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Prediction of Soil Moisture UsingMachine Learning

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ABSTRACT

The performance of the predictor is evaluated on the idea of Mean Squared Error (MSE) and test scores. The comparison results shows that call tree is giving an accuracy of 0.87 and Random Forest Classifier is giving an accuracy of 0.937500. Accurate estimates of root zone soil moisture (RZSM) at relevant spatio-temporalscales are essential for several agricultural and hydrological applications. Applications of machine learning (ML) techniques to estimate root zone soil moisture are limited compared to commonly used process based models supported flow and transport equations within the vadose zone. However, data-driven ML techniques present unique opportunities to develop quantitative models without having assumptions on the processes operating within the system being investigated. During this study, the Random Forest (RF) ensemble learning algorithm, is tested to demonstrate the capabilities and advantages of ML for RZSM estimation.

I. INTRODUCTION

Soil moisture prediction across large spatial scales is difficult thanks to the heterogeneity in soil texture, crop type, and crop residue cover. Point measurements that include gravimetric methods and in-situ electromagnetic sensors are accurate but havelimited spatial extent and need significant time and labor. Remotesensing tools are used recently to predict topsoil moisture, but efficiency and models applicable to multiple landscapes are still under study. Soil moisture is usually predicted using information collected from nearby weather stations and variables from soil andcrops using one among three empirical, regression, and machine learning methods. These methods include forecasting models like empirical formulas, water balance approach, dynamic soil water models, statistic models, and neural network models .

II. LITERATURE SURVEY

Water below the land surface appears in two zones - saturated and the unsaturated zone. When rainfall occurs, a part of it infiltrates into the ground. Some amount ofthis infiltrated rain is held up by the upper layer of soil in its pore spaces. This layer is immediately below the land surfaceand contains both air and water and is known as the unsaturated zone. When all the soil pores are completely filledwith water, then water seeps further down through the fracturesin 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 waterin this zone is called the groundwater.

Soil moisture has a strong influence on the distribution of water between various components of the hydrological cycle in agricultural fields. It helps in understanding the hydrology and climatic conditions that have high spatial and temporal variability. Precise measurement and/or prediction of soil moisture provide insights into expected infiltration and runoff generation during rainfall events and the management of water for agricultural purposes. In agricultural fields, soil moisture affects key farm activities from crop selection to timing of tilling, planting, fertilizer application, and harvesting due to infiltration, evaporation, runoff, heat, and gas fluxes.

Groundwater level is an indicator of groundwateravailability, groundwater flow, and 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 increasethe recharge rate to the aquifer by suitable means. Therefore, it is necessary to quantify the present rate of groundwater recharge, monitor the change in water table depth and then predict the future trend of water table depth before any intervention

Any phenomenon, which produces pressure change within an aquifer, results into the change of ground water level.

These changes in ground water level can be a result of changes in storage, amount of discharge and recharge, variationofstream stages and evaporation.

III. PROPOSED SYSTEM:

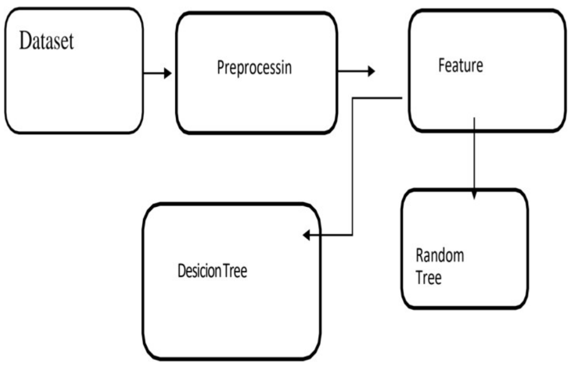

Fig: Proposed System

This is mainly in the form of estimation of the magnitude of a hydrological parameters. The factors that influence and control the groundwater level fluctuation were determined to develop a forecasting model and examine its potential in predicting groundwater level.

Models for prediction of water table depth weredeveloped based on Decision Tree Classifier and RandomForest Classifier with different combinations of hydrological parameters. The best combination was confirmed with factor analysis. The input parameters for groundwater level forecasting were derived using Time Series Analysis (TSA). Hydrological cycle parameters such as precipitation, surface runoff, evapotranspiration, interception, infiltration, change in soil moisture, river flow, and change in groundwater storage are part of Earth'sdynamic ecosystem. However, these methods provide point-based estimates of hydrological parameters.

VI .TRAINING AND TESTING THE DATASET

Pandas Visualization: Pandas is an open source high-performance, easy-to-use library providing data structures, such as dataframes, and data analysis tools like the visualization tools we will use in this article. Pandas Visualization makes it really easy to create plots out of a panda's dataframe and series. It also has a

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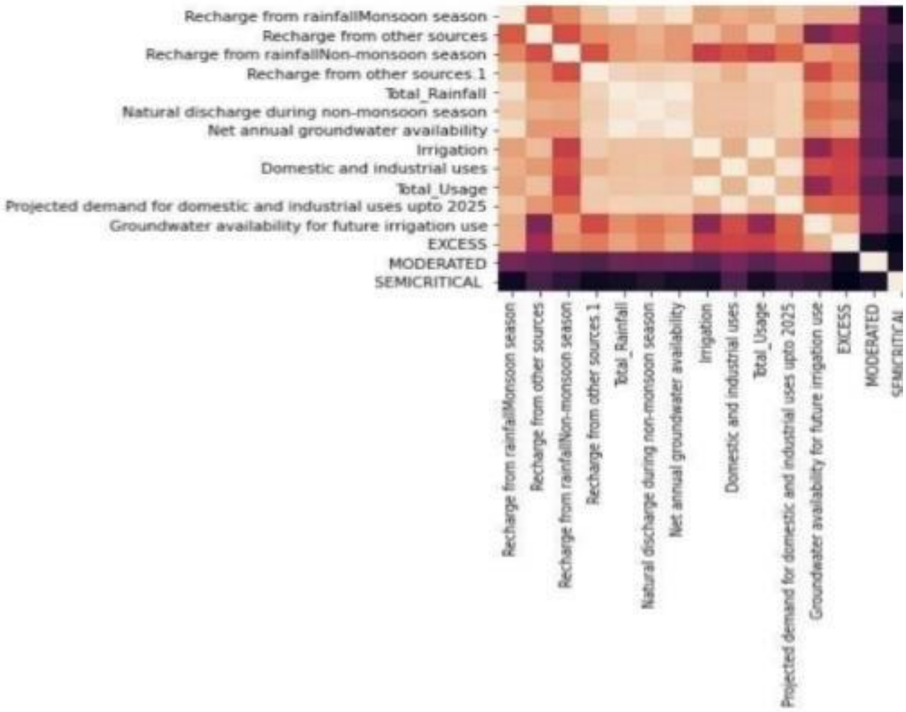
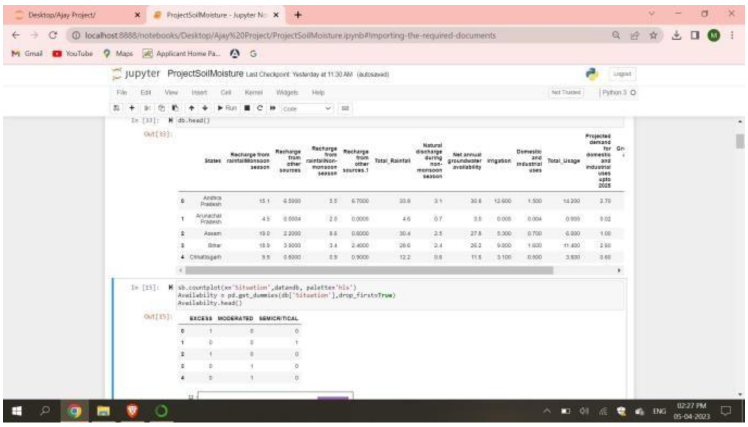
higher-level APIthan Matplotlib and therefore we need less code for the same results.

Heat Map: A Heatmap is a graphicalrepresentation of data where the individual values contained in a matrix are represented as colors. Heatmapsare perfect for exploring the correlation of features in a dataset. To get the correlation of the features inside a dataset we can call .corr() , which is a Pandas dataframe method. This will give use the correlation matrix. We cannow use either Matplotlib or Seaborn to create the heatmap.

lib:





III. RESULTS

In Matplotlib we can create a Histogram using the hist method. If we pass it categorical data like thepoints column fromthe wine-review dataset it will automatically calculate

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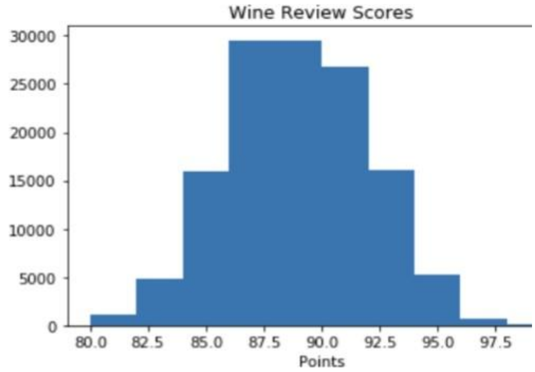
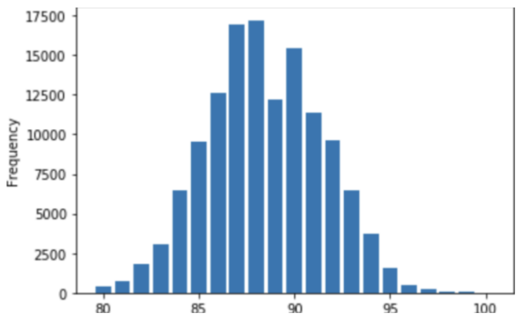
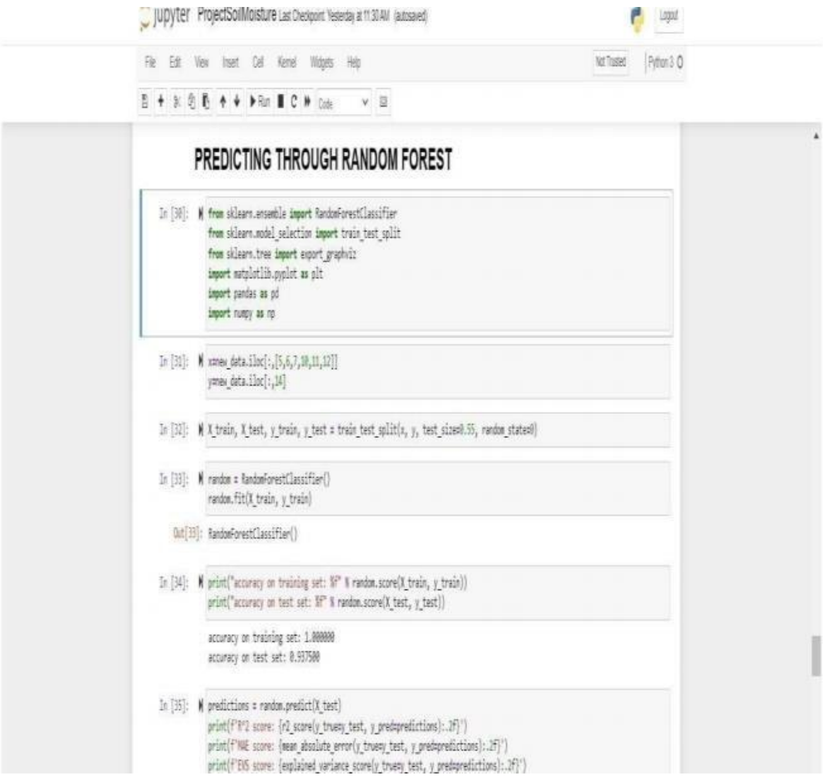


A bar-chart can be created using the bar method. The bar-chart isn't automatically calculating the frequency of a category so we are going to use pandas value_counts function todo this. The bar-chart is useful for categorical data that doesn't have a lot of different categories (less than 30) because else it can get quite messy.

IV. CONCLUSION

Based on the latest assessment involves estimation of dynamic ground water resources that was conducted in 2020 jointly by both respective State and Central Ground Water Board, we have taken that database and converted it to adata frame and with the help of different factors of how the groundwater is recharged and how the water comes in different seasons. Here features are the resources of water that causes the recharge of ground water. These data is used to train the different machine learning models like Random Forest Classifier and Decision Tree model and applying the Data Preprocessing methods and using the Anaconda Python Environment we have applied the data to the models using Sklearn module and this is a classification model. The model predict the amount of moisture present in soil using the data that is given as input to the model which asses the features and predict one of the four labels EXCESS, MODERATED, SEMI CRITICAL, CRITICAL which represents a range of quantity of moisture present in soil.





VII . REFERENCES

[1] R. Yamini Nivetha and C. Dhaya, "Developing a Prediction Model for Stock Analysis", Technical Advancements in Computers and Communications (ICTACC) 2017 International Conference on IEEE, 2017.

[2] 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 PhysicalGeography, vol. 35, no. 1, pp. 65–86, 2011.

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

[4] S. Lambot, E. C. Slob, I. van den Bosch, B. Stockbroeckx, and M. Vanclooster, "Modeling ofground-penetrating radar for accurate characterization of subsurface electric properties," IEEE Transactions on Geoscience and Remote Sensing, vol. 42, no. 11, pp. 2555–2568, 2004.