Chapter 3 : ROUGHNESS CHARACTERIZATION AND DISAGGREGATION OF COARSE RESOLUTION SMAP SOIL MOISTURE USING SINGLE CHANNEL ALGORITHM

3.1 INTRODUCTION

The Tau-omega Model, also known as the zero-order RTM [105, 106] provides the basis of the most of the algorithms used with passive radiometers to retrieve soil moisture content. The Tau-omega model is very reliable for understanding the different scattering processes of incident radiation from the Sun as described in section 1.9 of chapter 1. It needs some different parameters such as; LST, NDVI, and soil texture, along with the other parameters with a fixed range of values like vegetation parameter (b), roughness parameter (h), single scattering albedo (ω), and stem factor (s). h has a fixed range of values for the L-band frequency region [107] and is a sensitive parameter for the soil moisture estimation algorithm.

Soil surface roughness can be defined as the irregularities in the soil surface. The surface roughness also influences the microwave emissions from the ground due to the variation in the upper surface of the soil. These microwave emissions can be used to estimate the moisture content available in the soil. Therefore, the surface roughness may be one of the parameters influencing the accurate retrieval of the soil moisture via satellite observations. The soil surface roughness has been quantified by some parameters known as surface roughness parameter and denoted as *h*. This parameter is a function of the root mean square height of the soil surface and the wavelength of the electromagnetic radiations. Measurements of roughness parameter are so complicated for the satellite instrument; it can either be assumed or evaluated based on the ground-observations [99, 108, 109]. Verma et al., [110] and Davidson et al., [111] have shown the characterization of soil surface roughness to estimate soil moisture. The previous one showed the roughness characterization in the Dubois model [112] for soil moisture estimation using Sentinel-1 SAR data. The latter addressed this issue in the case of the agricultural field by exploiting a new database of roughness profile at the scale of SAR data.

Similarly, most of the studies of roughness characterization are based on the high-frequency range of the microwave region. Since L-band is the lowest frequency range of the microwave radiations and, therefore, it is most sensitive to the soil surface parameters. SCA, based on the Tau-omega model, describes the scattering processes of the solar radiations from the Earth's surface. Hence, this approach is also very much dependent on the surface roughness and the reported value of the roughness parameter for croplands in ATBD of SMAP L2 soil moisture product is 0.108 [59]. But ongoing through ground observation, it was always found to be higher for the agricultural fields of the Indian region. Thus, it is very much required to study the characterization of surface roughness for the Tau-omega model and the low-frequency L- band due to their sensitivity to surface roughness. Therefore, the present study shows the optimization of surface roughness for the Tau-omega model to retrieve soil moisture using L- band SMAP datasets. Besides from roughness characterization for SMAP soil moisture estimation, the SMAP soil moisture is also downscaled up to 1 km using the Triangle method. LST and NDVI are good indicators of soil moisture content, therefore, a polynomial regression formula for soil moisture, NDVI, and LST was used as a disaggregation approach for soil moisture.

This chapter aims to examine the sensitivity of the surface roughness parameter for estimating soil moisture from SMAP at two resolutions (at 36 km and 9 km) using SCA and then downscale the 9 km soil moisture product up to 1 km. This paper is also trying to find the appropriate roughness parameter values for the selected study area for dry and wet seasons. For this purpose, an optimization method has been adopted to determine the suitable surface roughness value for the soil moisture estimation algorithm. Since SMAP provides brightness temperature data products at two spatial resolutions, this dataset has been utilized in the soil moisture estimation method to acquire soil moisture at two spatial resolutions with the optimized surface roughness. The optimized soil moisture is further used to enhance the spatial resolution of the soil moisture product to obtain the Optimized Downscaled Soil Moisture (ODSM).

3.2 DATASETS

Brightness temperature provided by Level-1 data products of SMAP at two spatial resolutions of 36 km and 9 km was used to estimate soil moisture, and Level-2 soil moisture data values of SMAP at the same resolutions were used for comparing with the estimated values. Level-1 datasets of the SMAP are the instrument data, and the L1CTB and L1CTB_E radiometer products provide brightness temperature at 36 km and 9 km, respectively in the gridded form. While Level-2 datasets provide the retrieved soil moisture on a half orbit basis using Level-1 products and ancillary information. Similar to Level-1, L2SM_P, and L2SM_P_E data products provide soil moisture at 36 km and 9 km, respectively.

NDVI provided by MOD13A2 product of MODIS is used in this chapter to estimate VWC, whereas the LST provided MOD11B1, MOD11A1, and MYD11B1, MYD11A1 at different spatial resolutions are used in SCA and Triangle method for the estimation and disaggregation of soil moisture. To limit the effect of clouds on MODIS data, the dates are chosen for the cloud-free months of the study area. The MODIS NDVI and LST data were first aggregated to the equivalent scale (36 km and 9 km) of SMAP for using in the Tau-omega model to estimate soil moisture (36 km and 9 km). Later the 1 km data products of LST and NDVI were utilized as the input parameters in the downscaling algorithm along with the estimated soil moisture (9 km) to evaluate the ODSM (1 km).

Food and Agriculture Organization (FAO) provides soil texture maps, including clay maps. The information of clay percentage derived from this clay map and the aggregated LST were used as the inputs for the soil dielectric model to compute the dielectric constant of the soil surface.

Stevens Hydra probe was used for ground measurement of soil moisture. For spatial analysis, Hydra Go portable soil sensor was used to collect soil moisture values from the agricultural fields of wheat. The area of 40 x 40 km^2 of the Varanasi district was selected for data sampling, equivalent to the one pixel of the SMAP radiometer. The area of 9 x 9 km^2 and 1 x 1 km^2 was chosen at the center of this pixel (agricultural farm of the BHU) to validate estimated and downscaled soil moisture.

3.3 METHODOLOGY

3.3.1 Single-Channel Algorithm

SCA or zeroth-order RTM is more applicable for low vegetation or agricultural region [55]. It includes all the factors due to the geometry of the surface and low vegetation. It is described in detail in section 2.5.1 of chapter 2.

3.3.2 Impact of surface roughness on soil surface reflectance

Several studies have been presented to illustrate microwave emission from the soil by introducing some theoretical models [113, 114]. The brightness temperature computed by these algorithms and observed by the space satellite data showed significantly different values. This difference is due to not including the surface roughness parameter. Thus, it is necessary to include a roughness parameter to demonstrate the Earth's surface emission adequately. Sung and Holzer [115] and Ogilvy [116] investigated the scattering of the electromagnetic wave from the rough surface. These studies gave a comprehensive quantitative calculation for scattering from the rough surface. Choudhary et al. [99] developed a simplistic model to study the consequence of surface roughness on observed emissivity by modifying Fresnel's reflectivity and showing the qualitative effect of roughness on the brightness temperature through equation (2.6).

Values of h vary from 0 to 1 for smooth to rough surfaces. This parameter has a different range of values for various frequency bands. The roughness parameter computed by some traditional techniques is independent of frequency and soil moisture [117]. It is a "geometric" roughness and depends on soil texture, weather condition, cultivation, vegetation type, etc. The integrated roughness contains both geometric and dielectric roughness. However, after optimizing with the help of the Levenberg-Marquardt (LM) algorithm, the values of h have been found from 0.1 to 0.4 in L- band frequency region for different land covers.

3.3.3 Spatial disaggregation of soil moisture

The Triangle method described in section 2.5.2 of chapter 2 has been used here for the downscaling of SMAP soil moisture

Figure 3.1 shows the flow chart of the algorithm for soil moisture retrieval and disaggregation. SMAP L1C Brightness temperature, LST, NDVI, and soil texture were

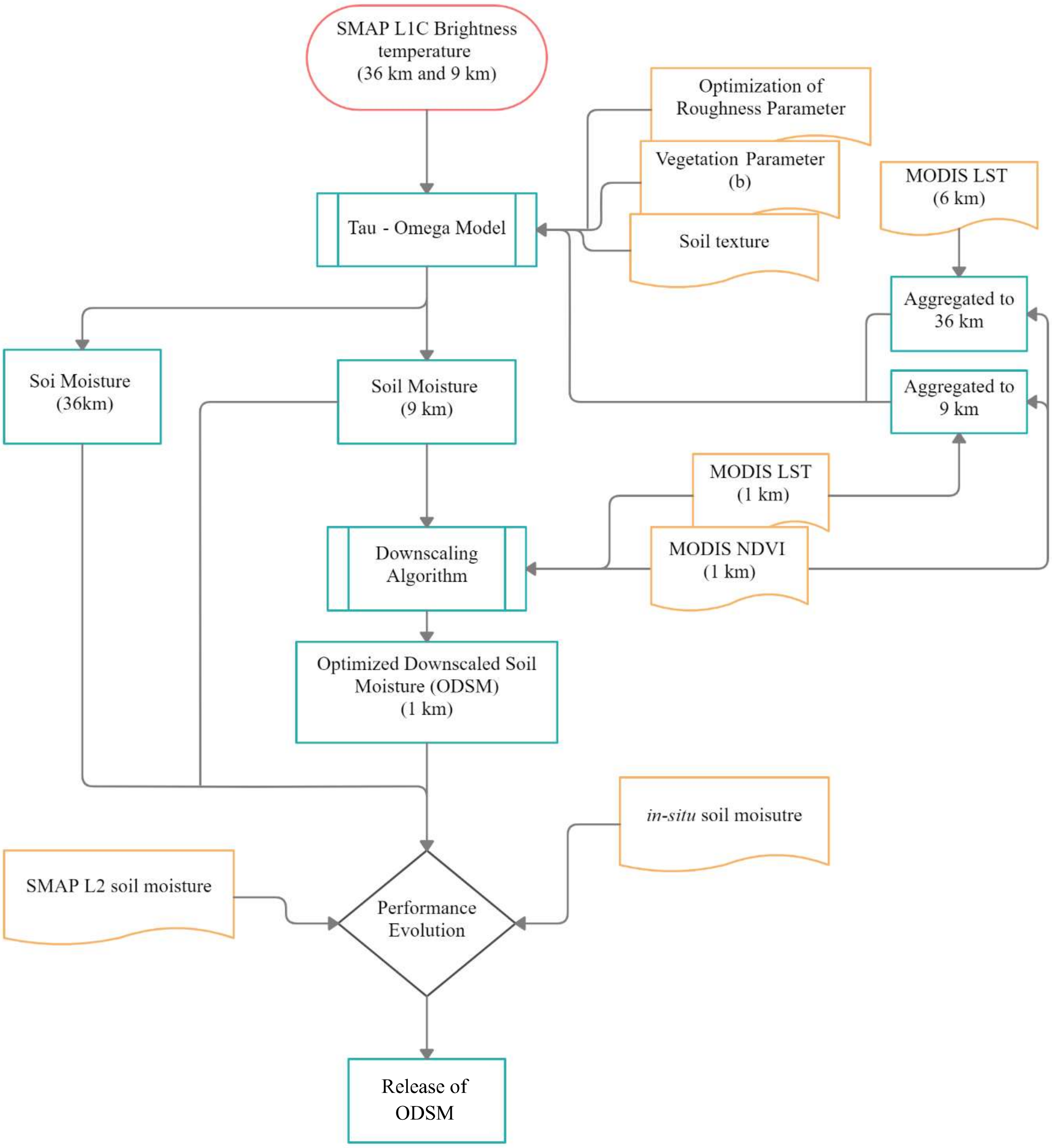


Figure 3.1 Flow chart of the methodology of soil moisture retrieval and downscaling.

used in the Tau-omega model for soil moisture retrieval with the optimization of the surface roughness parameter. The retrieval algorithm was used twice with the two spatial resolutions of SMAP brightness temperature (36 km and 9 km) and MODIS LST (6 km and 1km) to estimate soil moisture at two resolutions. Previously, a 6 km product of LST and a 1 km product of NDVI were aggregated to 36 km to calculate soil moisture at 36 km, and then the 1 km product of both LST and NDVI was aggregated to 9 km to retrieve soil moisture at 9 km. The ODSM (at 1 km) is then computed from the estimated soil moisture (9 km) with the help of a 1 km product of LST and NDVI in the polynomial regression method. The estimated soil moisture was then compared to the in-situ soil moisture along with the SMAP_L2_SM product.

3.4 RESULTS AND DISCUSSION

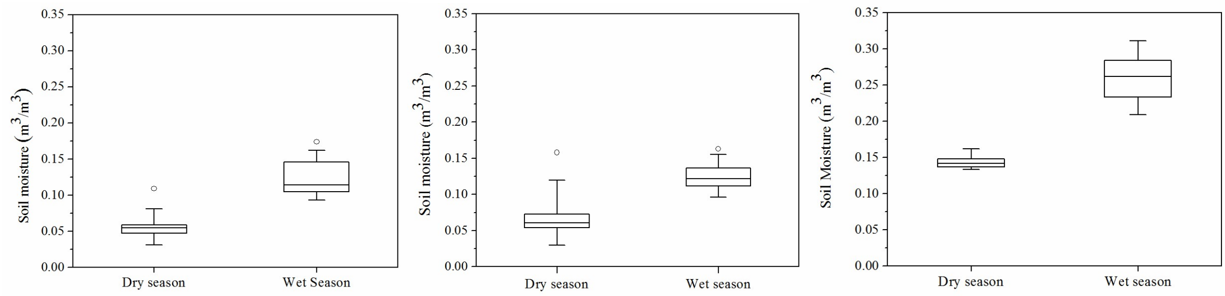
3.4.1 Assessment of SMAP L2 soil moisture and comparison with in-situ soil moisture datasets

SMAP Level-2 data products of soil moisture was downloaded at two spatial resolutions (36 km and 9 km) for two months of 2018 to analyse the variation in soil moisture for dry and wet seasons. These data products were then compared with the ground measurements of soil moisture by the Stevens Hydra probe. Figure 3.2 shows the whisker plot for the variation of soil moisture in the dry and wet seasons for SMAP Level-2 and Hydra probe. A box or whisker is used to display the distribution of a large number of datasets in a very convenient way. In this study, the whisker or box plot was used to show the distribution of soil moisture in different seasons for SMAP and ground measurements. The whisker plot showed that the assessed soil moisture from SMAP was not adequately accurate.

Soil moisture given by the Level-2 product of SMAP is always found below the Hydra probe soil moisture, as shown in Figure 3.2. The distribution of soil moisture for SMAP L2 at 9 km and 36 km is shown in Figures 3.2(a) and (b), respectively. SMAP soil moisture distribution is found to be almost identical at both the spatial resolutions, but soil moisture measured at the ground using the Hydra probe soil sensor is always found higher than that by SMAP L2, as shown in Figure 3.2(c). The average values of soil moisture are around 0.060 and 0.120 for dry and wet seasons, respectively, in both the spatial resolution of SMAP L2. In contrast, these are found to be around 0.140 and 0.260 for dry and wet seasons, respectively, by the Hydra probe observations. The analysis showed that SMAP underestimated the soil moisture values compared to the ground truth soil moisture.

3.4.2 Sensitivity analysis of surface roughness towards soil moisture retrieval

Literature shows that the surface roughness parameter *h* lies between 0.1 and 0.4 [107]. Since the study area is mostly homogeneous with the same characteristics of soil and surface cover, one single value of the roughness parameter can be considered for the whole study region. The values of 0.1, 0.15, 0.2, 0.25, 0.3, 0.35, and 0.4 of surface roughness parameter have been chosen to investigate the sensitivity of surface roughness for soil moisture estimations. For these different values of surface roughness parameter, soil



(a) (b) (c)

Figure 3.2 Whisker plot for (a) SMAP Level – 2 soil moisture (36 km) (b) SMAP Level – 2 soil moisture (9 km) (c) Hydra probe soil moisture with dry and wet seasons of the year 2018.

moisture was estimated using the Tau-omega model at two resolutions and validated with the Stevens Hydra probe ground truth data. To examine the effect of roughness on soil moisture estimation, data of two months (April and December 2018) representing two different seasons were used. Correlation analysis was carried out between the estimated and ground truth data for different values of h- parameter. It indicated a weak correlation between soil moisture measured by the Hydra probe instrument and provided by the Level-2 data product of SMAP. The Tau-omega model was used for estimating soil moisture up to 5 cm depth of the upper soil surface. It appears that a slight change in the value of the h- parameter profoundly influences the estimation of soil moisture.

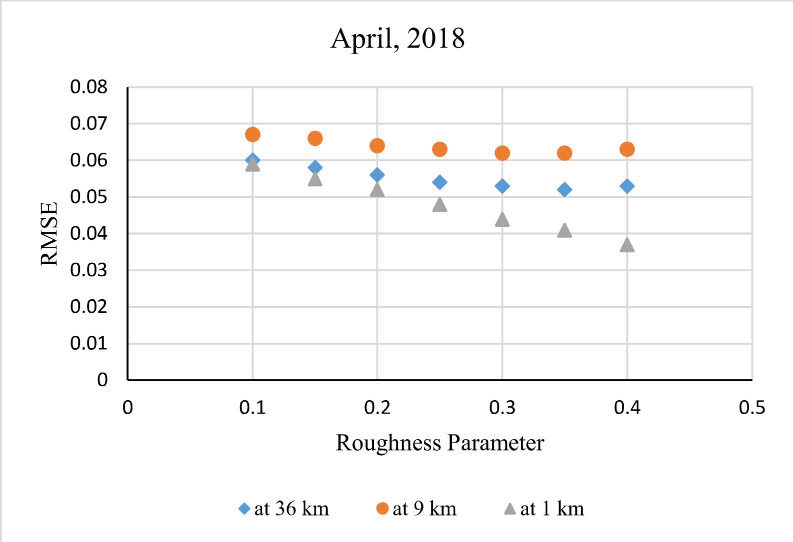
Table 3.1 comprises the values of RMSE and Bias at different values of roughness parameter h as well as SMAP Level-2 soil moisture for dry and wet seasons at three spatial resolutions (36 km, 9 km, and 1 km). The performance of the Tau-omega model was found well with the lowest RMSE at h = 0.35 and 0.25 for 36 km and h = 0.35 and 0.4 for 9 km and h = 0.4 and 0.2, 0.25 for 1 km for April and December, respectively. Table 3.1 shows that the ODSM provided the best results compared to estimated soil moisture and SMAP soil moisture at 36 and 9 km.

Figures 3.3(a) and (b) show calculated RMSE with varying roughness parameters at three spatial resolutions for April, 2018 and December, 2018, respectively. For both seasons, the highest RMSE was observed for the estimated soil moisture at 9 km, whereas

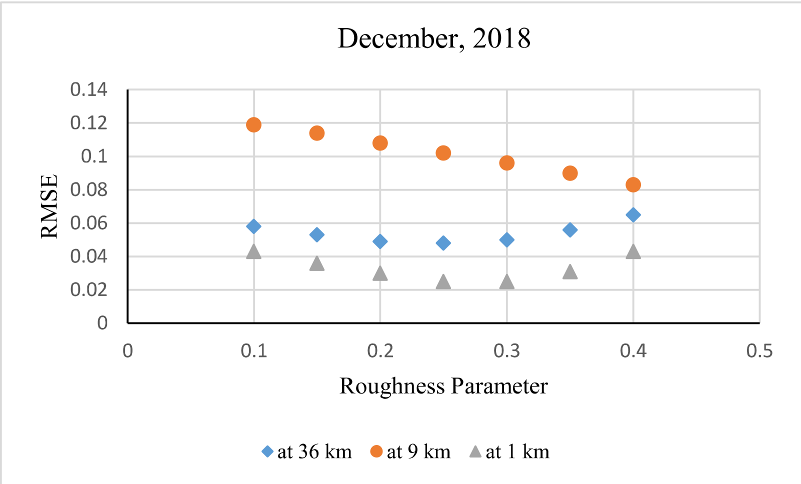
Table 3.1 Performance statistics of the estimated soil moisture (at 36 km and 9 km), ODSM (1 km) at different roughness and of SMAP L2 soil moisture for both the seasons.

Roughness Parameter (*h*)	At 36 km				At 9 km				At 1 km			
	April		December		April		December		April		December	
	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias	RMSE	Bias
0.1	0.060	-0.350	0.058	-0.186	0.067	-0.374	0.119	-0.284	0.059	-0.400	0.043	0.147
0.15	0.058	-0.323	0.053	-0.149	0.066	-0.348	0.114	-0.313	0.055	-0.376	0.036	0.081
0.2	0.056	-0.296	0.049	-0.109	0.064	-0.320	0.108	-0.342	0.052	-0.352	0.030	0.030
0.25	0.054	-0.267	0.048	-0.068	0.063	-0.291	0.102	-0.368	0.048	-0.326	0.025	-0.006
0.3	0.053	-0.237	0.050	-0.022	0.062	-0.262	0.096	-0.393	0.044	-0.299	0.025	-0.054
0.35	0.052	-0.206	0.056	0.026	0.062	-0.231	0.090	-0.417	0.041	-0.271	0.031	-0.091
0.4	0.053	-0.173	0.065	0.079	0.063	-0.197	0.083	-0.440	0.037	-0.243	0.043	-0.126
SMAP L2	0.090	-0.620	0.142	-0.532	0.084	-0.563	0.120	-0.519	-	-	-	-

the lowest RMSE was observed for the ODSM. The suitable value for the roughness parameter was obtained at 0.4 and 0.25, 0.3 for dry and wet seasons, respectively.



(a)



(b)

Figure 3.3 RMSE of the estimated soil moisture and ODSM at different roughness values for (a) April, 2018 and (b) December, 2018.

3.4.3 Performance analysis of satellite soil moisture estimation and downscaling approach

Scatter and Taylor plots provide the performance of the Tau-omega model and downscaling algorithm with varying values of roughness parameter for dry and wet seasons. Taylor diagram is basically a mathematical diagram designed to represent the comparison between several processes, methodology, or models to the observed reference values by three performance statistics variables simultaneously. These variables are correlation coefficient, standard deviation, and (centred) Root Mean Square Difference (RMSD) [118]. The first variable, the correlation coefficient shown on the arc of the diagram, and the data point nearest to the x-axis has the highest correlation. The next variable, standard deviation labels on the x-axis as well as on the y-axis, and for better interpretation, a solid radial line from the reference point is shown. The model closest to this radial line has the closest variability to the observed values. The other and primary variable of the Taylor diagram is RMSD, represented by several concentric radial lines with the reference data point at its center. So, the furthest point to this center (observed value) has the highest error compared to others. In the present study, the Taylor diagram was used to investigate the sensitivity of the roughness parameter on the estimation and downscaling of soil moisture, as shown in Figure 3.4. In contrast, Hydra probe soil moisture was considered as observed reference data. A white circle on the x-axis shows a reference point for observed soil moisture data, and coloured dots show estimated soil moisture at different surface roughness values, while the red dot is for SMAP L2 soil moisture. SMAP L2 soil moisture shows a better correlation for all cases except in Figure 3.4(d), despite having high variability and high RMSD with respect to the observed data in all parts of Figure 3.4. Therefore, all coloured data points correspond to the estimated soil moisture found closer to the observed soil moisture than SMAP L2 soil moisture for both the seasons and spatial resolutions. In the Taylor plot, the data point with a closer distance to the reference point represents the best fit with the observed data; hence estimated soil moisture shows improved results in comparison to the SMAP L2 soil moisture. Taylor diagram for estimated soil moisture at the resolution of 36 km shows the better result at the roughness value of 0.35 and 0.2, 0.25 for dry and wet seasons,

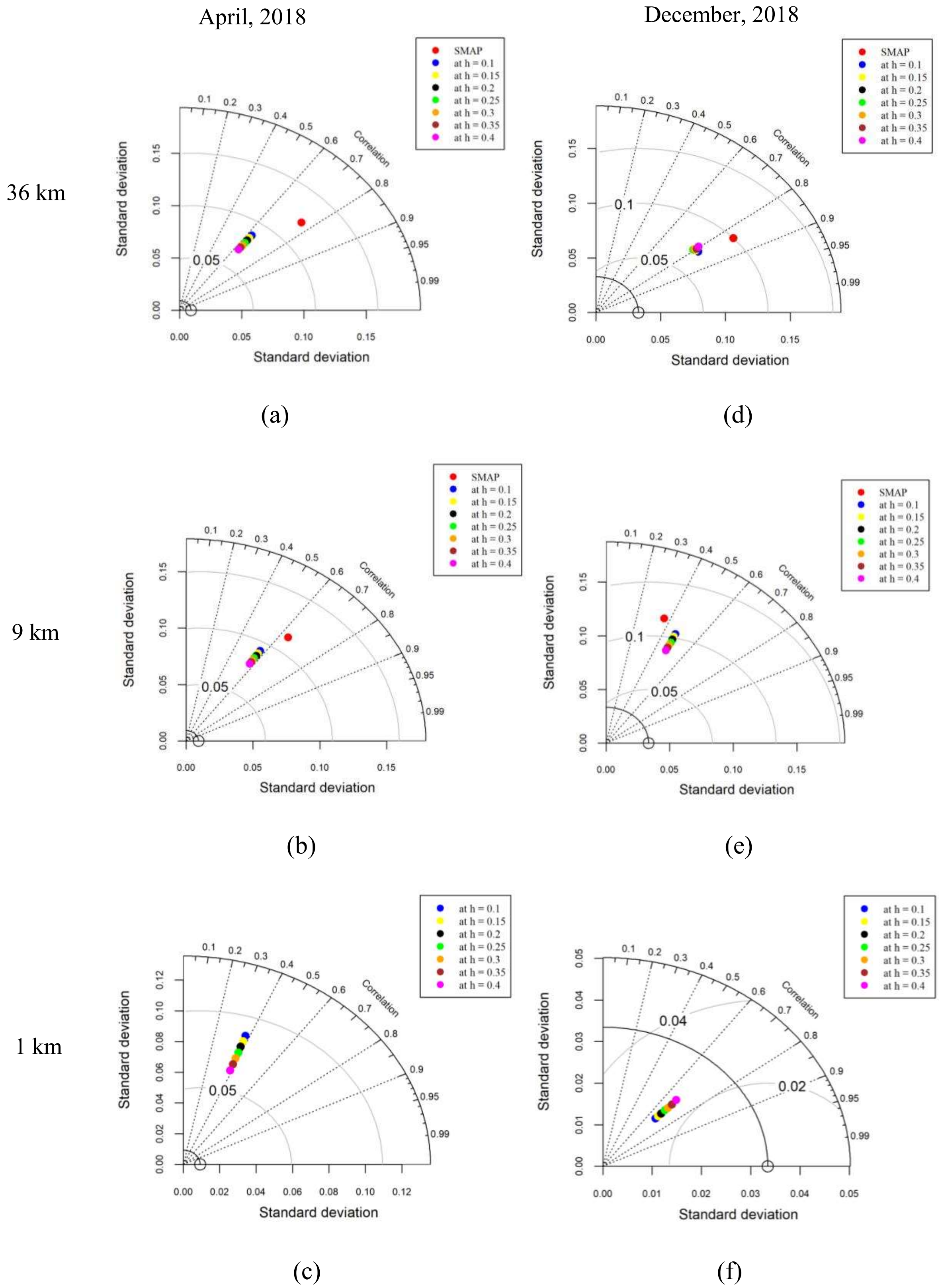
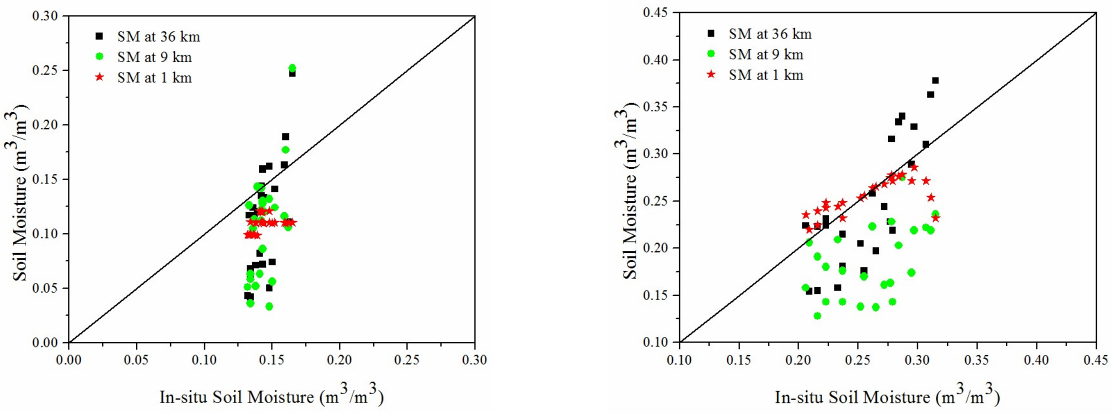


Figure 3.4 Taylor diagram at three resolutions for (a, b, c) April, 2018 and (d, e, f) December, 2018.

respectively, as shown in Figures 3.4(a) and (d), while at 9 km, 0.4, 0.35 indicates the best fit for both the seasons as shown in Figures 3.4(b) and (e) and for ODSM (1 km) the data points for the roughness value of 0.35, 0.4, and 0.2 to 0.3 are closest to the ground measured soil moisture as shown in Figures 3.4(c) and 3.4(f).

Figure. 3.5 shows the scatter plot between the measured soil moisture and in-situ soil moisture for three spatial resolutions of 36 km, 9 km, and 1 km, and the roughness parameter value with the lowest RMSE. The left one is for the dry season, and the right one is for the wet season. In both of these scatter plots, the data shown by red astric (ODSM) is closest to the one–one line. In contrast, the black square (estimated at 36 km) and the green circle (estimated at 9 km) are scattered across the line; this illustrates that the ODSM shows a better correlation with the ground truth soil moisture.

The soil moisture obtained by this approach was further compared with the spatial variations of soil moisture to examine its performance on the spatial scale. For this purpose, the method is additionally used with the spatial values of MODIS LST and NDVI (1km). Soil moisture values obtained by the polynomial relation derived in equation (2.26) were compared with the field measurements of soil moisture. The field data sampling was held on 18 April 2018 in the 40 x 40 km^2 area of the Varanasi district (described in section



(a) (b)

Figure 3.5 Comparison of estimated soil moisture (36 and 9 km) and ODSM with the in-situ soil moisture for (a) Dry season (b) Wet season.

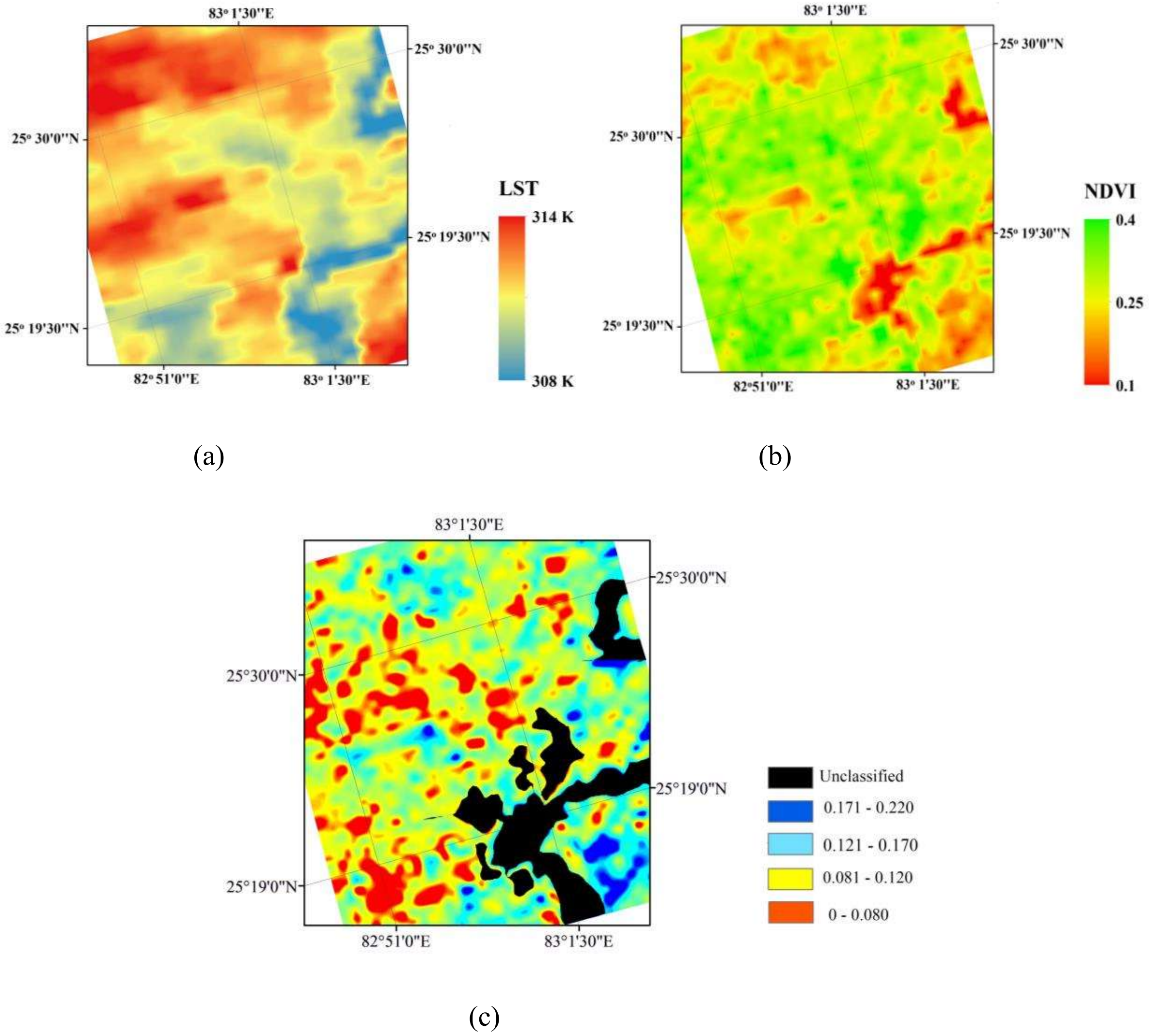


Figure 3.6 Spatial distribution of (a) LST, (b) NDVI, and (c) estimated soil moisture on 18 April 2018 according to the field observations.

2.3.1), considering one pixel of SMAP to collect in-situ data of soil moisture spatially. This region is mainly covered by agriculture. The datasets of MODIS NDVI and LST for the same date and area were picked up for validation. Spatial distribution images of MODIS LST and NDVI, shown in Figures 3.6(a) and (b), were used as the inputs for the downscaling algorithm to estimate soil moisture at a 1 km spatial scale. The soil moisture map of estimated soil moisture is shown in Figure 3.6(c), which indicates that downscaled soil moisture provides more detailed information than the SMAP soil moisture. Since this study is only based on agriculture, other classes such as water and urban have been masked in the soil moisture map. After generating the soil moisture map, resultant soil moisture values were compared with the field observation of soil moisture. Figure 3.7 shows the estimated soil moisture as a function of measured soil moisture in the field sampling. The comparison of estimated soil moisture with the spatial distribution of 1 km soil moisture shows the value of RMSE = 0.0231 and Bias = 0.0863. This indicates that the polynomial relation of LST, NDVI, and soil moisture is performing well with temporal and spatial variations.

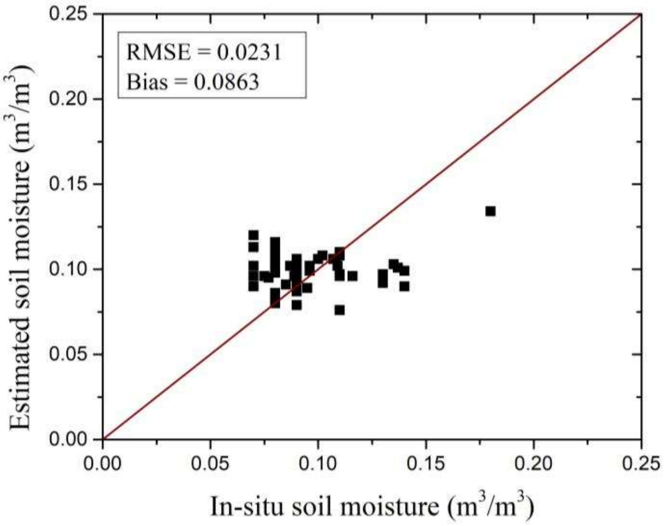


Figure 3.7 Scatter plot for the validation of soil moisture downscaling algorithm on the spatial scale.

3.5 CONCLUSION

This chapter mainly focuses on evaluating the sensitivity of surface roughness on estimation and disaggregation of soil moisture from SMAP using the Tau-omega model for two seasons (Dry and Wet). In–situ measurement of soil moisture during the rainy season is not possible due to the saturation of water in the soil and the limitations of the instrument used. Therefore, the monsoon season was skipped for the present study, and winter was chosen as the wet season. The current approach shows a better soil moisture estimation by the Tau-omega model than the SMAP L2 products. The soil moisture was retrieved at two spatial resolutions using the L1C data product of SMAP, available at two spatial resolutions (36 km and 9 km). The estimated soil moisture at 9 km was then downscaled to 1 km using a polynomial regression approach. Different values of roughness parameter were used for both estimation and disaggregation of soil moisture. The results obtained by the ODSM showed better results than the SMAP L2 soil moisture product. The lowest RMSE is found to be 0.0365 at h = 0.4 for the dry season and 0.0252 at h = 0.25, 0.30 for the wet seasons at 1 km of spatial resolution. The highest values of RMSE were found to be 0.0671 and 0.1194 at h = 0.10 for both seasons at 9 km of spatial resolution. The ODSM was found to be the closest to the ground truth soil moisture. The disaggregation approach performed well when validated with the temporal and spatial variations of soil moisture. The validation results indicated the high potential of the present approach with both temporal and spatial scales for the soil moisture estimation. The optimization of surface roughness for soil moisture estimation and downscaling indicates that the surface roughness parameter is a very sensitive parameter for soil moisture estimation and disaggregation.

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