature while underestimating another, potentially leading to misinterpretations. Secondly, the results are specific to the model in use; the derived importance values reflect the structure of our trained model and might not capture the intrinsic relationships in the data. Finally, this method assumes feature independence during permutation, an assumption that may not always align with real-world datasets.

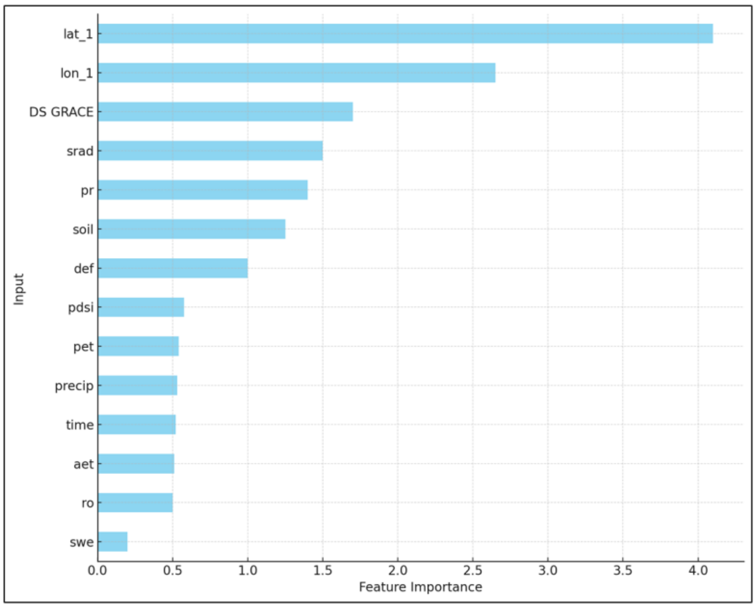


Figure 6. Feature importance analysis for the first ANNs model with downscaled (DS) GRACE data

Despite these limitations, our results indicated that latitude, longitude, and downscaled GRACE data exhibited the strongest relationship with the groundwater level, significantly enhancing the model's ability to make accurate predictions. This was likely because these three factors have a profound influence on the distribution and dynamics of groundwater, playing a pivotal role in predicting groundwater levels. The feature importance analysis highlights latitude, longitude, and downscaled GRACE data as the most significant contributors to the model's predictions. This result is consistent with the theoretical understanding that spatial positioning and large-scale hydrological data are critical for groundwater modeling. The prominence of GRACE data further underscores the advantage of integrating remotely sensed information into regional analyses. These findings suggest that future modeling efforts could benefit from further enhancing the spatial resolution of GRACE data and exploring its interaction with additional localized variables, such as land use and soil characteristics.

Besides the statistical assessment of our models, we also visually assess the model output in estimating the groundwater in the Delta. We chose several years and mapped the observed versus predicted data in Figure 7. We choose different months in eight years where there were significant hydrological events, with floods documented in "Weather.gov 2023" [55] and droughts in "Drought.Gov 2023" [56]. Furthermore, we visually compare our model output with USGS potentiometric data for 2018, 2018, and 2020.

In May 2017 and March 2019, significant flood events occurred in the Delta. Conversely, the years 2006, 2010, and 2012 were characterized by drought conditions in the Delta. The contour maps for these years, derived from both the observed water levels and the model predictions (Figure 7), demonstrated consistent agreement, with contours displaying comparable patterns and intensities. This agreement indicates that the ANNs model effectively captured the impacts of both floods and droughts on groundwater levels, enabling reliable predictions of water level changes. The model's ability to accurately reflect groundwater variability during extreme hydrological events, such as the floods of May 2017 and March 2019 and the droughts of 2006, 2010, and 2012, further validates its robustness. These results are supported by the contour maps, which not only demonstrate the model's capability to capture short-term anomalies but also highlight its effectiveness in reproducing long-term trends in groundwater dynamics. Such findings are particularly valuable for informing water resource management strategies under scenarios of increasing climate variability. These results hold significant implications for groundwater management, allowing for an improved understanding and forecasting of water level dynamics during both flood and drought events in the Delta.

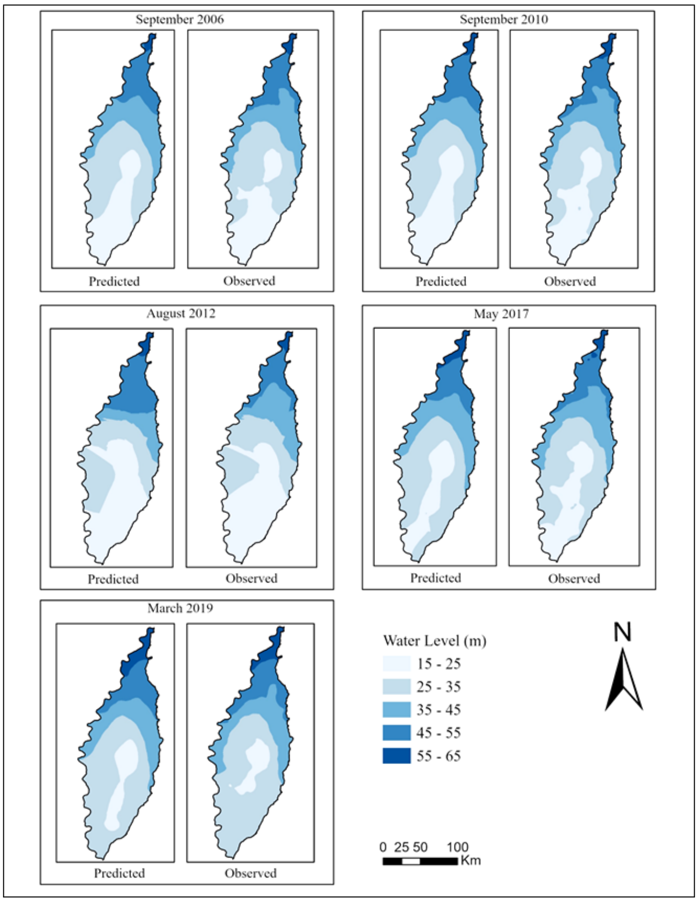


Figure 7. Water level comparison in the Delta: ANNs Model Predictions vs. Observed Measurements. Drought events: September 2006, 2010, and August 2012. Flood events: May 2017 and March 2019

We also chose years 2016, 2018, and 2020 to compare our findings with the USGS report on the potentiometric surface in the River Valley alluvial aquifer data that were available [57-60]. Our model results were similar to those from the USGS, as presented in Figure 8.

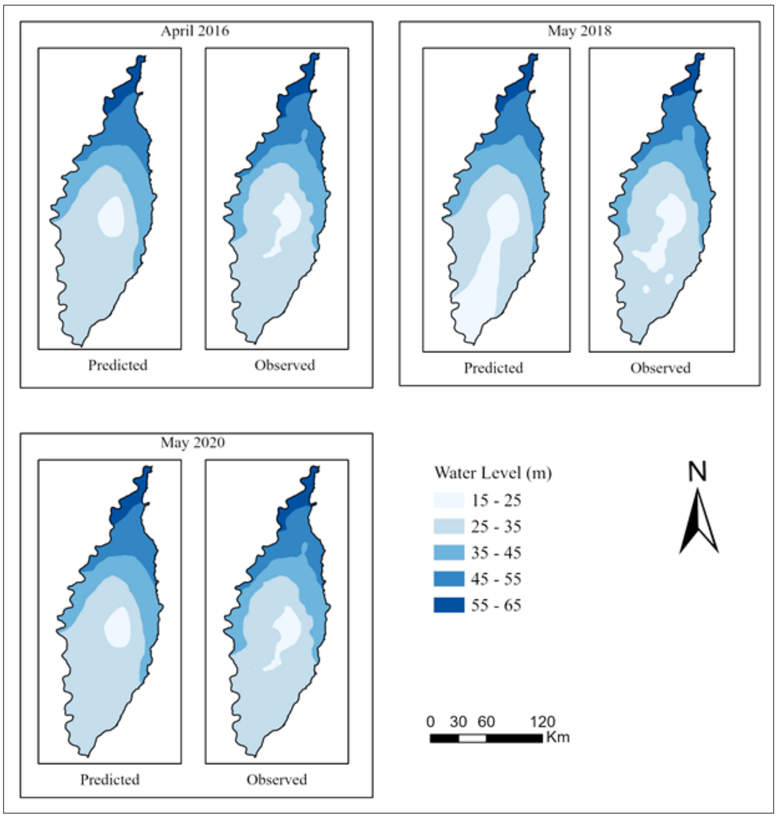


Figure 8. Comparison of Water Level Contour Maps in the Delta: ANNs Model Predictions vs. Observed Measurements from the USGS potentiometric surface reports

The comparison of the contour maps in both Figures 7 and 8 highlighted the effectiveness of the ANNs model in accurately predicting water levels in the Delta during years characterized by both floods and droughts.

The model's ability to capture and reproduce the spatial distribution of water levels during these extreme hydrological events is further validated by its consistency with the USGS potentiometric surface reports, as shown in Figure 8. This enhanced our understanding of groundwater dynamics and supported informed decision-making for effective groundwater management and planning.

4. Discussion

In this study, we implemented a two-phase ANNs modeling process to predict groundwater levels in the Mississippi Delta, building upon and improving the framework developed by Pulla et al. [38]. The theoretical foundation of this research lies in leveraging Artificial Neural Networks (ANNs) for their capacity to model nonlinear systems and handle large, multidimensional datasets. This choice was guided by the limitations of traditional statistical methods and computationally intensive models that often struggle to integrate complex hydrological and climatic variables at high spatial resolutions.

The dual-phase framework was designed with a clear theoretical basis. In Phase 1, ANNs were employed to downscale GRACE data by integrating high-resolution climatic and geospatial datasets. This aligns with the premise that combining satellite remote sensing with complementary data sources enhances predictive accuracy by capturing localized variations. These findings demonstrate the robustness of combining GRACE data with climatic predictors for improving groundwater prediction, as also highlighted by recent studies, such as Xue et al. [35] and Kalu et al. [36]. These works emphasize leveraging high-resolution geospatial and temporal data to address the limitations of coarse GRACE data. By achieving higher predictive accuracy through our ANN model, this study reinforces the importance of integrating remote sensing data with localized environmental variables. Phase 2 extended this approach by using the refined GRACE data alongside groundwater well observations and geographic parameters to predict water levels. The integration of these diverse inputs demonstrates the theoretical advantage of hybrid modeling approaches that synthesize remote sensing data and field measurements, creating models tailored to regional hydrological dynamics. This theoretical foundation highlights the synergy between machine learning and hydrology, showcasing how data-driven models can complement traditional methods. Future developments could build on this framework by incorporating dynamic system theory to address temporal variations more comprehensively or ensemble learning techniques to enhance predictive reliability across varying hydrogeological conditions.

The ANNs model developed in this study has provided consistent predictions of groundwater levels, which align well with observed data during extreme hydrological events. The time series comparisons detailed in Figure 5, along with the model's agreement with the potentiometric depressions reported in the literature [58-60], support the model's capability. Rather than superseding previous models, our approach complements and contributes to the ongoing discourse on the utility of integrating GRACE data with local hydrological variables. Our findings echo those of Weather.gov 2023 [55] and Drought.Gov 2023 [56], underscoring the effectiveness of such integrative approaches in capturing the nuances of spatial and temporal groundwater dynamics. This study's alignment with prior research confirms the reliability of our model and its potential as a tool for hydrological analysis.

The comparison of the saturated surface elevation maps in both Figure 7 and Figure 8 highlighted the effectiveness of the ANNs model in accurately predicting water levels in the Delta region during years characterized by both floods and droughts. The model's ability to capture and reproduce the spatial distribution of water levels during these extreme hydrological events is further validated by its consistency with the USGS potentiometric surface reports, as shown in Figure 8. This enhanced our understanding of groundwater dynamics and supported informed decision-making for effective groundwater management and planning.

Our study's two-phase ANNs approach for downscaling GRACE data and predicting groundwater levels in the Delta shows notable parallels and distinctions with recent research in this field. Sahour et al. [25] application of multiple statistical models, including ANNs, in Michigan, and Vishwakarma et al. [29] use of partial least squares regression, both aim to enhance GRACE data resolution, similar to our objective. However, our study specifically leverages ANNs for a focused region, achieving high R^2 values that underscore its predictive reliability. These findings align with Pulla et al.'s [38] framework, which applies a range of machine learning models for downscaling in Sunflower County, Mississippi, showcasing the versatility of such approaches.

While each study contributes uniquely to advancing hydrological modeling, our work particularly highlights the effectiveness of a targeted ANNs application in a complex hydrological setting. Unlike the broader frameworks explored by Pulla et al. [38], our model's design and regional focus offer detailed insights specific to the Delta. This distinction emphasizes our model's potential for localized groundwater management and complements the broader methodologies and applications presented in the referenced studies. Our findings add to the growing body of knowledge demonstrating the value of integrating GRACE data with machine learning for enhanced groundwater analysis.

Although the approach used in our research has produced encouraging outcomes, recognizing its limitations is crucial. The accuracy of the predictions relies heavily on the quality and resolution of the input data. In certain instances, data limitations could affect the model's performance, especially if spatial or temporal coverage is incomplete. Although the model's effectiveness is evident within the Delta, its applicability to other areas with distinct hydrogeological characteristics requires further investigation. The application of the permutation importance method has been instrumental in highlighting the significance of various features. Nonetheless, the potential for overestimation of feature importance due to correlated variables remains a consideration that must be taken into account when interpreting the model's behavior.

Looking ahead, we recommend that future research expand on this work by exploring a wider range of variables, including those that account for land use changes and anthropogenic activities, to enhance the model's robustness. Region-specific calibration and validation of the model are also essential due to the unique hydrogeological characteristics of different areas, as highlighted by the permutation importance method utilized in our study. Additionally, applying advanced downscaling methods could further refine the predictive accuracy of the model, particularly in diverse hydrogeological settings.

Despite these challenges, the two-step ANNs modeling approach significantly enhances the utility of using remotely sensed data in groundwater analysis. This method provides a valuable tool for policymakers and water resource planners, aiding in informed decision-making and supporting strategies for sustainable groundwater assessment.

5. Conclusion

This study presented a two-step approach for predicting groundwater level changes in the Mississippi Delta by combining downscaled GRACE mascon data with climatic and hydrological variables using Artificial Neural Networks (ANNs). The first phase successfully enhanced the spatial resolution of GRACE data, enabling more accurate regional-level groundwater analysis. In the second phase, the refined data, integrated with well observations and other influencing factors, allowed for precise predictions of groundwater dynamics with a high degree of accuracy. This approach demonstrated the value of machine learning in improving traditional hydrological modeling and addressing the challenges posed by coarse satellite data resolution.

The findings of this study highlight the practical benefits of the proposed method for groundwater resource management. The model can optimize water resource allocation, mitigate water-related risks, and support evidence-based policy decisions toward sustainable groundwater use. As climate change and water scarcity continue to threaten vulnerable regions, the importance of reliable and scalable predictive tools becomes increasingly clear. Moving forward, we recommend expanding the scope of future research by incorporating additional variables, such as land use and anthropogenic influences, and exploring innovative downscaling techniques. These improvements will enhance model robustness, extend applicability across diverse hydrogeological settings, and contribute to more nuanced and accurate groundwater assessments.

6. Declarations

6.1. Author Contributions

Conceptualization, H.Y. and L.D.Y.; methodology, A.R.A., H.Y., Z.G., and L.D.Y.; resources, A.R.A., H.Y., Z.G., and L.D.Y.; writing—original draft preparation, A.R.A.; writing—review and editing, A.R.A., H.Y., L.D.Y., and Z.G.; visualization, A.R.A. and Z.G.; supervision, H.Y. and L.D.Y.; project administration, H.Y. and L.D.Y.; funding acquisition, H.Y. and L.D.Y. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

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6.5. Conflicts of Interest

The authors declare no conflict of interest.

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