International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 07 Issue: 02 | Feb 2020 www.irjet.net p-ISSN: 2395-0072

Prediction of Ground Water Level based on machine Learning

Haritha kagita[1], Malathi. V[2], Thiyagarajan. A[3]

[1,2]UG Student, in CSE Department of Computer science & Engineering Agni College of Technology, Chennai, India
[3]Assistant Professor in CSE Department of Computer science & Engineering Agni College of Technology, Chennai, India

---***---

Abstract - *In this project work 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[1]. 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.*

Key Words: TSA, ANN,LOGISTIC REGRESSION,DECISION TREE,RANDOM FOREST

1. 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.

1.1 Existing System

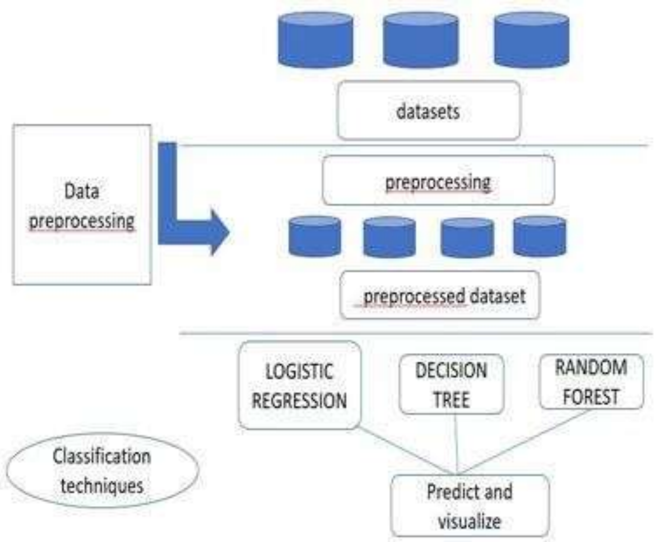
Groundwater level is an indicator of groundwater availability, groundwater flow, and therefore the physical characteristics of an aquifer or groundwater system. Due to increased population and decreased groundwater recharge, the demand increases and it may not be feasible to check the draft of groundwater 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.

1.2 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.

2. System Architecture



3. Modules

3.1. 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.

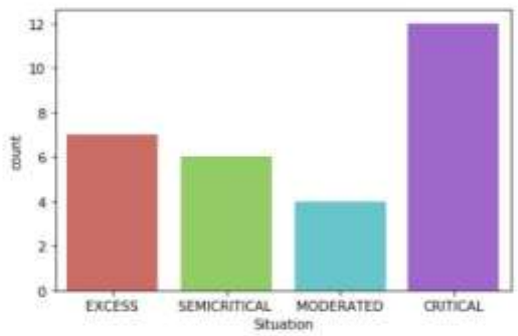


Fig 1: Analyzing Situation Attribute

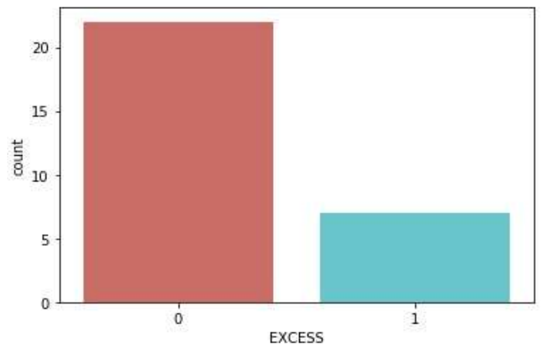


Fig 2. Analyzing Excess Attribute

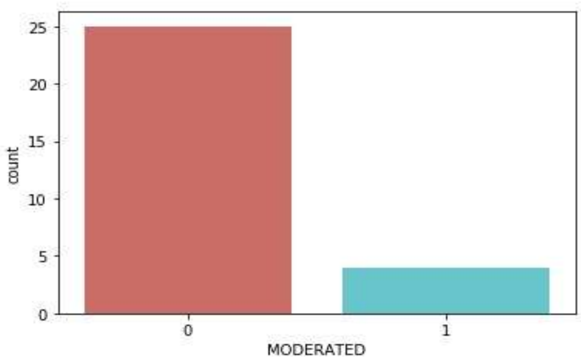


Fig 3. Analyzing moderate attribute

3.2. 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.

3.3. Random Forest

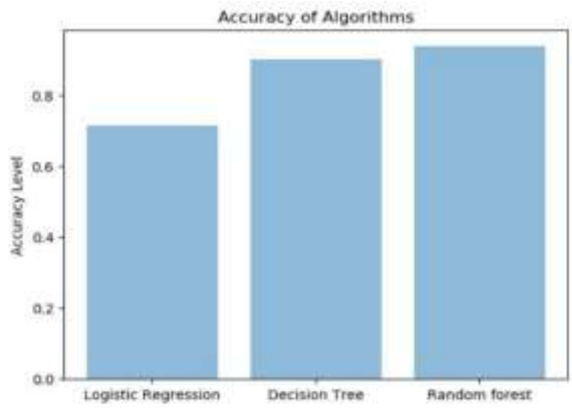
Random forest use bagging approach. It creates a bunch of decision tree by using a random subset of data. These datasets are needed to be trained several times in order to achieve good prediction performance. In this ensemble learning method, the output of all decision trees is combined together to make a final prediction.

3.4. Logistic Regression

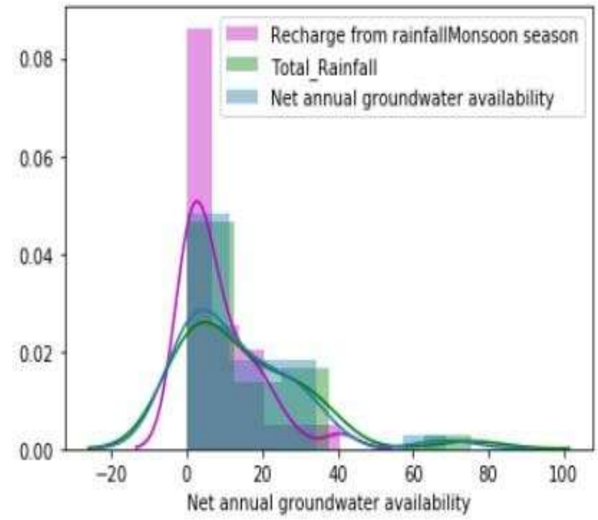
Logistic regression is used for classification task and not for regression task. Regression means the linear model fit into the feature space. It uses logical function to a linear combination of features. This is needed to predict the outcome of a dependent variable.

3.5. Decision Tree

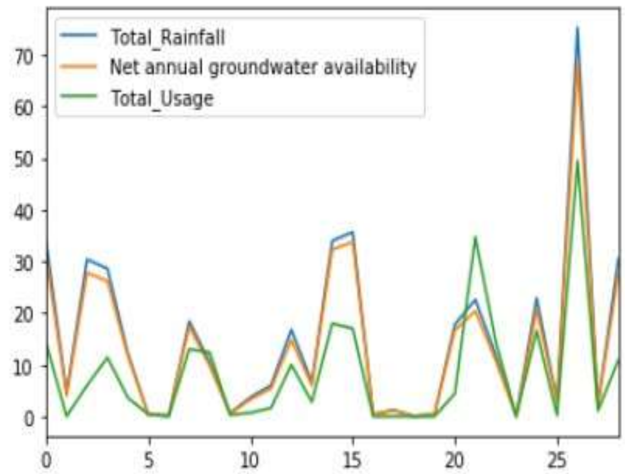
Logistic regression is used for classification task and not for regression task. Regression means the linear model fit into the feature space. It uses logical function to a linear combination of features. This is needed to predict the outcome of a dependent variable.



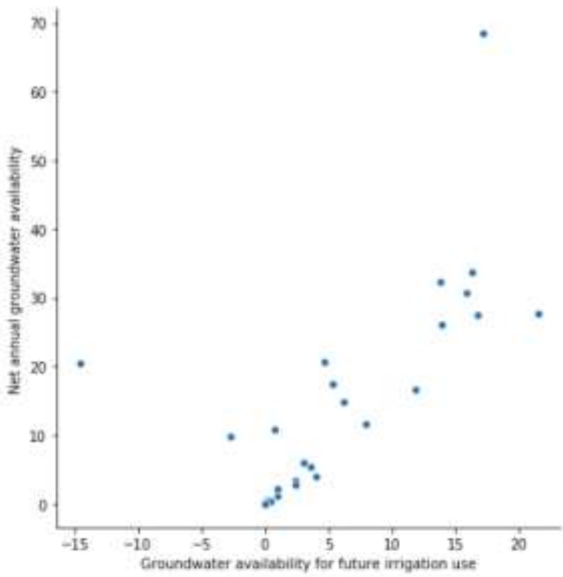
NET ANNUM GROUND WATER



TIME SERIES ANALYSIS



SCATTER PLOTS



4. 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 in Physical 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," Journal of 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.

BIOGRAPHIES

Haritha Kagita,
Computer Science and Engineering,
Agni College of Technology.

Malathi.V,
Computer Science and Engineering,
Agni College of Technology.

A. Thiyagarajan, M.E, (PHD),
Computer Science and Engineering,
Agni College of Technology.