Mapping Groundwater Potential Using Remote Sensing with Tri-Plateau Exponential Stereoscopic Scalable Quantum Cascaded Visual Attention Network

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Abstract — Though effective, remote sensing-groundwater potential mapping has limitations in the form of feature selection complexity, atmospheric errors, and the need for high-resolution imagery. Land cover variations, differences in soil makeup, and annual cycles could potentially affect accuracy, and deep models require significant computation for extensive application. Through the use of KOMPSAT-2 data, this paper demonstrates how Tri-Plateau Exponential Stereoscopic Scalable Quantum Cascaded Visual Attention Network (TP-ES-SQCVANet) beats groundwater potential mapping when it comes to enhancing the accuracy of classification and surmounting traditional hurdles. The Exponential Distribution Optimization (EDO) technique is applied for feature selection following preprocessing using the Adaptive Tri-Plateau Limit Tri-Histogram Algorithm (ATP-LTH). Reliable groundwater potential mapping using remote sensing is guaranteed by using the Planet Optimization Algorithm (POA) for optimization following the Stereoscopic Scalable Quantum Cascaded Visual Attention Network (SSQCVANet) for classification. The Python test script assesses groundwater potential mapping with the KOMPSAT-2 dataset. Receiver Operating Characteristic (ROC) technique was utilized to assess the performance of the model. Groundwater potential maps were also produced and compared through an ensemble method known as FR-BCT (Feature Reduction-Based Brightness Contrast Transformation). Test outcomes indicate that TP-ES-SQCVANet performs superior to existing methods, with 99.8% accuracy with FR-BCT and 99.9% accuracy with BCT (Brightness Contrast Transformation). These findings suggest that automatic systems could be more effective than manual systems. By identifying areas of high groundwater potential, the findings of this study can assist in sustainable groundwater resource management.

Keywords: Exponential Distribution Optimization, Groundwater Potential Mapping, KOMPSAT-2, Planet Optimization Algorithm, Remote Sensing

I. Introduction

One of the planet's most important and dynamic natural resources, water sustains a variety of living forms and developmental processes. However, its quality and availability have been greatly influenced by the fast population expansion. Due to lake and river water shortages in the summer, groundwater is an essential substitute for human requirements. The hydrology of groundwater is constantly threatened by shifting precipitation patterns and warming temperatures [1]. Groundwater has grown more and more important in the age of climate change, especially for irrigation. For many people, groundwater is their main—and frequently only source of fresh water, particularly for rural populations in low-income nations that are experiencing an increase in water insecurity [2]. Because it protects against climate extremes, boosts agricultural output, and lowers crop failures, groundwater-fed irrigation is essential to maintaining global food security and, eventually, alleviating poverty. Because more frequent and extreme climate events are driving changes in temperature, precipitation, soil moisture, and surface water availability, groundwater will become increasingly important as climate change increases [3].

Presently, groundwater is the most widely depleted resource globally, with yearly withdrawal rates approaching 982 km³. Almost 70% of this water is utilized for agricultural (33%), as well as drinking water (37%). However, future generations are seriously threatened by the continued overuse of this essential resource [4]. As demand for water continues to increase, it is essential to identify and safeguard possible groundwater regions for sustainable water management. Growing water demands in arid and semi-arid areas worsen shortages, which are made worse by over-extraction of groundwater and climate change. Morocco is experiencing a developing water issue as a result of its climate and diminishing water resources, much like many other desert nations [5]. Morocco is mostly dependent on hard rock aquifers, where groundwater availability is impacted by geological, hydrogeological, topographical, and climatological factors. This is because more than 75% of Morocco's territory is mountainous.

Groundwater potential areas (GWPA) in dry locations such as Morocco, Tunisia, Saudi Arabia, India, and Mexico have been the subject of much research in recent years. Several statistical models have been used in these investigations, and they have fared better than conventional hydrogeological prospecting techniques [6]. Renewable groundwater is mostly utilized for agricultural purposes in Makkah Al-Mukarramah province, although desalinated seawater is the main source of water for household usage. A significant wadi close to Makkah Al-Mukarramah city, Wadi Yalamlam, is essential to supplying local people' freshwater needs and sustaining the demands of the local agriculture. The potential and sustainability of Wadi Yalamlam's groundwater resources have been better understood because to the work of numerous researchers [7].

A. Novelty and contribution

The Novelty and contribution of this paper is given below:

- With higher classification precision and overcoming challenges, this study proves that TP-ES-SQCVANet performs better in groundwater potential mapping using the KOMPSAT-2 dataset.
- Pre-processing is done by Adaptive Tri-Plateau Limit Tri-Histogram Algorithm (ATP-LTH), which provides higher data quality as well as feature enhancement.

- To identify the characteristics and refine the important variables to offer maximum groundwater potential, Exponential Distribution Optimization (EDO) is utilized.
- Classification is done by the Stereoscopic Scalable Quantum Cascaded Visual Attention Network (SSQCVANet), which efficiently and highly accurately detects groundwater potential zones.
- By enhancing categorization parameters and prediction efficiency, the Planet Optimization Algorithm (POA) provides accurate mapping of groundwater potential using remote sensing.

II. LITERATURE SURVEY

In 2023, Echogdali et al. [8] have presented a sustainable method of estimating groundwater potentiality in space from fractal and geometric average models. Geospatial data, geometric average, and fractal models were used to map groundwater potential zones within the Tissent basin in south east Morocco. Topography, geology, hydrology, and hydrogeology were among the eight criteria examined in the study; the most important one was formation permeability. The groundwater potential map, which was validated using data from 52 wells, showed areas that were favourable (15.81%), moderate (21.36%), and unfavourable (62.83%). Although this approach minimizes the cost of hydrogeological investigations by optimizing well site selection, it may be constrained by model generalization and data availability.

In 2023, Masroor et al. [9] have presented, for mapping groundwater potential in Maharashtra, India's Parbhani District, a novel ensembles machine learning modelling method was used. An innovative ensemble method that combined ANN-MLP, RF, M5P, and SMOReg models was employed to evaluate the groundwater potential in the Parbhani district of Maharashtra. Groundwater potential zones were mapped by integrating ten site-specific characteristics, such as elevation, slope, drainage density, rainfall, and land use. According to the results, the district is primarily classified as moderate, with poor areas located in the north, center, and south. Although this approach improves the accuracy of groundwater assessments, it might need large datasets and powerful computers to function at its best.

In 2024, Halder et al. [10] have presented, The Waddai province in eastern Chad is an example of a semiarid region where groundwater potential zones are mapped using explanatory statistics. Using well locations for training and validation, the Frequency Ratio (FR) and Weight of Evidence (WoE) approaches were used to evaluate groundwater potential. Nine environmental, geological, and topographic parameters were used as predictors. The findings showed that lithology and slope had an impact on the southern and central regions' greater groundwater potential. Differences in class weights were found when compared to a Multi-Criteria Decision-Making approach that relies on experts. Predictive accuracy is increased by FR and WoE, but reliance on assumptions based on theory in poorly understood hydrogeological conditions is still a drawback.

In 2024, Halder et al. [11] have presented, Potential for groundwater mapping in an agricultural area of eastern India that is prone to drought using bagging and boosting ensembles deep learning algorithms. Using 161 data points and four machine learning models Random Forest (RF), Adaptive Boosting (AdaBoost), Extreme Gradient Boosting (XGBoost), and Voting Ensemble (VE) this study examines the groundwater potential in Bankura, West Bengal. The maximum accuracy was attained by VE with XGBoost (0.957). Reliable predictions were ensured by the strong performance of RF and AdaBoost. High accuracy and adaptability are advantages; low-potential zone uncertainty is a drawback. Significant variations in groundwater potential highlight the necessity of focused resource management techniques.

A. Problem Statement

A crucial resource for industry, agriculture, and drinking water, groundwater is becoming less available as a result of over-extraction and climate change. Conventional techniques for mapping groundwater are expensive and time-consuming. A cost-effective and efficient technique for identifying groundwater potential areas is by employing remote sensing and GIS-based techniques. To map groundwater potential effectively and facilitate sustainable water resource management and decision-making in water-scarce areas, this project will combine multi-source satellite imagery, geospatial analysis, and machine learning.

III. PROPOSED METHODOLOGY

Figure 1 Block Diagram of Proposed TP-ES-SQCVANet shows the process of groundwater potential mapping with KOMPSAT-2 imagery. The Adaptive Tri-Plateau Limit Tri-Histogram Algorithm (ATP-LTH) improves image quality in the data pre-processing phase of the process. Then, for best feature selection, the Exponential Distribution Optimizer (EDO) is utilized. The Stereoscopic Scalable Quantum Cascaded Visual Attention Network (SSQCVANet) classifies these high-quality features. It maps groundwater-related features such as water bodies, vegetation, urban areas, bare ground, soil, and clouds. The classification process is then analyzed by Planet Optimization Algorithm (POA) to ensure higher accuracy in groundwater potential mapping.

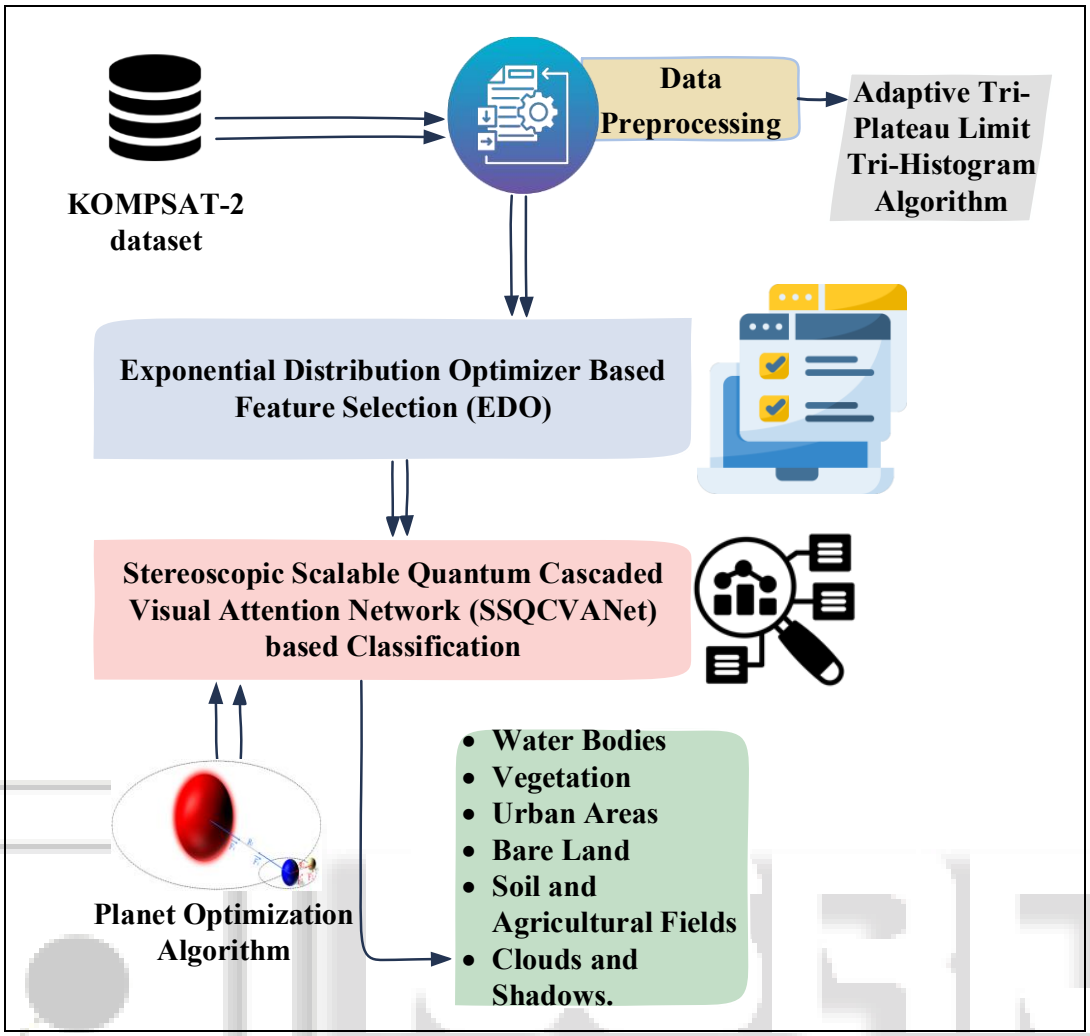

Fig. 1: Block diagram of proposed TP-ES-SQCVANet

A. Image acquisition

Groundwater potential mapping is facilitated by the panchromatic (1m) and multispectral (4m) high-resolution imagery of KOMPSAT-2. The satellite spectral bands (blue, green, red, and near-infrared) aid the analysis of geological structures, vegetation, and soil moisture that control groundwater recharge. Groundwater zones are identified with precision through the use of the satellite data, allowing for GIS-based modelling. Water flow pattern terrain analysis is complemented by integration with Digital Elevation Models (DEMs). The full imagery provided by KOMPSAT-2 supports improved decision-making in water resource management, especially in dry and semi-arid areas where groundwater is scarce.

Uniformity Pre-processing methods increase the precision of groundwater potential mapping by minimizing distortions and achieving homogeneity in KOMPSAT-2 imagery. Through increased spectral and spatial uniformity, the methods facilitate the recognition of groundwater recharge areas easily. Pre-processing makes remote sensing analysis more precise for efficient water resource estimation by eradicating variances of satellite images.

B. Preprocessing using Tri-Plateau Limit Tri-Histogram Algorithm (ATP-LTH)

As a pre-processing technique, Adaptive Tri-Plateau Limit Tri-Histogram Algorithm (ATP-LTH) [12] improves image quality for groundwater potential mapping by minimizing noise in KOMPSAT-2 data. Histogram equalization with standard enhancement improves contrast through better brightness distribution, retains critical features for accurate analysis, and improves visual definition. With improved feature extraction from satellite images, the technique facilitates simple identification of the groundwater recharge zones and improved overall accuracy for groundwater potential mapping with remote sensing.

A given image's I_{mages} histogram $FP_B(m)$, which offers essential data for image assessment and preprocessing, shows the fluctuation of pixel intensities at each brightness level m. Equation (1) provides a definition of it.

$$FP_B(m) = h_m \quad for\ m = 0,1,2,...(A-1), \tag{1}$$

where, $FP_B(m)$ denotes the level m of the pixel intensity histogram. h_m shows the frequency of pixels at the intensity level m. A is the total number of brightness

levels in the image. FP_B is the total number of pixels in the image is shown by. This relationship is represented mathematically by equation (2).

$$TP = \sum_{m=0}^{L-1} TP - TH(m) \quad (2).$$

This equation assists in enhancing contrast and reducing noise in groundwater potential mapping through the study of the pre-processing KOMPSAT-2 images' pixel intensity histogram. To promote image sharpness without excess, the proposed method integrates plateau limit sub-histograms with a distributed parameter. The redistributed parameter is computed using equation (3), ensuring more accurate feature extraction for remote sensing analysis of groundwater recharge areas.

$$\mathrm{Re}P = \frac{mean[I_L] + median[I_L]}{2} \quad (3).$$

$\mathrm{Re}P$ where, represents the reallocated parameter. I_L $mean[I_L]$ shows the intensity levels of the image. I_L $median[I_L]$ shows the average value of . symbolizes the midpoint of I_L. This technique balances feature intensity through mean and median correction, enhancing pre-processing of images for groundwater potential mapping. In remote sensing, it aids in the accurate delineation of groundwater recharge areas by enhancing the contrast and reduction of noise of KOMPSAT-2 images.

The block of feature selection applies KOMPSAT-2 imagery to identify the most relevant features for groundwater potential mapping upon receiving the pre-processed images.

C. Feature selection using Exponential Distribution Optimizer (EDO)

Important features to map groundwater potential using KOMPSAT-2 imagery are obtained through feature selection process after preprocessing. A nature-inspired method, Exponential Distribution Optimization (EDO) [13], represents solution candidates as exponentially distributed random variables. EDO enhances optimal search for groundwater-related features via probability-based choice. EDO takes advantage of the heightened probability density in the exponential distribution to iteratively focus on performing regions. The strength of EDO is its ability to efficiently solve complex and multi-mode optimization problems in order to enhance the accuracy of groundwater estimations.

1) Initialization

A randomly generated population of solutions serves as the starting point for the feature selection procedure for groundwater potential mapping utilizing KOMPSAT-2 data. Every solution optimizes important groundwater-related properties by treating locations as exponential random variables using an exponential distribution model. Its locations are treated as model-following exponential random variables that result in a vector of dimensions d, as shown in equation (4):

$$U winners_p = \lfloor U winners_{p,1}, U winners_{p,2}, ..., U winners_{p,d} \rfloor \quad (4).$$

where, $U winners$ is represent the initiate a population.

2) Fitness Function

Equation (5) shows the fitness function for the EDO optimization method.

$$Fitness function = f(b) + \mu \cdot \left\| b - b_{ref} \right\|^2 \quad (5).$$

where, b represents the solution's vector, $f(b)$ denotes the objective function, b_{ref} represents the reference solution, and μ denotes The parameter for regularization.

3) Exploration

The exploring stage of the EDO is demonstrated in this section. The technique identifies the interesting regions of the search area that are believed to have the best global reaction during the exploration stage. Two winners with an exponential distribution from the initial population are used to build the optimization model for the EDO exploration stage. Equation (6) is used to display the revised response.

$$Mean^{Time} = \frac{1}{N} \cdot \sum_{p=1}^{N} U winners_{q,p}^{Time}, \quad q = 1,2,...d \quad (6)$$

$Mean^{Time}$ where, stands for the average of each response in the initial population. The population size can be N divided to determine it by the sum of every random exponential variable that belongs to the same dimension.

4) Exploitation

In the exploitation phase of feature selection for groundwater potential mapping using KOMPSAT-2 imagery, the optimal solution is guided by ranking alternatives. The exponential distribution model utilizes mean, variance, and exponential rate to refine feature selection. The guiding solution, computed as the average of the top three solutions, improves accuracy. It is expressed in equation (7) given below,

$$U guide^{Time} = \frac{U guide_{Best1}^{Time} + U guide_{Best2}^{Time} + U guide_{Best3}^{Time}}{3} \quad (7)$$

where, the guiding solution at iteration $(Time)$ is determined by $U guide^{Time}$.

5) Termination

In KOMPSAT-2 imagery-based groundwater potential mapping, the termination condition is defined by increasing the number of iterations after each step. To improve model performance, feature subsets are optimized using the EDO-

based feature selection method, which chooses the most pertinent attributes. Predicting groundwater recharge zones is more accurate thanks to the improved characteristics.

After that, the classification block receives the chosen features from the KOMPSAT-2 images for analysis of groundwater potential mapping.

D. Classification using Stereoscopic Scalable Quantum Cascaded Visual Attention Network (SSQCVANet)

The Stereoscopic Scalable Quantum Cascaded Visual Attention Network (SSQCVANet) is used to analyze KOMPSAT-2 imagery in the groundwater potential classification approach [14, 15]. By combining spectral and spatial patterns, multi-scale quantum cascaded processing improves feature discrimination and achieves precise categorization. This cutting-edge methodology improves groundwater evaluation and sustainable water resource management by guaranteeing consistent performance across a variety of terrains.

Quantum convolution is used in the spatial features extraction process by Stereoscopic Scalable Quantum Convolutional Neural Networks (SSQCNNs), as seen in the following mathematical description (8).

$$QConv(Z) = D_\theta SD_\theta \tag{8}$$

where, $QConv(Z)$ is quantum convolution's output. D_θ is the quantum unitary transformation matrix. Y is the feature matrix of the supplied image. Stereoscopic imagery enhances depth-based feature learning, as determined by the following equation (9).

$$S_{FL}(Z_L, Z_R) = \sigma Z_L + \rho Z_R \tag{9}$$

where, Z_L and Z_R are representations of stereoscopic pictures on the left and right. σ and ρ are weight parameters. Quantum activation improves non-linearity in SSQCNNs. It can be found in equation (10).

$$Q_{AENL}(n) = \mu(DxD) \tag{10}$$

where, μ is The mechanism that initiates. D symbolizes quantum processes. The classification result for groundwater potential mapping from KOMPSAT-2 images is presented in equation (10). The Stereoscopic Scalable Quantum Convolutional Neural Networks (SSQCNNs) provide a solid basis for scalable and high-performance classification, ensuring precise groundwater recharge zone identification and enhancing the accuracy of water resource evaluation based on remote sensing.

The weight parameter of classification is tuned on the Planet Optimization Algorithm (Pl-OA).

E. Optimization using Planet Optimization Algorithm (POA)

Based on KOMPSAT-2 images, the objective of groundwater potential map optimization is enhancing the quality of feature extraction, reducing misclassification errors, and enhancing classification accuracy. Innovated by planetary motion and gravitational force, the Planet Optimization Algorithm (POA) [16] is used to optimize weight parameters of the SSQCVANet. POA offers better convergence and processing with ease through successfully navigating high-dimensional search spaces [17]. It perfectly suits challenging geospatial applications because thanks to its precision and diversity those benefits identifying zones of rechargeable groundwater in order to effectively manage water resources [18]. The above equation (11) describes the fitness function:

$$Fitness\ function = Min(\sigma, \rho) \tag{11}$$

where, σ, ρ are represent the SSQCVANet weight parameters.

The proposed technique of groundwater potential mapping using KOMPSAT-2 imagery enhances input data with ATP-LTH preprocessing. Exponential Distribution Optimizer (EDO) performs optimal feature extraction, while SSQCVANet classifies and predicts [19]. The Planet Optimization Algorithm (POA) also optimizes the neural network parameters to map groundwater potential accurately from high-resolution KOMPSAT-2 remote sensing imagery.

IV. Results and Discussion

The results of the suggested method, which was implemented by the Python platform, are presented in the research findings explained in this section [20]. The suggested analysis method is thoroughly assessed by comparing it to other methods already in use. All of the simulation needs is illustrated in Table 1.

Specifications	Description
Programming Language	Python
Version	3.7.14
OS	Windows 10
Dataset	KOMPSAT-2
Classes	Water Bodies, Vegetation, Urban Areas, Bare Land, Soil and Agricultural Fields, Clouds and Shadows.
Training network	Stereoscopic Scalable Quantum Cascaded Visual Attention Network (SSQCVANet)
Algorithm	Planet Optimization Algorithm (POA)

Table I: Simulation Specifications

A. Description of the Dataset

KOMPSAT-2 dataset Land cover classification, environmental observation, and groundwater potential mapping are facilitated by the KOMPSAT-2 dataset [8], which provides high-resolution multispectral (4m) and panchromatic (1m) imagery with precise spatial, spectral, and temporal information for remote sensing studies [21].

B. Performance Analysis of TP-ES-SQCVANet

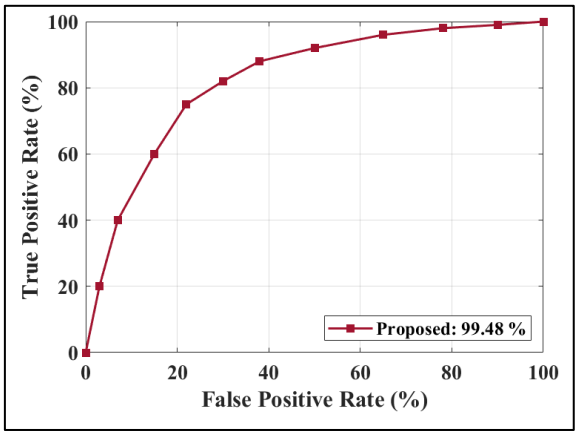

Fig. 2: ROC curve for KOMPSAT-2 dataset

Figure 2 ROC Curve for KOMPSAT-2 Dataset shows how well the suggested TP-ES-SQCVANet model performs when mapping groundwater potential. The model's efficacy is illustrated by the curve, which plots the True Positive Rate (%) against the False Positive Rate (%) [22]. With a high classification accuracy of 99.48%, the suggested approach performs better in terms of prediction [23].

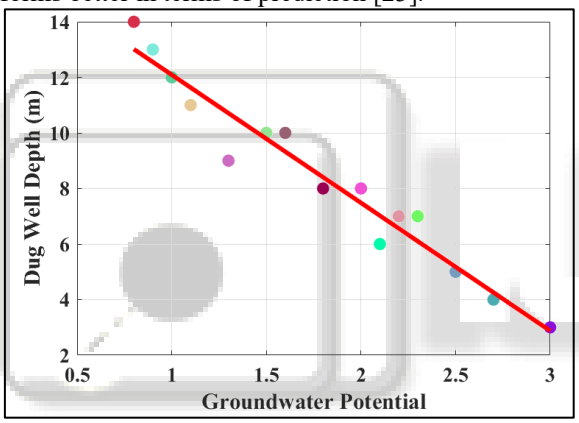

Fig. 3: Correlation between Groundwater Potential and Dug Well Depth

Groundwater potential and dug well depth have an inverse connection, as seen in Figure 3 Correlation between Groundwater Potential and Dug Well Depth. Higher water availability is shown by a decrease in the needed well depth as groundwater potential rises. The efficiency of the suggested TP-ES-SQCVANet model for mapping groundwater potential is validated by the red regression line, which emphasizes this trend [24].

Factors	Predictor Significance Values			
	SPC		T	
	BCT	FR-BCT	BCT	FR-BCT
Spatial Resolution	0.1543	0.0200	0.1732	0.0142
Spectral Bands	0.1327	0.1391	0.2841	0.1432
Temporal Coverage	0.0431	0.1632	0.3912	0.3912
Radiometric Resolution	0.1421	0.3851	0.1352	0.0417
Geometric Accuracy	0.1649	0.3912	0.5621	0.0571
Swath Width	0.1930	0.5391	0.4753	0.1385
Coverage Area	0.3721	0.3927	0.7314	0.2175

Table II: Lists Each Factor's Predictor Significance Values for the BCT and FR-BCT Models

The Brightness Contrast Transformation (BCT) and Feature-Reduced Brightness Contrast Transformation (FR-BCT) models' predictor significant values for the various KOMPSAT-2 dataset factors are shown in Table 2. A number of factors are assessed, including coverage area, swath width, radiometric resolution, spectral bands, spatial resolution, and temporal coverage. In both models, the Coverage Area has the highest importance (0.7314 for BCT and 0.3927 for FR-BCT), demonstrating its critical function.

V. Conclusion

Groundwater potential mapping via remote sensing has drawbacks include intricate feature selection, atmospheric distortions, and reliance on high-resolution data. Accuracy is impacted by seasonal variations, land cover, and soil composition, and deep learning models demand significant processing power for large-scale implementations. By overcoming traditional restrictions, the suggested TP-ES-SQCVANet architecture improves classification accuracy. Adaptive Tri-Plateau Limit Tri-Histogram Algorithm (ATP-LTH) pre-processing enhances the quality of the data, while Exponential Distribution Optimization (EDO) fine-tunes feature selection. The Stereoscopic Scalable Quantum Cascaded Visual Attention Network (SSQCVANet) is used for classification, and the Planet Optimization Algorithm (POA) is used for optimization. Superior accuracy is demonstrated by performance evaluation utilizing the Receiver Operating Characteristic (ROC) approach, which achieves 99.8% with FR-BCT and 99.9% with BCT. By precisely identifying high-potential zones, our findings aid in the management of groundwater resources in a sustainable manner.

References

[1] A. A. Ghanim, A. M. Al-Areeq, M. Benaafi, M. S. Al-Suwaiyan, A. A. A. Aghbari, and M. Alyami, "Mapping groundwater potential zones in the Habawnah Basin of Southern Saudi Arabia: An AHP-and GIS-based approach," Sustainability (Basel), vol. 15, no. 13, p. 10075, 2023. DOI: 10.3390/su151310075

[2] D. C. Wijesinghe, P. K. Mishra, N. C. Withanage, K. Abdelrahman, V. Mishra, S. Tripathi, et al., "Application of GIS, multi-criteria decision-making techniques for mapping groundwater potential zones: A case study of thalawa division, Sri Lanka," Water, vol. 15, no. 19, p. 3462, 2023. DOI: 10.3390/w15193462

[3] T. X. Bien, A. Jaafari, T. Van Phong, P. T. Trinh, and B. T. Pham, "Groundwater potential mapping in the Central Highlands of Vietnam using spatially explicit machine learning," Earth Sci. Inform., vol. 16, no. 1, pp. 131–146, 2023. DOI: 10.1007/s12145-022-00925-1

[4] Kumar, P. S., Kamath, R. N., Boyapati, P., Josephson, P. J., & Shadrach, F. D. (2022). IoT battery management system in electric vehicle based on LR parameter

estimation and ORMeshNet gateway topology. Sustainable Energy Technologies and Assessments, 53, 102696.

[5] Kaliappan, A. S., Mohanamurugan, S., & Nagarajan, P. K. (2020). Numerical investigation of sinusoidal and trapezoidal piston profiles for an IC engine. Journal of Applied Fluid Mechanics, 13(1), 287-298.

[6] F. Z. Echogdali, S. Boutaleb, M. Abioui, M. Aadraoui, A. Bendarma, R. B. Kpan, et al., "Spatial mapping of groundwater potentiality applying geometric average and fractal models: A sustainable approach," Water, vol. 15, no. 2, p. 336, 2023. DOI: 10.3390/w15020336

[7] Muda, I., Santosh, K., Aarif, M., Natrayan, L., Kaliappan, S., & Muthuperumal, S. (2024). Innovative Blockchain Protocol for Enhancing Transaction Security and Integrity in Decentralized Financial Ecosystems. In 2024 International Conference on Data Science and Network Security (ICDSNS) (pp. 1-6). IEEE. https://doi.org/10.1109/ICDSNS62112.2024.10691288

[8] F. Z. Echogdali, S. Boutaleb, M. Abioui, M. Aadraoui, A. Bendarma, R. B. Kpan, et al., "Spatial mapping of groundwater potentiality applying geometric average and fractal models: A sustainable approach," Water, vol. 15, no. 2, p. 336, 2023. DOI: 10.3390/w15020336

[9] M. Masroor, H. Sajjad, P. Kumar, T. K. Saha, M. H. Rahaman, P. Choudhari, et al., "Novel ensemble machine learning modeling approach for groundwater potential mapping in Parbhani District of Maharashtra, India," Water, vol. 15, no. 3, p. 419, 2023. DOI: 10.3390/w15030419

[10] A. D. O. Mahamat and A. Bounab, "The use of explanatory statistics for mapping groundwater potential zones in a semiarid area: Case of the Waddai province, eastern Chad," J. Afr. Earth Sci., vol. 205, p. 105012, 2023. DOI: 10.1016/j.jafrearsci.2023.105012

[11] K. Halder, A. K. Srivastava, A. Ghosh, R. Nabik, S. Pan, U. Chatterjee, et al., "Application of bagging and boosting ensemble machine learning techniques for groundwater potential mapping in a drought-prone agriculture region of eastern India," Environ. Sci. Eur., vol. 36, no. 1, p. 155, 2024. DOI: 10.1186/s12302-024-00981-y

[12] A. Paul, "Adaptive tri-plateau limit tri-histogram equalization algorithm for digital image enhancement," Vis. Comput., vol. 39, no. 1, pp. 297–318, 2023. DOI: 10.1007/s00371-021-02330-z

[13] Selvan, S., Ravindra, G., Kallappan, S., Natrayan, L., & Vinayagam, N. (2024). Investigation of the Use of Renewable Energy in Microgrid Applications. In 2024 Ninth International Conference on Science Technology Engineering and Mathematics (ICONSTEM) (pp. 1-5). IEEE. https://doi.org/10.1109/ICONSTEM60960.2024.10568631

[14] M. Abdel-Basset, D. El-Shahat, M. Jameel, and M. Abouhawwash, "Exponential distribution optimizer (EDO): A novel math-inspired algorithm for global optimization and engineering problems," Artif. Intell. Rev., vol. 56, no. 9, pp. 9329–9400, 2023. DOI: 10.1007/s10462-023-10403-9

[15] Suman, T., Kaliappan, S., Natrayan, L., & Dobhal, D. C. (2023, March). IoT based Social Device Network with Cloud Computing Architecture. In 2023 Second International Conference on Electronics and Renewable Systems (ICEARS) (pp. 502-505). IEEE. https://doi.org/10.1109/ICEARS56392.2023.10085574

[16] W. Zhang, W. Zhao, J. Li, P. Zhuang, H. Sun, Y. Xu, et al., "CVANet: Cascaded visual attention network for single image super-resolution," Neural Netw., vol. 170, pp. 622–634, Feb. 2024. DOI: 10.1016/j.neunet.2023.11.049

[17] Selvi, S., Mohanraj, M., Duraipandy, P., Kaliappan, S., Natrayan, L., & Vinayagam, N. (2023). Optimization of solar panel orientation for maximum energy efficiency. In 2023 4th International Conference on Smart Electronics and Communication (ICOSEC) (pp. 159-162). IEEE. https://doi.org/10.1109/ICOSEC58147.2023.10276287

[18] Balamurugan, P., Agarwal, P., Khajuria, D., Mahapatra, D., & Mammo, W. D. (2023). State-Flow Control Based Multistage Constant-Current Battery Charger for Electric Two-Wheeler. Journal of Advanced Transportation, 2023(1), 4554582. https://doi.org/10.1155/2023/4554582

[19] Kaliappan, S., Natrayan, L., & Rajput, A. (2023, September). Sentiment Analysis of News Headlines Based on Sentiment Lexicon and Deep Learning. In 2023 4th International Conference on Smart Electronics and Communication (ICOSEC) (pp. 1044-1047). IEEE. https://doi.org/10.1109/ICOSEC58147.2023.10276102

[20] Loganathan, A. S. Framework of transactive energy market strategies for lucrative peer-to-peer energy transactions. Energies 16 (1), 6 (2023). https://doi.org/10.3390/en16010006

[21] Arumugam, R. A., Komala, C. R., Barthwal, S., Kaliappan, S., & Natrayan, L. (2023). Design and Development of the Optical Antenna for Wireless Communications. In 2023 7th International Conference on Electronics, Communication and Aerospace Technology (ICECA) (pp. 1671-1676). IEEE. https://doi.org/10.1109/ICECA58529.2023.10395356

[22] Natrayan, L., Kaliappan, S., & Pundir, S. (2023). Control and Monitoring of a Quadcopter in Border Areas Using Embedded System. In 2023 4th International Conference on Smart Electronics and Communication (ICOSEC) (pp. 91-94). IEEE. https://doi.org/10.1109/ICOSEC58147.2023.10276196

[23] Chennai Viswanathan, P., Venkatesh, S. N., Dhanasekaran, S., Mahanta, T. K., Sugumaran, V. & Nanjagoundenpalayam S. (2023). Deep learning for enhanced fault diagnosis of monoblock centrifugal pumps: Spectrogram-based analysis. Machines, 11(9), 874. https://doi.org/10.3390/machines11090874

[24] Josphineleela, R., Kaliappan, S., Natrayan, L., & Bhatt, U. M. (2023). Intelligent Virtual Laboratory Development and Implementation using the RASA Framework. In 2023 7th International Conference on Computing Methodologies and Communication (ICCMC) (pp. 1172-1176). IEEE. https://doi.org/10.1109/ICCMC56507.2023.10083701

