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Two new soil moisture indices based on the NIR-red triangle space of Landsat-8 data

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ABSTRACT

In this study, the NIR-red spectral space of Landsat-8 images, which is manifested by a triangle shape, is deployed for developing two new Soil Moisture (SM) indices. First, ten parameters consisting of six distances and four angles were extracted using the position of a random pixel in this triangle. Then, some correlation assessments were made to derive those parameters that were useful for SM estimation, which were five parameters. To build a soil moisture index, all combinations of these five parameters, which were in total 31 different regression equations, were considered, and the best model was named the Triangle Soil Moisture Index (TSMI). The TSMI consists of three parameters. It showed a RMSE of 0.08 and correlation coefficient (R) of 0.67. Since the TSMI does not consider vegetation interface in SM estimation, the Modified TSMI (MTSMI), which takes into account the fraction of soil cover in each pixel, beside those parameters which were used in the TSMI, was developed (MTSMI: RMSE = 0.07, R = 0.74). The results of the TSMI and MTSMI were compared with each other, and with another soil moisture index (SMMRS introduced by Zhan et al. (2007)). It was concluded that the TSMI and MTSMI provide similar results for bare soil or sparsely vegetated surfaces. However, the MTSMI demonstrated a much better performance in densely vegetated surfaces. The accuracy of both the TSMI and MTSMI were significantly higher than the SMMRS. Moreover, the TSMI and MTSMI were validated by comparison with field measured SM data at five different depths. The results showed that satellite estimated SM by these two indices was more correlated with in situ data at 5 cm soil depth compared to other depths. Also, to show the high applicability of the proposed approach for SM estimation, we selected another set of field SM data collected in Australia. The results proved the effectiveness of the method in different study areas.

1. Introduction

Spatio-temporal distribution and variation of Soil Moisture (SM) is important in many studies, such as drought monitoring (Ghulam et al., 2007a,b; Raja Shekhar et al., 2014; Zhang et al., 2015), rainfall assessment (Van Rooy, 1965), water-budgeting processes (Jackson et al., 1981), evapotranspiration (Pengxin et al., 2003), forest management (Bowyer and Danson, 2004). Since soil has various spectral patterns in different wavelengths, Remote Sensing (RS) data ranging from visible to microwave has been widely used in SM assessment. Generally, all RS methods for SM monitoring can be classified into four categories: optical RS, thermal RS, microwave RS, and hybrid methods. In Section 1.1, different RS methods for SM monitoring are discussed and in Section 1.2, a brief description of NIR-red spectral space and its application in SM estimation, which is closely related to this study, is discussed.

1.1. Remote sensing approaches for soil moisture estimation

Optical RS methods usually apply the visible, Near Infrared (NIR) and Shortwave Infrared (SWIR) data for SM modeling. Many researches have used different vegetation indices to assess dryness and SM (Jackson et al., 1981; Ghulam et al., 2007b; Zhang et al., 2015). In this regard, several studies have reported that the Normalized Difference Vegetation Index (NDVI) has a noticeable utility for observing drought and SM (Kogan, 1990; Liu and Ferreira, 1991; Di et al., 1994). High correlation has been identified between the annual or monthly time integrated NDVI and drought related climate factors such as precipitation (Yang et al., 1998; Peters et al., 2002). The SWIR reflectance is sensitive to leaf liquid water content

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and has been shown to be more effective than the visible and NIR at monitoring SM changes, as long as the SM content remains at less than or equal to 50% of the volumetric water content (Lobell and Asner, 2002). In this group, it should be considered that the effects of surface roughness, soil structure and organic matters on the reflectance of visible and NIR bands is a main limitation for SM estimation (Zhan et al., 2007).

The history of thermal RS for SM monitoring can be traced back to the beginning of the 1970s. Thermal RS approaches which have been used for vegetation studies and SM estimation are classified into three groups: the thermal inertia method, the vegetation evapotranspiration method, and the Crop Water Stress Index (CWSI). These methods are established using the relationship between surface emissivity, temperature and SM, by mainly taking advantage of the water circulation and energy balance principle (Sohrabinia et al., 2012). The thermal inertia method is quite effective in bare SM estimation. However, it demonstrates poor correlation for highly vegetated surfaces. Furthermore, the retrieval of soil surface temperature contains some uncertainties, and therefore, the final error on SM extraction would be magnified (Zhan et al., 2007).

Microwave RS methods for SM estimation are mainly dependent on the relationship between SM, dielectric characteristics of a specific target, and radar backscatters. Microwave RS has the capability of acquiring data under almost any meteorological conditions and without an external source of illumination. There are mainly three groups of models that apply active RS data for SM estimation: backscattering models, statistical analysis techniques and neural network application. Like thermal RS, active microwave methods have some limitations in SM estimation over vegetated surfaces, because active microwaves are strongly affected by surface roughness and vegetation (Zhan et al., 2007). Also, passive microwave RS methods are promising approaches for SM estimation. In this regard, L-band passive microwave is the most applied channel to monitor SM (Jackson et al., 1995; De Lannoy et al., 2013). Two space missions use this technology at the global scale with frequent revisiting times: Soil Moisture and Ocean Salinity (SMOS, launched end of 2009), and Soil Moisture Active Passive (SMAP, launch scheduled in November 2014). The SMOS mission is the first space-borne mission dedicated to SM monitoring. SMOS has multi-angular capabilities, which are exploited by the SM retrieval approach: SM and vegetation optical depth are retrieved simultaneously based on SMOS multi-configuration observations, in terms of polarizations and incidence angles (Fascetti et al., 2016; Champagne et al., 2016). SMAP incorporates a radar and a radiometer, both operating at L-band and at the incidence (observation) angle = 40°. The spatial resolutions of the corresponding active and passive microwave signatures are ~39 km × 47 km and ~1 km × 1 km, respectively. The mission concept is to combine the complementary attributes of the radar observations (high spatial resolution but lower SM accuracy) and radiometer observations (higher SM accuracy, but coarse spatial resolution) to retrieve SM at a spatial resolution of 9 km (Entekhabi et al., 2010).

The combination of visible, NIR, thermal and microwave wavelengths mostly results in better accuracy for SM estimation (Yu et al., 2013). Wang et al. (2004) extracted SM information in sparsely vegetated rangeland surfaces with ERS-2/TM I data by correlating radar backscatters with NDVI and SM. Both Goward and Hope (1989) and Price (1990) found that the data in the LST versus the NDVI scatter-plot falls into a triangular shape. Moran et al. (1994) reported that the LST-NDVI space supported the "trapezoid" shape, namely the Vegetation Index/Temperature Trapezoid (VITT). Regarding this method it should be noted that the spatial resolution of visible, infrared and thermal bands of most satellites is not the same, and some useful information is lost as a result of spectral sampling, which should be carried out to construct the spectral space of the NDVI and LST.

Effective soil depth for the remote measurement of SM has been a controversial issue. Li and Dong (1996) examined the relationship between satellite-derived NDVI, brightness temperature and SM, and reported that the satellite data has a higher correlation with SM at a 20 cm soil depth compared to the other soil depths. Liu et al. (1997), and Zhang et al. (2015) reported that the effective soil depth for SM assessment of visible and NIR remote sensing data is 10 cm. Chauhan et al. (2003), Dunne et al. (2007) and Finn et al. (2011) found that RS methods have been relatively successful in measuring SM at a depth of 5 cm from the top soil surface in bare soil or soil with less vegetation cover. However, Ghulam et al. (2007b) reported that at 0–5 cm soil depth, soil surface is affected by wind speed and other external conditions, which could pose some uncertainties in SM modeling.

1.2. NIR-red triangle space

Generally, from the red to SWIR spectral region, the reflectance of bare soil increases slowly with two water absorption bands around 1.4 μm and 1.9 μm. As the amount of SM content increases, soil reflectance value decreases. When the NIR values are plotted against the red reflectance values for pixels fully covered by bare soil with different amounts of moisture, it is seen that the points are scattered around a certain line, called the soil line (Fig. 1). This line can be characterized by the following equation:

$$\rho_{NIR} = \gamma \rho_{red} + b \quad (1)$$

where, b, γ, ρ_{NIR} and ρ_{red} are the intercept, slope, NIR and red reflectance values, respectively. It should be noted that soil variability associated with reflectance values is important. Therefore, the distribution of the soil line is highly dependent on some parameters such as organic matter, particle size distribution, iron oxide content, soil mineralogy (Ångström, 1925). In most studies, researchers have used a soil line equation extracted from satellite images to develop their own models. However, it should be considered that these soil line equations are not globally valid, and consequently cannot be applied in other studies. Amani and Mobasheri (2015) tried to reduce the uncertainty involved with the position of the soil line by using the average of five different soil lines, introduced by different researchers for different soil types.

If one plots the NIR reflectance against the red reflectance for a part of an image containing both soil and vegetation, we generally see a triangle-shaped distribution of pixels, as shown in Fig. 1, which was discovered first by Richardson and Weigand (1977). Depending on the amount of vegetation cover, soil cover, SM content, vegetation species, and even plant growth stage in each pixel, its corresponding position in this scatter-plot is different. Pixels with high NIR and low red reflectance values are populated around the upper vertex of the triangle and indicate the densest canopy, while pixels near the soil line indicate little or no vegetation cover. The base of this triangle represents the soil line connecting water saturated soil (the lower left vertex) to the dry soil (the upper right vertex) (Jensen, 2009).

This scatter-plot has been widely used for monitoring of drought and SM, classifying satellite images, and developing several vegetation indices, such as Perpendicular Vegetation Index (PVI), Simple Ratio (SR), Soil-Adjusted Vegetation Index (SAVI), Leaf Area Index (LAI). Some of the studies, which deployed this scatter-plot for SM and drought assessment, are discussed in the following.

Zhan et al. (2007) introduced a new model called the Soil Moisture Monitoring by Remote Sensing (SMMRS) based on the distribution characteristics of SM data in the NIR-red spectral domain. Although their method was simple, the vegetation interference on SM assessment has not been taken into account, in their work. Therefore, the model suffers from mixed information about soil and vegetation. Taking advantage of the reflective and absorptive fea-