NEAR-SURFACE SOIL MOISTURE CONTENT MEASUREMENT BY GNSS REFLECTOMETRY: AN ESTIMATION MODEL USING CALIBRATED GNSS SIGNALS

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ABSTRACT

The microwave signal of GNSS L band is very sensitive to the electromagnetic property of soil surface, through measuring the reflected electromagnetic energy from soil, the relationship between power of GNSS reflected signals and soil dielectric constant can be built, and then soil moisture can be estimated. In order to improve estimation accuracy, both the direct and reflected GNSS signals need to be calibrated to eliminate the signal error. A soil moisture estimation model utilizing calibrated GNSS L band reflected signals is proposed in this paper, and the estimation accuracy is validated using SMEX02 data. The error of areas with different NDVI is calculated. The error of soil moisture estimation is 7.04% for bare soil condition of the verify areas. It is shown that this model is suitable for bare soil condition or areas with low vegetation coverage. For further research, in the case of soil with high vegetation coverage, the model should be modified through adding the vegetation effect into it.

Index Terms— soil moisture, bistatic radar, calibration, Global Positioning System, microwave remote sensing

1. INTRODUCTION

The versatile refracted, reflected and scattered signals of Global Navigation Satellite Systems(GNSS) have been successfully demonstrated to sound the atmosphere and ionosphere, ocean, land surfaces and the cryosphere as a new remote sensing tool. GNSS Reflectometry(GNSS-R) involves making measurements of the reflections from the earth of navigation signals. Techniques of utilizing GNSS-R to retrieve geophysical parameters(e.g. soil moisture[1], snow depth[2, 3], biomass[4]) from land surfaces have been developing in recent years. However, because of limitations in instruments, experiments and models, GNSS-R technique for land surface observing is still in its initial stage.

Soil moisture is a key component of the water cycle budget, and it influences the sensible and latent heat flux from the land surface to the atmosphere. The GNSS-derived signal is influenced most strongly by near-surface (0-5 cm) soil moisture, similar to ESA's Soil Moisture and Ocean Salinity mission (SMOS) and NASA's Soil Moisture Active Passive mission (SMAP). Existing ways for estimation of soil moisture content(SMC) by GNSS-R are mainly in three aspects: (a) Interference Pattern Technique(IPT)[5, 6], (b) Multipass effect and its relation to SMC[7, 8], and (c) Bistatic radar (bi-radar) equation method[9]. As for the bi-radar equation method, SMC can be estimated through building up relationship between power of GNSS reflected signals and soil dielectric constant. In order to improve estimation accuracy, both the direct and reflected GNSS signals need to be calibrated to eliminate the signal error[10]. So far, however, few existing models have taken the effect of calibration into account.

This paper presents an estimation model using calibrated GNSS signals, and the estimation accuracy is validated using GPS data of SMEX02(Soil Moisture experiment, 2002). The error of fields with different NDVI is calculated, and the effect of vegetation cover is also analyzed. The error of SMC estimation is 7.04% for bare soil condition of the verify areas. It is shown that this model is suitable for bare soil condition or areas with low vegetation coverage.

2. SMC ESTIMATION MODEL USING CALIBRATED GNSS SIGNALS

2.1 Traditional SMC model

Surface reflectivity of GNSS signals Γ_{GNSS} is expressed as:

$$\Gamma_{GNSS} = P_r / P_d \tag{1}$$

Where P_r represents power of reflected signal and P_d indicates the direct signal. As for specular points, the surface is perfectly smooth, so the Kirchoff Approximation

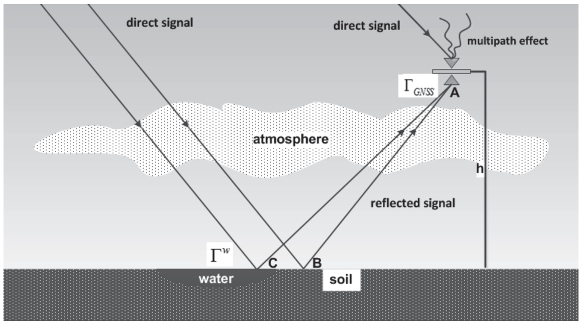

Fig .1 Theory of GNSS signal calibration

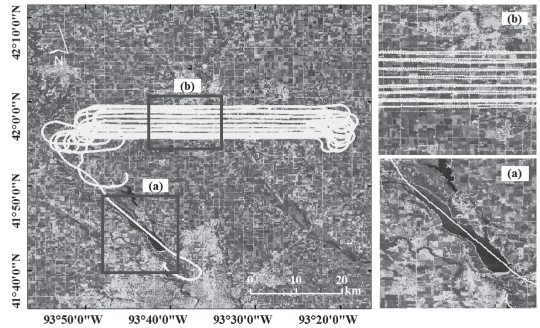

Fig .2 The flight route of June 25

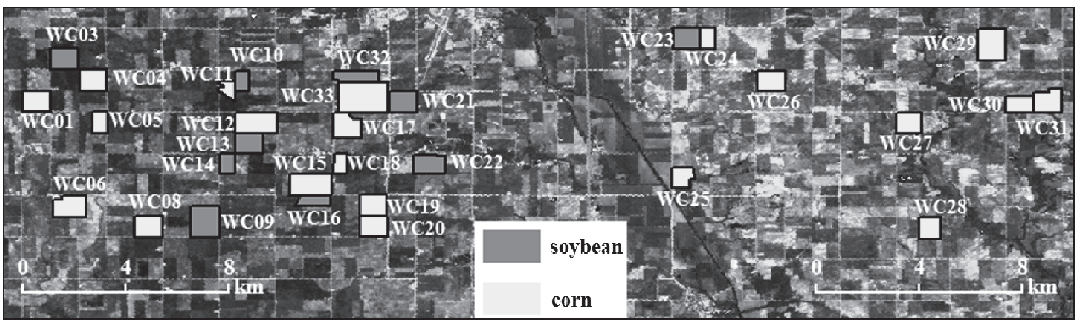

Fig .3 Distributions of corn and soybean fields in Walnut Creek

of reflectivity $\Gamma = |R(\gamma)|^2 \exp(-h\cos^2\gamma)$ [11] is simplified to:

$$\Gamma_{GNSS} = |R(\gamma)|^2 \quad (2)$$

Here, h is commonly called the roughness number [12] and h = 0 for specular points. γ represents the glancing angle. Through the expression of Fresnel reflection coefficient $R(\gamma)$ given by Ulaby et al [13], soil dielectric constant can be obtained, and then SMC can be estimated using the empirical model proposed by Hallikainen et al [14].

2.2 Improved model when signals are calibrated

Fig .2 shows the theory of GNSS signal calibration. The errors of signals received by antennas mainly include: (1) different multipath effects occurs when GNSS signal reach to RHCP antenna and when it reach to surface of soil; (2) Atmospheric attenuation occurs when the reflected signal travels from soil to LHCP antennas; (3) LHCP and RHCP antennas have different properties, which leads to differences in measurement of direct and reflected power. Therefore, both the direct and reflected GNSS signals need to be calibrated to eliminate the signal error.

Before modeling of SMC estimation, reflected signal of GNSS is calibrated using over-water method [10], and the calibration coefficient f_c is obtained using:

$$f_c = \Gamma^w_{GNSS} / \Gamma^w \quad (3)$$

Where Γ^w is the theoretical value of water reflectivity and Γ^w_{GNSS} is the water reflectivity obtained by GNSS.

Meanwhile, the directed signal is corrected through an n-order polynomial in order to reduce multipath effects. That is to say, P'_d is applied instead of the traditional P_d. The calibrated surface reflectivity Γ'_{GNSS} can be expressed as:

$$\Gamma'_{GNSS} = f_c \frac{P_r}{P'_d} \quad (4)$$

Finally, SMC model can be improved when using Γ'_{GNSS} instead of the traditional Γ_{GNSS}.

3. RESULTS

Data used for model validation is the airborne GPS data of SMEX02 on June 25th, downloading from the National Snow and Ice Data Center(NSIDC, http://nsidc.org/daac/). Fig .2 shows the flight route. In this figure, square (a) shows the track over a lake, and the data obtained is used to calibrate the reflected signals. Square (b) displays a sample region of the flight route over fields. The verify area locates in Walnut Creek, Iowa State of USA. There are 10 fields of soybean and 21 fields of corn(Fig .3), and all the fields are with different vegetation cover(Fig .4). Therefore, Vegetation Index(NDVI) is calculated to show the differences. Both traditional model(pre-calibration)

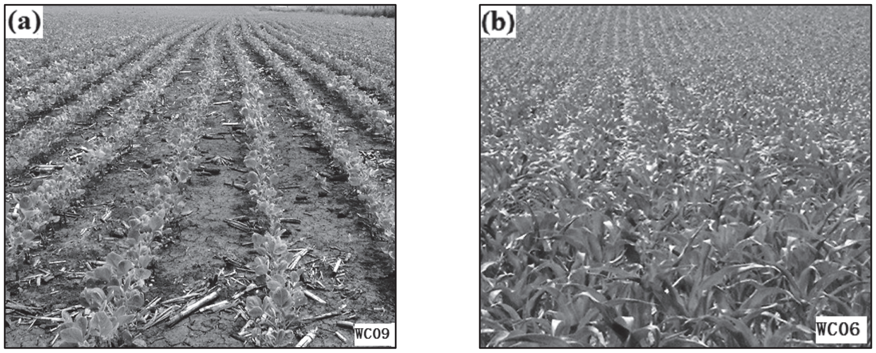

Fig .4 differences of vegetation cover between (a)soybean and (b)corn

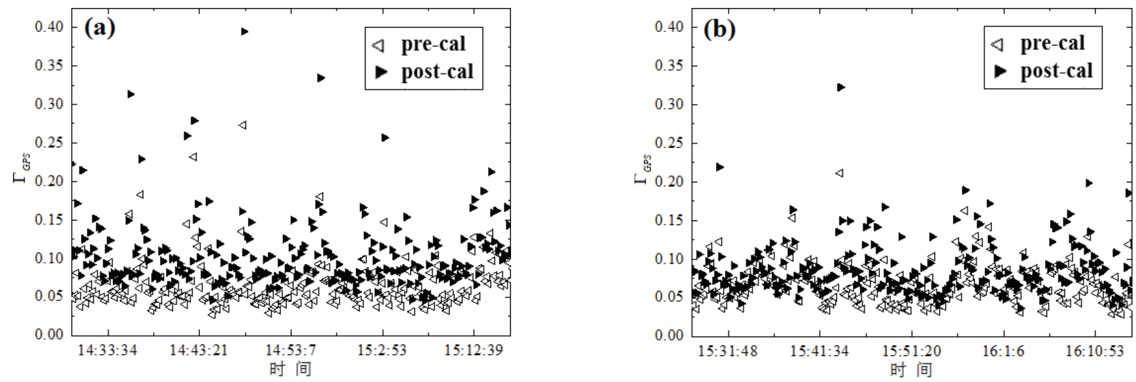

Fig .5 Comparison of reflectivity between pre-calibration and post-calibration (a) PRN24, (b) PRN10

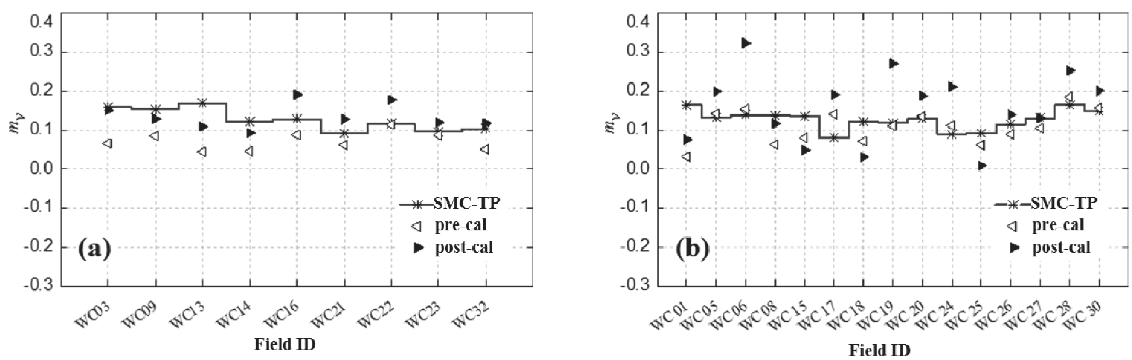

Fig .6 Comparison of soil moisture estimation (including pre-calibration and post-calibration) and the results from TP (a) soybean, (b) corn

and our model(post-calibration) are executed respectively. Surface volumetric soil moisture measured by Theta Probes(TP) is used as in situ data.

Fig .5 shows a comparison of soil reflectivity between pre-calibration and post-calibration. Here, we take PRN24 and PRN10 as examples and choose two periods of time(UTC 14:24:00~15:22:02, UTC 15:22:14~16:48:00). The results show that the soil reflectivity gets higher after calibration. The estimation error of SMC in different fields is calculated and then be classified into four groups according to NDVI levels(Table 1). It is shown in table 1 that for bare soil and low-vegetation area, a better result is achieved for our post-calibration model than that of pre-calibration. For high-vegetation area, however, our model gets an unsatisfactory result with error of 32.77%. This is highly related to the effect of vegetation cover. Fig .6 shows the comparison of SMC among pre-calibration estimation, post-calibration estimation and TP measurements. It can be recognized that corn fields get a nosier results than soybean because of the thick vegetation cover.

Table1 Estimation error of fields with different NDVI

NDVI	Vegetation cover	error of pre-calibration(%)	error of post-calibration(%)
0.0	none	47.81	7.04
0.0~0.3	low	--	--
0.3~0.6	mid	34.99	12.01
0.6~0.8	high	11.28	32.77

3. CONCLUSION

This paper presents a model for SMC estimation using calibrated GNSS signals. SMEX02 data is applied to validate the accuracy of SMC estimation. According to our research, the model is suitable for bare soil and low vegetation areas. As for high vegetation areas, the model should be modified while concerning the effect of vegetation cover. In general, the calculated reflectivity of soil becomes higher when signals are calibrated, and the estimated SMC becomes higher correspondingly. The post-calibration SMC is closer to that of TP measurement.

For further research, we will consider the effects of vegetation and try to build a modified model for SMC estimation under vegetation-covered conditions.

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