Soil moisture analysis using remotely sensed data in the agricultural region of Mongolia

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Soil moisture analysis using remotely sensed data in the agricultural region of Mongolia

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List of abbreviations

SM	Soil Moisture
SMC	Soil Moisture Contents
SMI	Soil Moisture Index
MI	Moisture Index
TDR	Time-Domain Reflectometry
MCA	Multi-Criteria Analysis
AHP	Analytical Hierarchy Process
WLC	Weighted Linear Combination
PWCM	Pairwise Comparison Matrix
CI	Consistency Index
CR	Consistency Ratio
PSMI	Predicted Soil Moisture Index
MLR	Multiple Linear Regression
ARIMA	Autoregressive Integrated Moving Average
AR	Auto-Regressive
MA	Moving Average
AIC	Akaike’s Information Criterion
BIC	Bayesian Information Criterion
ACF	Auto Correlation Function
PACF	Partial Auto Correlation Function
VI	Vegetation Index
NDVI	Normalized Difference Vegetation Index
NDMI	Normalized Difference Moisture Index
TWI	Topographical Moisture Index
EVI	Enhanced Vegetation Index
SAVI	Soil Adjusted Vegetation Index
MSAVI	Modified Soil Adjusted Vegetation Index
NTDI	Normalized day-night surface Temperature Difference Index
LST	Land Surface Temperature

ET	Evapotranspiration
PET	Potential Evapotranspiration
IDW	Inverse Distance Weighted
VIF	Variance Inflation Factor
RED	Visible red
NIR	Near-Infrared
TIRS	Temporal Infrared Sensor
SMOS	Soil Moisture Ocean Salinity
SMAP	Soil Moisture Active Passive
CCI	Climate Change Initiative
AMSR-E	Advanced Microwave Scanning Radiometer-Earth observing system
SSM/I	Special Sensor Microwave/Imager
SAR	Synthetic Aperture Radar
OLI	Operational Land Imager
ETM+	Enhanced Thematic Mapper Plus
EASE	Equal-Area Scalable Earth
GDEM	Global Digital Elevation Model
CRU TS	Climate Research Unit Time Series
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
MODIS	Moderate Resolution Imaging Spectroradiometer
GIS	Geographic Information System
UTM	Universal Transverse Mercator
NASA	National Aeronautics and Space Administration
EROS	Earth Resource Observation and Science
AppEEARS	Application for Extracting and Exploring Analysis Ready Samples
ESA	European Space Agency
JAXA	Japanese Aerospace Exploration Agency
IPCC	Intergovernmental Panel on Climate Change
UNESCO	United Nations Educational, Scientific and Cultural Organization
UNEP	United Nations Environment Programme

UNDRR	United Nations for Disaster Risk Reduction
FAO	Food and Agriculture Organization
MAS	Mongolian Academy of Science
MFALI	Ministry of Food, Agricultural and Light Industry
IRIMHE	Information and Research Institute of Meteorology, Hydrology and Environment
IGG	Institute of Geo-ecology and Geography
LAMGaC	Agency of the Land Administration and Management, Geodesy and Cartography
NSO	National Statistical Organization
GDP	Gross Domestic Product

CHAPTER 1

Introduction

This chapter is divided into five sections. Firstly, the general background is introduced on the topics of research status and methods (Section 1.1). Secondly, the soil moisture estimation methods were introduced, remote sensing applications for soil moisture (Section 1.2). Thirdly, about Mongolia and the current situation of climate and soil moisture (Section 1.3). Fourth, detailed information on the study area and hotspot area is presented and the reason why it has been chosen as the hotspot area (Section 1.4). Finally, the research questions and the dissertation outline will be discussed (Section 1.5).

1.1 Background

Although the surface soil moisture only constitutes 0.0012 % of all water available on earth (Shiklomanov 1993), it is distributed by rainfall into runoff and infiltration and one of the main drivers of the earth's water cycle (Figure 1—1). The soil moisture is also an essential component of the CO2 exchange on the land surface. Therefore, the knowledge on soil moisture influences for many studies such as ranging from the weather, climate and crop yield forecasts, water resource management, drought forecasts and ecosystem mapping to the ecosystem health (Hirschi, Viterbo, and Seneviratne 2006; Hirschi, Seneviratne, and Schär 2006; D. Zhang et al. 2015). The soil moisture (SM) is one of the most critical research parameters regarding the changes in hydrology, ecology, agriculture, climatology and the environment (Ren et al. 2019; L. Yang et al. 2019). Each plant species needs a different amount of soil moisture in order to absorb the water and nutrients efficiently and to stabilize the plant.

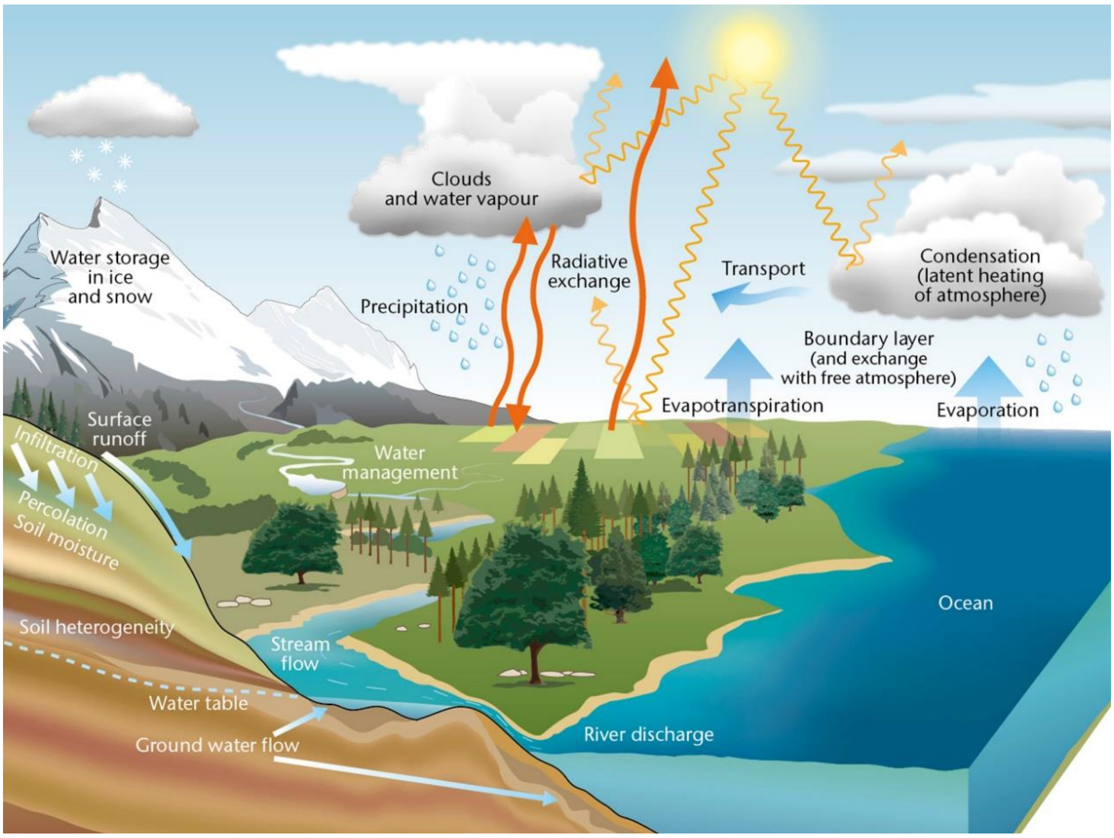


Figure 1—1. Diagram of the water cycle (modified by the https://www.metoffice.gov.uk/)

The soil moisture refers to the amount of water stored in the soil above the groundwater level. It is a significant environmental indicator controlling and regulating the interactions between the atmosphere and land surface (Arnold 1999; Robinson et al.

2008; Lin 2010). And the soil moisture is also one of the main factors in the infiltration/runoff dynamics. It is challenging, to define, it because other elements should be integrated such as vegetation, soil types and topography (Longobardi 2008). Relevant research regarding the multi-factor (i.e. precipitation, temperature, land cover and soil type) effects on the soil moisture variation are still rare, especially in the arid regions (Y. Wang et al. 2018). The soil moisture contents represent the water amount in the soil (usually described as a percentage). The soil moisture information is valuable in a wide range of governmental agencies and private companies dealing with the weather and climate, runoff potential and flood control, soil erosion and slope failure, reservoir management, geotechnical engineering and water quality (Arnold 1999). However, the soil variabilities and topographic and climatic conditions could significantly affect the soil moisture in a wide area.

The soil moisture mainly depends on the balance of precipitation and the evapotranspiration, as well as on the winter soil freezing and snow melting (Nandintsetseg and Shinoda 2011). The precipitation functions as the main input for the water balance. It can directly influence the soil moisture; the temperature controls the evapotranspiration and affects the soil moisture indirectly (Stéfanon et al. 2014). The soil moisture directly influences the evaporation rate, groundwater recharge and runoff generation and it affects the climate largely (Ray et al. 2017). It can be measured or estimated in various ways such as through *in situ* measurements (using climate stations and ground measurements) or by indirect observations by means of satellite images (remote sensing). Water is an important soil component. During the warm season, the increase in temperature leads therefore to enhanced evaporation (and thus is affecting the soil moisture). The total soil moisture significantly decreases from the north to the south of Mongolia (E. Natsagdorj and Renchin 2010) due to the regions of Mongolian vegetation (Yunatov and Dashnyam 1979). There is also a need for more detailed weather forecasts for the days showing a sharp increase in dryness (E. Natsagdorj and Renchin 2010), according to the vegetation zones such as the high mountains, taiga, forest-steppe, steppe, desert steppe and desert.

The Remote Sensing technology provides a powerful tool so as to estimate the soil moisture at several high spatial and temporal resolutions (H. Wang, Magagi, and Goita 2017). An approach based on satellite and climate data is useful for the policy-makers so as to develop appropriate agricultural areas (Guoxin, Shibasaki, and Matsumura

2004; Anderson, Reynolds, and Gugerty 2017). In Mongolia, multispectral images (e.g. MODIS and Landsat) were usually applied for environmental studies. Generally, high-resolution satellite data and microwave imagery are essential components in the natural resource management, rangeland production and crop monitoring. However, acquiring high resolution multispectral and microwave imagery is a big challenge for these applications because of the economic issues. It is the reason why limited research has been conducted using high-resolution satellite data or microwave data, especially in Mongolia. The latter needs facilities for satellite image processing and to monitor the spatial and temporal SM evolution, especially in the agricultural regions. Hence it is necessary to conduct further research in agricultural regions of Mongolia.

The traditional soil moisture observations (Engman 1991), Time-Domain Reflectometry (TDR) (Clarke Topp and Reynolds 1998); neutron probes and gamma-ray scanners (providing indirect SM measurements) mainly include single-point measurements or specific site measurements. The original soil moisture could be determined from the mass changes between the dry and wet soils. However, the *in situ* continuous observations are costly, and the regional sampling is time-consuming as they require repeated sampling observation points.

The soil moisture is always an important factor in agriculture, certainly in the semi-arid and arid circumstances (Arnold 1999), especially in Mongolia. The arid and semi-arid region of Central Asia stretches across huge terrains of both Mongolia and China (Sofue et al. 2017). Therefore, the Mongolian climate is classified as a semi-arid to the arid climate and is characterized by a long-lasting cold winter, dry and hot summer, low precipitation and large temperature fluctuations between day and night and also between summer and winter (Nandintsetseg, Greene, and Goulden 2007). The number of sunny days (with an average of 260 days per year) is high (Leary et al. 2013). The growing season for the agricultural production in Mongolia only amounts to 95 – 110 days, and because of the climatic conditions, it is unsuitable for the majority of the farming (Leary et al. 2013). The agricultural sector continues to focus heavily on the nomadic livestock, with 75 % of the area being pasture and only 3 % populated (Azzaya, Gantsetseg, and Munkhzul 2006). Research on the soil moisture methodology will be developed in the agricultural region of Mongolia and could provide valuable information for the decision-makers and farmers concerning their further actions and could prove to be a source for agricultural management, planning and drought monitoring.

1.2 Soil moisture and estimation methods

The soil moisture is the amount of water in the space between the soil particles. The surface soil moisture includes the water in the upper 10 cm of the soil, whereas the root zone soil moisture contains the water that is available for plants. The water contents are used in a variety of scientific and technical fields and is expressed as a ratio of 0 (fully dry) to the value of the porosity of the materials to the saturation. Considerable progress was made in the first half of the twentieth century in the understanding of the soil moisture regime. Descriptions on the history of soil moisture science can be found in Taylor and Ashcroft (1972), Rode (1969), Rose (1966), Childs (1969) and others. As examples, Taylor and Ashcroft (1972) published a book entitled “Physical edaphology: the physics of irrigated and non-irrigated soils”, including scientifically written subjects on the soil physics, soil moisture and soils, irrigation etc. and Rode (1969) produced a scientific book entitled “Theory of Soil Moisture: Moisture properties of soils and movement of soil moisture”.

The soil is the uppermost layer of the earth crust and supports all terrestrial life (Rattan and Manoj 2004). It is a major component of all terrestrial ecosystems and the most basic of all-natural resources. The soil is composed of mineral particles, organic matter and pore space, which is the void of space between the soil particles. The degree to which pore spaces are filled with water determines the soil moisture conditions (Figure 1—2). If the pore spaces are completely filled, and water drains freely from the soil under the influence of gravity as "gravity water," then the soil is called saturated. As the water drains from the soil, some pores will be got filled with air and water vapour. When the pores no longer drain under the influence of gravity, the capillary tension of the water holds the water in place. Some of the larger pores will have drained, but most still contain water. At this point, the soil is said to be at field capacity (Rattan and Manoj 2004; COMET program 2005). As the water continues to be removed from the soil through evapotranspiration, more pore space will lose water. As this process continues, only the tightly held water (next to the soil particles) remains. There is a point when the tension of the water to the soil particles becomes so tight that the water cannot be used by plant roots. This is called the "wilting point." (Figure 1—2).

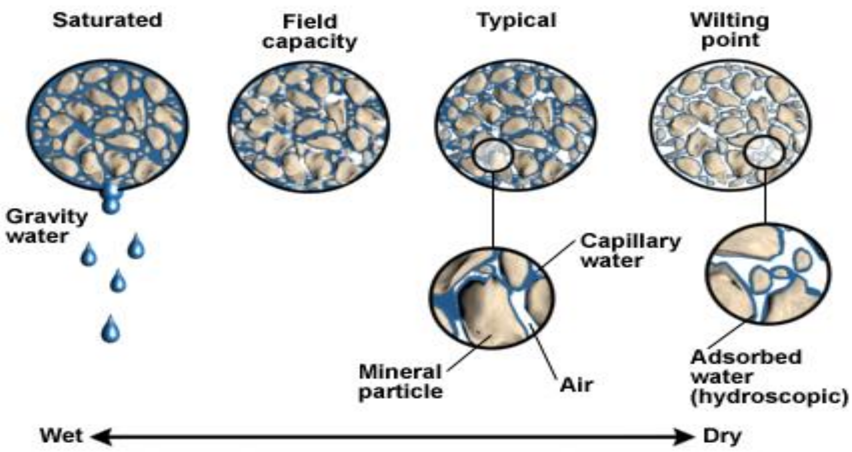


Figure 1—2. Generalized soil moisture conditions (modified by COMET program 2005)

The soil texture determines the amount of water held for different moisture conditions. The clay-type soils have very small mineral particles and very tiny pores. The sandy soils have larger mineral particles and thus larger pore spaces. Although it may seem counter-intuitive, smaller pore spaces in clay soil add up in a more considerable amount of space than in an equivalent volume of sandy soil. Clay, therefore, contains a higher percentage of soil water at field capacity compared to other soil texture types. Sandy soils, on the other hand, have larger mineral particles and a larger pore space but have a smaller percent of porosity and a corresponding lower percentage soil moisture at field capacity and wilting point as compared to clay. Concerning sandy textured soils, the soil becomes saturated at a much lower percentage of the soil moisture (COMET program 2005) (Figure 1—3).

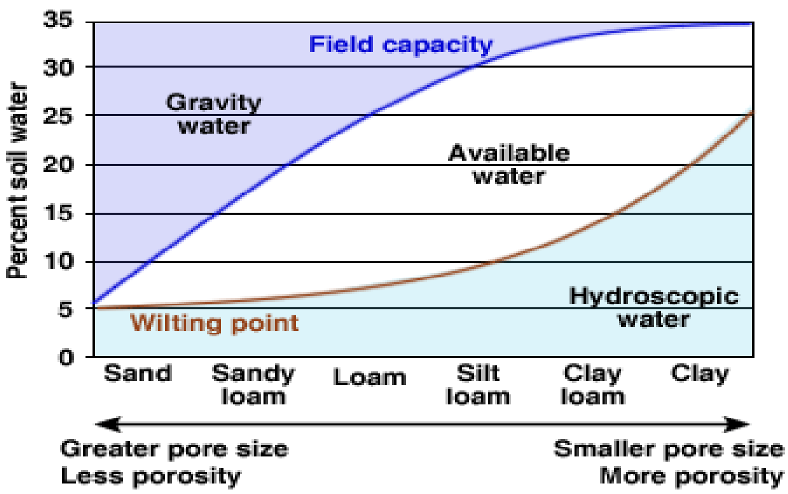


Figure 1—3. Soil moisture conditions for Various Soil Textures (modified by the (COMET program 2005))

During rainfall or snow melting, two types of surface runoff occur. The infiltration excess overland flow occurs in soil that is not saturated. In this case, the soil could be dry, but the soil properties or land cover do not allow for infiltration to keep up with high rainfall or snow melting rates. The saturation excess overland flow takes place when the soil becomes saturated, and there is no longer space for water to infiltrate. It could happen even with soil that would typically allow for large amounts of infiltration in sub-saturated conditions (Figure 1—4).

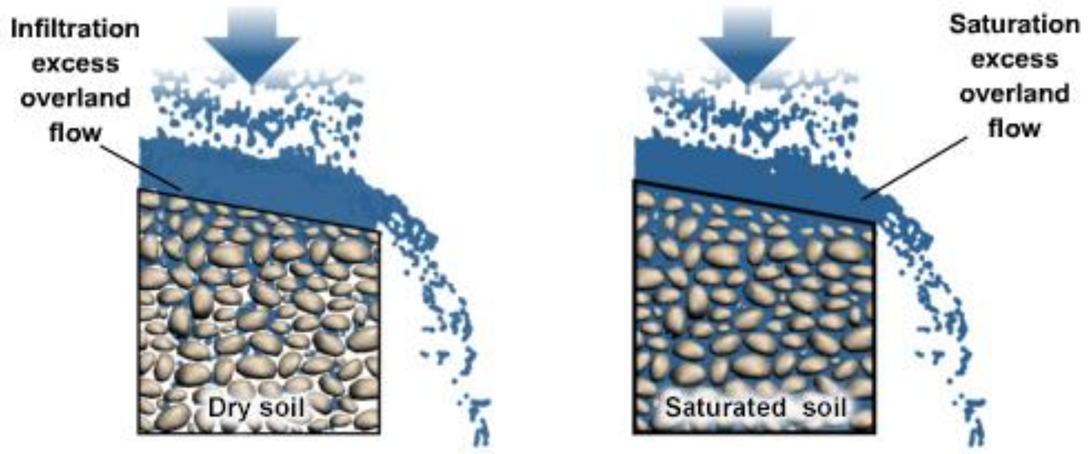


Figure 1—4. Types of surface runoff (modified by the (COMET program 2005))

The soil moisture measurement is essential to understand the soil behaviour, plant growth and numerous other physical soil processes (Rattan and Manoj 2004). It is useful for assessing the plant water requirements, irrigation planning and other properties and processes. The ratio of liquid water content is into the soil in the percentage of volume or weight and memory of previous rainfall. A substantial number of studies exist which describe the methods of soil moisture measurements (i.e. Robinson et al. 2008; Evett and Parkin 2005) and generally distinguish between the direct and indirect methods.

1.2.1 Direct methods of the soil moisture estimation

The direct methods are based on physical and chemical techniques of removing water from the soil, called the gravimetric method. It is the most accurate method to estimate the SM in gravimetric sampling (Engman 1991). However, this method is destructive and cannot be reproduced. According to this method, the soil samples are dried in order to calculate the moisture contents. The soil samples from the field are processed by putting the sample for 24 - 48 hours in an oven at 105 °C to 110 °C in order to measure the mass (of the dry soil) (Reynolds 1970).

$$SMC\ (\%) = \frac{a-b}{b} * 100 \tag{1-1}$$

Consider the formula mentioned above, where a stand for the weight of the wet soil (g) and b represents the weight of the dry soil.

Further soil processing methods are required so as to convert the gravimetric data (water mass per soil mass) into the volumetric values (water volume per soil volume). A comprehensive review of various SMC-methods has been published in (Verstraeten, Veroustraete, and Feyen 2008). Figure 1—5 shows the manner in which the soil samples are being collected from the field by means of a soil probe.

Figure 1—5. Collecting samples from the field by means of a soil probe kit (Photo E. Batmunkh)

The most advanced *in situ* equipment only measures the temporal variability on one particular location. In this study, we used a traditional method for the measurement of the soil moisture samples. The analytical error between the samples at one sampling point should not exceed 0,1 %.

1.2.2 Indirect methods of the soil moisture estimation (Remote sensing)

Many indirect methods already exist for the assessment of the soil moisture. For instance: neutron moisture metering, electrical conductance, Time-Domain Reflectometry (TDR), gamma scanner, thermal conductivity and remote sensing methods. The TDR, neutron and gamma scanners are typically used to measure the soil moisture (D. Zhang and Zhou 2016). However, these methods are point-scaled and cannot be used as a proxy for the regional soil moisture.

Microwave remote sensing: Based on the remote sensing data, indirect information on the soil properties could be gathered, providing an alternative tool to obtain quick estimates. Remote sensing techniques allow the observation of processes on the earth's surface at various spatial and temporal scales. The observation of the sub-surface state variables (such as the soil moisture) is, however, not straightforward (Van Doninck 2013). The four major remote sensing SM products available include the Advanced Microwave Scanning Radiometer – Earth observing system (AMSR-E) from the Japanese Aerospace Exploration Agency (JAXA), the Soil Moisture Ocean Salinity System (SMOS) from the European Space Agency (ESA), the Soil Moisture Active Passive (SMAP) from the National Aeronautics and Space Administration (NASA) and have a typical spatial resolution of approximately 40 km (Table 1—1). Such a low resolution could therefore only be used for the soil moisture monitoring on a global or regional scale (E. Natsagdorj et al. 2019). Figure 1—6 shows the launched satellites and data availability for the soil moisture analysis. Given the importance of SM, successful spatial and temporal assessments are difficult to obtain.

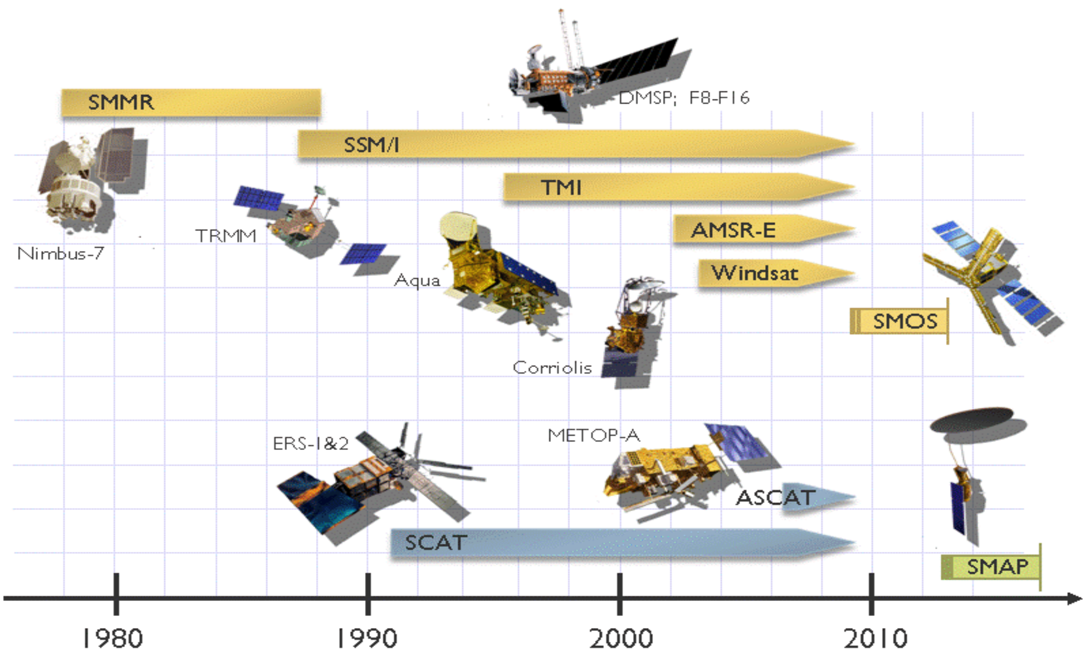


Figure 1—6. Active and passive microwave sensors used for the soil moisture data sets (Source: http://www.esa-soilmoisture-cci.org/node/93)

Table 1—1. Satellite soil moisture products

Satellite data	Available date	Source	Spatial resolution
SMAP (Soil Moisture Active Passive)	2015 – present	NASA	3, 9, 36 km
AMSR-E (Advanced Microwave Scanning Radiometer-Earth Observing System)	2001 – present	JAXA & NASA	12-56 km
SMOS (Soil Moisture and Ocean Salinity)	2011 – present	ESA	35-50 km
SSM/I (Special Sensor Microwave/Imager)	1987 – present	NOAA/NASA	20-60 km

During recent years, remotely sensed data with the Synthetic Aperture Radar (SAR) and radiometer sensors had been used so as to develop different methodologies to obtain the soil moisture. The SAR allows the monitoring of the surface characteristics, such as the soil moisture at spatial resolutions to ten meters under almost all weather conditions (García et al. 2019). Changes in the dielectric properties of soil in different soil moisture contents are measured in terms of the emitted microwave energy (Schmugge et al. 1974; Njoku and Kong 1977). Recently, the European Space Agency (ESA) launched the Sentinel 1-6 operational satellites and the database corresponding to the period 2014. The Sentinel-1 satellites (a 10 meter spatial resolution) are equipped with C-band SAR instruments that provide data in dual or single polarizations with a 12 days' temporal resolution. The Sentinel-1 radar images made it possible to retrieve the surface soil moisture, which will penetrate 1-2 cm into the soil (Q. Gao et al. 2017; Peng and Loew 2017; García et al. 2019). However, it is highly influenced by the surface roughness and the vegetation conditions.

The microwave remote sensing provides a better manner to capture the soil moisture on different spatial and temporal scales. The microwave techniques include the passive and active microwave approaches. The passive microwave radiometers record the naturally emitted radiation, while the active microwave sensors transmit electromagnetic waves and record the backscattered radiation (Jeu et al. 2008). The active and passive approaches offer various advantages because of their instrumental characteristics (Kolassa, Reichle, and Draper 2017). The remote sensing of the soil moisture is most sensitive in the electromagnetic spectrum in the range of 1 to 5 GHz (6 cm – 30 cm wavelength) due to a maximum stretching of the dielectric effect of dry soil to water. In the range of 1.4 – 1.427 GHz (21 cm – 21.4 cm wavelength), the L-band is most sensitive to SM signals (Lewis 2019). With the rapid development of satellite remote sensing technology, methods that utilize the optical, thermal infrared and microwave remote sensing for estimating the soil moisture have been developed (D. Zhang and Zhou 2016). To be noted is that the microwave remote sensing with a low spatial resolution is unsuitable for a specific region and small-scale applications. However, thermal and optical infrared remote sensing approaches have been applied to estimate the soil moisture because of their ability to provide information at a higher resolution (Leng et al. 2017).

Optical and Thermal remote sensing: Thermal infrared techniques are through modelling to get root-zone soil moisture (Crow, Kustas, and Prueger 2008). Optical (visible/near-infrared) is using solar radiation as a direct energy source, is a passive remote sensing method and is indirect to root-zone soil moisture. The reflectance of the dry and wet soils is different. In the dry soil, the radiant energy could be reflected from the surface of the dry soil (it penetrates the soil particles), where it could be absorbed or dispersed. The total reflectance of the dry soil is a function of specular reflectance and internal volume reflectance. In the wet soil, as the soil moisture increases, each soil particle could be encapsulated with a thin membrane of capillary water. The interstitial spaces could also be filled with water. The greater the amount of water in the soil, the greater the absorption of the incident energy and the lower the reflectance of the soil (Figure 1—7) (Condit 1970). In the thermal infrared radiation, changes in the surface soil temperature are due to differences in the soil moisture contents and could be monitored and related to the soil wetness (Cihlar, Sommerfeldt, and Paterson 1979). In the remote sensing community, the estimation of the soil moisture contents could usually be related to the volumetric water contents within a thin soil layer (i.e. top 5 cm of the topsoil profile) (Leng et al. 2019).

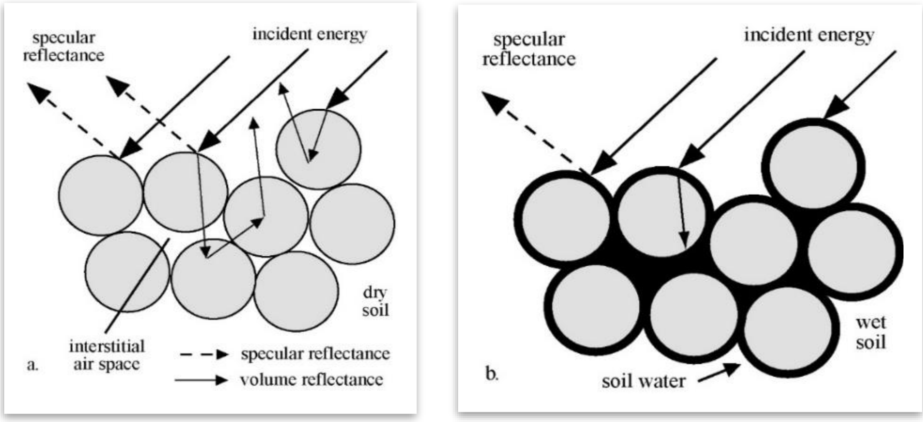


Figure 1—7. Reflectance of the dry (a) and wet (b) soil (Jensen 2006)

Many approaches have been developed using multispectral remote sensing so as to estimate the soil moisture such as statistical approaches, modeling and data assimilation, etc. The Soil Moisture Index (SMI) is based on an empirical parameterization of the relationship between the Land Surface Temperature (LST) and Normalized Difference Vegetation Index (NDVI) (Y. Zeng, Feng, and Xiang 2004; Parida et al. 2008; Potić, Bugarski, and Matić-Varenica 2017). The relation between the LST and NDVI is based on the experimental parameterization for the soil moisture index. Multispectral satellite data (visible, NIR and TIRS) were utilized for the assessment of the LST and the production of vegetation index maps (Saha et al. 2018). Many types of vegetation indices have been derived from the optical bands which are used for the soil moisture estimation, especially the NDVI. NDVI is the simplest, most efficient and commonly used one (Huete et al. 1997). Tucker (1979) first suggested the NDVI in 1979 as an index of vegetation health and density. Through previous studies, various studies have been performed so as to analyze and improve the methods of the surface soil moisture estimation based on the LST/NDVI space and considering the influence of the clouds, topography, vegetation type, spatial heterogeneity, climatic parameters, scales and so on (Xia et al. 2019).

The topography is the first order check, verification on the hydrological conditions' spatial variation that affect the spatial distribution of the soil moisture (Sørensen, Zinko, and Seibert 2006). The Topographical Moisture Index (TWI) was developed by Beven and Kirkby (1979). The TWI has not been applied in this research, but topography data have been considered. The topography does not only influence the soil moisture, but it also indirectly affects the pH of the soil (Högberg et al. 1990; Giesler, Högberg, and Högberg 1998). The soil moisture and pH are essential variables for the influence distribution (Giesler, Högberg, and Högberg 1998) and richness in species of vascular plants (Gough et al. 2000; Partel 2002; Zinko et al. 2005).

As mentioned above, many researchers have intensively studied the determining factors for the soil moisture such as the meteorological variables, soil types, land cover and vegetation. A few studies considered the elevation, slope and land surface temperature to be applicable for the soil moisture estimation. Also, based on this research results of soil moisture forecasting will be contributed in Mongolia.

1.3 About Mongolia and its current soil moisture situation

Mongolia is a land-locked country located in Central Asia and bordered by Russia and China, expanding between the latitudes of 41°35′N - 52°09′N and the longitude of 87°44′ E − 119°56′E with a total area of 1,565 million square kilometers (Figure 1—8). Mongolia has 73 % agricultural land, 0.5 % villages and other settlements, 0.35 % land under roads and networks, 9.2 % forest and forest resources, 0.4 % water and water resources and 16.1 % land for specials needs (Otgonbayar et al. 2017). Mongolia has six natural regions divided into the next vegetation types (Yunatov and Dashnyam 1979): the high mountains, taiga, forest-steppe, steppe, desert steppe, and desert zones (Figure 1—8).

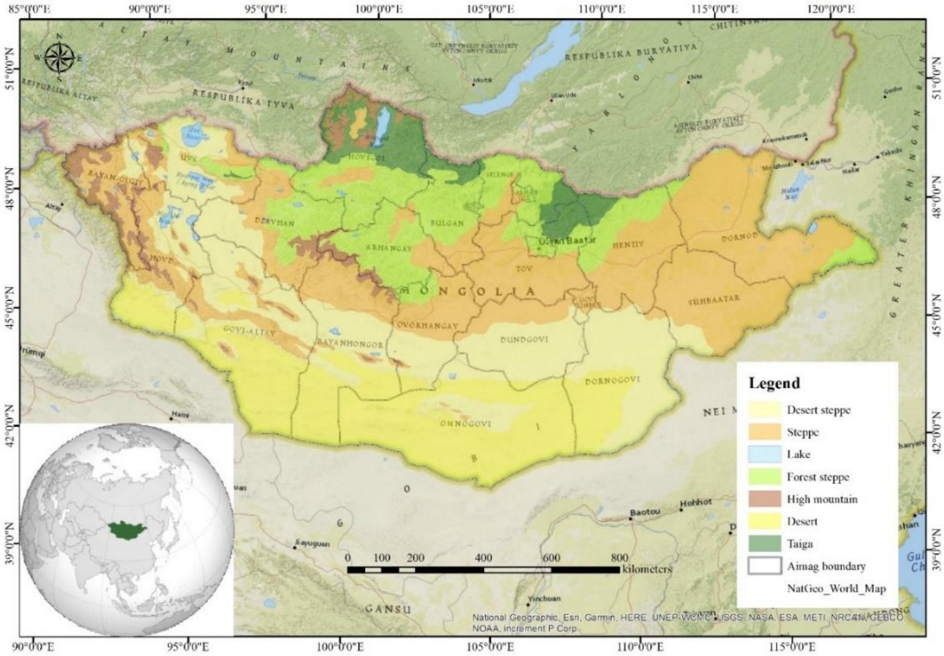


Figure 1—8. Location of Mongolia (Source: natural zone (Yunatov et al. 1979) and aimag boundary data from the Institute of Geography and Geo-ecology, Mongolian Academy of Science)

The Mongolian climate is highly continental with arid and semi-arid conditions (Nandintsetseg, Greene, and Goulden 2007) and has four distinct seasons, high-temperature fluctuations and little precipitation. The annual precipitation measures 300-400 mm in the taiga, high mountain and forest-steppe regions; 150-250 mm in the steppe; 100-150 mm in the desert steppe and 50-100 mm in the desert (Gobi) region. About 85 % of the total precipitation falls from April to September, of which about 50-60 % falls during July and August (Batima et al. 2005). The mean annual temperature measures -8 °C (northern areas) and 6 °C (southern regions) (Leary et al. 2013). Because of the majority of the Mongolian climate situation, its agricultural production is strongly limited by a short growing season (generally 80 to 100 days but varying from 70 to 130 days depending on the altitude and location), a low precipitation and a high evaporation (Leary et al. 2013). The importance of agriculture for the Mongolian economy and especially for the rural economy, makes a sustainable agricultural development a national priority. The agricultural sector provides income for 40 % of the population (Priess et al. 2015) and 14.5 percent of the Gross Domestic Product (GDP) from 2013 onwards. This makes it the third largest contributor to the GDP after retail (17.7 %) and mining (16.6 %) (Batzorigt 2014). Approximately 80 % of the total land area could be used for pastoral activities but less than 1 % is suitable for cultivation. The total size of arable land is estimated to be 12,000 km^2, of which 664,300 hectares is employed as cropland while 561,000 ha has been abandoned (Hofmann, Tuul, and Enkhtuya 2016). In the 1950s, Mongolia started land cultivation for the first time (Chuluunbaatar, Annor-Frempong, and Gombodorj 2017). Then the science-based agricultural production has been developing intensively in Mongolia (Gunguudorj 2009). Based on the agricultural production, there has been a demand to study the soil moisture estimation in 1959 (Erdenetsetseg 1996). As a result, one of the most significant sectors of the Mongolian economy is agriculture. Since the 1960s, agriculture has developed more intensively and widely. At present, Mongolia has 1.2 million hectares of arable land that produce environmentally clean, friendly products (Azzaya, Gantsetseg, and Munkhzul 2006). In order to develop the agricultural production, a number of national and international programs project and in effect in Mongolia. Major national programs that contributed to the agricultural product growth significantly include the *Atar*-III Campaign for the crop production, subsidy programs for agricultural products, producers and investment programs to support the purchase of agricultural equipment etc. (Chuluunbaatar, Annor-Frempong, and Gombodorj

2017). One of the key issues of the national objectives to increase the food security (agricultural production) is whether it could be achieved sustainably, that is without negative consequences for the water and soil resources (Priess et al. 2015). In addition, the last decades have seen a degradation of soils in the cultivated areas. There is a need to estimate new suitable cropland areas (especially sub-provinces and *bag (*administrative subdivision)).

The Mongolian steppe ecosystems play a crucial role in relieving the regional and even global climate variation through their interaction with the atmosphere (Yatagai and Yasunari 1995). Roughly, 124.3 million ha or 79 % of the land area is covered by grasslands and about 10 % is surrounded by forests or shrubland (Hilker et al. 2014). Soil moisture is the main source of natural water resources for agriculture and natural vegetation (Robock et al. 2000), especially in Mongolia. The latter usually does not inhibit the vegetation growth in spring. Thus, the spring precipitation is especially important to ensure pasture grass growth (Bolortsetseg 2002).

In Mongolia, a few researchers already devoted their PhD study to the soil moisture, such as Erdenetsetseg (1996); Erdenebat (2004) and Enkhbat (2016). They only used climate station measurements on their selected study areas. Most soil moisture studies are related to the estimated vegetables and the conditions of the vegetable growth.

Due to differences in geology and topography, we could distinguish six natural regions and specify the soil and vegetation distribution. Our study area is located in 1) mountain and taiga regions with cryomorphic taiga soils; 2) a mountain forest-steppe region with Chernozems, dark Kastanozems, dark-colored forest soils and derno taiga soils. Typical forest-steppe and steppe soil consist of chesnut soil and kastanozems (Tamura, Asano, and Jamsran 2013). The kastanozems soil is situated in arid regions such as southern and central Asia, northern Argentina, the western United States and Mexico (FAO 2019). They are common in Mongolia, especially in the agricultural region. It consists of humus and is found in relatively dry climatic zones (200-400 mm) but could also be employed for irrigated agriculture and grazing.

1.4 Study and hotspot area

We selected two study areas, the first of which is situated in the north-central part of Mongolia (Figure 1—9) and the second is a smaller hotspot called Bornuur soum located in the Tuv province, the center of the above-mentioned region (Figure 1—10).

The north-central part of Mongolia. This study area includes seven provinces (called "aimag"): Bulgan, Orkhon, Selenge, Darkhan-Uul, Tuv, Ulaanbaatar and the Khentii provinces, which are the main agricultural areas of Mongolia (Figure 1—9). The study area includes 80.9 % of the cropland of the total crop area in Mongolia (http://www.mofa.gov.mn/) (MFALI 2017).

In the study area, the average temperature is lower than the south of Mongolia. The average temperatures in the study area range between 15 and 20 °C during the summer season. The total annual precipitation measures between 250 - 300 mm in the taiga and forest-steppe regions, 150 - 250 mm in the steppe regions. In summer, most rainfall occurs; about 85 % - 90 % of this rainfall is the primary source of the soil moisture (L. Natsagdorj and Batima 2003).

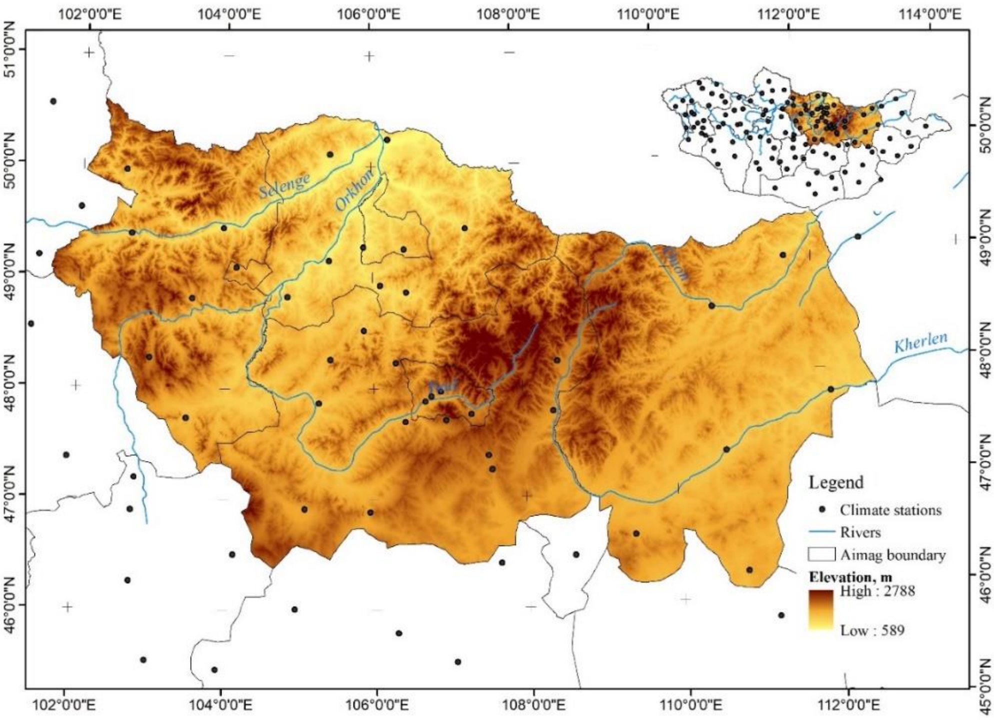


Figure 1—9. The first study area (Central part of Mongolia) (46°00'N-51°00'N and 102°00'E–112°30'E) (processed by ASTER-GDEM)

These study areas are located in a mountainous area which has elevations between 589 and 2,788 meters above sea level. The highest peak is Asralt Khairkhan (2,800 m), part of the Khentii mountain situated in the Tuv province. There are many rivers in the study area (i.e. Orkhon; Selenge; Tuul; Kherlen; Onon etc.). The Orkhon river flows 1,124 km from its source in the Khangai mountains to its mouth in the Selenge river. The Selenge river has a total length of 593 km with its mouth in the Baikal Lake in Russia.

The Kherlen river descends in the southern slopes of the Khentii mountains. It has a total length of 1,090 km with its mouth situated in the Hulun Lake in China. The Tuul river flows over 704 km, from its source in the Khentii mountains to its mouth at the Orkhon river (Figure 1—9). In the study area, the water supply mainly comes from the precipitation, snow and ice melting water and rivers originating in the mountains. Water is the main source for the agricultural sector, especially for livestock and farmers and has a major influence in the economy and ecology. The soil moisture is an important part of the water resources and is strongly related to the agriculture and ecosystem. For that reason, a soil moisture study could be an essential support for the decision-makers by providing information on the soil moisture in order to manage the agricultural systems and water resources in a better way.

Hotspot study area of Bornuur soum. Bornuur soum has an agriculturally based economy. It is located between E 48° - 49° and N 106° - 106°40' and the average altitude measures 1,240 meters above sea level (Figure 1—10).

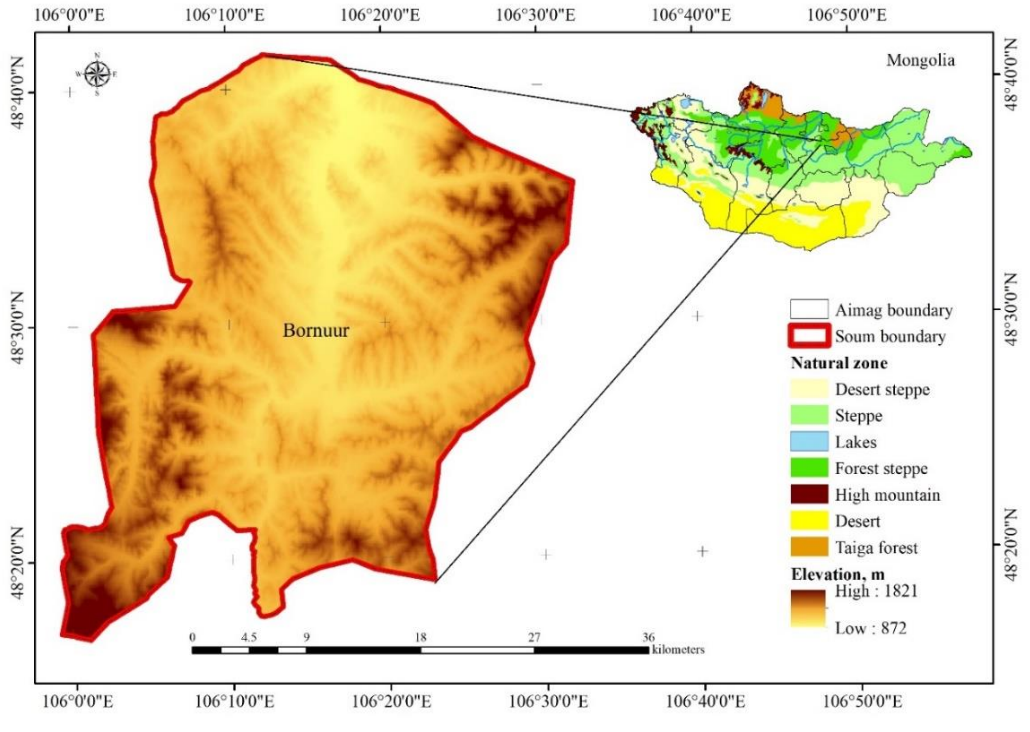


Figure 1—10. Second study area: the Bornuur soum, Tuv province in Mongolia (processed by ASTER-GDEM)

It is located 105 km north-west of Ulaanbaatar city (the capital city of Mongolia) and 155 km north-west of Zuunmod town (center of the Tuv province). The Tuv province is surrounded by the Khangai and Khentii mountains of the north-western and north-eastern provinces of the aimag and influenced by the extreme climatic conditions of the Kherlen and Tuul river basin, which are natural zones of steppe and forest steppe. The soum has low rainfall, a relatively warm summer and low air humidity.

1.5 Research objectives and dissertation outlines

1.5.1 Research objectives and questions

Understanding that soil moisture is essential for the current situation in Mongolian agriculture and new modeling (and methods) will be clarified in this dissertation. The research objectives are: (1) to estimate the long-term moisture index and to compare it to the soil moisture from climate stations and the Normalized Difference Vegetation Index (NDVI) for the growing season; (2) to develop a soil moisture model by means of a multi-regression analysis (based on the satellite images in agricultural regions of Mongolia); (3) to approach the optical satellite-based (LST & NDVI) soil moisture modelling and to monitor and predict an SM forecast; (4) to promote land suitability analysis using the multi-criteria analysis in the Bornuur soum of Mongolia. In order to achieve these objectives, the five following research questions should be answered.

Question 1: How could the moisture index (MI) be used to monitor and correlate with the SM measured at the climate stations at different depths (0-10 and 0-50 cm)?

There exists a long history of assessing the moisture conditions through the relation of the precipitation towards the temperature or evapotranspiration (Thornthwaite 1948; UNESCO 1979; Stephen 2006; Vicente-Serrano, Beguería, and López-Moreno 2010; Gobena and Gan 2013). Surface temperatures, precipitation and vegetation cover, influence the relative soil moisture (Nemani et al. 1993; Sandholt, Rasmussen, and Andersen 2002). Previous studies have not investigated the correlation between the soil moisture and the moisture index for long-term analysis. The moisture index could be seen as a measure to define both the water requirement periods and quantities of water surplus, as well as the water deficit by comparing the precipitation and potential evapotranspiration. How does the moisture index correlate with the soil moisture at different depths? Does the moisture index have an effect on the soil moisture in the study area? Could the moisture index be used for Mongolian agriculture? Exploring the answers to these questions could provide in chapter 2.

Question 2: How does the moisture index affect vegetation for the growing season?

Research shows that moisture index correlated positively with the vegetation growth (Piao 2005; Whitten 2009; Zhu et al. 2016). During the summer, an increase in temperature will influence heat stress in many plants, whereas a decrease in precipitation will reduce soil moisture which would reduce productivity and grazing pasture land (Whitten 2009). Most previous studies have been done during the growing season, which as from April to October. However, we will contribute data on moisture index from May to August using a combination of satellite and in situ data between 2000 and 2013. During the period, 2001, 2002, 2007 and 2009 years were obtained by slight and severe drought in Mongolia (Dorjsuren, Liou, and Cheng 2016) and vegetation cover was examined low during these years (Nanzad et al. 2019). The vegetation production in the study area is linked to the monthly precipitation and moisture availability. How does the moisture index correlate with the NDVI? Is it a proxy for vegetation? These questions could be answered during this research.

Question 3: How could we describe the integrated methodology for the SM through multispectral satellite data?

Based on the optical and temporal infrared satellite images, many approaches have been developed by evaluating the correlations between the soil moisture and soil reflectivity or land surface temperature and vegetation growth. Combining visible and thermal infrared remote sensing data could provide more information to estimate the soil moisture than the single one (D. Zhang and Zhou 2016). Therefore, it is crucial to assess the manner in which multispectral satellite images should be combined so as to obtain highly accurate soil moisture data of Mongolia. Which kind of factors has an effect on the soil moisture in mountainous areas? How do they influence the soil moisture? Which factors have a high correlation with the soil moisture in Mongolia? Is the soil moisture model useful? The answers to these questions are still unclear, and therefore, we need to tackle these issues urgently.

Question 4: How can NDVI and LST products be used to monitor soil moisture and predict it in Mongolia?

Spatial distribution of soil moisture with high-resolution images in Mongolia has long been one of the essential issues in remote sensing and agricultural community. The LST and NDVI were positively correlated with the soil moisture in the previous study. Many approaches have been developed to estimate soil moisture by means of LST and NDVI in different locations. However, their contributions remain unclear due to their complex interaction, especially in Mongolia. Clarifying the individual relations of LST and NDVI and soil moisture is vital for the agricultural management, water resources and drought monitoring. Previously, the soil moisture surveys have not employed multispectral remote sensing data in Mongolia. Only point-scaled measurements (meteorological stations and ground truth measurements) were used to estimate the soil moisture. How does the spatial distribution of soil moisture identify by the LST and NDVI? How can soil moisture time series data be estimated? How can be correlated between soil moisture and climate factors and crop yields in Mongolia? Exploring the answers to these questions could be clarified in chapter 4.

Question 5: How could the multi-criteria analysis evaluate for the cropland suitability?

The soil is a vital component of any ecosystem and is referred to as the pedosphere. Also, the soil plays a central role in the human ambition to sustain agricultural productivity (Rattan and Manoj 2004). Mongolian agriculture produces around 20 % of the total Gross Domestic Product (GDP). The agricultural sector contributes 14 % of the foreign currency revenues of Mongolia (Batzorigt 2014). In view of the government goals, a third crop rehabilitation campaign (national program) was (in 1959, 1976 and 2008 etc.) held in Mongolia. The Bornuur soum made development strategy in the near future. Main goals of the strategic plan are to improve the economy due to farming activity and to produce natural products (http://bornuur.to.gov.mn/). There's need to estimate agricultural land suitability analysis using multi-criteria based on crucial factors of the cropland. There are possibilities and advantages of using remote sensing techniques and geographic information systems in the Mongolian agricultural studies (Bayaraa and Tsolmon 2012). How does the soil moisture factor apply for the cropland suitability? Why is it crucial to estimate the cropland suitability in Mongolia? How many areas could be transformed into irrigated cropland in Mongolia? How are the soil types and texture in the study area? These questions will be clarified in chapter 5. In order to do so, a suitable crop database (for the agricultural sector) will ensure a greater reliability of the estimates and forecasts (which will help in the process of planning and policy-making).

1.6 Dissertation outline

The research questions stated above are addressed in the following chapters of this dissertation. In Figure 1—11, the outline of the dissertation is demonstrated.

Chapter 1 provides the research introduction; several chapters contribute to explain the primary objective. The estimation of the long-term soil moisture in the agricultural area will be found in Chapter 2, the integrated methodology for the soil moisture in Chapter 3, Chapter 4 deals with the spatial distribution of soil moisture over Mongolia and Chapter 5 carried out with developed methodology for applications such as the approach estimation for the cropland suitability. Chapters 2 through 5 correspond to the published papers for publications in international peer-reviewed journals.

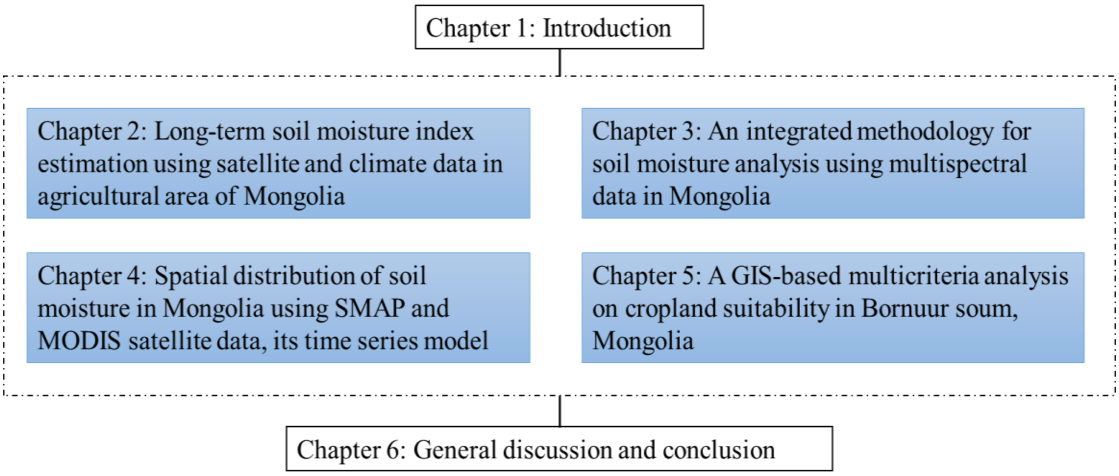


Figure 1—11. Outline of the dissertation

Chapter 2. Long-term moisture index' estimation using satellite and climate data in the agricultural area of Mongolia

Chapter 2, which was published in the "Geocarto International" of the Web of Science SCI journal (E. Natsagdorj et al. 2019). The paper has received more than 100 downloads and four citations. This chapter estimates the long-term moisture index (MI) using satellite and climatic data in the agricultural area. The objectives of this chapter are: (1) to interpolate the precipitation data from climate stations by means of a Geographic Information System (GIS); (2) to rate the long-term MI; using MODIS (3) to correlate between the estimated MI and the soil moisture from climate stations at different depths, 0 – 10 cm and 0 – 50 cm; (4) to estimate the relation between the estimated MI and NDVI. The surface soil moisture estimation plays a main role in investigating the importance of the soil moisture in different applications, such as in agriculture, hydrology, meteorology, forestry and natural disaster management (Hosseini and Saradjian 2011). Mongolia also needs facilities for satellite image processing and to monitor the long-term moisture analysis, especially in the agricultural region.

Chapter 3. An integrated methodology for the soil moisture analysis using multispectral data in Mongolia

This chapter, which was published as a paper in the "Geo-spatial Information Science" of the Web of Science SCI journal (E. Natsagdorj et al. 2017). The paper has received more than 2,000 downloads and seven citations. This chapter determines the integrated methodology for soil moisture (using multispectral data) by means of the predicted soil moisture index (PSMI)). The innovative part of the research is to consider the elevation, slope and aspects with other environmental drivers in mountainous and agricultural regions for the soil moisture estimation. The elevation, slope and aspects have been applied for this methodology (which have not been considered yet in previous studies in Mongolia). Additionally, we created a new function for the soil moisture by means of the LST and NDVI for the time-series analysis. It will be one of the new contributions of this thesis.

Chapter 4. Spatial distribution of soil moisture in Mongolia using SMAP and MODIS satellite data: A time series model (2010 - 2025)

Chapter 4, which was published in the "Remote Sensing" of the Web of Science SCI journal (Natsagdorj et al. 2021). The paper has received more than 300 downloads and a citation. This chapter will study on the distribution of soil moisture and compared the monthly precipitation/temperature and crop yield from 2010 to 2020. In this chapter, Soil Moisture Active Passive (SMAP) and Moderate Resolution Imaging Spectroradiometer (MODIS) data will be used, including the MOD13A2 Normalized Difference Vegetation Index (NDVI), MOD11A2 Land Surface Temperature (LST), and precipitation/temperature monthly data from the Climate Research Unit (CRU) from 2010 to 2020 over Mongolia. The soil moisture estimation approach and model in our study can serve as a valuable tool for confident and convenient observations of agricultural drought for decision-makers and farmers in Mongolia.

Chapter 5. A GIS-based multi-criteria analysis on cropland suitability in Bornuur soum, Mongolia

This chapter was published in the “International Archive Photogrammetry, Remote Sensing, Spatial Information Science” of ISI Conference Proceedings Citation Index (CPCI) of the Web of Science and SCOPUS (Natsagdorj, et al. 2020). The paper has received more than 100 downloads. This chapter to estimate best suitable area for supporting crop production in Bornuur soum, using a GIS-based multi-criteria analysis (MCA) and remote sensing. In this chapter, the GIS-based spatial MCA among the Analytical Hierarchy Process (AHP) method will be employed. The approach will enhance each criterion which as soil, topography and vegetation. The opinions of agronomist experts and a literature review will help in identifying criteria (soil data, topography, water and vegetation data) that are necessary to determine areas suitable for crops. The crop suitability method implies significant decisions on different levels, and the result will be used for cropland management plan to make a decision. It is an integral role in agricultural management and land evaluation.

Chapter 6 General discussion and conclusion that summarize and discuss the results of the former chapters and also mention important, potential subjects for possible potential *future research*.

CHAPTER 2

Long-term moisture index estimation using satellite and climate data in agricultural area of Mongolia

Modified from: Enkhjargal Natsagdorj, Tsolmon Renchin, Philippe De Maeyer, Chimgee Dari, Batchuluun Tseveen, (2019). Long-term soil moisture content estimation using satellite and climate data in agricultural area of Mongolia. Geocarto International. 34:7, 722-734 dio: [10.1080/10106049.2018.1434686](10.1080/10106049.2018.1434686)

2.1 Introduction

The global surface temperature has increased by 1.53 ºC during the period 1850-1900 to 2006-2015 (IPCC 2019). Due to the global warming, the changes in the moisture conditions were predicted (that would occur in some areas, triggered by drought) (G. Wang 2005; X. Gao and Giorgi 2008; Zhu et al. 2016). The processes of water balance, soil moisture, surface heat and evapotranspiration are undeniably related (Li et al. 2009). The Soil Moisture (SM) is driven by the climate, especially the precipitation and temperature (Feng and Liu 2015). The SM is a necessary component of the hydrological cycle (Hao et al. 2015) and plays a considerably important role in ecology and agriculture (Wen, Lu, and Li 2015). Several remote sensing vegetation indices are widely used to estimate the vegetation changes, e.g. the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Soil Adjusted Vegetation Index (SAVI) and Modified Soil Adjusted Vegetation Index (MSAVI) (Purevdorj et al. 1998; Sternberg et al. 2011; Hilker et al. 2014). The soil moisture has significantly decreased from north to south in Mongolia. We need to obtain more detailed weather forecasts during the warm season, indicating a sharp increase in dryness (E. Natsagdorj and Renchin 2010) according to the vegetation zones such as high mountains, taiga, forest-steppe, steppe, desert steppe and desert. The arid continental climate in Mongolia creates an extensive steppe area that embodies the primary source of forage for livestock, and the pastoral animal husbandry in the country's primary agricultural sector (Nandintsetseg and Shinoda 2011). The northern part of Mongolia has taiga forest covers, which extend to Siberia in Russia. More than half of the annual precipitation is observed during the summer season (Sato, Kimura, and Kitoh 2007). The precipitation is low (mainly in the warm season between June and September); the largest grazing areas (steppe and mountain steppe and forest) receive between 200 and 300 mm annually; the desert steppe between 100 and 200 mm; the desert receives less than 100 mm; only the northern zone possesses more than 300 mm. The majority of the precipitation amounts returns to the atmosphere through evapotranspiration; about 4 % infiltrates in the aquifer, and 6 % contributes to the surface flow (Suttie 2006).

According to the weather observations, the land surface temperature has increased by 2.14 ºC during the period 1940-2008 (Ministry of Environment 2014). During the growing season, the augmented temperature is leading to an enhanced evaporation (and is thus affecting the soil moisture). The average temperature in the warmest month is

15-20 °C in the north and 20-25 °C in the south of Mongolia. The summer continues lasts three months. The maximum summer air temperature might reach 35-39 °C in the north and 38-41 °C in the south (Battsetseg 2015).

The soil moisture is one of the most critical environmental variables in view of the land surface climatology, hydrology and ecology. It mainly depends on the balance of the precipitation and evapotranspiration, as well as on the soil freezing and snow melting during winter (Nandintsetseg and Shinoda 2011). The moisture conditions are balanced between the precipitation and evapotranspiration (on the land surface), which are limiting factors affecting the plant growth and agricultural distribution under a certain temperature (Zheng 2000). It took a long time to evaluate the moisture conditions by the ratio of precipitation, temperature and evapotranspiration (Thornthwaite 1948; UNESCO 1979; UNEP 1992). A paper by Pei et al. (2009) demonstrated the manner in which remote sensing could help to extract the snow information from a region in northern Xinjiang, located south of the border with Mongolia.

Global soil moisture products are available such as the Soil Moisture Ocean Salinity (SMOS) from the European Space Agency (ESA), Soil Moisture Active Passive (SMAP) from the National Aeronautics and Space Administration (NASA) and the Advanced Microwave Scanning Radiometer - Earth observing system (AMSR-E) from the Japanese Aerospace eXploration Agency (JAXA), etc. These products have a low resolution that could be applied for the global and regional scale soil moisture monitoring. This considerable variation is problematic for the products with a low spatial resolution (Wen, Lu, and Li 2015). Because of the importance of the SM, the execution of the spatial and temporal assessment seems to be complicated.

In this chapter, the northern central part of Mongolia has been selected, which provides the main products for the agricultural sector (MFALI 2017). In this region, the soil moisture variability is mainly controlled by the precipitation during the growing season (Nandintsetseg and Shinoda 2014). This study could be (quickly and easily) applied so as to estimate the climate moisture contents in the region of interest.

Therefore, a study on the moisture conditions in the northern and central part of Mongolia during 2000-2013 has been carried out (concerning the growing season). The objectives of the study include: (1) to interpolate the precipitation data from the climatic stations using the geographic information system (GIS); (2) to estimate the long-term moisture index using the *in-situ* and MODIS data; (3) to correlate between the estimated moisture index and soil moisture from the climatic stations at different depths (0-10 cm and 0-50 cm); (4) to assess the relationship between the estimated moisture index and the NDVI (in addition to the correlation between the NDVI and the precipitation/temperature from the climatic stations). The surface soil moisture estimation plays a leading role in the investigation of the soil moisture importance in various applications, such as agriculture, hydrology, meteorology, forestry and natural disaster management (Hosseini and Saradjian 2011). Mongolia also needs satellite image processing and monitoring to perform a long-term moisture analysis (especially in the agricultural area).

2.2 Study area

The seven provinces (shown in Figure 1—9) were chosen and dealt with in this chapter. The study area is located in the mountainous area with elevations between 590 and 2,800 m. The study area has a lower average temperature than the southern region (represented in Mongolia). The average temperature ranges between 15 and 20 °C during the summer season. The total annual precipitation is situated between 250-300 mm in the taiga and forest-steppe regions and 150-250 mm in the steppe regions. In summer, most rainfall would occur (about 85 % - 90 %); this rainfall forms the main source of the soil moisture (L. Natsagdorj and Batima 2003). The study area includes 80.9 % of the cropland of the total crop area in Mongolia (http://www.mofa.gov.mn/) (MFALI 2017). The soil moisture in Mongolia is mainly influenced by the precipitation and evapotranspiration; it also depends on the soil type and texture.

2.3 Dataset description

2.3.1 Climatic data

The climate station data (temperature, precipitation) were obtained from 38 climatic stations between 2000 and 2013 during May-August for the vegetation growing season. The precipitation (mm) and temperature (ºC) data have been acquired monthly (and on average) and are based on the daily observation data. There are only 6 stations are available for SM (noted with symbol (***)**) and they had observations beneath 50-cm depths (Table 2—1) and thus the data for the 0-10 cm and 0-50 cm soil layers were analyzed. The soil moisture contents (obtained by gravimetric methodology) were acquired at 0-10 cm and a 0-50 cm depth with a monthly interval (7th, 17th and 27th day of each month) from May to August. The 50-cm soil layer includes the major rooting zone of the grasses that dominate most parts of the Mongolian steppe (Shinoda, Nachinshonhor, and Nemoto 2010). The 38 stations are widely spread over the study area. Figure 1—9 shows the location of the climate stations. The precipitation, temperature and soil moisture contents' data were averaged over the monthly intervals from May to August. These climatic data were provided by the Information and Research Institute of Meteorology, Hydrology and Environment (IRIMHE) of Mongolia (http://www.icc.mn/) (IRIMHE 2016). The geographical locations, elevations and station names of the 38 stations are represented in Table 2—1.

Table 2—1. Climate stations with information on the geographical location (* SM available stations).

ID	Aimag name	Station name	Longitude (°E)	Latitude (°N)	Elevation (m)
1	Bulgan	Gurvanbulag	103° 28' 52.02"	47° 44' 8.93"	1,095
2	Bulgan	Mogod	102° 58' 38.92"	48° 16' 24.77"	1,438
3	Bulgan	Selenge	103° 57' 48.19"	49° 26' 46.57"	794
4	Bulgan	Teshig	102° 36' 10.54"	49° 57' 52.63"	1,047
5	Bulgan	Khutag-Ondor	102° 41' 42.66"	49° 23' 28.85"	940
6	Selenge	Orkhontuul	104° 50' 23.6"	48° 49' 57.34"	847
7	Selenge	Orkhon	105° 24' 34.23"	49° 9' 28.94"	780
8	Selenge	Tsagaannuur	105° 25' 59.4"	50° 6' 50.5"	779
9	Selenge	Eroo	107° 17' 22.63"	49° 25' 50.61"	790
10	Darkhan	Shariin Gol	106° 26' 18.74"	49° 15' 10.68"	930
11	Selenge	Bayangol*	106° 6' 11.83"	48° 55' 39.2"	833
12	Selenge	Zuunkharaa	106° 27' 40.58"	48° 51' 43.18"	878
13	Tuv	Buren	105° 4' 11.09"	46° 55' 1.68"	1,286
14	Tuv	Bayan-Onjuul	105° 56' 19.5"	46° 53' 4.1"	1,386
15	Khentii	Darkhan	109° 24' 51.34"	46° 37' 0.08"	1,266
16	Khentii	Galshar	110° 51' 15.27"	46° 13' 16.21"	1,223
17	Khentii	Binder	110° 36' 37.54"	48° 36' 56.97"	1,044

18	Khentii	Dadal	111° 38' 0.9"	49° 1' 15.24"	951
19	Khentii	Bayan-Ovoo	112° 7' 5.31"	47° 46' 54.66"	916
20	Tuv	Lun	105° 15' 42.9"	47° 52' 14"	1,027
21	Tuv	Ugtaaltsaidam	105° 25' 22.98"	48° 15' 44.73"	1,157
22	Tuv	Bayanchandmani	106° 18' 11.9"	48° 13' 38.29"	1,298
23	Ulaanbaatar	Buyant Ukhaa	106° 38' 57.12"	48° 7' 35.3"	1,243
24	Tuv	Altanbulag	106° 25' 6.25"	47° 41' 46.27"	1,227
25	Tuv	Bayan	107° 33' 35.36"	47° 15' 8.45"	1,487
26	Ulaanbaatar	Nalaikh	107° 18' 20.17"	47° 45' 27.03"	1,421
27	Ulaanbaatar	Baganuur	108° 23' 48.83"	47° 45' 38.29"	1,344
28	Ulaanbaatar	Ikh surguuli	107° 10' 5.68"	47° 55' 52.29"	1,418
29	Tuv	Mongonmorit	108° 28' 44.5"	48° 12' 28.53"	1,439
30	Tuv	Jargalant	105° 52' 37.99"	48° 31' 24.86"	995
31	Ulaanbaatar	Bagakhangai	107° 31' 6.08"	47° 22' 50.5"	1,474
32	Darkhan	Salkhit*	105° 53' 6.12"	49° 16' 30.05"	718
33	Orkhon	Bayan-Ondor*	104° 8' 29.05"	49° 5' 42.42"	1,273
34	Bulgan	Bulgan*	103° 32' 26.83"	48° 48' 47.8"	1,209
35	Selenge	Sukhbaatar	106° 14' 6.5"	50° 14' 35.87"	695
36	Tuv	Zuun Mod*	106° 58' 7.01"	47° 42' 11.8"	1,533
37	Khentii	Undurkhaan*	110° 40' 5.73"	47° 19' 7.1"	1,026
38	Ulaanbaatar	Ulaanbaatar	106° 46' 35.58"	47° 55' 19.23"	1,331

2.3.2 MODIS (Moderate Resolution Imaging Spectroradiometer) products

MODIS has been applied during a fourteen-year (2000-2013) period so as to observe the dynamic range of the moisture contents during the growing season. MODIS has typical products, among which the MOD16 evapotranspiration product that is used to calculate the regional water and energy balance and the soil water status. J. Zhang et al. (2007) have applied a similar approach to detect anomalies through the MODIS land products and a time series' analysis. Accordingly, the monthly composite of the 1 km spatial resolution MOD16A3 and MOD16A2 (Mu, Zhao, and Running 2011; 2013) products from MODIS and the National Aeronautics and Space Administration (NASA) Earth Observing System (http://lpdaac.usgs.gov/) data were employed. These products are freely downloadable online.

The MOD16A3 produces a monthly composite of the MODIS terrestrial evapotranspiration (ET) and potential evapotranspiration (PET) products. The ET and PET are commonly utilized as an indicator of the terrestrial water availability. The PET of the MODIS was a mosaic and has been projected using the ENVI-IDL 4.7 from HDF-EOS to GeoTIFF. It allows the projection from the MODIS Sinusoidal (SIN) grid to the Universal Transverse Mercator (UTM) zone 48N projection in the study analysis. Hosseini and Saradjian (2011) have demonstrated an excellent example of the manner in which the MODIS data could be applied for the soil moisture estimation.

2.3.3 SPOT-VEGETATION (SPOT-VGT)

The decade synthesis (SPOT-VGT) is computed from all the passes on each location acquired during the 10-day periods. These periods will be defined according to the legal calendar: from the 1st to the 10th, from the 11th to the 20th, from the 21st to the end of each month (F. Zhang, Wu, and Liu 2003). In this research, one applied the average for each month. The geometric correction for the SPOT-VGT was performed in the ENVI-IDL 4.7 and projected into the UTM zone 48N. The SPOT Vegetation dataset (used in this study) has been monthly averaged for the growing season from 2000 to 2013.

The NDVI is widely adopted to look into the status quo and the variation of the vegetation cover at a particular location. The Normalized Difference Vegetation Index (NDVI) was estimated by means of the following equation (2-1) (C.J Tucker 1979; C.J Tucker and Sellers 1986a):

$$NDVI = \frac{NIR - RED}{NIR + RED} \qquad (2\text{-}1)$$

, where RED is the visible light of the red wavelength (from 400-700 nm) and NIR demonstrate the intensity of the near-infrared wavelength (from 700-1,100 nm).

2.4 Methodology

The seasonal contrast between the precipitation and evapotranspiration determines the soil moisture dynamics and thus the water availability for plant use (Hao et al. 2015). Remote sensing techniques deliver a powerful tool to estimate the soil moisture at several spatial and temporal resolutions (Jabbar, Guangdao, and Zhenfei 2004; H. Wang, Magagi, and Goita 2017).

In this chapter, one used the PET (derived from MODIS) and climate data from the stations to estimate the long-term moisture index (spatial resolution of 1 km) of the growing season (in 2000-2013) in order to calculate the moisture index in the study area (equation 2-3) (Also see the research of Zhang et al. (2007)). The overall description of the study consists of three parts: (1) the interpolation of the precipitation from the climatic stations (equation 2-2); (2) the estimation of the long-term moisture index (equation 2-3); (3) the correlation between the estimated MI and soil moisture from the climate stations at different depths (equation (2-4); (4) the relation between the estimated MI and NDVI. Figure 2—1 shows a detailed flowchart of this chapter.

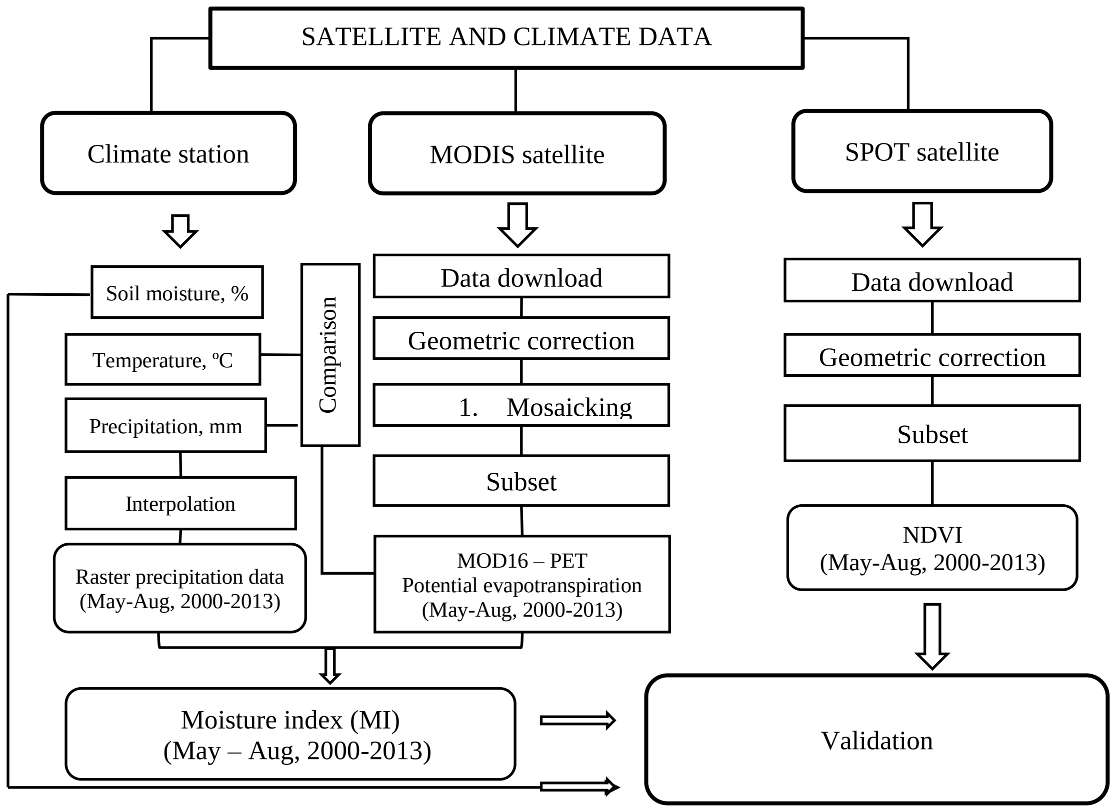


Figure 2—1. Flowchart of this chapter

2.4.1 Kriging interpolation method

The geostatistical analysis has been used as the main analytical tool to execute climatic and environmental factors' and studies for relationships between soil moisture and environmental factors (Nyberg 1996; Western et al. 1999). The Kriging interpolation method (Oliver and Webster 1990; Yamamoto 2005; 2007) was applied through ArcGIS to obtain a spatial distribution of the precipitation. The Kriging interpolation assumes that the distance or direction between the sample points reflects a spatial correlation that could be used to clarify the surface variation. The Kriging method shows similarity with the IDW (Inverse Distance Weighted); it weighs the surrounding measured values to derive a prediction for an unmeasured location. The general formula for both interpolators is created as the weighed sum of the data, equation (2-2):

$$\hat{Z}(s_0) = \sum_{i=1}^{N} \lambda_i Z(s_i) \qquad (2\text{-}2)$$

, where: $Z(s_i)$ = the measured value at the i^{th} location

λ_i = an unknown weight for the measured value at the i^{th} location

s_0 = the predicted location

N = the number of the measured values

In the IDW, the weight λ_i solely depends on the distance to the predicted location (Oliver and Webster 1990). However, with the Kriging method, the weights are not only based on the distance between the measured points and the predicted location but also the overall spatial arrangement of the measured points. In order to use the spatial arrangement in the weights, the spatial autocorrelation must be quantified. Thus, in the ordinary Kriging method, the weight, λ_i, depends on a fitted model to the measured points, the distance to the predicted location and the spatial relation among the measured values around the predicted location.

2.4.2 Estimation of the long-term moisture index (MI)

The moisture index from this chapter was looked into by Thornthwaite (1948). This methodology estimates the moisture index using the precipitation and evapotranspiration data from the growing season as expressed by the following equation (2-3) (Thornthwaite 1948; UNESCO 1979; Stephen 2006).

$$MI = \frac{P}{PET(DaysPerMonth)} * 100\% \qquad (2\text{-}3)$$

, where PET is the Potential EvapoTranspiration produced from the MOD16A2 and P represents the total monthly precipitation in mm/day and r month. It represents a dimensionless index that ranges from -1 to 1. The MI is multiplied by 100 so as to create entire numbers (Grundstein 2009). The MI is determined by the percentage of the moisture contents. The distribution of the moist regions in the study area is based on this moisture index and shown in the representation of the changes in moisture contents for the growing season during 2000-2013 in the study area. Figure 2—2 (a-n) is demonstrated as the mean MI for May-August 2000-2013. The driest years are 2000 (Figure 2—2a), 2002 (Figure 2—2c) and 2007 (Figure 2—2h), while the wettest years include 2012 (Figure 2—2m) and 2013 (Figure 2—2n).

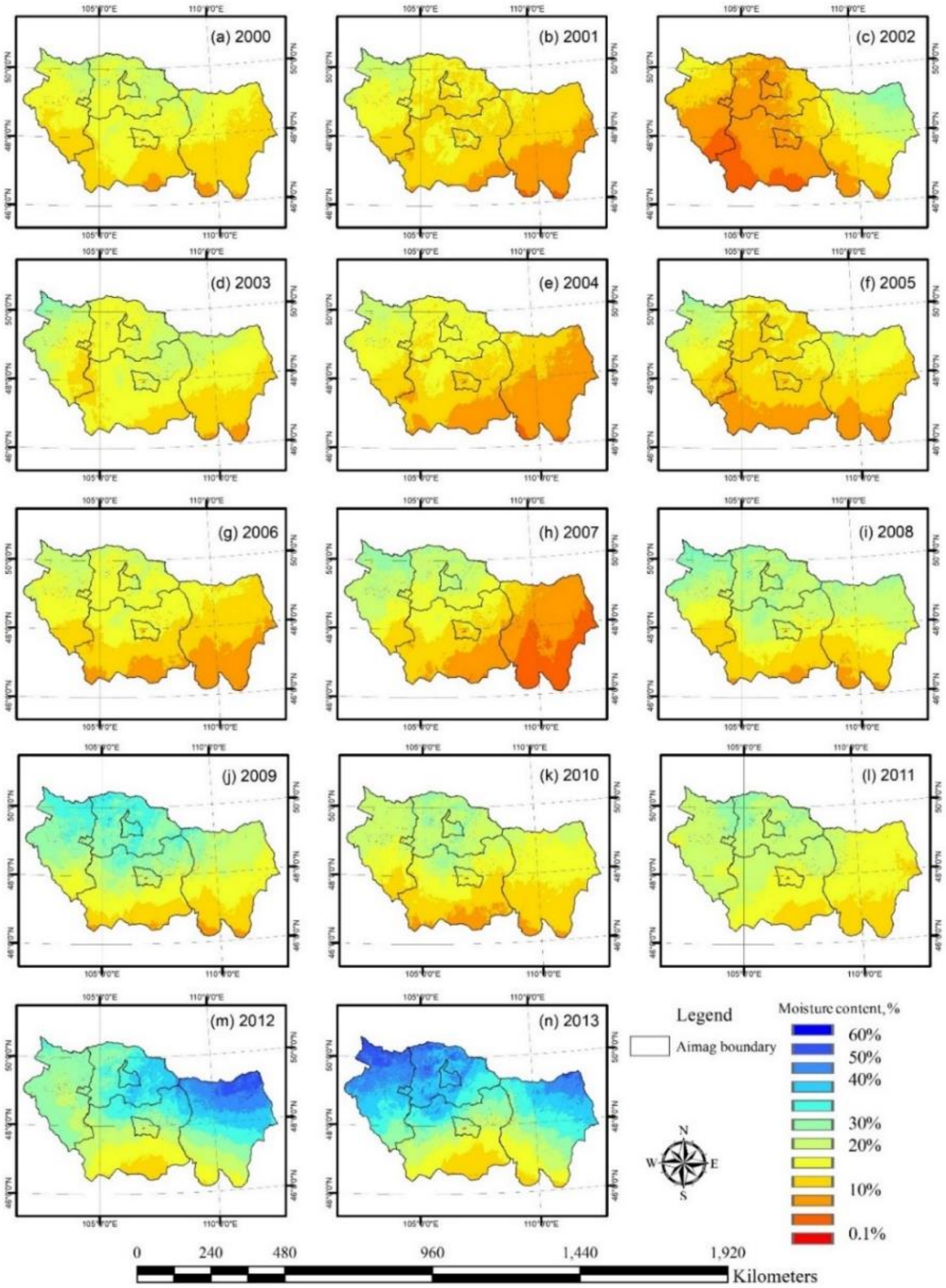


Figure 2—2. Mean moisture index in the study area during the growing season (May - Aug) of 2000-2013

From this methodology, the following argument was identified: If the precipitation (P) is high then moisture index (MI) will also be high and the potential evapotranspiration (PET) is high to MI below.

(P ↑ = MI ↑; PET ↑ = MI ↓ either P ↓ = MI ↓; PET ↓ = MI ↑)

2.4.3 Pearson's correlation for the MI validation

The Pearson's correlation (r) was applied for the comparison between the MI and soil moisture from the climate stations (equation 2-4). The equation of the coefficient of Pearson (r) is given in the following equation (2-4) (Sedgwick 2012):

$$r = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i}^{n}(X_i - \bar{X})^2 \sqrt{\sum_{i}^{n}(Y_i - \bar{Y})^2}}} \qquad (2\text{-}4)$$

, where X_i and Y_i represent the individual derivations and measurements of the variables X and Y, respectively. $\bar{X}$ and $\bar{Y}$ demonstrate the means of X and Y, respectively (Sedgwick 2012). The linear Pearson's correlation (r) was determined on a monthly timescale (May-August) for the derived satellite and climatic data. Equation (2-4) was also utilized to investigate the relation between the estimated MI and NDVI.

2.5 Data analysis

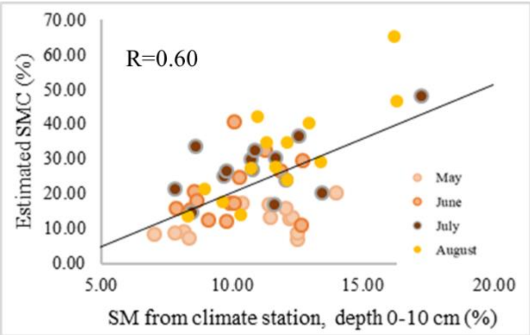
The validation of the estimated moisture index from this chapter: In general, the estimated moisture index performed reasonably well (using satellite and climatic data). Figure 2—3a and Figure 2—3b describe the correlation between the estimated moisture index and the SM from the climate stations at a 0-10 cm and 0-50 cm depth.

represents the correlations of the estimated MI with the vegetation and SM measurements from the climatic stations for the growing season (May-August). It indicates that the values of the correlation coefficient (r) amounted to 0.60 between the estimated MI and soil moisture at a 0-10 cm depth from the station that was statistically significant ($p < 0.001$) (Figure 2—3a) and the correlation coefficient (r) measured 0.38 between the estimated MI and the soil moisture at a 0-50 cm depth from the statistically significant station ($p < 0.01$) (Figure 2—3b). In the growing season, the correlation between the estimated MI and SM (0-10 cm) from the climate stations was high in July (0.59) and August (0.84). Regarding the 0-50 cm depth, the correlation was lower than the 0-10 cm dept (Table 2—2 and Figure 2—3).

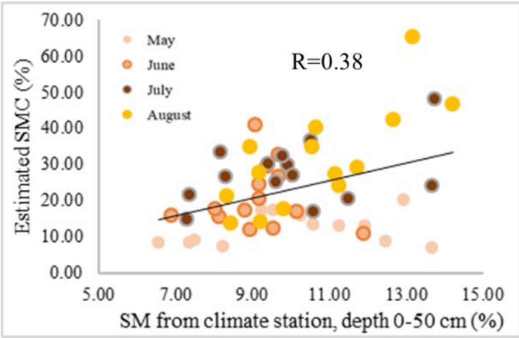
Table 2—2. The correlation among the estimated MI with different depths in soil moisture from the climate stations (in the study area) during the growing season in 2000–2013

Months	Number of stations	Estimated MI vs Soil moisture (0 - 10 cm)	Estimated MI vs Soil moisture (0 - 50 cm)
May	6	0.50*	0.27
June	6	0.33	0.04
July	6	0.59**	0.41
August	6	0.84***	0.75**

Significance level of the correlation coefficient (r): ***($p < 0.001$), **($p < 0.01$), *($p < 0.05$), ($p < 0.1$)



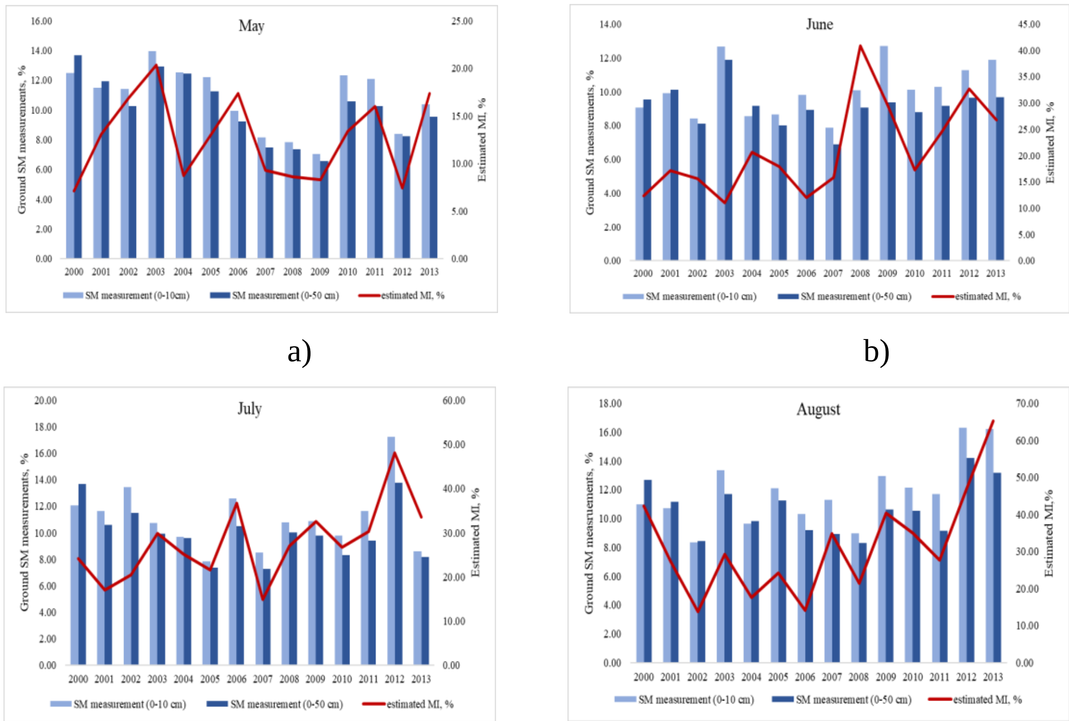
a)



b)

Figure 2—3. Scattered diagram between the SM measurements from the climate stations at different depths and the estimated MI for the growing season of 2000 - 2013: (a) estimated MI and SM measurements from the climate stations at a 0 - 10 cm depth, (b) estimated MI and SM measurements at a 0 - 50 cm depth

Figure 2—4 shows the difference between the MI and soil moisture from the climate station at different depths (0–10 and 0–50 cm). The snow water (melting) roughly corresponds to an increase in SMC from October to April (6.9 mm) plus the estimated evapotranspiration during this period (4.2 mm) (Zhang, et al. 2008), this case was shown in May 2004 provided that the SM was higher than the moisture index since the snow water was not provided in this research.



c) d)

Figure 2—4. (a-d) Temporal variations of the estimated MI among different depths in soil moisture of the climate stations for 2000-2013. The SM of a 0-10 cm depth (%: light blue bar), the SM of a 0-50 cm depth (%: dark blue bar), the estimated MI (%: red line): (a) in May; (b) June; (c) July and (d) August.

The climate variables from the stations: The average temperature of the stations in the study area measured approximately 16 °C, the mean precipitation was 191 mm, and the average soil moisture amounted to 10.9 % during the growing season (2000-2013). Figure 2—5 shows the time series plots of the climate variables during the growing season. The total mean precipitation was situated between 137 mm (2002) and 263 mm (2013); the average temperature ranged from 15.06 °C (2003) to 17.68 °C (2007) and the soil moisture measured between 8.96 % (2007) and 13.30 % (2012) during the study period. Droughts occurred during the summers of 1999-2002 (Natsagdorj and Batima 2003). Figure 2—5 shows the long-term climatic data in which the wettest years were 2003, 2012 and 2013 and the driest years 2002, 2004 and 2007.

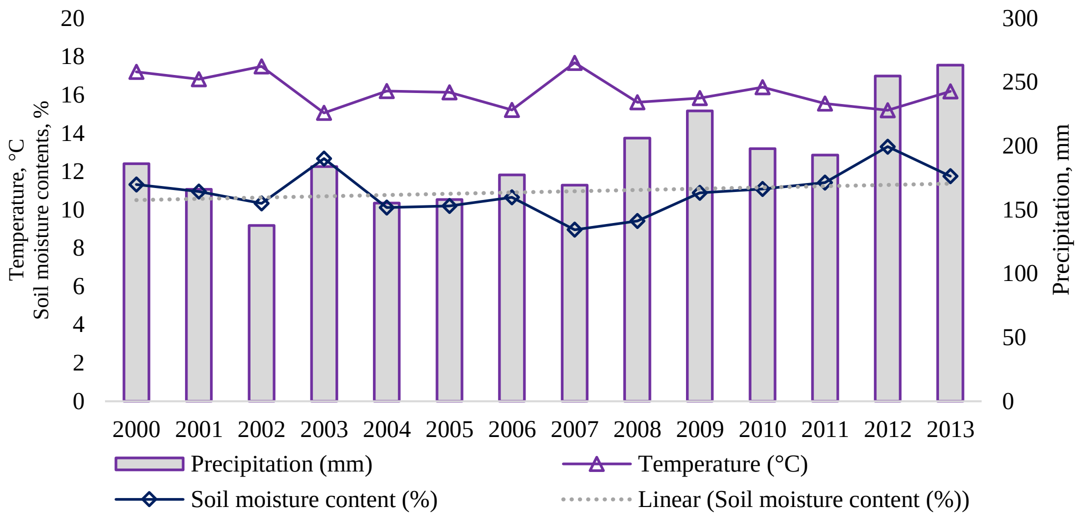


Figure 2—5. Time series of the climatic data regarding the temperature (°C), precipitation (mm) and soil moisture contents' (%) averages during the growing season of 2000 - 2013.

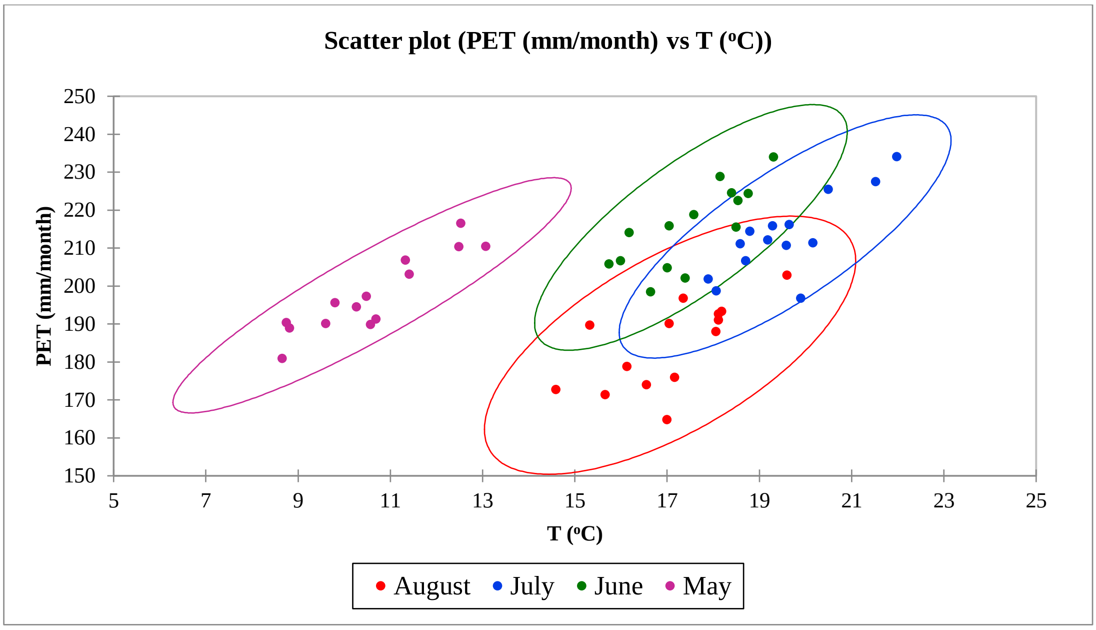
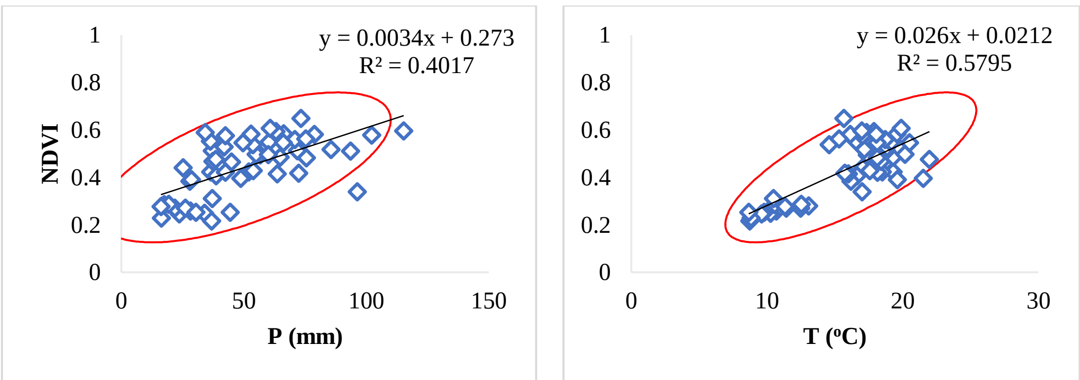


Figure 2—6. Scatter plot between the PET (mm/months) and temperature (ºC): May (pink); June (green); July (blue) and August (red)

Regarding the PET validation derived from MODIS, we could tell that the PET is positively correlated with the temperature from the climate stations. The determination coefficients amounted to 0.43 in August, 0.62 in July, 0.61 in June and 0.83 in May, respectively (Figure 2—6).

The correlation between the NDVI and precipitation/temperature from the climate stations: The vegetation production in the study area is linked to the monthly precipitation and moisture availability. One created a relation between the NDVI and estimated MI for the growing season of 2000-2013. The Mongolian steppe is one of the largest remaining grassland ecosystems in the world (T. Hilker, E. Natsagdorj and H. Richard, et al. 2014).

In the research work of Hilker, et al. (2014), the NDVI was relatively stable or increased in some areas (in the northern part of the country). A decrease of up to 0.05 in the mean yearly NDVI took place in several southern provinces, especially in the most southern part of the country. Similar work and results have been obtained by Mushtak, Hu and Zhang (2012) in their research on the desertification of arable lands in the North Shaanxi area of China. A similar long-time series' analysis of the NDVI data sets from 1981 to 2001 was carried out on the precipitation by Zhang, et al. (2012), whose study covers the north-central part of Mongolia (which contains forested and steppe area). The NDVI in this area was more relatively stable or rose. The biomass below the ground appeared to affect the one situated aboveground at the initial vegetation growth (as detected by the NDVI) during spring. That signifies that the larger (or smaller) rootstock of the steppe plants produced during the wetter (or drier) growing season might be maintained in the frozen soil during winter and might provide a basis for the production of a larger (or smaller) aboveground biomass in spring (Banzragch and Masato 2011). Besides, the vegetation growth depends on the temperature, precipitation and moisture contents.



a) b)

Figure 2—7. The scatter plot between the NDVI and precipitation (mm) as shown in (a), temperature (ºC) and shown in (b): the red circle is the confidence ellipse (confidence interval of 95 %)

The correlation between the NDVI and the precipitation explains that the determination coefficient was 0.402, statistically significant ($p < 0.0001$). While the correlation between the NDVI and temperature was 0.579, being statistically significant ($p < 0.0001$) as well (Figure 2—7 and Table 2—3).

Table 2—3. Correlation coefficient and p-values between the NDVI and precipitation/temperature from the climate stations for the growing season (May-August)

NDVI	P (mm)	T (ºC)
Coefficients of determination	0.402	0.579
Correlation matrix	0.634	0.761
p-values	< 0.0001	< 0.0001

The Correlation between the MI and NDVI: Figure 2—8(a-b) shows the relation between the NDVI and MI: The correlation coefficient was 0.28 between the NDVI and MI of May; 0.37 in June; 0.55 in July and 0.42 in August (Table 2—4 and Figure 2—8a). The correlation coefficient measured 0.67 ($p < 0.01$) between the NDVI of July and the MI amount from May and June; 0.71 ($p < 0.01$) between the NDVI of July and the MI amount from May and July; 0.72 ($p < 0.01$) between the NDVI of August and the MI from May and August and 0.78 ($p \leq 0.001$) between the NDVI of August and the MI amount from June and July (Table 2—5 and Figure 2—8b). The 95 % confidence interval is described by different colour ellipses for each month, e.g. the NDVI of July and the amount of MI from May and June (pink), NDVI of July and amount of MI from May and July (green), NDVI of August and amount of MI from May and August (blue) and the NDVI of August and amount of MI from June and July (red) as shown in Figure 2—8a.

Table 2—4. Correlation coefficient and p-values between the MI and NDVI from May to August

	May	June	July	August
R	0.28	0.37	0.55	0.42
p-values	0.331	0.173	0.04	0.135

Table 2—5. Correlation coefficient and p-values between the amount of MI (May-Aug) and the highest growing months of the NDVI (July and August)

Variables	NDVI (Jul)	p-value	Variables	NDVI (Aug)	p-value
MI (May+Jun)	**0.668**	**0.009**	MI (May+Aug)	**0.722**	**0.004**
MI (May+Jul)	**0.711**	**0.004**	MI (Jun+Jul)	**0.788**	**0.001**

Values in bold are different from 0 with a significance level of alpha=0.05

The results of this analysis (Table 2—4) explain that the moisture index has a weak correlation with the NDVI for the growing season (May-August). However, Table 2—5 demonstrates that the amount of moisture index (May-August) has a slightly strong correlation with the NDVI of the highest growing months (July and August), which makes it a significant predictor of the vegetation growth (which strongly depends on the amounts of moisture index and precipitation of previous months).

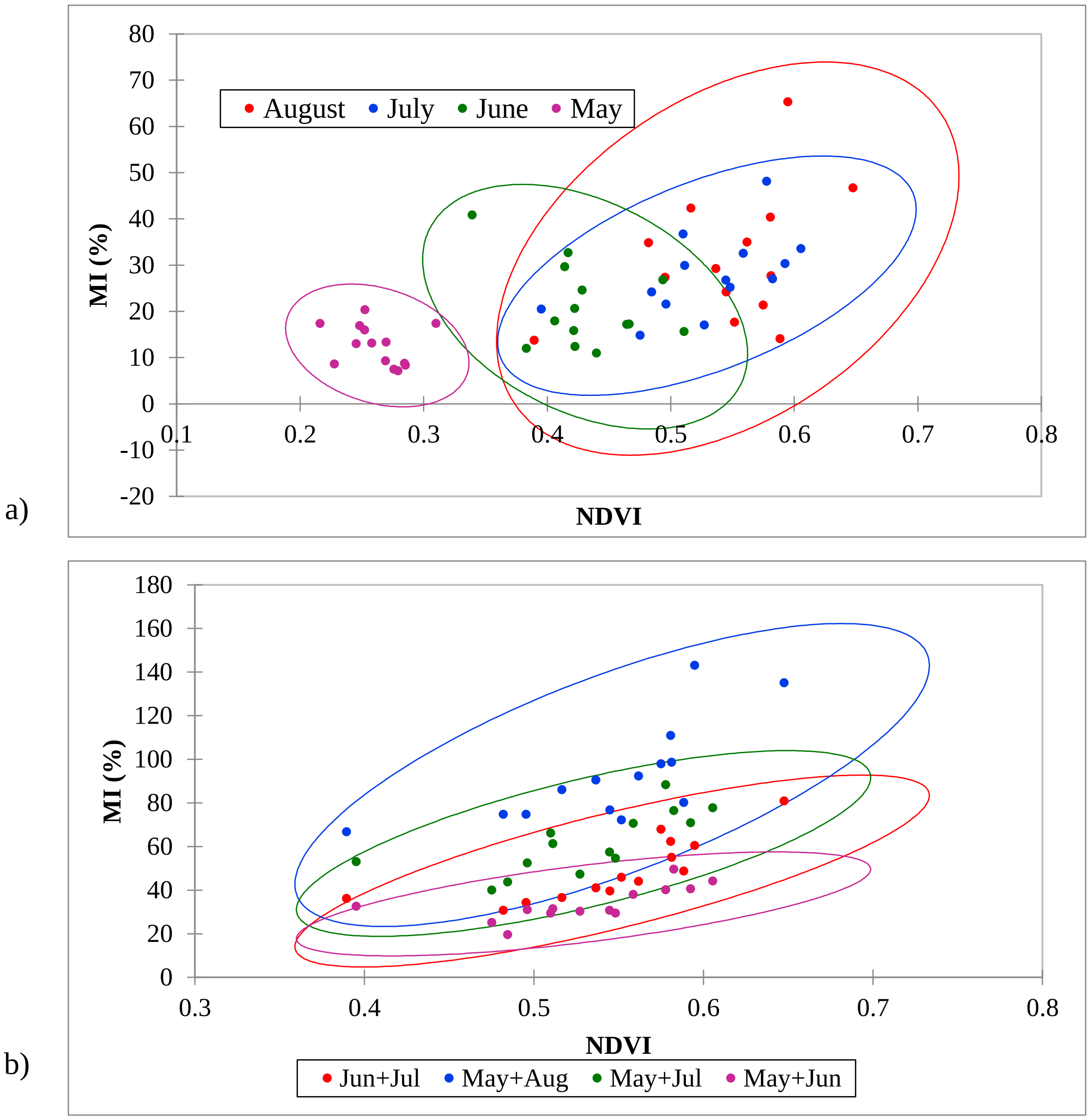


Figure 2—8. Scatter plots between the NDVI and estimated MI a) for each month; b) the correlation coefficients between the highest month of the NDVI (July and August) and the MI amount from May to August

2.6 Results and discussion

The research output provides the monthly moisture contents (MI), which comprise useful resource data on drought monitoring, irrigation, dust and pasture land degradation. The northern part of Mongolia has a high soil moisture due to the precipitation (400 mm) and snow water from the high mountains, while the southern part of Mongolia shows a low soil moisture (due to the precipitation of 100 mm) (Nandintsetseg and Shinoda 2014). The spatial moisture maps demonstrate a significant increasing trend for the growing season from 2000 to 2013 (Figure 2—9).

Though significant dust events occur every spring, limited research work has been carried out yet on the dust storm sources in southern Mongolia and northern China. The distribution of the number of dust storm days mainly happens in the south Gobi region, which borders China. The number of annual days with dust storms is less than five days in central and northern Khangai, Khuvsgul and the Khentei mountainous areas of Mongolia, 10-17 days in the western region of the Great Lakes, and 20-37 days for the desert and semi-desert areas of Mongolia (Tsolmon, Ochirkhuyag, and Sternberg 2008). The moisture map could be considered as one of the main factors defining a dust storm. As the Mongolian grassland has been gradually decreasing (Hilker et al. 2014), drought has nevertheless been rising (Sternberg 2018). Our research on the MI is an essential factor to monitor the land degradation and droughts.

This study demonstrates a correlation between the estimated MI and SM from the climate stations (also with the NDVI). In comparison, it is indicating a relationship between the NDVI and the precipitation/temperature from the climatic stations. From Figure 2—3a and Figure 2—3b, one could deduct a correlation between the estimated MI and SM (from the stations each month), which shows different results such as the correlation of the dry months (May-June) which was low and a high correlation of the wet months (July-August). This analysis confirms that in the arid region, the soil moisture deficit is mainly attributed to the limited precipitation and even a small increase in the total precipitation has substantial effects on the soil moisture (Y. Wang et al. 2018). The NDVI is significantly related to the precipitation and temperature (Figure 2—7). From the results, one could see that the vegetation growths inversely correlated with the MI and the precipitation in the dry months (and strongly correlated in the arid region during the wet months).

The long-term MI was rated by means of the monthly PET and mean precipitation through the growing season (May-August) for the period 2000 - 2013. The highest soil moisture amounted to 65.3 % in 2013 and the lowest moisture was 7.11 % in 2000.

Figure 2—9 represents the mean MI from May to August during 2000-2013. For August, the mean MI was estimated the highest at 31.4 %, while the latter demonstrated the lowest amount (12.6 %) in May. From the results, one observed that the results of the driest (2000/2002/2004/2007) years matched with the research of Nandintsetseg and Shinoda (2011).

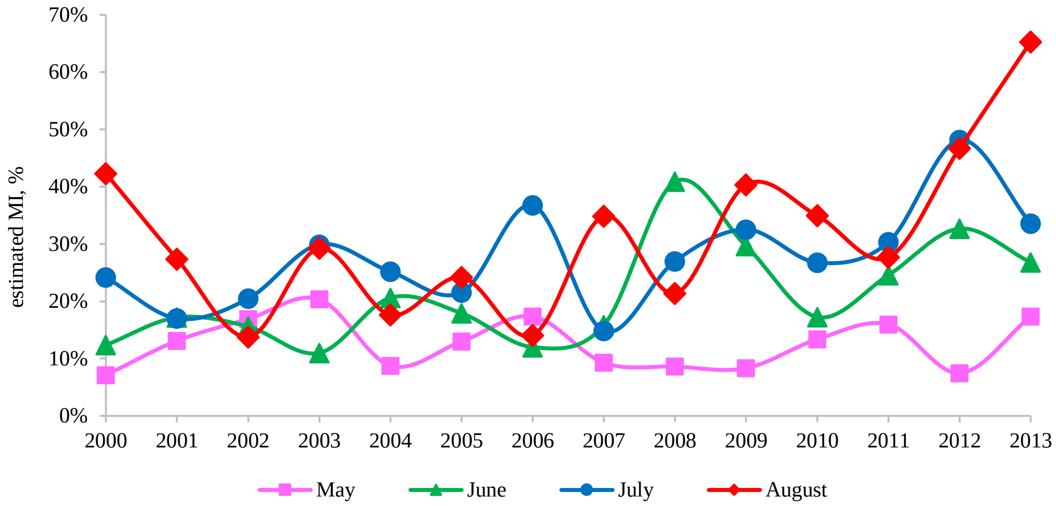


Figure 2—9. The long-term MI (%) for the growing season during 2000-2013 (May-August)

The advantage of this study is that it proves useful to monitor various environmental issues. The national policy-makers will be able to utilize this information in order to create suitable agricultural areas. The long-term satellite-derived and climatic data were acquired for the period of May-August 2000-2013. The SM measurements from the climate stations (at different depths) were employed for the validation of the estimated MI. Then, one rated the relation between the estimated MI and NDVI during the study period.

2.7 Conclusion

The moisture index was developed for the northern central part of Mongolia, based on the PET from MODIS and the interpolated precipitation from the climate stations during the growing season of May-August, 2000-2013, which were combined by the *in-situ* and satellite data. Furthermore, the 14-year spring/summer data on the temperature, precipitation and soil moisture of the climate stations (from 38 climate stations) have been analyzed for each month during the growing season (May-August). The SM could reflect the precipitation, evapotranspiration, infiltration and runoff. It functions as a strong check-up on the water portioning between the atmosphere and surface (E. Natsagdorj et al. 2017). From the MI estimation, one could deduct a high moisture in 2012 and 2013 and a rather low amount during 2000, 2002 and 2007. The results proved that the estimated MI and SM measurements from the climate stations correlated positively, while the estimated MI and NDVI connected well.

While comparing the estimated MI with the SM from the climate stations (at different depths), positive correlations in the study area could be noticed during the growing season (2000-2013). For the depth of 0-10 cm, the correlation between the estimated MI and the soil moisture from the climate stations was 0.58 (Figure 2—3a) and for the depth of 0-50 cm, the correlation measured 0.38 (Figure 2—3b). It was statistically significant at both depths ($p < 0.001$) and ($p < 0.01$), respectively. A good relation is visible between the NDVI and estimated MI regarding the growing season of 2000-2013 (Figure 2—8). From the results, one could conclude that the moisture contents from previous months are strongly affecting the vegetation growth of the next months. This fact proved evidence of the correlation between the MI amount (May to July) and the highest month in the NDVI, meaning that the previous month's moisture contents affected the vegetation growth of the following month. However, the moisture index could not express enough SM and it is more suitable for drought monitoring and water balance studies.

This research methodology is suitable for use in the agricultural regions and practical applications of droughts and desertification monitoring in Mongolia. The work of Hadeel, Jabbar, and Chen (2011) also demonstrates similar results on the detection of environmental degradation indicators. The long-term MI data will provide valuable information for the decision-makers and farmers concerning their further actions. A satellite and climatic data approach is useful for the policy-makers so as to develop suitable agricultural regions (Guoxin, Shibasaki, and Matsumura 2004) and (Anderson, Reynolds, and Gugerty 2017). The disadvantage of this research included that the data were obtained from the spring-summer season (slightly lacking inaccurate results). Therefore, further research will being describe separate seasons (spring and summer). Further research will deal with the moisture data, which have already proven to be a good data source for the agricultural management, planning and drought monitoring.

CHAPTER 3

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

Modified from: Enkhjargal Natsagdorj, Tsolmon Renchin, Martin Kappas, Batchuluun Tseveen, Chimgee Dari, Oyunbileg Tsend and Ulam-Orgikh Duger (2017). An integrated methodology for soil moisture analysis using multispectral data in Mongolia. Geo-spatial Information Science. 20(1), 46-55 dio:10.1080/10095020.2017.1307666.

3.1 Introduction

The soil moisture (SM) represents a significant environmental indicator controlling and regulating the interaction between the atmosphere and the land surface (D. Zhang et al. 2015). Besides, it is sensitive to climate change (Delworth, Manabe, and Stouffer 1993). Furthermore, the SM regulates the ratio of the runoff and infiltration and controls significant energy fluxes (Vivoni et al. 2007). Moreover, the SM also plays an essential role in the plant productivity and has a direct influence on the crop productivity (Saha et al. 2018). The SM distribution in the landscape (both spatial and temporal) is therefore a crucial variable for the climate system modeling. It embodies one of the most critical environmental variables concerning the land surface climatology, hydrology and ecology. Given the importance of the SM, its spatial and temporal assessment is difficult.

The soil moisture affects the natural vegetation and increases agricultural production (Hillel 1998). However, many factors have an impact on the soil moisture, which namely the temperature, precipitation, evapotranspiration, soil types, texture, topographical conditions and vegetation (van den Hurk et al. 2012; Subin et al. 2013). Different soil characteristics might lead to soil moisture heterogeneity (Ismail 1991). The topographical conditions' effect on the soil moisture is determined by the runoff and infiltration (Liu et al. 2019), and the vegetation cover could display the soil moisture balance (T. Yang et al. 2018). A steeper slope facilitates a more significant run–off and a lower residence time for rainwater, whereas gentle slopes have a lower run-off, allowing more time for greater soil infiltration by the rainwater (Lamchin et al. 2017). Many soil studies only used the index, wetness index and point measurements from the station. For example, Mohamed and Kimura (2014) employed the normalized day-night surface temperature difference index (NTDI) with a moisture availability (m_a) from the Mongolian Steppe during the growing season, and it showed a significant inverse exponential correlation with m_a. This result indicates that the NTDI is useful as a surrogate of the moisture availability in the steppe fields of central Asia. Cornick, Djebbar, and Alan Dalgliesh (2003) developed the approach and compared the results with other methods (of selecting the moisture reference years) for hydrothermal simulation. These utilized the climate stations' data for their model (Cornick, Djebbar, and Alan Dalgliesh 2003; Attorre et al. 2007). The latter determined the moisture index using the precipitation and potential evapotranspiration. The moisture index, related to the potential amount of available precipitation, was the most important factor explaining the distribution of the Dracaena Cinnabari. The information on climate change and SM from a special sensor microwave/imager (SSM/I) was used for the African continent (Lu et al. 2013). They concluded that such information is useful in a climate change study but it is at a point scale and also only available at limited locations. The standard procedure for the SM assessment calibrations (against all other SM-methods) includes the gravimetric method from the soil probes in the field. This standard procedure is typically a point measurement. Because of the local scale variations in the soil properties, terrain (slope, exposition) and vegetation cover, the derivation of representative SM-distributions at the field sites is very difficult. Furthermore, the field methods are labour intensive, expensive and sometimes hard to manage in the Mongolian landscape. The most accurate method to estimate the SM is gravimetric sampling, as already mentioned above. The soil sample from the field should be measured immediately by putting the sample for 24 to 48 h in drying in an oven at 105 °C in order to measure the mass of the dry soil.

Further soil bulk densities are required to convert the gravimetric sampling (water mass per soil mass) into volumetric values (water volume per soil volume). A comprehensive review of various SMC methods is suggested (Verstraeten, Veroustraete, and Feyen 2008). In contrast with previous remote sensing (RS) techniques (which are combined with additional GIS data) that are effective because of their spatially aggregated data assessments. By nature, the SM is a very heterogeneous variable, and it varies (on a small scale) in soil properties and drainage patterns. Therefore, information on the soil types, soil properties and terrains is essential. The satellite images cover relative large scale areas but in order to examine soil moisture that the presence of vegetation adding complexity to the interpretation.

Remote sensing and GIS provide excellent tools to monitor the suitability for the development of agricultural land in Mongolia (Ghar et al. 2005). In particular, the soil moisture monitoring and mapping studies constituted efforts of large scale modeling at the required spatial and temporal scales in the active microwave remote sensing (Schmugge et al. 1974; Engman 1991; Jeu et al. 2008; Kolassa, Reichle, and Draper 2017). Understanding the spatial and temporal variability of the moisture patterns is critically important for the food security in Mongolia and other regions in central Asia. For this reason, it is essential to investigate the SM and other suitable drivers for the development of agricultural lands in Mongolia. This chapter focused on the establishment of a model (for the SM estimation) using optical satellites and ground truth data for the kastanozem soils (the kastanozem soil is the common soil type in Mongolia).

Kastanozem accommodates dry grassland soils, among the lands' short-grass steppe belt, located south of the Eurasian tall-grass steppe belt with Chernozem. The Kastanozem soils are potentially fertile soils; a periodic lack of soil moisture is the main obstacle for high yields. Small grains, irrigated food and vegetable crops are the principal crops grown (FAO of the United Nations 2015). The Kastanozem soil is widely distributed, which occupies half of the Mongolian territory (Avaadorj and Baasandorj 2003). However, the kastanozem soils experience problems due to wind and water erosion, especially on the fallow lands (FAO of the United Nations 2015). The Bornuur soum is one of the leading agricultural regions in Mongolia. Soum's economy is directly dependent on its agricultural production (Hugjliin Ezed NGO 2008). In this chapter, we will develop the soil moisture index, and we aim to specify the different factors related to the soil moisture. As mentioned above, we selected the kastanozem soil of Bornuur soum in this chapter, which is the ordinary soil type in Mongolia. Determining the soil moisture in the agricultural areas often takes time and money, especially in the cropland regions. Therefore, the estimation of SM using RS techniques is saving time and money. Recent soil moisture studies could be identified from the optical remote sensing techniques in a high spatial resolution such as the Landsat TM/ETM/OLI, Moderate-resolution Imaging Spectroradiometer (MODIS) images.

Many researchers have studied the soil moisture mapping by the interaction between the land surface temperature (LST) and the vegetation index (VI). In other hands, the topographic data have been applied for flood study and soil erosion in order to estimate the SM conditions (Murphy, Ogilvie, and Arp 2009; Mason et al. 2016). Besides, the drought studies (based on the vegetation index) are the opposite research of the soil moisture studies, which means that the soil moisture plays a main role in the drought monitoring. The soil moisture conditions from the vegetation changes might be indicated by the vegetation indicator methods. However, these methods only consider the fact that the water stress is leading to reductions in the NDVI and do not account for other factors such as changes in temperature and precipitation (D. Zhang and Zhou 2016). The LST and VI demonstrate extensive information (visible to thermal infrared sensors) that could reflect on the soil moisture conditions (F. Zhang et al. 2014). To the best of our knowledge, no multiple factors (satellite-based) have been carried out already.

Furthermore, various factors are relevant to research concerning the soil moisture such as the vegetation, land surface temperature, elevation, slope and aspects that have an effect on the soil moisture. In previous studies, multiple regression analyses have not been applied for the soil moisture estimation. The innovative part of our research aims to consider the elevation slope and the aspects with other environmental drivers in forested mountainous and agricultural areas for the soil moisture estimation. The elevation, slope and aspects were applied for this methodology (which have not been considered yet in previous studies). Hence it is essential to continue further research in the agricultural region. Mongolia needs the satellite image processing for SM monitoring. It will be useful for agriculture and pasturelands. This chapter explains that it is important to consider the elevation, slope and aspects for the SM in the mountainous regions. In this chapter, we will select the factors that affect the soil moisture and develop the predicted soil moisture index in the kastanozem soils and then to make a validation to the accurately developed model with satellite images and field measurements.

3.2 Study area

The study area is Bornuur soum from the central agricultural region in the Tuv province (48° - 49° E and 106° - 106° 40’ N) and is located in the forest-steppe zone. It is one of the best areas of Mongolia for growing irrigated vegetables, grain and forage crops, sunflower, oats and corn (Douglas et al. 2004).

Four types of soils (cambisols, gleysols, kastanozems and leptosols) are dominant in Bornuur soum (Dorjgotov 2003). The kastanozem soil has been chosen in this study (Figure 3—1). The Mongolian horizontal zone is clearly represented in the central (comparatively plain) part of Mongolia, in which the area of kastanozem soils is divided into three subzones: dark kastanozem, kastanozem and light kastanozem (Dorjgotov 2003). The Kastanozem soil is widely distributed, occupying 50 % of the kastanozem soils of the total area in Mongolia (Avaadorj and Baasandorj 2003) (Figure 3—1). The Mongolian chernozem is unsuitable for cultivation as opposed to the kastanozem. Most of the cultivated areas are occupied kastanozem soils in Mongolia (Bazarradnaa 2018). The study area has only one meteorological station (Bornuur station) in the center of soum. The Bornuur station collects the precipitation, air temperature and soil moisture.

The annual rainfall amounts to 250-350 mm. The minimum air temperature in January measures -30 °C, the maximum air temperature in July is +35 °C, and the average temperature is 15-20 °C (L. Natsagdorj and Batima 2003). The elevation of the study area is located 872-1,821 meter above sea level. The thematic soil map was modified from the Mongolian soil map of the Institute of Geo-ecology (IGG), the Mongolian Academy of Sciences (MAS)[1] based on the soil classification of the Food and Agricultural Organization (FAO) (Ochirbat 2015) (Figure 3—1). The kastanozem soils from the study area were investigated in view of the soil moisture analysis.

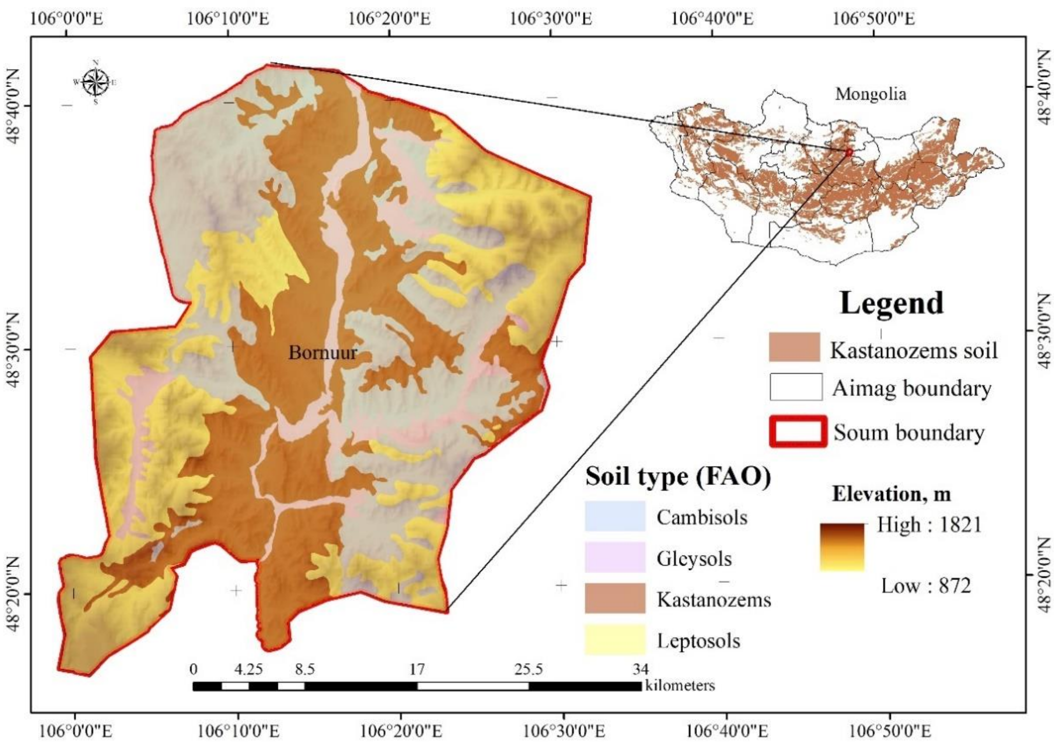


Figure 3—1. The geographical location of the study area. (Bornuur soum, Tuv province, Mongolia); (source: soil map was modified from the soil map of Mongolia of the IGG, MAS)

3.3 Datasets

3.3.1 Remote sensing data

Many approaches have been developed by the relation between the surface temperature and the vegetation cover (Y. Zeng, Feng, and Xiang 2004; Hosseini and Saradjian 2011; F. Zhang et al. 2014; T. Yang et al. 2018). In this chapter, the Landsat and ASTER satellite images were combined for the enhancement of the soil moisture modeling.

[1] Institute of Geo-ecology, MAS (http://geo-eco.mn/)

Landsat ETM+ & OLI8 satellite data

The Landsat 7 enhanced the thematic mapper (ETM) image (September 19, 2011, path 132, row 26), the Landsat 8 operational land imager (OLI) and the thermal infrared sensor (TIRS) images (July 4 and August 21, 2015) downloaded from the USGS earth resource observation and science (EROS) center website and applied it for this chapter. The Landsat ETM+ has a strip. We used the Landsat gap-fill method so as to remove the strips (http://glovis.usgs.gov/).

Table 3—1. Landsat ETM and OLI&TIRS spectral bands [2]

Landsat – 7 ETM+ Bands (µm)			Landsat – 8 OLI & TIRS Bands (µm)		
			30 m Coastal/Aerosol	0.435-0.451	I band
I band	30 m, Blue	0.441-0.514	30 m Blue	0.452-0.512	II band
II band	30 m Green	0.519-0.601	30 m Green	0.533-0.590	III band
III band	30 m Red	0.631-0.692	30 m Red	0.636-0.673	IV band
IV band	30 m NIR	0.772-0.898	30 m NIR	0.851-0.879	V band
V band	30 m SWIR	1.547-1.749	30 m SWIR	1.566-1.651	VI band
VI band	60 m TIR	10.31-12.36	100 m TIR	10.60-11.19	X band
			100 m TIR	11.50-12.51	XI band
VII band	30 m SWIR	2.064-2.345	30 m SWIR	2.107-2.294	VII band
VIII band	15 m Panchromatic	0.515-0.896	15 m Panchromatic	0.503-0.676	VIII band
			30 m Cirrus	1.363-1.384	IX band

The Landsat Enhanced Thematic Mapper Plus (ETM+) sensor is carried on the Landsat 7 platform. The images consist of seven spectral bands with a spatial resolution of 30 meters for the Bands 1-5 and 7. The resolution of Band 8 (panchromatic) measures 15 meters. All bands could collect one of two gain settings (low or high) for the increased radiometric sensitivity and dynamic range, while Band 6 receives both the low and high gain (Bands 61 and 62, respectively) for all scenes. The approximate scene size is 170 km north-south by 183 km east-west (106 mi by 114 mi). The Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) images consist of 9 spectral bands with a spatial resolution of 30 meters for the Bands 1 to 7 and 9. The ultra-blue Band 1 is useful for the coastal and aerosol studies. Band 9 is useful for the cirrus cloud

[2] Source: http://landsat.usgs.gov/band_designations_landsat_satellites.php

detection. The resolution for Band 8 (panchromatic) is 15 meter. The thermal bands 10 and 11 are handy to provide more accurate surface temperatures and are collected at 100 m. The approximate scene size is 170 km north-south by 183 km east-west (106 mi by 114 mi)^2 (Table 3—1) (U.S. Geological Survey 2018).

Additionally, in order to improve the satellite imagery and the impact of the atmospheric effects, we made an atmospheric correction to estimate the actual surface reflectance of each band. In this chapter, we applied visible blue, near-infrared and thermal bands of the Landsat images.

ASTER satellite data

We applied the advanced spaceborne thermal emission and reflection radiometer (ASTER) satellite, global digital elevation model (GDEM) data with a 30 meter resolution in order to develop the elevation, aspects and slope. The ASTER GDEM covers the land surface between 83 °N and 83 °S and is composed of 22,600 1°-by-1° tile. The ASTER GDEM is shaped into a GeoTIFF format with geographic lat/long coordinates and a one arc-second (30 m) grid of elevation postings. It is referenced to the WGS 84/EGM 96 geoids. The pre-production estimated accuracies for this global product amounted to 20 m with a 95 % confidence for the vertical data and 30 meters (95 % confidence) for the horizontal data (http://gdem.ersdac.jspacesystems.or.jp/).

3.3.2 Ground truth data and meteorological data

The SM data were collected during the field trips in Bornuur, a Tuv province using the traditional method. We took soil samples from a 0-50 cm depth (September 2011 and July-August, 2015) (Table 3—2), (Figure 3—1, all the corresponding soil types are kastanozem). The traditional method was developed as follows. Firstly, we collected the soil sample data and found out its weight. The next step was to dry the soil. The traditional methods allowed us to measure the moisture amount by means of dried soil samples (Equation (1-1)). Detailed information is provided in section 1.2.1.

There is only one meteorological station which is named Bornuur (48°31’33” E, 106°11’45” N). In this chapter, we applied the soil moisture from the station data for a comparison with the developed SM model and the ground truth measurements. The soil moisture has been obtained at the Bornuur station in 2001. The soil moisture contents (by gravimetric techniques) were acquired at a 0-20 cm depth (in a monthly interval) from July to September (2010-2015). However, the meteorological station did not receive complete data as some information contained errors (and a lack of data) due to particular technical requirements and conditions.

Table 3—2. Ground truth measurements (September 19-20, 2011)

№	Latitude	Longitude	Acquired (MM/DD/YEAR)	SM (%)	SM (mm)
1	48° 37' 43.68"	106° 9' 11.88"	9/20/2011	7.63	9.474
2	48° 37' 45.12"	106° 9' 14.76"	9/20/2011	10.302	8.609
3	48° 37' 46.56"	106° 9' 16.92"	9/20/2011	7.974	9.238
4	48° 36' 52.56"	106° 6' 52.56"	9/20/2011	6.494	8.446
5	48° 36' 50.4"	106° 6' 50.4"	9/20/2011	6.517	10.313
6	48° 36' 52.56"	106° 6' 47.16"	9/20/2011	5.49	7.651
7	48° 40' 49.08"	106° 16' 23.52"	9/19/2011	7.817	7.947
8	48° 40' 49.8"	106° 16' 28.56"	9/19/2011	7.199	10.103
9	48° 40' 50.16"	106° 16' 32.88"	9/19/2011	9.388	11.635
10	48° 40' 44.4"	106° 16' 24.6"	9/19/2011	8.84	12.275
11	48° 40' 45.48"	106° 16' 28.92"	9/19/2011	8.227	10.841
12	48° 40' 45.84"	106° 16' 31.08"	9/19/2011	8.651	9.084
13	48° 37' 43.79"	106° 9' 11.99"	9/19/2011	8.987	11.48
14	48° 37' 45.3"	106° 9' 14.62"	9/19/2011	9.656	12.26
15	48° 37' 46.7"	106° 9' 16.99"	9/19/2011	11.092	14.01
16	48° 36' 52.7"	106° 6' 52.2"	9/19/2011	7.966	12.11
17	48° 36' 54.9"	106° 6' 50.4"	9/19/2011	6.737	13.57
18	48° 36' 52.6"	106° 6' 47.3"	9/19/2011	7.558	11.75
19	48° 40' 20.28"	106° 15' 22.14"	9/19/2011	8.222	10.50
20	48° 40' 19.85"	106° 15' 19.22"	9/19/2011	8.845	11.23
21	48° 40' 19.09"	106° 15' 16.7"	9/19/2011	8.022	10.50
22	48° 40' 21.54"	106° 15' 37.51"	9/19/2011	7.848	9.87
23	48° 40' 22.8"	106° 15' 41.87"	9/19/2011	9.706	12.34
24	48° 40' 23.27"	106° 15' 44.17"	9/19/2011	9.380	12.09
25	48° 40' 39.72"	106° 15' 31.43"	9/19/2011	14.108	7.49
26	48° 40' 41.2"	106° 15' 35.82"	9/19/2011	9.829	12.54
27	48° 40' 42.35"	106° 16' 0.84"	9/19/2011	13.112	14.54
28	48° 40' 49.12"	106° 16' 23.77"	9/19/2011	7.676	9.63
29	48° 40' 49.15"	106° 16' 28.63"	9/19/2011	10.871	15.09
30	48° 40' 50.77"	106° 16' 33.24"	9/19/2011	7.475	17.44

31	48° 40' 44.51"	106° 16' 24.96"	9/19/2011	5.819	11.44
32	48° 40' 45.26"	106° 16' 28.7"	9/19/2011	6.960	10.85
33	48° 40' 45.84"	106° 16' 31.15"	9/19/2011	8.232	13.57

3.4 Methodology

3.4.1 Integration method for the soil moisture analysis

The equation (3-1) is used as an atmospheric correction for the images in this research (Chavez 1996). The atmospheric correction has been applied for the Landsat images in order to remove the effects of the atmosphere on the reflectance values of images. The atmospheric effects in optical remote sensing are essential and complex, dramatically changing the spectral nature of the radiation reaching the remote sensor (Liang, Li, and Wang 2012).

$$REF = \frac{\pi \cdot (Lsat - Lhaze)}{TAUv \cdot (Eo \cdot \mathrm{Cos}(TZ) \cdot TAUz + Edown)} \qquad (3\text{-}1)$$

, where *REF* represents the spectral reflectance of the surface;
Lsat the satellite spectral radiance for the given spectral bands;
Lhaze demonstrates the upwelling spectral radiance (path radiance), the value derived from the image using dark-object criteria; calculated by using the dark object criteria (the lowest value at the basis of the histogram slope from either the blue or green band);
TAUv shows the atmospheric transmission along the path from the ground to the sensor, assumed to be 1 because of the nadir look angle;
Eo is the solar spectral irradiance; *TZ* the solar zenith angle;
TAUz stands for the atmospheric transmission along the path from the sun to the ground surface;
Edown illustrates the down-welling spectral irradiance in the atmosphere (Chavez 1996). The method scheme is shown in Figure 3—2.
The moisture index (MI) was calculated using the Landsat ETM+ bands (1 and 4) and Landsat 8 OLI/TIRS bands (2 and 5) (Dupigny-Giroux and Lewis 1999). The equation (3-2) for the study area in the kastanozem soil is calculated as (Figure 3—3 a):

$$MI = \frac{NIR}{VisBlue} \qquad (3\text{-}2)$$

, where *NIR* is the near-infrared channel (0.772 ~ 0.898 μm) and (0.851 ~ 0.879 μm); *VisBlue* represents the visible blue channels (0.441 ~ 0.514μm) and (0.452-0.512 μm).

The MI values are identified between 0 to 2.44 during September 2011, of which close to zero represents the bare and dry soil (and high values indicate more moisture). The MI values could be classified as higher than 2.44 (Dupigny-Giroux and Lewis 1999).

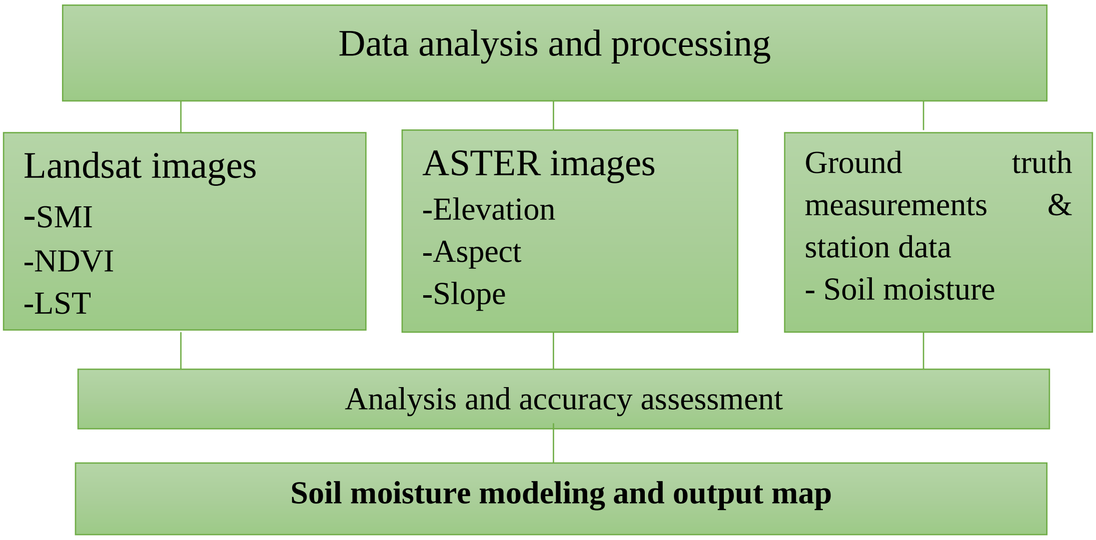


Figure 3—2. Method scheme

The red (*RED*) and *NIR* channels from the ETM were applied in the equation (3-3) for the NDVI calculation (Compton J. Tucker 1979; C.J Tucker and Sellers 1986b) (Figure 3—3 b):

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{3-3}$$

, where *NIR* is the near-infrared channel (0.772 ~ 0.898 µm) and (0.851 ~ 0.879 µm); *RED* represents the visible red channels (0.631 ~ 0.692 µm) and (0.636 ~ 0.673 µm). The NDVI values are normalized to a range between -1 and 1, of which values over 0.1 display the vegetation and values approaching to one show a highly vegetated area and forests. The negative values indicate water, bare soil, snow or ice surface (C.J Tucker and Sellers 1986). In this chapter, the NDVI values were calculated from -0.37 to 0.56 in September 2011. The LST was calculated using the equation (3-4) by (Weng, Lu, and Schubring 2004) (Figure 3—3c):

$$LST = (BT + w \cdot \frac{BT}{p}) \cdot \ln(e) \tag{3-4}$$

, where *BT* demonstrates the satellite brightness temperature (K);

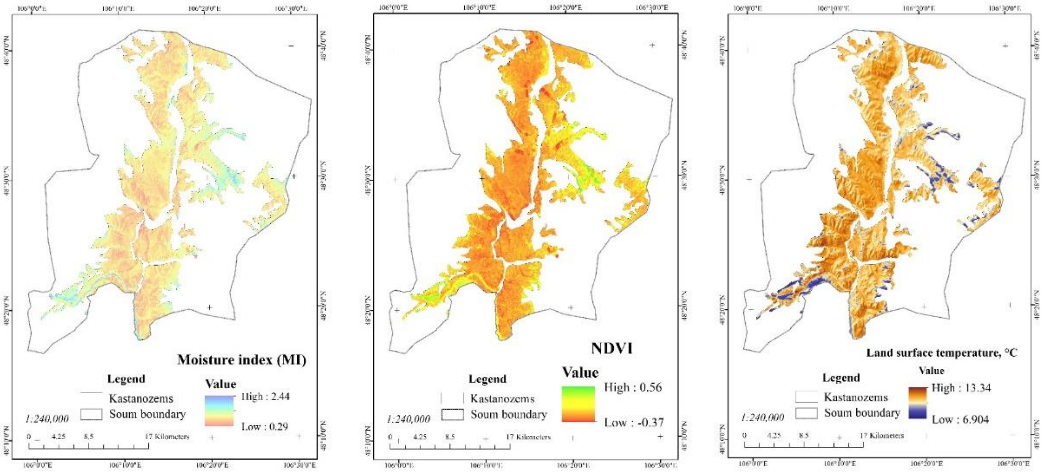
w shows the wavelength of the emitted radiance (11.5µm);

p=h*c/s (1.438*10^–2 m K), *h* illustrates the Plank's constant (6.626*10^–34 Js);

s is the Boltzman constant (1.38*10^–23 J/K),

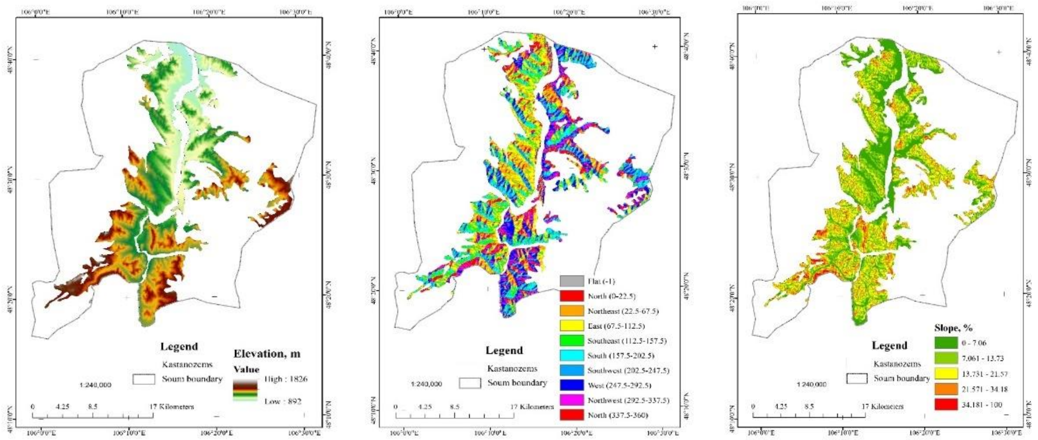
c demonstrates the light's velocity (2.998*10^8m/s);

e=0.004*P_v+0.986; P_v=(NDVI–$NDVI_{min}$/$NDVI_{max}$–$NDVI_{min}$)^2 stands for the vegetation proportion. The LST is estimated from 6.9 to 13.34 °C during September 2011.



a) b) c)

Figure 3—3. a) MI map from Landsat +ETM7; b) NDVI map from Landsat +ETM7; c) LST map from Landsat +ETM7



a) b) c)

Figure 3—4. (a) Elevation map, (b) Aspect, (c) Slope in the Bornuur soum; source: ASTER-SRTM 30 m resolution data.

3.4.2 Multi-regression soil moisture model

For the elevation, aspect and slope we used the ASTER satellite, GDEM data for a 30 m resolution. Figure 3—4 illustrates the elevation, aspect and slope from a 30 m ASTER resolution in the kastanozem soil, Bornuur soum.

In order to develop a model for the SM estimation, we applied the regression analysis. The output from the analysis was compared to the ground truth data.

Every plant needs a different soil moisture amount. A vegetation change could allow changes in the soil infiltration, field capacity and soil moisture effect. The LST indirectly affects the soil moisture through the evapotranspiration, while the soil moisture has an impact on the evapotranspiration (van den Hurk et al. 2012). Higher temperatures will increase the potential evapotranspiration and could possibly result in an increased drought occurrence, although the actual changes will be controlled by the available moisture from the precipitation (Saha et al., 2018). Topographical factors (elevation, aspect and slope) might affect the soil moisture through the infiltration and runoff surface. The southern and western parts of the study area are characterized by rolling hills (exceeding 7 % and some of these reach as high as 34 %). The central and northern parts of the study area are characterized by undulating plains and low slopes (Figure 3—4c).

We assume that the SM has been derived from satellites and that it depends on variables such as the LST, NDVI, elevation, aspect and slope. F represents the function of the dependent variables, as shown in equation (3-5).

$$\text{PSMI=F (NDVI, LST, Elevation, Aspect, Slope)} \qquad (3\text{-}5)$$

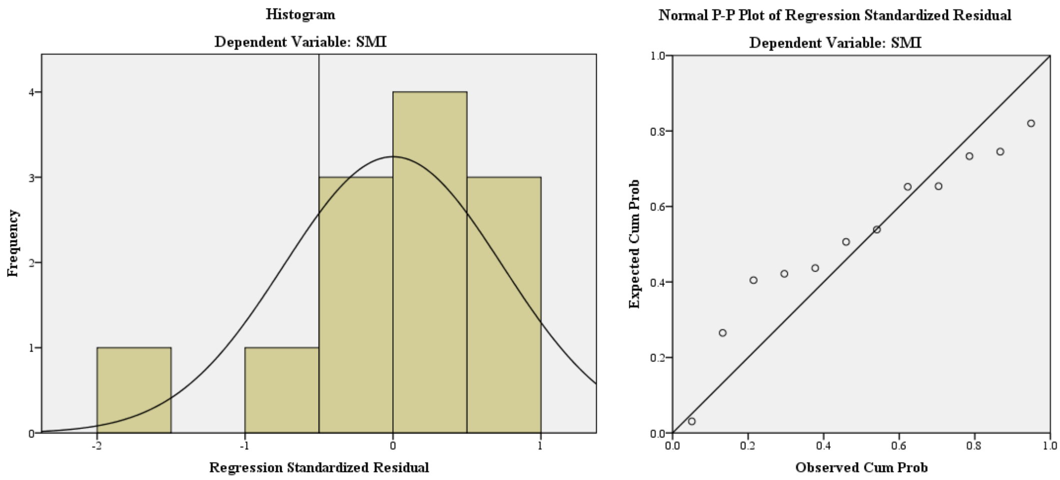
We selected therefore the multivariate regression analysis for this assumption. The multi-dimensional linear regression model could be described as:

$$y_i=\beta_0+\beta_1 x_{i1}+\beta_2 x_{i2}+\beta_3 x_{i3}+\beta_4 x_{i4}+\beta_5 x_{i5} \qquad (3\text{-}6)$$

, where y_i is the observation variable; β_0 the intercept, β_1~β_5 represent the coefficients; x_i stands for the variables.

Firstly, a collinearity test for all variables (NDVI, LST, elevation, aspect and slope) was performed and described in Table 3—3. B is the regression coefficient of the unstandardized coefficients, std.error illustrates the Standard error of the unstandardized coefficients, beta shows the beta coefficient of the standardized coefficients, t demonstrates the t-statistics for the coefficients, sig. stands for the significance of the collinearity. In order to develop the SM model, we utilized multiple regression analyses (Equation 3-6). The variance inflation factor (VIF) values are situated between 1 ~ 10, which shows that there is no multicollinearity for the regression model (Table 3—3). Also, the correlation analysis showed that there are no strong correlations between the independent variables. The (independent) latter include the NDVI, LST, elevation, aspect and slope.

Secondly, the multivariate regression analysis requires normal variables (based on the normality test). Figure 3— 5 presents the histogram of the residuals so as to demonstrate a histogram with a normal overlay of the residuals' distribution. This gives us an indication on whether or not our sample could predict a normal distribution in the soil moisture index. In a normal P-P plot, the distribution is considered to be normal to the extent that the plotted points match with the diagonal line (Figure 3— 5). In this study, all the assumptions of the multiple linear regression analyses are tested and a model was built so as to predict the soil moisture index.



a) **b)**

Figure 3— 5. (a) Histogram and (b) P-P plot for the Normality test.

Based on the assumption (Equation (3-5)), we developed a model to obtain the predicted soil moisture. Equation (3-7) was utilized for the set-up of the predicted SMI (PSMI):

$$PSMI = 0.542 + 1.183 * NDVI + 0.022 * LST - 0.0002 * Elevation - 0.00001 * \mathrm{Aspect} - 0.004 * \mathrm{Slope} \quad (3\text{-}7)$$

Table 3—3. Result of the regression analysis

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	β	Std. Error	β			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 (^{0}C)	0.022	0.004	0.728	5.953	0.001	0.201	4.965
Elevation (m)	-0.0002	0.000	–0.257	–1.647	0.151	0.124	8.097
Aspect (0-360^0)	–0.00001	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

Coefficients*

*: Dependent variable: MI

Model summary: R = 0.99; R^2 = 0.982; Adjusted R^2 = 0.967; Sig. F Change 0.000.

From the model, the PSMI was positively depending on the NDVI and LST, negatively depending on the Elevation, Aspect and Slope. As shown in Table 3—3, the NDVI has the leading role of the model and the LST is less, others are slightly and inversely correlated. However, the model was tested on multicollinearity and multivariate normality. By testing whether or not these assumptions were assured by the data which should use the multiple regression analysis to build a model for the dependent and independent variables under consideration. Normally, the LST should be inversely proportional with the moisture index but our model has shown a positive proportion with the PSMI.

3.5 Results of the analysis

3.5.1 Soil moisture model (PSMI) results

So as to validate the model, we chose 33 samples from Table 3—2, in which the ground truth for SM has been measured. The scatter plot of the PSMI from the model (and the SMI from satellites) is shown in Figure 3—6 with (R^2 = 0.903) determining the kastanozem soil. The ground measurement data were compared with the PSMI from the model (R^2 = 0.65) (Figure 3—7).

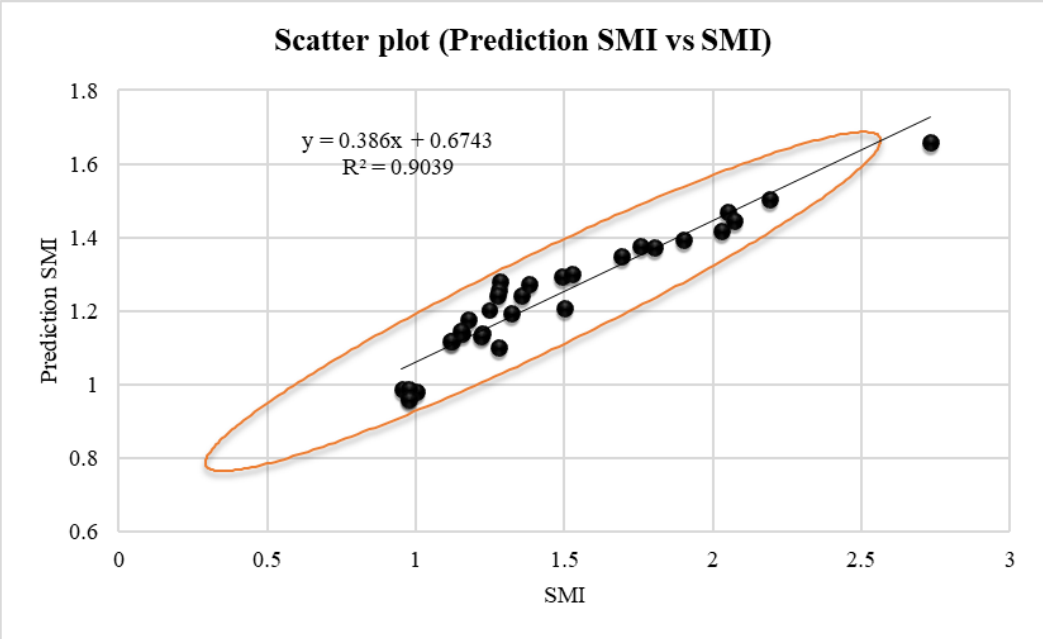


Figure 3—6. Relation of the SMI from the satellites and PSMI.

We applied the equation (3-7) for the estimation of the kastanozem soil in Table 3—4. This output was compared with the ground truth data and showed a positive moisture relation. For the test model, the equation (3-7) was applied to the samples in Bornuur (Table 3—4), and we developed a soil moisture map (Figure 3—8). The results of the PSMI model were compared with the (traditional) SM ground measurement data in the Tuv province ($R^2 = 0.65$).

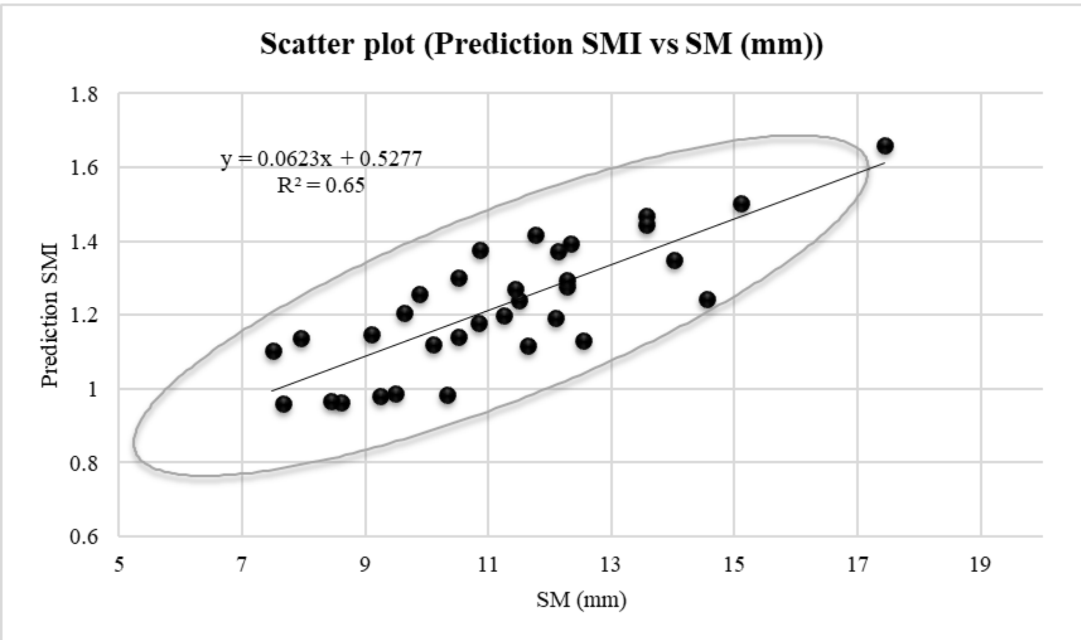


Figure 3—7. Relation of the ground soil moisture measurements and PSMI.

Table 3—4. Kastanozem soil's measurements in Bornuur soum, 2011, September 18-20.

SM ground truth measurements (mm)	SMI from satellites	NDVI	LST (°C)	Elevation (m)	Aspect (0-360^0)	Slope (%)	PSMI
9.474	0.95	0.03	31.19	1,072	285.95	4.77	0.99
8.609	0.97	0.03	29.75	1,070	270.00	2.62	0.97
9.238	1.00	0.04	29.75	1,071	270.00	1.97	0.98
8.446	0.98	0.00	33.08	1,181	288.43	6.22	0.97
10.313	0.98	0.01	33.08	1,188	285.95	4.77	0.99
7.651	0.97	0.01	32.38	1,173	298.61	8.22	0.96
7.947	1.15	–0.01	38.62	900	185.71	6.59	1.14
10.103	1.12	–0.02	37.71	905	185.19	3.62	1.12
11.635	1.12	–0.01	37.71	899	18.43	7.26	1.12
12.275	1.28	0.10	38.39	900	263.66	2.97	1.28
10.841	1.17	0.02	38.62	904	236.31	4.73	1.18
9.084	1.15	0.00	37.94	904	243.43	2.93	1.15
11.48	1.36	0.27	29.92	1,072	175.10	6.71	1.24
12.26	1.49	0.31	29.92	1,070	175.10	4.20	1.30
14.01	1.69	0.38	29.92	1,071	210.06	11.56	1.35
12.11	1.80	0.43	29.98	1,194	55.89	13.56	1.37
13.57	2.05	0.49	29.98	1,188	13.67	7.49	1.47
11.75	2.03	0.45	29.98	1,173	58.40	11.61	1.42
10.50	1.52	0.29	29.75	934	130.03	5.27	1.30
11.23	1.25	0.16	33.08	935	147.70	9.43	1.20
10.50	1.22	0.10	33.08	936	147.30	6.31	1.14
9.87	1.28	0.20	32.38	930	73.30	3.56	1.26
12.34	1.90	0.20	38.62	927	161.60	1.43	1.40
12.09	1.32	0.18	29.92	930	158.90	0.00	1.20
7.49	1.28	0.13	29.98	912	145.50	9.48	1.10
12.54	1.22	0.14	29.98	918	171.50	3.54	1.13
14.54	1.27	0.23	29.98	919	185.90	3.35	1.24
9.63	1.50	0.28	29.75	900	63.43	27.57	1.21
15.09	2.19	0.50	29.75	905	210.97	16.55	1.50

17.44	2.73	0.60	29.75	899	177.88	8.58	1.66
11.44	1.38	0.21	33.08	905	24.77	8.07	1.27
10.85	1.76	0.36	29.92	904	10.01	9.48	1.38
13.57	2.07	0.46	29.98	904	8.13	21.56	1.45

In previous studies, the soil moisture index values have been studied in many ways. For example, Carrão et al. (2016) have classified the SMI value in the following way (e.g. lower than -1.0 means dry and extremely dry; -1.0 to 1.0 nearly normal; 1 to 1.5 moderately wet; 1.5 to 2.0 severely wet and higher than 2.0 extremely wet). Additionally, Hunt et al. (2009) and Haider and Adnan (2014) have studied the soil moisture index and the aridity index. In their study, the moisture index values have been examined in the wettest area and showed figures higher than one (and for the dry area lower than one), especially in the arid and semi-arid region.

In this chapter, the PSMI values have estimated a range from 0 to exceeding 5. This signifies the following: 0 to 1 indicate the dry area; 1 to 1.5 values demonstrate moderate soil moisture and higher than 1.5 indicates high soil moisture, as explained in Figure 3—8. For further analysis, the PSMI was applied for the same study area during July and August 2015. Then, the results will be compared to the ground truth measurements and the meteorological stations.

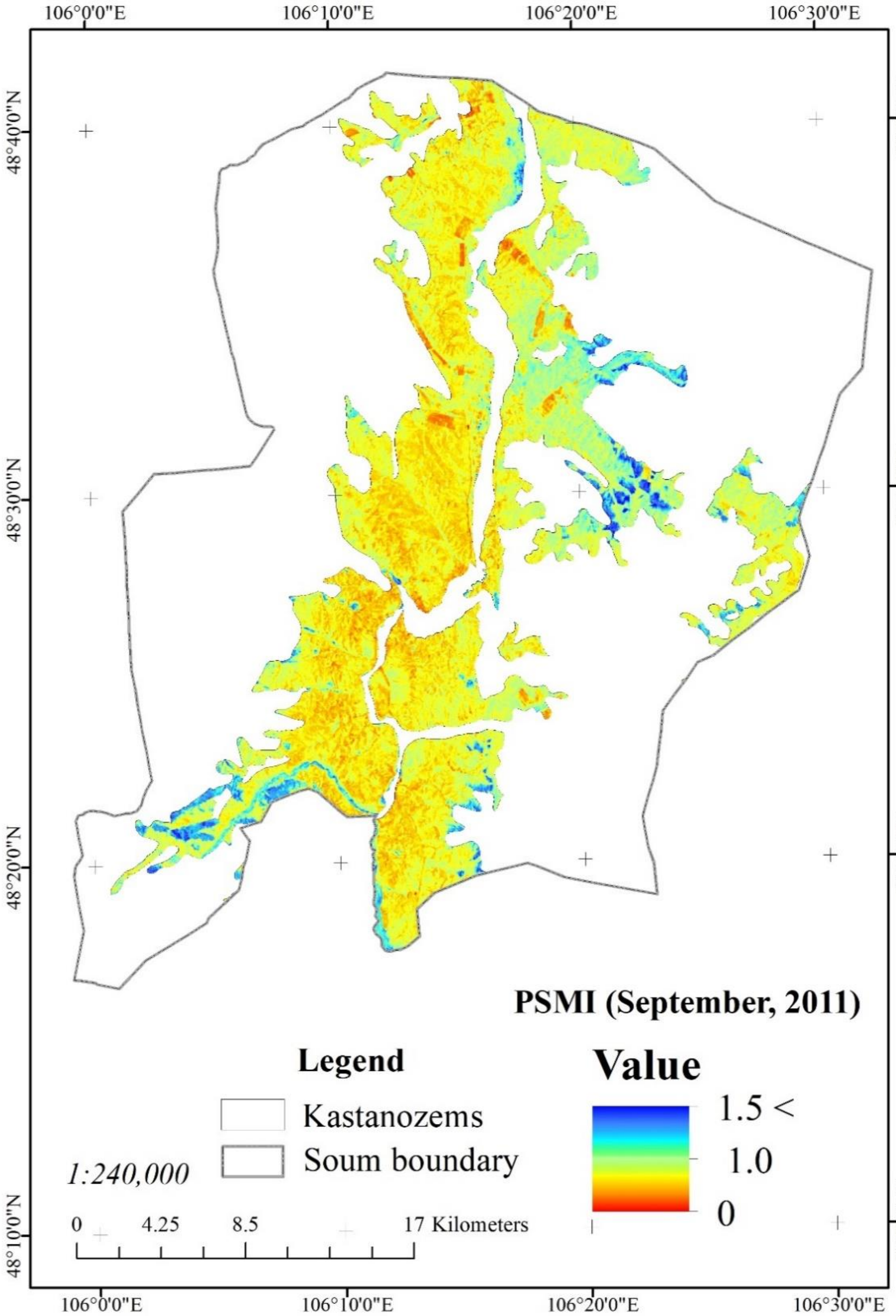


Figure 3—8. Soil moisture map from the model on the kastanozem soil in September 2011.

The output map concerning the kastanozem soil modeling is shown in Figure 3—8. The maximum value of the PSMI data is 1.56, the minimum amounts to 0.0. We divided the PSMI into 3 classes, which are low (0.0 ~ 1.0), moderate (1.1 ~ 1.5) and high (1.6 ~

high). Also, we classified the ground truth measurements into three similar classes (low, moderate and high). We randomly overlaid our ground truth points on the map and made a validation. In Table 3—5, we presented the matrix evaluation for the validation. The PSMI results were compared with the ground truth measurements (Table 3—5). The PSMI results have been compared with the SM distribution model Erdenetsetseg (1996). The correlation coefficients respectively amounted to 69 % and 66 %. We also compared the predicted soil moisture index (PSMI) with the estimated MI (previous chapter, developed by Natsagdorj et al., 2018) from this study and noticed a good relation (r = 0.77).

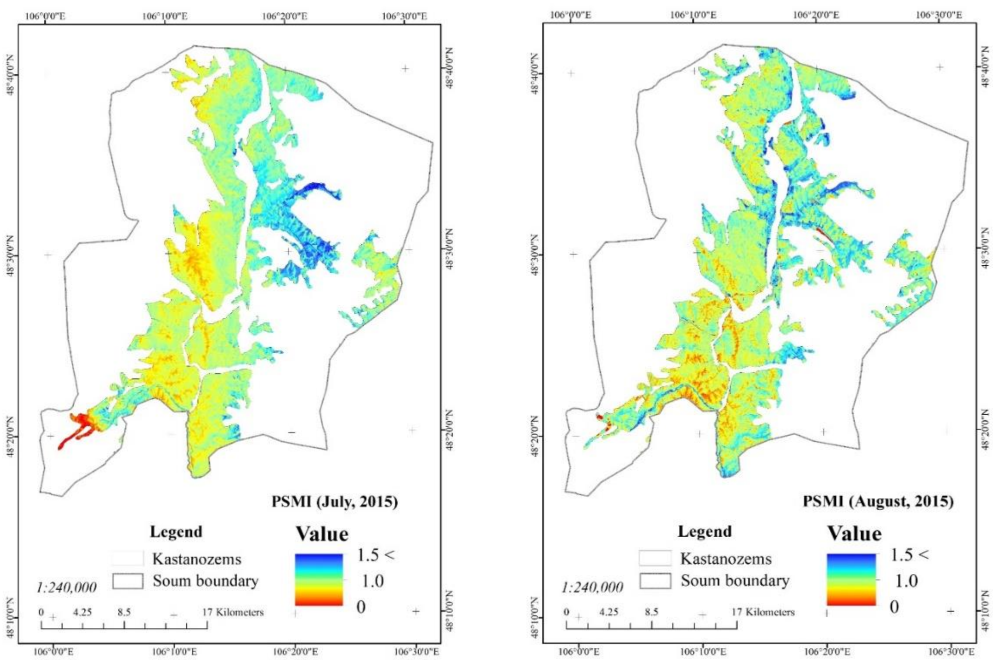
The positive results (Figure 3—6 and Figure 3—7) should be investigated further and need a more detailed analysis of the high-resolution satellite data.

Table 3—5. Comparison of the developed model and ground measurements.

		Classes derived from the satellite data			
		0~1.0	1.0~1.5	1.5 <	Total
Grand observed classes	Low	5	2	0	7
	Moderate	4	16	3	23
	High	0	1	2	3
	Total	9	19	5	33
Accuracy (%)		55.55	84.21	40.00	
Overall accuracy (%)				**69.70**	

3.5.2 Comparison between the meteorological station data and the PSMI

The PSMI was developed based on the satellite images in September 2011. Further research, a developed PSMI model was applied to the same study area in July and August 2015, estimated from multiple variables (e.g., the NDVI, LST, Elevation, Aspect and Slope). The PSMI maps of July and August 2015, as shown in Figure 3—9 (a, b). Furthermore, the PSMI (September 2011 and July/August 2015) was compared with the Bornuur climate station data (July to August 2010-2015).



a) b)

Figure 3—9. Soil moisture map from the model on the kastanozem soil: a) July 2015; b) August 2015

The Bornuur station is located in the central part of Bornuur soum, which is characterized as the area of kastanozem soil. Figure 3—10 shows the monthly SMC with 20-cm depths from 2010 to 2015 at the Bornuur station. During the obtained years, a low SMC was observed, i.e., 5.27 % in September 2011 and 9.68 % in July 2014. However, a high SMC was observed (22.54 %) in August 2012 and (20.59 %) (August) 2015. In this chapter, the PSMI model has been applied during September 2011 and July/August 2015. From the trend of SMC, we could conclude that 5.27 % was observed in September 2011, 17.29 % in July 2015 and 20.59 % was found during August 2015. Table 3—6 displayed the comparison of the PSMI and climate station data, the ground truth measurements for each month of the applied model. The model was developed in the year showing the lowest soil moisture (September 2011). Then, the developed model was applied for July and August 2015, as shown in Figure 3—9. The comparison of the PSMI and SMC (from the station) has been demonstrated in Figure 3—11 (with the acquired date).

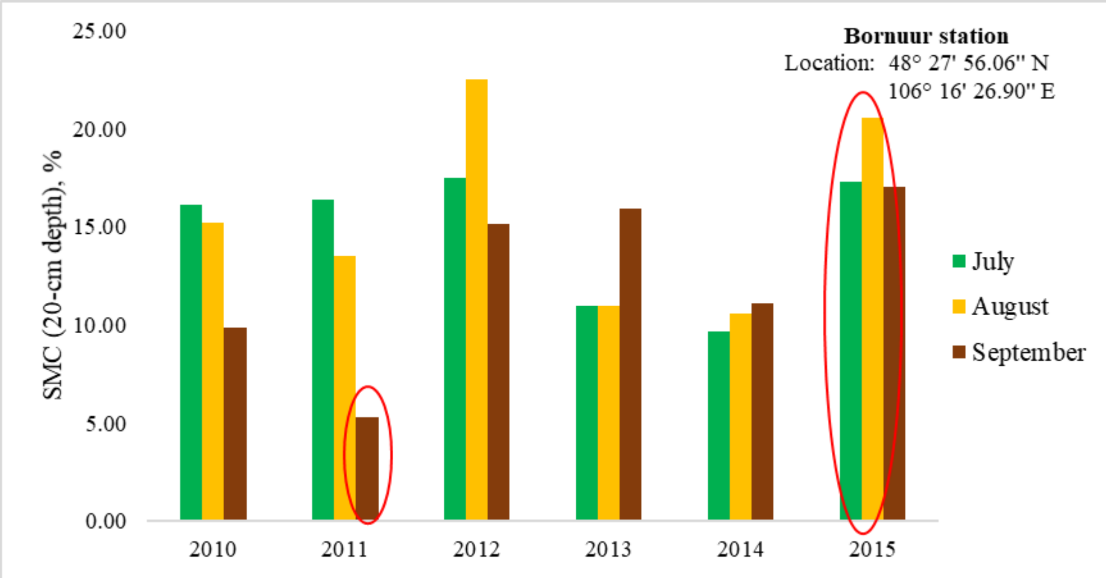


Figure 3—10. Bornuur meteorological station data (the red circle shows that the model was applied)

Table 3—6. Comparison of the developed model and ground measurements

Description	Date satellite data	Mean PSMI	SM from the climate station, %	Ground truth measurements, % (average of measurements)	Acquired month of ground truth measurements	Correlation coefficients between the PSMI and ground truth data
Model developed	Sep 18, 2011	0.77	5.2733	8.564561	Sep 19-20, 2011	0.81, 69.7%
Model applied	July 4, 2015	1.02	17.2946			
Model applied	August 21, 2015	1.15	20.5867			

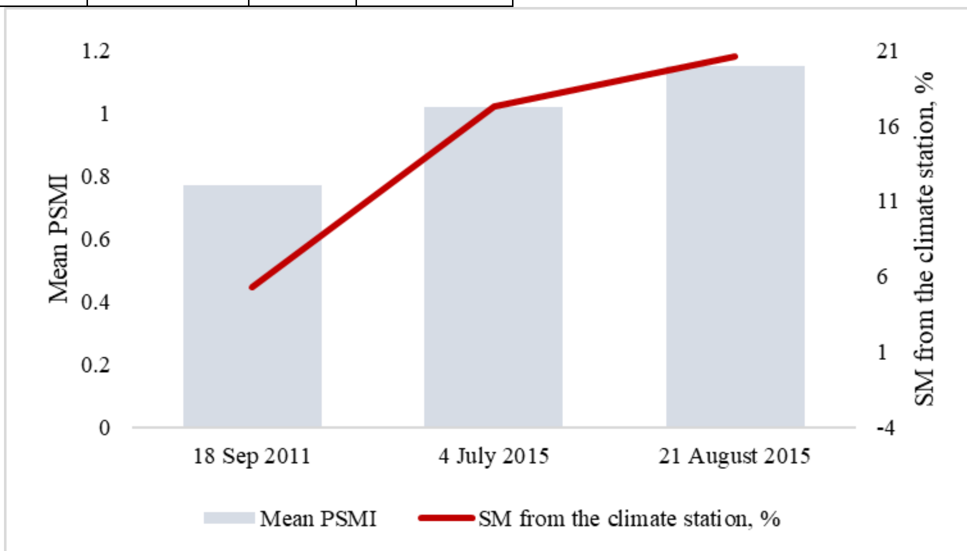


Figure 3—11. Comparison between the Bornuur meteorological station data and the PSMI in the kastanozem soil

3.6 Conclusion

The SM is vital for Mongolian agricultural development. An SM analysis is needed in order to assist the dryland grain growers in making improved and informed decisions. Since less research has been carried out on dry land, the policy-makers were not able to make decisions for the crop growers in central agricultural areas (on a regional level). This research will aid the crop sector to develop the agricultural lands and to improve the crop quality so as to expand the Mongolian food demand. The SM monitoring will also provide useful insights for the pasture land management in other regions of Mongolia. The model, developed for this chapter, could also be applied with other satellite images which as Sentinel, SPOT and MODIS satellite etc. Only the forest-steppe region has been considered for the analysis. This model could be applied in the same area of the kastanozem soil, using remote sensing methodologies. However, the accuracy of the model should carry out with numerous soil moisture samples.

The SM modeling development will provide information for Mongolia's agriculture and animal husbandries such as cropland, pastureland, vegetation growth and biomass. The national policy level will (be able to) use this information so as to develop suitable agricultural areas. The crop fields in this area are typical along the mountains, low mountains and hills, which have a certain relief. As there is no sufficient implemented soil protection in the region, this place might be affected by wind and water disasters. Our research model could be widely applied and utilized in the agricultural and environmental sectors (in similar areas). However, this model should be elaborated in order to apply other regions (in an accurate manner, using many soil moisture samples).

Our model was established in an agricultural region in the central part of Mongolia. Foreign scientists mostly rate the SM through satellite data (with climate station data). This research innovation embraced the SM estimation using drivers (which include the vegetation, land surface temperature, elevation, aspects and slope in the kastanozem soil). Our research applied the elevation and slope drivers for the forested mountains and agricultural areas.

In the future, we will apply the integrated model all over the Mongolian landscape. Since Mongolia disposes of six different landscapes, the SM monitoring is vital for the Mongolian agricultural development. A regional plan exists so as to develop the agricultural land(s) in the Mongolian forested mountainous areas.

CHAPTER 4

Spatial distribution of soil moisture in Mongolia using SMAP and MODIS satellite data, its time series model (2010 - 2025)

*Modified from: Enkhjargal Natsagdorj, Tsolmon Renchin, Philippe De Maeyer, Bayanjargal Darkhijav (2021). Spatial distribution of soil moisture in Mongolia using SMAP and MODIS satellite data, its time series model (2010 - 2025). Remote Sensing, 13(3), 347. DOI:*https://doi.org/10.3390/rs13030347.

4.1 Introduction

The soil moisture (SM) plays a vital role in the terrestrial water cycle and has been assessed in many field studies, e.g. in the water management, agricultural irrigation management, crop production, vegetation cover, drought and global climate change (Deryng et al. 2011; X. Gao et al. 2014; Park et al. 2017; X. Wang et al. 2018). In addition, the soil moisture indicates the groundwater conditions and links the exchange of water and energy between the atmosphere and land surface. There are many ways to estimate the soil moisture, including direct and indirect methods. The most accurate method is a direct measurement in the field (gravimetric method) to estimate the soil moisture by point measurements (E. Natsagdorj et al. 2017) but this is costly (Rahimzadeh-Bajgiran and Berg 2016). Therefore, remote sensing techniques have become popular for estimating the soil moisture on a regional scale due to the sensing ability of the regional SM with low-resolution images. Microwave remote sensing methods have been used on a global and regional scale to establish some models (D. Zhang and Zhou 2016; Peng and Loew 2017). To date, some highly advanced SM products have been developed e.g. the Soil Moisture Active Passive (SMAP) from the National Aeronautics and Space Administration (NASA), Soil Moisture Ocean Salinity (SMOS) and Climate Change Initiative (CCI) from the European Space Agency (ESA). In optical and thermal remote sensing, many researchers have established methods based on the relationships between the SM and soil reflection/soil temperature and vegetation cover(Jung et al. 2017; Hong et al. 2018; Vani, Pavan Kumar, and Ravibabu 2019). Using a combined microwave and optical remote sensing data might provide more precise information on the soil moisture rather than estimation only based on data from one type of remote sensing.

Remote sensing technology is a powerful method for the soil moisture monitoring on a regional level. Many studies have established that the SMAP products generate accurate in situ measurements and could be used in various fields of study such as agriculture, environmental monitoring and hydrology (Brocca et al. 2017). They have also been intensively validated by several studies over the past few years (Chan et al. 2016; X. Zhang et al. 2017; F. Chen et al. 2017). For instance, Zeng et al. (J. Zeng et al. 2016) approved a SMAP product for the preliminary evaluation of the soil moisture compared to the in situ measurements from the three networks that cover different climatic and land surface conditions; moreover, the results show that the SMAP product is in a good agreement with the in-situ measurements. However, it has a limited application to agricultural studies because the SMAP products only provide 3, 9 or 36 km spatial resolution data on a global or regional scale. In this paper, we used the SMAP products at a spatial resolution of 9 km for the development of a soil moisture model by combining SMAP and optical/thermal satellite images. The combination of the optical/thermal and microwave remote sensing potentially expands the application possibilities (D. Zhang and Zhou 2016).

In previous studies, various researchers have investigated and developed methods based on the Land Surface Temperature (LST) / Normalized Difference Vegetation Index (NDVI), in view of vegetation types and topography and climate parameters, among other factors (Lambin and Ehrlich 1996; Nemani and Running 1997; Jung et al. 2017; Chae, Park, and Lee 2017; Saha et al. 2018). These approaches have mainly used reflectance to estimate the SM in visible/thermal infrared sensors. Dandridge et al. (Dandridge, Fang, and Lakshmi 2020) used the LST/NDVI data to obtain an enhanced spatial resolution of the soil moisture from SMAP at 9 km down to 1 km. Natsagdorj et al. (E. Natsagdorj et al. 2017) developed a model for the soil moisture by means of the multiple regression analysis and the model showed that the type of the soil moisture index (from the satellite measurements) depends on the LST, NDVI, elevation, slope and aspect. The results indicate a good correlation between the developed model and ground truth measurements in the sub provinces of Mongolia. The lack of field measurements for the SM makes it challenging to validate the remote sensing SM estimates in Mongolia, because the territory is so widespread (1,565 million square km).

Due to the characteristics of the Mongolian climate, the agricultural production is strongly limited by a short growing season (generally 80 to 100 days but varies from 70 to 130 days depending on the altitude and location), low precipitation, and high evaporation (Leary et al. 2013). The Mongolian steppe ecosystems are crucial for relieving the regional and even global climate variation through their interaction with the atmosphere (Yatagai and Yasunari 1995). Many studies have demonstrated that in Mongolia, due to the harsh continental climate and the distance from the sea, the processes of soil drying, desertification and degradation are intensifying due to the loss of vegetation and changes in soil moisture due to global warming. Therefore, to study the impact of climate change, there is an urgent need to consider the soil moisture as one of its indicators. Few studies of soil moisture have been conducted with point-scale measurements (Nandintsetseg and Shinoda 2011; Shinoda and Nandintsetseg 2011). In

Mongolia, SM distribution data with a higher resolution are needed for practical applications such as agricultural management, water management and flood and drought monitoring. Therefore, a time series analysis of the long-term soil moisture was conducted using the AutoRegressive Integrated Moving Average (ARIMA) model (Box, Jenkins, and Reinsel 2016).

Few previous studies have examined the soil moisture and river flow forecasting (Singh, Kaur, and Kumar 2020); on the other hand, various reviews have addressed the drought monitoring (Mishra and Desai 2005; Han et al. 2010; Tian, Wang, and Khan 2016; Karthika and Thirunavukkarasu 2017). The SM forecast data support farmers in organizing their resources for the crop production. The ARIMA model is commonly used in the time series models. There are many methods and criteria to rank and select the AutoRegressive (AR), Moving Average (MA) or ARIMA models for a given purpose. These models are suitable for limited data values and short-term forecasting (Singh, Kaur, and Kumar 2020). However, the main advantages of the ARIMA model forecasting are that it only requires time series data (Tian, Wang, and Khan 2016). In this chapter, we have used the ARIMA model to investigate the time series analysis of the soil moisture dynamics between 2010 and 2020, based on the SMAP and MODIS satellite images. This chapter focused on that so as to obtain a higher spatial resolution (1 km) soil moisture map than the SMAP (9 km) provided us with. Then, the SMAP data periods 2015-2020 were used in order to build a model. From the model, the spatially distributed monthly soil moisture data will contribute to the return back in time (2010-2020) and towards the future by means of the ARIMA model.

The main objectives of this chapter are to estimate a monthly soil moisture distribution map and to build appropriate models to forecast future trends. Because of the stochastic nature of the monthly soil moisture, we used a time series analysis for the monthly soil moisture forecasting. A process is considered stationary if its statistical properties, such as the average and variance, do not change over time. A monthly soil moisture map was estimated from the remote sensing data developed in Mongolia. The modeling and prediction of the soil moisture were done through statistical methods based on ARIMA. In this chapter, the soil moisture modeling and forecasting were performed by means of the conventional method, the Box–Jenkins time series model. The monthly soil moisture distribution map has not been considered yet in previous studies in Mongolia and is expected to be useful for agriculture, hydrology, and climate science.

4.2 Study Area and Data Preprocessing

4.2.1. Study Area

Mongolia is a landlocked country situated in Central Asia, bordered by Russia and China (Figure 1—8). The climate conditions and environment of Mongolia have been explained in Section 1.3. Mongolia has six vegetation zones, as previously mentioned (Yunatov 1979). Overall, Mongolia is a recognized, semi-arid and arid climate region characterized by a continental climate and vulnerable environment.

4.2.2 Remote sensing data

4.2.2.1 SMAP

On 31 January 2015, NASA launched the SMAP, which has an initial L-band with both radar and radiometer data to assess the soil moisture (Entekhabi et al. 2010). The daily coverage started on 31 March, 2015 at a spatial resolution of 3–36 km. The average monthly SMAP data were obtained using the daily SMAP with a 9 km resolution. We have downloaded the daily SMAP L3 Radiometer Global Daily 9 km EASE-Grid Soil moisture data (SPL3SMP_E.003) through the Application for Extracting and Exploring Analysis Ready Samples (AppEEARS) between 2015 and 2020 (O'Neill et al. 2019). The AppEEARS is a useful tool for a time series analysis in specific regions and on certain scales. It provides data by enabling users to download only the necessary information (geospatial datasets using spatial, temporal and band/layer parameters) from several federal archives (https://lpdaacsvc.cr.usgs.gov/appeears/). The downloaded images were preprocessed with the ENVI 5.3 and ArcGIS 10.3 software to obtain the monthly soil moisture data.

4.2.2.2 MODIS

We used the MODIS products during a 10-year period (2010–2020) to observe the dynamic range of the NDVI and LST. The authors Zhang et al. (J. Zhang et al. 2007) utilized a similar approach to detect anomalies using the MODIS land products via a time series analysis. Accordingly, the monthly composites of a 1 km spatial resolution MOD13A3 (Didan 2015) and MOD11A2 (Wan, Hook, and Hulley 2015) data from MODIS and the National Aeronautics and Space Administration (NASA) Earth Observing system (https://lpdaac.usgs.gov/product_search/) were applied. The MODIS vegetation indices (MOD13A3) version 6 data are provided monthly at a 1 km spatial resolution in the sinusoidal projection (Didan 2015). The MOD11A2 version 6 product provides an average eight-day-per-pixel Land Surface Temperature and Emissivity (LST&E) with a 1 km spatial resolution (Wan, Hook, and Hulley 2015). We calculated the eight-day LST as monthly averages by means of the product version 6 (MOD11A1). The Application for Extracting and Exploring Analysis Ready Samples (AppEEARS) tool offers the vegetation and LST products of MODIS for long-term data (AppEEARS Team 2020).

4.2.3 CRU and Meteorological Data

The CRU TS (Climatic Research Unit gridded Time Series) data are broadly used in climate studies and are available at 0.5 × 0.5 degrees over the whole Earth surface. It provides a monthly land-based gridded high-resolution dataset from 1901. The CRU dataset is derived by the interpolation of monthly weather station observations of extensive networks. The database is updated annually (Harris et al. 2020). The CRU TS global data are freely downloadable and accessible online (https://crudata.uea.ac.uk/cru/data/). We have applied the CRU TS v4 to this chapter to obtain available temperature and precipitation data between 2010 and 2019.

The meteorological station data were provided by the Information and Research Institute of Meteorology, Hydrology and Environment (IRIMHE) on the Mongolian website (http://tsag-agaar.gov.mn/). There are limited stations for soil moisture measurements in croplands in Mongolia. The soil moisture contents were acquired at depths of 0–20 cm and 0–50 cm at monthly intervals (the 7th, 17th and 27th day of each month) from April to September due to the seasonal conditions (E. Natsagdorj et al. 2019). The soil moisture contents were averaged over the monthly intervals from May to August (2015–2020). The selected meteorological stations are shown in Table 4—1 and the locations of the stations have been categorized into two vegetation zones.

Table 4—1. Location of the agricultural meteorological stations of soil moisture.

Aimag Name	Station Name	Vegetation Zones	Latitude (°N)	Longitude (°E)	Elevati on (m)
Arkhangai	Tuvshruulekh	Forest steppe	47°23′12.9″ N	101°54′30.9″ E	1,619
Khuvsgul	Tarialan	Forest steppe	49°36′32.98″ N	101°59′4.52″ E	1,218
Selenge	Tsagaannuur	Forest steppe	50°6′37.83″ N	105°27′7.28″ E	786
Selenge	Eruu	Forest steppe	49°44′56.52″ N	106°39′40.48″ E	673
Selenge	Baruunkharaa	Forest steppe	48°54′47.21″ N	106°5′23.11″ E	811
Selenge	Orkhon	Steppe	49°8′37.57″ N	105°24′8.44″ E	756
Selenge	Orkhontuul	Steppe	48°50′7.6″ N	104°48′23.09″ E	831

Selenge	Zuunkharaa	Forest steppe	48°51′37.86″ N	106°26′35.31″ E	883
Bulgan	Ingettolgoi	Forest steppe	49°27′33.8″ N	103°59′5.20″ E	763
Bulgan	Bulgan	Forest steppe	48°49′5.39″ N	103°31′8.18″ E	1,221
Dornod	Onon	Steppe	49°6′51.42″ N	112°39′29.35″ E	894
Dornod	Choibalsan	Steppe	48°4′53.16″ N	114°32′16.21″ E	747
Dornod	Khalkhgol	Steppe	47°37′48.86″ N	118°37′20.21″ E	987
Uvs	Baruunturuun	Steppe	49°39′31.10″ N	94°24′14.62″ E	1,232
Uvurkhang ai	Kharkhorin	Forest steppe	47°11′40.99″ N	102°49′47.78″ E	1,480
Tuv	Erdenesant	Steppe	47°20′0.35″ N	104°29′34.13″ E	1,364
Tuv	Ugtaal	Steppe	48°15′29.19″ N	105°24′19.01″ E	1,161
Tuv	Jargalant	Forest steppe	48°31′35.61″ N	105°52′50.67″ E	1,015
Tuv	Bayanchand mani	Forest steppe	48°13′37.57″ N	106°17′2.89″ E	1,255
Tuv	Bornuur	Forest steppe	48°28′7.56″ N	106°15′37.16″ E	1,023
Khentii	Gurvanbayan	Steppe	48°11′4.95″ N	110°19′22.03″ E	1,207
Khentii	Undurkhaan	Steppe	47°18′29.62″ N	110°37′28.29″ E	1,035
Sukhbaatar	Baruun-Urt	Steppe	46°40′21.92″ N	113°16′57.07″ E	981

4.2.4 Crop Yield Statistical Data

The soil moisture is one of the most important factors in the agricultural sector of Mongolia. The National Statistical Organization (NSO) website (http://nso.mn/) of Mongolia provides information on the crop yields in the sub-provinces every year. The NSO has been accumulating data on croplands and harvests collected by the agricultural enterprises and local farmers through the statistical departments and offices of each state. The crop yield information has been applied for the validation of the soil moisture distribution in Mongolia from 2010 to 2019. The total harvest includes the amount of potatoes, fodder crops, cereals, fruits, vegetables, etc. (in thousands of tons) and the crop yield information is averaged every year. The crop yield is shown as the amount of the agricultural production per unit area (from 1 hectare). The crop yield per hectare is estimated as the ratio of the total harvest to the total sown area (NSO 2020).

4.3 Methodology

In this chapter, the structure of the spatial distribution of the soil moisture and time series analysis (based on the SMAP and MODIS products) is provided in the flowchart of Figure 4—3. The first involved the data download and processing, e.g. by the SMAP satellite, NDVI and LST from the MODIS satellite. After the data processing, a multiple linear regression model was developed. The prepared monthly soil moisture contents from the station, temperature/precipitation of the CRU data and yearly crop yield information from the NSO were applied for the validation of the estimated soil moisture in Mongolia. Finally, the time series analysis and forecasting model were used for the prediction of the estimated monthly soil moisture.

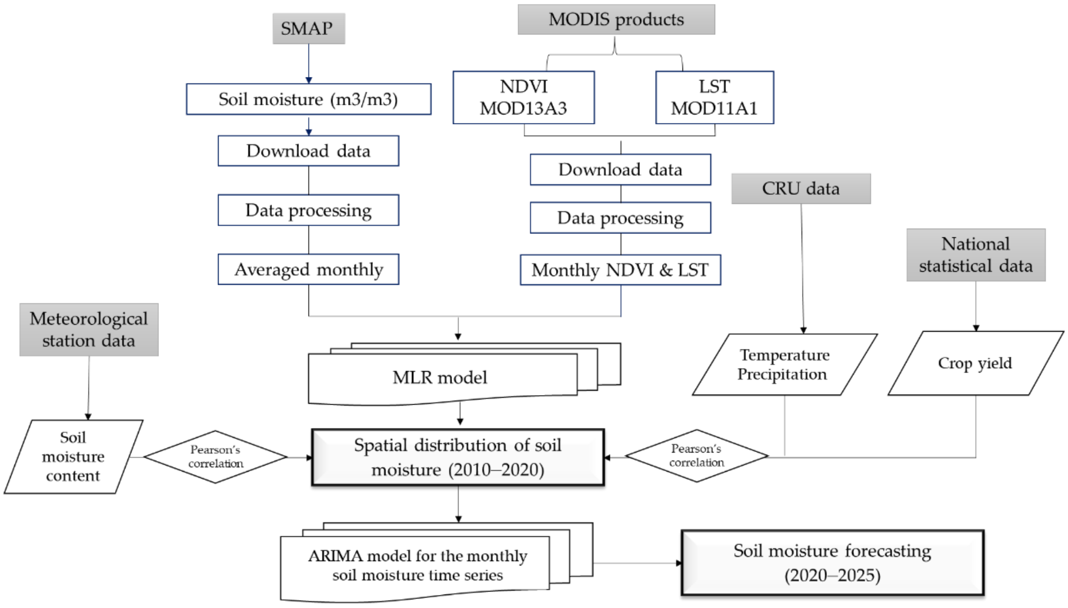


Figure 4—1. Flowchart of the soil moisture distribution in Mongolia based on satellite images.

4.3.1 Multiple Linear Regression—SM-MOD

A multiple linear regression model has often been used in natural resource studies and involves the calculation of the dependent variable Y by applying a linear combination of the independent variables X_i. The linear regression form is shown in the following equation (Weisberg 2005):

$$Y_i = \beta_0 + \sum_{m=0}^{n} \beta_m * X_{m,i} \tag{4-1}$$

, where β_0, β_m ($m > 0$) are constant terms corresponding to the connection, the regression coefficients, and the model error, $X_{m,i}$ show the corresponding variables, respectively. The input variables (X_i) describe the output variable (Y_i) according to the results of the multiple regression model. Therefore, each input variable has different information, which means that all input variables should not be collinear. We used p-value statistics to estimate the significance of each variable for the variable selection input (Weisberg 2005). The variance inflation factor (VIF) is applied so as to detect the collinearity (also called multicollinearity) among the predictors in the regression models (Harrell 2001; Murray et al. 2012). The VIF values are situated between 1 and 10, which means that there is no multicollinearity for the regression model. After these analyses, a combination of *p*-value and VIF measures was used. Besides, the independent variables are normally distributed for the assumptions of the linear regression model. Table 4—2 shows the statistical variables computed from the satellite images.

Table 4—2. Statistical variables of the input, minimum (Min), maximum (Max), mean and standard deviation (SD).

Variable	Unit	Min	Max	Mean	SD
SMAP (dependent)	m^3/m^3	0.037	0.157	0.090	0.024
LST (independent)	Celsius	−19.065	39.902	15.680	18.469
NDVI (independent)		0.024	0.381	0.186	0.097

4.3.2 ARIMA Model

The Box–Jenkins time series models are named after the statisticians George Box and Gwilym Jenkins (Box and Jenkins 1970). These models generate forecast values based on the statistical parameters of observed time series' data and are applied in many fields. The Box–Jenkins Autoregressive Integrated Moving Average (ARIMA) model is a combination of the Autoregressive (AR), Integrated (I) and Moving Average (MA) terms. The Box–Jenkins model describes a wide class of models forecasting univariate time series that can be made stationary by applying transformations such as the differencing of non-stationary series one or more times so as to achieve stationarity (Box and Pierce 1970; Box, Jenkins, and MacGregor 1974).

A seasonal ARIMA model is denoted by ARIMA (p, d, q), where *p* is the number of the autoregressive terms, q shows the number of the moving average terms and d represents the number of differences applied to the series (Rahman and Hasan 2017).

The AR (p) model is defined as:

$$X_t = c + \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \cdots + \varphi_p X_{t-p} + u_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + u_t \qquad (4\text{-}2)$$

where φ_1, φ_2, …, φ_n illustrate the autoregressive coefficients, c is a constant, and u_t demonstrates white noise. In the autoregressive model of order p, the value of the time series at t, X_t depends upon the previous *p*-values and random disturbance (the stochastic part).

The MA (p) model is defined as:

$$u_t = \theta_1 z_{t-1} + \theta_2 z_{t-2} + \cdots + \theta_q z_{t-q} = z_t + \sum_{i=1}^{q} \theta_i z_{t-i} \tag{4-3}$$

, where θ_1, θ_2, …, θ_q denote the moving average coefficients and $\{z_t\}$ presents a white noise process with mean 0 and variance σ^2. Combing the autoregressive and moving average models, we will get Equation (4-4):

$$x_t = c + \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \cdots + \varphi_p X_{t-p} - \theta_1 z_{t-1} - \theta_2 z_{t-2} - \cdots - z_{t-q} \tag{4-4}$$

, where x_t denotes the dth difference of X_t.

The latter defines the autoregressive moving average (ARIMA) process of p and q order and difference d or ARIMA (p, q) (Box, Jenkins, and Reinsel 2016).

There are many methods and criteria to select the order of an AR, MA or ARIMA model. One of these is based on the so-called information criteria and computes the values of the Akaike's information criterion (AIC) and the Bayesian information criterion (BIC) or Schwarz criterion, with preferred smaller values of AIC and BIC (Hyndman and Koehler 2006; Adnan et al. 2017). The most commonly used approach for checking the model's adequacy is to examine the residuals by means of the autocorrelation function (ACF) and partial autocorrelation function (PACF) graphs. If the selected model is appropriate, the residual graphs of the correlation functions should be white noise, indicating no remaining correlation.

4.3.3 Model Validation

The model has been performed to evaluate the next step. The Pearson's correlation (r) (Sedgwick 2012) was applied for the comparison of the estimated soil moisture and the observed soil moisture and crop yield values. The coefficients of the Pearson's correlation (r) are given in Equation (4-5):

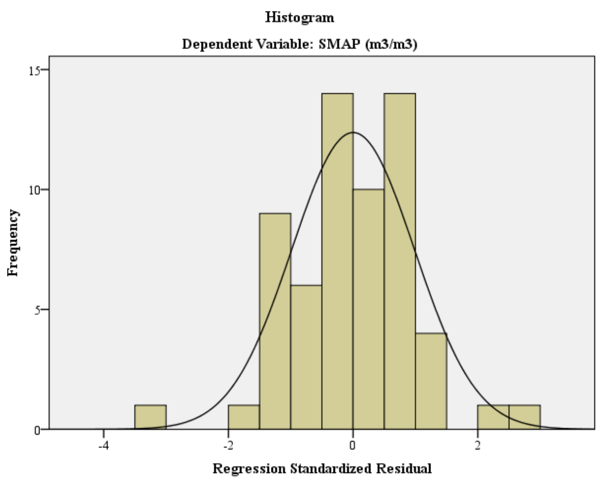
$$r = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_i^n (X_i - \bar{X})^2 \sqrt{\sum_i^n (Y_i - \bar{Y})^2}}} \tag{4-5}$$

, where X_i and Y_i are the individual derivations and measurements of the variables X and Y, respectively. $\bar{X}$ and $\bar{Y}$ denote the means of X and Y, respectively. The correlation coefficient (r) ranges between −1 and 1. If r is equal to zero, this means that there is no linear association between the variables. If r is equal to 1, there is a perfect positive linear relationship between the variables and all sampled individuals would be exactly on the same straight line with a positive slope. If $0 < r < 1$, this illustrates a positive linear trend but the sampled individuals would be scattered around this common trend line; the smaller the absolute r value, the less well the data could be characterized by a single linear relationship. If r is positive and the r values are close to 1, this describes a valuable relationship between the variables (Puth, Neuhäuser, and Ruxton 2014). Linear Pearson's correlation (r) was determined on a monthly timescale (Sedgwick 2012; E. Natsagdorj et al. 2019) for the satellite-derived and meteorological station/NSO data.

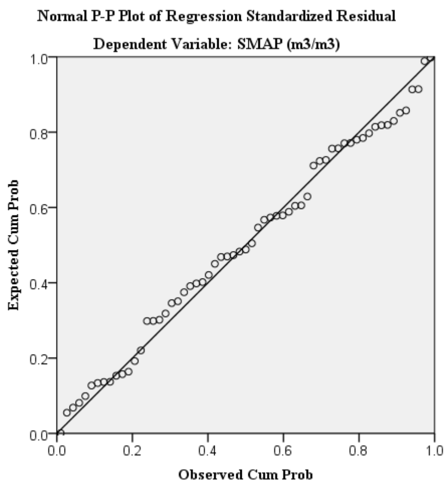
4.4 Results

4.4.1 SM-MOD—Multiple Linear Regression Model

The equation (4-1)'s linear regression model was applied for the estimation of the soil moisture in Mongolia with a 1 km resolution. The multicollinearity tests for all variables (NDVI and LST) were determined in Table 4—3. The VIF values were lower than five, which shows that there was no multicollinearity for the regression model. Also, the histogram normality test has been checked by the Jarque-Bera test for the linear regression model. In this test, if the probability of Jarque-Bera was greater than 0.05 or 5 %, we accepted the null hypothesis (which means that the residuals are normally distributed as shown by the histogram and p-p plot in Figure 4— 2).



(a)



(b)

Figure 4— 2. (a) histogram and (b) P-P plot for the Normality test

Table 4—3 summarizes the multiple linear regression model coefficients, *p*-values, standard error, *t*-statistics and VIF statistics. The monthly NDVI and LST explained 78 % of the variation in soil moisture. The F-statistics were less than 0.05, which means that this model could be used for the soil moisture analysis.

Table 4—3. Result of the linear regression model.

Variable	Coefficient	Std. Error	*t*-Statistics	Prob.	Collinearity Statistics	
					Tolerance	VIF
Interception	0.043899	0.003721	11.79743	0.0000		
NDVI	0.288958	0.027357	10.56239	0.0000	0.300	3.336
LST (Celsius)	−0.000505	0.000144	−3.499165	0.0009	0.247	4.041
R-squared	0.780878	Adjusted R-squared	0.773322	Mean dependent variable	0.089744	
SD dependent variable	0.023754	SE of regression	0.011310	Akaike info. criterion	−6.078392	
Prob (F-statistics)	0.000000					

In this chapter, we assumed that the SM is derived from the satellites and depends on the independent variables NDVI and LST, while SMAP is the dependent variable. From the assumption, a multiple regression model has been developed. Finally, the MLR model resulted in Equation (4-6):

$$SM_{MOD} = 0.044 + 0.289 * NDVI - 0.00005 * LST \qquad (4\text{-}6)$$

, where SM_{MOD} is the modelled soil moisture; the constant coefficients were estimated from Table 4—3. Figure 4—3 shows the graphs of the actual, fitted and residual values of linear regression. The figure suggests that in most of the studied months, the correlation between the real-life situation and the model was high.

The soil moisture (SM-MOD) was calculated using Equation (4-6), with values in m^3/m^3. The lowest value 0 indicates dry areas and the highest value 0.35 m^3/m^3 indicates wet areas. Figure 4—4 represents the spatial distribution of the monthly soil moisture in Mongolia. The monthly SM maps have been averaged by month between 2010 and 2020. During the years 2010–2020, the winter has demonstrated the lowest soil moisture (November, December and January) and spring also had a low soil moisture (February, March and April). The summer showed a high soil moisture amount in May, June and July. However, autumn denoted the highest soil moisture in

August, September and October (Figure 4—4). Apparently, an increased soil moisture is observed in the northern part, which contains taiga, forest-steppe and steppe zones, while the low soil moisture is restricted to the southern part of Mongolia, which is mostly characterized by the desert steppe and desert vegetation.

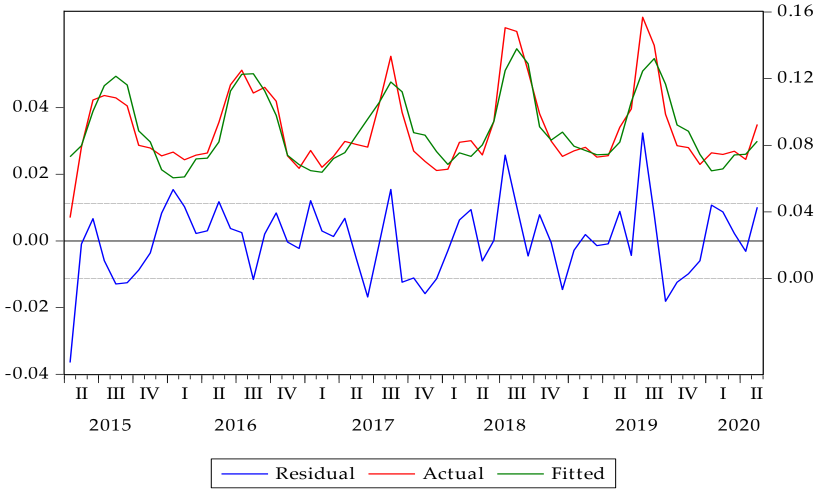


Figure 4—3. Actual, fitted and residual values of the multiple regression model.

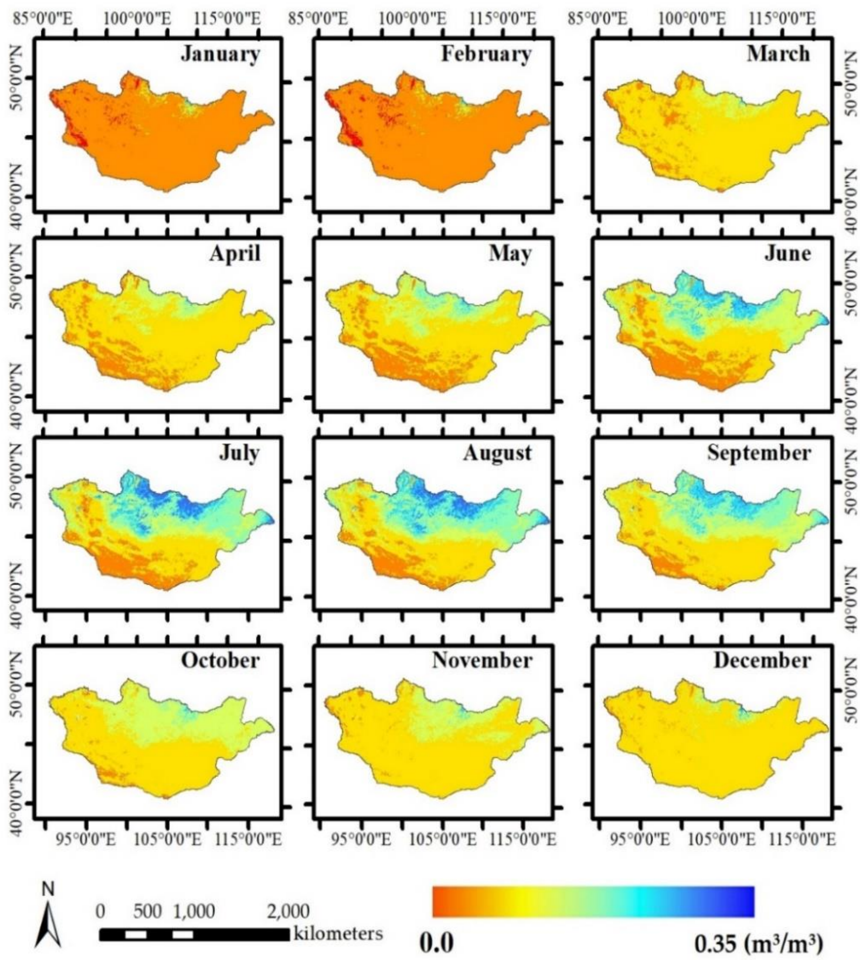


Figure 4—4. Spatial distribution of the soil moisture contents from the model (SM_{MOD}) (averaged monthly from 2010 to 2020).

4.4.2 Comparison between the MLR Model and SMC from the Meteorological Stations

In general, the estimation of the soil moisture from the model was reasonably accurate, as confirmed by applying satellite images. Figure 4—5(a–d) describes the correlation between SMAP and SM-MOD with the SMC from the meteorological stations at a 0–20 and 0–50 cm depth. Table 4—4 shows the correlations of the SMAP and SM-MOD with the SMC from the meteorological stations at different depths.

Table 4—4. Correlation between the (a) SMAP and (b) SM-MOD with the SMC from the meteorological stations at different depths from May to August 2015–2020.

(a)	**SMAP (m^3/m^3)**	**SMC/0–20 cm/(m^3/m^3)**	**SMC/0–50 cm/(m^3/m^3)**
	p-values (Pearson)	<0.0001	0.005
	Coefficients of determination (Pearson)	0.078	0.087
	Correlation (Pearson)	0.279 **	0.181 **
	RMSE	0.094	0.098
	Bias	0.0016	0.0021
	Confidence intervals (95%)	(0.194, 0.359)	(0.094, 0.266)
(b)	**SM-MOD (m^3/m^3)**	**SMC/0–20 cm/(m^3/m^3)**	**SMC/0–50 cm/(m^3/m^3)**
	p-values (Pearson)	<0.0001	0.005
	Coefficients of determination (Pearson)	0.037	0.016
	Correlation (Pearson)	0.191 **	0.126 **
	RMSE	0.090	0.091
	Bias	0.0016	0.0020
	Confidence intervals (95%)	(0.104, 0.276)	(0.038, 0.213)
** Correlation is significant at the 0.01 level (2-tailed).			

The correlation coefficients (r) between the SMAP and SMC from the meteorological stations were 0.279 (Figure 4—5a) and 0.181 (Figure 4—5b) at a 0-20 and 0–50 cm depth, respectively. This was statistically significant, with root mean square error (RMSE) values of 0.094 m^3/m^3 and 0.098 m^3/m^3, as shown in Table 4—4a. Table 4—4b indicates that the values of the correlation coefficients (r) measured 0.191 between the SM-MOD and SMC at a 0–20 cm depth from the meteorological stations, which was statistically significant, with an RMSE of 0.090

m3/m3 ($p < 0.0001$; Figure 4—5c), and 0.126 between the SM-MOD and SMC at a 0–50 cm depth from the meteorological stations, which was also statistically significant, with an RMSE of 0.091 m3/m3 ($p < 0.005$; Figure 4—5d). The confidence intervals of 95 % were situated between the SM-MOD and SMC at a 0–20 cm depth from the meteorological stations from 0.104 to 0.276 and with the SMC at a 0–50 cm from the meteorological stations from 0.038 to 0.213.

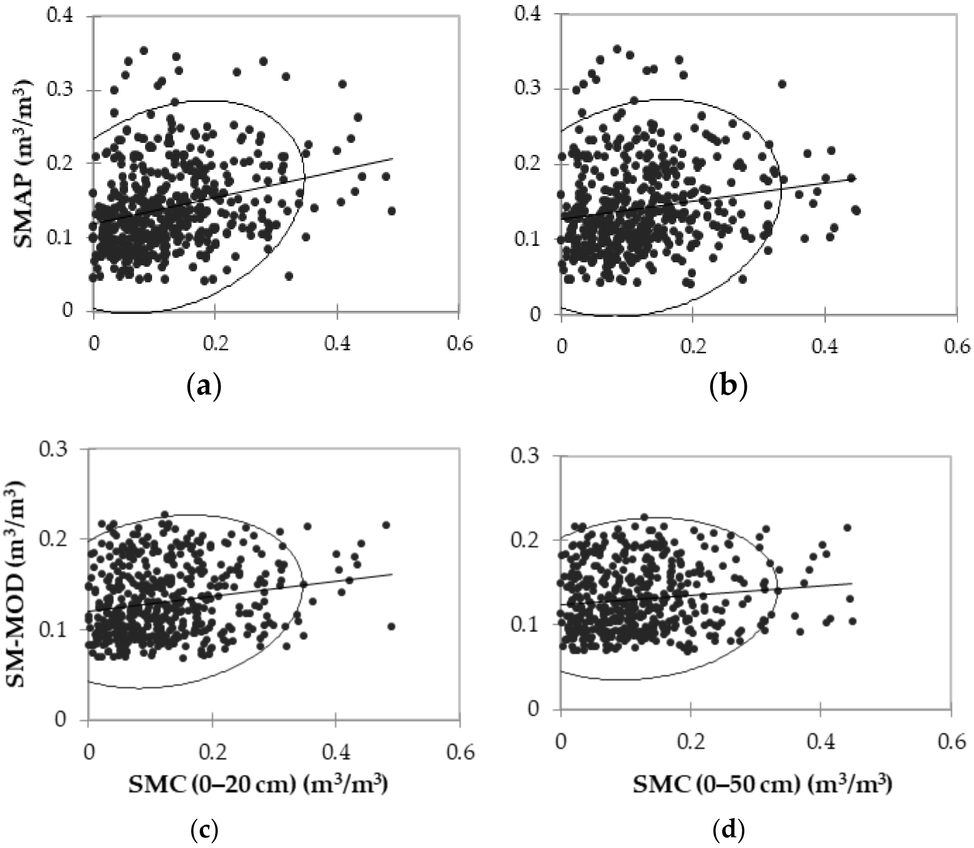


Figure 4—5. Scatter diagram of the SMAP and SM-MOD with SM measurements from the meteorological stations for different depths from May to August 2015–2020 in the study area: (a) SMAP and SMC from the meteorological stations at a 0–20 cm depth; (b) SMAP and SMC from the meteorological stations at a 0–50 cm depth; (c) SM-MOD and SMC from the meteorological stations at a 0–20 cm depth; (d) SM-MOD and SMC from the meteorological stations at a 0–50 cm depth.

4.4.3. Comparison between the SM-MOD and CRU Data

We also examined the trends of the monthly precipitation and temperature from the CRU data. Figure 4—6 displays the time series of the monthly precipitation, temperature and SM-MOD in Mongolia from 2010 to 2020. The highest precipitation was observed during July 2018 and the highest SM-MOD value was noticed in August 2018. From the comparison, we could see that when the precipitation was high, the following month's soil moisture was also high, which means that the soil moisture directly depends on the precipitation in Mongolia. In addition, the soil moisture has been slightly increasing in Mongolia (by 0.97 % over 20 years).

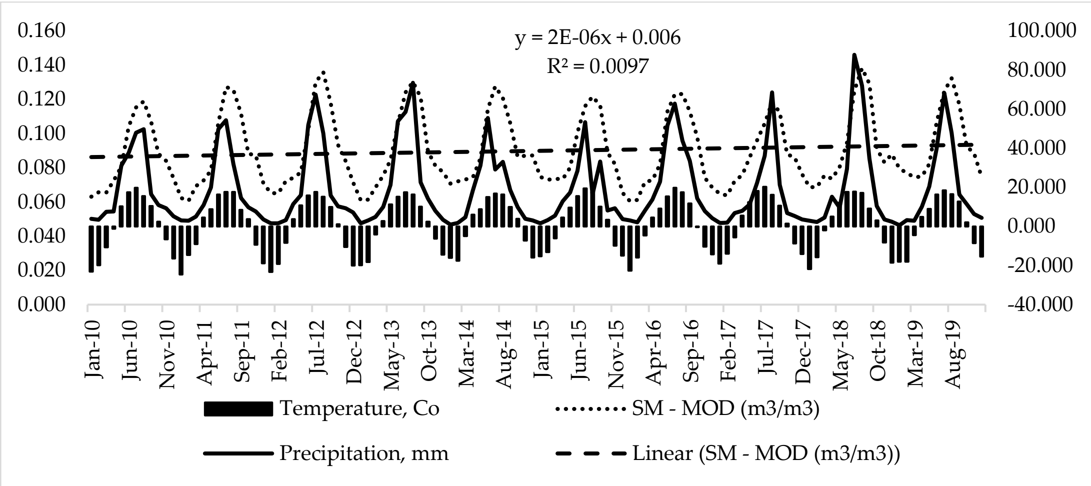


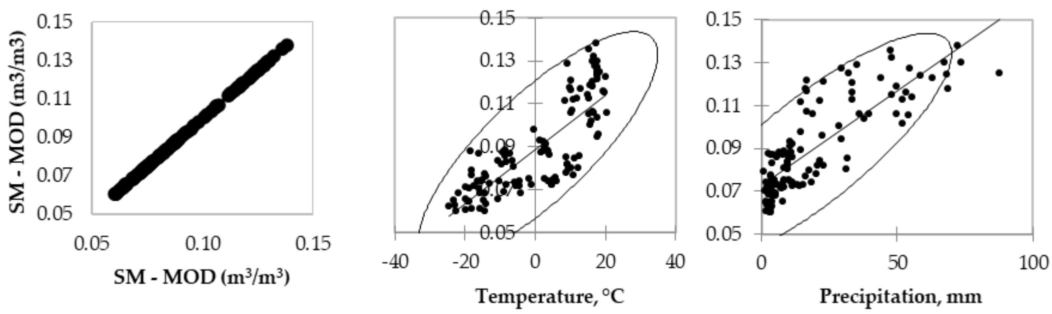
Figure 4—6. Comparison between the monthly precipitation (mm), temperature (°C), and SM-MOD (m^3/m^3) in Mongolia from January 2010 to December 2019.

Figure 4—7a–c describes the correlation between the SM-MOD and the temperature and precipitation. Table 4—5 shows the correlations of the SM-MOD with the temperature and precipitation from the CRU data in Mongolia. It indicates that the values of the correlation coefficients (r) were 0.802 between the SM-MOD and temperature, which was statistically significant ($p < 0.0001$; Figure 4—7b) and 0.826 between SM-MOD and precipitation, which was also statistically significant ($p < 0.0001$; Figure 4—7c). The confidence intervals of 95 % were measured (between SM-MOD from the model and the monthly temperature): from 0.728 to 0.858 and with a monthly precipitation from 0.759 to 0.876.

Table 4—5. Correlation among the monthly SM-MOD with the monthly temperature (°C) and monthly precipitation (mm) from the CRU data between 2010 and 2020.

Variables	**SM-MOD (m^3/m^3)**	**Temperature, °C**	**Precipitation, mm**
Confidence intervals (95%)/lower bound	1	0.728	0.759
Confidence intervals (95%)/upper bound	1	0.858	0.876
Correlation matrix (Pearson)	**1**	**0.802**	**0.826**
p-values (Pearson)	**0**	**<0.0001**	**<0.0001**
Bias	0	0.025	0.026

Values in bold are different from 0, with a significance level alpha = 0.05.



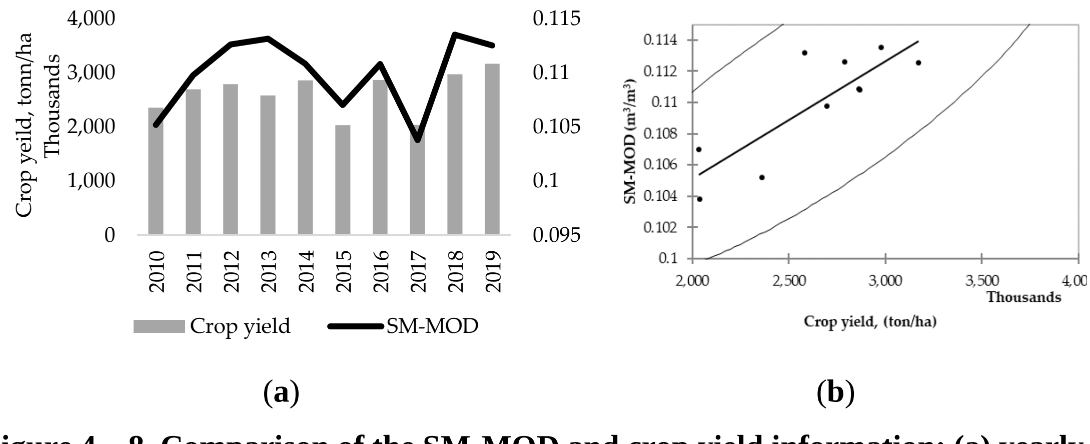
(a) (b) (c)

Figure 4—7. Scatter diagram of the monthly SM-MOD (m³/m³), monthly temperature (°C) and monthly precipitation (mm) in the study area from 2010 to 2020: (a) SM-MOD and SM-MOD; (b) SM-MOD and temperature (°C) and (c) SM-MOD and precipitation (mm).

4.4.4 Comparison between the SM-MOD and Crop Yield

We considered the crop yield information of every year to correlate with the SM-MOD from the model. The National Statistical Organization (NSO) has provided every province's crop yield information since 2010. Figure 4—8 shows the trends of the averaged SM-MOD from May to September 2010–2019 and the observed total crop yield data for each year (2010–2019).

In order to apply the model to the utilization, we examined the relationship between the SM-MOD and crop yield in Mongolia. The results show that there is a significant trend (visible) in the SM-MOD. It was statistically significantly ($p < 0.003$) correlated with the crop yield, with $r = 0.835$ (Table 4— 6 and Figure 4—8).



(a) (b)

Figure 4—8. Comparison of the SM-MOD and crop yield information: (a) yearly crop yield (ton/ha) and averaged SM-MOD from May to September (2010–2019); (b) scatter diagram of the SM-MOD and crop yield information.

Table 4— 6. Correlation between the averaged SM-MOD from May to September 2010–2019 and the yearly crop yield from NSO for 2010–2019.

Variables	SM-MOD (m^3/m^3)	Crop Yield (ton/ha)
Coefficients of determination (Pearson)	1	0.697
Correlation matrix (Pearson)	**1**	**0.835**
p-values (Pearson)	0	0.003
Bias	0	-0.005

Values in bold are different from 0, with a significance level alpha = 0.05.

4.4.5 ARIMA Model of Soil Moisture

We selected the most appropriate model for the time series from the possible models. We selected our model using these criteria: firstly, the most significant coefficients; secondly, the lowest volatility; thirdly, the highest adjusted R-squared; and lastly, the lowest Akaike's Information Criterion (AIC) / Schwarz Information Criterion (SIC). Since the theory behind the ARMA estimation is based on stationary time series, we firstly used the transformation based on a logarithm and we considered the first difference of the soil moisture time series. According to the unit root test, the differenced series are stationary (series), so we applied the plots of the ACF and PACF to identify the structure of the model. The plots and statistical tests illustrated that the ARIMA (12, 1, 12) model was suitable for the log time series of the soil moisture. The estimation results and the actual, fitted residual graphs of the model are shown in Table 4—7 and Figure 4—9, respectively. The residual diagnostics' tests suggest that the estimation residuals are white noise. The final results indicate the good performance of the model and we could say that about 82 % of the soil moisture variability was predicted by the selected model (Table 4—7).

The selected model is written as follows:

$$d(X_t) = 0.0006 + 0.9993X_{t-12} + 0.0006X_{t-1} - 0.95z_{t-12} \qquad (4\text{-}7)$$

or, equivalently, as

$$X_t = 0.0006 + 0.9993X_{t-12} + 0.0006X_{t-1} - 0.95z_{t-12} \qquad (4\text{-}8)$$

, where X_t is the log value of the soil moisture at time t and z_t the error term at time t.

The above mentioned model shows that the soil moisture at time t depends on the value of the soil moisture of previous months and also on the error terms of 12 months ago.

Table 4—7. Results of the time series' analysis for the soil moisture.

Dependent Variable: DLOG (SM-MOD)		Method: Least Square		
Sample: 2010M02–2020M05		Included Observations: 124		
Failure to Improve Objective (Non-zero Gradients) after 90 Iterations				
Coefficient Covariance Computed Using Outer Product of Gradients				
Variable	Coefficient	Std. Error	*t*-Statistics	Prob.
C	0.000560	0.116782	0.004795	0.9962
AR (12)	0.999321	0.000118	8501.412	0.0000
AR (1)	0.000625	0.000160	3.899161	0.0002
MA (12)	−0.950003	0.020568	−46.18744	0.0000
SIGMASQ	0.003390	0.000392	8.655254	0.0000
R-squared	0.822436	Mean dependent variable		0.002194
Adjusted R-squared	0.816468	SD dependent variable		0.138724
SE of regression	0.059430	Akaike info. criterion		−2.485006
Sum squared residuals	0.420300	Schwarz criterion		−2.371285
Log likelihood	159.0703	Hannan–Quinn criterion		−2.438809
F-statistic	137.7955	Durbin–Watson statistic		2.030050
Prob (F-statistic)	0.000000			

The Partial AutoCorrelation (PAC) measures the correlation between the observations that are p periods apart after controlling the correlations at intermediate lags (i.e. lags less than p). The correlogram of the residuals is flat, which indicates that the information has been captured (Figure 4—9). A flat correlogram of the residuals is ideal. Therefore, the forecast will be based on this model.

Sample: 2010M01–2020M05 Included observations: 124

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	−0.051	−0.051	0.3333	0.564
		2	0.006	0.004	0.3384	0.844
		3	0.066	0.066	0.8956	0.827
		4	−0.040	−0.034	1.1075	0.893
		5	0.053	0.049	1.4795	0.915
		6	−0.107	−0.107	2.9887	0.810
		7	0.077	0.073	3.7843	0.804
		8	0.079	0.080	4.6240	0.797
		9	−0.019	0.005	4.6748	0.862
		10	−0.102	−0.128	6.1135	0.806
		11	0.035	0.032	6.2821	0.854
		12	0.021	0.016	6.3463	0.898
		13	0.009	0.036	6.3567	0.932
		14	−0.074	−0.082	7.1445	0.929
		15	−0.066	−0.080	7.7684	0.933
		16	0.000	−0.039	7.7684	0.955
		17	−0.070	−0.031	8.4925	0.955
		18	0.081	0.102	9.4620	0.948
		19	−0.026	−0.024	9.5652	0.963
		20	0.110	0.087	11.374	0.936

Figure 4—9. Correlogram of residuals squared of the autocorrelation function (ACF) and partial autocorrelation function (PACF).

One of the main purposes of the ARMA and ARIMA models is to provide short-term forecasts. Hence, we have predicted the soil moisture values using the selected model from 2020 to 2025. Figure 4—10 shows the forecasting results for the soil moisture from 2020 to 2025 with a 95 % confidence interval, which is the range within (which) the actual dependent value should fall a given percentage of the time (the level of confidence). For the forecasting, the root mean squared error was 0.002 and the bias proportion 0.044. Figure 4—11 compares the actual soil moisture and the soil moisture forecasting (in m^3/m^3) from January to May 2020. The prediction from February and April is almost the same as for the actual soil moisture, although there were slight deviations when predicting March and May. Overall, the model demonstrated an accurate forecast of the soil moisture.

The essence of an appropriate ARIMA model is to forecast the future trends of the series. Hence, we utilized the past information of the soil moisture series (itself). The forecast was based on the final selected model, ARIMA (12, 1, 12).

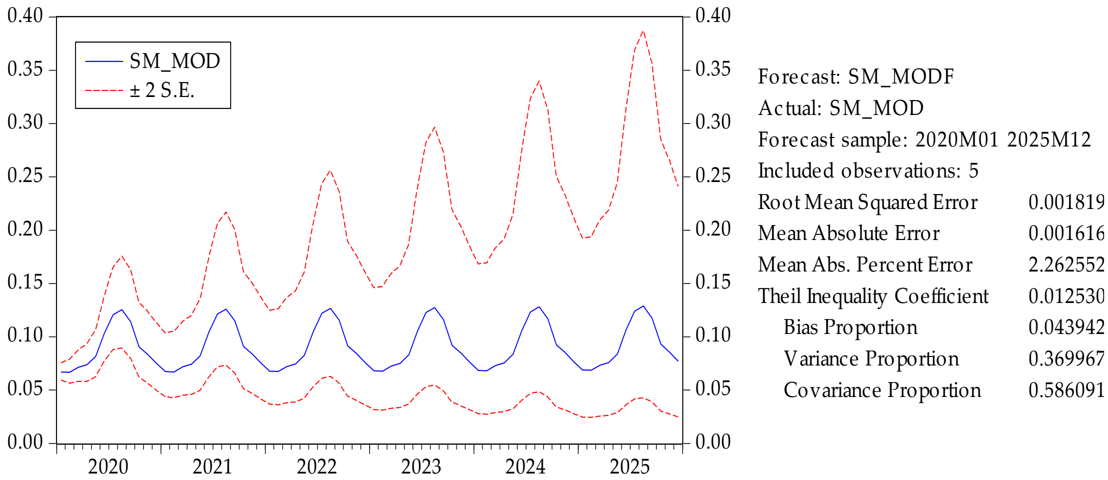


Figure 4—10. Soil moisture forecasting from the ARIMA model (m^3/m^3).

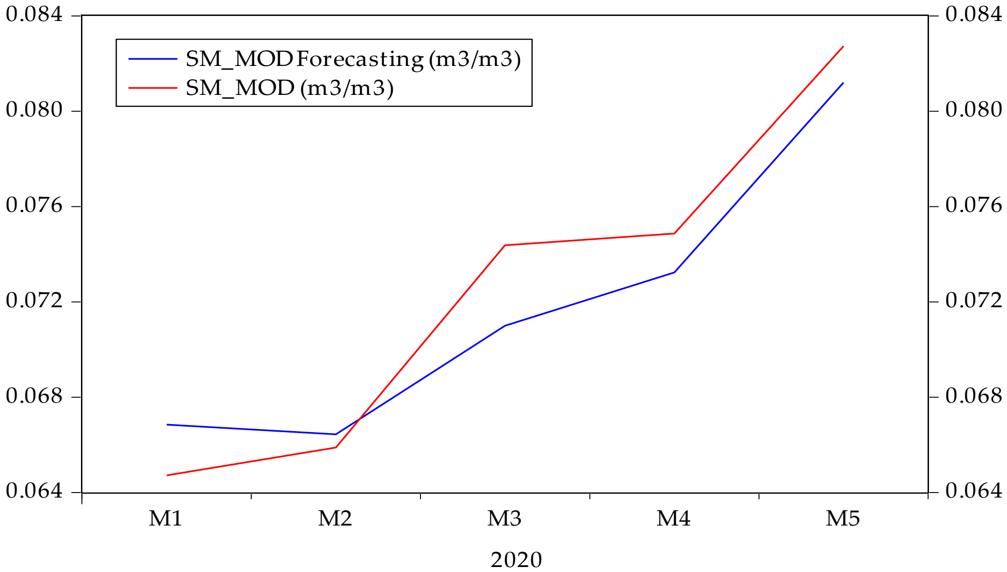


Figure 4—11. Comparison graph of the real soil moisture and soil moisture forecast.

The forecasting values of the soil moisture are given in Figure 4—12, with the kernel density of the values on the y axis.

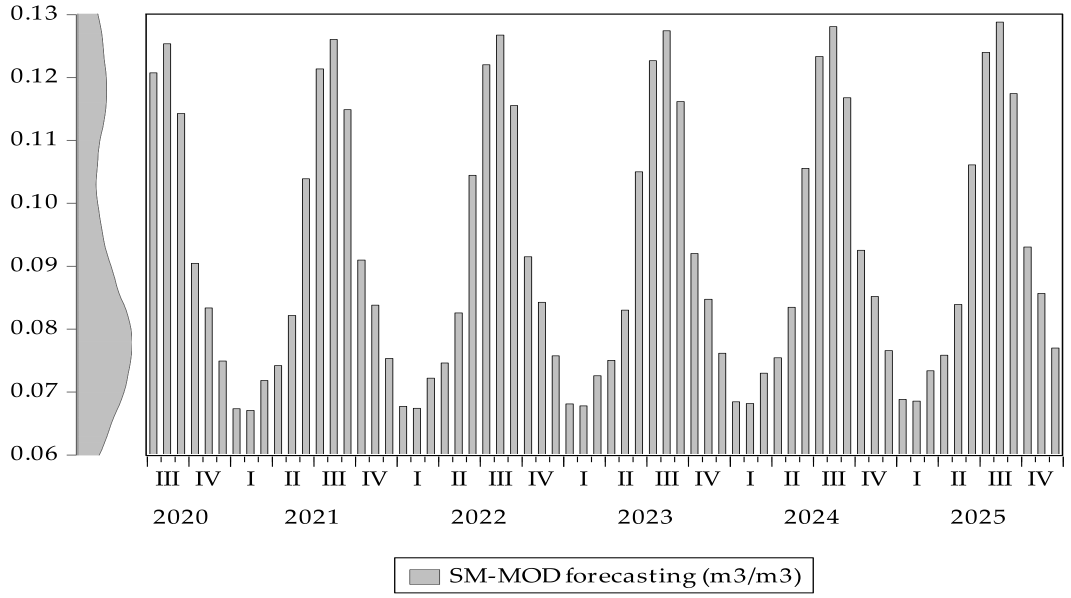


Figure 4—12. Predicting the soil moisture trend until December 2025.

4.5 Discussion

In the present study, we used a linear regression model to estimate the spatial distribution of the soil moisture in Mongolia by considering the satellite images (SMAP and MODIS). We estimated the monthly (January–December) soil moisture in Mongolia during the period 2010–2020. The SM model performance was validated by a comparison with the SMC from the agricultural meteorological stations, with data on precipitation, temperature, crop yield, etc. The correlation has shown that the model (SM-MOD) gives accurate information on the soil moisture for each month. Moreover, the present model has the advantage of recognizing the soil moisture spatial distribution with a high spatial resolution (1 km); this is the first time such information has been gathered for Mongolia. Therefore, we have established the ARIMA model for soil moisture forecasting based on estimated soil moisture between 2010 and 2020. The results provide the monthly spatial distribution of the soil moisture, which contains valuable data for use in numerous contexts, including the agricultural management, drought monitoring, assessment of climate change, flooding and in determining the pasture and land degradation. The land degradation in central Mongolia is mostly caused by overgrazing; however, changes in the summertime precipitation have also occurred (Hilker et al. 2014). The Mongolian grassland has been decreasing and droughts are still increasing (Sternberg 2018). Our research on the time series' analysis for the monthly SM-MOD forecasting is vital for the monitoring of the land degradation and drought.

The outcomes of the correlation coefficients are low because of the limited available data in the agricultural meteorological stations. However, the correlation was statistically significant at $p < 0.0001$ (0–20 cm) and $p < 0.005$ (0–50 cm), respectively between the SM-MOD and SMC from the meteorological stations at different depths. From Figure 4—7, we could see that the previous month's precipitation directly impacted the soil moisture during the growing season (June–September). The correlation between the SM-MOD and temperature had correlation coefficients (r) of 0.80 (statistically significant at $p < 0.0001$) and 0.83 (statistically significant at $p < 0.0001$). However, the SM-MOD compared with the crop yield for each year (2010–2019) demonstrated a correlation coefficient (r) of 0.84.

Therefore, the time series' analysis for the monthly soil moisture forecasting was developed based on the established ARIMA model. From the study, we selected the ARIMA (12, 1, 12) model, which was most suitable for the SM-MOD time series, for the prediction, in which the values of the soil moisture (SM-MOD) have been predicted from 2020 to 2025 (using the selected model). The forecasting results are shown with a 95 % confidence interval. The time series SM-MOD data will provide valuable information for the decision-makers and researchers. The SM-MOD time series and forecasting data are good data sources for the long-term agricultural management, planning, climate change and drought monitoring.

In terms of applications, this multiple linear regression model is a practical tool for a reliable and timely drought monitoring; thus, the advantage of this research lies in providing valuable information for the decision-makers and farmers. In further studies, we will investigate the seasonal soil moisture in different vegetation zones (using this method along with the field measurements).

4.6 Conclusions

The soil moisture is an essential factor for the agricultural lands in Mongolia. The model applied in this paper is suitable for use in the agricultural areas and has interesting applications for the agricultural management (irrigation, pasture and hayfield yield) and drought monitoring in Mongolia. A time series' analysis is one of the main tools for analyzing and predicting future trends of the soil moisture. Most former studies have examined the soil moisture by comparing it with climatic factors that were analyzed based on the correlation analysis and multilinear regression (D. Zhang and Zhou 2016; Y. Wang et al. 2018; Xia et al. 2019). The LST/NDVI combination method proves to be a robust method to estimate the SM; this combination is easy to operate and has a strong physical basis (D. Zhang and Zhou 2016).

In general, the model's performance in determining the soil moisture was practically assessed by means of satellite images. This study took Mongolia as the study area, dividing it into six vegetation zones. The linear regression method was applied in the soil moisture estimation using SMAP and MODIS satellite images. From the model, the spatial distribution of the soil moisture has been developed monthly from 2010 to 2020. The soil moisture was high in the north, while a low soil moisture was observed in southern Mongolia, especially during the warm season. Then, the output maps were compared with the soil moisture contents from the agricultural meteorological stations and the precipitation/temperature from the CRU data. The results show that the estimated soil moisture was statistically significantly correlated with the actual soil moisture contents reported by the stations. Moreover, the estimated soil moisture (SM-MOD), when compared with the crop yield, showed a high correlation, though there is a need for more accurate, detailed ground-measured data. Finally, we have performed a time series' analysis of the soil moisture from 2010 to 2020 and predicted the soil moisture in this study area until 2025. Overall, the developed SM model and time series' method could be applied to investigate the changes in the soil moisture in Mongolia, so it is reasonable to use these in agriculture, hydrology and climate science. However, this linear regression model should be elaborated to suit each vegetation zone or eco-climate regions in the applied study area.

CHAPTER 5

A GIS-based multicriteria analysis on cropland suitability in Bornuur soum, Mongolia

Modified from: Enkhjargal Natsagdorj, Tsolmon Renchin, Philippe De Maeyer, Rudi Goossens, Tim Van de Voorde, Bayanjargal Darkhijav (2020). A GIS-based multicriteria analysis on cropland suitability in Bornuur soum, Mongolia. International Archive Photogrammetry, Remote Sensing, Spatial Information Science. XLIII-B4-2020, 149–156, https://doi.org/10.5194/isprs-archives-XLIII-B4-2020-149-2020

5.1 Introduction

Agriculture is an essential economic sector in Mongolia, contributing to more than 20 % of the annual GDP and representing 14 % of the currency revenues (FAO 2011). Mongolia's agro-ecosystems are incredibly vulnerable; due to global climate change, which is expected to result in higher temperatures and increased evaporation (Batima et al. 2005; Angerer et al. 2008). These weed covered lands induce land degradation and desertification. As a result, land degradation directly influenced by agricultural products (Gantumur et al. 2018). When they could be reclaimed, an enormous potential would improve the agro-production in the country (MFALI 2017). At present, the total size of the arable land is estimated to be 1.2 million hectares, of which 664,300 ha is used as cropland while 561,000 ha has been abandoned (Hofmann, Tuul, and Enkhtuya 2016). However, determining which land is the most suitable for agricultural development is essential to enhance food safety and also to stop the later food crises (Pederson et al. 2013). In Mongolia, in order to improve the agro-production and to provide food security, croplands should be enhanced in areas in which they thrive the most.

The Mongolian agricultural regions are located in the northern central part of Mongolia, which is characterized by a mountainous and forested area. The Mongolian government has been continuously increasing its expenditures for agricultural development by initiating programs to reclaim abandoned agricultural lands, to create favourable economic conditions, to increase production and to ensure food safety (e.g. *Atar 3*) (Hofmann, Tuul, and Enkhtuya 2016). The agricultural products, especially potato and wheat, slightly rose as a result of the national government program. But the dominant vegetables' import was increased by 11.7 times, such as 5,438.4 tons in 1995 and it expanded to 64,107 tons in 2016. Besides, 96 % - 99 % of which came originated from China (Otgonbayar et al. 2017). However, without the total consumption of vegetables (excluding potatoes), around 45 % have been imported (Statistical Information System 2016). That means that the Mongolian food security strongly depends on the neighbouring countries. Mongolia needs to develop its agricultural sector in agricultural management, especially primary crop production.

At present, a widely used GIS application makes the land assessments more flexible, with scientific analysis (G Pan and Pan 2012). The Geographic Information Systems (GIS) is most suited to handle broad extensive data on a multiple (spatial, temporal and scale) from different sources for cost-effective and productive analysis over time (Y. Chen, Yu, and Khan 2010). Therefore, there is an increasing interest in the corporation of the GIS capacity in MCA processes. The Multi-Criteria Analysis (MCA) is one of the usual valuable approaches concerning land use, environmental planning and agricultural management, too (Perveen et al. 2007; Quan et al. 2007; Y. Chen, Yu, and Khan 2010; Kamau, Kuria, and Gachari 2015; Otgonbayar et al. 2017). It is the operational instrument for supporting decision-making issues through various criteria (Grima, Singh, and Smetschka 2018; Zabihi et al. 2019).

The Analytical Hierarchy Process (AHP) is a multi-criteria analysis method that is applied with GIS, which determines the weights toward the selected criteria. AHP method has progressed via (Saaty 1980) has been employed in GIS-based MCA (Carver 1991; Marinoni 2004; G Pan and Pan 2012; Dragićević, Lai, and Balram 2014; Montgomery et al. 2016; Memarbashi et al. 2017). The latter commonly utilized in land-use suitability (Akinci, Özalp, and Turgut 2013; Kamau, Kuria, and Gachari 2015; Otgonbayar et al. 2017; Zabihi et al. 2019). Pan and Pan (2012) applied a GIS-based cropland suitability analysis using natural and socio-economic factors to provide insight into the adaptation of measures to the local conditions regarding the crop layout and farming systems. The GIS-based multi-criteria analysis is widely used in the land suitability analyses from many countries. However, the application of the method in a cropland suitability analysis has not been performed in small Mongolian areas (such as sub-provinces), as proven, from the available literature.

The study provides to support the land manager and agronomists, including the regions' estimation based on the significant criterion that was promoted through the FAO (Food and Agricultural Organization) and adjusted at the farmers. This chapter provides over the determination of the cropland suitability area by means of a GIS-based AHP tool of Bornuur soum to identify the crop production suitability classes. The purpose of this chapter is to estimate cropland suitability that could support the crop production in Bornuur soum in the best possible way by means of multi-criteria analysis (MCA): (1) to identify the influencing criteria for new croplands in Bornuur soum based on a literature review and to specify the classes of the criteria based on the structure of the Food and Agricultural Organization (FAO); (2) to develop a cropland suitability map and to conduct an accuracy assessment with the field measurements from Bornuur soum. There are few studies have been carried out in Mongolia using multicriteria analysis for different purposes, such as a land suitability evaluation (Otgonbayar et al. 2017; Purevtseren and Indraa 2018) and desertification/land degradation (Lamchin et al. 2017). In this chapter, it is employing the AHP tool through approach the cropland suitability over Bornuur soum that will be considered in this article.

Sustainable land-use planning is an essential condition that the evaluation of land suitability analysis surround and their suitability for a designed application concerning the grouping of certain land areas (Sarkar, Ghosh, and Banik 2014a). For land crop suitability, some cognitive factors should be carried out which as moisture, digital elevation model, vegetation cover and effect of topography (Forkuo and Nketia 2011). Several types of research has been done on the land suitability analysis based on GIS, e.g. (Quan et al. 2007; Perveen et al. 2007; Y. Chen, Yu, and Khan 2010; G Pan and Pan 2012; Kamau, Kuria, and Gachari 2015; Otgonbayar et al. 2017); Sarkar et al. 2014; *etc*. In this article, our approach is demonstrated by means of a GIS-based multi-criteria study to a cropland suitability estimation in Bornuur soum, Mongolia.

5.2 Study area

The Mongolian agriculture is divided into five regions: Tuv, Khangai, West, East and Gobi. The total agricultural area of Mongolia measures 1,269,498 ha (65 % of which is situated in Tuv, 11 % in Khangai, 10 % in the West, 14.07 % in the East and 0.03 % in the Gobi region) (MFALI 2017). Therefore, we selected a study area from the most critical agricultural part in Mongolia, the Tuv region. Bornuur *soum* (second-level administrative subdivision) possesses an agriculturally based economy. Bornuur is located between E 48°- 49° and N 106° - 106° 40’ and the average altitude is 872-1,821 meter above sea mean level (E. Natsagdorj et al. 2017). Bornuur soum has a total land area of 114,483.21 ha and is located in the central agricultural zone of Mongolia (Hugjliin Ezed NGO 2008). It is situated in a convenient climatic region, including healthy rich soil. Bornuur soum has four soil types: Cambisols, Gleysols, Kastanozems and Leptosols (Figure 5—1). Before the 1990s, the soum was the central part of the Mongolian agriculture. Agriculture was a significant employer and prominent in all sectors of the soum (Sandmann 2010).

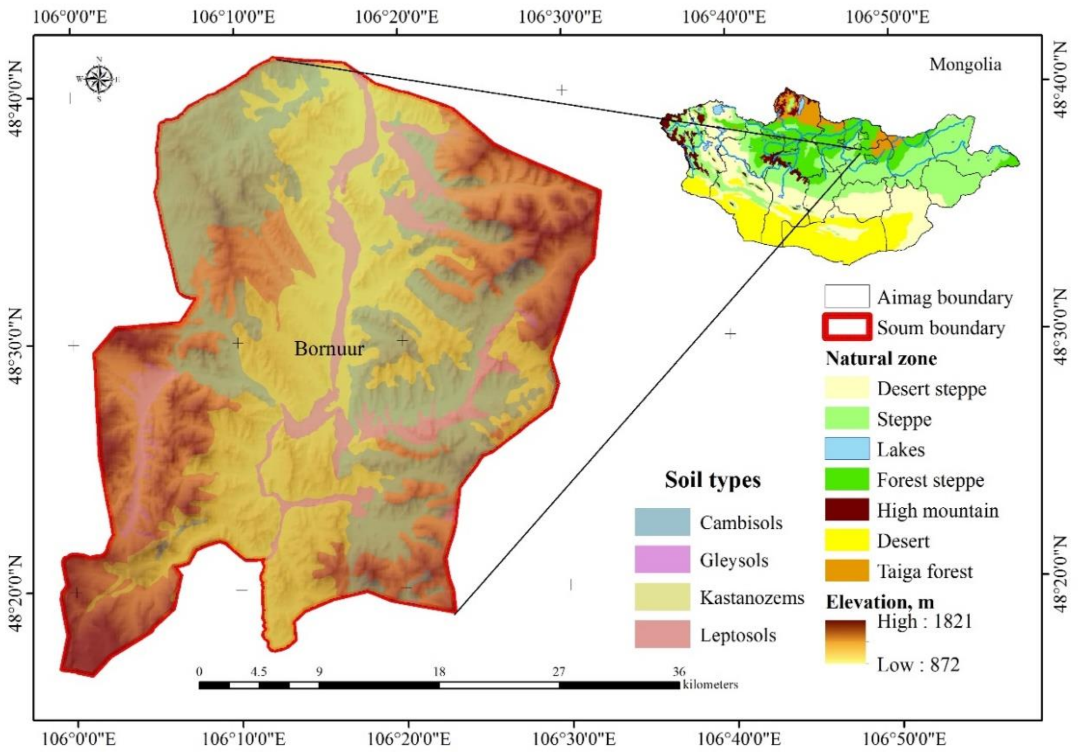


Figure 5—1. The Bornuur soum's soil map, Tuv province, Mongolia (E 48° - 49° and N 106° - 106° 40')

5.3 Data collection and preparation

Crop suitability study was utilized within this research that obtained the following sources. From literature about crop production in Mongolia, we selected vegetable areas that contain many factors such as the soil parameters (soil type, soil texture, soil pH and soil humus), elevation, slope, vegetation, water supply, etc. (FAO 1976; Kamau, Kuria, and Gachari 2015; Otgonbayar et al. 2017). The soil data and a cropland cadastral map were collected from the Land Administration and Management, Geodesy and Cartography (LAMGaC) of Mongolia (Figure 5—1).

The soil thematic map on a 1:50,000 scale (provided by LAMGaC) was reprocessed using ArcGIS 10.3.1 to provide thematic data and then further converted into a raster layer. The four parameters include the soil texture, soil humus, soil pH and soil type were selected. Bornuur soum has a suitable soil type for the cropland with the FAO structure (FAO 1976) of the land suitability criteria. Thematic maps were acquired for each of the factors in Bornuur soum.

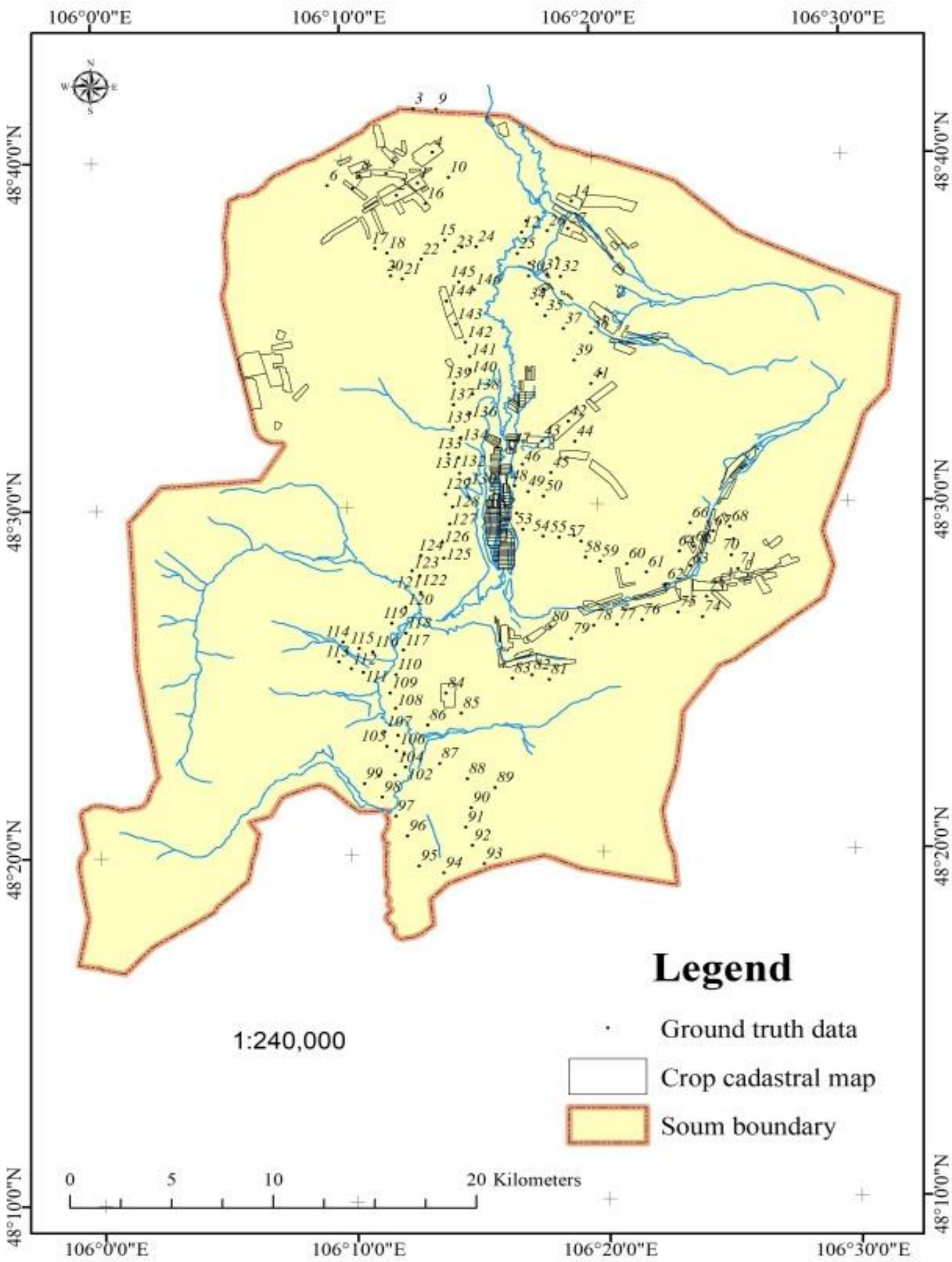


Figure 5—2. Cropland cadastral and field data of the Bornuur soum

A field survey has been carried out archive data in Bornuur soum during 1998 – 2015. However, some field samples (36) have been collected during the field trips in July-August, 2015, with the agronomists of Bornuur soum, Tuv province. The entire 146 samples have been used from the archive and field trip in this study (Figure 5—2). The soum has extensive records of cropland and pasture land use, in digitally and on paper. Based on an expert's knowledge and archive notes, the field measurements were classified into a cropland suitability rate (Table 5—1). The archive notes include information on soil and vegetation such as the organic matter, soil texture, soil moisture, soil pH, etc. Additionally, the vegetable products of the archive data were used for a suitability classification. The suitability classes were made by local agronomists and specialists. For example, the damaged area (soil erosion, bare land) has been classified for the unsuitable. The soil texture (heavy clay), soil pH (7.8-8.5) and vegetation types (Artemisia frigida, Artimisia adamsii and Potentilla bifurca, *etc*.) are chosen as marginal suitable (52 samples). The soil texture (sand), soil humus (2-3 %), soil pH (7.5-7.8) and vegetation types (herb grass) are seen as moderate suitable (71 samples). The soil texture (light clay, mid-siltstone), soil humus (more than 3 %) and current croplands are considered to be highly suitable (21 samples) (Table 5—1). Concerning the data validation, the field samples will be utilized in the result section.

The questionnaire was collected from 24 farmers and experts, who have been working in their field long-term. 18 of them possess a small-scaled farm which measures less than 10 hectare and the farmers especially grow potato, wheat and vegetables. 6 farmers have a big-scaled farm (exceeding 10 hectare) and the farmers/companies cultivate wheat, potato and fodder crops.

Table 5—1. The field data classification into suitability classes (based on the soil and vegetation archive data)

Field samples	Highly unsuitable	Unsuitable	Moderate suitable	Highly suitable
Classes	S1	S2	S3	S4
Criteria	damaged area (bare land)	Soil texture (heavy clay), soil pH (7.8-8.5) and vegetation types (Artemisia frigida, Artimisia adamsii and Potentilla bifurca, etc.)	Soil texture (sand), soil humus (2-3%), soil pH (7.5-7.8) and vegetation types (herb grass)	Soil texture (light clay, mid-siltstone), soil humus (more than 3%) and current croplands
$\sum 146$	2	52	71	21

Note: Artemisia frigida, Artimisia adamsii and Potentilla bifurca etc: the prevalence of these plants is the sign of land degradation (Bulgamaa et al. 2018)**.**

In this chapter, we used Landsat OLI8 and ASTER satellite images. More detailed information can be seen in Section 1.3.1 and 1.3.4. In order to obtain the slope and elevation data from the advanced spaceborne thermal emission and reflection (ASTER), the satellite global digital elevation model (GDEM) data were used with a 30-meter resolution. The Landsat 8 operational land imager (OLI) with 30-meter resolution data (path 132, row 26) was used for the estimation regarding the Normalized

Difference Moisture Index (NDMI) and Normalized Difference Vegetation Index (NDVI) between July / August (2014-2019) for this research. Table 5—2 described a data list that we applied for the benefit of this research.

Table 5—2. Used data

Data type	Data description	Data source
Soil data	Soil pH, soil humus, soil texture, soil type	Land Administration and Management, Geodesy and Cartography (LAMGaC)
Digital Elevation Model	Aster GDEM V2 2011, the resolution is 30m	U.S Geological Survey (USGS) and Earth Remote Sensing Data Analysis Centre (ERSDAC)
Normalized Difference Vegetation Index (NDVI); Normalized Difference Moisture Index (NDMI)	*NDVI=(NIR-Red)/(NIR+Red)* *NDMI=(NIR-MIR)/(NIR+MIR)*	Landsat TM/OLI satellite images between 2014 and 2019 (McDonald et al. 1998; Jin, Sader, 2005; Woodcock et al. 1994)
Cropland cadastral map	Current cadastral survey	Land Administration and Management, Geodesy and Cartography (LAMGaC)
Field survey	146 samples collected using a handheld GPS, Accuracy 1-5 m	Field survey and agronomist expert's (1998-2015) archive information
Questionnaire	The questionnaire was prepared that are related to the crop suitability criterion	Collected from the local farmers and experts (24 local farmers and experts)

5.4 Methodology and analysis

The multi-criteria analysis method (based on GIS) was applied to determine the cropland suitability. Based on our literature review, only a few scientific studies have been performed on land suitability evaluation in Mongolia (Otgonbayar et al. 2017; Purevtseren and Indraa 2018). Although no reviews are available on the physical planning of croplands in the small regions of Mongolia using the spatial multicriteria analysis method. The process adopted for the crop suitability of the study area has executed the methodology illustrated in Figure 5—3. This latter illustrates the employed method in this chapter.

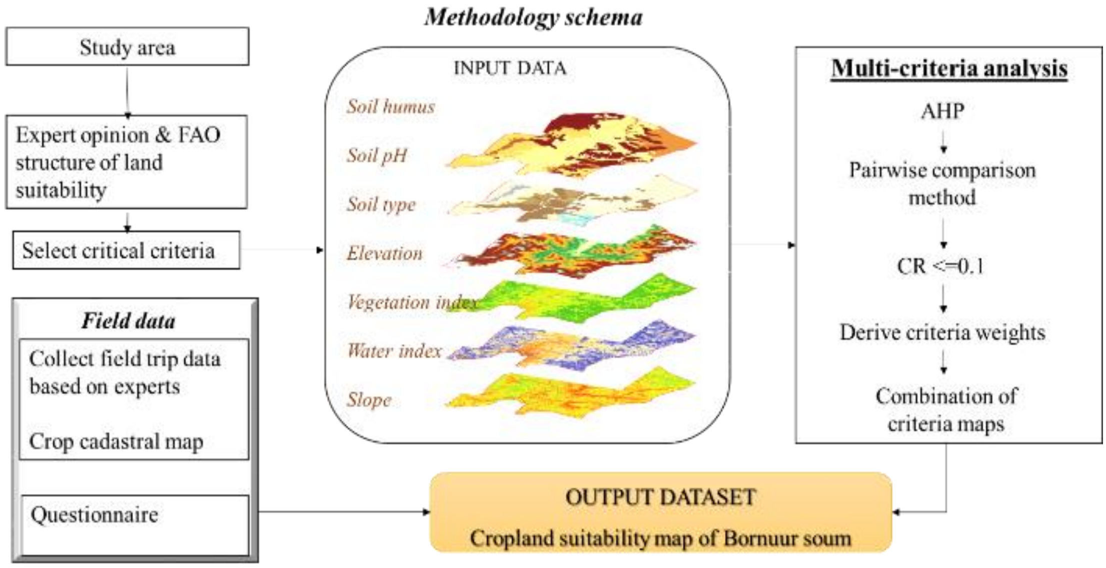


Figure 5—3. Flowchart methodology of the cropland suitability. FAO: Food and Agricultural Organization; AHP: Analytical Hierarchy Process; CR: Consistency Ratio

5.4.1 Selection of the suitability criteria

In the study area, the most important economic sector is agriculture, especially the crop sector. A literature review of various references and consultation of local agronomist experts helped to identify the necessary criteria (soil texture, soil type, soil pH, soil humus, elevation (altitude), slope, vegetation and moisture) in order to estimate suitable areas for crop production. Suitability classes were made set up on formation from the FAO land suitability analysis and ranging from highly suitable, moderately suitable and unsuitable to highly unsuitable in Bornuur soum, Mongolia. These classes were estimated according to the FAO guideline, literature review and agronomist expert's opinions (Table 5—3).

5.4.2 MCA for assigning the weight to each criterion

The Analytical Hierarchy Process (AHP) is a standard mathematical method introduced by (Saaty 1977) that is used when analyzing complex decision problems (Saaty 1977; 1990). The AHP, pairwise comparison matrix estimates the weights of each criterion (w_i).

Pairwise comparison matrixes involve the comparison of all possible pairs of criteria in order to estimate which of them are from a higher priority. Saaty (1980) suggests a scale from 1 to 9 in which value 1 indicates that the criteria are equally essential and value 9 means that the considered criterion is superior to the other criteria (Table 5—4).

The crop suitability classes were assigned score 9, 7, 5 and 3, respectively. The classes with higher scores are highly suitable for crop production and by applying these scores, the estimated suitability classes and all thematic maps were reclassified.

Table 5—3. Criteria for the cropland suitability based on the experts and the FAO (1984) for the structure in Bornuur soum

Factor/Criterion	Highly suitable	Moderately suitable	Unsuitable	Highly unsuitable
Soil texture (class)	Light clay & mid-siltstone	Sand	Heavy clay	Clay
Soil type	Kastanozems, Gleysols, Gambisols and Leptosols			
Soil pH	5.5 – 7.5	5.2-5.5 7.5-7.8	4.5-5.2 7.8-8.5	8.5< 4.5>
Soil humus (%)	3 <	2.0 – 3.0	1.0 - 2.0	1 >
Elevation (meter)	1,500 >	1,500 – 2,000	2,000 – 3,500	3500 <
Slope (degrees)	0 - 6	6 - 9	9 - 12	12 <
NDVI (index)	0.35 <	0.25 - 0.35	0.15 – 0.25	0.15 >
NDMI (index)	0.35 <	0.25 - 0.35	0.15 – 0.25	0.15 >

Table 5—4. Scale concerning pairwise correlation (Saaty 1990; Saaty and Vargas 2013; Burnside, Smith, and Waite 2002)

Numerical expression	Comparative importance	Suitability rating
1	Equal importance	Unsuitable
3	Moderately importance of one factor covering another	Marginal suitable
5	The strong or crucial importance	Moderate suitable
7	Extreme importance	Highly suitable
9	Extremely importance	
2, 4, 6, 8	Moderate values	

5.4.3 Weighted linear combination (WLC) estimation of the criteria

We rated all criterion set up on the information from the literature review and the local experts.

In order to estimate the related criteria weight, the AHP method has been applied to compute every criterion weight. A pairwise comparison matrix (PWCM) held taken using information from the literature review and the local experts concerning determining the value of weights regarding each related criterion through another. In AHP method, a consistency index intervenes in the Consistency Ratio (CR), has been applied to designate the possibility that matrix judgements obtained a randomly created by means of equation (5-1) (Hossain et al. 2013):

$$CR = \frac{CI}{RI} \tag{5-1}$$

, where *RI* is mean of the resulting consistency index depending on the quantity of the matrix, given by Saaty (Hossain et al. 2013; Sanare and Ganawa 2015).

The *CR* index represents the consistency of the PWCM. If the *CR* exceeds 0.1, that weighting rate is unacceptable and if the ratio value is lower than 0.1, that weighting rate means acceptable (Hossain et al. 2013). The Consistency Index (*CI*) is described in equation (5-2):

$$CI = \frac{m_{\max} - n}{n - 1} \tag{5-2}$$

, where *CI* stands for the Consistency Index, $m_{\max}$ the maximum own value and n represents the matrix order.

After estimating the weights of the values of the criteria using the AHP tool, all criteria maps have been overlaid applying the cropland suitability (equation 5-3). Cropland suitability map could be calculated from the Weighted Linear Combination (WLC) of criteria used by the equation (5-3). The WLC method is one of the most commonly used in GIS-MCA (Malczewski 2000).

$$CS = \sum_i w_i * c_i \tag{5-3}$$

, where *CS* represents the final cropland suitability value, w_i shows the weight of criterion *i* and c_i demonstrates the standardized criterion score *i* (Gorsevski, Jankowski, and Gessler 2006).

The weights of seven criterion and ranks represent in Table 5—5, according to the literature review and local experts' interviews. We have estimated CR = 0.094 and this shows that the judgement has a reasonable consistency. The w_i is the weight value for each criterion and normalizes the amount of the sections facing unity while $\sum w_i = 1$ (Helmut et al. 2013).

Table 5—5. Defined ranking and weights of the criteria

Id	Name of the criteria	Ranking	Weight
1	Soil texture (*ST*)	2	0.193
2	Soil pH (*pH*)	7	0.223
3	Soil humus (*SH*)	1	0.132
4	Elevation (*E*)	5	0.158
5	Slope (*Sl*)	4	0.106
6	NDMI (*NDMI*)	6	0.109
7	NDVI (*NDVI*)	3	0.078
Consistency ratio (CR): 0.094			

5.4.4 Accuracy assessment

The confusion matrix can provide different measures of accuracy. For the accuracy assessment of the cropland suitability map, the confusion matrix has been used. A confusion matrix is usually applied as a quantitative method of characterizing image classification accuracy. It is a table that shows the connection between the output map and the field measurements (Story and Congalton 1986).

5.5 Results and discussion

In order to obtain the weighted linear combination of different criteria for the cropland suitability in Bornuur soum, seven criteria images were overlaid applying the cropland suitability (equation 5-4).

$$CS = w_i * ST + w_i * pH + w_i * SH + w_i * E + w_i * Sl + w_i * NDVI + w_i * NDMI \qquad (5\text{-}4)$$

, where: CS - Cropland Suitability, $w_i = j$; $\sum w_{i} = 1.0$, a weighted index for influencing criterion, ST - Soil Texture, pH - Soil PH, SH - Soil Humus, Sl - Slope, E - Elevation, $NDVI$ - Normalized Difference Vegetation Index, $NDMI$ - Normalized Difference Moisture Index

In this chapter, a multi-criteria analysis was applied to Bornuur soum using an ArcGIS weighted overlay tool. In the suitability analysis, weights measure the influence of the considered suitability criteria (Helmut et al. 2013), which are shown in Table 5—3. Multi-criteria analysis was created mentioning the following equations (5-5). The tool works with multiple raster inputs, representing several criteria. In this suitability model, the output values from the approach could range from unsuitable to highly suitable. The w_i stands for the weighted indexes (Table 5—5) for each criterion on cropland suitability in Bornuur soum. Thus, the weighted linear combination of criteria through equation (5-5) has been estimated.

$$CS = 0.19 * ST + 0.22 * pH + 0.13 * SH + 0.16 * E + 0.11 * Sl + 0.08 * NDVI + 0.11 * NDMI \qquad (5\text{-}5)$$

In the present case, the cropland suitability classes consisting of four ranges applied in this study adjusted the FAO system (FAO 1976). They are specified as: highly suitable, moderately suitable, marginal suitable and not suitable. Seven criteria (soil texture, soil pH, soil humus, elevation, slope, NDVI and NDMI) were chosen based on the study objective and in particular the data availability. The soil thematic data were converted into raster layers and prepared in ArcGIS. The elevation and slope were produced from DEM. The NDVI and NDMI were calculated from the Landsat satellite images with a 30 m resolution during 2014-2019. All selected criteria were classified into 4 classes as an integer raster displaying different cropland suitability set up on the origin rates in Table 5—3. The results of this chapter provide all criteria, as shown in Figure 5—4. The best suitable areas for cropland signify indicated within green colour and unsuitable areas occur in red (Figure 5—4). Given the validation, we applied a confusion matrix evaluation between the output maps regarding the cropland suitability and field data. The output maps for the crop suitability apply several criteria such as the soil texture, pH, soil humus, elevation, slope, NDMI and NDVI. The soil type criteria were not applied for the criteria on cropland suitability in the study area. Soum has suitable soil types for the cropland that are maintained in the FAO structure of the land suitability criteria (FAO 1976). The output map for suitability described four classes with the relative suitability for cropland. These classes are explained as follows: unsuitable in red, marginal suitable in light yellow, moderate suitable in light green and highly suitable in dark green (Figure 5—5). The output map from the cropland suitability area approach is demonstrated in Figure 5—5.

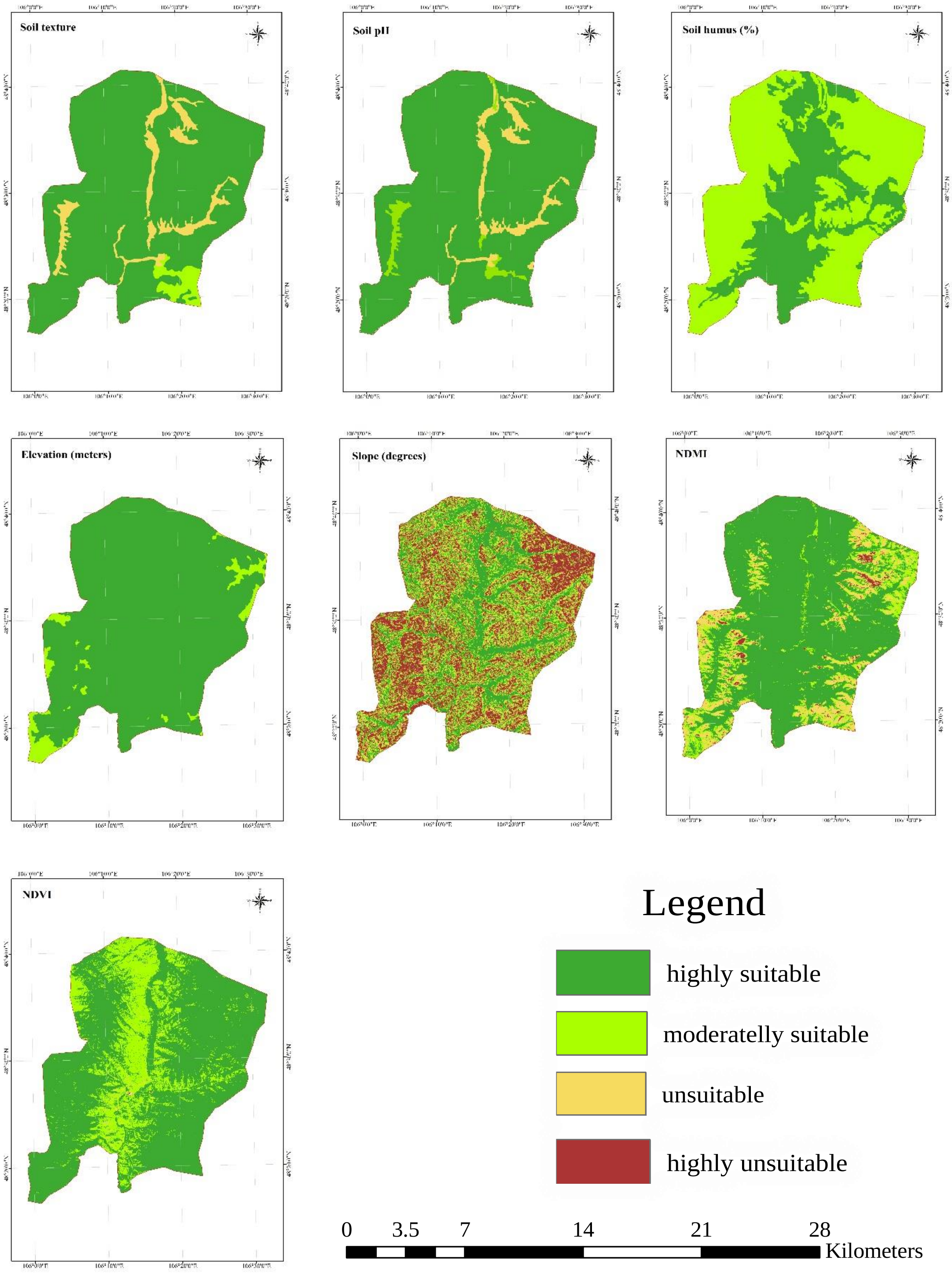


Figure 5—4. Criteria maps for the cropland suitability which as classified via table 3.

In order to make validations, the output map from the approach was compared with the crop cadastral map from the Agency for Land Administration and Management, Geodesy and Cartography and the field data from the field survey, respectively. Firstly, the cropland cadastral map overlapped the output suitability map. Currently, there are 259 croplands in Bornuur soum in total. Around 95 % of the croplands are located in the highly suitable and moderate suitable part of the output map of suitability.
The result of the cropland suitability analysis reveals that 46.12 % is highly suitable for cropland, 34.68 % is moderate suitable, 13.64 % unsuitable and 5.56 % highly unsuitable (Figure 5—5).
Additionally, the questionnaires data related to the cropland suitability criteria were collected from the local farmers and experts. During the study, we gathered several questionnaires from the local farmers and experts (24 respondents) during 2019. The questionnaire was prepared as a patch and selection test that included twelve questions which are related to the criteria on crop suitability (Figure 5—6).
The questionnaire was prepared for the local farmers and the questions based on a classification of criteria. The latter comprised questions about soil parameters (soil pH, soil texture, soil type, soil moisture), slope and elevation made on the form (Figure 5—6). The result reveals that 74.2 % proves highly suitable for cropland, 19.2 % is moderate suitable, 1.67 % marginal suitable and 5.0 % is not necessary (Table 5—6).

The field data were classified into four levels (Table 5—1), the same as for the crop suitability output map in the study area. The output crop suitability map was sufficiently accurate for field data. Then, a validation was made by means of the confusion matrix evaluation. A strong relation (71.23 %) is noticeable between the output map of suitability and the field survey (Table 5—7). The overall accuracy compared with the field data measures 71.23 % of the pixels that are identically classified for both datasets. The most representative and complied proof was the kappa coefficient of 0.56, which describes a moderate agreement within the output crop suitability and the field data.

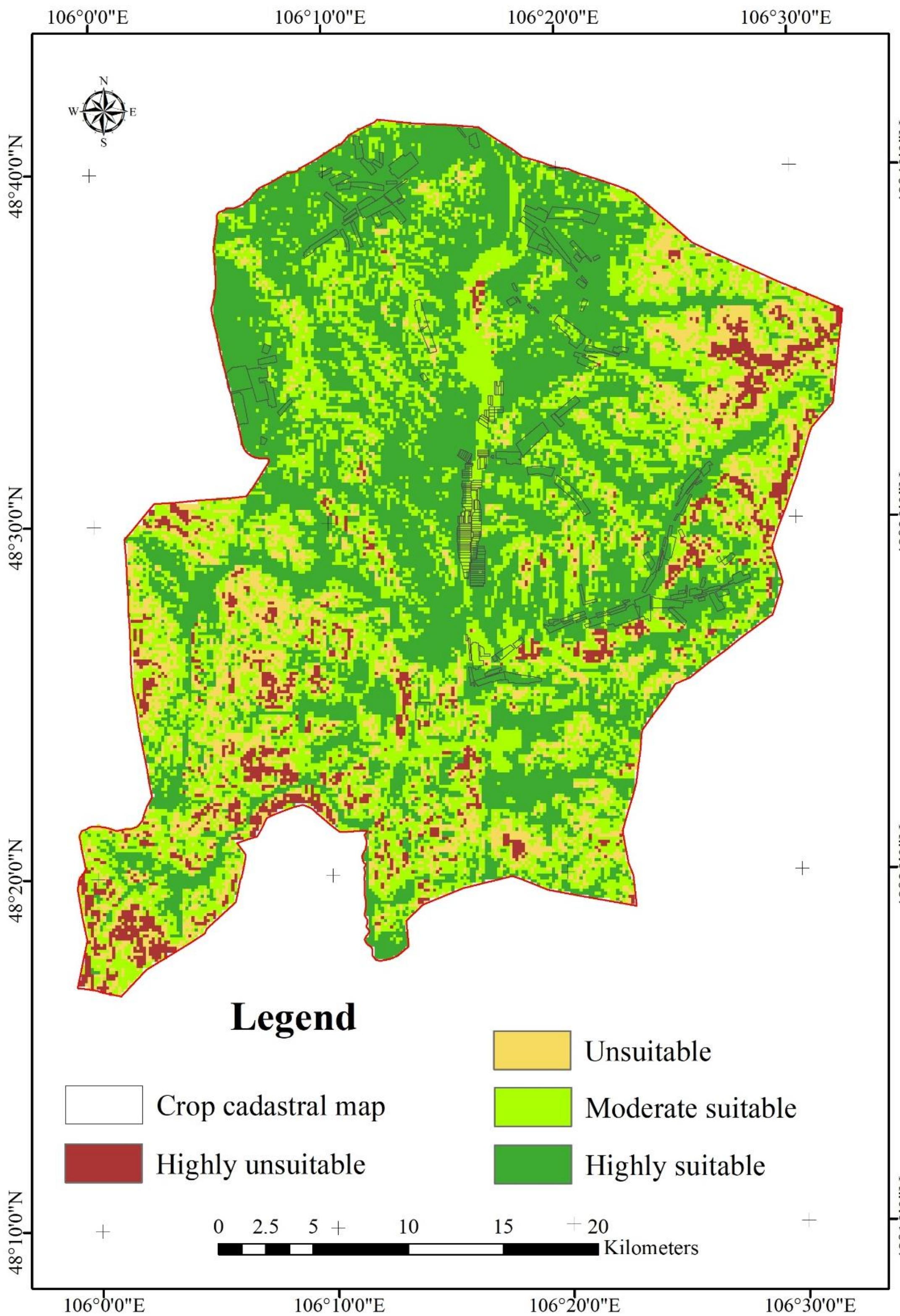
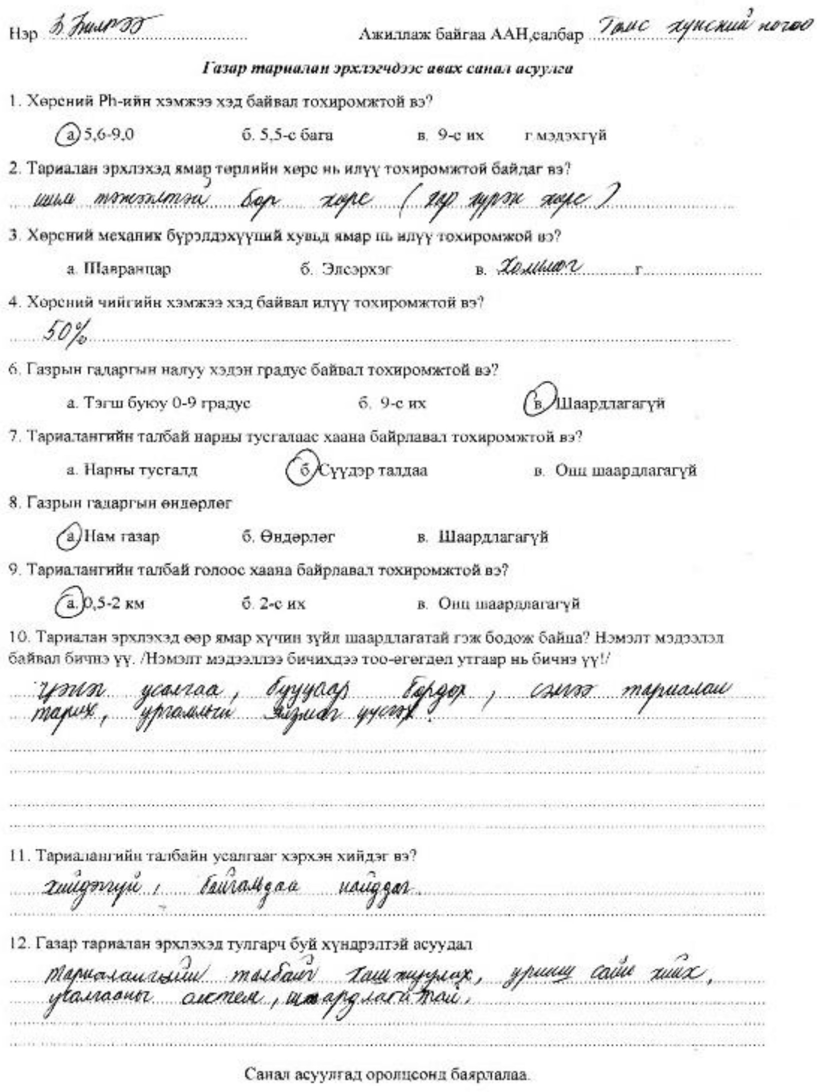


Figure 5—5. The output map of the cropland suitability in Bornuur soum


Нэр Б.Билгээ .... Ажиллаж байгаа ААН,салбар Таис хүнсний ногоо

Газар тариалан эрхлэгчдээс авах санал асуулга

1. Хөрсний Ph-ийн хэмжээ хэд байвал тохиромжтой вэ?

а) 5,6-9,0 б. 5,5-с бага в. 9-с их г мэдэхгүй

2. Тариалан эрхлэхэд ямар төрлийн хөрс нь илүү тохиромжтой байдаг вэ?

шим тэжээлтэй бор хөрс (шар шороон хөрс)

3. Хөрсний механик бүрэлдэхүүний хувьд ямар нь илүү тохиромжой вэ?

а. Шаврангар б. Элсэрхэг в. Холимог г.

4. Хөрсний чийгийн хэмжээ хэд байвал илүү тохиромжтой вэ?

50%

6. Газрын гадаргын налуу хэдэн градус байвал тохиромжтой вэ?

а. Тэгш буюу 0-9 градус б. 9-с их в. Шаардлагагүй

7. Тариалангийн талбай нарны тусгалаас хаана байрлавал тохиромжтой вэ?

а. Нарны тусгалд б. Сүүдэр талдаа в. Огт шаардлагагүй

8. Газрын гадаргын өндөрлөг

а. Нам газар б. Өндөрлөг в. Шаардлагагүй

9. Тариалангийн талбай голоос хаана байрлавал тохиромжтой вэ?

а. 0,5-2 км б. 2-с их в. Огт шаардлагагүй

10. Тариалан эрхлэхэд өөр ямар хүчин зүйл шаардлагатай гэж бодож байна? Нэмэлт мэдээлэл байвал бичнэ үү. /Нэмэлт мэдээллээ бичихдээ тоо-өгөгдөл утгаар нь бичнэ үү!/

үрийн усалгаа, бууцаар бордох, сайн тариалан тарих, урамшуулал эдийн засгийн дэмжлэг үзүүлэх

11. Тариалангийн талбайн усалгааг хэрхэн хийдэг вэ?

хийдэггүй, байгалиасаа чийгээр

12. Газар тариалан эрхлэхэд тулгарч буй хүндрэлтэй асуудал

тариалангийн талбай ташуурдах, үрийн сайн чанар, усалгааны систем, шаардлагатай,

Санал асуулгад оролцсонд баярлалаа.

Figure 5—6. Questionnaire form (in Mongolian)

Table 5—6. Results of the questionnaire

Question	*pH*	*STY*	*STE*	*SM*	*Sl*	*E*
High suitable	14	22	12	-	21	20
Moderate	10	-	9	-	-	4
Unsuitable	-	-	2	-	-	-
Highly unsuitable	-	-	-	-	-	-
Not necessary		2	1	-	3	-

Note: pH – soil pH, STY- soil type, STE-soil texture, SM-soil moisture, Sl-slope, E- elevation

Table 5—7. Confusion matrix and accuracy estimates for the cropland suitability map.

		Classes derived from the MCA				Sum	Commission	Producer's accuracy (%)
		Highly unsuitable	Unsuitable	Moderate suitable	Highly suitable			
Field measurements	Highly unsuitable	**6**	2			8	0.25	75.0
	Unsuitable	1	**17**	7	8	33	0.48	51.5
	Moderate suitable		1	**28**	9	38	0.26	73.7
	Highly suitable			14	**53**	67	0.21	79.1
Sum		7	20	49	70	**146**		
Omission		0.14	0.15	0.43	0.32			
User's accuracy (%)		85.71	85.00	57.14	67.92			
Overall accuracy: 71.23 %; Kappa coefficient: 0.56								

5.6 Conclusion

A GIS-based multicriteria analysis has recently been put to use for an agricultural land suitability evaluation. The newly created area selection provided by means of the multi-criteria analysis method shows unbeaten future prospects in that direction, especially for the small provinces. These methods will allow a more precise, rapid and low-priced environmental and agricultural management activity.

Recent agricultural studies have maintained the developing approach for the cropland suitability rating by means of the multi-criteria evaluation method. Mongolia also needs satellite image processing for the cropland studies, as it is valuable for agricultural and land management.

In Bornuur soum, as all soil types are suitable for cropland. We selected other criteria such as soil parameters, topography, vegetation and moisture index in this chapter. The multi-criteria analysis was applied for the cropland suitability approach based on GIS in Bornuur soum. GIS has proven to be an effective, operational tool for complex evaluation processes of cropland suitability (G Pan and Pan 2012). From this chapter, we executed an estimation of the cropland suitability approach, using GIS in the agricultural area in Mongolia.

Our study evaluated the cropland extent in Bornuur soum, investigating the cropland suitability map based upon various criteria before-mentioned that vegetation, soil parameters, moisture and topography. The results shown in the output map are reasonable. The agreement with the crop cadastral map amounts to approximately 95 %, from the questionnaire 74 % of the respondents chose the highly suitable answer while 71 % of the field data (Table 5—7), respectively. The conducted cropland suitability maps confirmed that 46.12 % is highly suitable for cropland, 34.68 % moderate suitable, 13.64 % is marginal suitable and 5.56 % unsuitable (Figure 5—5).

The decision methods that are handled in the land-use evaluation problems cannot be randomly selected without appropriate justification (Dujmovic, Tré, and Dragicevic 2009; Y. Chen, Yu, and Khan 2010; Zabihi et al. 2019). In this chapter, a multi-criteria analysis has been established in an agricultural region in the central part of Mongolia. The innovation of this research was meant to develop suitable cropland regions, which utilized both satellite images and GIS. The study employed the elevation and slope factors for the forested mountainous and agricultural areas. It can be applied to various regions and environments. The additional factors should also be considered. The approach could function as an advantageous indicator so as to take further agricultural management decisions and to advise the regional decision-makers. The advantages of this approach are to allow researchers to determine new, suitable agricultural regions in various areas.

The result of this chapter could be used for the soum government in order to advise local farmers in suitable areas. In terms of practical application, this approach proves to be a useful tool to obtain reliable and reasonable agricultural studies, thereby providing valuable information for the decision-makers and farmers. In the future, this study could be referred to map the land suitability of other soums and over the country with further and more processed parameters. The cropland suitability databases in the agricultural sector will ensure the essential reliability of the estimates and forecasts, which will undoubtedly be helpful in the process of planning and policy-making.

CHAPTER 6

General discussion and conclusion

This chapter includes two main sections as the general discussion (section 6.1) and general conclusion (section 6.2). Section 6.1.1 addresses the summary and discussion of research questions. Then, the critical reflections of each chapter are mentioned in section 6.1.2. In section 6.1.3, the recommendations for future work are proposed. In section 6.2, the main findings of this dissertation and future research work are concluded in this chapter.

6.1 General discussion

6.1.1 Summary and discussion of the research questions

The Mongolian ecological systems are vulnerable; agricultural lands (1.11 million square kilometers covering 71.6 % of the territory) are being destroyed at an increasing pace, which results in the expansion of the Gobi desert (UNDRR 2019). Also, the Mongolian climate is highly continental, which includes the arid and semi-arid regions. The research on soil moisture could be useful for the agricultural management and climate change impact. In this dissertation, we have contributed to the soil moisture mapping of Mongolia in a different way: firstly, we studied the moisture index for the long-term use of remote sensing and meteorological data; secondly, we developed the soil moisture index by a linear regression analysis based on satellite images; thirdly, the Mongolian soil moisture map was created by the MODIS NDVI and LST images, then determined the soil moisture prediction until 2025. Lastly, the estimation of the cropland suitability using MCA could be helpful for the rural agricultural planning. Based on this dissertation's focus, remotely sensed data were carried out on this research rather than the direct SM methods (gravimetric and volumetric), the RS methods are powerful tools to monitor the regional SM within the spatial and temporal variations. Following the general objectives, five research questions were considered.

Question 1: How could the moisture index (MI) be used to monitor and correlate with the SM measured at the climate stations at different depths (0-10 and 0-50 cm)?

Question 2: How does the moisture index affect vegetation for the growing season?

Question 3: How could we describe the integrated methodology for the SM through multispectral satellite data?

Question 4: How can NDVI and LST products be used to monitor soil moisture and predict it in Mongolia?

Question 5: How could the multi-criteria analysis evaluate for the cropland suitability?

These five research questions were rephrased and answered in Chapter 2 to 5. An overview of the research objectives, employed methods and findings are given in Table 6—1. This table aids to understand the links between the research objectives and research questions and the manner in which these are presented in each chapter.

Table 6—1. Overview of the main contents of this dissertation

Chapter	RQ	Objectives	Employed methods	Main results
Chapter 2: Long-term soil moisture index estimation using satellite and climate data in the agricultural area of Mongolia	Q1 and Q2	- to interpolate the precipitation data from the climate stations; - to estimate the long-term moisture index using the in-situ and MODIS data; - to correlate between the estimated moisture index and soil moisture contents from the climate stations at different depths, 0 - 10 cm and 0 - 50 cm; - to assess the relationship between the estimated moisture index and NDVI.	- Kriging method - Moisture Index (Thornthwaite and Matter 1955) - Pearson's correlation	- The MI was mapped in the study area. The wettest years were 2012 and 2013 while the driest years were 2000 and 2002. - The moisture index correlated with the SM from the climate station that shows high figures in wet months, besides the dry months were low. - The vegetation growth inversely correlated with the MI in the dry months while it strongly correlated during the wet months in the arid region. - The amount of MI (May-August) had a slightly strong correlation with the NDVI of the highest growing months (July-August), which means that the amount of the moisture contents and precipitation could predict the vegetation growth.
Chapter 3: An integrated methodology for soil moisture analysis using multispectral data in Mongolia	Q3	- To select the factors that might affect the soil moisture in the kastanozem soil; - To develop an integrated methodology using the multi-regression model; - To make a validation to the accurately developed model with satellite images and field measurements.	-Multi-regression model	- The NDVI, LST, Elevation, Aspect and Slope were selected for the factors that might affect the soil moisture. - The predicted soil moisture index (PSMI) was developed using the multi-regression model on the kastanozem soil in Bornuur soum. - A validation between the PSMI and field measurements was made in September 2011 (r = 0.81) - The MI (chapter 2) was compared with the PSMI, noticing a good relation (r=0.77).

Chapter 4: Spatial distribution of soil moisture in Mongolia using SMAP and MODIS satellite data: A time series model (2010 - 2025)	Q4	- To estimate a monthly soil moisture distribution map (SM-MOD); - To compare the soil moisture distribution, precipitation/temperature and crop yield; - To build appropriate models to forecast future trends.	- Multiple linear regression (SM-MOD) - ARIMA model - Pearson's correlation	- The increased soil moisture is observed in the northern part, which is taiga, forest-steppe, and steppe zones, while a low soil moisture is restricted to the southern part of Mongolia, which is mostly desert steppe and desert zones. - From the results, the SM strongly depends on the precipitation in Mongolia (Figure 4.6) ($r=0.83$ with $p<0.0001$). The correlation between the SM-MOD and crop yield that was statistically significant ($p<0.003$) and the correlation coefficient was 0.84. - We selected the ARIMA(12, 1, 12) model which was more suitable for a soil moisture time series analysis from 2010 to 2020. - We have predicted the values of the soil moisture from 2020 to 2025.
Chapter 5: A GIS-based multi-criteria analysis on cropland suitability in Bornuur soum, Mongolia	Q5	- To select criteria - To estimate the best suitable area for supporting the crop production in Bornuur soum; - To use a GIS-based multi-criteria analysis (MCA) and remote sensing.	- Multicriteria analysis (MCA) - Weighted linear combination (WLC) - Confusion matrix	- The seven criteria (soil texture, soil pH, soil humus, elevation, slope, NDVI and NDMI) were chosen. - From the results, the cropland suitability analysis reveals that 46.12 % is highly suitable for cropland, 34.68 % is moderate suitable, 13.64 % unsuitable and 5.56 % highly unsuitable. - A strong relation (71.23 %) is noticeable between the output map of suitability and the field survey. - From the results of a questionnaire we could conclude that 74.2 % proves highly suitable for cropland, 19.2 % is moderate suitable, 1.67 % unsuitable and 5.0 % is not necessary.

Question 1: How could the moisture index (MI) be used to monitor and correlate with the SM measured at the climate stations at different depths (0-10 and 0-50 cm)?

The changes in the moisture condition (which would occur in some areas) were predicted, triggered by drought due to the global warming (G. Wang 2005; X. Gao and Giorgi 2008; Zhu et al. 2016). The processes of the water balance, soil moisture, surface heat and evapotranspiration are gently related (Li et al. 2009). The Thornthwaite moisture index is useful as an indicator of the supply water in an area relative to the demand under the prevailing climatic conditions (Willmott and Feddema 1992). The moisture index is applied in a wide variety of climatic studies that can be derived from commonly available data such as the temperature and precipitation and proves thus suitable for long term studies (Grundstein 2009). The MI has been used to describe the distribution of the vegetation, soils and climate (Mather 1978). Nyamtseren et al. (Nyamtseren, Feng, and Deo 2018) investigated the temporal trends of the moisture index during 1961-2015 based on the temperature and precipitation from 70 climate stations in Mongolia. From this study, the moisture index and aridity indexes could more effectively represent climate types of Mongolia.

In Mongolia, the impact of global warming is challenged even now, and the temperature has increased by 2.07 °C compared to the mean (Dagvadorj, Batjargal, and Natsagdorj 2014). Extreme and continued droughts have taken place in Mongolia due to the impact of climate change (Batima et al. 2005). In previous studies, we saw that the years 2001, 2002, 2005, 2007 and 2009 were significantly affected by slight to severe droughts in Mongolia (Dorjsuren, Liou, and Cheng 2016; Chang et al. 2017; Nanzad et al. 2019). However, the driest years were 2001, 2002, 2004 and 2007 in the northern central part of Mongolia. Moreover, the results of the moisture index could be considered as drought impacts.

The moisture index has been utilized with the observations of the climate stations from former studies. In this research, the moisture was higher in the northern part of the study area, which includes the taiga and forested zones (for seven provinces). That proves that the forested area holds more soil moisture than the unforested area such as the steppe and desert steppe zones. How does the moisture index correlate with the soil moisture from the climate stations? In order to answer this question, we contributed to the moisture index map for the agricultural region of Mongolia by means of the

Thornthwaite method. The correlation between the moisture index and soil moisture from the climate station at different depths with 0-10 cm (r=0.60) and 0-50 cm (r=0.38). The moisture had increased during the growing season 2000 to 2013. The result shows that the moisture index (employed to investigate the manner in which the surface moisture has changed) modified in the study area during these 14 years. However, Zhu et al. (Zhu et al. 2016) investigated the variations of the Thornthwaite moisture index in the Hengduan mountains of China that correlated with the MI and soil relative moisture contents using the climate stations data. This correlation was positive in spring, summer and autumn but negative during winter. Furthermore, the impact of the changes in the moisture index, especially the decrease, could extend drought and desertification (Tabari et al. 2014). It suggests that the moisture index changes could be illustrate conditions of drought and desertification.

Question 2: How does the moisture index affect vegetation for the growing season?

The NDVI provides spatially continuous data on the vegetation cover and has been used for a comparison with the moisture index to obtain information on the manner in which the moisture index affects the vegetation growth during the growing season. Zhu et al (Zhu et al. 2016) studied the Thornthwaite moisture index. From the results, we could conclude that an increase in precipitation and a decrease of evaporation, leading to a rise of the moisture index. The MI has a strong correlation with the vegetation coverage as the correlation between the NDVI and MI was positive in spring and summer but negative during autumn and winter (Zhu et al. 2016). The overall increase in temperature will cause heat stress in many plants and the reduced precipitation (during the summer months) will result in a reduced soil moisture availability during the growing season (which would likely reduce the productivity and cause problems for the grazing animals) (Whitten 2009). In this study, the moisture index slightly high correlated with the NDVI (0.42-0.55) during the wettest (July and August) months and demonstrated a low correlation (0.28-0.37) during the dry months (May and June). However, the MI amount (May-August) has a strong correlation with the NDVI of the highest vegetation months (July and August) (i.e. the correlation coefficient was 0.71 ($p < 0.01$) between the NDVI of July and the MI amount from May and July; 0.72 ($p < 0.01$) between the NDVI of August and the MI from May and August and 0.78 ($p \leq 0.001$) between the NDVI of August and the MI amount from June and July). Besides, the relationship between the rainy season (May-October) NDVI and the MI was correlated (R^2=0.61, p<0.001) in China (Piao 2005).

Our study area included taiga, forest-steppe and steppe vegetation zones. Bao et al. (Bao et al. 2015) has examined the vegetation dynamics in Mongolia and their response to climate change in the vegetation zones. From the meadow steppe to the typical steppe and then to the desert steppe, the moisture index decreased for all growing-season months, with the largest differences visible in July and August. Therefore, the relationship between the monthly NDVI and precipitation became stronger as the moisture index declined from the meadow steppe to the typical steppe and then to the desert steppe, particularly in July and August because the largest difference in the moisture index occurred in July and August. However, the negative impact of the temperature on the meadow steppe vegetation growth in July and August was still more significant in Mongolia (Bao et al. 2015). Nanzad et al. (Nanzad et al. 2019) recognized that the years affected less by drought were 2011, 2012 and 2013 with 79 % - 87 % of the total area identified as in normal and wet conditions. The wettest years were recorded in 2012 and 2013. This could be a measurement for the drought conditions using the moisture index while the predictor of the vegetation growth strongly depends on the previous months of the moisture index amount and precipitation, especially in the arid and semi-arid region.

Question 3: How could we describe the integrated methodology for the SM through multispectral satellite data?

Many methodologies already exist to estimate the soil moisture using remote sensing data. We found the predicted soil moisture index (PSMI) based on the factors (NDVI, LST, Elevation, Aspect and Slope) that could influence the soil moisture in the kastanozem soil. Then, we compared this with the ground truth measurements; the correlation amounted to r=0.81. The PSMI values have estimated a range from 0 to exceeding 3.0, which signifies that a value of 0 is dry and a value of more than 1 indicates a wet area. However, the spatial distribution of the surface soil moisture indexes identified that the values indicated 0 to 1, which means that the value 0 was dry and the value 1 denoted the wet area. Thus, it is suggested that the estimated SMI could be used to understand the drought severity and the variability in the soil moisture (Xia et al. 2019; Lee, Jung, and Kim 2019). Jung et al. (Jung et al. 2017) have compared the

SMI and standardized precipitation index (SPI) in the northern part of South Korea. The SPI was determined from the automatic climate stations that indicate the drought level (Angelidis et al. 2012; Asadi Zarch, Sivakumar, and Sharma 2015). The coupling with the SPI and SMI might be utilized as a meteorological drought index in the forested area and the agricultural drought index in the cultivation area (Jung et al. 2017). The above mentioned studies applied the MODIS LST/NDVI and meteorological stations' data. Besides, the PSMI was estimated using drivers (vegetation, land surface temperature, elevation, aspects and slope in the kastanozem soil) in the forested and cultivated area, so it could also be applied for the drought monitoring. Overall, in order to improve the accuracy between the predicted soil moisture index and the ground truth measurements, the temporal and spatial scales should be the same. So, the PSMI should be enhanced in other soil types and vegetation zones (in future studies).

Question 4: How can NDVI and LST products be used to monitor soil moisture and predict it in Mongolia?

The soil moisture is an important factor for the agricultural land in Mongolia and there is a need for an actual spatial soil moisture distribution with a low spatial resolution since it has a widespread territory (1,565-million-kilometer square). We found a model to estimate the monthly spatial distribution of the soil moisture in Mongolia using SMAP and MODIS. Many investigations have confirmed that the LST and NDVI products could provide an estimation of the soil moisture. The NDVI and LST from the optical/thermal remote sensing data have been widely utilized for the estimation of the soil moisture (Hosseini and Saradjian 2011; F. Zhang et al. 2014; E. Natsagdorj et al. 2017; Saha et al. 2018; Xia et al. 2019). These studies have examined the soil moisture by comparing it with the climate variables (which are based on the correlation and multi-linear regression analysis). The integration methods of LST and NDVI might demonstrate to be vital methods so as to estimate the soil moisture, which is easy to operate and has a strong physical basis (D. Zhang and Zhou 2016). In addition, we have contributed to the spatial soil moisture distribution map and made a time series analysis of Mongolia between 2010 and 2020. The highest soil moisture occurred from June to September, while the lowest (soil moisture) was obtained during the winter months and from March to April and October. Hence, the cold season climate with a low evapotranspiration and strong soil freezing rather prolongs the decay time scale of the autumn soil moisture anomalies in the cold, arid climate of Mongolia (Nandintsetseg and Shinoda 2014).

In Mongolia, the available soil moisture measured about 30 % of the soil field capacity during the warm season, while in the desert zone the available soil moisture was close to the wilting point throughout the year (Nandintsetseg and Shinoda 2011). In addition, our model has illustrated the monthly soil moisture in Mongolia from 2010 to 2020. The soil moisture was high in the north and a low soil moisture was noticed in southern Mongolia. Then, the output soil moisture map was compared with the soil moisture measurements from the meteorological stations and the precipitation/temperature from the CRU data. Moreover, the crop yield data were compared to the output of the soil moisture. We have investigated a time series analysis of the soil moisture between 2010 to 2020, therefore the predicted soil moisture until 2025. Overall, the developed SM model and time series method could both be used to investigate the changes in the soil moisture in Mongolia. However, this linear regression model should be adapted to suit each vegetation zone in the applied study area. Significantly, the soil moisture prediction would enhance the action on the agricultural and water management to qualify the water resource utilization and to reduce the inefficient costs for farmers, etc.

Question 5: How could the multi-criteria analysis evaluate for the cropland suitability?

Agriculture is one of the most critical sectors of the Mongolian economy. Mongolia needs to improve the local agricultural management based on scientific research. A multi-criteria analysis (MCA) is one of the useful, valuable approaches for the land use, environmental planning and agricultural management (Y. Chen, Yu, and Khan 2010; Perveen et al. 2007; Kamau, Kuria, and Gachari 2015; Otgonbayar et al. 2017; Quan et al. 2007). How could the multi-criteria analysis evaluate the cropland suitability? In order to answer this question, we stipulated the objectives of this research were: firstly, to identify the influencing criteria for new croplands in Bornuur soum based on a literature review and to specify the classes of the criteria based on the structure of the Food and Agricultural Organization (FAO); secondly, to develop a cropland suitability map and to conduct an accuracy assessment on the field measurements from Bornuur soum.

In Bornuur soum, seven criteria were selected for the multi-criteria analysis, which are the soil texture, pH, humus, elevation, slope, normalized difference moisture index and normalized difference vegetation index. The cropland suitability analysis examined that 46.12% is highly suitable for cropland, 34.68% moderate suitable, 13.64% unsuitable and 5.56 % highly unsuitable. However, Mongolia has 10.1% of the territory that is highly suitable, 14% suitable, 15.5% moderately suitable, 16.3% unsuitable, 12.9% highly unsuitable for cropland, with 31.2% as the constraint area (Otgonbayar et al. 2017). Our study area included the highly suitable and suitable area of Otgonbayar et al. (2017) research. The finding ‘new area for cropland suitability using the MCA method’ shows excellent prospects, especially in the small provinces. The MCA methods allow a more accurate, rapid and low-priced environmental and agricultural management activity. Forkuo et al. (2011) suggested that the land crop suitability analysis should consider the following factors: humidity, digital terrain models, land use, vegetation cover, geology and influence of the topography. In the present study, we considered most of the factors that were mentioned above. The cropland suitability method could even be improved if the crop mapping model is updated for the production of many crops and the model has been extended so as to cover the region (Forkuo et al 2011). In terms of practical application, these methods prove that it is a useful tool to examine, supplying reasonable agricultural studies, thereby contributing to relevant information for the local decision-makers and farmers.

Overall, throughout the dissertation, the NDVI has been used for the validation (chapter 2), a proxy for the SM variability (chapter 3 & 4) and to define the cropland suitability area. The vegetation indices are extremely sensitive to water stress; that is why it is common to use in the drought monitoring. Many studies have been performed and the proposed drought indices based on the vegetation indicators, especially the NDVI, are widely applied to detect the drought conditions based on the vegetation health and greenness conditions (Nanzad et al. 2019; D. Zhang and Zhou 2016). But it is sensitive to darker and wet soil conditions. However, the soil moisture conditions from the vegetation changes could be indicated by the vegetation indicator methods. These methods only consider the fact that water stress leads to reductions in the NDVI and do not account for other factors such as the temperature and precipitation. Therefore, the combination of the NDVI and LST has been considered in this dissertation and has a strong physical basis (easy to operate).

6.1.2 Critical reflections

This dissertation contributed to a study on soil moisture mapping (regional and small area) and by comparing the ground SM, vegetation and crop yields, soil moisture prediction trends were made regarding Mongolia. Also, a cropland suitability analysis using the MCA methods was performed in Bornuur soum. Some critical facts are presented regarding the data, methodology and results of each chapter.

Chapter 2: In this chapter, the moisture index was developed using satellite and meteorological data for the northern central part of Mongolia during the growing season (May-August, 2000-2013). All data were processed with a 1 km spatial resolution that correlated the MI with the SM from the meteorological stations and the correlation coefficient measured 0.58 at a 0-10 cm depth and 0.38 at a 0-50 cm depth. There are only six meteorological soil moisture stations that used to validate the moisture index data, which is the main limitation. However, the moisture index could not express the adequate soil moisture. Besides, the moisture index is more suitable for drought monitoring and water balance studies.

Chapter 3: In this chapter, the multi-regression method was applied to estimate the soil moisture index in kastanozem soil from multiple variables (e.g. the NDVI, LST, Elevation, Aspect and Slope), which affects the soil moisture. These variables were selected, determined from the satellite images. The PSMI was developed based on only 33 samples, which is a small number for the study area. Further studies have to collect many samples in order to make a more accurate model. There is only one climate station in the study area. Hence, we made ground truth measurements in September 2011 and July-August 2015. However, the ground truth measurements were time-consuming and money, besides we cannot measure the daily and monthly ground truth data in the study area. So, there is a need to improve the long-term ground measurement technology and to obtain information from the farmers, etc. In this chapter, we did not provide the soil parameters (e.g. soil texture, soil humus, pH), further studies still need to be included. Optical remote sensing methods have some limitations for the soil moisture which are the vegetation interference, a poor temporal resolution, atmospheric and night effects.

Chapter 4: In this chapter, we used the linear regression method for estimating the spatial distribution of the soil moisture in Mongolia by considering satellite images (SMAP and MODIS). The advantages of this study in the soil moisture analysis are the following: an acceptable spatial resolution; a broad coverage; free satellite images; the possibility for the data to be improved with ground/field measurements. The limitations of the satellite images are that we used the land cover dependence and the validation of the results is tough without field data or meteorological station data. For the validation, we applied the agricultural station data, precipitation, temperature and crop yield information. But the soil moisture in situ data from the agricultural stations were limited in Mongolia, i.e. 23 stations which are located in the forest-steppe and steppe vegetation zones. However, the developed SM model and time series method could be used to investigate the changes in the soil moisture in Mongolia, so it is reasonable to use these in agriculture, hydrology and climate science. Nevertheless, this linear regression model should be adapted to suit each vegetation zone in the applied study area. It represents other interesting research on the soil moisture for future study.

Chapter 5: In this chapter, the multi-criteria analysis (MCA) and weighted linear combination (WLC) were used for the cropland suitability and the confusion matrix was applied for the validation. The MCA is widely used for the suitability analysis of the environment, land and agricultural studies. For the validation, we collected some questionnaires from the farmers and local experts. During the questionnaire, most local farmers noted that they do not irrigate their fields, especially for wheat and potato. Because local farmers cultivate wheat and potato in large fields, so they rely on natural irrigation. That means there is a need for more accurate information on the soil moisture and valuable land use planning in this study area. This cropland suitability analysis is essential for the land use planning in Bornuur soum.

6.1.3 Recommendations for future work

Some work deserves to be made in the future (based on this dissertation). In this section, we are trying to clarify which future actions are being proposed on the following topics.

a) Future work for datasets

The Remote sensing data have conducted the model for the soil moisture analysis. We examined the soil moisture estimationin different ways (e.g. firstly, the estimated moisture index using satellite and in-situ data; secondly, a developed model to estimate the predicted soil moisture index based on the Landsat and ASTER satellite images; thirdly, the monthly spatial soil moisture distribution based on SMAP and MODIS, which has been executed in Mongolia for the first time). In future work, we would suggest soil parameters and other reasonable factors on soil moisture to be considered. We will use synthetic aperture radar (SAR) images for the soil moisture in an agricultural region in future work. Especially, the C-band Sentinel-1 (A&B) SAR data are freely downloadable, a frequent review and large geographical coverage that includes continuous data on the next decades from the Copernicus program of ESA. They revealed that the Sentinal-1 (S-1) has advanced observational capabilities to SAR derived near surface soil moisture products at a low resolution under the project Exploit-S-1 (http://exploit-s-1.ba.issia.cnr.it). The advantages of the Sentinal-1 is a highly accurate soil moisture and a high spatial and temporal resolution (D. Zhang and Zhou 2016). Besides, we will collect more field data, even do some observations, as on the precipitation, soil texture and soil water infiltration, etc. although it might be time-consuming and requires much money.

b) Future work for the model development

In view of further model development, it is better to consider the season and vegetation zones. We developed a model for the soil moisture analysis using multispectral data. This dissertation investigated the performance of the model (PSMI) based on satellite images versus those using ground truth measurements. In future work, we will add variables such as the soil texture, SAR data analysis to develop our model. We will try to combine the multispectral and SAR images so as to develop the soil moisture modelling. Also, high resolution multispectral satellite images (SPOT constellation, Sentinel-2 etc.) might be applied on this model in order to develop the fields.

c) Future work on the research topic

The Mongolian agriculture needs more detailed research on pastureland, cropland, hayfields etc. From the arable lands, 561,000 ha area was abandoned, there should be a re-use of these lands into pasture or croplands. Future research will focus on these arable lands and the hayfield area. In the Mongolian case, the difficulty is to find the right SAR images for the agricultural region. Thanks to the SAR images, it would be possible to use the soil moisture estimation for the small areas (field survey and cropland), especially the Sentinel-1 A&B SAR data. Our future study will focus on an integrated data analysis for the soil moisture, which will utilize multispectral and SAR images. Besides, further studies will investigate the seasonal soil moisture in different vegetation zones. Moreover, we will describe the manner in which climate change influences in the agricultural regions of Mongolia.

6.2 General conclusion

This dissertation discussed the soil moisture analysis in the agricultural region of Mongolia. The soil moisture is one of the essential variables of the water cycle and plays a vital role in the agriculture, water management, land (drought) and vegetation cover change as well as climate change studies. In order to estimate the soil moisture using remote sensing images that are reasonable and possible, we firstly estimated the combined data (as climate and satellite data) and then we developed a model for the soil moisture (and made a validation) in Bornuur soum, Tuv province, Mongolia. Through all chapters, multispectral data were used based on freely accessible information (connected with the soil moisture analysis).

Firstly, we have assessed the moisture index using satellite and climate data in the agricultural region of Mongolia (based on the potential evapotranspiration from MODIS and the interpolated precipitation from the meteorological stations during the growing season from May to August 2000-2013). The northern part of Mongolia consists of taiga and forest-steppe regions, which possess half of the annual precipitation observations during the summer season. The precipitation is an important variable for the soil moisture, that means that the SM variability is controlled by the precipitation during the growing season. Furthermore, the growing season (regarding 14 years' meteorological data) was involves a precipitation acquisition (total mean precipitation) between 137 mm (2002) and 263 mm (2013), while the average temperature ranged from 15.06 °C (2003) – 17.68 °C (2007) and the soil moisture measured between 8.96 % (2007) and 13.30 % (2012), respectively. From the results of the moisture index, we noticed that the driest years were (observed in) 2000-2002, 2004 and 2007. Natsagdorj and Batima (2003) concluded that from 1999 to 2002 droughts occurred in Mongolia during summer. We tried to identify the manner in which the moisture index could represent the soil moisture (by their relationship). The moisture index was compared with the SM from the meteorological stations at different depths and showed positive correlations in the study area (which was 0.58 at a 0-10 cm depth and 0.38 at a 0-50 cm depth; statistically significant). Besides, a high correlation was seen in the high vegetation cover (July and August) and a low correlation in the low vegetation cover (May and June) between the moisture index and in-situ soil moisture. However, former studies have demonstrated that the moisture index should rather be utilized for drought and water balance studies (than the soil moisture).

Secondly, the moisture index correlated with the NDVI during the growing season 2000-2013. The correlation between the moisture index and NDVI for each month (May-August) was examined as weak correlation coefficients (r) from 0.28 to 0.55. However, the amount of the moisture index (May-August) correlated with the NDVI of the highest vegetation months (July and August), a strong correlation was obtained as a range of correlation coefficients from 0.67 to 0.79. Besides, this significant predictor of vegetation growth strongly depends on the previous months of the moisture index amount. This moisture index is suitable for use in the agricultural areas and also for practical applications on desertification, land degradation monitoring, agricultural management and drought monitoring. Mongolia also needs a high-resolution satellite image processing for the SM analysis.

Thirdly, we developed a model for the SM estimation in a small agricultural area (Bornuur soum) in Mongolia. The Bornuur soum is located in a favourable climatic region with good, fertile soil and is the most important agricultural region of Mongolia. Then, we focused on the development of an estimation model SM (PSMI) through satellite and ground truth measurements. The PSMI was developed from the regression analysis, which was used for satellite images in September 2011. The result of the PSMI was compared with the ground truth SM measurements' data in Bornuur soum, Tuv province, Mongolia. For the validation, we compared the PSMI with the ground truth SM measurements; the correlation was 0.66. The model was also applied for July and August 2015. The estimated predicted soil moisture index values range from 0.0 to exceeding 3.0 in the kastanozem soil, which signifies that the values lower than 1.0 are dry and higher than 1.0 indicating wet areas. During the observed years (2011 and 2015), a low soil moisture (5.27 %) was observed in September 2011 and a high soil moisture (20.59 %) was noticed during August 2015 (from the meteorological station data). Besides, the predicted soil moisture index mean value (0.77) was obtained in September 2011 and 1.15 in August 2015. We applied the matrix evaluation for the validation and the correlation coefficient amounted to 69.7 %. The model should be improved concerning the soil parameters in further studies (for the estimated cropland suitability area as well as for the Bornuur soum of Mongolia). In addition, the PSMI could be applied for different satellites such as the Sentinel-2, SPOT XS with high-resolution satellites (which are distributed from the ESA).

Fourthly, the spatial distribution of the soil moisture (with high-resolution images in Mongolia) has been one of the essential issues in remote sensing and the agricultural community for a long time. Therefore, we obtained the distribution of the soil moisture and we have compared the monthly precipitation/temperature and crop yield from 2010 to 2020. The Soil Moisture Active Passive (SMAP) and Moderate Resolution Imaging Spectroradiometer (MODIS) data were employed, including the MOD13A2 Normalized Difference Vegetation Index (NDVI), MOD11A2 Land Surface Temperature (LST) and precipitation/temperature monthly data from the Climate Research Unit (CRU) in Mongolia from 2010 to 2020. Multiple linear regression methods have previously been used for the soil moisture estimation and the Autoregressive Integrated Moving Arima (ARIMA) model was utilized for the soil moisture forecasting. The results show that the correlation was statistically significant between SM-MOD and SMC from the meteorological stations at different depths ($p < 0.0001$ at 0–20 cm and $p < 0.005$ at 0–50 cm). The correlation between the SM-MOD and temperature, as represented by the correlation coefficient (r), was 0.80 and was considered statistically significant ($p < 0.0001$). However, when the SM-MOD was compared with the crop yield for each year (2010–2019), the correlation coefficient (r) measured 0.84. The ARIMA (12, 1, 12) model was selected for the soil moisture time series analysis when predicting the soil moisture from 2020 to 2025. The soil moisture was low in the south and a high soil moisture was observed in northern Mongolia during the warm season. The soil moisture will be slightly increasing during the study years (2010-2025). In our study, the soil moisture estimation approach and model might serve as a valuable tool for confident and convenient observations of agricultural droughts for the decision-makers and farmers in Mongolia.

Fifthly, Land degradation has been increasing in the Mongolian cropland region, especially in the cultivated areas. The country has challenges to identify new croplands with sufficient capacity for cultivation, especially for the local decision-makers. GIS applications could tremendously help science by making land assessments. This part estimated the best suitable area for supporting the crop production in Bornuur soum, using a GIS-based multi-criteria analysis (MCA) and remote sensing. The MCA and AHP tools play an essential role in the multi-criteria analysis. Therefore, the results of these methods enable the choice of an appropriate cultivation area in Bornuur soum, Tuv province. The approach was enhanced for each criterion such as the soil, topography and vegetation. The opinions of the agronomists (experts) and a literature review helped to identify the criteria (soil data, topography, water and vegetation data) that are necessary to determine the suitable crop areas. The output was reasonable: the detailed cropland suitability maps indicate that 46.12 % is highly suitable for cropland, 34.68 % is moderate suitable, 13.64 % unsuitable and 5.56 % is highly unsuitable. The comparison (with the crop cadastral map) amounts to approximately 95 %, from the questionnaire: 74 % of the respondents chose the highly suitable answer while 71% of the field data, respectively. Correspondingly, the mapped locations (for a newly created crop production area) matched (95 %) with the current location of the agricultural cropland areas in Bornuur soum. The crop suitability method implies significant decisions on different levels and the result will be used for a cropland management plan (in order to make a decisions). It has an integral role in the agricultural management and land evaluation. Future research should develop this method further by including socio-economic (potential citizens for agriculture, current crop growth, water resources, *etc*.) and environmental variables (rainfall, vegetation types, permafrost distribution, *etc*.) so as to obtain specific results. However, the latter could also be applied for a single crop type (mainly barley, wheat and potato) in Mongolia.

Appendix

This chapter contains detailed information on the soil types and ground truth points in the hotspot study area (Bornuur soum).

A.1 Soil types

There are four types of soils included in the Bornuur soum, Tuv province, Mongolia. There are Cambisols, Gleysols histic, Kastanozems arenic and Leptosols umbric. The table 7.1 shows the information of the soil types collected from the Food and Agriculture Organization (FAO). Table 7.2 has shown ground truth measurements of 2015 in the Bornuur soum, Mongolia.

Appendix table 1. The soil types information of the hotspot study area

Soil types	Information
Cambisol	Cambisols are characterized by the absence of a layer of accumulated clay, humus, soluble salts, or iron and aluminum oxides. They differ from un-weathered parent material in their aggregate structure, color, clay content, carbonate content, or other properties that give some evidence of soil-forming processes. Because of their favorable aggregate structure and high content of weatherable minerals, they usually can be exploited for agriculture subject to the limitations of terrain and climate. Cambisols are the second most extensive soil group on Earth, occupying 12 percent of the total continental land area—mainly in boreal polar regions, in landscapes with high rates of erosion, and in regions of parent material resistant to clay movement. They are not common in humid tropical climates. In order for a soil to qualify as a Cambisol, the texture of the subsurface horizons must be sandy loam or finer, with at least 8 percent clay by mass and a thickness of 15 cm (6 inches) or more. These soils naturally form on medium to fine-textured parent materials under any climatic, topographic, and vegetative-cover conditions. They differ from Leptosols and Regosols by their greater depth and finer texture and are often found in conjunction with Luvisols.
Gleysols	Gleysols are formed under waterlogged conditions produced by rising groundwater. In the tropics and subtropics they are cultivated for rice or, after drainage, for field crops and trees. Gleysols found in the polar regions (Alaska and Arctic Asia; about half of all Gleysols) are frozen at shallow depth and are used only by wildlife. These soils occupy about 5.7 percent of the continental land area on Earth.

	Gleysols are technically characterized by both chemical and visual evidence of iron reduction. Subsequent downward translocation (migration) of the reduced iron in the soil profile is associated with gray or blue colours in subsurface horizons (layers). Wherever oxidation of translocated iron has occurred (in fissures and cracks that may dry out), red, yellow, or brown mottles may be seen. Gleysols are related to the Entisol and Inceptisol orders of the U.S. Soil Taxonomy, wherever the latter occur under waterlogged conditions sufficient to produce visual evidence of iron reduction.
Kastanozems	Kastanozems are humus-rich soils that were originally covered with early-maturing native grassland vegetation, which produces a characteristic brown surface layer. They are found in relatively dry climatic zones (200–400 mm [8–16 inches] of rainfall per year), usually bordering arid regions such as southern and central Asia, northern Argentina, the western United States, and Mexico. Kastanozems are principally used for irrigated agriculture and grazing. Kastanozems have relatively high levels of available calcium ions bound to soil particles. These and other nutrient ions move downward with percolating water to form layers of accumulated calcium carbonate or gypsum. Kastanozems are related to the soils in the Mollisol order of the U.S. Soil Taxonomy that form in semiarid regions under relatively sparse grasses and shrubs. Related FAO soil groups originating in a steppe environment are Chernozems and Phaeozems.
Leptosols	Leptosols are soils with a very shallow profile depth (indicating little influence of soil-forming processes), and they often contain large amounts of gravel. They typically remain under natural vegetation, being especially susceptible to erosion, desiccation, or waterlogging, depending on climate and topography. Leptosols are approximately equally distributed among high mountain areas, deserts, and boreal or polar regions, where soil formation is limited by severe climatic conditions. Because of continual wind or water erosion or shallow depth to hard bedrock, Leptosols show little or none of the horizonation, or layering, characteristic of other soils. Leptosols are related to the soils in the Entisol order of the U.S. Soil Taxonomy that are found in high mountains, deserts, or boreal and polar regions of the world.

A.2 Translation of questionnaire

Questionnaire from agricultural experts and farmers

1. How much is the ideal of soil pH?

a. 5,6-9,0 b. Lower than 5,5 c. Higher than 9

2. How much percent of soil humus is suitable?

a. Lower than 2 b. Higher than 2 c. Not necessary

3. What kind of soil is most suitable for cultivation?

....

4. Which soil texture is the most suitable for cultivation?

a. Clay b. Sand c. ....

5. How much soil moisture is the most suitable?

....

6. What is the ideal slope of the ground?

a. Smooth or 0-9 degrees b. Higher than 9 degrees c. Not necessary

7. Where should the cropland be placed in direct sunlight?

a. Direct sunlight b. In shadow c. Not necessary

8. How is the elevation should be?

a. Low b. High c. Not necessary

9. Where is the most suitable location for the farm from the river?

a. 0,5-2 km b. Far than 2 c. Not necessary

10. What other factors do you think are needed for farming? Please write if you have additional information. / When writing additional information, please write in numerical data! /

....

11. How is the field irrigated?

....

12. Any difficulties doing cultivation.

A.3 Ground truth data

Appendix table 2. Part of ground truth data in Bornuur soum /July – August 2015/

id	Latitude	Longitude	Elevation, m	Acquired date	Field information
1	48°39'19.54"N	106°13'3.36"E	986	7/20/2015	suitable
2	48°38'59.32"N	106°12'12.08"E	1003	7/20/2015	suitable
3	48°41'27.87"N	106°12'55.40"E	-	7/20/2015	not suitable
4	48°40'12.70"N	106°13'40.31"E	956	7/20/2015	moderate
5	48°39'37.01"N	106°11'48.70"E	1013	7/20/2015	suitable
6	48°39'17.41"N	106° 9'25.94"E	1158	7/20/2015	suitable
7	48°39'12.00"N	106°10'27.01"E	1046	7/20/2015	most suitable
8	48°39'34.40"N	106°10'44.08"E	1055	7/20/2015	most suitable
9	48°41'27.19"N	106°13'51.36"E	-	7/20/2015	not suitable
10	48°39'28.56"N	106°14'17.46"E	1131	7/20/2015	slightly
11	48°38'11.79"N	106°17'22.73"E	912	7/20/2015	most suitable
12	48°37'52.50"N	106°17'10.92"E	916	7/20/2015	suitable
13	48°37'27.96"N	106°14'47.07"E	1012	7/20/2015	suitable
14	48°38'44.79"N	106°19'12.13"E	919	7/21/2015	suitable
15	48°37'40.50"N	106°14'6.06"E	1059	7/21/2015	slightly
16	48°38'43.99"N	106°13'21.35"E	1030	7/21/2015	suitable
17	48°37'27.93"N	106°11'18.62"E	1132	7/21/2015	slightly
18	48°37'19.26"N	106°11'46.98"E	1129	7/21/2015	slightly
19	48°36'55.71"N	106°12'2.23"E	1201	7/21/2015	moderate
20	48°36'39.86"N	106°11'54.85"E	1195	7/21/2015	slightly
21	48°36'34.16"N	106°12'22.55"E	1201	7/21/2015	slightly
22	48°37'8.34"N	106°13'8.65"E	1160	7/21/2015	slightly
23	48°37'20.75"N	106°14'29.46"E	1035	7/21/2015	slightly
24	48°37'28.65"N	106°15'21.86"E	960	7/21/2015	suitable
25	48°37'15.81"N	106°17'0.00"E	920	7/21/2015	most suitable
26	48°37'54.18"N	106°18'12.76"E	915	7/22/2015	suitable
27	48°37'57.31"N	106°19'2.84"E	927	7/22/2015	suitable
28	48°37'6.72"N	106°18'35.00"E	953	7/22/2015	suitable
29	48°36'58.46"N	106°17'28.58"E	922	7/22/2015	suitable
30	48°36'36.51"N	106°17'26.35"E	949	7/22/2015	suitable
31	48°36'37.94"N	106°18'10.58"E	939	7/22/2015	suitable
32	48°36'34.98"N	106°18'42.57"E	1022	7/22/2015	slightly
33	48°36'13.71"N	106°18'0.59"E	947	7/22/2015	most suitable
34	48°35'47.79"N	106°17'44.76"E	1009	7/26/2015	slightly
35	48°35'27.80"N	106°18'3.74"E	1068	7/26/2015	slightly
36	48°35'23.86"N	106°20'27.38"E	978	7/26/2015	suitable
37	48°35'4.46"N	106°18'46.88"E	999	7/26/2015	suitable
38	48°34'56.50"N	106°19'53.51"E	974	7/26/2015	suitable
39	48°34'9.95"N	106°19'11.20"E	994	7/26/2015	most suitable
40	48°33'47.02"N	106°20'15.18"E	1154	7/26/2015	slightly

41	48°33'29.45"N	106°19'51.29"E	1117	7/26/2015	slightly
42	48°32'24.95"N	106°18'55.07"E	994	7/26/2015	most suitable
43	48°31'51.40"N	106°17'52.03"E	983	7/29/2015	suitable
44	48°31'50.01"N	106°19'10.16"E	1067	7/29/2015	most suitable
45	48°30'56.18"N	106°18'11.25"E	1132	7/29/2015	slightly
46	48°31'11.84"N	106°17'2.73"E	1066	7/29/2015	slightly
47	48°31'38.28"N	106°16'37.92"E	968	7/29/2015	suitable
48	48°30'34.61"N	106°16'43.72"E	989	7/29/2015	suitable
49	48°30'24.21"N	106°17'15.86"E	1082	7/29/2015	slightly
50	48°30'15.78"N	106°17'52.21"E	1071	7/29/2015	suitable
51	48°29'59.51"N	106°16'20.90"E	983	7/29/2015	suitable
52	48°29'46.88"N	106°16'46.75"E	1051	7/29/2015	slightly
53	48°29'19.09"N	106°17'0.87"E	1007	7/29/2015	suitable
54	48°29'7.05"N	106°17'49.41"E	1119	7/29/2015	slightly
55	48°29'4.42"N	106°18'27.85"E	1282	7/29/2015	slightly
56	48°29'7.56"N	106°19'4.10"E	1273	7/29/2015	slightly
57	48°28'57.48"N	106°19'20.55"E	1234	7/29/2015	moderate
58	48°28'29.57"N	106°19'30.41"E	1207	8/2/2015	slightly
59	48°28'21.56"N	106°20'4.78"E	1132	8/2/2015	suitable
60	48°28'16.90"N	106°21'9.20"E	1147	8/2/2015	slightly
61	48°28'2.09"N	106°21'55.16"E	1139	8/2/2015	most suitable
62	48°27'40.39"N	106°22'39.66"E	1074	8/2/2015	suitable
63	48°28'12.22"N	106°23'41.13"E	1086	8/2/2015	suitable
64	48°28'37.29"N	106°23'14.94"E	1258	8/2/2015	slightly
65	48°28'44.59"N	106°23'49.35"E	1117	8/2/2015	most suitable
66	48°29'26.02"N	106°23'42.07"E	1234	8/2/2015	slightly
67	48°29'11.27"N	106°24'37.39"E	1110	8/2/2015	suitable
68	48°29'18.37"N	106°25'16.76"E	1205	8/2/2015	slightly
69	48°28'57.16"N	106°25'25.20"E	1220	8/2/2015	slightly
70	48°28'29.14"N	106°25'19.29"E	1195	8/2/2015	moderate
71	48°28'5.28"N	106°25'34.47"E	1149	8/2/2015	suitable
72	48°27'46.89"N	106°24'53.59"E	1107	8/3/2015	suitable
73	48°27'18.62"N	106°24'18.75"E	1144	8/3/2015	suitable
74	48°26'43.63"N	106°24'7.62"E	1133	8/3/2015	suitable
75	48°26'52.49"N	106°23'9.37"E	1215	8/3/2015	slightly
76	48°26'40.00"N	106°21'42.57"E	1172	8/3/2015	moderate
77	48°26'31.98"N	106°20'42.35"E	1107	8/3/2015	slightly
78	48°26'31.65"N	106°19'46.83"E	1083	8/3/2015	slightly
79	48°26'9.05"N	106°18'51.93"E	1211	8/3/2015	slightly
80	48°26'31.07"N	106°18'2.04"E	1036	8/3/2015	suitable
81	48°24'59.09"N	106°17'57.73"E	1294	8/3/2015	slightly
82	48°25'7.56"N	106°17'16.66"E	1237	8/3/2015	slightly

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SUMMARY

The soil moisture (SM) is one of the essential variables of the water cycle and plays a vital role in agriculture, water management, land (drought) and vegetation cover change as well as climate change studies. A soil moisture study is vital for agricultural applications such as water resources, pasture growth, hayfield, cropland management and productivity, etc. Mongolia is located in the semi-arid and arid climate regions in Central Asia. The country has four distinct seasons, large temperature fluctuations and little precipitation. However, the soil moisture in Mongolia is mainly influenced by the precipitation and evapotranspiration. There is only 5.5 % irrigated cropland of the total cropland area in Mongolia. That means the irrigated system practically does not exist for the agricultural lands in Mongolia. Also, there is a need to describe new cropland areas based on a scientific approach. The local farmers and decision-makers need soil moisture information for the regional and small areas. Besides, the soil moisture estimation approach and model from this study could serve as a valuable tool for confident and convenient observations of agricultural droughts for the decision-makers and farmers in Mongolia. Therefore, we should develop a methodology for the soil moisture estimation using remote sensing data, which are practical for application on the spatial and temporal scales. The remote sensing techniques provide us with an excellent possibility for the development of models and approaches.

Concentrating on the soil moisture in Mongolia, this dissertation tried to estimate the soil moisture in different ways with the following purposes: (1) to calculate the moisture index using a combination of in-situ and satellite images and to compare these to the in-situ SM and NDVI (normalized difference vegetation index); (2) to develop the soil moisture index based on multispectral satellite data in kastanozem soil and to compare this with the in-situ measurements; (3) to estimate and predict the soil moisture using a combination of SMAP (soil moisture active passive) and NDVI/LST (land surface temperature) data and to correlate with the crop yield and climate data; (4) to determine the cropland suitability area by means of a GIS-based methodology and to validate with the in-situ measurements and local experts'/farmers' opinion. According to the objectives, the main conclusions could be expressed as follows:

(1) The Mongolian north-central part contains 80.9 % of the croplands of total crop area. The moisture index has been determined by a combination of in-situ and satellite

images that can be used for drought monitoring, water resources and agricultural management. The interpolated in-situ precipitation and potential evapotranspiration data were applied to this research. The moisture index was compared with the soil moisture contents from the meteorological station at different depths and had positive correlations in the study area for the growing season. The results represented a low correlation in dry months, while a high correlation was noticed during the wet months. Also, the moisture index correlated with the vegetation cover for each month (May-August). There were good correlations between these and the correlation coefficients ranged from 0.67 to 0.79. Besides, the moisture contents of previous months affected the vegetation growth of the following months. Overall, the monthly spatial moisture index could be used for the water resources and agricultural management, besides the practical applications for drought and desertification monitoring, especially the agricultural drought monitoring. There is a need for high spatial resolution soil moisture data in Mongolia.

(2) In Mongolia, the kastanozem soil is widely distributed (50 % of the total area) and most of the cultivated areas are occupied in the kastanozem soils of Mongolia. Therefore, we developed a model called PSMI (predicted soil moisture index) for the estimation of the soil moisture using multispectral data (Landsat TM, ETM+ and OLI) with a 30 meter resolution in the small agricultural region. The correlation between the PSMI from the model and the SMI from the satellite measured 0.90 for the kastanozem soil. The ground truth measurement data were compared with the PSMI from the model and the correlation coefficient was 0.65. In addition, we compared the predicted soil moisture index (PSMI) with the moisture index (MI) and detected a good relation (r=0.77). The development of the SM modelling will provide information for Mongolia’s agriculture and animal husbandry (like cropland, pastureland, vegetation growth and biomass). Besides, the PSMI model could be estimated by the Sentinel and SPOT XS as high-resolution images. The national policy level will be able to use this information in order to develop suitable agricultural areas.

(3) Many studies have investigated and developed methods for the estimation of the soil moisture based on satellite images but the spatial distribution of the soil moisture has not yet been considered in previous studies on Mongolia. Therefore, we have acquired the distribution of the soil moisture and related the monthly precipitation/temperature and crop yield from 2010 to 2020. The spatial distribution of

the soil moisture was estimated by means of the multiple regression model from the Soil Moisture Active Passive (SMAP) and Moderate Resolution Imaging Spectroradiometer (MODIS) including the MOD13A2 Normalized Difference Vegetation Index (NDVI) and MOD11A2 Land Surface Temperature (LST). The output has been compared with the monthly in-situ soil moisture, temperature/precipitation and yearly crop yield from 2010 to 2020. The correlation coefficients were good and statistically significant between the monthly estimated soil moisture and monthly in-situ soil moisture, temperature/precipitation and yearly crop yield data, respectively. Therefore, the ARIMA model has been applied for the soil moisture forecasting from 2020 to 2025. Besides, during this period, the soil moisture was slightly increasing in Mongolia. The model could be estimated from other satellite images.

(4) The Mongolian cropland only covers 1 % of the entire territory and around 45 % of the total consumption of vegetables (excluding potatoes) is imported from neighbouring countries. Therefore, there is a need to determine the cropland suitability areas based on scientific knowledge in order to enhance the crop production. Bornuur soum was selected to assess the cropland suitability, which is located in the central agricultural region of Mongolia. The cropland suitability approach was created based on various criteria, which include vegetation, soil parameters, moisture and topography. Then, the result was compared with the crop cadastral map, field survey and questionnaire respondents from the experts and farmers. The output data were matched with the crop cadastral map (around 95 %), with the questionnaire of the respondents 74 % and 71 % of the field data, respectively. The represented results in the output map are reasonable and could be applied for the soum government to advise the local farmers and land management. This approach could be developed by considering the additional factors because of the location and climate effect.

This dissertation developed the SM modelling in the agricultural region of Mongolia, which has produced different methodologies and one practical study maintained. The soil moisture model will provide information for the agriculture and animal husbandry such as cropland, pastureland, vegetation growth and biomass. In addition, the national policy level will be able to use this information so as to develop suitable agricultural areas and it might also be applied for the regional agricultural plan in Mongolia.

Samenvatting (Dutch summary)

Bodemvocht (SM) is een van de essentiële variabelen van de watercyclus. Het speelt een vitale rol in landbouw, waterbeheer, verandering van land (droogte) en vegetatiebedekking, en klimaatveranderingsstudies. Onderzoek naar de bodemvochtigheid is van vitaal belang voor landbouwtoepassingen zoals watervoorraden, de groei van weilanden, hooiland, akkerbeheer en productiviteit, enz. Mongolië ligt in semi-aride en aride klimaatgebieden in Centraal-Azië. Het land heeft vier duidelijke seizoenen, grote temperatuurschommelingen en weinig neerslag. De bodemvochtigheid in Mongolië wordt echter hoofdzakelijk beïnvloed door neerslag en evapotranspiratie. Slechts 5,5 % van het totale landbouwareaal in Mongolië is geïrrigeerd. Dat betekent dat het geïrrigeerde systeem niet veel landbouwgrond in Mongolië beslaat. Ook is er behoefte aan een beschrijving van nieuwe akkerbouwgebieden op basis van een wetenschappelijke benadering. Lokale boeren en beleidsmakers hebben informatie nodig over de bodemvochtigheid op regionaal en kleiner gebieden. Bovendien kunnen de aanpak en het model voor bodemvochtschatting in onze studie dienen als een waardevol instrument voor betrouwbare en handige waarnemingen van droogte in de landbouw voor besluitvormers en boeren in Mongolië. Daarom is er een nood om een methodologie te ontwikkelen voor de schatting van bodemvocht met behulp van teledetectiegegevens die praktisch toepasbaar is op ruimtelijke en temporele schalen. De teledetectietechnieken bieden ons een uitstekende mogelijkheid voor de ontwikkeling van modellen en benaderingen.

In dit proefschrift, dat zich concentreert op de bodemvochtigheid in Mongolië, is geprobeerd de bodemvochtigheid op verschillende manieren in te schatten met de volgende doelen (1) de vochtigheidsindex berekenen met behulp van een combinatie van in-situ- en satellietbeelden en vergelijken met de in-situ SM en NDVI (Normalized Difference Vegetation Index); (2) een bodemvochtigheidsindex ontwikkelen op basis van multispectrale satellietgegevens in kastanozembodems en vergelijken met in-situ-metingen; (3) het bodemvocht schatten en voorspellen met behulp van een combinatie van SMAP (Soil Moisture Active Passive) - en NDVI/LST-gegevens en correleren met gewasopbrengst- en klimaatgegevens; (4) het geschiktheidsgebied voor akkerland bepalen met behulp van een GIS-gebaseerde methodologie en valideren met de in-situ-

metingen en de mening van plaatselijke deskundigen/boeren. Overeenkomstig de doelstellingen kunnen de belangrijkste conclusies als volgt worden geformuleerd:

(1) Het noord-centrale deel van Mongolië omvat 80,9 % van het totale gewasareaal. De vochtigheidsindex is bepaald door een combinatie van in-situ- en satellietbeelden die kunnen worden gebruikt voor droogtebewaking, waterhuishouding en landbouwbeheer. De geïnterpoleerde in-situ neerslag- en potentiële evapotranspiratiegegevens werden toegepast op dit onderzoek. De vochtigheidsindex werd vergeleken met het bodemvochtgehalte van het meteorologisch station op verschillende diepten en vertoonde positieve correlaties over het hele studiegebied voor het groeiseizoen. De resultaten vertoonden een lage correlatie in de droge maanden, terwijl de hoge correlatie zich in de natte maanden voordeed. Ook correleerde de vochtigheidsindex met de vegetatiebedekking voor elke maand (mei-augustus). Er waren goede correlaties tussen beide, en de correlatiecoëfficiënten lagen tussen 0,67 en 0,79. Bovendien had het vochtgehalte van de voorgaande maanden invloed op de vegetatiegroei in de volgende maanden. Over het geheel genomen kan de maandelijkse ruimtelijke vochtigheidsindex worden gebruikt voor waterbeheer en landbouwbeheer, naast praktische toepassingen van droogte- en woestijnvormingsmonitoring, vooral droogtemonitoring in de landbouw. Er is behoefte aan bodemvochtgegevens met een hoge ruimtelijke resolutie in Mongolië.

(2) In Mongolië zijn kastanozembodems wijdverspreid, bijna 50% van het totale gebied, en de meeste van de bebouwde gebieden bevinden zich op de kastanozembodems van Mongolië. Daarom hebben we een model ontwikkeld met de naam PSMI (Predicted Soil Moisture Index) voor de schatting van bodemvocht met behulp van multispectrale gegevens (Landsat TM, ETM+ en OLI) met een resolutie van 30 meter in de kleine landbouwregio. De correlatie tussen de PSMI van het model en de SMI van de satelliet was 0,90 voor kastanozems bodem. De meetgegevens van de grondwaarheid werden vergeleken met de PSMI van het model, en de correlatiecoëfficiënt was 0,65. Bovendien vergeleken we de voorspelde bodemvochtigheidsindex (PSMI) met de vochtigheidsindex (MI) en vonden een goede relatie (r=0,77). De ontwikkeling van het SM-model zal informatie opleveren voor de landbouw en veeteelt in Mongolië (zoals akkerland, weiland, vegetatiegroei en biomassa). Bovendien kan het PSMI-model worden geschat aan de hand van Sentinel- en SPOT XS-beelden, die een hoge resolutie hebben. Het nationale beleidsniveau zal

in staat zijn om deze informatie te gebruiken om geschikte landbouwgebieden te ontwikkelen.

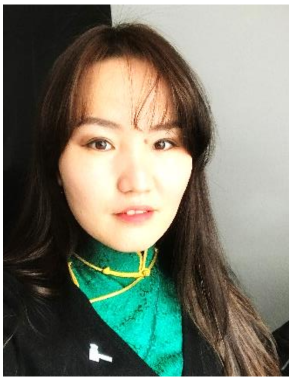
(3) Er zijn veel studies die methoden hebben onderzocht en ontwikkeld voor het schatten van bodemvocht op basis van satellietbeelden, maar de ruimtelijke verdeling van bodemvocht is in eerdere studies in Mongolië nog niet in aanmerking genomen. Daarom hebben we de verdeling van het bodemvocht bepaald en de maandelijkse neerslag/temperatuur en gewasopbrengst van 2010 tot 2020 met elkaar in verband gebracht. De ruimtelijke verdeling van het bodemvocht werd geschat met behulp van een meervoudig regressiemodel op basis van de Soil Moisture Active Passive (SMAP) en de Moderate Resolution Imaging Spectroradiometer (MODIS), waaronder de MOD13A2 Normalized Difference Vegetation Index (NDVI) en MOD11A2 Land Surface Temperature (LST). De output werd vergeleken met de maandelijkse in-situ bodemvochtigheid, temperatuur/precipitatie en jaarlijkse gewasopbrengst van 2010 tot 2020. De correlatiecoëfficiënten waren goed en statistisch significant tussen de maandelijkse geschatte bodemvochtigheid en de maandelijkse in-situ bodemvochtigheid, temperatuur/precipitatie en jaarlijkse gewasopbrengstgegevens, respectievelijk. Daarom is het ARIMA-model toegepast voor bodemvochtvoorspellingen van 2020 tot 2025. Bovendien is het bodemvocht in Mongolië in deze periode licht gestegen. Het model kan worden geschat op basis van andere satellietbeelden.

(4) Het akkerland in Mongolië beslaat slechts 1% van het gehele grondgebied en ongeveer 45% van de totale consumptie van groenten (met uitzondering van aardappelen) wordt ingevoerd uit de buurlanden. Daarom is het nodig om op basis van wetenschappelijke kennis geschiktheidszones voor akkerland te bepalen om de akkerbouwproductie te verbeteren. Voor de beoordeling van de geschiktheid van akkerland werd Bornuur soum gekozen, gelegen in de centrale landbouwregio van Mongolië. De geschiktheidsbenadering voor akkerland werd opgesteld op basis van verschillende criteria, zoals vegetatie, temperatuur van het landoppervlak, bodemparameters, vochtigheid en topografie. Vervolgens werd het resultaat vergeleken met de kadastrale kaart van de gewassen, veldonderzoek en de vragenlijsten die door deskundigen en boeren werden ingevuld. De outputgegevens kwamen voor ongeveer 95% overeen met de kadastrale kaart van de gewassen, voor 74% van de vragenlijst van de respondenten en 71% van de veldgegevens. De resultaten in de outputkaart zijn redelijk en kunnen worden toegepast door de soumregering om de plaatselijke boeren

en het landbeheer te adviseren. Deze aanpak kan worden ontwikkeld rekening houdend met extra factoren als gevolg van de locatie en het klimaat effect.

Dit proefschrift heeft een SM-modellering ontwikkeld in de landbouwregio van Mongolië. Het bodemvochtmodel zal informatie opleveren voor landbouw en veeteelt, zoals akkerland, weiland, vegetatiegroei en biomassa. Bovendien zal het nationale beleidsniveau deze informatie kunnen gebruiken om geschikte landbouwgebieden te ontwikkelen en kan het worden gebruikt voor het regionale landbouwplan in Mongolië.

Curriculum vitae (Biography)



Enkhjargal Natsagdorj was born in Ulaanbaatar city (Mongolia) on November 11th, 1987. In 2008, she graduated from Mongolian State University of Agriculture (MSUA) and obtained her bachelor diploma of Land management. In 2010, she graduated from the National University of Mongolia (NUM) and received her master of science degree in Remote sensing and Geographic Information system. In the same year, she started her work as a teaching assistant in the NUM-ITC-UNESCO Space science and Remote sensing Laboratory at the National University of Mongolia. In 2013, she began her doctoral education at the National University of Mongolia.

During her doctoral study, she had done her exchange research program in 2012 at the Oregon State University (OSU), Oregon, USA and in 2015 at the University of Vienna, Austria. In 2016, she started her doctoral program at the Ghent University, Belgium. From December 2016 until April 2021, Enkhjargal studied at Ghent University, fund by the ERASMUS-IMPAKT mobility program (10 months) and department of Geography, Ghent University. Her PhD research focuses on soil moisture analysis using remote sensing data. Enkhjargal has already contributed to several international conferences and author of several papers that have been published.

HER PUBLICATION LIST BELOW:

Refereed journal articles in international journals:

(1) Thomas Hilker, **Enkhjargal Natsagdorj,** Richard H. Waring, Alexei Lyapustin, Yujie Wang (2013). "*Satellite observed widespread decline in Mongolian grasslands largely due to overgrazing*", Global Change Biology, Volume 20, pages 418–428, DOI: http://doi.org/10.1111/gcb.12365.

(2) **Enkhjargal Natsagdorj,** Tsolmon Renchin, Martin Kappas, Batchuluun Tseveen Chimgee Dari, Oyunbileg Tsend, Ulam-Orgikh Duger (2017). "*An integrated methodology for soil moisture analysis using multispectral data in Mongolia*", International journal of Geo-Spatial Information Science, Volume 20, № 1, pages 46-55, DOI: http://doi.org/10.1080/10095020.2017.1307666.

(3) **Enkhjargal Natsagdorj,** Tsolmon Renchin, Philippe De Maeyer, Chimgee Dari, Batchuluun Tseveen (2019) *"Long-term soil moisture content estimation using satellite and climate data in the agricultural area of Mongolia"*, Geocarto International,

Volume 34, № 7, pages 722-734, DOI: https://doi.org/10.1080/10106049.2018.1434686.

(4) **Enkhjargal Natsagdorj,** Tsolmon Renchin, Phillipe De Maeyer, Batchuluun Tseveen. Chimgee Dari, Erdenebaatar Dashdondog (2019). *"The soil moisture analysis using multispectral data in the central part of Mongolia".* ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci., IV-2/W5, 485-491, DOI: https://doi.org/10.5194/isprs-annals-IV-2-W5-485-2019.

(5) Batchuluun Tseveen, **Enkhjargal Natsagdorj**, Altangerel Balgan, Tsolmon Renchin, Bayanmunkh Norovsuren & Zaya Mart (2020) "*Impact of logging operations on forest ecosystem in the Khantai mountain region and forest cover mapping*". Forest Science and Technology, 16:3, 123-133,
DOI: https://doi.org/10.1080/21580103.2020.1796830.

(6) **Enkhjargal Natsagdorj**, Tsolmon Renchin, Philippe De Maeyer, Rudi Goossens, Tim Van de Voorde, Bayanjargal Darkhijav (2020). *A GIS-based multi-criteria analysis on cropland suitability in Bornuur soum, Mongolia*. International Archive Photogrammetry, Remote Sensing, Spatial Information Science. XLIII-B4-2020, 149–156, DOI: https://doi.org/10.5194/isprs-archives-XLIII-B4-2020-149-2020.

(7) **Enkhjargal Natsagdorj,** Tsolmon Renchin, Philippe De Maeyer, Bayanjargal Darkhijav (2020). "*Spatial distribution of soil moisture in Mongolia using SMAP and MODIS satellite data, its time series model (2010 - 2025)". Remote Sensing, 13(3), 347.* DOI*:* https://doi.org/10.3390/rs13030347.