Evaluating the Impact of Pumping on Groundwater Level Prediction in the Chuoshui River Alluvial Fan Using Artificial Intelligence Techniques

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Abstract

Over the past decade, excessive groundwater extraction has been the leading cause of land subsidence in Taiwan's Chuoshui River Alluvial Fan (CRAF) area. To effectively manage and monitor groundwater resources, assessing the effects of varying seasonal groundwater extraction on groundwater levels is necessary. This study focuses on the CRAF in Taiwan. We applied three artificial intelligence techniques for three predictive models: multiple linear regression (MLR), support vector regression (SVR), and Long Short-Term Memory Networks (LSTM). Each prediction model evaluated the extraction rate, considering temporal and spatial correlations. The study aimed to predict groundwater level variations by comparing the results of different models. This study used groundwater level and extraction data from the CRAF area in Taiwan. The dataset we constructed was the input variable for predicting groundwater level variations. The experimental results show that the LSTM method is the most suitable and stable deep learning model for predicting groundwater level variations in the CRAF, Taiwan, followed by the SVR method and finally the MLR method. Additionally, when considering different distances and depths of pumping data at groundwater level monitoring stations, it was found that the Guosheng and Hexing groundwater level monitoring stations are best predicted using pumping data within a distance of 20 kilometers and a depth of 20 meters.

Keywords

Artificial Intelligence, Chuoshui River Alluvial Fan, Groundwater Level Prediction, Water Pumping.

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I. Introduction

Groundwater is the most important freshwater resource, and is widely used for industrial, commercial and agricultural purposes. The Chuoshui River Alluvial Fan (CRAF) is an important agricultural and industrial area that uses a significant amount of groundwater resources. However, excessive groundwater use can lead to serious environmental problems, including changes in river flow, land subsidence, and seawater intrusion [1]-[2]. In order to manage groundwater resources sustainably, and to detect the changes in groundwater levels, the interaction between pumping rate and groundwater level is studied at different temporal and spatial scales [2]. The pumping rate of the wells can be calculated using a numerical model and the relationship between electricity consumption and pumping rate. A time-series analysis was used to establish a time-dependent groundwater level processing model, and artificial intelligence was applied to predict groundwater level variations and analyze how much groundwater extraction would lead to irreversible land subsidence [3]. In this study, the calculated pumping rate ws used in conjunction with the time-dependent groundwater level processing model to establish a groundwater extraction prediction mechanism to achieve the goal of predicting and warning about groundwater level changes.

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The establishment of groundwater resource management requires a better understanding and monitoring of the relationship between groundwater level fluctuations and the spatial distribution of land subsidence [4]-[5]. During the data processing, analysis, and modeling, groundwater sensors were used to collect real-time groundwater level data over a long period of time. However, abnormal conditions of groundwater sensors, measurement failures, network connectivity problems, human errors, and other factors can lead to abnormal data at monitoring stations, resulting in data errors or loss [6]. Previous studies have utilized time series techniques to analyze the spatio-temporal distribution of groundwater level data and systematically clean and impute missing values. Time series techniques can quantify the autoregressive characteristics of the data as well as the corresponding variabilities associated with short-term fluctuations [7]. In the field of time series techniques, this study utilized the recursive seasonal-trend decomposition method to analyze the trend variations of groundwater levels in the Chuoshui River area. In addition, the Bayesian maximum entropy method was applied to impute the uncertain groundwater

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level data to ensure the integrity of the groundwater level dataset. Artificial intelligence techniques can efficiently compute non-linear data and use optimal algorithmic functions to model and analyze the groundwater environment. Prediction of groundwater level fluctuations is a critical aspect of ensuring effective groundwater management and availability in the future [8]-[12].

The dataset used in this study consists of groundwater level and extraction data from the CRAF area in Taiwan. The aim was to assess the occurrence of groundwater level decline in the CRAF area, and to analyze the relationship between groundwater extraction and the level of decline to determine groundwater use. We then used regression techniques to predict the trend changes in groundwater levels in the absence of extraction [11], [13]. This approach involves establishing a spatio-temporal data-driven framework that analyzes the temporal nature of the groundwater level dataset to obtain spatiotemporal characteristics of groundwater use in the CRAF area. The extracted spatio-temporal characteristics were then incorporated into the groundwater level prediction model together with the extraction data [12]-[13]. We compared three artificial intelligence techniques in our prediction methods: multiple linear regression (MLR), support vector regression (SVR), and Long Short-Term Memory Networks (LSTM) [7] [14], [15]. Each predictive model can be used to validate the effectiveness of these techniques and compare the accuracy of groundwater level predictions. The research question was to explore suitable predictive models to forecast the trend of groundwater level variations from 2020 to 2021. From the results of the predictive assessment, the strengths and weaknesses of each predictive model were identified and a suitable pumping dataset was found for predicting groundwater level variations. The generation of an appropriate pumping dataset was based on the location and depth of the groundwater monitoring station as a central zone, collecting data from nearby pumping wells.

The remainder of the paper is organized as follows: Section 2 explains the related works. Section 3 explains the research methodology. Section 4 gives an overview of the experimental results, and Section 5 presents the conclusions.

II. Related Works

A. Linear Regression Applied to Groundwater Level Prediction

The study of groundwater levels begins with data collection and observation through sensors installed at groundwater monitoring stations [16]. Under the influence of specific ecological and climatic processes, the normal fluctuations in groundwater levels show stability, resulting in regular patterns of rise and fall. This results in time series data with a continuous distribution [17]-[18]. Groundwater level data exhibit linear correlations, and previous studies have utilized linear models to achieve the best possible fit and use of such data. The principle behind this is to use the method of least squares to model the relationship between one or more independent variables and a dependent variable in regression analysis [19]-[20]. Due to their suitability for handling regression problems with continuous data, linear regression models have been widely used in previous research for statistical analysis and prediction of groundwater data [21]-[23]. In the study by Yan et al., a linear regression model was developed to predict groundwater levels in the coastal plains of eastern China using data such as precipitation, evaporation, river water levels, and tides. By analyzing the trend of groundwater level variations and performing linear regression analysis, satisfactory prediction results can be obtained with effective data and computational models [23].

We are investigated how pumping behavior affects groundwater level variations. However, the pumping data have a non-normal distribution and are difficult to fit into a multiple linear regression model. Considering this, the multiple linear regression model was not the optimal choice, and so we opted for machine learning models based on classifiers for data analysis and modeling [14], [24], [25]. In this study, we incorporated support vector regression and Long Short-Term Memory Networks (LSTM), a type of recurrent neural network, to handle both linear and non-linear relationships in the data, thus achieving better analytical results.

B. Support Vector Regression Applied to Groundwater Level Prediction

Excessive groundwater pumping may affect groundwater level fluctuations and cause land subsidence in the CRAF area in Taiwan. Previous studies have focused on the problem of irreversible land subsidence caused by excessive groundwater extraction [24], [26]. In the field of artificial intelligence, the support vector regression (SVR) model is utilized to analyze the trend changes between linear groundwater levels and non-linear extraction data. As a machine learning model based on classifier design, SVR minimizes structural risk and exhibits strong adaptability, global optimization and excellent generalization ability with respect to the data [27]. Previous studies have demonstrated that the SVR model has better predictive performance when analyzing non-linear data [11], [28] - [30]. El Bilali [30] used four machine learning models, including adaptive boosting, random forest, artificial intelligence and support vector regression, to assess and predict the water quality of the Berrechid aquifer in northwestern Morocco. The results of the research showed that Support Vector Regression had less sensitivity to input variables and better generalization capabilities compared to Adaptive Boosting and Random Forest. Therefore, it was more suitable for evaluating and predicting different types of data [30]. Mirarabi et al. [31] conducted a performance comparison between support vector regression and artificial intelligence models using groundwater data from the Hashtgerd Plain in Alborz Province, Iran. They found that the accuracy of both models declined over time.

Based on the above, we have found that Support Vector Regression (SVR) can be effectively utilized for both linear and non-linear regression analysis. This model can improve its predictive performance by optimizing the model parameters and performing data pre-processing [32]-[35]. Therefore, optimizing the parameters of the SVR model in research has a crucial positive impact on improving model performance.

C. Recurrent Neural Network Applied to Groundwater Level Prediction

In recent years, the extensive utilization of sensor techniques in groundwater monitoring has resulted in a greater number of influencing factors that need to be analyzed and investigated [36]. In the past, predictive models were often limited to capturing shallow correlations in the data, and were unable to uncover deeper relationships, resulting in inaccurate predictions [37]-[38]. Hinton and colleagues proposed the use of unsupervised learning with Deep Belief Networks (DBNs), which have the advantage of using hierarchical feature representations to model deep and complex nonlinear relationships [39]. The exceptional performance of such networks has made deep learning a trendsetter. Among them, Recurrent Neural Networks (RNNs) are widely regarded as effective methods for capturing the temporal dependencies in sequential data [40]-[42]. However, according to relevant studies, traditional RNNs are only suitable for processing short sequences. When applied to long sequential data, they can suffer from problems such as vanishing gradients, where the network struggles to remember long-term information, or exploding gradients [43]-[44]. To address this problem, Hochreiter and Schmidhuber [45] proposed Long Short-Term Memory Networks (LSTMs), a model that introduced memory cells capable of storing information for longer periods of time. This breakthrough allowed for more effective modeling and prediction of long sequential data. Gers et al. [46] improved the LSTM by introducing the forget gate mechanism, which allows the model to selectively retain or discard information from the previous cell state. This enhancement significantly improved the predictive performance of the model.

The LSTM method has gained considerable prominence in groundwater research. Zhang et al. [47] used it to predict the depth of groundwater levels in agricultural regions of China. The results indicated that LSTM excels in capturing the intricate relationships between linear and non-linear dynamics present in long-term sequential data, making it a key factor in improving the efficiency of agricultural irrigation and groundwater management. Vu et al. [48] utilized the LSTM method to reconstruct missing groundwater level data in the Normandy region of France. The result demonstrated the effectiveness of this approach in successfully reconstructing the missing groundwater level data, thereby improving the accuracy and reliability of hydrological forecasting and management.

Based on the current literature review, this study used the MLR, SVR, and LSTM methods to analyze the data from groundwater monitoring stations and the electricity consumption data from pumping wells in the Chuoshui River alluvial fan area of Taiwan. These models are utilized for deep learning modeling and analysis. In addition, this study incorporated optimization algorithms to enhance the predictive performance of the models, thereby improving the accuracy of groundwater level prediction.

III. Methods

A. Study Area

The CRAF is the largest alluvial fan plain in Taiwan [26]. It stretches from the Wu River in the north to the Beigang River in the south, from the Taiwan Strait in the west to the Bagua Mountain Plateau and the Douliu Hills in the east. The area is about 2,100 square kilometers. The main river is the Chuoshui River. Flowing from east to west, the Chuoshui River crosses the alluvial fan in the central mountain range before emptying into the Taiwan Strait [49]-[50]. Fig. 1 shows the geographical extent of the entire CRAF area, represented by solid lines.

The CRAF area consists of four underground aquifer layers and three aquitard layers. To access the groundwater resources, most of the pumping wells extract water from aquifer 1 and aquifer 2 [26]. In addition, the groundwater monitoring stations have a numerical code (1, 2, 3, 4) appended to their names, indicating the specific aquifer layer in which the groundwater monitoring station is located.

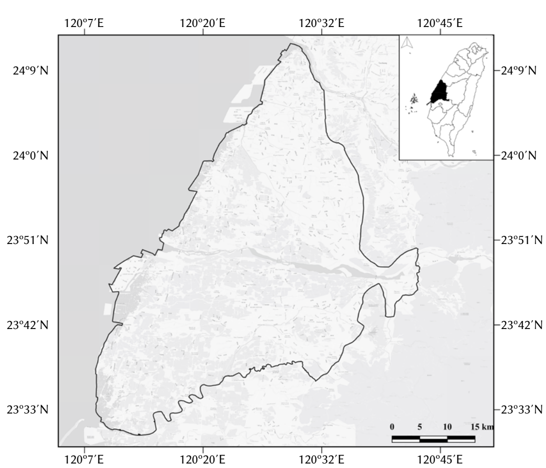

Fig. 1. The geographical location of the Chuoshui River Alluvial Fan.

B. Groundwater Level Data Acquisition and Processing

This study used groundwater level data collected from 2007 to 2021. The data were obtained from the Integrated Service System for Ground Subsidence Monitoring of the Water Resources Agency and the Hydrological Information Network of the Ministry of Economic Affairs, Water Resources Agency. The data collection period for the Integrated Service System for Ground Subsidence Monitoring extended until December 31, 2022, with groundwater level data provided at 24-hour intervals. The data collection period for the Hydrological Information Network of the Ministry of Economic Affairs started from January 1, 2020 to the present, with groundwater level data provided at 10-minute intervals.

The Python programming (version 3.8.10) can be used to pre-process and store groundwater level data. Python libraries such as Pandas, NumPy, Requests, and InfluxDB_Client can be used to write a web crawler program that downloads the raw groundwater level data and stores it in an InfluxDB (version 2.0.9) database [51]. Although the collected groundwater level data come from different sources, there are common elements between the two datasets. The dataset from the Hydrological Information Network of the Ministry of Economic Affairs can be matched with the code data from the Integrated Service System for Ground Subsidence Monitoring of the Water Resources Agency. If the time series and water level values of the groundwater data are the same, this indicates that the information has been collected from the same groundwater level monitoring station. The processed groundwater level information can be organized as shown in Table I.

TABLE I. Data on Groundwater Level

Name	Descriptions	Examples
ST_NO	Groundwater level monitoring station code	07010111
NAME_C	Chinese name of the groundwater level monitoring station, with a number indicating the aquifer level.	Guosheng (1)
Time	Timestamp of observation	2022-01-01T00:00:00Z
Water_Level(m)	Groundwater level height, with data units in metres.	16.943

From the Integrated Service System for Ground Subsidence Monitoring of the Water Resources Bureau and the Hydrological Information Network of the Ministry of Economic Affairs, a total of 260 groundwater monitoring stations within the CRAF area were considered for organizing the time-series groundwater level datasets. However, not every monitoring station has complete groundwater level data available. Therefore, a comparison was made between the data collected from the groundwater monitoring stations and the map of abandoned groundwater monitoring wells [52]. It was found that there were anomalies and abandoned statuses in the data collection for 95 monitoring stations.

In the end, we had 165 monitoring stations that were currently active and had complete data. These 165 groundwater monitoring stations are located at different depths. Fig. 2 shows the distribution and number of groundwater monitoring stations in the different aquifers. (A) The first aquifer of the CRAF contains 62 groundwater monitoring stations, most of which are located at depths between 25 and 100 meters. (B) The second aquifer of the CRAF contains 55 groundwater monitoring stations, most of which are located at depths between 73 and 182 meters. (C) The third aquifer of the CRAF contains 32 groundwater monitoring stations, with most stations located at depths ranging from 142 to 248 meters. (D) The fourth aquifer of the CRAF contains 18 groundwater monitoring stations, most of which are located at depths between 218 and 302 meters. In Fig. 2, it is

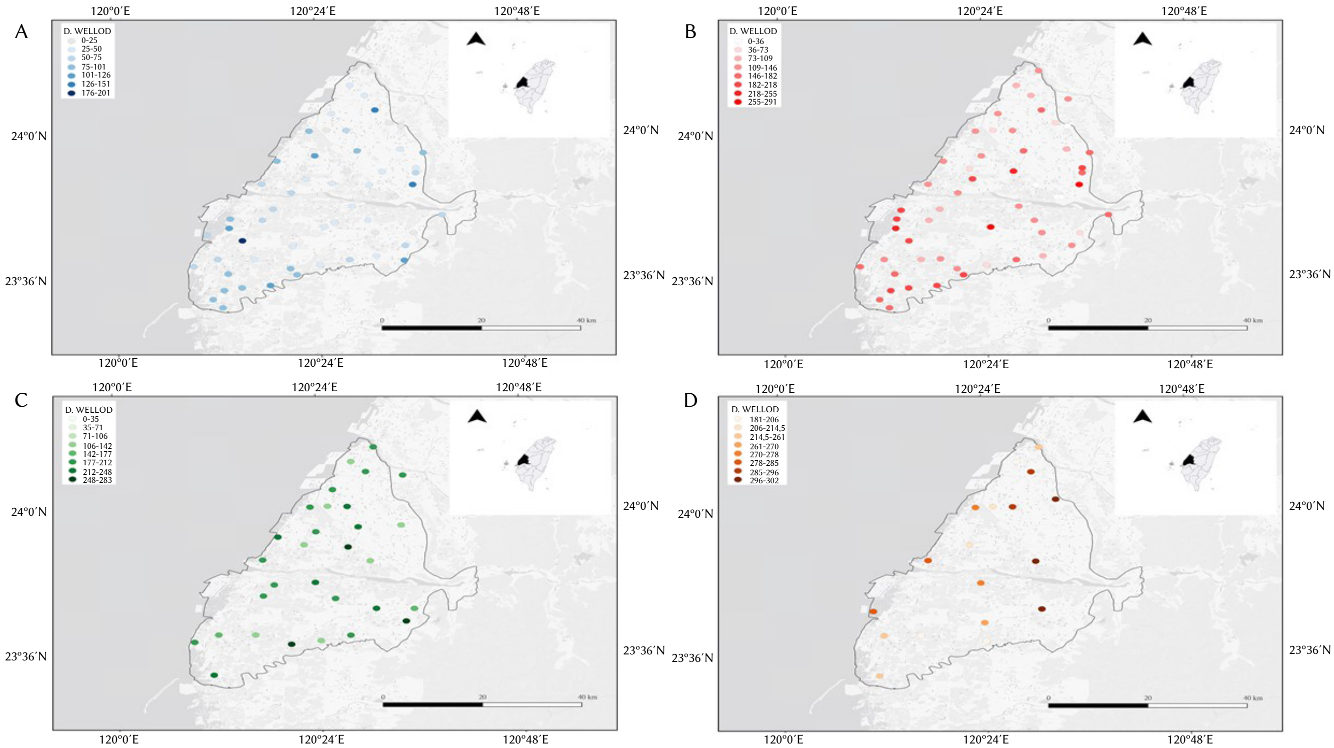

Fig. 2. Map showing the distribution of groundwater level monitoring stations in the Chuoshui River Alluvial Fan.

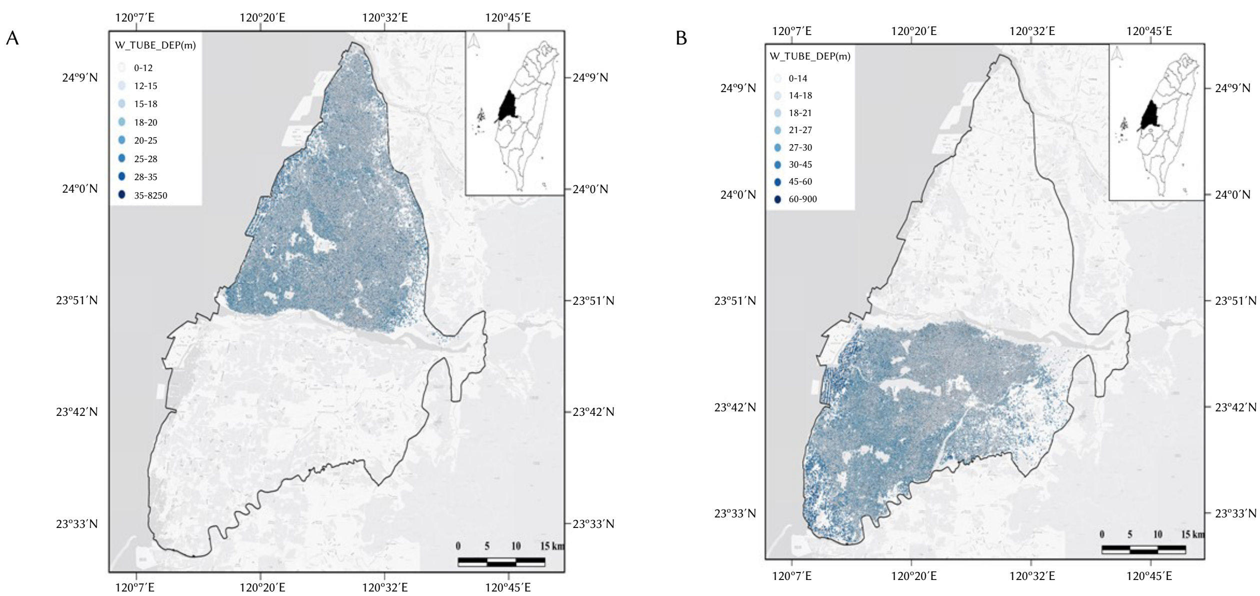

Fig. 3. Map of pumping well station distribution in the Chuoshui River Alluvial Fan.

evident that each groundwater level monitoring station is situated at a different aquifer depth. Therefore, this study aimed to compare the accuracy of different deep learning models in predicting groundwater level variations within the context of the same aquifer depth. This allowed us to construct groundwater level prediction models for similar groundwater environments.

C. Water Pumping Data Acquisition and Processing

The study collected water extraction data from the CRAF area in Taiwan between 2007 and 2021. This included electricity consumption data from pumping wells located in Changhua County and Yunlin County. The electricity consumption of the pumping wells was collected using electricity meters, with data provided at monthly intervals. The electricity consumption data were used to simulate the groundwater extraction volume for each month. The water extraction data record the coding of the pumping wells, their latitude and longitude coordinates, installation depths, and electricity consumption, as shown in Table II.

There are a total of 242,586 pumping wells in the CRAF area, including 125,905 wells in Changhua County and 116,681 wells in Yunlin County. Fig. 3 shows the locations of the pumping wells installed in Changhua County and Yunlin County, indicating the depth ranges of the pumping well stations.

TABLE II. Data on Pumping Wells

Name	Descriptions	Examples
WELL_NO	Pumping well code	10237500000004
TIME	Observation timestamp	2007-01-01T00:00:00
Pumping_well_power	Electricity consumption data of pumping wells	0.0
Lon	Longitude (WGS84)	120.506997
Lat	Latitude (WGS84)	24.075657
W_TUBE_DEP	Depth at which the station is located underground in metres	16.0

This study used the method of determining flow rate based on the relationship between electricity consumption and pumping volume to calculate the pumping volume of water wells in the Yunlin and Changhua regions. The hybrid pumping equipment includes an electronic water meter, an electronic electricity meter, and a pumping motor on/off time recorder. The electronic electricity meter records the monthly electricity consumption. By utilizing the electricity consumption data and the water/electricity ratio specific to each local pumping well, the pumping flow rate can be calculated to determine the pumping volume for each month. The water/electricity ratio is expressed in cubic meters per kilowatt-hour and represents the pumping volume of water per unit of electricity consumed. It can be obtained by dividing the pumping flow rate by the power consumption [53]. Fig. 4 shows the time series chart of the pumping volume for pumping station 10237500000004. The water/electricity ratio parameter for this pumping station is 12.9 cubic meters per kilowatt-hour. The pumping period is from 2007 to July 2021, and the unit of water volume is cubic meters.

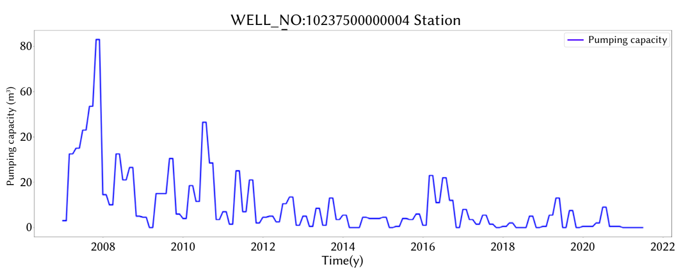

Fig. 4. The time series chart of the pumping volume for pumping station with ID 10237500000004.

D. Groundwater Level Prediction Techniques

To analyze the impact of pumping rates on groundwater level changes, this study proposes a groundwater level prediction model to determine how much the pumping wells within a certain range and depth will influence the accuracy of predicting groundwater levels. This method provides an actionable approach to manage and monitor groundwater levels, allowing an understanding of how the groundwater level changes at a single groundwater observation station are influenced by pumping wells within specific ranges and depths. In this study, we employed the method of determining flow rate based on the relationship between electricity consumption and pumping volume to accurately calculate the pumping data. Three models were used to predict the variations in groundwater levels: multiple linear regression, SVR, and LSTM. By analyzing the accuracy of predicting groundwater levels, we were able to evaluate the strengths and weaknesses of these models. The workflow of prediction modeling and validation settings is illustrated in Fig. 5.

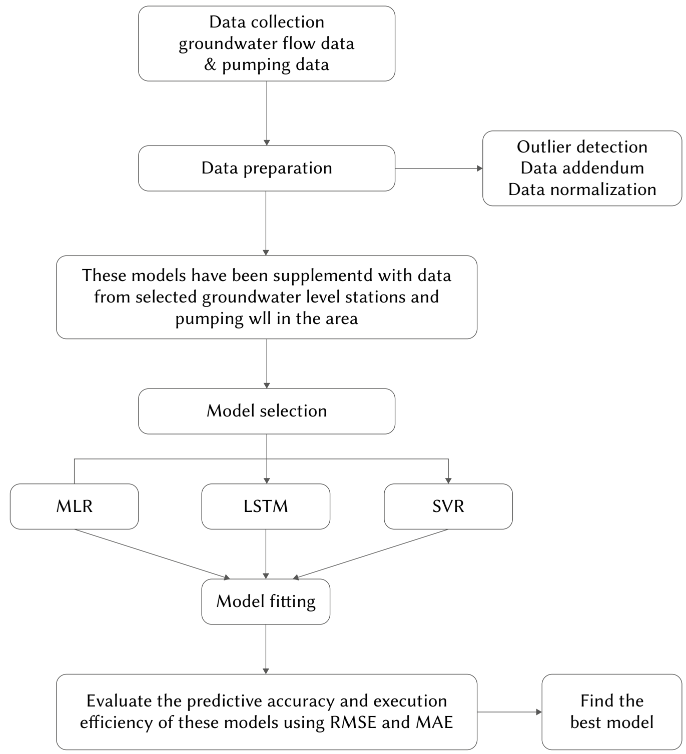

Fig. 5. The flowchart of the groundwater level prediction model.

In Fig. 5, this study begins with the selection of potential features from the collected data. Both pumping volume and groundwater level data are subjected to outlier detection, imputation, and normalization processes to obtain the appropriate format [1], [54], [55]. However, the relative position and depth between groundwater monitoring stations and pumping wells can affect the model construction and the accuracy of groundwater level prediction. During the model execution, the information from groundwater observation stations is selected as the target for model construction. Additionally, data from pumping wells located at different distances and depths were collected based on the position and depth information of the groundwater observation stations [56]. The collected pumping volume dataset served as the input dataset, and the groundwater level data served as the output dataset. Both datasets are used together to train, validate, and test the candidate deep learning models, including multiple linear regression, support vector regression, and LSTM models. These models were used to estimate the groundwater levels at the groundwater monitoring stations. The aim was to understand how pumping wells within a certain radius distance influence the prediction accuracy of groundwater levels at the observation stations.

In the final step, the estimated groundwater data and the observed groundwater data were used to test the models. The prediction accuracy of the models was compared using metrics such as root mean square error and mean absolute error. This analysis helps to identify which ranges and depths of pumping volume datasets are suitable for the groundwater monitoring stations.

E. Evaluation Metrics

Accurately assessing the performance and accuracy of deep learning models is crucial. We seek to evaluate the predictive performance of multiple linear regression, support vector regression, and LSTM models in predicting groundwater levels [1]. The accuracy of the aforementioned deep learning models is assessed using root mean square error (RMSE) and mean absolute error (MAE) for evaluation purposes. These two metrics are commonly used to measure the accuracy of predicting groundwater levels. The RMSE is more sensitive to outliers and is suitable for errors that follow a Gaussian distribution. On the other hand, MAE calculates the average weighted error for all errors [11], [14]. The evaluation of the RMSE and MAE in this study represents the accuracy of the deep learning model in predicting the groundwater level sequence from 2020 to August 2021. By comparing the predicted groundwater levels obtained from the deep learning model with the original groundwater levels, RMSE and MAE results were generated. When MAE = 0, RMSE = 0, or if they approach 0, it indicates the highest consistency between the predicted values and the observed values, demonstrating a better performance of the model in predicting groundwater levels.

IV. Results

This study focused on the alluvial fan area of the Chuoshui River to investigate the relationship between groundwater level variations and pumping behavior. In this study, groundwater level monitoring stations in Changhua County, including Guosheng, Tianwei and Hexing, and in Yunlin County, including Dongguang, Wencuo and Fengrong, were selected as research objects. These stations were selected because they showed more than 98% of normal values after analysis using the recursive seasonal trend decomposition method, which requires minimal adjustment for abnormal values [57], [58]. By using the installation locations and depths of each groundwater observation station, we created different datasets of pumping rates under various geographic conditions. The generation of pumping rate datasets primarily focused on pumping well stations located within a radius of 10 and 20 kilometers and at depths of ±10, 15, and 20 meters relative to each groundwater observation station. Table III shows the number of pumping well stations requiring data collection and organization under five distance and depth conditions. The collected data were aggregated as input variables to predict the groundwater level variations at the monitoring stations.

TABLE III. Number of Well Used to Collect Pumping Station Data

Sampling range	**Groundwater monitoring station**					
	Guo sheng	Tian wei	Hexing	Dong guang	Wen cuo	Feng rong
10km/10m	968	4275	7494	5322	1195	2219
10km/15m	1565	6629	11790	8002	1862	3399
10km/20m	2475	9235	17402	10716	2510	4676
20km/15m	7680	12038	20598	16450	11000	10583
20km/20m	12186	16699	30856	22227	15035	14431

Using data from pumping well stations as input variables, we constructed MLR, SVR and LSTM models to predict groundwater level variations from January 2020 to August 2021. Despite their different implementation methods, MLR, SVR, and LSTM models all belong to the field of machine learning and deep learning techniques. In this study, the pumping well station data were pre-processed and normalized to reduce errors. 89% of the pumping data were used for model building to analyze the groundwater level variations between 2007 and 2020 and to determine the initial prediction values. Training performance was evaluated by selecting the lowest RMSE and correlation coefficient. In addition, 11% of the pumping data were used for testing and predicting subsequent groundwater level variations [59]. In this study, the MLR model used the linear regression algorithm. The SVR model was configured with parameters such as a linear kernel, an epsilon value of 0.01, gamma set to auto mode, and a soft margin (C) value of 1. The LSTM model was constructed with 3 input layers, 2 dropout layers with a dropout rate of 0.2, and 1 output layer. The optimizer used for the LSTM was the Adam optimizer with a learning rate of 0.0001 [60]. All of these models were used to predict groundwater level fluctuations, and Tables IV to IX show the tested groundwater level monitoring stations paired with different samples of the pumping environment. By using the MLR, SVR and LSTM models to predict groundwater level variations for each groundwater level monitoring station from January 1, 2020 to August 1, 2021, the RMSE and MAE values were obtained to evaluate the prediction accuracy of the models [61].

The datasets from each groundwater observation station and pumping station are input into the artificial intelligence prediction process for predicting groundwater levels. Tables IV to IX display the predictive accuracy for each groundwater observation station. By identifying the lowest RMSE (Root Mean Square Error) and MAE (Mean Absolute Error) values, it is possible to determine the suitable pumping station datasets within a certain range of distance and depth that match the location and observation depth of each groundwater observation station.

TABLE IV. Performance Evaluation of Using Three Models to Predict Groundwater Level Variations at Guosheng (1) Station

	MLR		**SVR**		**LSTM**	
Sampling range	RMSE	MAE	RMSE	MAE	RMSE	MAE
10KM/10M	0.536	0.388	0.346	0.293	0.308	0.256
10KM/15M	0.512	0.367	0.510	0.398	0.291	0.242
10KM/20M	0.450	0.366	0.424	0.311	0.344	0.268
20KM/15M	0.451	0.327	0.373	0.309	0.341	0.255
20KM/20M	0.227	0.181	0.425	0.328	0.287	0.236

The installation location of the Guosheng groundwater monitoring station is located at longitude 120° 56’ 91” and latitude 24° 09’ 26”, at a depth of 24 meters. Table IV shows the prediction accuracy for the Guosheng groundwater monitoring station. It was found that the most suitable pumping volume dataset for predicting groundwater level variations at the Guosheng groundwater monitoring station is within a distance difference of 20 kilometers and a depth difference of 20 meters. Furthermore, based on the RMSE and MAE values, it was determined that the Multiple Linear Regression (MLR) model is the most suitable for predicting groundwater level variations at the Guosheng groundwater monitoring station. Therefore, Fig. 6 shows the groundwater level time series plot for the Guosheng groundwater monitoring station. The red line represents the actual groundwater level time series, while the blue line represents the groundwater level time series predicted by the MLR model.

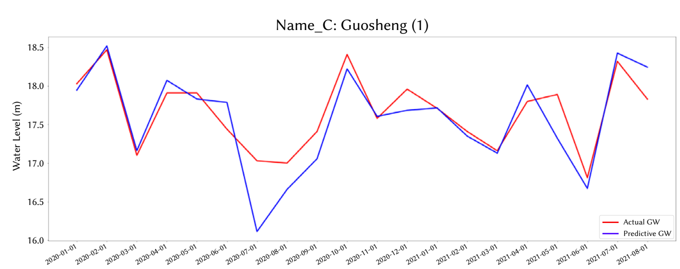

Fig. 6. The actual groundwater level and predicted groundwater level chart for the Guosheng groundwater monitoring station.

TABLE V. Performance Evaluation of Using Three Models to Predict Groundwater Level Variations at Tianwei (1) Station

	MLR		SVR		LSTM	
Sampling range	RMSE	MAE	RMSE	MAE	RMSE	MAE
10KM/10M	0.408	0.354	0.484	0.368	0.350	0.261
10KM/15M	0.390	0.324	0.306	0.242	0.285	0.228
10KM/20M	0.506	0.405	0.484	0.367	0.388	0.252
20KM/15M	0.372	0.299	0.361	0.283	0.547	0.378
20KM/20M	0.388	0.310	0.390	0.297	0.225	0.185

The installation location of the Tianwei groundwater monitoring station is at longitude 120° 52' 73" and latitude 23° 89' 13", at a depth of 36 meters. Table V presents the prediction accuracy for the Tianwei groundwater monitoring station. It was found that the most suitable pumping volume dataset for predicting groundwater level variations at the Tianwei groundwater monitoring station is within a distance difference of 10 kilometers and a depth difference of 15 meters. Furthermore, based on the RMSE and MAE values within a distance of 10 kilometers and a depth of 15 meters, it was determined that the Long Short-Term Memory (LSTM) model is the most suitable for predicting groundwater level variations at the Tianwei groundwater monitoring station. Therefore, Fig. 7 shows the groundwater level time series chart for the Tianwei groundwater monitoring station. The red line represents the actual groundwater level time series, while the blue line represents the groundwater level time series predicted by the LSTM model.

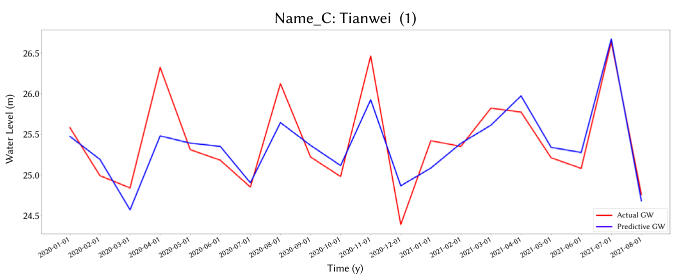

Fig. 7. The actual groundwater level and predicted groundwater level chart for the Tianwei groundwater monitoring station.

TABLE VI. Performance Evaluation of Using Three Models to Predict Groundwater Level Variations at Hexing (1) Station

	MLR		SVR		LSTM	
Sampling range	RMSE	MAE	RMSE	MAE	RMSE	MAE
10KM/10M	0.721	0.418	0.692	0.445	0.521	0.365
10KM/15M	0.596	0.390	0.551	0.360	0.604	0.415
10KM/20M	0.701	0.446	0.687	0.463	0.447	0.341
20KM/15M	0.555	0.365	0.885	0.544	0.513	0.406
20KM/20M	0.727	0.437	0.229	0.186	0.319	0.250

The installation location of the Hexing groundwater monitoring station is at longitude 120° 45' 81" and latitude 23° 89' 40", at a depth of 23 meters. Table VI represents the prediction accuracy for the Hexing groundwater monitoring station. It was found that the most suitable pumping volume dataset for predicting groundwater level variations at the Hexing groundwater monitoring station is within a distance difference of 20 kilometers and a depth difference of 20 meters. Furthermore, based on the RMSE and MAE values within a distance of 20 kilometers and a depth of 20 meters, it was determined that the Support Vector Regression (SVR) model is the most suitable for predicting groundwater level variations at the Hexing groundwater observation station. Therefore, Fig. 8 shows the time series of groundwater levels for the Hexing groundwater monitoring station. The red line represents the actual groundwater level time series, while the blue line represents the groundwater level time series predicted by the SVR model.

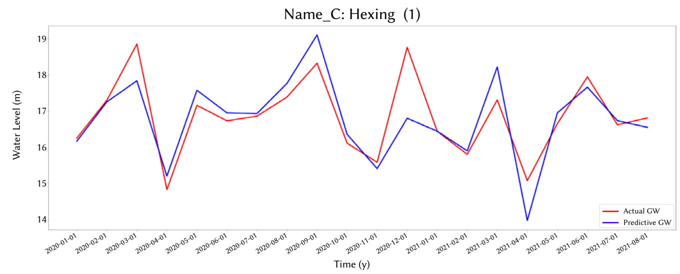

Fig. 8. The actual groundwater level and predicted groundwater level chart for the Hexing groundwater monitoring station.

TABLE VII. Performance Evaluation of Using Three Models to Predict Groundwater Level Variations at Dongguang (1) Station

	MLR		SVR		LSTM	
Sampling range	RMSE	MAE	RMSE	MAE	RMSE	MAE
10KM/10M	1.074	0.852	1.515	1.073	0.738	0.574
10KM/15M	1.585	1.297	1.245	1.021	0.633	0.500
10KM/20M	1.493	1.102	1.281	1.071	0.904	0.686
20KM/15M	1.185	0.887	1.537	1.103	0.875	0.652
20KM/20M	1.483	1.060	1.562	1.272	0.811	0.653

The installation location of the Dongguang groundwater monitoring station is at longitude 120° 27' 20" and latitude 23° 65' 19", at a depth of 33 meters. Table VII represents the prediction accuracy for the Dongguang groundwater observation station. It was found that the most suitable pumping volume dataset for predicting groundwater level variations at the Dongguang groundwater observation station is within a distance difference of 10 kilometers and a depth difference of 15 meters. Furthermore, based on the RMSE and MAE values within a distance of 10 kilometers and a depth of 15 meters, it was determined that the Long Short-Term Memory (LSTM) model is the most suitable for predicting groundwater level variations at the Dongguang groundwater monitoring station. Therefore, Fig. 9 shows the groundwater level time series plot for the Dongguang groundwater monitoring station. The red line represents the actual groundwater level time series, while the blue line represents the groundwater level time series predicted by the LSTM model.

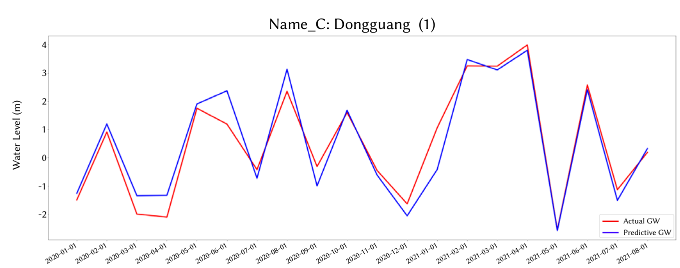

Fig. 9. The actual groundwater level and predicted groundwater level chart for the Dongguang groundwater monitoring station.

TABLE VIII. Performance Evaluation of Using Three Models to Predict Groundwater Level Variations at Wencuo (1) Station

	MLR		SVR		LSTM	
Sampling range	RMSE	MAE	RMSE	MAE	RMSE	MAE
10KM/10M	0.483	0.408	0.466	0.398	0.460	0.351
10KM/15M	0.397	0.331	0.441	0.341	0.441	0.341
10KM/20M	0.493	0.348	0.449	0.373	0.339	0.246
20KM/15M	0.387	0.299	0.395	0.282	0.446	0.322
20KM/20M	0.468	0.364	0.347	0.303	0.390	0.296

The installation location of the Wencuo groundwater monitoring station is at longitude 120° 51' 20" and latitude 23° 65' 77", at a depth of 35.67 meters. Table VIII represents the prediction accuracy for the Wencuo groundwater observation station. It was found that the most suitable pumping volume dataset for predicting groundwater level variations at the Wencuo groundwater monitoring station is within a distance difference of 10 kilometers and a depth difference of 20 meters. Furthermore, based on the RMSE and MAE values within a distance of 10 kilometers and a depth of 20 meters, it was determined that the Long Short-Term Memory (LSTM) model is the most suitable for predicting groundwater level variations at the Wencuo groundwater monitoring station. Therefore, Fig. 10 shows the groundwater level time series plot for the Wencuo groundwater monitoring station. The red line represents the actual groundwater level time series, while the blue line represents the groundwater level time series predicted by the LSTM model.

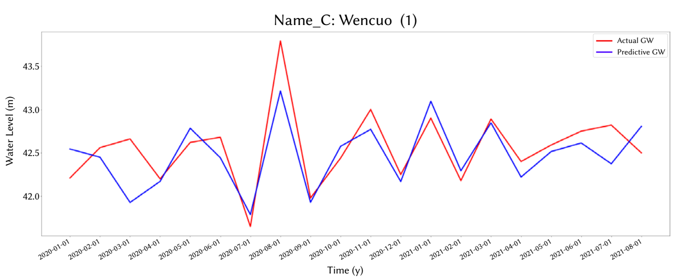

Fig. 10. The actual groundwater level and predicted groundwater level chart for the Wencuo groundwater monitoring station.

TABLE IX. Performance Evaluation of Using Three Models to Predict Groundwater Level Variations at Fengrong (1) Station

	MLR		SVR		LSTM	
Sampling range	RMSE	MAE	RMSE	MAE	RMSE	MAE
10KM/10M	0.693	0.593	0.872	0.704	0.961	0.670
10KM/15M	0.947	0.745	0.770	0.608	0.812	0.558
10KM/20M	0.700	0.510	0.797	0.661	0.672	0.495
20KM/15M	0.922	0.652	0.642	0.492	0.813	0.530
20KM/20M	0.646	0.512	0.700	0.524	0.753	0.577

The installation location of the Fengrong groundwater monitoring station is at longitude 120° 31' 09" and latitude 23° 79' 07", at a depth of 51.82 meters. Table IX represents the prediction accuracy for the Fengrong groundwater monitoring station. It was found that the most suitable pumping volume dataset for predicting groundwater level variations at the Fengrong groundwater observation station is within a distance difference of 10 kilometers and a depth difference of 20 meters. Furthermore, based on the RMSE and MAE values within a distance of 10 kilometers and a depth of 20 meters, it was determined that the Long Short-Term Memory (LSTM) model is the most suitable for predicting groundwater level variations at the Fengrong groundwater observation station. Therefore, Fig. 11 shows the groundwater level time series chart for the Fengrong groundwater observation station. The red line represents the actual groundwater level time series, while the blue line represents the groundwater level time series predicted by the LSTM model.

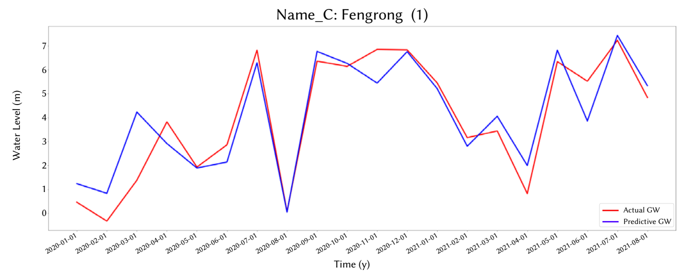

Fig. 11. The actual groundwater level and predicted groundwater level chart for the Fengrong groundwater monitoring station.

Based on the results from Tables 4 to 9, we obtained the most suitable applied pumping dataset for predicting groundwater level variations for each groundwater monitoring station. Consequently, from the optimal execution environment, the RMSE and MAE values from the optimal execution environment were used to identify the best and most stable deep learning model. The RMSE values for the MLR method ranged from 0.2 to 1.6, and the MAE values ranged from 0.18 to 1.3. For the SVR method, the RMSE values ranged from 0.2 to 1.3, and the MAE values ranged from 0.18 to 1.1. For the LSTM method, the RMSE values ranged from 0.28 to 0.7, and the MAE values ranged from 0.2 to 0.5. The findings of this research indicate that the best model for predicting groundwater level variations is the LSTM method, followed by the SVR method, and finally the MLR method.

V. Conclusion

This study applied artificial intelligence techniques to predict groundwater level variations in the CRAF area of Taiwan from 2020 to August 2021. We investigate the performances of the MLR, SVR, and LSTM methods in predicting groundwater levels with limited data. The dataset includes groundwater level and pumping data collected from the CRAF area. The pumping dataset was constructed by extracting pumping well data from the positions and depths around groundwater level monitoring stations as input variables, while the groundwater level data obtained from groundwater level measurement stations serve as output variables. The positions and depths of each groundwater level observation point acted as reference points, and the collection of pumping data at different distances and depths affected the accuracy of predicting groundwater level variations using the MLR, SVR, and LSTM methods. From the results, it was observed that the Guosheng and Hexing groundwater level measurement stations are suitable for executing the groundwater level prediction procedure using pumping data within a radius of 20 kilometers and a depth of 20 meters. In the experimental results, we found that the LSTM model shows stability, strong generalization capabilities, and high prediction accuracy in groundwater level prediction. By comparing the results of applying the best pumping conditions at six groundwater level monitoring stations, it is evident that the MAE and RMSE values of the LSTM method tend to be smaller than those produced by the MLR and SVR methods. Additionally, the LSTM method provides the best predictive models for groundwater level at four groundwater le vel monitoring stations. Therefore, the results of this study will contribute to the planning and management of groundwater resources.

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