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Analysis of CYGNSS Soil Moisture Retrieval Based on ANN over a Selected Region in Ethiopia

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Abstract: Soil moisture (SM) plays a vital role in agriculture, ecosystem functioning, water conservation, weather predictions and climate models. High spatial and temporal frequency data of soil moisture is crucial for agricultural and other important applications. Recent advancements have brought attention to the possibility of using GNSS reflectometry (GNSS-R) for applications on land such as snow sensing, soil moisture retrieval, sea surface monitoring and other applications in addition to positioning, navigation, and timing applications of GNSS. Cyclone Global Navigation Satellite System (CYGNSS) is designed to improve hurricane forecasting by studying the interaction between the ocean and the atmosphere within tropical cyclones. However recent studies show the opportunity of this system for high spatio-temporal soil moisture retrieval. This study presents a machine learning-based approach to get SM at a selected region in Ethiopia using CYGNSS data and analysis of the result. Artificial Neural Network (ANN) model is developed and used to predict soil moisture. The Soil Moisture Active Passive (SMAP) global soil moisture data have been used as reference data in the ML algorithm. The proposed approach has achieved a good correlation between predicted values of soil moisture and reference values from SMAP.

Key Words: CYGNSS; SMAP; soil moisture; surface reflectivity; artificial neural network.

1. Introduction

The water cycle between the ground and the atmosphere on Earth is actively influenced by soil moisture[1]. Soil moisture (SM) plays an important role in various environmental processes, influencing ecosystem functioning, hydrological cycles, vegetation states, agricultural productivity, and climate patterns[1][2]. As a result, SM monitoring on a broad scale is crucial for agricultural research and the assessment of environmental parameters. It is also important for improving weather and climate forecasts.

Satellites particularly designed for soil moisture monitoring include: SMAP, which measures soil moisture around the world using both active (radar) and passive (radiometer) sensors; Soil Moisture and Ocean Salinity (SMOS), which uses a microwave radiometer; and Sentinel-1, which is part of the Copernicus program. Both SMAP and SMOS are equipped with an L-band microwave radiometer payload[3]. However, the coarse spatial resolution of passive microwave satellites, such as SMAP and SMOS, is around 40 km. Furthermore, vegetation structure and surface roughness have a significant impact on readings from synthetic aperture radar (SAR) systems, such as Sentinel-1 and TerraSAR-X[4]. Moreover, radar technology such as Scatterometer and Synthetic Aperture Radar can provide detailed soil moisture information with high

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precision and less frequent revisits (more than 12 days). However, it may not meet the requirements for agricultural applications alone[5].

A bi-static microwave remote sensing technology called Global Navigation Satellite System reflectometry (GNSS-R) relies on receiving reflected GNSS signals from the Earth's surface. Rather than being used for position, navigation, and timing, GNSS-reflectometry technology could be used to determine the relationship between ecosystem processes such as land-atmosphere, water, energy exchange, and vegetation productivity and the correlation between sea surface, soil moisture, freeze/thaw state, and the associated environmental characteristics. The study of sea surface anomalies, snow, and land features has advanced using ground, air, and spaceborne measurements sparked by GNSS-R[6]. In addition to the existing passive and active radar systems, GNSS-R has the potential to provide a new method of monitoring SM globally through the use of satellite receivers[2]. For soil moisture retrieval, a GNSS-R receiver is analogous to a passive radiometer due to surface roughness and surface dielectric properties. Its use of L-band, constellations of tiny satellites, and its stringent receive-only nature give it a significant potential for SM remote sensing. It also provides minimal revisit periods and great spatial resolution. Studies have shown that the GNSS bistatic radar signals are sensitive to the features of the land surface, including soil moisture when they are forward dispersed off the land surface and subsequently received by a separate passive receiver. UK-DMC, TDS-1, and CYGNSS are the most commonly used spaceborne GNSS-R programs for soil moisture detection.

To enhance weather forecasts, NASA's CYGNSS was launched in December 2016. It measures ocean winds between 38° north and 38° south latitudes[7]. The CYGNSS mission can make measurements from a total of 32 channels at once across its constellation of eight microsatellites. Over the ocean, its average return time is seven hours. Currently, some noteworthy outcomes have been discovered using CYGNSS data for the SM application. The availability of spaceborne data obtained by the CYGNSS constellation has led to a surge in interest in the issue of recovering SM on a broad spatial scale from such datasets. One of these was put out by Kim and Venkat[8], who suggested using the relative signal-to-noise ratio of CYGNSS to recover SM. The regional daily SM estimation was then created by fusing the rSNR of CYGNSS with the SM of SMAP[13]. The correlation coefficient (R) between the SM acquired by CYGNSS and SMAP in regions with intermediate vegetation conditions is 0.77, whereas it decreases to 0.68 in areas with high densities of vegetation. Chew and Small[2] discovered a link between the change in CYGNSS reflectivity and the change in SM in SMAP and used a linear regression approach to explain this relationship. Some past studies on CYGNSS soil moisture retrieval mainly concentrated on analyzing the temporal changes in SNR time series or the pre-sumed linear correlation between CYGNSS recorded signal-to-noise ratio (SNR)[2][9]. However, surface characteristics, such as vegetation water content, surface roughness, topography, and soil type, have an impact on the CYGNSS reflectivity signal. Yan et al. estimated SM using simulated data applying machine learning techniques[10]. They only take reflectivity, elevation angle, and dielectric constant into account. Lwin et al. used the Support Vector Machine (SVM) approach to estimate global Soil Moisture (SM)[11]. Senyurek et al.[12] and Eroglu et al.[1] have looked at the usage of non-parametric, non-linear machine learning algorithms. Yan et al.[13] recover global SM estimations using ML regression; however, their approach is only effective when the input is comparable to the land types utilized during training. Tyagi et al study, at a chosen agricultural area in India, established an Artificial Neural Network (ANN) framework to estimate SM by taking into account the effects of vegetation and roughness[14].

Nonlinear models are better and more robust than linear models. The nonlinear relationship between CYGNSS signals and surface soil moisture has been constructed in this study using a machine learning (ML)-based technique with high spatial and temporal resolution. A multi-layer ANN has been employed to train the nonlinear relation. Surface reflectivity derived from ddm snr of CYGNSS data, VWC to provide valuable information about the water status of plants and canopies, and roughness to represent the irregularities and variations in the Earth's surface at a small scale obtained from the SMAP SM 9km data set are input characteristics to the learning process. The model is trained using monthly averaged soil moisture values, and its prediction is then evaluated.

2. Datasets

2.1 CYGNSS Data

A constellation of 8 microsatellites known as the CYGNSS Mission was successfully launched in December 2016 in order to improve hurricane forecasting and gain a better understanding of the processes that drive hurricane intensity. The CYGNSS mission's objective is to determine the near-surface wind speed under all precipitation scenarios. A delay Doppler mapping instrument (DDMI) is a component of every observatory. It collects signals reflected off the water surface as well as direct signals from GPS satellites. CYGNSS can acquire information on wind speed, direction, and other aspects of the structure and severity of tropical cyclones by examining the specific characteristics of GPS signals that are reflected off the ocean's surface. A crucial part of the NASA Earth-observing satellite constellation known as the Cyclone Global Navigation Satellite System (CYGNSS) program is the Delay Doppler Mapping Instrument (DDMI). The Doppler shift and delay information obtained from GPS signals bouncing off the water surface are used by the DDMI to compute surface wind speeds[6]. Daily NetCDF (.nc format) data corresponding to each of the CYGNSS satellites is provided. The Doppler frequency shift and time delay function make up the DDM. The received signals are analyzed and divided into various delay and Doppler bins in order to produce a Delay Doppler Map The signals are divided by the delay binning according to how long it takes for a signal to travel from a satellite to the surface of the Earth and back.

Four levels of data products from the CYGNSS mission are publicly available. NetCDF files are created for Level 1, 2, and 3 data products and are made publicly accessible via the NASA Physical Oceanography Data Active Archive Center (PO.DAAC). CYGNSS Level 1, version 2.1 data which is available in NetCDF files format in PO.DAAC (podaac.jpl.nasa.gov/dataset/CYGNSS_L1_V2.1) is used in this work. CYGNSS full data set of 2020, and some data set of 2021 is used for training. The rest of 2021 dataset is used for evaluation.

When computing the coherent component of scattered power, the bistatic radar range equation is used, which is given as[5]:

$$P_{rl}^{r} = \frac{P_r^t G^t}{4\pi\left(R_{ts}+R_{sr}\right)^2}\frac{G^r\lambda^2}{4\pi}\Gamma_{rl} \qquad (1)$$

where P_{rl}^{r} is the coherently received SNR power, P_r^t is the transmitted GNSS signal power, G^t is transmitter antenna gain, R_{ts} is the range between the transmitter and specular reflection point and R_{sr} is the range between the specular reflection point and receiver, G^r is the receiver antenna gain, λ is the GPS wavelength and Γ_{rl} is our required parameter, which is surface reflectivity[5].

Surface reflectivity, one of the surface properties over land, can be used as a stand-in for SM by inverting the bi-static radar equations. From the above equation, we can solve the surface reflectivity of Γ_{rl} ($P_{r,eff}$) (in dB)[2] [6]:

$$\begin{aligned} P_{r,eff} &= 10P_{rl}^{r} - 10\log\left(P^tG^t\right) - 10\log\left(G^r\right) \\ &+20\log\left(R_{ts}+R_{sr}\right) + 20\log\left(4\pi\right) - 20\log\left(\lambda\right) \end{aligned} \qquad (2)$$

As the focus of this study was only changes in surface reflectivity, ‘4π’ and ‘λ²’ are ignored, the surface reflectivity of Pr,eff (in dB) is then[2][6]:

$$\begin{aligned} P_{r,eff} &= 10P_{rl}^{r} - 10\log\left(P^tG^t\right) \\ &-10\log\left(G^r\right) + 20\log\left(R_{ts}+R_{sr}\right) \end{aligned} \qquad (3)$$

The CYGNSS variables required are: sp_rx_gain (G^r), rx_to_sp range (R_{sr}), tx_to_sp range (R_{ts}) and gps_eirp (P^tG^t). These variables are first converted to a dB scale.

The topography and vegetation, in addition to the SM content, have an impact on the entire DDM. We attempt to build methods that learn the pertinent characteristics from ddm_snr (surface reflectivity) for the SM estimation issue and, by doing so, improve SM estimation accuracy.

Using the same SMAP projection, we made a global cylindrical projection using the Equal-Area Scalable Earth (EASE 2.0) 9 km × 9 km grid cell. Three equal-area projections and an infinite number of potential grid definitions make up the Equal-Area Scalable Earth Grid (EASE-Grid). Through the use of a hierarchical grid cell structure, EASE-Grid enables scalable depictions of the Earth's surface at various spatial resolutions maintaining the integrity of the equal-area feature. It was designed to be a flexible system for consumers of gridded data on a worldwide scale, particularly those who utilize remotely sensed data; however, it is **also** becoming more and more popular as a standard gridding format for data from other sources[15].

2.2 SMAP Data

The two instruments that the SMAP satellite carries are the radiometer and the L-band radar. The radar instrument sends microwave pulses in the direction of the ground, then measures the radar signals that are reflected back. It can estimate the moisture content of the top few centimeters of soil by examining the features of the radar returns. The radiometer, on the other hand, monitors the Earth's surface's natural microwave emissions, which are controlled by the amount of moisture in the soil's topmost layer. SMAP produces worldwide, high-resolution maps of soil moisture levels using data from both devices every two to three days.

SMAP SM is available on a 9-km grid [16]. The data is available at nsidc.org/data/spl3smp_e/versions /5[17]. The information obtained from the radiometer readings is combined and processed to create the SMAP radiometer level 3 data output. This data product creates relevant and helpful information by combining many observations made within a certain time frame and spatial extent. The table below presents an overview of the SMAP Enhanced L3 Radiometer system, which provides global daily 9 km EASE gridded soil moisture data[17].

The SMAP Enhanced L3 Radiometer Global and Polar Grid Daily 9 km EASE-Grid Soil Moisture, Version 5 data include information on vegetation water content and surface roughness in addition to soil moisture measurements. This extensive dataset is a useful resource for a variety of agricultural and environmental applications since it offers insightful information about these important characteristics.

Table 1. Overview of SMAP (Soil Moisture Active Passive) [17]

Platform(s)	SMAP
Spatial Resolution	9kmx9km
Spatial Coverage	N: 90S: -85.044 E:190 W: -180
Spatial Reference System(s)	WGS 84 / NSIDC EASE-Grid 2.0 North (EPSG:6931) WGS 84 / NSIDC EASE-Grid 2.0 Global (EPSG:6933)
Temporal Resolution	1day
Temporal Coverage	31 March 2015 to present
Data Format	HDF5
Sensor(s)	SMAP L-band radiometer
Parameter(s)	Brightness Temperature, Surface soil moisture

Soil moisture (SM), vegetation water content (VWC) and surface roughness are derived from the data set.

2.3 Target Region

The target region in this study is located around Gambella National Park. Gambella National Park is found in Ethiopia's Gambella Region. Several rivers, notably the Baro, Akobo, and Gilo rivers, cut through the park's primary habitats of grasslands, wetlands, and savannas. With high temperatures, Gambella has a hot and muggy environment. April to October is the wet season, at which time a sizable portion of the park is completely inaccessible. The average annual precipitation is one of the highest in the country.

Figure 2 Target region location from Ethiopia relief location[18]

3. Methodology

Accurate soil moisture measurements are essential for managing agricultural activities, understanding hydrological processes, and predicting drought conditions. Space-borne GNSS-R offers a non-destructive and cost-effective method for estimating soil moisture content across large areas.

The retrieval of soil moisture generally follows these steps. First, ddm snr is extracted from the CYGNSS data and after applying some common quality controls, the surface reflectivity is derived from the bistatic radar range equation. Soil moisture, vegetation water content, and surface roughness are extracted from the downloaded data of the SMAP satellite. Finally, models are built to develop the relationship between the geophysical parameters and the reference soil moisture, which leads to soil moisture retrieval from the inputs.

3.1 Data Preprocessing

Quality control procedures must be applied to the CYGNSS data to filter out inaccurate or noisy data points. Signal-to-noise ratio values less than 2 dB are eliminated. Another quality control applied is the removal of observations with an antenna gain on the receiver less than zero. The initial step in obtaining soil moisture is to calculate surface radar

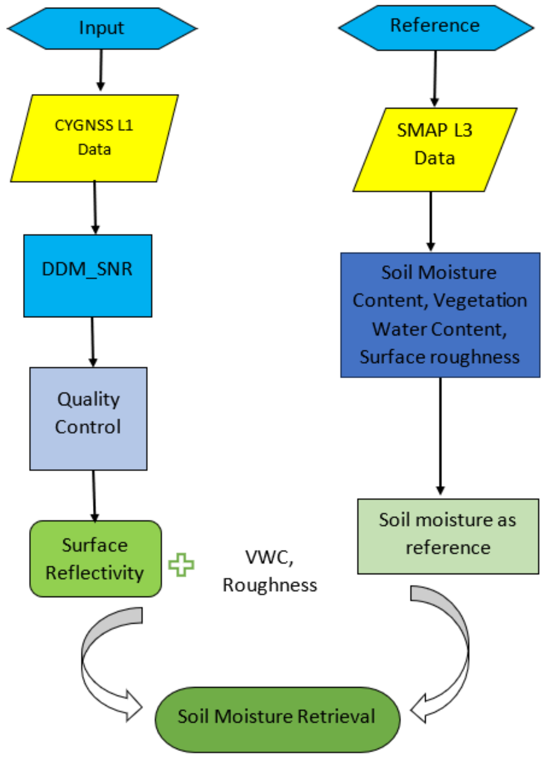

Figure 1 Soil Moisture Retrieval

reflectance using CYGNSS information. There is a DDM that corresponds to each specular point and is used to calculate surface reflectivity. The surface reflectivity is calculated according to the formula derived from the bistatic radar equation. The boundaries are set as latN = 8.3; latS = 7.7; lonW = 33.3; lonE = 34.2. The obtained surface reflectivity values are averaged for each month.

The SMAP data here is stored in a grid format, with each grid representing a specific geographical area and having a resolution of 9 kilometers. Meanwhile, CYGNSS measures the reflected signals from GPS satellites and uses these measurements to derive information about wind speed and direction over the oceans. Matching the time and space between CYGNSS and SMAP data is necessary to build our model.

Specifically, the CYGNSS reflectivity on the same days is taken and aligned with the corresponding SMAP grids based on the specular point locations. The specular point corresponds to the location on Earth's surface where the received signal from GPS satellites is at its maximum intensity. Once the CYGNSS reflectivity is matched to the SMAP grids according to their specular point locations, the average reflectivity value is calculated within each grid

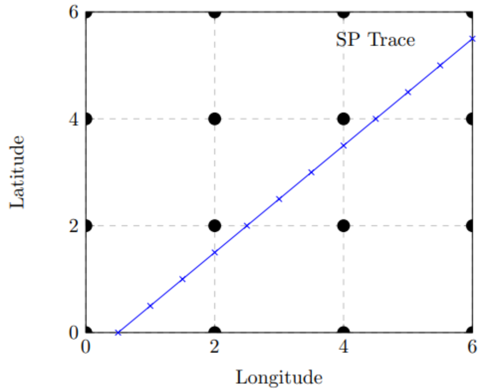

Figure 3 Time and space matching between CYGNSS and SMAP data

Figure 4 describes the monthly averaged surface reflectivity values of our target region in the months February, May and September. In theory, reflectivity values are typically expressed as a percentage or a decimal between 0 and 1, where 0 represents no reflection (perfect absorption) and 1 represents total reflection (perfect reflection). But in this work, reflectivity is calculated using the power of reflected signal received onboard and the power of direct signal estimated by ground GNSS network, so the value does not lie in the set of 0 to 1. From the results we can see that higher values of reflectivities are obtained in the month September. This can be a good indication that higher values of soil moisture will also be obtained in the same month. Also, the variations of surface reflectivities in the different months are expected to have similarity with the averaged soil moisture values of respective months from the SMAP data.

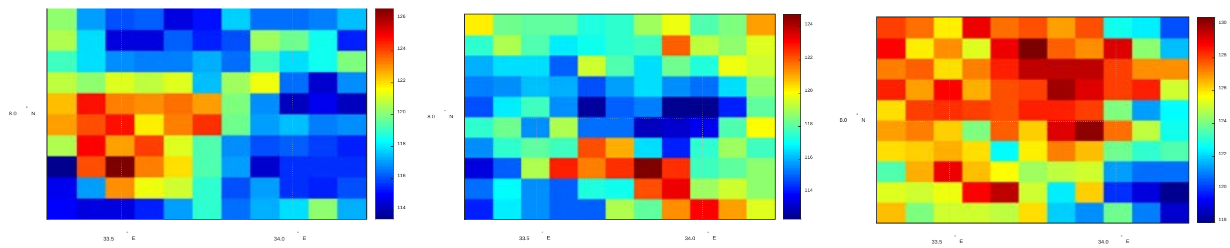

Figure 4 CYGNSS monthly averaged surface reflectivity of the target region in 2020 a) February b) May c) September

From Figure 5, it can be observed that the area has less soil moisture in May. In August, the regions experienced significant precipitation, leading to nearly saturated soil conditions in September. As a result, the soil moisture content values remained consistently high across the entire region. Comparing the three months average soil moisture values, the values were higher in most part of the region in September because the surface was almost wet. All year round, there are four seasons in Ethiopia. Typically, June to August is considered summer. Due to the monsoon season, there will likely be frequent thunderstorms and heavy rain. It is essential to agriculture because it maintains soil moisture levels and supplies water for irrigation all year long. summer's abundant rainfall contributes to the soil's saturation, which supports agricultural growth. For basic crops including millet, sorghum, teff, and maize, this is a critical time of year. September to November, is when spring arrives. The change from the wet to the dry season is what defines it. Rainfall is less frequent throughout this season, which causes the soil

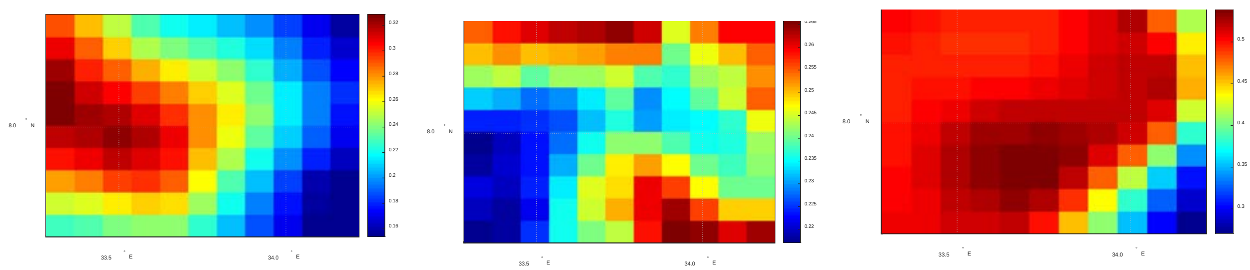

Figure 5 Monthly Averaged Soil Moisture content received by the SMAP in 2020 a) February b) May c) September

to gradually become less wet. But until the dry season arrives, the summer's leftover rainfall helps late-season crops thrive and keeps the soil somewhat wet. Winter, which lasts from December to February, is colder than other seasons. Most of Ethiopia receives little to no rainfall in this season. The amount of moisture in the soil decreases when there isn't any rain. This causes the soil to become arid and dry, which makes it difficult for crops to thrive without irrigation. Autumn lasts from March to May. The arid conditions of the Bega season are somewhat alleviated by this season. There is short but significant rainfall, which contributes to the soil's increased moisture content. This is the time of year when farmers sow crops like wheat, barley, and legumes. So, high values of soil moisture are expected during the summer and the beginning of the harvest season.

3.2 Neural Network

Machine Learning is used to try to create normal, nonlinear relationships between input and output data[13]. As the quantity of data provided grows, ML can automatically adapt and learn. The SM retrieval procedure is known to entail nonlinearity, however. In order to resolve this, we looked at the possible use of a non-parametric, non-linear machine learning algorithm, namely ANN.

In neural networks, the process of standardizing or scaling the input data to a common range is referred to as "normalization of data sets." It is a crucial stage in the preprocessing process that enhances neural network performance and convergence. So, normalization is performed on all the data sets. Surface radar reflectivity from CYGNSS observations, VWC to represent the vegetation's canopy, and roughness generated from the SMAP SM 9km data set are input characteristics to the learning process. Three successive layers of a densely connected neural network make up the model. Trial and error was used to determine the number of units in the first two levels, with the realization of good results acting as the stop condition. The last layer has just one unit, as we want the network to predict a single value. Surface radar reflectivity, VWC, and surface roughness are the three inputs that make up the input layer. The predicted SM is the only node in the output layer.

Mean squared error (MSE) has been chosen as the loss function throughout the model compilation process since our goal is to minimize the discrepancy between the model's projected values and the actual expected values. We further chose to measure the mean absolute error in the metrics to ascertain how much the model prediction deviates from the projected values. After the model is constructed, we fit the training data into it. We decided to use an 8-batch size and 70 epochs to train the model. We evaluate the model on the test data set.

4. Results and discussion

To assess the effectiveness of the developed ANN model, an analysis aimed to examine the relationship between the soil moisture data obtained from the CYGNSS and SMAP remote sensing systems is performed in Figures 6 and 7.

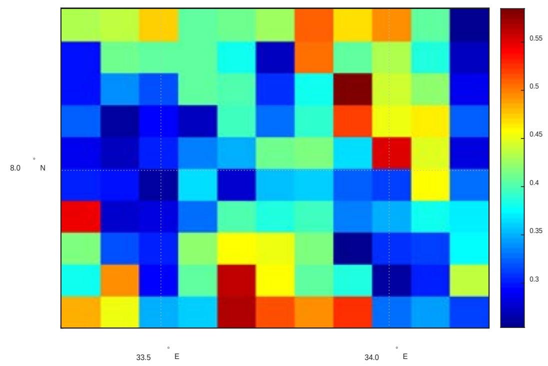

Figure 6 predicted one-month average Soil moisture

By comparing the CYGNSS soil moisture (SM) measurements with the SMAP SM data, the correlation analysis provided insights into the performance of the ANN model in predicting and capturing soil moisture patterns.

It has been noted that good alignment exists within the CYGNSS soil moisture (SM) data. Specifically, lower levels of soil moisture have been identified in the western part of the area, while higher levels are evident in the lower central and north-eastern parts of the selected region in this month. This trend is consistently observed in both the

CYGNSS-derived soil moisture and the reference SMAP soil moisture values for this month. The observed patterns indicate a significant correlation between the two datasets, highlighting the reliability of the CYGNSS SM data and its agreement with the SMAP SM measurements during the specified time frame.

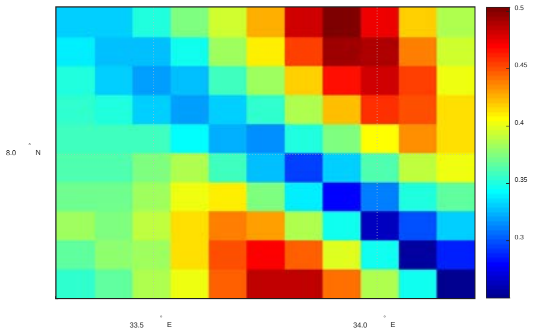

Figure 7 Reference soil moisture from SMAP of the same month

Metrics like mean square error (MSE) and mean absolute error (MAE) are often used to assess how well an ANN is doing. The average squared difference between the expected and actual outputs is measured by the MSE. The computation involves calculating the mean of the squared deviations between every anticipated and actual output. Because of the squaring procedure, MSE prioritizes greater mistakes. Better accuracy and a tighter match between the expected and actual values are indicated by a lower MSE. The average absolute difference between the expected and actual outputs is measured by the MAE, on the other hand. The average of the absolute disparities between each expected and matching actual output is used to compute it. MAE does not take the direction into account, treating them all equally. The developed model (Figure 8) is assessed and obtained a result of Mean Squared Error (MSE): 0.004 m^3/m^3 and Mean Absolute Error (MAE): 0.052 m^3/m^3. This shows a good prediction value for soil moisture.

The Pearson correlation coefficient is calculated from the actual and predicted values shown in Figure 8. The model has a correlation coefficient R of 0.79 on the test samples. The result shows a greater relationship between the geophysical parameters used as an input in the model and soil moisture values. Also, from the extracted surface reflectivity value, we can observe that CYGNSS is a promising tool for soil moisture retrieval because the surface reflectivity values were higher in September indicating a wet season.

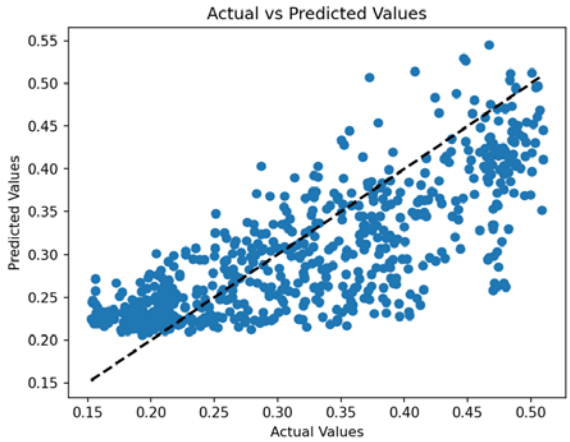

Figure 8 Scatter of actual and retrieved SM

5. Conclusion

In summary, this study has significantly improved our understanding of the connection between surface soil moisture and CYGNSS data by utilizing an advanced machine learning technique with high spatial and temporal resolution. Through the creation of a model for CYGNSS dataset training and soil moisture content retrieval using Artificial Neural Networks (ANN), we have demonstrated the capability of this method to enhance the accuracy of satellite-based soil moisture estimation.

Our results show a strong agreement between the soil moisture data processed from CYGNSS through ANN and the SMAP data, confirming the effectiveness of our proposed approach. The Mean Absolute Error (MAE) and Mean Squared Error (MSE) values of 0.052 m^3/m^3 and 0.004 m^3/m^3, respectively, underscore the precision and reliability of our developed model. This emphasizes the robust and versatile nature of ANN, highlighting its critical role in improving the accuracy of satellite-based soil moisture estimation.

While CYGNSS was originally designed to track tropical ocean winds, our study reveals its potential for regional soil moisture retrieval. Even with these promising results, it's crucial to remember that CYGNSS research for soil moisture measurement is still in its early stages. It will take further research and validation to fully evaluate accuracy, improve retrieval algorithms, and develop reliable methods.

The ongoing exploration of CYGNSS-based soil moisture retrieval holds great promise for applications in agriculture, hydrology, and climate studies. Continued research efforts will deepen our understanding of the complex relationship between CYGNSS data and surface soil moisture, contributing to the development of robust and accurate satellite-based monitoring systems. As we navigate through the initial stages of this research, fostering collaboration and innovation is very important to unlock the full potential of CYGNSS in soil moisture estimation.

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