An integrated methodology for soil moisture analysis using multispectral data in Mongolia

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ABSTRACT
Soil moisture (SM) content is one of the most important environmental variables in relation to land surface climatology, hydrology, and ecology. Long-term SM data-sets on a regional scale provide reasonable information about climate change and global warming specific regions. The aim of this research work is to develop an integrated methodology for SM of kastanozems soils using multispectral satellite data. The study area is Tuv (48°40′30″N and 106°15′55″E) province in the forest steppe zones in Mongolia. In addition to this, land surface temperature (LST) and normalized difference vegetation index (NDVI) from Landsat satellite images were integrated for the assessment. Furthermore, we used a digital elevation model (DEM) from ASTER satellite image with 30-m resolution. Aspect and slope maps were derived from this DEM. The soil moisture index (SMI) was obtained using spectral information from Landsat satellite data. We used regression analysis to develop the model. The model shows how SMI from satellite depends on LST, NDVI, DEM, Slope, and Aspect in the agricultural area. The results of the model were correlated with the ground SM data in Tuv province. The results indicate that there is a good agreement between output SM and SM of ground truth for agricultural area. Further research is focused on moisture mapping for different natural zones in Mongolia. The innovative part of this research is to estimate SM using drivers which are vegetation, land surface temperature, elevation, aspect, and slope in the forested steppe area. This integrative methodology can be applied for different regions with forest and desert steppe zones.

1. Introduction
Soil moisture (SM) presents an important environmental indicator controlling and regulating the interaction between the atmosphere and the land surface. Furthermore, SM regulates the ratio of runoff and infiltration and controls major energy fluxes. Moreover, SM is also an important factor in plant productivity and it has direct influence on crop productivity. Therefore, the distribution of SM in the landscape, both spatial and temporal, is a key variable of climate system modeling. SM is one of the most important environmental variables in the relation to land surface climatology, hydrology and ecology. In face of the importance of SM, its spatial and temporal assessment is difficult. The standard procedure for SM assessment against all other SM-methods are calibrated the gravimetric method from soil probes in the field. This standard procedure is typically a point measurement. Because of local scale variations in soil properties, terrain (slope, exposition), and vegetation cover the derivation of representative SM-distributions in the field sites is very difficult. Furthermore, field methods are labor intensive, expensive, and sometimes difficult to undertake in the Mongolian landscape. The most accurate method to estimate SM is gravimetric sampling as mentioned above. The soil sample from the field has to be immediately measured by putting the sample for 24–48 h in a drying oven at 105 °C, to measure the mass of the dry soil. Further soil bulk densities are required to convert gravimetric (water mass per soil mass) to volumetric values (water volume per soil volume). A comprehensive review about various SMC-methods is presented (Verstraeten, Veroustraete, and Feyen 2008). In contrast with the previous, remote sensing (RS) techniques which are combined with additional GIS-data are effective because of their spatially aggregated data assessment. By nature, SM is a very heterogeneous variable and varies on small scales with soil properties and drainage patterns. Therefore, information about soil
types, soil properties and terrain are important. Satellite measurements integrate over relative large-scale areas, with the presence of vegetation adding complexity to the interpretation.

The annual evaporation is 150–250 mm in the steppe zone and over 150 mm in desert steppe and deserted zones. There is SM decrease from north to south (Tsoozol et al. 2008).

The Mongolian horizontal zone is clearly represented in the central comparatively plain part of Mongolia, where the zone of kastanozems soils are divided into three subzones (dark kastanozem, kastanozem, light kastanozem) (Dorjgotov 2003). Remote sensing and GIS provide excellent tools for monitoring suitability for development of agriculture land in Mongolia (Ghar et al. 2005). Understanding the spatial and temporal variability of moisture patterns is critically important for food security in Mongolia, and other regions of central Asia. For this reason, it is essential to make research on SM and other suitable drivers for development of agricultural land in Mongolia. This research focused on developing a model for estimation of SM using satellite and ground truth for kastanozems soils. The kastanozems soil is the common type in Mongolia.

Many soil studies used only index, wetness index and point measurement from station. For example, Mohamed used the normalized day-night surface temperature difference index (NTDI) with moisture availability \(m_a\) over Mongolian Steppe during the growing season, and showed a significant inverse exponential correlation with \(m_a\). This result indicates that the NTDI is useful as a surrogate of moisture availability in the steppe terrain of central Asia (Mohamed and Kimura 2014). Cornicka et al. developed the approach and compared results with other methods of selecting moisture reference years for hydrothermal simulations. They used climate stations’ data for their model (Cornicka, Djebar, and Dalgliesh 2003; Attorre et al. 2007) determined the moisture index using precipitation and potential evapotranspiration. The moisture index, related to the potential amount of available precipitation, was the most important factor explaining the distribution of Dracaena Cinnabari. Information of climate change and SM from special sensor microwave/imager (SSM/I) was used for African continent (Lu et al. 2013). They concluded that such information is useful in climate change study, but it is only at point scale and is only available at limited locations.

The innovation part of our research is to consider elevation slope and aspects with other environmental drivers in forested mountain and agricultural areas for soil estimation. The elevation, slope and aspect were applied for this methodology which have not been considered in previous studies.

Mongolia also needs satellite image processing for the SM analysis. It will be useful for agriculture and pastureland. This paper proposes that it is important to consider elevation, slope, and aspect for SM in mountainous areas.

2. Study area

The study area is Bornuur soum from the central agricultural area in Tuv province (48°40′30″N, 106°15′55″E) and located in the forest steppe zone (Figure 1). Four different soil types: kastanozems, greysols, leptosols, cambisols dominate in Bornuur (Dorjgotov 2003). Precipitation is 200–300 mm/year and elevation of

![Figure 1. Study area (Bornuur soum in Tuv province in Mongolia).](image-url)
the study area is 872–1821 m. Bornuur is one of the crop areas in Mongolia. The dominate plants are allium Mongolicum, Iris potaninii, Patriniasibirica, and Scutellariabacalensis (Bayartogtokh et al. 2015).

The thematic soil map with four types of soils and color combination bands 5, 4, and 3 from ETM (Figure 2) was used for the comparison in the research. The kastanozems soils from the study area were investigated for the SM analysis.

3. Data-set
3.1. Landsat ETM + & OLI8 satellite data
Landsat 7 enhanced thematic mapper (ETM) image (19 September 2011, path 132, row 26) was downloaded from the USGS earth resource observation and science center (EROS) website, and applied for this research. Landsat ETM + has a strip. We used Landsat gapfill method to remove the strips.

3.2. Advanced spaceborne thermal emission and reflection radiometer satellite data
In order to develop elevation, aspect, slope we used advanced spaceborne thermal emission and reflection radiometer (ASTER) satellite, global digital elevation model (GDEM) data with 30-m resolution. The ASTER GDEM covers land surfaces between 83°N and 83°S, and is composed of 22,600 1°-by-1° tiles. The ASTER GDEM is in GeoTIFF format with geographic lat/long coordinates and a 1 arc-second (30 m) grid of elevation postings. It is referenced to the WGS84/EGM96 geoid. Pre-production estimated accuracies for this global product were 20 m at 95% confidence for vertical data and 30 m at 95% confidence for horizontal data.

3.3. Ground truth data
SM data was collected during the field trips in Bornuur, Tuv province using traditional method. We took soil samples from the depth 0–50 cm in September 2011 (Table 1, all the corresponding soil types are kastanozems). Traditional method was developed in the following way: the first is to collect soil sample data in the study area and found its weight; the next is to dry soil. Traditional method allowed us to measure amount of moisture using dried soil samples (Equation (1)).

\[ W = \frac{a \cdot 100}{b} \]  

where \( W \) is the SM from traditional method; \( a \) is the amount of water in soil; \( b \) is the dried soil.

4. Integration method for soil moisture analysis
The Equation (2) is used as atmospheric correction for the images in this research (Chavez 1996). The correction map is in Figure 2.

| Latitude | Longitude | Acquired date | SM (%) | (g) (mm) |
|----------|-----------|---------------|--------|----------|
| 48°37’09” | 106°09’09” | 9/20/2011     | 5.6153 | 7.6299   | 9.474     |
| 48°37’09” | 106°09’09” | 9/20/2011     | 5.7114 | 10.3022  | 8.609     |
| 45°12’14.76” | 106°09’11.88” | 9/20/2011 | 5.9329 | 7.9736   | 9.238     |
| 46°56’16.92” | 106°09’09” | 9/20/2011     | 7.0703 | 6.4935   | 8.446     |
| 52°56’52.56” | 106°06’06” | 9/20/2011     | 7.3942 | 6.5171   | 10.313    |
| 50°04’50.04” | 106°06’06” | 9/20/2011     | 3.4012 | 5.4895   | 7.651     |
| 48°36’52.56” | 106°06’06” | 9/20/2011     | 2.6161 | 7.8169   | 7.947     |
| 49°08’23.52” | 106°16’16” | 9/19/2011     | 2.1816 | 9.3878   | 11.635    |
| 49°08’28.56” | 106°16’16” | 9/19/2011     | 2.4655 | 7.1989   | 10.103    |
| 48°40’50.16” | 106°16’16” | 9/19/2011     | 2.1605 | 8.8401   | 12.275    |
| 48°40’50.16” | 106°16’16” | 9/19/2011     | 2.2932 | 8.2269   | 10.841    |
| 45°48’28.92” | 106°16’16” | 9/19/2011     | 2.2607 | 8.6510   | 9.084     |

Figure 2. Color composite image from Landsat + ETM bands which are 5, 4, and 3 and thematic soil map (source: Institute of Geography, Mongolian Academy of Science).
SMI was calculated using the Landsat + ETM 7 bands 1 and 4 (Dupigny-Giroux and Lewis 1999) Equation (3) for the study area in kastanozems soil (Figure 4).

$$\text{REF} = \frac{\pi \cdot (\text{Lsat} - \text{Lhaze})}{\text{TAUv} \cdot (\text{Eo} \cdot \cos(TZ) \cdot \text{TAUz} + \text{Edown})}$$

where REF is the spectral reflectance of the surface; Lsat is the satellite spectral radiance for given spectral bands; Lhaze is the upwelling spectral radiance (path radiance), value derived from image using dark-object criteria; calculated using the dark object criteria (lowest value at the base of the slope of the histogram from either the blue or green band); TAUv is the atmospheric transmittance along the path from ground to sensor, assumed to be 1 because of nadir look angle; Eo is the solar spectral irradiance; TZ is the solar zenith angle; TAUz is the atmospheric transmittance along the path from the sun to the ground surface; Edown is the down welling spectral irradiance at the atmosphere (Chavez 1996).

The method schema is illustrated in Figure 3.

Figure 4. SMI map from Landsat + ETM7.

Figure 5. NDVI map from Landsat + ETM7.

Figure 6. LST map from Landsat + ETM7.

SMI was calculated using the Landsat + ETM 7 bands 1 and 4 (Dupigny-Giroux and Lewis 1999) Equation (3) for the study area in kastanozems soil (Figure 4).
The red (RED) and NIR channels from ETM were applied in Equation (4) for NDVI calculation (Sellers et al. 1994) (Figure 5):

\[
NDVI = \frac{NIR - RED}{NIR + RED}
\]

where NIR is the near infrared channels (0.77–0.90 μm); VisBlue is the visible blue channels (0.45–0.52 μm).

**Figure 7.** (a) Elevation map, (b) Aspect, (c) Slope in Bornuur soum; source: ASTER-SRTM 30-m resolution data.

\[
SMI = \frac{NIR}{VisBlue}
\]
\[ LST = \left( \frac{BT + w \cdot BT}{p} \right) \cdot \ln(e) \]  

(5)

where \( BT \) is the satellite brightness temperature (K); \( w \) is the wavelength of emitted radiance (11.5 \( \mu \)m); \( p = h \times c / s \) (1.438 \( \times 10^{-2} \) m K), \( h \) is the Plank’s constant (6.626 \( \times 10^{-34} \) Js); \( s \) is the Boltzman constant (1.38 \( \times 10^{-23} \) J/K); \( c \) is the velocity of light (2.998 \( \times 10^8 \) m/s); \( e = 0.004 \times P_v + 0.986 \), \( P_v = (NDVI - \text{NDVI}_{\text{min}})/(\text{NDVI}_{\text{max}} - \text{NDVI}_{\text{min}})^2 \) is the proportion of vegetation.

For elevation, aspect, and slope, we used ASTER satellite, GDEM data for 30 m resolution. Figure 7 illustrates the relationship of SMI from satellite and PSMI.

For the relationship of ground soil moisture measurement and PSMI, Figure 9 illustrates the result.

**Table 2. Result of regression analysis.**

| Model       | Unstandardized coefficients | Standardized coefficients | Collinearity Statistics |
|-------------|-----------------------------|----------------------------|-------------------------|
|             | B  | Std. error | Beta | t   | Sig. | Tolerance | VIF |
| (Constant)  | 0.542 | 0.225 | 2.407 | 0.053 |       |           |
| NDVI        | 1.183 | 0.226 | 0.348 | 5.238 | 0.002 | 0.682 | 1.466 |
| LST (°C)    | 0.022 | 0.004 | 0.728 | 5.953 | 0.001 | 0.201 | 4.965 |
| Elevation (m) | 0.000 | 0.000 | -0.257 | -1.647 | 0.151 | 0.124 | 8.097 |
| Aspect (0–360°) | -7.167E-006 | 0.000 | -0.005 | -0.054 | 0.959 | 0.321 | 3.116 |
| Slope (%)   | -0.004 | 0.005 | -0.073 | -0.829 | 0.439 | 0.390 | 2.563 |

*Dependent variable: SMI.
the elevation, aspect, and slope from 30-m resolution from ASTER in kastanozems soil, Bornuur soum.

In order to develop the model for estimation SM we used the regression analysis. Outputs from the analysis were compared to ground truth data.

We assume that SM is derived from satellite and depends on variables such as LST, NDVI, elevation, aspect, and slope. $F$ is function of dependent variables, shown as Equation (6).

$$PSM = F(NDVI, LST, Elevation, Aspect, Slope)$$ (6)

Therefore, for this assumption, the multivariate regression analysis was selected. The multidimensional linear regression model can be described as follows:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \beta_4 x_{i4} + \beta_5 x_{i5}$$ (7)
From the assumption (Equation (6)), we developed the model for predicted soil moisture. Equation (8) was used for the development of predicted SMI (PSMI) of the model in this research:

\[
\text{PSMI} = 0.348 \times \text{NDVI} + 0.728 \times \text{LST} - 0.257 \times \text{Elevation} - 0.005 \times \text{Aspect} - 0.073 \times \text{Slope}
\]

5. Results of analysis

To validate the model, we selected 12 samples from Table 1 (additional 21 points) where ground truth for SM was measured.

The scatter plot of the PSMI from the model and SMI from satellite is shown in Figure 8 with \((R^2 = 0.9039)\) shows the strong correlation coefficient between NTDI and \(m_i\) for kastanozems soil. The ground measurement data was compared with the PSMI from the model \((R^2 = 0.65)\) (Figure 9).

We used the Equation (8) for the estimation of kastanozems soil in the Table 3. This output was compared with ground truth data and shows moisture positive relation.

For the test model, Equation (8) was applied to another 25 points in Bornuur (Table 4) and developed soil moisture map (Figure 10).

The results of the PSMI model was compared with the ground SM measurement (traditional) data in Tuv province.

The output map from the modeling for kastanozems soil is shown in the Figure 10. The maximum value of PSMI data is 1.56, the minimum is 0.0. We divided PSMI into 3 classes which are low (0.0–1.0), moderate (1.1–1.5), and high (1.6–high). Also, we classified ground truth measurements into 3 similar classes (low, moderate, and high). We overlaid randomly our ground truth points on the map and made validation. In Table 5, we present the matrix evaluation for the validation.

The result of PSMI was compared with ground truth measurement (Table 5). The correlation coefficients were, respectively, 69 and 66%.

The positive results (Figures 8 and 9) should be investigated further, and it needs a more detailed analysis of high-resolution satellite data.

6. Conclusion

SM is vital for Mongolian agriculture development. SM analysis is needed to assist dryland grain growers to make improved and informed decisions. Since less research has been carried out in dry land, policy makers at regional level were not available to make decisions for crop growers in central agricultural areas. This research will aid the crop sector to develop agriculture land, and improve crop quality to expand the Mongolian food demand. SM monitoring also will provide useful insights for pasture land management in other regions of...
Mongolia. The model developed for this research could be applied for other ecological zones in kastanozems soil. Only forest steppe region was taken for the analysis. This model can be applied for the other regions of kastanozems soil using remote sensing methodologies.

Development of the SM modeling will provide information for Mongolia’s agriculture and animal husbandry (like cropland, pastureland, vegetation growth, and biomass). The national policy level will be able to use this information to develop suitable agriculture areas. This area’s crop fields are typical along the mountain, low mountains, hills, which have a certain amount of relief. As there are not any implemented sufficient soil protection works in the region, this place might become affected by wind and water disasters. Our research model can be applied and used for agricultural and environmental sectors widely in similar regions.

Our model was developed in an agricultural area in the central part of Mongolia. Foreign scientists mostly estimate SM using satellite data with climate station data. The innovation of this research was to estimate SM using drivers which are vegetation, land surface temperature, elevation, aspect, and slope in kastanozems soils. Our research applied elevation and slope drivers for forested mountain and agricultural areas. This integrative methodology can be applied for different regions with forested and desert steppe zone.

In the future, we will apply the integrative model all over the Mongolian landscapes. Since Mongolia has six different landscapes. SM monitoring is important for Mongolian agricultural development. There is a regional plan to develop agricultural land in Mongolian mountain forested areas.

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