Landscape Analysis of Soil Moisture using Weather Parameters through Machine Learning

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Abstract

This study proposes the correlation coefficient between Soil Moisture, weather parameters such as air temperature, precipitation, rainfall and surface temperature. The model was applied to the mid Asia region. The results showed that soil moisture and surface temperature had a strong negative correlation, soil moisture and air temperature also had a consequent negative correlation, the relation between Soil moisture and collectively rainfall and precipitation have a strong positive correlation, the soil moisture derived from NASA's LPRM_AMSR2 data was observed a correlation coefficient of 0.45 with gridded rainfall, and -0.59 with air temperature and ground temperature, thus concluding a strong correlation between soil moisture and weather parameters. The derived weather parameters considered were from Aphrodite's Water Resource which was used to conduct this study. A prediction was made to determine soil moisture by applying different weather parameters as the correlating input to determine the exact accuracy using an LSTM model.

Keywords: Soil moisture, Long short-term memory, Correlation, Prediction, Remote sensing.

1. Introduction

Soil properties has been an essential feature to researches on resource management, agriculture and climate change. There has been a vast interest and requirement in studying and creation for analysing and evaluating the constant change in Geographical Topography. Many studies show that just inducing the affluent factors and recognizing changes required would not suffice but a detail study and evaluation is required for monitoring these changes. In order to visualize the issue, we are considering data from the climate models, existing soil datasets of different terrains, weather anomalies and socio-economic events and then analyse how the properties of soil is changing a given particular topographic area [1-4]. As the generation advances with science and technology and to a completely digital era where we would need data to maintain periodic analysis of soil terrains. Our study being a part of the evaluation in determining how much the correlation between weather parameters of Aphrodite's and the NASA's surface soil moisture.

2. Materials and Analogies

2.1 Study Areas

The region that we covered for our correlation includes parts of central Asia and the Indian subcontinent. The area covers a wide topographic region from plains, plateaus, mountain systems to stepped and desserts. This region provides a proper field of view for study in representing relation among different parameters, making it a feasible area of study for determining efficient accuracy among various factors and grids [5,6].

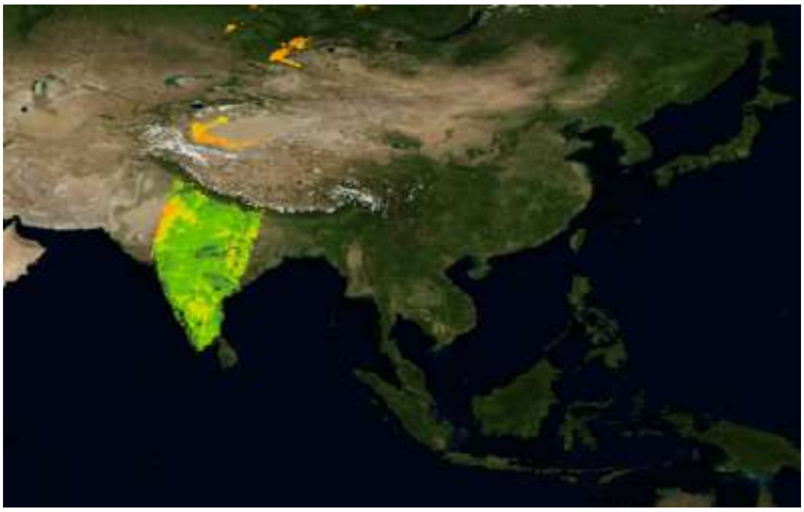

Fig.1. Soil Moisture Plot. (Rendered on SNAP)

A. Data

This study uses interpolated gridded data and passive microwave remote sensing data. The gridded fields of daily mean and EOD (End of day) average was obtained from Aphrodite's Water Resource.

Table 1. 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

This gridded set was pre-prepared by interpolation of gauge observations of ground station. Climatology 'mean' which was derived is the average of daily products. The products considered from Aphrodite's Water Resource was atmospheric temperature, Rain. The remote sensing data used was collected from NASA's AMSR2/GCOM-W1 surface soil moisture (LPRM) repository.

Data Preprocessing included: (1) using SNAP (Sentinel Application Platform) software to cross-reference AMSR and SMOR data and gridded patterns to visualize data points. (2) using Pandas and NumPy for segmentation and convert data into chunks of manageable CSVs from NetCDF for better management of gridded data. (3) using Plotly to visualize the obtained data.

3. Method

The most optimal choice in selecting the model for processing time-based analysis was Long Short-Term Memory (LSTM) model. GIS is an authoritative system of record for such data provision, clustering more options for feature engineering and data exploration that may increase the accuracy and depth of the model [7].

3.1 Spearman's Correlation Coefficient

The weather parameters considered in relation to Soil moisture was analysed using Spearman's Correlation Coefficient to determine the relationship. The Spearman's correlation coefficient can relate two entities having a nonlinear relationship. The below equation gives a representation of the equation for the correlation coefficient.

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

ρ = Spearman's correlation coefficient.

di = Difference between observations of the two ranks.

n = No. of Observations

3.2 Long Short-Term Memory (LSTM)

LSTM are efficient with long-term dependencies and it was introduced in 1997 by Hoch Reiter & Schmid Huber. It was further refined and fine-tuned to meet specific requirements and objectives; it can analyse order dependence between items. Rather having context pre-specified and fixed problems, it has a promising learning curve of predicting better for forecasting time series data.

Figure 2 describes the general equation and representation of LSTM for a single time-step and also depicting its input and output. x(t) represents the input of LSTM that was obtained from the output of CN. The inputs and outputs from the previous timestep are h(t-1) and c(t-1) with o(t) being the output of the LSTM for this timestep. In the configuration of multiple timesteps c(t) and h(t) is generated for the next timestep.

3.3 Selection of model parameters

Corresponding to the model there are three parameters in relation with Soil Moisture and Climatic Weather. The Soil parameters taken from the gridded data for the pre-processed NASA's AMSR considered in this study includes land surface temperature and land surface soil moisture obtained from remote sensing data, while meteorological system parameters include temperature average and atmospheric precipitation.

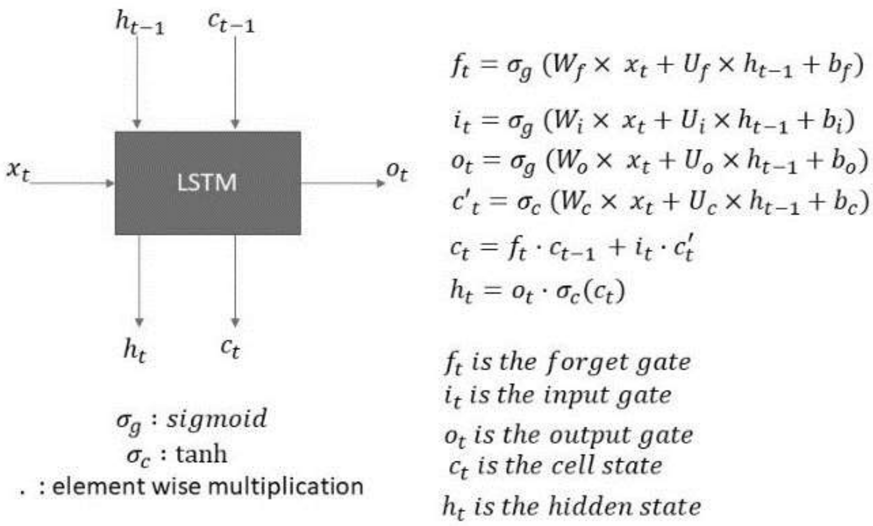

Fig.2. Base structure of LSTM

Using the above parameters, the correlation coefficient was calculated after which, parameters with moderate to high correlation was derived and were selected to participate in modelling. Considering the results, surface temperature had a strong negative correlation among the climatic factors.

4. Results

The correlation determined between the different weather parameters and soil moisture at different geographic positions are shown as follows.

The correlation between land surface Temperature and Soil Moisture is -0.868 which indicates that there is a negative correlation, hence we can say that the correlation is strong as it is close to -1, which signifies that as one of the parameters increases the other decreases making it inversely relational.

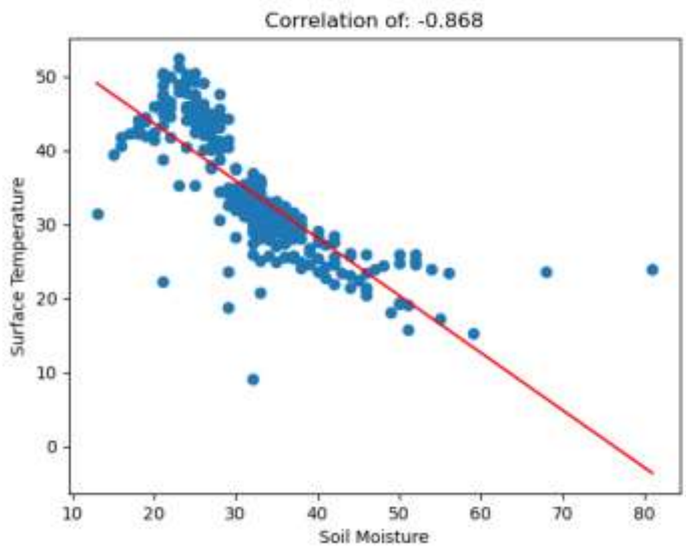

Fig.3. Correlation between Surface Temperature and Soil Moisture

Similarly, the correlation between atmospheric temperature and soil moisture is negatively correlated with a coefficient of -0.868 which indicates that there is a negative correlation between the former and the latter, hence we can say that the relation is moderate.

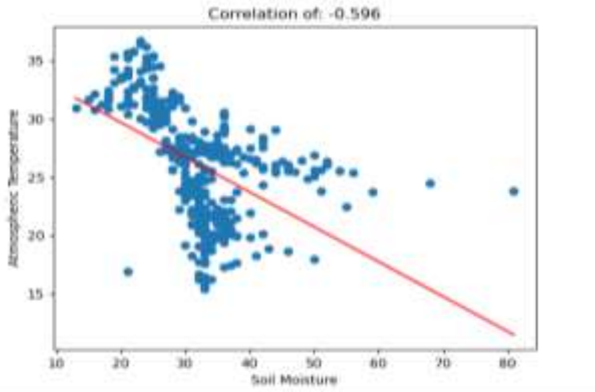

Fig.4. Correlation between Atmospheric Temperature and Soil Moisture

Unlike the previous two correlations, precipitation has a positive coefficient of 0.450, which depicts moderate relationship between Soil Moisture and precipitation.

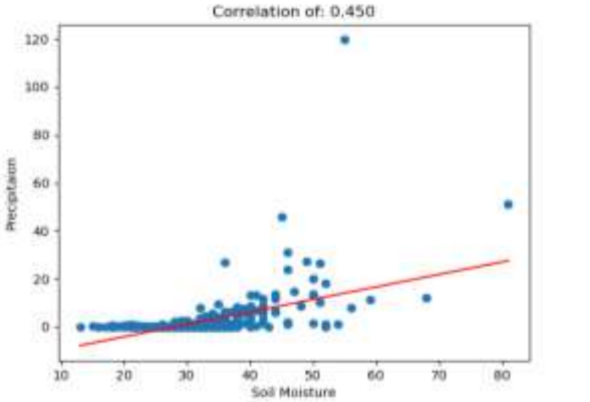

Fig.5. Correlation between Precipitation and Soil Moisture

Hence concluding that weather parameters favor a strong relationship with soil moisture from the obtained results, making it more prominent to use as a model input for predictive analysis. The predictive analysis that was determined using the parameters yielded a moderate to high accuracy when inserted to the model. The model inputs were divided into two segments each assessed upon to relate to weather and soil separately. The weather parameters used were a segment of atmospheric temperature, precipitation (V1801_R1), and precipitation (V1901) for general distribution. The obtained prediction stood with an accuracy of 84%.

The below graph shows the differential results obtained between the predicted results vs the actual outputs of precipitation when corresponding to the two different versions used.

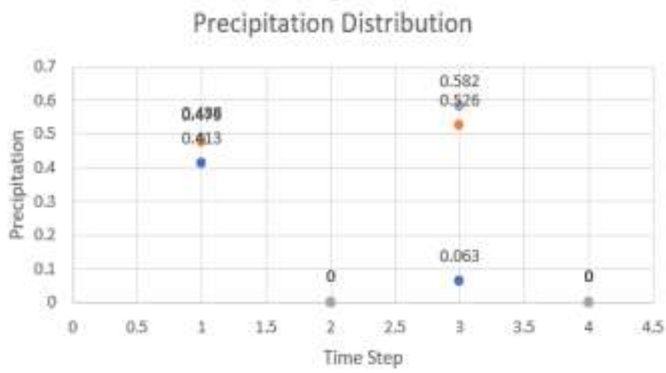

Fig.6. Predictive Distribution of Precipitation Over 3 Timesteps.

Similarly, when temperature was added as an attribute along with the two variations of precipitation, it is regarded as routinely predictable as it has recurred consistently under a range of different conditions.

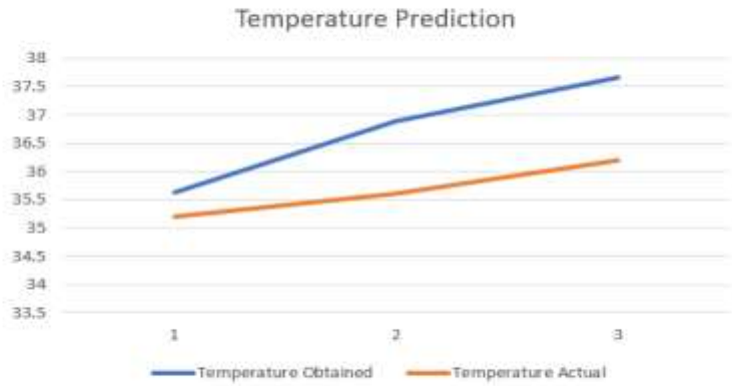

Fig.7. Three timesteps of Predicted Temperature

The weather parameters having a better correlation is a key parameter in determining soil moisture. Thus, the parameters for the next segment of evaluation are atmospheric temperature, surface temperature and soil moisture also being the next set of inputs for the model.

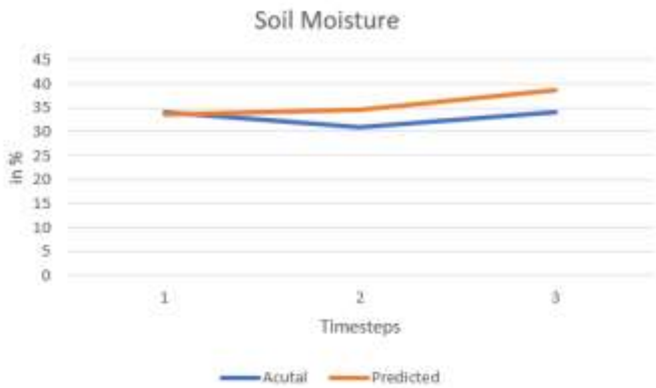

Fig.9. Three timesteps of Predicted Surface Temperature

5. Conclusion and Future Work

This study determines the predictability of soil moisture using Weather Parameters through LSTM. There were two segments considered to evaluate the relationship. The first segment included weather parameters which had a distinct property with two different adjusted precipitation. The next segment was evaluated using the same configuration with soil moisture, surface temperature and atmospheric temperature.

Initial results concluded that soil moisture and the surface temperature correlated negatively along with precipitation having a positive correlation with soil moisture making it optimally efficient as a parameter. The model is trained inclusively on multiple locations spread over different terrains considering the segment one parameters for one instance and segment two parameters for the other. This generated a conclusive analysis on soil moisture's predictable parameters and its relation with weather and surface temperature. Considering the vast study area that was taken, we have generated only sufficient enough conclusion as to consider the as mentioned parameters. Future usability on the scheme can yield even better relational analysis on collective reproduction of usage stats and data trends.

References:

[1]. Petropoulos, G.P.; Ireland, G.; Barrett, B. Surface soil moisture retrievals from remote sensing: Current status, products & future trends. Phys. Chem. Earth Parts A/B/C 2015, 83–84, 36–56.

[2]. Vrije Universiteit Amsterdam (Richard de Jeu) and NASA GSFC (Manfred Owe) (2014), AMSR2/GCOM-W1 surface soil moisture (LPRM), Edited by Goddard Earth Sciences Data and Information Services Center (GES DISC) (Bill Teng), Greenbelt, MD, USA, Goddard Earth Sciences Data and Information.

[3]. Services Center (GES DISC), Accessed: [Data Access Date], 10.5067/CGDEOBASZ178I. S. Jacobs and C. P. Bean, “Fine particles, thin films and exchange anisotropy,” in Magnetism, vol. III, G. T. Rado and H. Suhl, Eds. New York: Academic, 1963, pp. 271–350.

[4]. Owe, M., R. de Jeu, and T. Holmes (2008), Multisensor historical climatology of satellite-derived global land surface moisture, Journal of Geophysical Research, F01002, doi:10.1029/2007JF000769R. Nicole, “Title of paper with only first word capitalized,” J. Name Stand. Abbrev., in press.

[5]. Yatagai, A., M. Maeda, S. Khadgarai, M. Masuda and P. Xie (2020): End of the Day (EOD) Judgment for Daily Rain-Gauge Data, Atmosphere, 11(8), 772, DOI: 10.3390/atmos11080772. [Link]

[6]. Yatagai, A., K. Kamiguchi, O. Arakawa, A. Hamada, N. Yasutomi and A. Kitoh (2012): APHRODITE: Constructing a Long-term Daily Gridded Precipitation Dataset for Asia based on a Dense Network of Rain Gauges, Bulletin of American Meteorological Society, doi:10.1175/BAMS-D-11-00122.1. [Link]

[7]. Yatagai, A., and P. Xie (2006): Utilization of a rain-gauge-based daily precipitation dataset over Asia for validation of precipitation derived from TRMM/PR and JRA-25. SPIE 0604-53, DOI:10.1117/12.723829.