Kasetsart J. (Nat. Sci.) 48 : 254 - 262 (2014)

Daily Monitoring of Soil Moisture in Thailand by FY-2E Satellite

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ABSTRACT

Soil moisture is an important factor in monitoring and warning of drought and landslide disasters. Direct observations of soil moisture are point-based which restricts measuring soil moisture across a wide area continuously. In Thailand, soil moisture measurements are also observed only for a specific purpose. A method for soil moisture estimation throughout the country does not exist due to the same limitation. Recent advanced technology in satellite remote sensing provides alternatives to indirectly estimate soil moisture with high temporal and spatial resolutions. This study presents an efficient technique to observe daily soil moisture based on apparent thermal inertia derived from FY-2E satellite data. The technique can estimate daily soil moisture throughout Thailand at 5 × 5 km pixel resolution. The results exhibited good consistency between observed daily soil moisture and other relevant factors, for example, diurnal temperature change and daily rainfall. This work suggests that the proposed technique is a feasible solution for daily soil moisture monitoring nationwide.

Keywords: apparent thermal inertia (ATI), daily soil moisture, diurnal temperature, FY-2E, soil moisture estimation

INTRODUCTION

The global warming effect has an impact on the severity of disasters worldwide. Each year, Thailand experiences flood and drought alternately. In 2011, the Big Flood caused unimaginable losses and casualties to Thai people. That incident prompted calls for an effective water management and early disaster warning mechanism to mitigate the tragic results. The ability to observe factors contributing to such disasters is crucial to making informed decisions. Two relevant factors are rainfall and soil moisture. Rainfall is widely accepted as a triggering factor for flood and landslide disasters and also plays a major role in drought disaster (Larsen, 2008; Jessup and Colucci, 2012). However, only heavy rainfall can cause damage in hazardous terrains with sufficient soil moisture. While weather forecast systems are becoming more complicated in order to predict rainfall events worldwide with the aid of satellite, radar and ground-based observations, this is not the case for soil moisture estimation.

In general, soil moisture has high spatial and temporal variations. Direct observations of soil moisture are point-based which restricts the measurement of soil moisture across wide areas continuously. Indirect observation methods usually derive soil moisture through mathematical models that describe the relationship between remotely sensed data and soil moisture data. Therefore, it is difficult to develop a soil moisture estimation model in Thailand where ground truthing of data is extremely limited. There is no evidence in the

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Received date : 08/08/13 Accepted date : 28/11/13

literature of dynamic soil moisture maps available for effective drought/landslide monitoring and warning system from any agencies in Thailand. The current study developed a feasible method for soil moisture estimation with high spatial and temporal resolution to effectively support disaster monitoring and warning under the constraint of using minimal ground truth observations.

Recent advanced technology in satellite remote sensing provides alternatives to estimate soil moisture with high temporal and spatial resolution (Wang and Zhang, 2005). Several techniques have been proposed for the indirect evaluation of soil moisture (Wang and Qu, 2009). Among them, satellite data based on optical, thermal infrared, passive microwave and active microwave measurements are used (Schmugge, 1978), each with different physical principles, advantages and constraints: optical remote sensing techniques observe soil reflection with limitations due to surface penetration and cloud contamination but have the advantage of fine spatial resolution and wide coverage; thermal infrared techniques sense surface temperature with similar advantages and constraints to that of optical techniques; passive microwave techniques mainly observe brightness temperature, dielectric properties and soil temperature (Moran *et al*., 2004). These techniques have advantages in low atmospheric noise and moderate surface penetration but with low spatial resolution, while active microwave techniques offer similar advantages to passive microwave with high spatial resolution but their narrow swath width results in low temporal resolution and limited coverage area (Moran *et al*., 2004).

Considering the purpose of the study, optical and infrared techniques would fulfill the requirements of temporal resolution and wide coverage. Regarding optical remote sensing techniques, soil moisture has a negative effect on reflectance (Curcio and Petty, 1951). Several empirical approaches have been proposed to describe the relationship between soil moisture and its reflectance (Leone and Sommer, 2000; Lobell and Asner, 2002; Liu *et al*., 2003). However, little attention has been paid to the use of the optical domain compared with the thermal infrared domain because the spectral characteristics of soil depend on numerous factors, such as mineral composition, organic matter, soil texture, and surface roughness (Asner, 1998) causing wide variation when applied to other locations outside the calibration conditions (Wang and Qu, 2009).

Thermal infrared techniques measure the thermal emission of the Earth with wavelengths between 3.5 and 14 μm (Curran, 1985). This method is based on the relationship of the remotely measured surface soil temperature and the soil moisture. Techniques proposed range from the simple such as the thermal inertia method (Tramutoli *et al*., 2001) to complicated techniques such as the temperature/vegetation index method (Moran *et al*., 1994). The thermal inertia method showed that surface soil moisture is correlated with the diurnal range of the surface soil temperature (Friedl and Davis, 1994). Verstraeten (2006) found that the apparent thermal inertia (ATI) derived directly from multispectral satellite imagery can be used to calculate the volumetric soil moisture using a linear empirical equation. This method is simple and easy to use and has a clear physical meaning; however, it can achieve high accuracy only when applied to a region with little or no vegetation cover (Xue and Ni, 2006). The normalized difference vegetation index (NDVI) and land surface temperature (LST) are combined to estimate soil moisture under the soil-vegetation-atmosphere-transfer (SVAT) model (Carlson *et al*., 1994). This method overcomes the drawback of the ATI technique at the expense of model complexity. A support vector machine (SVM) based on statistical learning theory has also been applied to increase the accuracy of satellite-retrieved soil moisture estimates (Ahmad *et al*., 2010) as well as the artificial neural network (ANN) model (Jiang and Cotton, 2004). However, the SVM and ANN techniques require large numbers of training data sets to achieve the expected accuracy which is not possible with currently accessible data.

To address the lack of land assimilation data and NDVI derived from earth observation satellites, this study presents an efficient technique to observe diurnal soil moisture using apparent thermal inertia (ATI) derived directly from FY-2E satellite data. FY-2E is a geostationary satellite located above the equator at longitude 105°E (Dong and Zhang, 1998). This enables it to obtain images of the whole of Thailand every hour. Hourly visible (VIS) and infrared (IR) data, broadcast through the DVB-S system supported by the Chinese government, is received and archived by the Chulabhorn Satellite Receiving Station (CSRS) at Kasetsart University and the technique provides nationwide daily soil moisture estimation at 5 × 5 km spatial resolution (Dong and Zhang, 1998). Similar work (Tramutoli *et al.*, 2001) has shown that the ATI index can provide useful information related to an indirect estimate of soil moisture.

MATERIALS AND METHODS

Data and study sites

Two groups of datasets were involved in this study—FY-2E satellite observations and soil moisture measurements. Hourly satellite data from five radiometers scanning channels are received by CSRS in (.VSR) format with the data structure shown in Figure 1. The data from each channel are extracted and converted into numerical data using a conversion table provided in the documentation (DOC) sectors. IR data bits are converted into brightness temperatures while VIS data bits are converted into percent albedo. All converted data are archived in an XML file with 16-bit PNG format. The use of numerical methods for satellite data retrieval is more efficient compared to the image processing method as the latter process uses a sample of data from the image and converts it into a most likely approximation.

The characteristics of the five sensors onboard are shown in Table 1. The long wave infrared channel (IR1) and the split window channel (IR2) represent infrared surface/cloud-

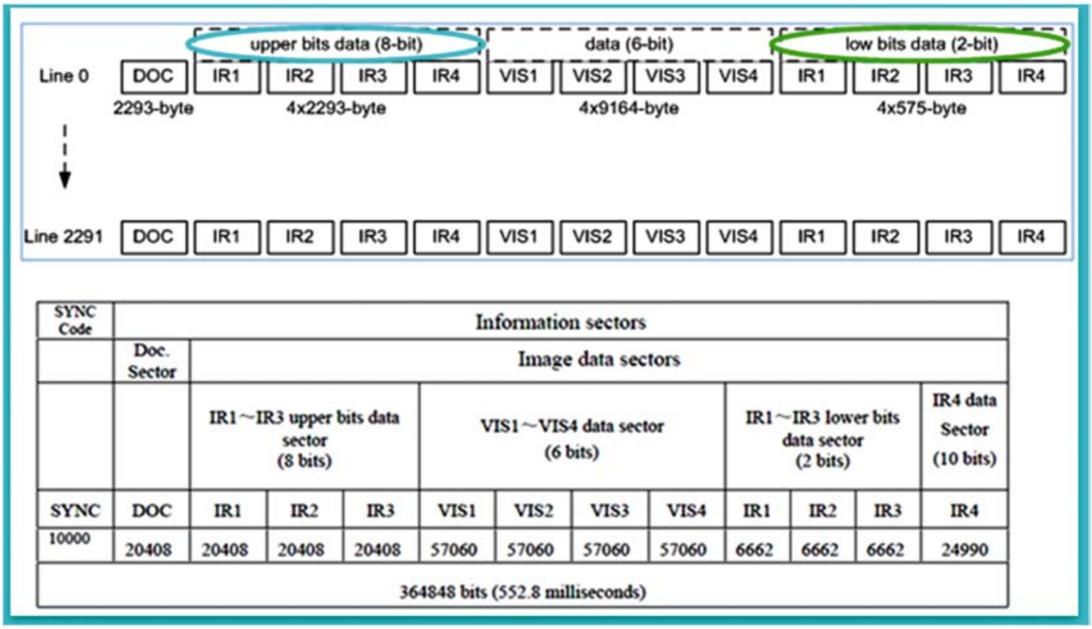

Figure 1 Structure of FY-2E satellite data format.

Table 1 FY-2C/E onboard sensor characteristics.

Channel ID	Channel name	Wave length (μm)	Spatial resolution (km)
IR1	Long wave infrared	10.80	5.00
IR2	Split window	12.00	5.00
IR3	Water vapor	6.80	5.00
IR4	Medium wave infrared	3.80	5.00
VIS	Visible	0.73	1.25

top temperature. The water vapor channel (IR3) measures the moisture content in the middle atmosphere that indicates deep convective clouds. The medium wave infrared channel (IR4) is usually used for the detection of fog and low-level clouds at night due to the influence of visible light on the brightness temperature of this channel. The visible channel (VIS) is used primarily for observing visible cloud and other surface features including surface albedo. The model developed in this study uses only IR1 and VIS data for computing the diurnal temperature and surface albedo, respectively.

Soil moisture data were provided by the Geotechnical Engineering Research and Development Center (GERD), Kasetsart University. Two study sites in Uttaradit province, northern Thailand, were considered. The sites were DK station located in Maepoon district and NL station located in Namlee district whose GPS values are shown in Figure 2. The former is covered with vegetation whereas the latter is mostly bare soil. The data were collected for one year from July 2010 until June 2011. The soil moisture sensors used at each station return voltages corresponding to the percentage of soil moisture measured every minute. However, the voltage values were occasionally out of the specified range of the sensors. Therefore, data were first filtered for quality control before being converted into the percentage of soil moisture (PSM) using the calibration TDR files for each station.

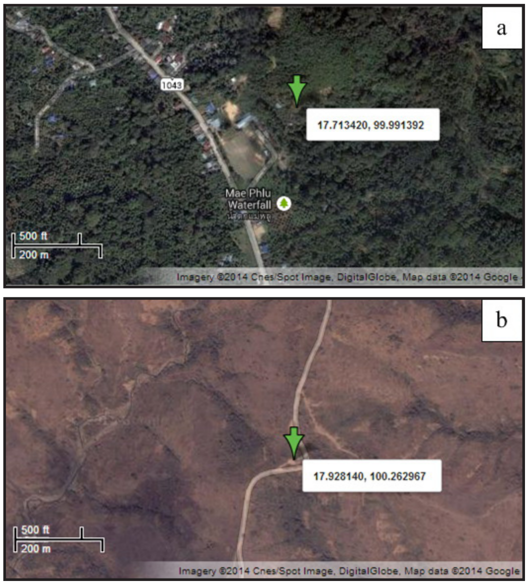

Figure 2 Locations in Uttaradit province, northern Thailand showing location coordinates of: (a) DK station in Maepoon district; and (b) NL station in Namlee district (sourced from Google Earth).

Soil moisture estimation models

Soil moisture estimation models were developed based on the concept of thermal inertia (TI). Soil TI is a physical property describing the impedance to temperature change (Verstraeten, 2006) which can be expressed using Equation 1:

$$TI = \sqrt{(\lambda C_T)} \quad (1)$$

where λ is the soil thermal conductivity and C_T is the soil heat capacity. The TI proportionally increases as the soil water content increases, thereby reducing the diurnal temperature fluctuation range.

With advances in satellite technology,

satellite remote sensing has the capability to measure the Earth's surface temperature and relate it to soil moisture. An apparent thermal inertia (ATI) derived directly from satellite sensing data is a simple surrogate of TI. Claps and Laquardia (2004) showed the relationship between the ATI and the surface albedo (α) and the diurnal temperature range (ΔT) derived from satellite data using Equation 2:

$$ATI = \frac{1-\alpha}{\Delta T} \tag{2}$$

The volumetric soil moisture (W_S) can be calculated using the linear empirical equation in Equation 3:

$$W_S = a_0 \cdot ATI + a_1, \tag{3}$$

where a_0,a_1 are empirical parameters.

A conceptual diagram of the study is shown in Figure 3. The surface albedo (α) is derived from the VIS channel of the FY-2E satellite. Hourly data received from the satellite vary not only due to soil moisture but also due to the distance and the angle between the sun and the satellite positions. Therefore, the daily averaged surface albedo is computed from data received from 1100 to 1600 hours on that day.

The diurnal temperature range (ΔT) is defined as the difference between the land surface temperatures at midday and midnight. The calculation of land surface temperature directly from FY-2E is a very complicated task consisting of many parameters for radiometric calibration, cloud screening procedures, emissivity correction, topology correction and atmospheric correction which make it infeasible at present. Therefore, the brightness temperature derived from the IR1 channel is used instead for cloud screening (at IR1 > 287K). The midday (T_{day}) and midnight (T_{night}) surface temperatures are approximated using the average brightness temperature received during 1100 to 1600 hours and 2300 pm to 0400 hours, respectively, to reduce any cloud contamination effect on the measured temperature.

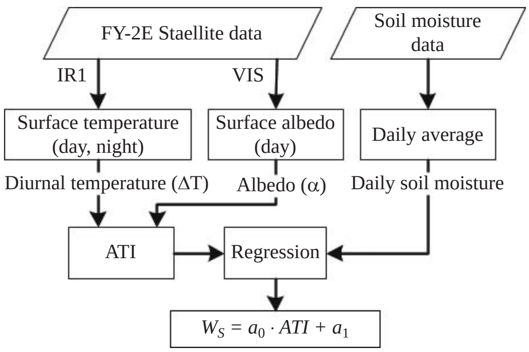

Figure 3 Conceptual diagram showing development of soil moisture estimation model based on apparent thermal inertia (ATI) method using FY-2E satellite data. (W_S = Volumetric soil moisture and a_0,a_1 = Empirical parameters.)

Figure 4 shows the time diagram of satellite data used to approximate the surface albedo and diurnal temperature range. These data are mapped with averaged soil moisture measured by both stations on the same day. Both satellite-derived parameters are used to calculate the daily ATI that corresponds to the average percentage of soil moisture (PSM). After cloud screening and data qualification processes, the data collected from July 2010 to June 2011 resulted in 79 and 97 available datasets, respectively, for model development using linear regression. The model that describes the relationship between PSM and ATI can be expressed using Equation 4:

$$PSM = a_0 \cdot ATI + a_1, \tag{4}$$

where a_0 = 22.667 and a_1 = 37.224 for DK station and a_0 = -15.829 and a_1 = 50.05 for NL station.

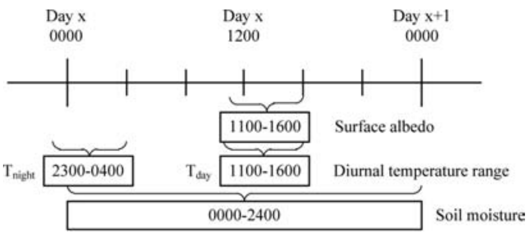

Figure 4 Surface albedo and diurnal temperature range derived from FY-2E satellite and land soil moisture measured by stations used for model development (all numbers are in 24-hour time format).

The NL model contradicted the physical meaning of thermal inertia and soil moisture relationship even though the surrounding area was not densely covered with vegetation. Therefore, the DK model was chosen to investigate the feasibility of using satellite-derived ATI for monitoring the variation of land soil moisture.

RESULTS AND DISCUSSION

Temperature and rainfall are factors contributing to soil moisture variations. In particular, the soil water content tends to dry up under high temperature when there is no rainfall. Due to limited ground truthing, the accuracy of the soil moisture estimation model cannot be assessed. However, the feasibility of soil moisture estimation for disaster management was studied by comparing the estimated soil moisture with the diurnal temperature and daily rainfall. Two data sets downloaded from the website of the Thailand Meteorological Department (TMD; http://www.tmd.go.th) were selected for comparison purposes. The first data set consisted of Thailand weather maps indicating daily maximum and minimum temperatures and daily rainfall on 19 March 2013. The soil moisture for each 5 × 5 km pixel was estimated based on the DK model using IR1 and VIS data from the FY-2E satellite received on the same day. The daily soil moisture map was then generated across the country. Figure 5a indicates the area with a high percentage of soil moisture in the circled area. Compared to other regions shown on the map, this result is in agreement with the daily rainfall (Figure 5b) around that area where more rainfall is related to higher percent soil moisture. Moreover, the maximum temperature on that day is in the lowest range (Figure 5c) compared to other areas while the minimum temperature is in the highest range (Figure 5d). This implies that the encircled area had a lower diurnal temperature change than other areas which corresponds to the higher percentage of soil moisture estimated from the model. The white areas indicate where the model returned no value due to the cloud screening process leaving insufficient data for the computation.

The other data set consisted of 3-hourly temperatures in Uttaradit province obtained from the TMD website and collected from 13 March to 30 March 2013. These data were used to compute the daily maximum and minimum temperatures for calculating the temperature difference (Figures 5c and 5d, respectively), as a surrogate for the daily diurnal temperature range. The corresponding daily soil moisture estimates shown in Figure 5a were computed using IR1 and VIS data from the FY-2E satellite at the pixel co-located with the TMD weather station in Uttaradit. For the period of this study, the diurnal temperature range tended to decrease while the estimated daily soil moisture tended to increase, conforming to the expected relationship between the two parameters.

The results in Figure 6 show good agreement between the satellite-observed soil moisture and other relevant factors (the diurnal temperature change and daily rainfall). This work suggests that soil moisture observation by the FY-2E satellite has potential for daily soil moisture monitoring across the country. Consequently, the results can be used to generate relevant information supporting an effective disaster monitoring and warning system, for example, a dynamic hazard map for a landslide monitoring and warning system.

CONCLUSION

An application of FY-2E meteorological satellite data was used for daily soil moisture estimation to support disaster monitoring and warning. This indirect observation of soil moisture can achieve both high temporal and spatial resolution nationwide. A simple ATI method was chosen under the constraint to use only FY-2E data. Theoretically, this ATI value has a linear relationship with the soil water content. Two different sites were selected for empirical model development: the DK station and the NL station in Uttaradit. Albedo and the diurnal temperature range derived from VIS and IR channel were successfully used to calculate the apparent thermal inertia (ATI). The result was expanded to successfully estimate daily soil moisture across Thailand. Based on the temperature and rainfall data from TMD, the results from the model showed that daily estimated soil moisture changes were in agreement with the diurnal temperature range and daily rainfall. Although the model accuracy cannot be assessed (due to limited ground truth data), it was considered an efficient tool for daily soil moisture estimation to support disaster monitoring and warning in Thailand.

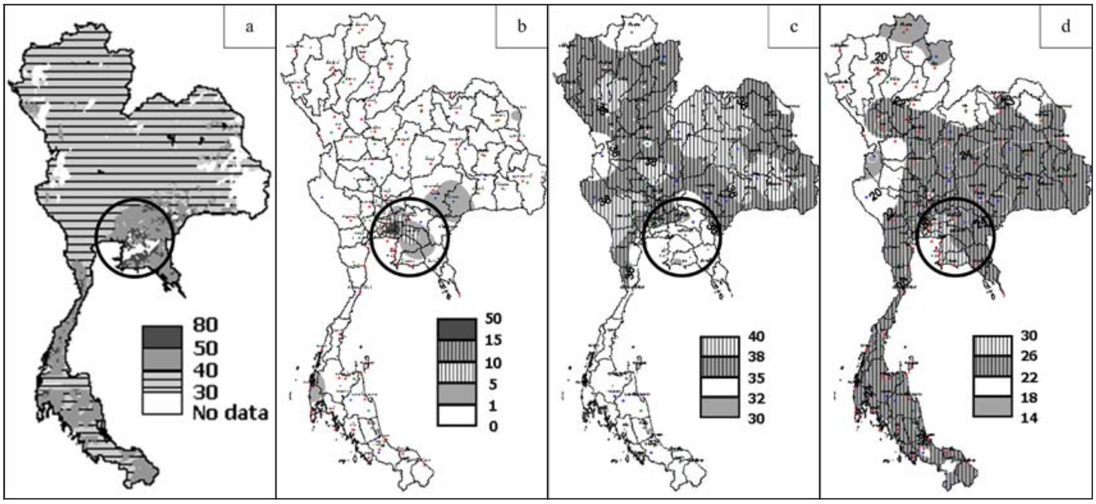

Figure 5 Modeled output and relevant meteorological data for 19 March 2013 from the Thai Meteorological Department (a) Percentage daily soil moisture (white color indicates no data); (b) Daily rainfall (mm); (c) Maximum temperature (^{o}c); and (d) Minimum temperature (^{o}c). The circled area shows high soil moisture content.

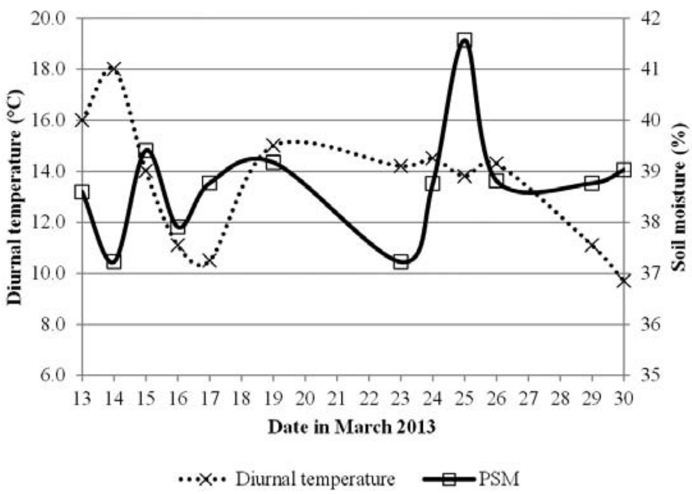

Figure 6 Relationship between daily diurnal temperature (^{o}C) and percentage of soil moisture (PSM) in Uttaradit province from 13 March to 30 March 2013.

ACKNOWLEDGEMENTS

This study was supported by the Kasetsart University Research and Development Institute (KURDI). The authors thank the Geotechnical Engineering Research and Development Center (GERD), Faculty of Engineering, Kasetsart University for their kind provision of soil moisture ground truth data.

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