Chapter

Perspective Chapter: Validation of SMOS Satellite Soil Moisture Estimates Using Capacitance Probes over the Different Ecological Zones in Northern Ghana

Patrick N.L. Lamptey, Kwaku Amaning Adjei, Charles Gyamfi, Abigail Agyei Yeboah, Caroline Edinam Doe and Stephen Aboagye-Ntow

Abstract

Researchers assessed the performance of L2 satellite soil moisture estimates from the European Space Agency's SMOS satellite using in-situ data from capacitance SM probes. The in-situ measurements are from monitoring stations (at 10, 20, 30 cm depth) at two sites, Yendi and Jirapa in the Northern part of Ghana, West Africa. They are in two different sub-ecological zones of the Savanna in the North of Ghana. These sub-ecological zones are Western Sudan Savanna (Jirapa) and Open Guinea Savanna (Yendi). The correlation between SMOS SM estimates and the in-situ measurements was observed to improve with depth. In addition, the 10 cm depths capacitance probe SM measurements were observed to agree relatively better with the SMOS SM estimates. The L2 SMOS SM estimates performed much better in the dry season compared to the rainfall season for both ascending and descending orbital estimates. The 10 cm depth SM measurements recorded the best RMSE in both the dry and rainfall seasons. The descending dry season RMSE for the two sites ranging between 0.045 and 0.058 m^3/m^3 was relatively close to the SMOS expected accuracy. However, the RMSE and MBE were observed to deteriorate with depth.

Keywords: soil moisture, capacitance probes, remote sensing, SMOS

1. Introduction

Agriculture is the backbone of Ghana's economy. In the Ministry of Food and Agriculture's report on Agriculture in Ghana [1], the sector contributed 19.7% to the national Gross Domestic Product (GDP) in 2018. However, this has seen a decline from 22.7% in 2016. 38.3% of the Ghanaian population is employed in agriculture and its value chain industries [1]. In Ghana, farmers primarily cultivate staple foods like maise, millet, rice, sorghum, etc., and cash crop production like cocoa, coffee, rubber, etc. However, Ghana's reliance on rainfall for crop production [2] makes an agricultural activity a high-risk business [3]. In addition to rainfall variability, pest and plant diseases also contribute to a decline in agricultural production.

Crop yield is more often primarily determined by the amount of water available, the so-called water-limited yield [4]. For many reasons, soil moisture is an essential geophysical parameter, especially in agriculture. Soil water serves as a solvent and carrier of food nutrients for plant growth, regulating soil temperature and aiding in chemical and biological activities and photosynthesis.

Soil moisture has a significant effect on plants and an extended period of soil water scarcity can affect plant development and yield [5]. Therefore, the importance of soil moisture (SM) as an environmental variable to plants and animals cannot be overemphasised. The presence and quantity of SM determine the quality and sustainability of the existing ecosystem. Soil moisture or volumetric water content refers to the amount of water a particular soil contains, and this has a vital role in groundwater recharge, crop uptake, and soil chemistry.

In their work to assess the role of SM information in agricultural decision-making by farmers in the Northern part of Ghana [6] concluded that SM information is critical to farming activities such as sowing and fertilisation. They observed that SM information is not available and accessible by farmers. Unfortunately, there is a lack of dedicated SM monitoring networks in Ghana and, for that matter, most parts of Africa [3, 6]. The Northern sector is one of the most water-limited regions of Ghana with a unimodal rainfall pattern (one rainy season) followed by a dry season [7]. As a result, farmers have only one favourable season to grow crops within a year as compared to bimodal pattern of the south. Farmers in the Northern sector run a risk of crop failure with variation in the onset, distribution, dry spells, intensity, and cessation of the rainy season. This risk has become heightened with the increasing incidence of extreme climate variability, events, and climate change. It is evident that developing a Climate information service with SM information will help improve farmers decision-making in their daily farming activities [6].

With cheaper and easy-to-install capacitance SM probes [5], it has become easy to monitor SM. Moreover, in-situ SM monitoring presents advantages such as direct measurement of the SM at varying depths and ease of installation. For sufficient information on the spatio-temporal variability of SM, a high density and frequent measurements of in-situ probes must be installed [8]. However, when it comes to large-scale monitoring of SM, the in-situ techniques encounter challenges due to their limited spatial coverage owing to their point measurement. Setting up the in-situ monitoring networks include the cost of probes, labour and are intrusive [9]. The cost implication has been a major limiting factor for the establishment of the much needed in-situ measuring networks across Ghana and Africa as a whole.

Earth observation technology presents a unique opportunity to overcome the high cost of in-situ monitoring of environmental and geophysical parameters such as soil moisture. Satellite monitoring of geophysical parameters such as SM has reached an advanced stage with the launch and development of Soil Moisture and Ocean Salinity [10] and Soil Moisture Active and Passive [11] satellites. Satellite estimates of SM have wide spatial coverage with improved temporal resolution.

Recent years have seen an increase in efforts to help calibrate and validate hydrological models and remote sensing products, as well as to better understand the temporal and spatial distribution of soil moisture across the various African areas. In addition, a number of research were conducted in Africa to validate and enhance the indirect estimation of soil moisture [12, 13].

Remote sensing methods typically offer sporadic updates of coarse spatial resolution, but for a lesser cost, worldwide surface soil moisture can be measured [14, 15] Microwave, optical, and thermal satellite sensors are frequently used to derive estimates of soil moisture [15, 16]. Soil Moisture and Ocean Salinity (SMOS) is one of the soil moisture products, that has been successfully utilised to extract surface soil moisture with a temporal resolution of 2–3 days, globally [15–18].

However, due to the factors that affect the satellite sensor measurements [19] used in deriving the SM estimates, it is imperative to assess the accuracy of the SM products to ascertain its representativeness over the various climatic regions and land use land cover types (LULC). In global research conducted by Pierdicca et al. [20], the inter-comparison of soil moisture estimates produced from ASCAT and SMOS products demonstrated a reasonable correlation with r2 value of 0.65 and RMSE value of 4.3 over the northern Africa region. Their findings demonstrated that the two products' consistency differed depending on the season, geographic region, and surface land cover [20].

Earlier satellite SM products assessment work carried out by [12] over the West African region (Mali, Niger and Benin) showed that SMOS L3 SM products provided the best agreements compared to AMSR-E NSIDC product, the AMSR-E VUA product and the MetOp ASCAT product. They suggested that the Benin site's comparatively greater RMSE value was due to the presence of a denser vegetation cover. Their research showed that the SMOS-L3SM product had limited use in the dense vegetation. Similar works have been carried out in different regions of the world [21–24]. In taking advantage of spatial and temporal benefits of Earth Observation SM products there need to carry out local scale validation of SMOS SM products. With virtually no effective SM networks in Ghana [3], satellite SM estimates present a novel opportunity for Ghana and the African continent. This research uses in-situ data acquired using capacitance probe SM measurements to assess the performance of Soil Moisture and Ocean Salinity satellite (SMOS L2 SM) from the European Space Agency. The validation was carried out over two northern agroecological zones: the Western Sudan savanna (Jirapa) and Open Guinea Savanna (Yendi).

2. Study area

The study area is in the Northern part of Ghana, specifically the Upper West region (Jirapa) and the Northern Region (Yendi). The agroecological zone in the Upper West region is categorised as the Western Sudan savanna, and the Northern region is classified as the Open Guinea Savanna. The Northern part of Ghana has two main seasons: rainfall and dry. The rainfall season begins in April/May and ceases between October and November, followed by the dry season in December, which ends in March/April. This part of the country is extensively arid (water-limited) region with agriculture as the major economic activity. The agricultural activities are predominantly rainfed and hence are significantly impacted by climate variability and change. Drought and crop failures, as well as flooding, are the major natural disasters affecting these communities. Therefore, two stations, Jirapa (jita) and Yendi (yeku), in the Western Sudan Savanna and the Open Guinea Savanna agroecological zones, respectively (**Figures 1** and **2**), were selected.

3. Data and methodology

3.1 Data

Researchers acquired in-situ SM data from the Ghana Meteorological Agency (GMET) Automatic Weather network under the Ghana Agricultural Sector Investment Program (GASIP). GASIP (https://www.gasip.org/) installed 10 Automatic Weather Stations (AWS) in 10 communities to improve the accuracy of weather information to smallholder farmers. The automatic weather station network use ADCON SM1 capacitance probes measuring SM content at 10, 20 and 30 cm depths.

The SM1 Capacitance probe is a highly flexible capacitance-based SM and temperature monitoring system. It is configured to measure SM contents at 30 minutes intervals at the respective depths. Soil Moisture and Ocean Salinity (SMOS) satellite is a European Space Agency (ESA) satellite mission which forms part of the Living Planet Program. The SMOS mission aims to advance scientific knowledge of the Earth's water cycle, contribute to better weather and extreme-event forecasting and help improve climate models. It uses a novel passive Microwave Imaging Radiometer using an Aperture Synthesis (MIRAS) instrument operating at 1.4GHz (L-band).

It senses faint microwave emissions from the Earth's surface to map SM levels, sea surface salinity, sea ice thickness and other geophysical variables. SMOS is a polar-orbiting satellite that ascends (south-north pole) and descends (north-south pole) twice a day with 2/3 day revisit times. The satellite orbital pass times are morning (05:15–06:30 am) and evening (5:30–6:50 pm) for ascending and descending,

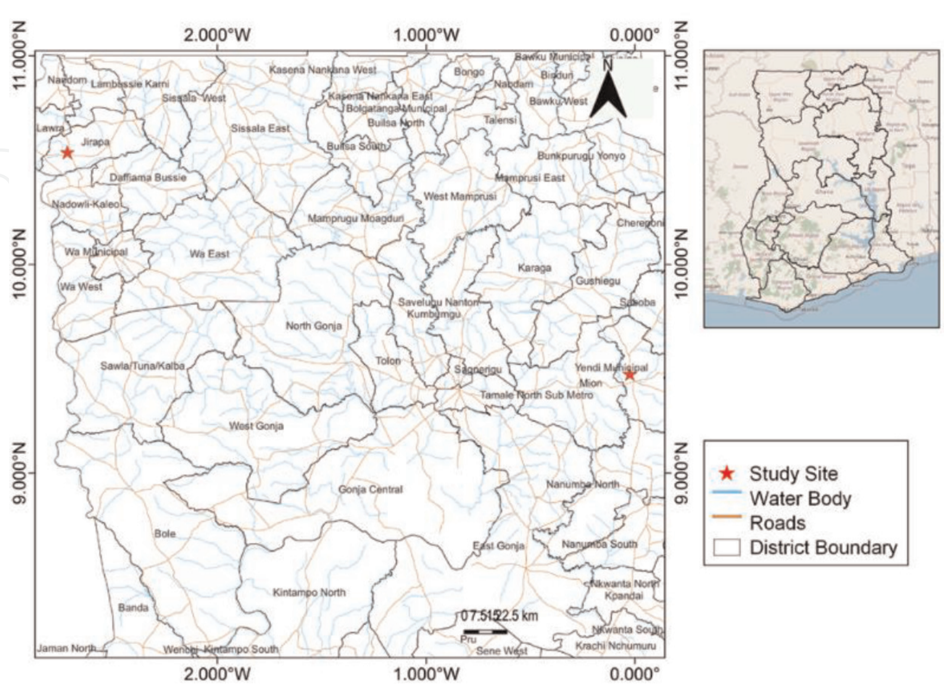

Figure 1.
Map of the study area.

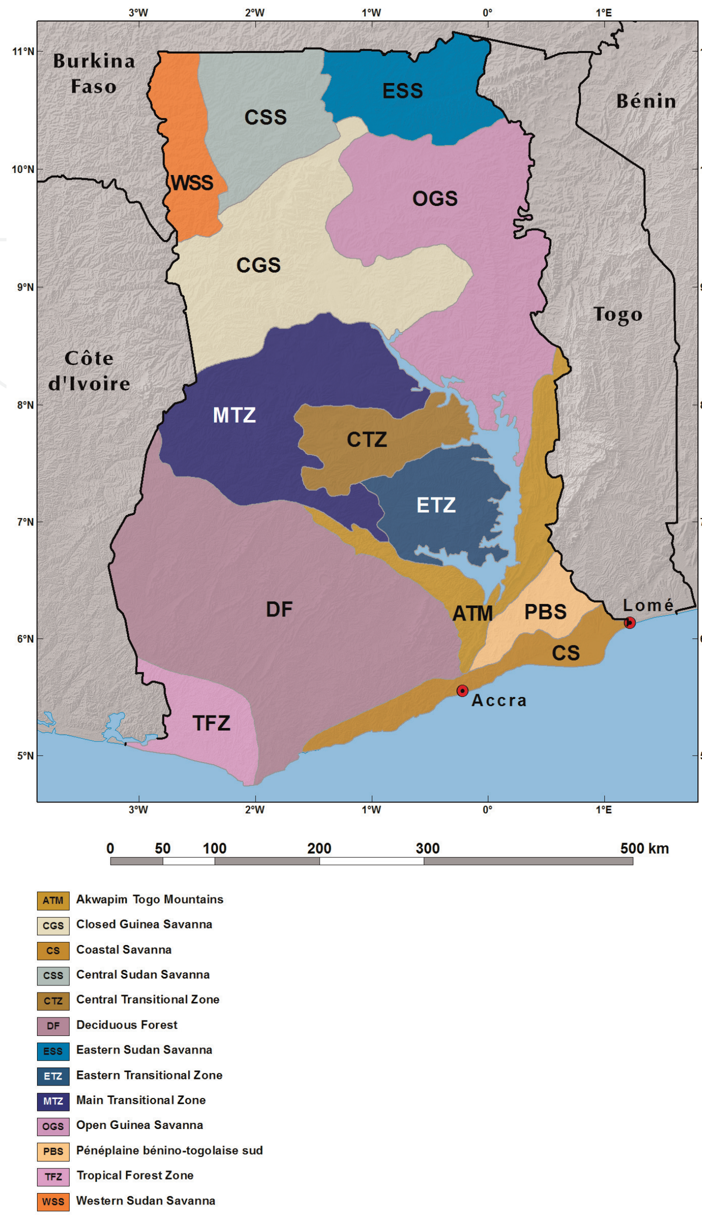

Figure 2.
Agroecological zones of Ghana [25].

respectively. The expected accuracy of the SMOS L2 SM product is 4% (0.04 RMSE). The dataset used spans 2 years from January 2020 to December 2021.

3.2 Methodology

SMOS L2 SM estimates data products for the study sites were obtained using the point extraction tool from ESAs SNAP toolbox. These SM estimates were then statistically compared to in-situ SM measurements (10, 20, 30 cm depth) from the study sites. The following statistical analyses were used to assess the accuracy and agreement between the SMOS L2 SM estimates and the in-situ measurements. The statistics included Mean Bias Error, Pearson Correlation Coefficient, Root Mean Square Error (RMSE) and the Willmott Index of Agreement. Similar statistical metrics have also been used in previous studies, e.g. [12, 23, 26–28]. The SMOS L2 SM estimates were

Statistics	Equation
Mean Bias Estimate (MBE)	$Bias = \frac{1}{n}\sum_{i=1}^{n}(Y_i - X_i)$
Pearson Correlation Coefficient (r)	$r = \frac{\sum(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum(x_i-\bar{x})^2\sum(y_i-\bar{y})^2}}$
Root Mean Square Error (RMSE)	$RMSE = \left[\frac{1}{n}\sum_{i=1}^{n}(X_i - Y_i)^2\right]^{\frac{1}{2}}$
Index of Agreement (d)	$d = 1 - \frac{\sum_{i=1}^{n}(X_i-Y_i)^2}{\sum_{i=1}^{n}(\lvert Y_i-\bar{X}\rvert+\lvert X_i-\bar{X}\rvert)^2}$
X, Y = in-situ and SMOS estimates respectively; and i = individual observations.	

Table 1.
Statistical criteria for SMOS SM validation.

assessed on their seasonal, orbital, and ecological agreement with in-situ measurements. Researchers aggregated the in-situ SM contents data to daily mean measurements. The SMOS L2 SM estimates for the respective orbitals were then compared to the daily mean in-situ SM measurements (**Table 1**).

4. Results and discussion

4.1 Data trends

4.1.1 In-situ trends

The two study sites showed similar rainfall trends as climatologically known (unimodal rainfall pattern) for the Northern sector of Ghana. For example, it was observed from **Figure 3** that the rainfall starts in April and peaks in August/September. Also, the dry season begins in November and ends in March.

The temperature for the study period (2 years) was observed to show a seasonal trend (sinusoidal with) highest being recorded in March/April, and the lowest in

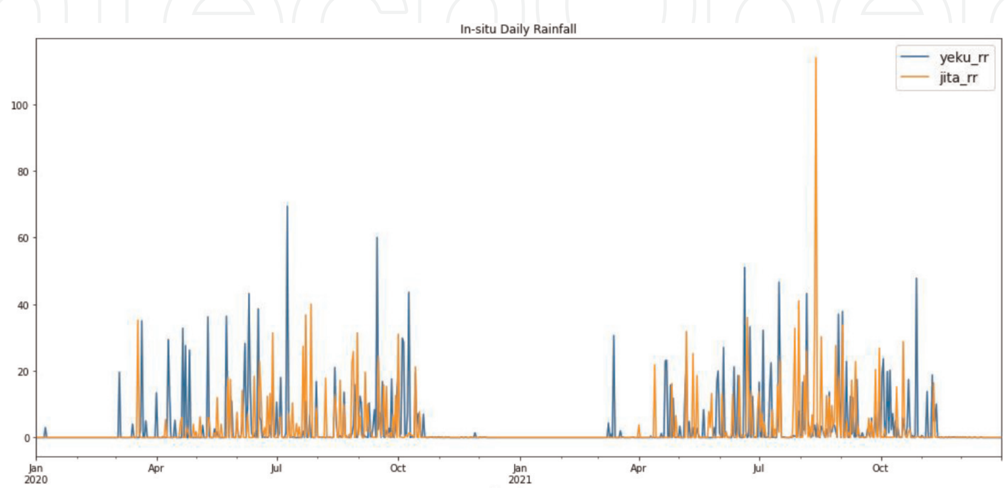

Figure 3.
Daily rainfall trend for the two study sites.

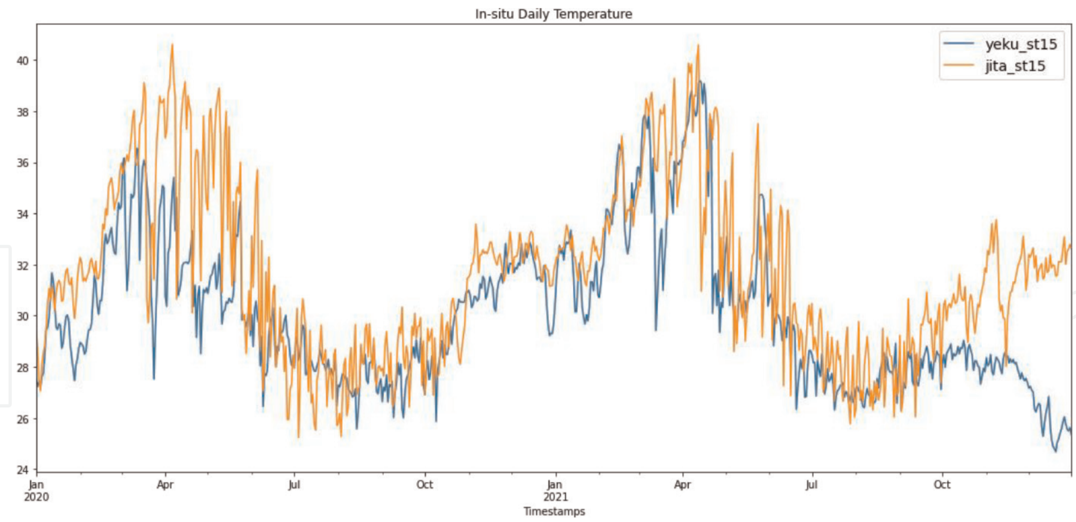

Figure 4.
Mean daily air temperature for the two study sites.

August (**Figure 4**). The temperature showed a negative correlation with the rainfall pattern, with temperature decreasing as rainfall increases.

Soil moisture at various depths for both sites at various depths in **Figure 5** shows an increasing trend from April. SM content at Jirapa (jita_sm) is generally higher than at Yendi (yeku_sm) at all depths. However, Yendi recorded higher SM contents at 10 cm depths than Jirapa 10 cm depths. Shows relatively high mean SM contents at Yendi for the 10 and 30 cm depths.

Although the 10 cm depth SM contents for both sites were different, there was a reasonably good agreement for the mean, standard deviation, and minimum and maximum statistics at the 30 cm depths. At 10 cm depths at Yendi recorded higher mean SM contents and with high variability than at Jirapa at same depths. It shows a rapid increase in SM immediately after rainfall events, followed by a fast decrease resulting from evaporation and infiltration processes. SM at 10 cm depths (surface SM) were generally low with low variability. The 20 cm depth recorded the highest mean and variability for both sites. At deeper depths (20, 30 cm), the SM response is lagged and somewhat less. However, a persistent high SM content results from consistent rainfall events (rainfall season) and low air temperatures during the rainfall season (**Table 2**).

4.1.2 SMOS satellite SM estimates trends

The satellite SM estimates at the two study sites showed a similar trend to the in-situ estimates. From April SM contents began increasing in both years at both locations. SMOS SM estimates are consistently high from July through to October, decreasing to their lowest in November.

They remained consistently low from December to March the following year. The SM estimates correspond well with the rainfall patterns. Mean and maximum SMOS SM contents were relatively high in the descending estimates compared to the ascending (**Table 3**). SMOS estimates were consistently higher at Yendi compared to Jirapa for both orbits. The variability (standard deviation) however, was higher for descending than the ascending SMOS estimates with Yendi recording the highest variability (**Figure 6**).

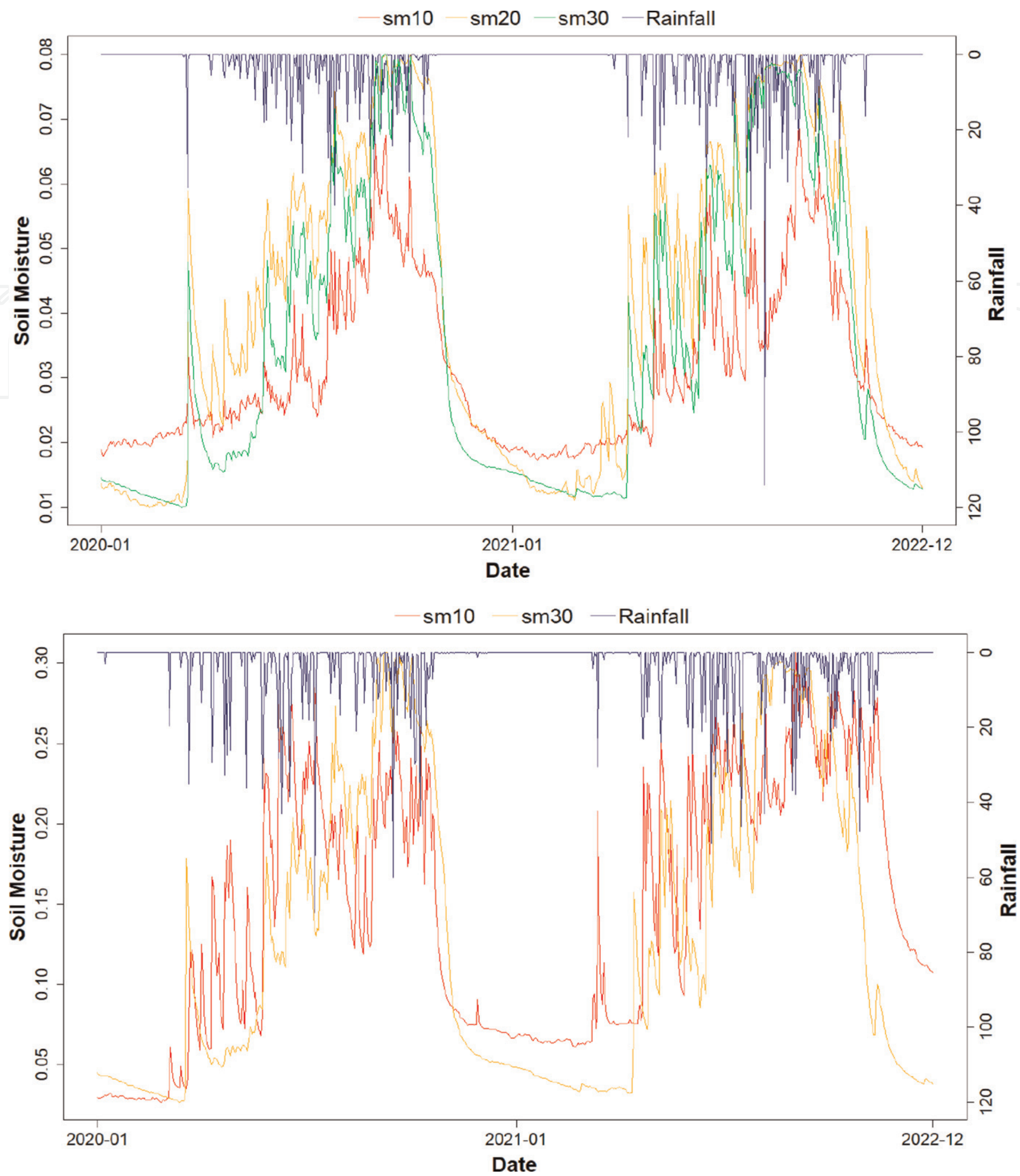

Figure 5.
Daily mean SM (m^3/m^3) and rainfall (mm) trends for the study sites (top: Jirapa; bottom: Yendi).

Sites	jita_sm10	jita_sm20	jita_sm30	yeku_sm10	yeku_sm30
Mean	0.031	0.399	0.365	0.147	0.375
Stand. Dev.	0.013	0.103	0.094	0.080	0.099
Minimum	0.017	0.263	0.260	0.027	0.224
Maximum	0.070	0.564	0.547	0.307	0.513

Table 2.
In-situ SM summary statistics at Jirapa(jita_sm10 & 20) and Yendi(yeku_sm10 & 20).

4.2 SMOS SM estimates validation

Tables 4 and **5** show the validation statistics of the SMOS SM estimates of Jirapa and Yendi in the Savanna zone of Ghana. The performance of the SMOS SM estimates

Orbit	Ascending orbit		Descending Orbit	
Sites	**yeku_sat**	**jita_sat**	**yeku_sat**	**jita_sat**
Count	296.000	290.000	300. 000	300. 000
Mean	0.135	0.132	0.143	0.136
Minimum	0.012	0.022	0.108	0.104
Maximum	0.395	0.0.383	0.457	0.450

Table 3.
Statistics for ascending (left) and descending (right) SMOS L2 SM estimates.

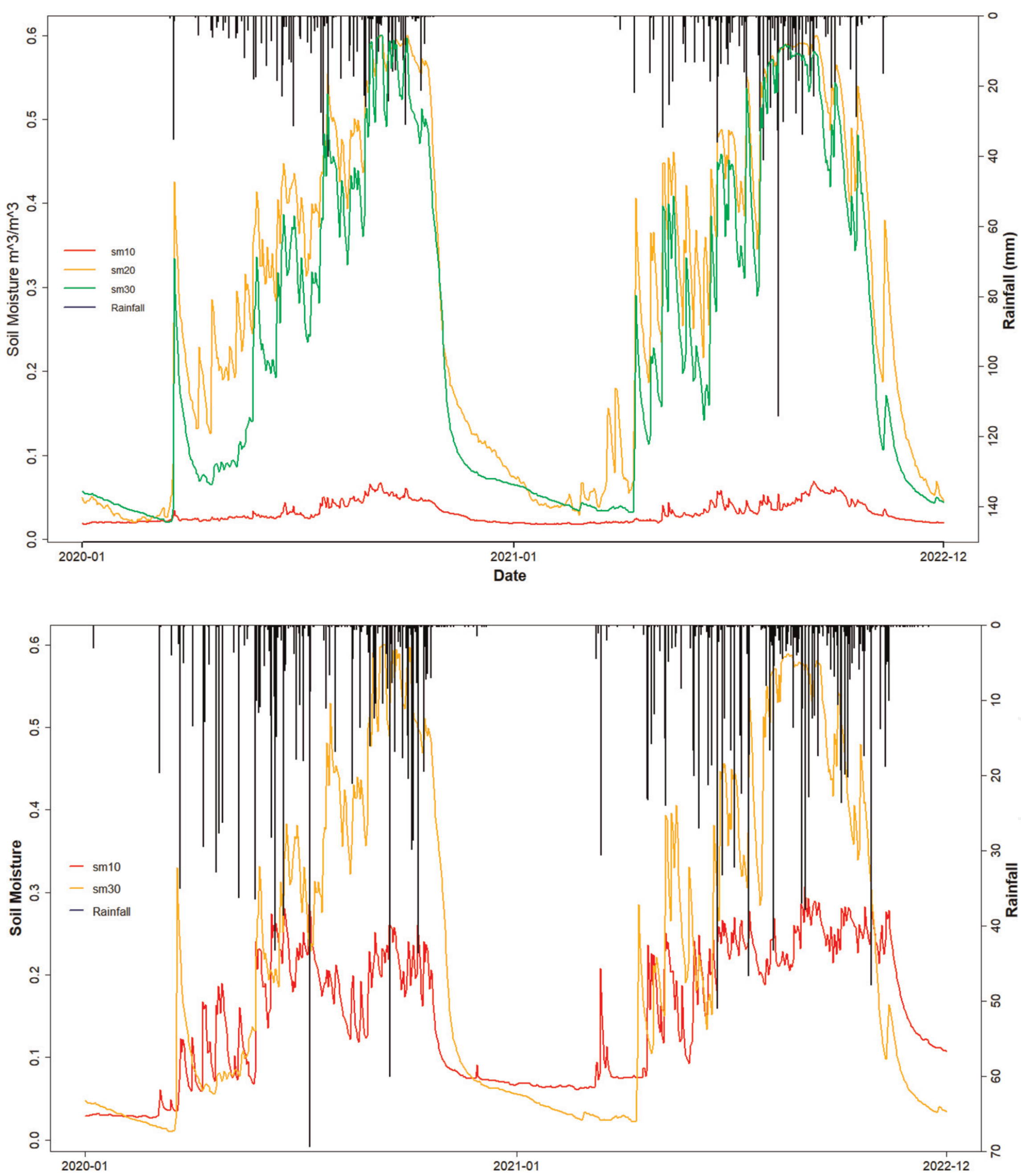

Figure 6.
SMOS ascending (above) and descending (below) SM estimates.

Sttion	Depth	R	RMSE	MBE	IA
Ascend			Rain		
Jirapa	10	0.526	0.183	−0.164	0.440
Jirapa	20	0.692	0.292	0.285	0.365
Jirapa	30	0.677	0.249	0.241	0.412
Yendi	10	0.489	0.067	0.000	0.699
Yendi	30	0.486	0.256	0.248	0.329
		Descend			
Jirapa	10	0.557	0.189	−0.165	0.437
Jirapa	20	0.663	0.293	0.283	0.376
Jirapa	30	0.673	0.249	0.239	0.430
Yendi	10	0.469	0.081	−0.013	0.643
Yendi	30	0.489	0.245	0.232	0.379

Table 4.
Statistics of the validation analysis for all the data.

was assessed by comparing in-situ SM measurements at 10, 20 and 30 cm depths with SMOS ascending and descending SM estimates for both sites. A general comparison was initially performed after which seasonal (rainy and dry) assessment was carried out.

4.2.1 All data

Coefficients of correlation for all the datasets compared to SMOS estimates showed high correlation coefficients ranging from 0469 to 0.692. In addition, Jirapa showed a relatively higher correlation for both orbit and at respective depths than Yendi. Root means square errors (RMSE) for both the ascending and descending data were similar, ranging between 0.067 and 0.293m^3/m^3 at both orbits. The lowest RMSE was recorded at Yendi for ascending pass, while the highest was at Jirapa for descending pass. The mean bias error (MBE) recorded similar results for both orbital passes. Apart from Jirapa's 10 cm depth, which was underestimated for both orbits, all others were overestimated. The 10 cm depth at Yendi recorded relatively low MBE (0.008–0.013) for both orbitals. The agreement index (IA) for both orbitals at most depths was relatively low (0.329–0.699), apart from 10 cm Yendi, which recorded 0.643 (descending) and 0.699 (ascending) (**Table 5**).

4.2.2 Rainfall season

The rainfall season recorded similar results for both ascending and descending orbits (**Table 3**). The correlation for the ascending pass ranged between 0.486 and 0.692, whilst that of the descending ranged between 0.4699 and 0.673. However, Jirapa showed a relatively higher correlation (0.526–0.692) than Yendi (0.469–0.489). The RMSE recorded similar results at Jirapa for both orbitals which were relatively high (0.183–0.293 m^3/m^3) which was relatively higher than Yendi's. Yendi

Station	Depth	R	RMSE	MBE	IA	R	RMSE	MBE	IA
Ascend				Rain				Dry	
Jirapa	10	0.526	0.183	−0.164	0.440	0.322	0.048	−0.034	0.375
Jirapa	20	0.692	0.292	0.285	0.365	0.616	0.258	0.256	0.170
Jirapa	30	0.677	0.249	0.241	0.412	0.500	0.233	0.231	0.167
Yendi	10	0.489	0.067	0.000	0.699	0.508	0.063	0.034	0.647
Yendi	30	0.486	0.256	0.248	0.329	0.550	0.253	0.245	0.264
				Descend					
Jirapa	10	0.557	0.189	−0.165	0.437	0.404	0.045	−0.037	0.395
Jirapa	20	0.663	0.293	0.283	0.376	0.474	0.256	0.253	0.147
Jirapa	30	0.673	0.249	0.239	0.430	0.366	0.230	0.228	0.147
Yendi	10	0.469	0.081	−0.013	0.643	0.532	0.058	0.031	0.651
Yendi	30	0.489	0.245	0.232	0.379	0.553	0.252	0.244	0.234

Table 5.
Statistics of the validation analysis for rainfall and dry seasons.

recorded relatively low RMSE (0.067 m^3/m^3) for ascending compared to the descending (0.081 m^3/m^3) at the 10 cm depths. However, the 30 cm depth recorded relatively high RMSE. Most SMOS data points were generally overestimated, as shown by the MBE. However, 10 cm depth measurements by SMOS SM were underestimated. This is evident at Yendi which recorded the lowest MBE for both orbital passes. The index of agreement showed relatively low values (<0.450) for both orbital passes. However, the measurements of the Yendi 10 cm depths showed relatively higher IA (0.699, 0.643) for ascending and descending orbits, respectively.

4.2.3 Dry season

The statistics for the dry season validation were relatively different for both orbital passes (**Table 5**). The correlation coefficient for the ascending pass ranged between 0.322 and 0.616, whilst that of the descending ranged between 0.404 and 0.553. The highest correlation coefficient was recorded at Jirapa 20 cm depth for ascending SMOS estimates, whilst Yendi 30 cm depth recorded the highest for descending pass SMOS estimates.

However, the mean correlation coefficient was relatively higher a Yendi than at Jirapa. RMSE for the ascending pass ranged between 0.048 and 0.258 m^3/m^3, while the descending pass ranged between 0.045 and 0.256 m^3/m^3. During the dry season, the lowest RMSE was recorded at the 10 cm depth of Jirapa and Yendi. The SMOS SM estimates for the dry season were generally overestimated for both orbital passes. However, the 10 cm depth SMOS L2 SM at Jirapa was underestimated for ascending and descending orbits. SMOS L2 SM estimates at 10 cm depth recorded the lowest MBE (−0.037 to 0.034). The index of agreement was generally low, especially at deeper depths (20, 30 cm) except for 10 cm depth Yendi which recorded relatively higher IA (0.647–0.651) for both orbits.

4.3 Discussion

The SMOS SM estimates were overestimated during the rainy season at the 10 cm depths, whereas the vice versa is true for the dry season. This is attributed to the sensitivity of the SMOS sensor and sensing depth. This finding is corroborated by [12] and [21], contrary to previous studies dry bias associated with SMOS SM products. The dry bias is attributed mainly to the mostly low vegetated areas [12] observed in the Savanna zones. There was an improvement in the correlation of SMOS SM estimates with increasing depth. The savanna region has very low vegetation cover coupled with high ambient temperature, which leads to quick evaporation of surface SM resulting in the main source of microwave emissions from SM at deeper depths (**Figure 7**).

The RMSE for both sites were mostly greater than 0.04m^3/m^3 accuracy expected for the SMOS SM estimates. Jirapa recorded relatively good RMSE at 10 cm depths during the dry season ranging between 0.045 and 0.048 m^3/m^3. Yendi recorded RMSE ranging between 0.058 and 0.081 m^3/m^3 at the 10 cm depths throughout the analysis. The lowest RMSE (0.058 m^3/m^3) was recorded in the descending dry season. The 10 cm depth SM measurements were observed to agree relatively well with the SMOS

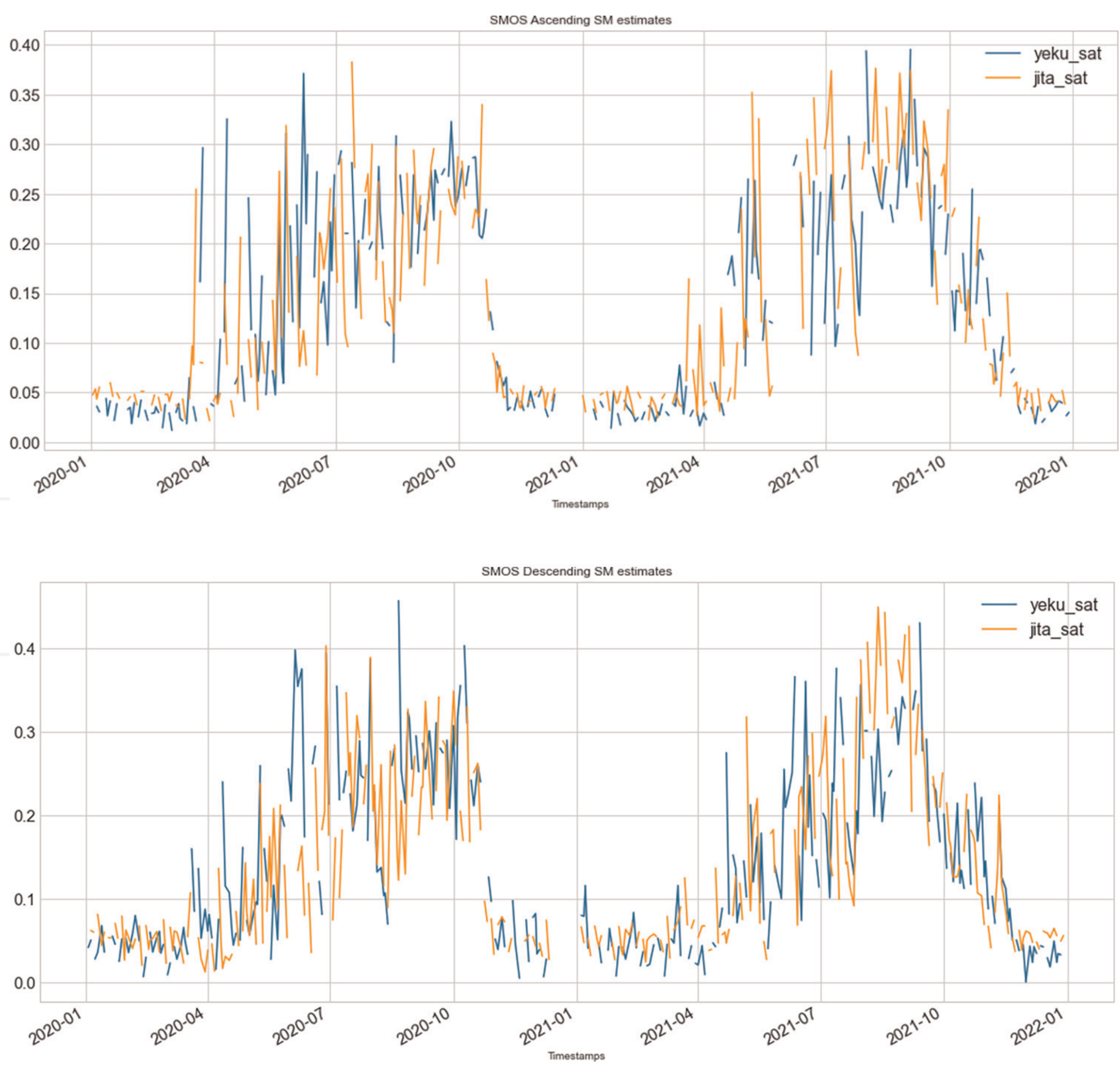

Figure 7.
Plot of validation statistics for orbital and seasonal SMOS SM estimates.

SM estimates than the 20 and 30 cm depths. This was evident in the calculated agreement indices (IA) for both sites at all depths for the respective orbit passes. A slight improvement in the IA was observed at the 30 cm depths. It was observed that there was a deterioration in the RMSE and MBE at the 20 cm depths and a slight improvement at the 30 cm depths at both sites for all seasons and orbital estimates.

Generally, the Descending orbit SMOS SM estimates performed relatively better than the ascending estimates. The descending estimates were observed to show relatively higher variability than the ascending. This can be explained by the relatively higher ambient temperature gradient [29] during the descending pass, which occurs late afternoon. There is relatively uniform thermal equilibrium within the soil vegetation atmosphere continuum [30].

5. Conclusions

- The correlation between SMOS SM estimates and the in-situ measurements improved with depth for both orbitals at Yendi and Jirapa.

- RMSE and MBE deteriorated with depths at both stations for both ascending and descending orbitals.

- The 10 cm depths capacitance probe SM measurements agree better with the SMOS SM estimates.

- SMOS SM estimates at Yendi and Jirapa performed well during the dry season compared to the rainy season, especially at the 10 cm depths.

- Jirapa performed relatively well during the dry season compared to the rainfall season for both orbits. However, the 10 cm depth MBE and RMSE showed significant improvement in the dry season.

- During the dry season the 10 cm depth SM estimates produced relatively close RMSE to the 0.04 m^3/m^3 accuracy of the SMOS SM estimates.

The researchers conclude that there is great potential in using Satellite estimates of soil moisture for improving the livelihoods of small holder farmers. They suggest the need for downscaling these products to higher spatial resolutions for use in models and advisories to policy makers and farmers.

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Conflict of interest

The authors declare no conflict of interest.

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