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Landscape Soil Moisture Analysis with Machine Learning using Weather Parameters

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***Abstract*— The correlation coefficient between soil moisture and weather variables such air temperature, precipitation, rainfall, and surface temperature is proposed by this study. The region of mid Asia was subjected to the model. The findings demonstrated a strong inverse relationship between soil moisture and surface temperature, a corresponding inverse relationship between soil moisture and air temperature, and a strong inverse relationship between soil moisture and precipitation. The soil moisture derived from NASA's LPRM_AMSR2 data was observed to have a correlation coefficient of 0.45 with gridded rainfall, and -0.59 with air temperature and ground temperature. The Aphrodite's Water Resource was employed to conduct this analysis, and the resulting meteorological factors taken into consideration were from there. Applying various weather parameters as the corresponding input to make a prediction about soil moisture and then measuring the accuracy with an LSTM model.**

***Index Terms*— Soil moisture, long short-term memory, Correlation, Prediction, Remote sensing.**

I. Introduction

The characteristics of the soil have been a crucial component in studies on resource management, agriculture, and climate change. There has been a significant demand for research and the provision of tools for analyzing and evaluating geographic topography's ongoing evolution. Numerous studies demonstrate that simply recognizing the need for change and introducing the affluent components will not be sufficient; a thorough investigation and evaluation will be needed to track these improvements. We consider data from climate models, existing soil records of various terrains, weather anomalies, and socio-economic events in order to illustrate the problem, and we then analyze how the soil's characteristics are altering a given specific topographic area [1-4]. We would require data to keep a periodic analysis of soil terrains as the generation evolves with science and technology to a fully digital era. Our research was considered as part of the evaluation to ascertain the degree of association between NASA's surface soil moisture data and Aphrodite's weather characteristics.

II. Materials And Analogies

A. Study Areas

Parts of central Asia and the Indian subcontinent are included in the region that we studied for our correlation. The region includes a variety of topographical features, including plains, plateaus, mountain ranges, tiered terrain, and deserts. This region offers a suitable field of view for research into the relationships between numerous parameters

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making it a viable topic of study for figuring out the correctness of various factors and grids efficiently [5,6].

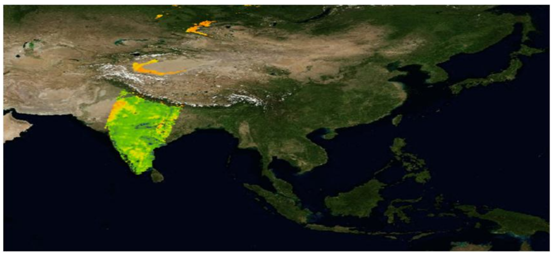

Figure 1 Soil Moisture Plot. (Rendered on SNAP)

B. Data

Both passive microwave remote sensing data and interpolated gridded data are used in this investigation. The daily mean and EOD (End of Day) average gridded fields were taken from Aphrodite's Water Resource.

TABLE I DATA DESCRIPTION

Data	**Spatial Resolution**	**Temporal Resolution**	**Resource**	**Utilization**
Soil Moisture	25 km x 25 km	Daily	National Aeronautics and Space Administration, (NASA) U.S.A.	Input for Model, Accuracy Verification
Surface Temperature	25 km x 25 km	Daily	National Aeronautics and Space Administration, (NASA) U.S.A.	Input for Model
Precipitation (V1801_R1)	25 km x 25 km	Daily	Aphrodite's Water Resource. Japan.	Input for Model
Daily Precipitation Rate Adjusted (V1901)	25 km x 25 km	Daily	Aphrodite's Water Resource. Japan	Input for Model
Atmospheric Temperature (End of Day)	25 km x 25 km	Daily	Aphrodite's Water Resource. Japan	Input for Model

Interpolation of gauge observations from a ground station was used to create this gridded collection in advance. The average daily product is the 'mean' of climatology. The weather, rain, and Aphrodite's water resource were taken into consideration. NASA's AMSR2/GCOM-W1 surface soil moisture (LPRM) repository served as the source of the remote sensing data utilized.

Data preprocessing included: (1) utilizing gridded patterns to show data points using SNAP (Sentinel Application Platform) software to cross-reference AMSR and SMOR data. (2) Segmenting data from NetCDF into manageable CSV chunks using Pandas and NumPy for better gridded data handling. (3) plotting the acquired data using Plotly.

III. METHODS

Long Short-Term Memory (LSTM) model was the best option when choosing a model for processing time-based analysis. For this type of data provision, GIS is an official system of record, clustering more choices for feature engineering and data exploration that could improve the precision and depth of the model [7].

A. Spearman's Correlation Coefficient

The association between the meteorological variables and soil moisture was examined using Spearman's Correlation Coefficient. Two things with a nonlinear relationship can be related using the Spearman's correlation coefficient. The correlation coefficient's equation is depicted in the equation below.

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}$$

ρ = Spearman's correlation coefficient.
di = Difference between observations of the two ranks.

n = No. of Observations

B. Long Short-Term Memory (LSTM)

Hoch Reiter & Schmid Huber first introduced the LSTM in 1997, and it is effective with long-term dependency. It can analyze order dependence between things and was further improved and customized to satisfy specific requirements and goals. The learning curve for forecasting better predictions for time series data seems promising rather than having context-specific and fixed difficulties.

The main equation and representation of the LSTM for a single time-step, as well as its input and output, are shown in Figure 2. The input of the LSTM, which was derived from the output of CN, is represented as x(t). The output of the LSTM for this timestep is o(t), and the inputs and outputs from the previous timestep are h(t-1) and c(t-1). For the following timestep, c(t) and h(t) are formed in the setting of multiple timesteps.

C. Selection of Model Parameters

Three parameters related to soil moisture and climatic weather exist according to the model. Land surface temperature and land surface soil moisture, which were obtained from remote sensing data, were taken from the gridded data for the pre-processed NASA's AMSR taken into consideration in this study, while meteorological system parameters included average temperature and atmospheric precipitation.

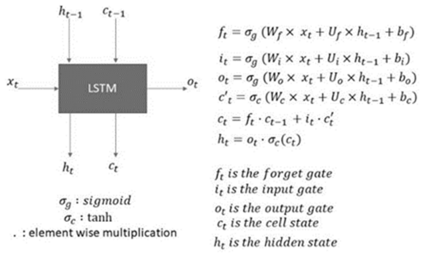

Figure *2*. Base structure of LST

The correlation coefficient was determined using the aforementioned parameters, and then parameters with moderate to high correlation were derived and chosen to take part in modelling. According to the findings, there was a significant negative association between surface temperature and the climatic variables.

IV. RESULTS

The following chart illustrates the relationship found between various meteorological variables and soil moisture at various geographic locations.

We can say that there is a strong correlation between land surface temperature and soil moisture because their correlation is close to one, or -0.868, which means that as one of the parameters rises, the other falls, making them inversely related.

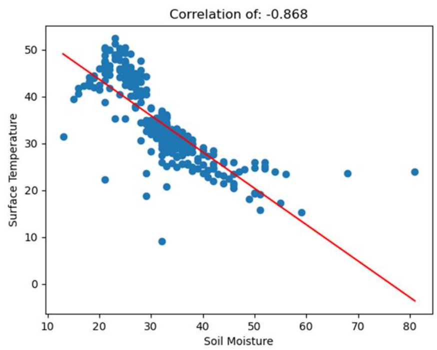

Figure 3. Correlation between Surface Temperature and Soil Moisture

Similar to this, there is a moderate negative correlation between atmospheric temperature and soil moisture, with a value of -0.868 indicating that there is a negative association between the former and the latter.

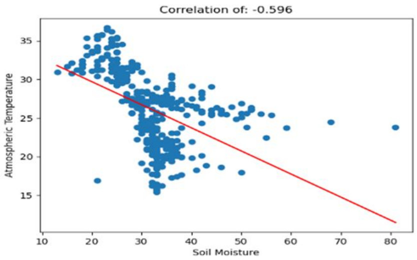

Figure 4. Correlation between Atmospheric Temperature and Soil Moisture

Precipitation has a positive coefficient of 0.450, which indicates a moderate association between soil moisture and precipitation, in contrast to the preceding two correlations.

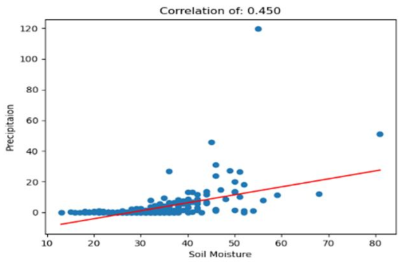

Figure 5. Correlation between Precipitation and Soil Moisture

Inferring from the obtained results that meteorological variables support a strong association with soil moisture, it is more obvious that this relationship should be used as a model input for predictive analysis.

When incorporated into the model, the predictive analysis that was determined utilizing the parameters produced results with moderate to high accuracy. The model inputs were split into two sections, each of which was evaluated in relation to soil and weather separately. A portion of the atmospheric temperature, precipitation (V1801_R1), and precipitation (V1901) for general distribution were the meteorological parameters employed. The made prediction has an 84% accuracy rate.

The graph below displays the discrepancies between the anticipated outcomes and the precipitation outputs as they relate to the two different versions that were employed.

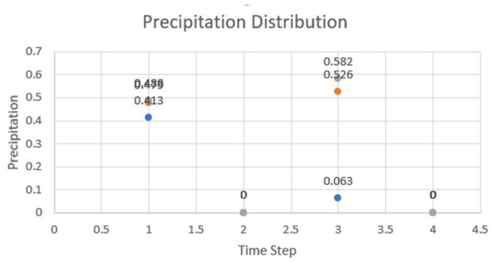

Figure 6. Predictive Distribution of Precipitation Over 3 Timesteps

The addition of temperature as an attribute, along with the two types of precipitation, is seen as habitually predicted because it has occurred consistently under a variety of different circumstances.

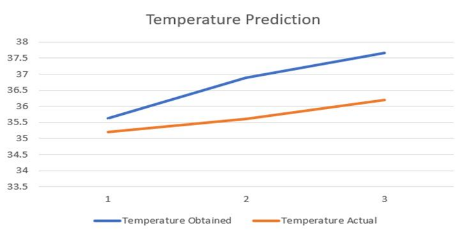

Figure 7. Three time steps of Predicted Temperature

One of the most important factors in evaluating soil moisture is the meteorological variables that have a greater association. Soil moisture, surface temperature, and air temperature are also the next set of inputs for the model, and they serve as the parameters for the following assessment segment.

V. Conclusion And Future Work

Through the use of LSTM and weather parameters, this study estimates the predictability of soil moisture. To examine the association, two segments were considered. Weather parameters from the first segment featured two different adjusted precipitation, which was a distinctive property. Using the same configuration, the following segment's soil moisture, surface temperature, and air temperature were assessed.

Initial findings showed a negative link between soil moisture and surface temperature as well as a positive correlation between soil moisture and precipitation, making soil moisture an ideal measure. The model is trained on numerous sites scattered over various terrains, taking segment one parameter into account for one instance and segment two parameters into consideration for the other. This led to a thorough investigation of the predictable factors of soil moisture and its relationship to the environment, including weather and surface temperature. Given the size of the study region, the conclusions we have drawn are only adequate when considering the previously indicated factors. The scheme's potential for use in the future could result in even more accurate relational analyses of usage statistics and data patterns via collective reproduction.

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