
ISSN: 2321-2152
IJMECE
International Journal of modern electronics and communication engineering
E-Mail
editor.ijmece@gmail.com
editor@ijmece.com
www.ijmece.com

ISSN 2321-2152
www.ijmece.com
Vol 13, Issue 2, 2025

# PREDICTION OF GROUND WATER LEVEL BASED ON MACHINE LEARNING

[1] Minhaj Begum, [2] Nangunoori shreya,[3] Annaldas Sakshi,[4] Srija Reddy Bolla

[1]Assistant professor in Department of Information Technology, Bhoj Reddy Engineering College for Women

[2,3,4,]UG Scholars in Department of Information Technology, Bhoj Reddy Engineering College for Women

## Abstract

we perform analysis of groundwater level data from various states. We have analyzed this data for the states and developed seasonal models to represent the groundwater behavior. Three different type of models were developed-periodic, polynomial and rainfall models. While periodic and polynomial models capture trends on water levels in observation wells, the rainfall model explores the link between the rainfall levels and water levels. The periodic and polynomial models are developed only using the water level data of observation wells while the rainfall model also uses the rainfall data. All the data and the models developed with a summary of analysis. The larger aim is to build these models to predict temporal changes in water level to aid local water management decisions and also give region specific input to Government planning authorities e.g. Groundwater Survey and Development Agency to flag water status with more information.

## I INTRODUCTION

Water below the land surface appears in two zones - saturated and therefore the unsaturated zone. When rainfall occurs, a neighbourhood of it infiltrates into the bottom. Some amount of this infiltrated rain is delayed by the upper layer of soil in its pore spaces. This layer is immediately below the land surface and contains both air and water and is known as the unsaturated zone. When all the soil pores are completely filled with water, then water seeps further down through the fractures in the rock. After a certain depth all pores in the soil are completely filled with water, this part forms the saturated zone. The top of saturated zone is known as the water table and water in this zone is called the groundwater.

## II LITERATURE REVIEW

**Soil moisture: A central and unifying theme in physical geography David R. Legates**

Soil moisture is a critical component of the earth system and plays an integrative role among the various subfields of physical geography. This paper highlights not just how soil moisture affects atmospheric, geomorphic, hydrologic, and biologic processes but that it lies at the intersection of these areas of scientific inquiry. Soil moisture impacts earth surface processes in such a way that it creates an obvious synergistic relationship among the various subfields of physical geography. The dispersive and cohesive properties of soil moisture also make it an important variable in regional and microclimatic analyses, landscape denudation and change through weathering, runoff generation and partitioning, mass wasting, and sediment transport. Thus, this paper serves as a call to use research in soil moisture as an integrative and unifying theme in physical geography.

**Soil moisture retrieval from space: the Soil Moisture and Ocean Salinity (SMOS) mission**

Microwave radiometry at low frequencies (L-band: 1.4 GHz, 21 cm) is an established technique for estimating surface soil moisture and sea surface salinity with a suitable sensitivity. However, from space, large antennas (several meters) are required to achieve an adequate spatial resolution at L-band. So as to reduce the problem of putting into orbit a large filled antenna, the possibility of using antenna synthesis methods has been investigated. Such a system, relying on a deployable structure, has now proved to be feasible and has led to the Soil Moisture and Ocean Salinity (SMOS) mission, which is described. The main objective of the SMOS mission is to deliver key variables of the land surfaces (soil moisture fields), and of ocean surfaces (sea surface salinity fields). The SMOS mission is based on a dual polarized L-band radiometer using aperture synthesis (two-dimensional [2D] interferometer) so as to achieve a ground resolution of 50 km at the swath edges coupled with multiangular acquisitions. The radiometer will enable frequent and global coverage of the globe and deliver surface soil moisture fields over land and sea surface salinity over the oceans. The SMOS mission was proposed to the European Space Agency (ESA) in the framework of the Earth Explorer Opportunity Missions. It was selected for a tentative launch in 2005. The goal of this paper is to present the main aspects of the baseline mission and describe how soil

**Soil moisture retrieval from amsr-e, IEEE transactions on Geoscience and remote sensing**

The Advanced Microwave Scanning Radiometer (AMSR-E) on the Earth Observing System (EOS) Aqua satellite was launched on May 4, 2002. The AMSR-E instrument provides a potentially improved soil moisture sensing capability over previous spaceborne radiometers such as the Scanning Multichannel Microwave Radiometer and Special Sensor Microwave/Imager due to its combination of low frequency and higher spatial resolution (approximately 60 km at 6.9 GHz). The AMSR-E soil moisture retrieval approach and its implementation are described in this paper. A postlaunch validation program is in progress that will provide evaluations of the retrieved soil moisture and enable improved hydrologic applications of the data. Key aspects of the validation program include assessments of the effects on retrieved soil moisture of variability in vegetation water content, surface temperature, and spatial heterogeneity. Examples of AMSR-E brightness temperature observations over land are shown from the first few months of instrument operation, indicating general features of global vegetation and soil moisture variability. The AMSR-E sensor calibration and extent of radio frequency interference are currently being assessed, to be followed by quantitative assessments of the soil moisture retrievals.

## III EXISTING SYSTEM

Groundwater level is an indicator of groundwater availability, groundwater flow, and therefore the physical characteristics of an aquifer or groundwater system. Due to increased population and decreased groundwater recharge, the demand increases and it may not be feasible to check the draft of groundwater resources. The only available option is to extend the recharge rate to the aquifer by suitable means. Therefore it is necessary to quantify this rate of groundwater recharge, monitor the change in water level depth then predict the long run trend of water level depth before any intervention. The disadvantage of refereed project is any phenomenon, which produces pressure change within an aquifer, results into the change of spring water level. These changes in spring water level are often a result of change in storage, amount of discharge and recharge, variation of stream stages and evaporation.

## IV OBJECTIVE

•to quantify the relative influence of climate variability, crop irrigation demand, and streamflow on groundwater level change and

• to develop an empirical (data-driven) model of the hydrologic system. We used simulated crop irrigation demand as a model input in lieu of unavailable groundwater pumping data. We developed and tested our model in the context of two major agriculture-dominated aquifers, for which we used the model to predict groundwater level change (seasonal, 1980–2012) using high-resolution and noisy input variables. While we tested and applied these methods on well-studied aquifers, we intend that the method be applied in regions lacking high-resolution subsurface information

## V PROPOSED SYSTEM

This is mainly in the form of evaluation of the magnitude of a hydrological parameters. The factors that influence and control the water level fluctuation were determined to develop a forecasting model and examine its potential in predicting water level . Models for prediction of water level depth were developed supported with different combinations of hydrological parameters. The best combination was confirmed with factor analysis. The input parameters for water table forecasting were derived using statistical Analysis (TSA). The advantage of this project is most of the researches used ANN alone to predict water table but this study incorporated correlational analysis alongside statistic forecasting to extend the accuracy and usefulness of prediction.

## VI IMPLEMENTATION

Filed Survey Field survey was administered to determine the observation well locations suitable for the study area. The wells were selected in such a way that areas of different elevations are suitably covered. The spatial locations were identified by conducting GPS (Global positioning system) survey. The groundwater level was recorded periodically.

Factor Analysis In factor analysis the correlation between input parameters Potential evapotranspiration (PET), temperature, humidity and rainfall were analyzed using Statistical Package for Social Sciences (SPSS) for monsoon and non-monsoon season. Any factor having component value less than 0.5 was extracted as it is less significant for the input combination.

Random Forest Random forest use bagging approach. It creates a bunch of decision tree by using a random subset of data. These datasets are needed to be trained several times in order to achieve good prediction performance. In this ensemble learning method, the output of all decision trees is combined together to make a final prediction. YOLOv2 and YOLOv3 Logistic Regression Logistic regression is used for classification task and not for regression task. Regression means the linear model fit into the feature space. It uses logical function to a linear combination of features. This is needed to predict the outcome of a dependent variable.

Decision Tree Logistic regression is used for classification task and not for regression task. Regression means the linear model fit into the feature space. It uses logical function to a linear combination of features. This is needed to predict the outcome of a dependent variable.

## VII RESULTS

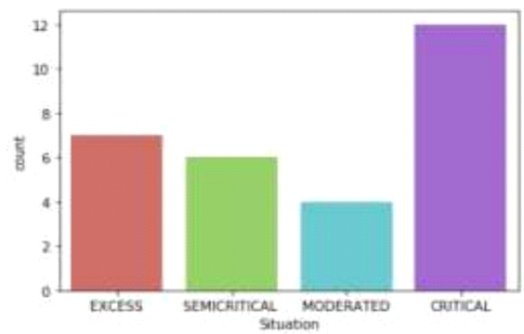



Fig 1: Analyzing Situation Attribute

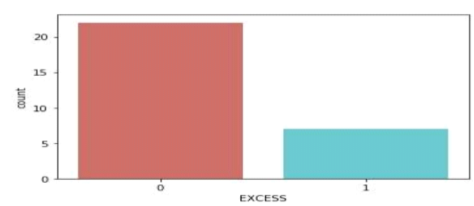



Fig 2. Analyzing Excess Attribute

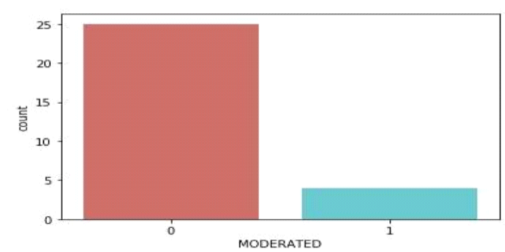
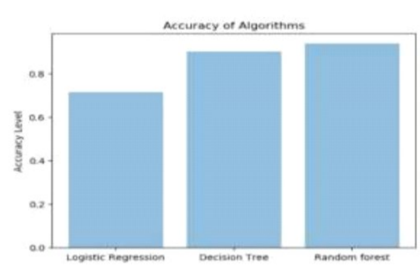
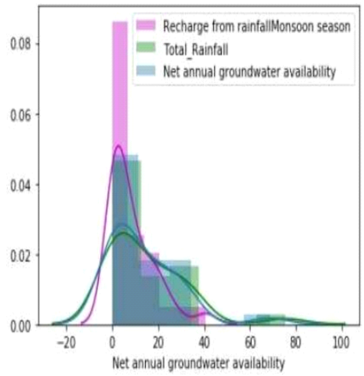



Fig 3. Analyzing moderate attribute

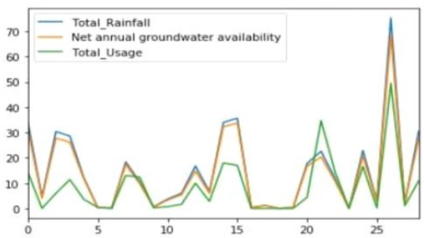



NET ANNUM GROUND WATER

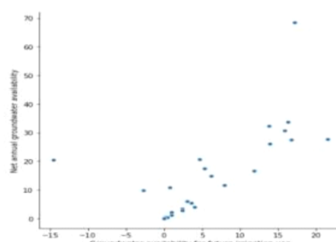
ISSN 2321-2152
www.ijmece.com
Vol 13, Issue 2, 2025




TIME SERIES ANALYSIS




SCATTER PLOTS




## VIII CONCLUSION

This paper introduces various machine learning algorithm before which we have collected weather information of both monsoon and non-monsoon then checked soil parameter after that for predicting transient groundwater levels in groundwater system under variable pumping and weather. Various prediction horizons are used, including daily, weekly and monthly prediction horizons. It was found that albeit modelling performance (in terms of prediction accuracy and generalization) for both approaches was generally comparable.

## REFERENCES

[1].D. R. Legates, R. Mahmood, D. F. Levia, T. L. DeLiberty, S. M. Quiring, C. Houser, and F. E. Nelson, “Soil moisture: A central and unifying theme in physical geography,” Progress inPhysical Geography, vol. 35, no. 1, pp. 65–86, 2011.

[2] Y. H. Kerr, P. Waldteufel, J.-P. Wigneron, J. Martinuzzi, J. Font, and M. Berger, “Soil moisture retrieval from space: The soil moisture and ocean salinity (smos) mission,” IEEE transactions on Geoscience and remote sensing, vol. 39, no. 8, pp. 1729– 1735, 2001.

[3] E. G. Njoku, T. J. Jackson, V. Lakshmi, T. K. Chan, and S. V. Nghiem, “Soil moisture retrieval from amsr-e,” IEEE transactions on Geoscience and remote sensing, vol. 41, no. 2, pp. 215–229, 2003.

[4] R. H. Reichle, R. D. Koster, J. Dong, and A. A. Berg, “Global soil moisture from satellite observations, land surface models, and ground data:Implications for data assimilation,”Journalof Hydrometeorology, vol. 5, no. 3, pp. 430–442, 2004.

[5] S. Lambot, E. C. Slob, I. van den Bosch, B. Stockbroeckx, and M. Vanclooster, “Modeling of ground-penetrating radar for accurate characterization of subsurface electric properties,” IEEE Transactions on Geoscience

and Remote Sensing, vol. 42, no. 11, pp. 2555–2568, 2004.

[6] M. S. Dawson, A. K. Fung, and M. T. Manry, "A robust statisticalbased estimator for soil moisture retrieval from radar measurements," IEEE transactions on geoscience and remote sensing, vol. 35, no. 1, pp. 57–67, 1997.

[7] G. Satalino, F. Mattia, M. W. Davidson, T. Le Toan, G. Pasquariello, and M. Borgeaud, "On current limits of soil moisture retrieval from ers-sar data," IEEE Transactions on Geoscience and Remote Sensing, vol. 40, no. 11, pp. 2438–2447, 2002.

[8] L. Pasolli, C. Notarnicola, and L. Bruzzone, "Estimating soil moisture with the support vector regression technique," IEEE Geoscience and remote sensing letters, vol. 8, no. 6, pp. 1080–1084.

[9] S. Ahmad, A. Kalra, and H. Stephen, "Estimating soil moisture using remote sensing data: A machine learning approach approach," Advances in Water Resources, vol. 33,no. 1, pp. 69–80, 2010.

[10] B. Zaman, M. McKee, and C. M. Neale, "Fusion of remotely sensed data for soil moisture estimation using relevance vector and support vector machines,"International journal of remote sensing, vol. 33, no. 20, pp. 6516–6552, 2012.