ASSESSMENT OF DROUGHT RISK WITH ITS IMPACT ON WHEAT YIELD

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Abstract – *In England where agricultural is the primary source of income for the majority of the population. In terms of micronutrients, England topsoil are less fruitful. In recent decades, it has been discovered that soil fertility is linked to sustainable agriculture, and that preserving soil fertility can increase present crop output levels. A number of factors, such as the type of crop to be produced, need the use of a decision support system in agriculture. Water use may be optimised to a significant extent by monitoring soil moisture as the water table drops day by day. Because moisture content is helpful to agricultural development, the steps involved in crop production can be improved when we can accurately anticipate moisture levels. We need to know the moisture content of any area or place so that we can estimate how likely it is to face a famine.*

We utilised Decision Tree Classifier and Random Tree Classifier as machine learning approaches throughout this work. These methods were used on a sample data gathered from several internet resources. Mean Squared Error (MSE) and test scores are used to measure the predictor's effectiveness.

Key Words: **Drought, Heat of soil, Water-level, Famine, Machine Learning, Decision-Tree Classifier, Random Forest Classifier**

1. INTRODUCTION

A famine is defined as a period of protracted water scarcity, whether from the atmosphere, surface water, or subsurface water. Droughts can last weeks or months, although they can be proclaimed in as little as 15 days. It has the potential to have a significant influence on the afflicted region's ecology and farming, as well as impair the regional economy. Annual dry seasons in the tropics substantially enhance the danger of dehydration and subsequent bushfires. Drought conditions can be aggravated by heat waves, which accelerate the evaporation of vapour. Dehydration is a common occurrence in most regions of the world's climate. Due to climate change, however, these frequent droughts have grown more intense and irregular. Drought linked to climate change has been documented since 1900, according to research based on dendrochronology, or tree ring dating.

Drought tolerance adaptations such as decreased leaf area and waxy cuticles have been found in many plant species, even those in the Cactaceae (or cactus) family. Others thrive as buried seeds during dry seasons. Arid biomes including such deserts & grasslands are created by quasi dryness. Water shortages that have lasted for a long time have resulted in mass emigration and a humanitarian catastrophe.

Water shortages have a negative impact on food production and human civilization, therefore they are classified as a natural, divine, or human-caused calamity (which itself could be supernatural causes, malediction, sin, ...). It is one of the earliest known climatic occurrences, appearing in the Gilgamesh Epic and linked to the Biblical narrative of Joseph's entrance in Egypt and the subsequent Exodus. Water shortages are generally seeping, slowly developing catastrophes that can then be watched with time as they grow. Although some drought occurrences (such as flash drought) can emerge very rapidly, droughts are typically creeping, slowly emerging disasters that can be tracked over time as they develop. Changes in rainfall patterns, heat, and ground and surface water supplies are among the surveillance indexes.

Famine has a wide range of effects that are dependent on the socioeconomic context of the afflicted population. When choosing dryness indicators for a specific drought monitoring and early alert system, it's critical to first determine the sorts of effects wherein an area is prone. Early warning systems for dehydration keep track of, assess, and exchange data on water source, weather, and hydrological.

2. OBJECTIVES

a) The main objective of this paper is to create a system that would detect changes in few environmental parameters that could predict the beginnings of a drought.

b) This paper helps to increase the efficiency of automated/regular farming by not only predicting the fertility level of a farmland but also it's potential to become a barren land.

c) To build a working model such that with high efficiency in terms of accuracy.

d) Prediction of parametric changes can be made very efficiently and effectively.

e) The system also aids government in rescue missions related to drought prone areas.

f) Evaluating Machine learning models for automated decision making.

3. EXISTING SYSTEM

The availability of groundwater, the flow of groundwater, and the physical features of an aquifers or underground water system are all indicators of groundwater level. Demand rises as a result of growing population and decreasing groundwater recharge, and it may be impossible to check the draw of groundwater resources. The only viable alternative is to enhance the aquifer's recharge rate using appropriate techniques. As a result, prior to any intervention, it is important to measure the current rate of groundwater recharge, monitor the change in water table depth, and then estimate the future trend of water table depth.

4. PROPOSED METHODOLOGY

This usually takes the form of calculating the amplitude of hydrologic models. The elements that impact and regulate groundwater storage variation were identified in order to create a forecasting model and test its predictive ability. Models for predicting the depth of the water table have been created. Using different combinations of hydrological factors, a Decision Tree Classifier and a Random Forest Classifier were used. Factor analysis was used to establish the optimal configuration. Time Series Analysis was used to determine the input parameters for groundwater level predictions (TSA).

All hydrological cycle elements impact earth's dynamic ecology: precipitation, surface runoff, evapotranspiration, interception, infiltration, change in soil moisture, river flow, and change in groundwater storage. These methods, but at the other extreme, provide estimates of meteorological variables based on points.

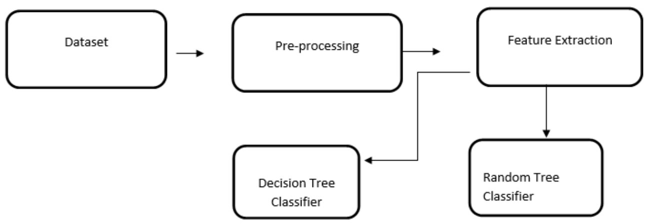

Fig 1: Process flowchart

4.1. MACHINE LEARNING

Machine Learning is a technique that helps us to learn from various examples and can improve on its own without having to be explicitly programmed by a developer. The accomplishment is based on the concept that a computer may train through information (for illustration) to create accurate results on its own. To anticipate an outcome, machine learning integrates data with statistical techniques. This information is subsequently used by the company to provide valuable intelligence. Data mining and Bayesian predictive modelling are both strongly connected to machine learning. The computer takes data as input and generates replies using a formula.

Machine learning also is utilized to do tasks such as detecting fraud, preventive analytics, investment decisions, job automation, and so on. Machine learning differs substantially from traditional programming. A developer codes all the rules in conventional programming in cooperation with just an expertise in the sector about which technology is now being built. Every rule is built on a logical basis, and the computer will execute the logical statement and produce an output. More regulations must be created as the system becomes more sophisticated. Maintaining it can rapidly become untenable. All learning takes place in the brain of machine learning. The machine learns in the same way that humans do. Individuals gain knowledge from their experiences. The more information we have, the easier it is to make predictions. By comparison, the probability of victory is lower in an unknown circumstance than in a repeated exposure. Computers are taught in much the same way. The machine examines an example in order to generate an accurate forecast.

Training and inference are the two main goals of machine learning. First and foremost, the system learns by pattern recognition. The data helped to make this finding. Among the most important tasks for a data scientist would be to carefully evaluate the data to provide to the computer. A feature vector is a collection of attributes used to solve an issue. A vector may be regarded as a subset of information that is utilized to find a solution.

5. PHASES

Following are the independent phases implemented in the system:

i. Field survey
ii. Factor analysis
iii. Time series analysis (TSA)
iv. Prediction using Random Tree Classifier

5.1. Field Survey

- A ground survey was conducted to determine the best locations for observation wells in the research region. The reservoirs were chosen because then regions of varying altitudes would be adequately covered.
- A GPS assessment was used to determine the geographical positions.
- The subsurface water level was measured on a regular basis.

5.2. Factor Analysis

- For monsoon and non-monsoon seasons, the association between input parameters

Potential evapotranspiration (PET), heat, moisture, and rainfall was examined using the Statistical Package for Social Sciences (SPSS).

- Any variable with a component value of the less than 0.5 was removed from the analysis since it is less important for the input combination.

5.3. Time Series Analysis

At this point, the input parameters required for groundwater level prediction were papered. The parameters were anticipated based on historically observed data.

- This research employed time series analysis with a moving average method.

Random Forest Classifier with Decision Tree Classifier Estimation:

- Decision Tree Classifier and Random Forest Classifier are information processing paradigms inspired by biological nerve systems, such as the human brain.
- It is made up of a large number of interconnected functioning units called neurons that work together.
- As illustrated in Fig 5.4.1, a Decision Tree Classifier and a Random Forest Classifier include input, hidden, and output layers, with each level containing an array of processing components.
- The architecture of a neural network represents the pattern of connections between nodes, as well as the technique for computing connection weights and the input vector.

5.4. Prediction using Random Tree Classifier

- Choose small selection from a group of statistics.
- For each sample, create a decision tree and acquire a forecast result out of each decision tree.
- Make a check for every papered outcome.
- As the final forecast, choose the prediction with the most votes.

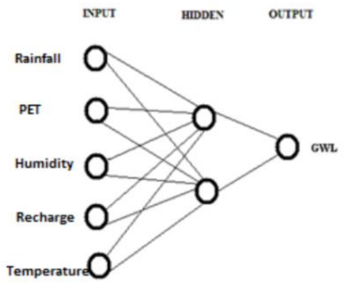

Fig 2: Prediction layer diagram

6. RESULTS

The result is viewed through an ui that has been created.

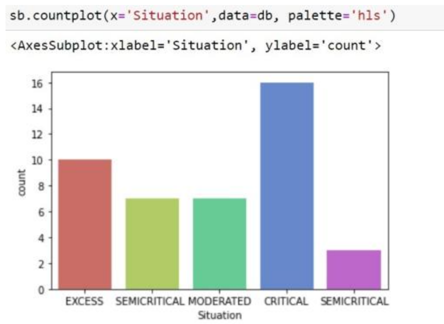

Fig 3: Bar graph of results obtained by data analysis

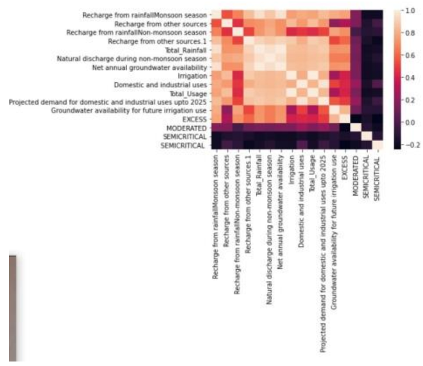

Fig 4: Heat-map

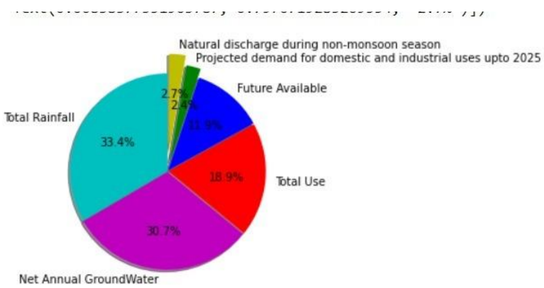

Fig 5: Rainfall and underground water composition

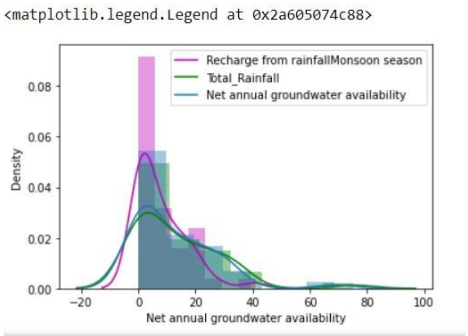

Fig 6: Net annual groundwater availability

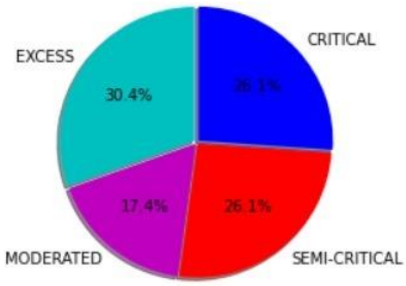

Fig 7: Pie chart for comparison

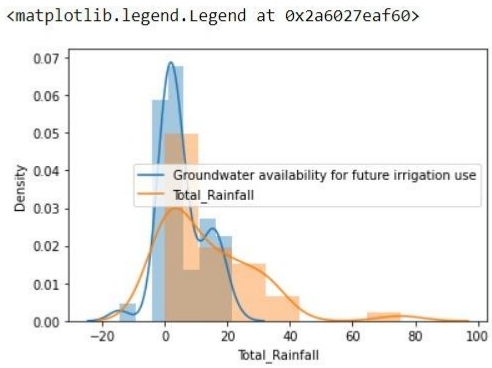

Fig 8: Total rainfall

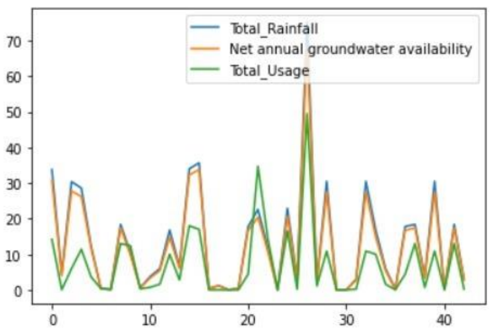

Fig 9: Total rainfall

7. ANALYSIS

Our paper uses conventional Machine Learning techniques that require only modest technological knowledge to create a working model of a drought monitoring system that could aid people in preparing for predicted drought conditions caused by a variety of factors such as rapidly depleting underground water levels, heavy rains, as well as other variables.

8. CONCLUSION

This work offers several machine learning algorithms for forecasting transitory groundwater levels in a complicated groundwater system under changing pumping and meteorological conditions. We first gathered weather data, both monsoon and non-monsoon, and then examined soil parameters. Daily, weekly, biweekly, monthly, and bimonthly prediction horizons were utilized, as well as forecast scopes. Even while the modeling efficiency (in terms of classification accuracy and generalization) both for techniques was usually equal, it must have been discovered that now the results were not.

Beyond the boundaries of a college/university paper, machine learning algorithms that support high-level automation and self-learning systems can be further developed. This research revealed advancements in the field of catastrophe management. Based on the findings, the system has given the fastest response time of the parametric changes from the sensors to the website or mobile android app.

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