Estimation of soil moisture using SAR and Optical imagery in Area with Semi-arid and rainy seasons

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Abstract: The objective of this work was to find a model to estimate surface soil moisture by using the available andfree satellite imagery data of synergy of single polarized C-band sentinel-1 and Optical Sentinel-2 Data acquired in dry and wet seasons on study site in Niger.Water cloud model (WCM) was selected in this study due to its ability to describe backscattering coefficients interms of soil proprieties and vegetation proprieties. First, we founded the relation between Sentinel-1 backscattering coefficientsσ^0_{VV} and σ^0_{VH} in C-bandthat are adjusted to minimizevegetation effect, and ground measurement of soil moisture [downloaded from the International Soil Moisture Network (ISMN)], using linear regression with Gradient descent. The sensitivity of the SAR backscatter to in situ measurement was estimated as 0.7 and 0.43db/Vol% for VV and VH polarizations, respectively. Second, the Normalized Difference Vegetation Index (NDVI) was used as vegetation descriptor in the WCM, it is extracted directly from the preprocessed sentinel-2 optical images. The Calibration of WCM consists in fitting the model against ground measurements and estimated parameters for VV and VH polarization by minimizing the sum of squares of the differences between the simulated and measured radar signal.
Keywords: Water Cloud Model (WCM); Synthetic Aperture Radar (SAR); Sentinel-1 and Sentinel-2; the C-band;Surface soil moisture; NDVI.

1. Introduction:

Soil Moisture can be defined as the temporary storage of water in the upper layer of surface (0 to 5 cm). The volume of the water that can be contained in this portion of the surface seems to be negligible as compared to the total amount of the water, but it's this percentage of water that affects the agricultural activities. For that, a good description of Soil Moisture at the field scale can be crucial before sowing, and during the growth stage in order to control de scheduling date and the volume of water needed in the field for irrigation input.

There are many ways to acquire SM, from direct field measurements, such as the time domain reflectometry[1], and gravimetric method [2]. Unfortunately these methods are impractical at large scale due to spatiotemporal variability of surface texture, topography, and the distribution of the crop cover, also it is expensive and time-consuming. Luckily, remote sensing is the relevant alternative to this issue that can provide SM map over wide area and with timing flexibility.

However optical and thermal remote sensing is easy to compute and very useful to monitor the quantity, quality and behavior of the vegetation [3]. But it is also showing some limitation to estimate soil moisture due to the poor penetration capability of this range of waves in vegetated area.

Microwave remote sensing, both active and passive, revealed its high potential to estimate soil moisture with/without existence of crop cover. The key factor behind using this method for soil moisture retrieval is itsclosely relation with dielectric constant [4], there is large difference between water dielectric (-80) and dry soil dielectric (3 to 4) and wet soil dielectric (up to 30). It should be noted that other factors are affecting SM estimation, from sensor side, we have wavelength, Incidence angle and polarization, and from target side (Soil) we have surface roughness and crop cover in addition to dielectric constant parameter.

The backscattering models are defined as inverse functions describe two main attributes such as SAR Signals and soil surface parameters, in literature these models are categorized into three groups theoretical, such as Integral Equation Model(IEM) [5], empirical model such as and semi-empirical such as Dubois[1995] [6] et al and Oh et al [1992][7]. The most widely used models in inversion procedure are (IEM) and Oh, Dubois. However several studies shows that the agreement between measured SAR signals and those predicted by the models, are not encouraged [8][9] because the backscattering model cannot be retrieved without calibrating the target parameters and the sensor configuration.

The dependence of physical models to the surface roughness, which is in situ measurement, makes it difficult to apply, however these methods are applicable only on bared soil, so the presence of vegetation makes the estimation very difficult.

The water cloud model (WCM) [10]. Is the most used model in the vegetated area because it is composed of two terms, the first one describes the backscatter coefficient of the bare soil attenuated with the vegetation and the second term describes the contrition of the vegetation in the reflected signal.

The motivation for this study is to perform an algorithm to retrieve Soil moisture using the available and free data provided by the European Union's Earth Observation program “Copernicus”. We will combined sentinel –1 SAR images(C-band) in both VV and VH polarizations and sentinel-2 optical images (IR and NIR bands) and Soil moisture in situ measurement provides by International Soil Moisture Network (ISMN)], mapping at field scale.The resulting parameterized WCM permits the estimation of soil moisture over agricultural areas. In this paper, section 2 the study area and the ground measurements. Section 3 present the semi empirical model used to describe SAR backscattering model, section 4 partial result and discussion section 5 will give conclusion and perspectives.

2-Dataset Description:

- Study area:

The study area that were selected for the collection of field data is in the south-west part of Niger: Banizoumbou [13, 53°N; 2, 67°E](Figure 1). The climate is semi-arid with a rainy season between Mai and October. Total rainfall was 392.7mm with several interruptions at the beginning of the season and an early cessation followed by a late rain on 05 October

2018. The landscape is composed of Plateaus formed by Tertiary fluvio-lacustrine deposits,with low slopes, covered with tiger bush or spotted bush depending on the alternation of bare soil and small trees that formed the bush. The bare soil of plateaus is characterized by an important crusting due to strong precipitations in the rainy season which runs off the surface. Water infiltrates in the vegetated bands and thus plays an important role in the maintenance of these vegetated areas. Three main classes are identified on plateau: bare soil (with gravel), sparse vegetation, and dense vegetation [11].

Figure 1. Location of Banizoumbou study sites in Niger.

- Sentinel-1 Images:

Twenty two C-band SAR images acquired by sentinel-1 sensor between January and December 2018(Table1), over the study site were downloaded from https://scihub.copernicus.eu/. The images were acquired in GRD (**Ground Range Detected Geo-referenced Product**) mode with the available S1A satellite in this area during the study period. GRD image are giving data at cross polarization VH (vertical-horizontal) and co-polarization VV (vertical -vertical) , the incidence angle over the study site in about 38°.the acquired images were preprocessed using SNAP, in 7 steps:

1. Subset,
2. Apply orbit-File,
3. Thermal noise removal,

4. Radiometric calibration,
5. Terrain-Correction,
6. Speckle-Filter (Lee 5 x 5),
7. LinearToFromdB.

- Sentinel-2 Images:

At dates very close to the SAR images (less than 4 days), table 1 shows twenty two free cloud Sentinel-2 images were acquired over the stud site. The optical images was pre-proceeded over SNAP software in 3 steps: 1. Subset, 2.Geometric correction (resampling to 10m), 3.Atmosphrique correction with NDVI map. Were used to calculate the NDVI. As the dates of the optical images were.

- In Situ Measurements:

The ground measurement of the study area was giving by the International Soil Moisture Network (ISMN),[12]. The measurement were acquired hourly using calibrated time domain reflectometry (TDR)[1]: CS616 probes. Soil moisture were collected over depths of 0-5 cm. the measurement was maximized overs 24 hours to have 1 value per day. The soil moisture values ranged between 0.76 and 26.37 vol %

Table1: Dates of sentinel-1/sentinel-2 overpasses over our area of interest during the study period.

Sentinel-1 acquisition date	Sentinel-2 acquisition date
05/01/2018	04/01/2018
17/01/2018	19/01/2018
10/02/2018	08/02/2018
22/02/2018	26/02/2018
18/03/2018	20/03/2018
30/03/2018	30/03/2018
11/04/2018	09/04/2018
23/04/2018	24/04/2018
10/06/2018	08/06/2018
14/07/2018	13/07/2018
28/07/2018	28/07/2018
09/08/2018	07/08/2018
21/08/2018	12/08/2018
02/09/2018	06/09/2018
14/09/2018	11/09/2018
26/09/2018	21/09/2018
08/10/2018	06/10/2018
20/10/2018	21/10/2018

01/11/2018	26/10/2018
13/11/2018	11/10/2018
19/12/2018	20/12/2018
31/12/2018	30/12/2018

3-Backscattering models:

In this study, the Water Cloud model (WCM) developed by [13], was used to model the radar backscattered signal in vegetated area as a function of soil and vegetation parameters. This semi-empirical model is widely used in the agricultural sites, to estimate the soil moisture with/without vegetation cover. It can be easily performed in an inversion procedure to get the Soil moisture as output while SAR and optical calibrated images were used as input. For a given polarization (VV or VH), the Water Cloud model defines the backscattered radar signal in linear scale as the sum of the contribution from the vegetation, the soil attenuated by the vegetation.

$$\sigma^0_{tot,vv} = \sigma^0_{veg,vv} + \tau^2 * \sigma^0_{sol,vv} \quad (1)$$

$$\sigma^0_{veg,vv} = a_{\ vv} * V_1 * \cos(\theta) * (1 - \tau^2)(2)$$

$$\tau^2 = \exp(-2 * b_{\ vv} * V_2 * \sec(\theta)) \quad (3)$$

Where a_{vv}andb_{vv} are fitted parameters of the model that depend on the vegetation descriptor and the radar configuration. V_1 =V_2 are the vegetation descriptors. θIs the incidence angle.

4-result and Discussion:

In this paper, the SAR backscattering coefficient and NDVI were averaged on the experimental field using SNAP software, the subset covers 10 km x 10 km. The local measurement of soil moisture was maximized overs twenty four values acquired during the day. The first step is to find the relationship between backscattering coefficient given by SAR Image and ground measurement. Second step consists in determining the parameters a_{vv} and b_{vv} for which the mean square error between the empirical model WCM and the backscatter coefficient is minimal. To retrieve the optimal values of a_{vv}andb_{vv}, we will use the non-linear support vector regression.

Relation between Soil moisture and SAR backwatering coefficient:

As confirmed in several studies realized over bare soil [14], SAR backscattering coefficient in both vv and vh polarization was related to in situ soil moisture using linear regression (figure 2), and it was optimized using the gradient Descente, the measured soil moisture was ranged between 0.74 and 9.1 vol.%. and σ^0_{VV} and σ^0_{VH} ranged between -13.14 dB to -19.96 dB and -21.48 dB to 25.35 dB, respectively. The figure 3 shows that measured soil moisture is more correlated with vv backscattering coefficient than vh backscattering. The correlation coefficient were about 0.67 for VV polarization and 0.65 for VH polarization. The sensitivity

ISSN 2515-8260 Volume 08, Issue 03, 2021

of the σ_{VV}^0 and σ_{VH}^0 to de measured soil moisture was estimated as 0.7 and 0.43 dB/vol. % for VV and VH respectively. An increase in soil moisture of 5% can generates an increase of 3.5 dB in VV and only 2.15 dB in VH.

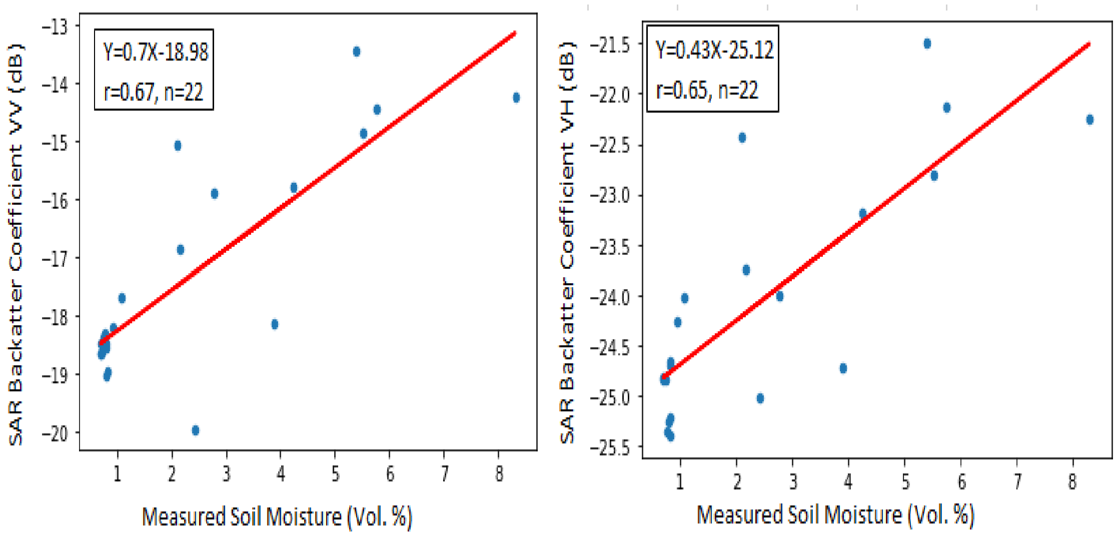

Figure 2: the relationship between SAR backscatter coefficient and measured soil moisture at 5cm for VV and VH polarization with the linear regression plot with red color.

<u>Soil moisture, SAR backwatering coefficient and NDVI index Trends:</u>

Figure 3 shows that the trend of the backscattering coefficient coincides with the trend of soil moisture especially during the rainy period, also the vegetation index has a good correlation with soil moisture trend, that's why the NDVI is used us vegetation descriptor in WCM model.

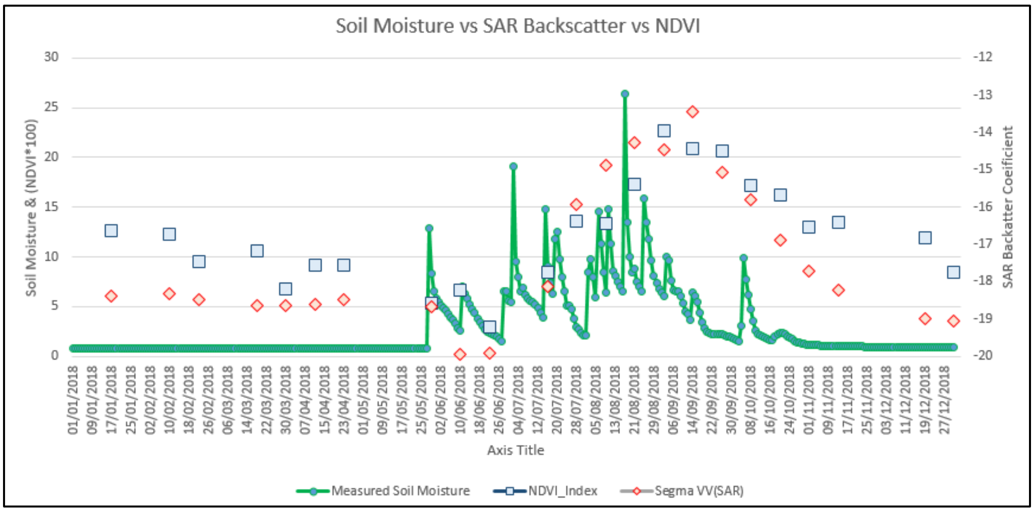

Figure 3: daily Trend of measured soil moisture during 2018 vs. SAR backscattering dataset vs. Sentinel-2 NDVI index.

Relation WCM Coefficient and SAR backscattering coefficient:

The WCM model calibration was performed using the training dataset (Table 1). WCM parameterization consists in fitting the model against ground measurements (equations (1) (2) (3)). The parametersa_{vv} /a_{vh} and b_{vv} /b_{vh} for VV were estimated for the VV and VH polarizations by minimizing the sum of squares of the differences between the simulatedand measured radar signal. After having determined the optimal parameters, it becomes possible to simulate the WCM components ($\sigma^0_{veg,vv}$,τ^2, and $\sigma^0_{sol,vv}$) and consequently the total backscatter coefficient ($\sigma^0_{tot,vv}$) using NDVI, soil moisture as inputs. NDVI=V_1 =V_2 values between 0.03 and 0.2 were used in the fitting and the validation of WCM.

Figure shows that the relationship between WCM coefficient and SAR backscattering coefficient is non-linear, that's why we were used a non-linear support vector machine to optimize the WCM,

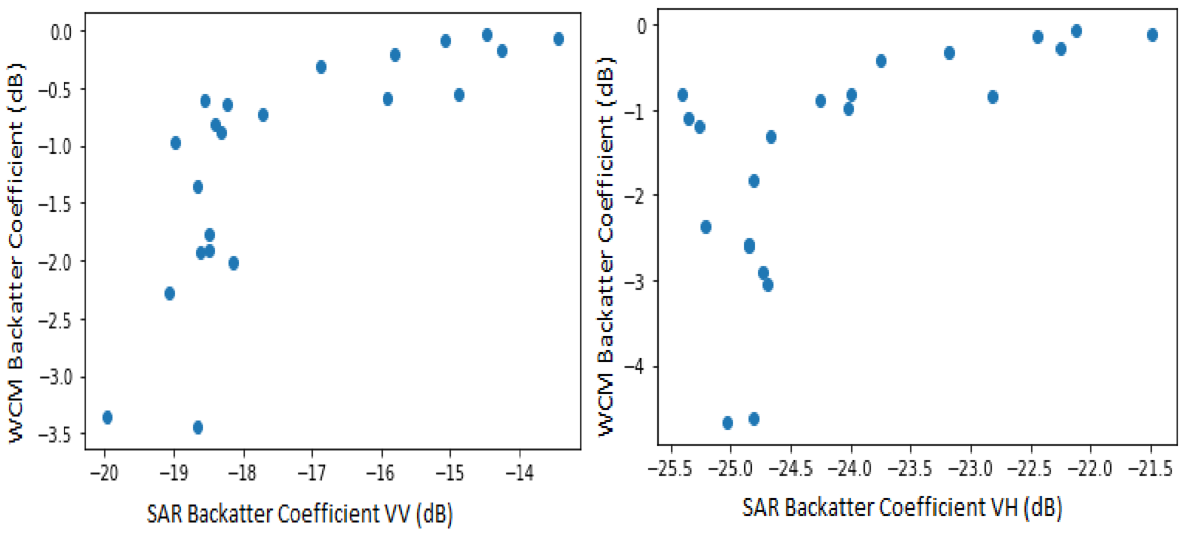

Figure 4: the relationship between SAR backscatter coefficient and estimated WCM backscattering coefficient VV and VH polarization.

Table2: The optimal values of the water cloud model (WCM) parameters for each polarization (VV and VH) are presented in the table below:

Polarization	**WCM Parameters**		**R^2**	**No of samples**
VV	$\boldsymbol{a_{vv}}$**=0.99**	$\boldsymbol{b_{vv}}$**=-0.0008**	**0.657**	**22**
VH	$\boldsymbol{a_{vh}}$**=1.00**	$\boldsymbol{b_{vh}}$**=-0.0029**	**0.504**	**22**

The Table2 shows that, Correlation coefficient (**R^2**) were about 0.657 for VV polarization and 0.5 for VH polarization. The VV polarization is significantly correlated with Soil Moisture field measurement compared to VHwhich showed more dispersion.

5-Conclusion and perspectives:

the motivation for this study comes from, that European Space Agency (ESA) is giving a periodic (every 6 days) sentinel-1 and sentinel-2 images with high resolution for free, also the International soil Moisture Network[ISMN] is archiving hourly and daily field measurement of soil moisture, meteorological data,..., also the data is given for free within 24 hours.

The aim of this research was to calibrate the water cloud model in C-band. This calibration will allow in the future the development of a radar signal inversion approach [13] over agricultural fields by coupling radar and optical data (Sentinel 1 and Sentinel 2).

The calibration of the WCM were performed using experimental dataset of soil moisture back, SAR scattering coefficient calculated from SAR images and NDVI values calculated from optical images. The accuracy of the calibrated WCM will be evaluated with an RMSE for both VV and VH polarizations.

Acknowledgments: This research was supported by European Space Agency (ESA) for kindly providingthe Sentinel-1 and Sentinel-2 images and the International Soil Moisture Network: https: //ismn.geo.tuwien.ac.at/ for Kindly providing in situ measurement.

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