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Soil Moisture Retrieval Using SAR

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Abstract

This paper presents the spatial distribution of soil moisture in the Qinghai Lake catchment area using Dubois and water cloud model.

The theoretical basis of soil moisture inversion is determined. The basic situation of the research area “Qinghai Lake catchment” is introduced. The software used in the research is then introduced, as SNAP, Envi Sarscape 5.1 and ArcGIS. Then, the ground measurement is also introduced. The volumetric soil water content at a depth of 5 cm was measured using TDR instrument. Soil roughness was also measured by "manual profiler" method. The accurate measurement position is determined by using GPS. In addition, the Radarsat-2 SAR satellite data are obtained synchronously.

The water cloud model was used to remove the influence of vegetation. Then, a combination of the water cloud model and Dubois model as well as the vegetation parameters were used to determine the parameters of water cloud model in HH and VV polarization. Subsequently, the water cloud model and the Dubois model were used to compute for the soil moisture in the Qinghai Lake catchment. Finally, the correlation coefficient between observed and retrieved soil moisture was 0.79, which proves the validity of the method.

Keyword*:* Soil Moisture Content, Dubois Model, Water Cloud Model (WCM), Synthetic Aperture Radar (SAR), Dielectric constant.

INTRODUCTION

Surface moisture content generally refers to the water contained in the upper part of soil, which potentially evaporates into the atmosphere due to the activity cycles of the ecosystem. Soil moisture (SM) determination is always of paramount interest to society, since soil moisture does not just represent aspects of the ecosystem but has also been used for numerous models and applications. These models includes, Hydrological Modeling[30], Numerical Weather Forecasting[20], Modeling of Land Surface Evaporation, Prediction of Surface Runoff in road drains construction [27]–[30], Agriculture forecast, Disaster prediction modeling and Environmental Monitoring Modeling. These models have really helped in flood control and monitoring of droughts in various parts of the world over the years. The determination of Surface moisture content is necessitated by the fact that, Water makes up about 71% of the

Earth’s surface, while the other 29% consists of continents and islands. 96.5% of all the Earth’s water is contained within the oceans as salt water, while the remaining 3.5% is freshwater, lakes and frozen water locked up in glaciers and the polar ice caps.

Besides about 69% of all fresh water is ice, which means if all ice could be melt the Earth’s surface will be perfectly smooth, and the level of the sea would rise to 2.7 kilometers in altitudes (Matt Williams 2016). This makes soil moisture a very delicate issue of importance to humanity. There are numerous methods for the determination of the surface moisture content. In Geotechnical, the gravitational or point method of Surface moisture detection technique is deemed the best method for determining soil moisture until the discovery of the synthetic Aperture Radar (SAR) method. Synthetic Aperture Radar (SAR) is a side looking Radar system that generates a high-resolution image of the earth surface for remote sensing applications and process data at the microwave portion of the electromagnetic spectrum with a wavelength of approximately 1mm to 1m and at 0.3 to 300 GHz frequency.

In this regard, this paper has used, a dual polarized (co-polarized and cross-polarized) side looking “Radarsat-2” SAR imagery data taken by a Canadian Radarsat-2 satellite to retrieve the soil moisture at Qinghai Lake catchment (China). The moisture content is then computed using the Dubois Model, taking the dielectric constant (ε) as a principal factor. This is due to the fact that, the sensitivity of microwave to soil is solely based on the variation of the dielectric constant, which is proportionally dependent on the soil moisture [31]. Numerous models which includes, empirical [21]–[25]. Semi-empirical [22], and electromagnetic scattering theories such as the Integral Equation Model (IEM) [32] were available for the analysis, but the Dubois model has been used for this paper because of its effectiveness.

The Dubois Model deals with the effect of vegetation and cloud in its analysis. The research area (Qinghai Lake) is a vegetation dominant wetland. Therefore,

in other to factor the effect of scattering from vegetation cover as well as scattering from the underlying soil surface (RADARSAT can penetrate clouds and vegetation cover) Dubois is considered for this research work.

Dataset

This research paper used a C- Band Polari metric data, from a RADARSAT-2 satellite data of Qinghai Lake, taken on 10th August, 2015 and 14th August 2015 respectively. The two images have been analyzed and processed to obtain a backscattering coefficient, which is used for the retrieval of the Moisture Content, under vegetation at Qinghai Lake in this research thesis report.

Both data images have a spatial resolution not exceeding 30m. The SAR Imagery data taken on 14th August, 2015 is in an VH and VV dual polarization schemes, whiles the image taken on 10th August, 2015 is in an HH and HV dual polarization schemes. The VH and VV dual polarization data is a slant image with a left range near side incidence angle of 19.373568^{o} and a far range incidence angle of 31.273327^{o}. The HH and HV dual polarization data is a slant image with a left range near side incidence angle of 30.299315^{o} and a far range incidence angle of 39.257874^{o}.

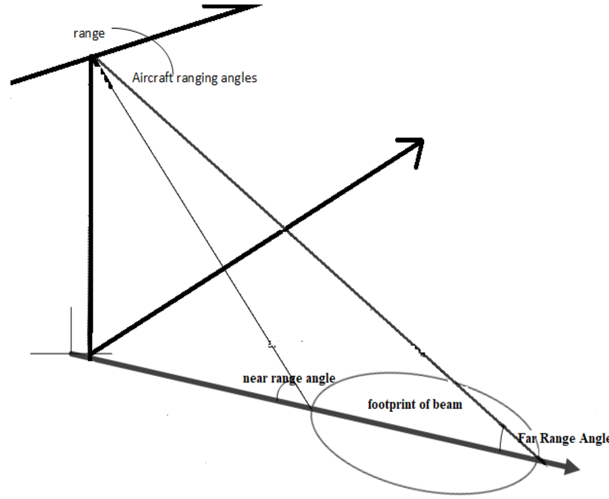

Figure .1. Imagery Data in Nadir direction [6]

a) Research Area

Qinghai Lake. Qinghai Lake is the largest inland and salt-water lake in china (as of now).

The lake (Qinghai Lake) is bounded by four continuous mountains with extensions of broad grassland in front of it.

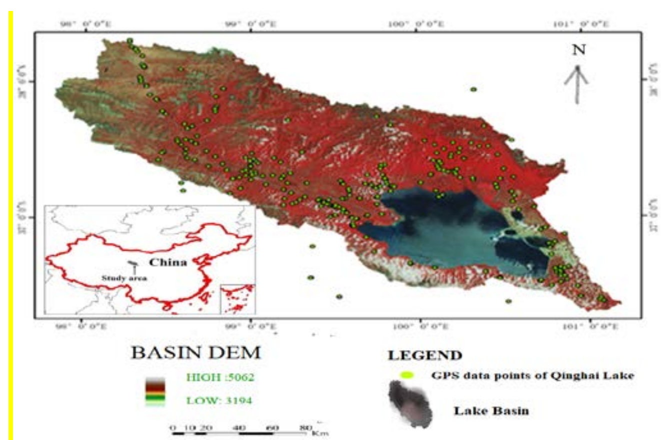

Figure.2. Plot of Qinghai Lake Catchment

b) Data Processing

Soil moisture determination denotes a measure of the backscattered ray's incident on a soil surface to compute for the amount of moisture it contains.

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The first step was to convert the "Data Imagery" to a standard backscattering coefficient, which was later analyzed using the Dubois Model

Data Importation: File - Open Product - Import

Radiometric Calibration: Menu Panel (Radar- Radiometric - Calibrate)

Speckle Filtering: Select Radar - Speckle Filtering- Single Product Speckle Filter.

Geometric Correction: Menu Panel (Radar- Terrain Correction – Range - Doppler Terrain Correction)

Exportation: Menu panel (File- Export – Other -View in Envi)

Backscattering coefficient retrieval: Pixel – Coordinates - Elevation/Sample

1. METHOD

Dubois method was selected for this research work after weighing in on all possible models and approaches. Some of these approaches include,

Modal Approach: Developed on the principles of the Empirical model [25]

Artificial Neural Network (ANN) Approach: Developed on the principles of the electromagnetic scattering theories such as the Integral Equation Model (IEM) [32].

The ANN approach considers factors like, corrected Radar Backscattering, Incidence Angle, NDVI and Terminal Infrared [18] Temperature (TIRn). The TIRn is Dependent on the Dielectric properties of soil

Dubois Approach: The Dubois approach considers factors like, Dielectric Constant of the Soil (Ɛ), Vegetation Cover (Vc) of the area, look Angle (θ), and Co- Polarization (HH OR VV) [31].

In addition, taking into consideration the data used (C-band RADARSAT-2 data with a 30m spatial resolution) the DUBOIS approach was deemed appropriate for SMC analysis of Qinghai Lake.

The Dubois approach has been used for the mapping of the soil moisture for Qinghai Lake in China.

The flow chart for the procedure used to retrieve the soil moisture is as follows.

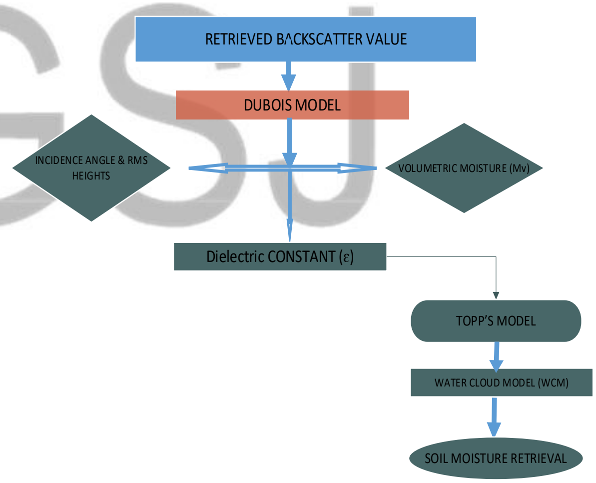

Figure.4. Methodology Flow Chart

a) Backscatter Values Retrieval

Soil moisture determination denotes a measure of the backscattered ray's incident on a soil surface to compute for the

The first step towards the actualization of this thesis report was to convert the "Data Imagery" to a standard backscattering coefficient, which was later analyzed using the Dubois Model to retrieve the soil moisture used for this paper.

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Dubois Model: Data analysis is the most critical stage of "Soil Moisture Mapping using RADATSAR-2 data". At this stage, the selected methodology is critically perused and analyzed using the data backscatter, to factor all external factors that affected the data backscatter in a way or the other.

The quantitative relationship between the co – polarized backscattering coefficient of the soil surface and root square (RSM) of the HH and VV polarizations.

$$\boldsymbol{\sigma}_{vv}^{o},\ soil\ =\ 10^{-2.35}\left(\frac{\cos^{3}\theta}{\sin^{3}\theta}\right)10^{0.046\varepsilon\tan\theta}\left(ks.Sin\theta\right)^{1.1}\lambda^{0.7} \quad (1)$$

$$\boldsymbol{\sigma}_{hh}^{o}, soil\ =\ 10^{-2.75}\left(\frac{\cos^{1.5}\theta}{\sin^{5}\theta}\right)10^{0.046\varepsilon tan\theta}\left(ks.Sin\theta\right)^{1.4}\lambda^{0.7} \quad (2)$$

Where,

$\boldsymbol{\sigma}_{vv}^{o}$ is the Observed Backscattering Coefficient of VV Polarization

$\boldsymbol{\sigma}_{hh}^{o}$ is the Observed Backscattering Coefficient of HH Polarization

Wavelength (λ) is the ratio of the speed of light in a vacuum (c) to the frequency (V). $\lambda = c / v$

Therefore,

Angular Wave Number (K). It is the ratio of ($2\times\pi$) to the wavelength (λ). (K = $2\pi/\lambda$) (3)

Incidence Angle (θ) and RMS Heights (S): The Incidence Angle is the angle made by a light ray or wave hitting a surface and the line perpendicular to that surface. However, in the case of this imagery data, two inclined angles were made in the case of both the HH and VV polarized imagery data.

The incidence angle for the HH polarized imagery data was 34.7785945^{c} and the incidence angle for the VV polarized imagery data was 25.323419º.

Soil roughness parameters RMS surface heights were derived from heights of the profiles measured by a 30 cm pin-profiler with a pin height of 4.0 cm. The distance between every two pins is 3.0 mm.

Large numbers of observations are taken with one-dimensional profile meter, and analyzed to obtain the values of RMS surface heights and correlation lengths. This in turn was used to estimation for the Radar Backscattering Coefficient.

A range of roughness values RMS surface heights from 0.7862cm to 4.6503cm obtained in measurements with the one-dimensional profile meter.

Figure.5. Manual Profiler [14]

b) Dielectric Constant (ε)

The dielectric constant of Radar Backscatter is expressed as a function of co – polarized Backscattering coefficient and sensor

Configuration parameters [3]

$$\varepsilon = \frac{1}{0.024\times\tan\theta}\log_{10}\left(\frac{10^{0.19}\lambda^{0.15}\sigma_{vv}^{o}, soil}{(\cos^{1.82}\theta)(\sin^{0.93}\theta)(\sigma_{hh}^{o}soil)^{0.786}}\right) \quad (4)$$

But for the sake of the Retrieval of the Soil Moisture at Qinghai Lake, where the sensor parameters are determined by the dielectric constant which is essentially dependent on the Volumetric Soil Moisture (Mv)

The moisture content hence Dielectric Constant was determined using the Empirical Relationship deduced by Topps Model [19]

$$\varepsilon = 3.03 + 9.3M_v + 146M_{v^2} - 76.7M_{v^3} \qquad (5)$$

The Dielectric Constant (ε) is computed at GPS Location, Log.100.8387977, and lat.36.56796733 using Equation **5** and **Table. 1**. As follows,

Table 1. Parameters for a GPS location

K values	wavelength	roughness from site	moisture content	Volumetric moisture
1.13	5.56	0.7862	2.6	0.026a

$$\varepsilon = 3.0O3 + 9.3M_V + 146M_{V^2} - 76.7M_{V^3}$$

c) Volumetric Moisture Content (M_v)

"Time Domain Reflectometry (TDR)" method for the soil Moisture determination at various GPS Locations on the project site. TDR technology delivers very accurate determination of soil moisture content compared to some other methods. TDR is able to retrieve soil moisture on an instant basis hence giving an undisturbed data without any imprecision in value, and this attribute makes the TDR method for soil moisture determination is accurate and precise. The operation principles of the TDR method describe the correlation of the frequency – dependence of the soil to its moisture contents.

The principle involves inserting a sensor into the soil and applying standard waveforms analysis to determine the average moisture content at specific GPS locations on the site.

The analysis for the retrieval of the moisture content at every location was done for a depth of 3.8cm, 7.6cm, 12cm and 20cm.

After that, a sensitivity analysis was run to determine the point at which the moisture content was accurate and could directly affect the Dielectric constant.

This was done by plotting a graph of the moisture content values at various depth (3.8cm, 7.6cm, 12cm and 20cm.), after which it was known that the 3.8cm depth had the highest correlation value (r^2) of 0.9619.

So, the moisture values at a depth of 3.8cm were used for the analysis of the data of Qinghai Lake.

The readings of the soil moisture from the TDR are in a mass of cubic meters and must be converted to volumetric percentages by divided by hundred (100), as was done in the case of this project.

d) Soil Backscatter

The Equations (1), (2), (3), and (4), were used to compute for the soil backscatter soil backscatter in VV Polarization, Soil Backscatter in HH polarization, the Dielectric constant and the water cloud model respectively as follows; for GPS Location, Longitude. 100.8387977, Latitude 36.56796733. Table 2. Presents the GPS Location parameters.

Table 2. GPS locational Parameters

k values	wavelength	roughness from site	moisture content	Dielectric cons	θ_{HH}	θ_{VV}
1.13	5.56	0.7862	0.026	3.369147921	34.7785945	25.323419

HH Polarization (Log. 100.8387977, lat 36.56796733)

Water Cloud Model (WCM): The Water Cloud Model is analyzed to eliminate assumed total canopy backscattering coefficient σ_{pp}^{o} as the sum of vegetation Backscattering [28] s.

This is necessary because, wetlands mostly have vegetation cover throughout the year and these vegetation cover always has direct effect on the imagery data, and that was the same situation at Qinghai Lake.

WCM estimation is necessary because the dielectric constant of vegetation matter is much smaller (by order of magnitude) than the dielectric constant of water. In addition, vegetation canopy is usually composed of 99% air by volume. In this regard, it is proposed that the cloud canopy can be modeled as a cloud whose droplets are held in place by vegetative matter.

Such model was developed assuming that the canopy "cloud" contains identical water droplets randomly [21]. The ration of vegetation method and water cloud model is then employed to remove the influences of vegetation on the imagery backscatter. In this regards the Leaf Area Index (LAI), the Volumetric Water Content (VWC), Normalized Difference Vegetation Index (NDVI), and Enhanced Vegetation Index (EVI) were selected to parameterize the vegetation.

By default, the WCM assumes that the observed canopy backscattering coefficient σ_{pp}^{o} can be represented as the sum of vegetation volume scattering σ_{PP}^{O}, Veg. and the bare soil scattering attenuated by vegetation σ_{pp}^{o}, soil [9].

Finally, in computing for the WCM, the vegetation calibration is incorporated into the soil moisture retrieval algorithm.

The WCM is setup as follows,

$$\sigma_{PP}^{O} = \sigma_{PP}^{O}, veg + \tau^2 \sigma_{PP}^{O}, soil \qquad (9)$$

$$\sigma_{PP}^{O}, veg = A_v \cos\theta(1-\tau^2) \qquad (10)$$

$$\tau^2 = \exp(-2B_v / \cos\theta) \qquad (11)$$

Where,

τ^2 is the Attenuation Factor. A & B are the Model coefficient dependent on vegetation type [22]. V is the vegetation water contents also known as the LAI (leaf area index).

However, in computing for the attenuation $\left(\tau^2\right)$, the vegetation contribution is split into two by vegetation layers.

In this respect the attenuation is computed as a being the two-way transmissivity of the vegetation and expanded using the Maclaurin series instituted by Kseneman and Gleich (2013) [15].

So, the attenuation (τ2) is then computed as,

$$\tau^2 = \exp(-2B_v / \cos\theta) = 1 - (\frac{2Bv}{\cos\theta}) + (\frac{2B^2v^2}{\cos^2\theta}) + ... (6)$$

And these combinations, brings the WCM equation to a point as it is expressed by Binbin He et al 2015 [17] as,

$$\sigma_{pp}^{0} = 2ABV^2 + (1 - \frac{2BV}{\cos\theta})\sigma_{pp}^{0}, soil \qquad (7)$$

A and B in this instance being the Parameters of the Model are computed using the Gauss-Newton Non-Linear Least Square regression method, by calibrating for each type of vegetation factors such as the vegetation type, remote sensing parameters and polarization types were used for the computations [22]. Since the project location is having only Alpine Meadows and grasslands, A and B parameters are obtained for the study area using,

$$v = -\frac{\cos\theta}{2B} Ln \frac{\sigma^{\circ} - A\cos\theta}{\sigma_{pp}^{0} - A\cos\theta} \qquad (8)$$

Nevertheless, A and B can be represented using Debye – Cole dual dispersion model for estimating dielectric of vegetation materials, Where the LAI (kg/m²) is the canopy descriptor. Since A directly represent the vegetation growth condition and B is dependent on the Radar Frequency and wavelength of the Radar sat – 2 satellites. The value of A is

Zero for bare land and could be any value between 0 and ∞, for thick forest land [21].

The values of A and B were deduced using Matlab and Python software's.

It is obvious that after the simulations, it was observed that the vegetation was more dominant in the VV Polarization Mode than the HH polarization mode. Therefore, the VV polarization is used to simulate the vegetation backscatter.

Subsequently the computation of Vegetation parameter A and B, τ^2 is computed for every GPS location using Equation (11) $\sigma^o_{pp,Veg}$, is then computed from Equation (10).

Consequently, the results above are used to compute total backscatter (σ^o_{pp}).

e) Soil moisture

The soil moisture at the various GPS locations at Qinghai Lake is then modelled as a subsidiary of the Dielectric Constant (Ɛ), since the Dielectric Constant (Ɛ) of soil is directly proportional to the amount of moisture in the soil at every point in time.

The dielectric constant of soil is modelled using the Dubois model as a basis [17].

$$\varepsilon = 11.00X\left(\frac{\sigma^o_{vv} - a_{vv}v^2}{b_{vv}v+1}\right) - 8.64X\left(\frac{\sigma^o_{hh} - a_{hh}v^2}{b_{hh}v+1}\right) + 64.54 \quad (12)$$

Where,

Ɛ is the dielectric constant of soil,

σ^o_{vv} is the Total Backscatter in VV polarization (a_{vv} = 2AB in VV polarization mode)

b_{vv} is the total Backscatter in HH polarization (b_{vv} = - 2B/cos θ in VV polarization mode)

σ^o_{hh} is the Total Backscatter in HH polarization

a_{hh} = 2AB in HH polarization mode.

b_{hh} = - 2B/ cosθ in HH polarization mode

V is the Leaf Area Index,

The soil moisture is then subsequently computed for using the Dielectric Constant (Ɛ), for the various GPS locations, and the Topp's Models as follows,

$$\varepsilon = 3.03 + 9.3M_v + 146M_{v^2} - 76.7M_{v^3} \quad (13)$$

Where M_v is the soil moisture and Ɛ is the dielectric constant

In relative terms, Equation 13is used to determine the dielectric constant (Ɛ) when the volumetric soil moisture is known. Likewise, the volumetric soil moisture (Mv) could be deduced from the dielectric constant as was used by the top, as

$$M_v = \left(\left(-5.3 \times 10^{-2}\right) + \left(2.92 \times 10^{-2}\varepsilon\right) - \left(5.5 \times 10^{-4}\varepsilon^2\right) + \left(4.3\times 10^{-6}\varepsilon^3\right)\right) (14)$$

2. Results and Discussions

The results obtained from the retrieval of the soil moisture is all detailed and discussed as such without any manipulation.

Accuracy and Model Validation: There is always the prudency of determining the accuracy of the Biomass parameter values A and B. These values must pass the accuracy test before their viability could be accepted.

In this regards, the measured and computed biomass Values are plotted against each other and a comparison is conducted using the correlation Coefficient of the determinant coefficients (R^2) and the root Means square error (RMSE).[19]

Where,

$$RMSE = \sqrt{\sum \frac{(B_m - B_{mo})^2}{N}} \quad (15)$$

B_m represent the Biomass value Measured from the remote sensing data. B_{mo} also represents the biomass value measured from the field. N also represents the number of valid points.

Two –thirds of the data points from the field survey (about 56 points) were used to set the vegetation parameters of the vegetation backscattering.

The remaining one third (approximately 26 points), was also used for the validation of the data points.

Figure 7 and 8, represent a scatter plot of the VV and HH predicted and observed backscatter of Qinghai Lake in decibel (db). In both HH and VV polarization models, the backscattering plot proved linear in both cases but had moderate correlations of about (R^2 = 0.56 in HH and R^2 = 0.618 in VV polarization). The sample size for both plots is 26 data points each.

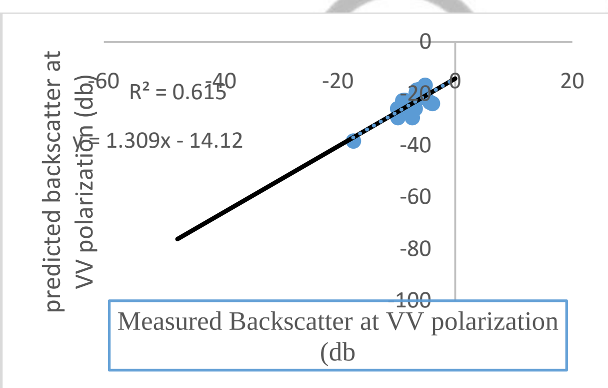

Figure.7. VV Backscatter Verification Plot

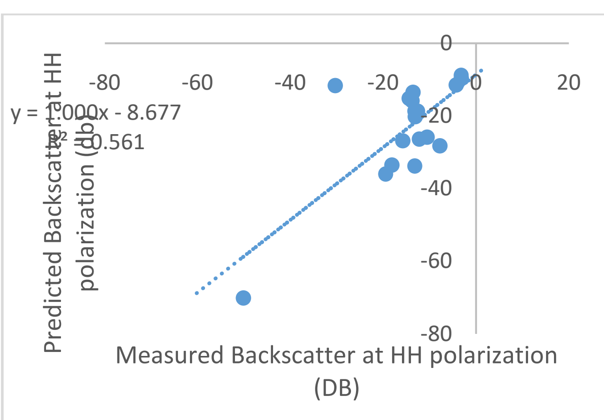

Figure.8. HH Backscatter Verification Plot

Vegetation Backscattering Model Validation: The totality of all 86 data points was used to compute for the relationship between the vegetation biomass and the vegetation moisture content. The results proved straight with a correlation coefficient of R^2 = 0.713.

It is concluded that, the vegetation Biomas is relatively proportional to the equivalence of the water content. Proving the accuracy of the vegetation parameter models. The sample size for this graph is 86 data points.

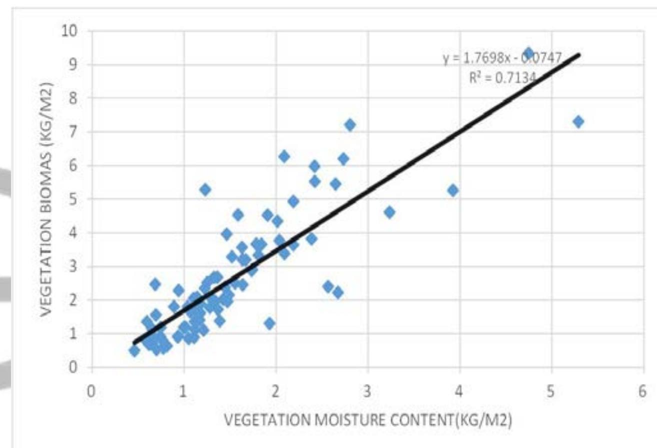

Figure. 9. Vegetation Verification plot

This confirms that the higher the backscattering zone, the larger the deviation from 1:1 lives than the lower backscattering zones and justify Svoray and Shoshang.

Soil Moisture (Sm) Accuracy: From the soil moisture backscatter, the analysis of the Dubois Model is assessed that the dielectric constant is relatively proportional to the soil moisture.

This means the higher the dielectric constant, the higher the volumetric moisture content of the soil.

A strict analysis has also been ascertained in this research, using the Topps's model where the Dielectric Constant (ε) of the soil could be deduced from the volumetric soil moisture (M_v) using equation 14. Then the same way could the volumetric Soil Moisture (M_v) also be derived from the Dielectric Constant (ε).

The same procedure was used to derive the volumetric moisture content of Qinghai Lake using the Topps's Model in the shadows of the Dubois approach.

The optimal coefficient (s), of the Dielectric constant is 130 and was obtained from the observed dielectric constant of the TDR moisture Content and the estimated Moisture Content.

$$S_{\min} = \sqrt{\frac{1}{n}\sum_{i=0}^{n} | \varepsilon_{obs} - \varepsilon_{est} |^2} \qquad (16)$$

Although it has been known from previous analysis that the dielectric Constant (ε) of dry soil is three (3). Therefore, with this logic, any figure of dielectric constant above three depicts the presence of moisture in the soil. From the analysis with both the estimated and observed dielectric constant on the Qinghai Lake

The dielectric constant ranged from min 3.37 to max 97.54, which is greater than 3 hence indicating that there was moisture at all GPS location of the research area (Qinghai Lake)

Fig.10. shows the correlation between the simulated (Measured) and Predicted (Observed) soil moisture of Qinghai Lake. The observed moisture was by TDR soil moisture retrieval method whiles the measured soil moisture was done with simulated algorithm of the Dubois Model (Dubois et al) and the Topps's Model.

After Calibration of the algorithm, the Correlation Coefficient R^2 obtained from the algorithm is 0.79.

Since the RMSE and the Pearson Correlation Coefficient are used to ensure evaluation of the soil moisture retrieval accuracy and based on the result of the Correlation Coefficient R^2 and RMSE, depicting an almost 80% accuracy of the soil moisture method used.

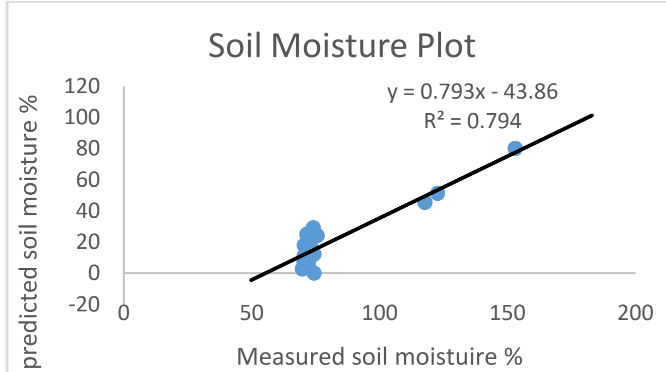

Figure .10. Soil Moisture Accuracy Plot

3. CONCLUDING REMARKS

The main objective of this study was to Retrieve the soil moisture under vegetation at Qinghai Lake using the Dubois Approach and the Water Cloud model.

The semi- Empirical approach was used to model the Dielectric Constant of soil at specific GPS Locations (86 Point Locations) on the Qinghai Lake catchment area of the lakes basin.

The co-polarized backscattering (HH and VV), the Vegetation Parameter, the water cloud model (WCM) and subsequently the soil moisture model were all developed and modeled. The results showed that,

- The lowest retrieval error is 3.0% with the Pearson Correlation Coefficients $R^2 = 0.79$.
- The Dubois model was very effective and efficient because it factored and charge of the effect of multiple polarizations, effects from the RADARSAT-2 data and in the case eliminated the effect of the RSM heights that was justified through the methodology and soil moisture values of the area.
- The average delineated coefficient of proportionality between the Dielectric constant and the soil moisture at Qinghai Lake is 0.0108

REFERENCES

[1]. *F. Mattie et al. Soil Moisture Retrieval through a Merging of Multi – Temporal L- Band SAR Data and Hydrologic*

International Journal of Scientific & Engineering Research -IJSER (ISSN 2229-5518)

Modeling. Hydrol. Earth Syst. Sci. Discuss. Vol.13 no.3.pp381 – 385. Feb, 2009

[2]. *S. Srinivasan et al. Modified Dubois Model For Estimating Soil Moisture With Dual Polarized SAR Data. Journal Of Indian Society Of Remote Sensing. 41(4): pp 865–872 May, 2013.*

[3]. *H. Mcnairn, A. Merzouki, and A. Pacheco. Estimating Surface Soil Moisture Using RadarSat.. Remote Sensing and Spatial Information Science. J. Volume*

XXXVIII, Part 8, pp 576 – 579.2010

[4]. *K. D. Zielinska et al. Assessment of Carbon Flux and Soil Moisture in Wetlands Applying Sentinel-1 Data.Remote Sensing. J.. Vol 8, Iss 9.pp 756.Sept, 2016.*

[5]. *Md. Rezwan Molla et al. Studying The Extent of Genetic Diversity among Goosy piumarboreum L. Genotypes/Cultivars Using DNA finger printing. Science PG. J. Vol 4, Iss 6. Pp 153 – 164. Dec 2016.*

[6]. *G. S. Robinson. "Edge Detection By Compass Gradient Masks", Computer Graphics And Image Processing. IEEE Xplore. vol. 6, pp. 492-502, 1977.*

[7]. *M. Trudel, F. Charbonneau and R. Laconte. Using Radarsat-2 Polarimetric and Envisat-Asar Dual-Polarization Data for Estimating Soil Moisture over Agricultural Fields. Canadian Journal of Remote Sensing. 2012: vol 38, Iss 4. Jun 2014.*

[8]. *W. Wagner, and C. Pathe. Has Sar Failed In Soil Moisture Retrieval. Envisat & Ers Symposium, Salzburg, Austria 6-10 (Esa Sp-572, 2005. Sept 2004*

[9]. *R. Bindlish and A. P. Barros. Parameterization of Vegetation Backscatter In Radar-Based Soil Moisture Estimation. Remote sensing for environment J: 76:pp: 130 -137 .2001*

[10]. *Camillo.P. and Schmugge .T. Soil Moisture Storage in the Root Zone from Surface Measurement. Soil Science.J. pp135, 245-264. (1983)*

[11]. *J. Zeng, et al. Evaluation Of Remotely Sensed And Re – Analysis Soil Moisture Products Over The Tibetan Plateau Using In-Situ Observations. Remote Sensing of Environment .J. Vol 163 no.1:pp. 91-110. 2015*

[12]. *M.A. Karam et al.Microwave Scattering Model for Layered Vegetation. IEEE. J. Vol 53. Issue .1.pp. 16 -30. 1992.*

[13]. *R. Lecanto and F. Brissette. Mapping Near-Surface Soil Moisture with Radarsat-1 Synthetic Aperture Radar Data.Water Resources Research. J. Vol 40. No 1. Pp 10. 2004.*

[14]. *M. Kseneman, and D. Gleich. Soil-Moisture Estimation from X-Band Data Using Tikhonov Regularization and Neural. IEEE. J. Vol.51. Issue 7. part 1. pp 3885 – 3898. 2013 .*

[15]. *S. Paloscia. , et al. Soil Moisture Mapping Using Sentinel – 1 Image:Algorithm and Preliminary Validation. Remote Sensing of Environment.* ***J.*** *DOI: 10.1016/j.rse.2013.02.027*

[16]. *Xiaojing Bai & Binbin He. Potential of Dubois Model for Soil Moisture Retrieval in Prairie Areas Using SAR and Optical Data.Internal Journal of Remote Sensing. Vol.36.Issue 22.pp.5737-5753.2015.*

[17]. *A. Scott et al. Mapping Root Zone Soil Moisture Using Remotely Sensed Optical Imagery. Research Gate.J. Vol.125.Issue 5. DOI: 10.1061/(ASCE)0733-9437(2003*

[18]. *Alexakis .DD. et al. Soil Moisture Content Estimation Based on Sentinel-1 and Auxiliary Earth Observation Products. US National Library of Health . Vol.17.Issue 5 .pp. 1455. Doi: 10.3390/S17061455. 2017.*

[19]. *Minfeng Xing et al. Integration Method to Estimate Aboveground Biomass in Arid Prairie Regions Using Active and Passive Remote Sensing Data.Journal Of Applied Remote Sensing. Vol 8.Issue 1. 2014.*

International Journal of Scientific & Engineering Research -IJSER (ISSN 2229-5518)

[20]. *M. R. Saradjian and M. Hosseini. Soil Moisture Estimation by Using Multi-Polarization SAR Image. Advance in Space Research.J. Vol 48. pp 278 – 286. 2011.*

[21] *E. P. W & Attema, F. T. Ulaby. Vegetation Modeled As A Water Cloud.Radio .* IEEE Journal *of Selected Topics in Applied Earth Observations and Remote Sensing. Vol 13 Issue 2. pp 357 – 364. 1978*

[22]. *F. Kirimi et al. Influence of Vegetation Cover on the Oh Soil Moisture Retrieval Mode. A Case Study of the Malinda Wetland, Tanzania. Scientific research journal. Vol 5. Pp 28 – 42. 2016.*

[23] *Irene, E.Teubner, et al. Assessing the Relationship between Microwave Vegetation Optical Depth and Gross Primary Production. SCI.J. Vol 65. Issue 1. pp 79 -91. 2018.*

[24] *S. S. Saatchi and M. Moghaddam. Estimation of Crown and Stem Water Content and Biomass of Boreal Forest Using Polarimetric SAR Imagery. Transactions On Geoscience And Remote Sensing.J. Vol 38. No. 2. 2000.*

[25] *Ulaby F. T et al.. Microwave Remote Sensing. IEEE Trans [J], Artech House,1982, 2, 1982.*

[26]] *Shi He et al. Evaluation Of Radar Backscattering Models Using L- And C-Band Synthetic Aperture Radar Data . IEEE Xplore., Vol. 9 No.1.pp 2- 44. 2015*

[27] *I . Hosni, et al. Estimation of Physical Parameters of a Multilayered Multi-Scale Vegetated Surface . XXIII ISPRS Congress. Vol. XLI-B1. 2016,*

[28] *T. J. Jackson, and T. J. Schmugge. Vegetation Effects on the Microwave Emission of Soils. IEEE Trans J. Vol 36. Issue 3. Pp 203 – 212. 1991.*

[29] *P. Marzahn and R. Ludwig. On the derivation of soil surface roughness from multi parametric PolSAR data and its potential for hydrological modeling. Hydro. Earth Syst. Sci.J. Vol 13. Issue 3. Pp 381 -394. 2009.*

[30] *L.Brocca et al. Improving the Representation of Soil Moisture by Using a Semi- Analytical Infiltration Model.Wiley Online Libray. J. https://doi.org/10.1002/hyp.9766.2012*

[31] *Didier Dubois et al. A Logical Approach to Interpolation Based On Similarity Approach. STIC. J. Vol . 19 No. 1. Pp 1 – 36. 1997.*

[32] *Tegen and Fung 1994. Modelling Of Mineral Dust Transport in the Atmosphere. Journal of Geophysical research. Vol 99. Issue D11. Pp 22897 – 22914.1994.*

[33] *Z. Bartalis et al. Initial Soil Moisture Retrievals from the METOP-An Advanced Scatterometer. Geophysical Research letters. J. Vol 34 ,issue 20. 2007.,*

[34] **N.** *Baghdadi et al. Analysis of Terrasar-X Data and Their Sensitivity to Soil Surface Parameters over Bare Agricultural Fields. ELSEVIER. J. Vol 112. Pp 4370 – 4379. 2008.*

[35] *Zribi M.et al. Surface Soil Moisture Estimation from the Synergetic Use of the (Multi-Incidence and Multi-Resolution) Active Microwave ERS Wind Scatterometer and SAR Data. Remote sensing Env.J. Vol 86. No 1. Pp 30 – 41. doi: 10.1016/S0034-4257 (03)00065-8.*

[36] *E.T. Engman and R.J Gurney. Remote Sensing In Hydrolog. EARTH SURFACE AND LANDFORM BOOK.. Vol 17. Issue 6. https://doi.org/10.1002/esp.3290170615. ISBN 0-412-24450-0. 1992.*

[37] *A. Oldak et al. . Mapping near – Surface Soil Moisture on Regional Scale Using ERS-2 SAR Data. International Journal Of Remote Sensing Vol24. Issue 18. Pp4579 – 4598. 2003.*

[38] *Idso S.B et al. The Utility of Surface Temperature Measurements for The Remote Sensing of Surface Soil Water Status.Geophysical research .J. 80: doi: 10.1029/JC080i021p03044. ISSN: 0148-0227. 1975.*

[39] *N. Baghdadi et al. Semi-Empirical Calibration Of IEM Backscattering Model Using Radar Images And Moisture And Roughness Field Measuremen. Taylor and francis Online . J. Vol 25. Issue 18. Pp 3593 – 3623. 2003.*