

Prediction of Groundwater Level Using Machine Learning

Prathiksha P¹ and Sandhya R²

Post Graduate Student, Department of computer Applications¹

Associate Professor, Department of computer Application²

Jawaharlal Nehru New College of Engineering, Shimoga, Karnataka, India

Abstract: *In this paper, Prediction of groundwater level is made from different states. In order to describe this information for the states and created seasonal models to depict groundwater activity, The developed models in this manner may be expanded for use by the individual remote sensing techniques created by the Division for Self-Organizing Cognitive Computing (CSOIS). When it came to minimising, Support vector regression consistently beat other techniques both root mean square error and mean absolute error. Additionally, Models that could be constructed using only local geographic information seemed to have more error than those that could be established with taking a global feature from a Gaussian Mixture Model.*

Keywords: MLP, ANN, Ground water, Prediction etc.

I. INTRODUCTION

The water content in the best ten cm of soil is generally what causes surface soil suddenness. While such water only makes up a small portion of the total amount of water, it is vital to many various hydrological, biochemical, characteristic, and some other techniques. Groundwater is a significant renewable resource in many countries that provides the greatest amount of the water a country desperately needs. Groundwater is a significant renewable resource in many countries that provides the greatest amount of the water a country desperately needs. Other consumers of groundwater besides businesses and include Producers that use it to irrigate crops and water animals, households and public water system based on wells and groundwater, as well as international businesses and corporations that do it for their functions and procedures. The height where all soil pores have genuinely been substantially filled with water is known as the pore space. Groundwater was situated near the top of the subsurface, at the water level.

II. LITERATURE SURVEY

Turlapati Samsritha et al. [1] In this proposed work uses different kinds of modeling techniques. This model can give the satisfactory and encouraging resulting, the main goal of developing this model is to produce good soil moisture, this is very helpful for formers to understand the fields approximate conditions. And guiding to the irrigation and fertilizer applications. Finally the paper introduces to set the rules before which collect the climate statistics. Haritha Kagita et al. [2] In this paper various Machine learning techniques can be used before collecting the weather information like monsoon and non-monsoon. Soil checking is mandatory. That predicates ground water system under weather and based on pumping different horizon for the prediction. Finally a prediction is based on modeling performance. Eslam A.Hussein et al. [3] In this paper automatic groundwater prediction can be implemented. This approach uses the various regression model to predicate groundwater images based on groundwater maps. Finally the machine learning techniques can yield the accurate prediction using SVR predictor, it can be automatically selected previous value in same pixels square root for rescaling. Mattia Vaccari et al. [4] countries like India groundwater places vital role here this proposed work uses 3 algorithms for classification such as Naive Bayes, Random forest and C5.0 with data analytics tools. Which predicates waterers Low or high for purpose of during passed on the quality of water. Random forest and Naïve bayes predicate the best accuracy result.

III. PROPOSED METHODOLOGY

The Multi-Layer Perceptron (MLP) network is the most used ANN architecture for regression or prediction. a middle layer at the very least in the input layer, and an output layer makes up the lines of the MLP network's layered architecture.



Several neurons typically help compensate a layer. Directed synapses connect each neuron in one layer to each neuron inside the successive layer.

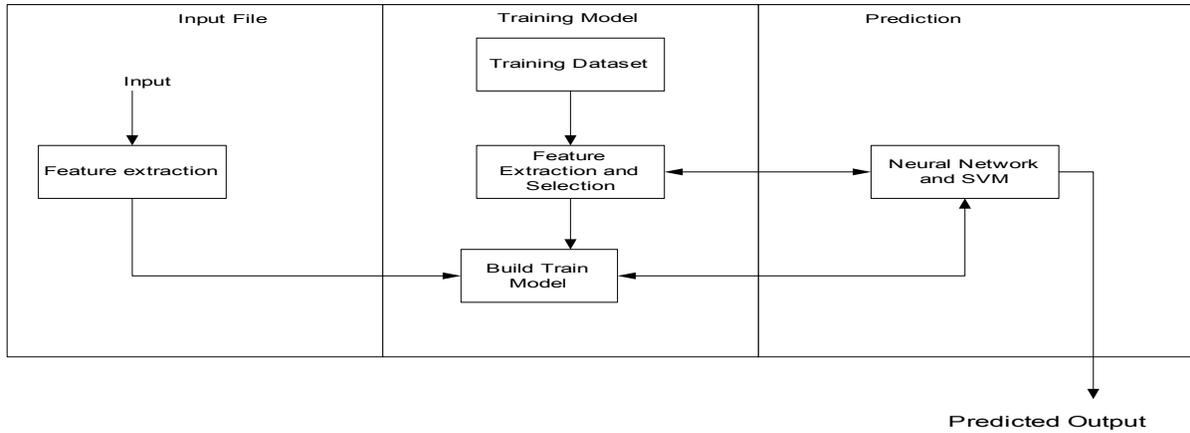


Figure 1: Proposed System

IV. RESULT ANALYSIS

The depicted graph will give the idea of the processing of a single module system as a result analysis

Graphs:

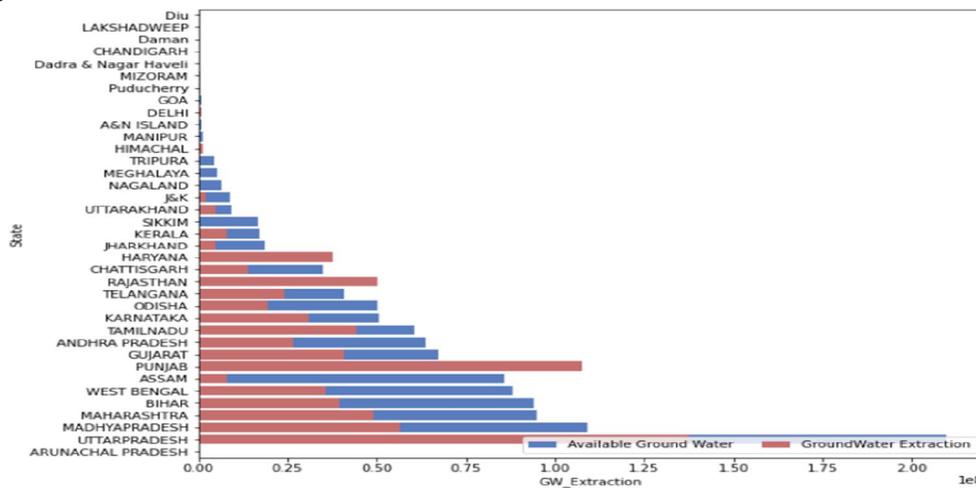


figure 2: Ground water Extraction

In the figure 2 indicates that extraction of ground water and ground water available details based on states.

- indicates Groundwater Extraction
- indicates Groundwater Available

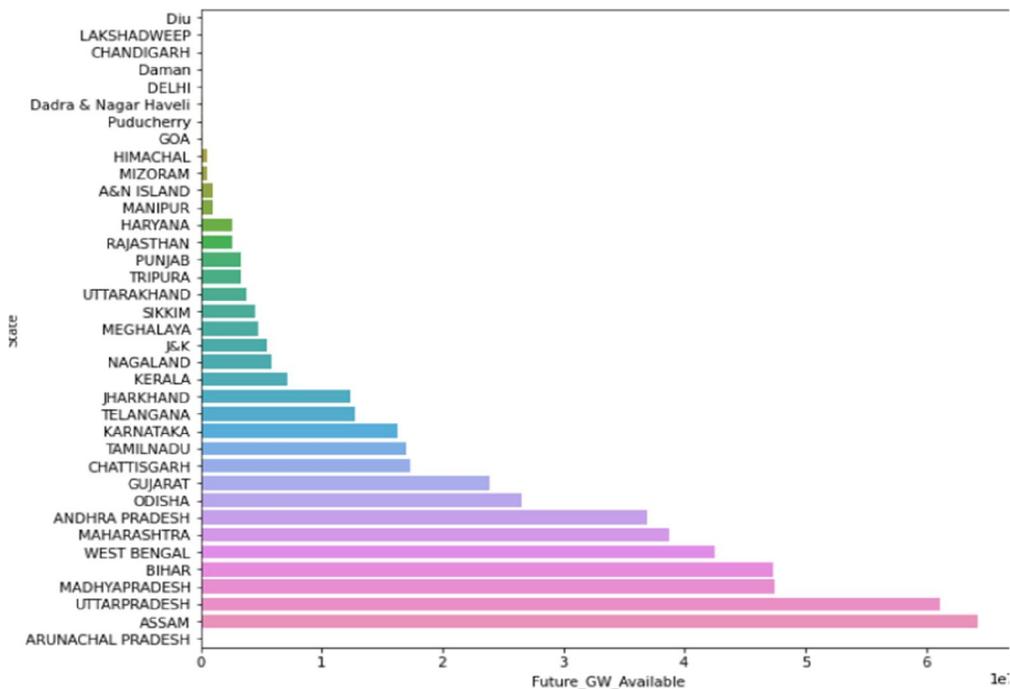


Figure 3: Future Groundwater Available

Figure 3 represents the Future groundwater rate available in different states.

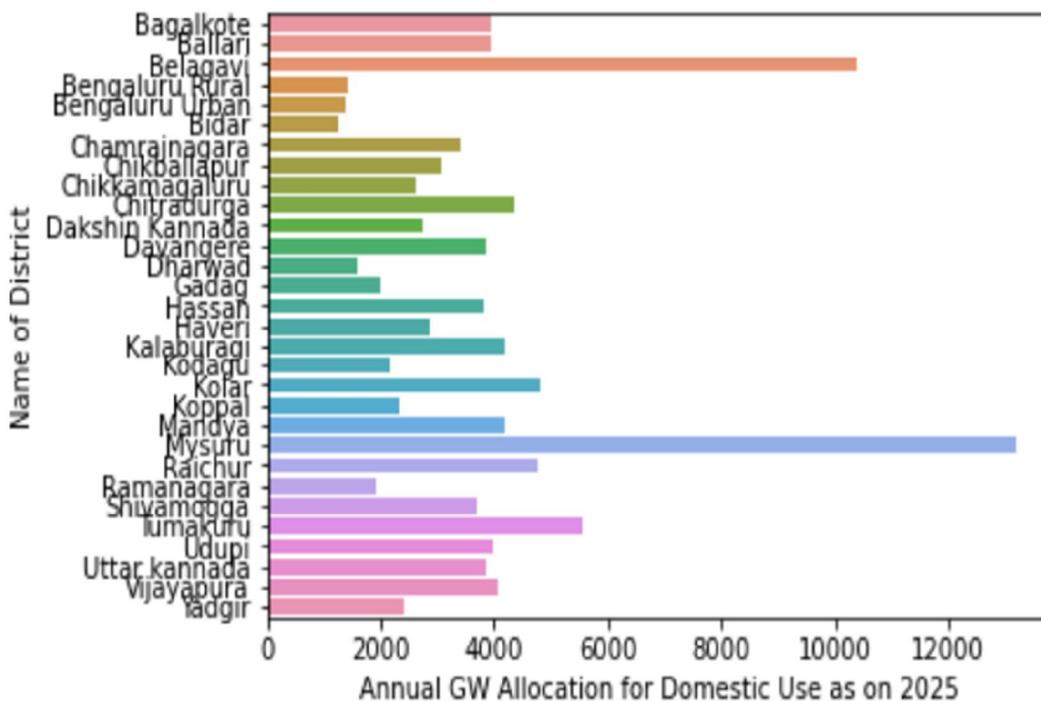


Figure 4: Groundwater for Domestic use

Figure 4 Represents the Annual Groundwater allocation for Domestic use, with name of the district

V. CONCLUSION

This research evaluated the GRACE dataset's automatic prediction of groundwater TWS. The multiple access forecasts full groundwater images from the a sequence of monthly groundwater maps that used a regression-based approach. Our results demonstrated that by using the appropriate machine-learning techniques can generate predictions that are significantly more accurate. Pixels values are automatically selected by using the SVR predictor.

REFERENCES

- [1]. Adamowski, J.; Fung Chan, H.; Prasher, S.O.; Ozga-Zielinski, B.; Sliusarieva, A. Comparison of multiple linear and nonlinear regression, autoregressive integrated moving average, artificial neural network, and wavelet artificial neural network methods for urban water demand forecasting in Montreal, Canada. *Water Resour. Res.* 2012, 48. [CrossRef]
- [2]. Assembly, U.N.G. Transforming Our World: The 2030 Agenda for Sustainable Development. 2015. Available online: <http://www.naturalcapital.vn/wp-content/uploads/2017/02/UNDP-Viet-Nam.pdf> (accessed on 15 July 2020).
- [3]. Braune, E.; Xu, Y. Groundwater management issues in Southern Africa—An IWRM perspective. *Water SA* 2008, 34, 699–706. [CrossRef]
- [4]. Cao, G.; Zheng, C.; Scanlon, B.R.; Liu, J.; Li, W. Use of flow modeling to assess sustainability of groundwater resources in the North China Plain. *Water Resour. Res.* 2013, 49, 159–175. [CrossRef]
- [5]. Felix Landerer. JPL TELLUS GRACE Level-3 Monthly Land Water-Equivalent-Thickness Surface Mass Anomaly Release 6.0 Version 03 in netCDF/ASCII/GeoTIFF Formats; Ver. RL06 v03; PODAAC: Pasadena, CA, USA, 2020. [CrossRef]
- [6]. Ghasemian, D. Groundwater Management Using Remotely Sensed Data in High Plains Aquifer. Ph.D. Thesis, The University of Arizona, Tucson, AZ, USA, 2016.
- [7]. Levy, J.; Xu, Y. Groundwater management and groundwater/surface-water interaction in the context of South African water policy. *Hydrogeol. J.* 2012, 20, 205–226. [CrossRef]
- [8]. Lo, M.H.; Famiglietti, J.S.; Yeh, P.F.; Syed, T. Improving parameter estimation and water table depth simulation in a land surface model using GRACE water storage and estimated base flow data. *Water Resour. Res.* 2010, 46. [CrossRef]
- [9]. Natkhin, M.; Steidl, J.; Dietrich, O.; Dannowski, R.; Lischeid, G. Differentiating between climate effects and forest growth dynamics effects on decreasing groundwater recharge in a lowland region in Northeast Germany. *J. Hydrol.* 2012, 448, 245–254. [CrossRef]