Disaggregation of SMAP radiometric soil moisture measurements at catchment scale using MODIS land surface temperature data

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Abstract

Satellite soil moisture observations often require the enhancement of spatial resolution prior to being used in climatic and hydrological studies. This study employs the thermal inertia theory to downscale the 36 km radiometric data of the NASA's Soil Moisture Active/Passive Mission (SMAP) into 1 km resolution.

Regressions between daily temperature difference and daily mean soil moisture were established over Krui River catchment. The values of daily surface temperature difference were derived from MODIS Terra and Aqua, while the soil moisture data is collected from the Scaling and Assimilation of Soil Moisture and Streamflow (SASMAS) network. In this study, the regression analysis was conducted for each season separately and further classified into six classes based on the type of vegetation cover and clay content. SMAP data covering the Merriwa River catchment was disaggregated by using the algorithms formulated at the Krui River catchment to evaluate the applicability of using predefined algorithms on Merriwa River catchment, a catchment with similar characteristics. A comparison between downscaled soil moisture data and in situ data at the Krui and Merriwa River catchments shows a reasonable match with RMSE 0.136 and 0.146 cm^3/cm^3 respectively. The study shows promising results towards developing a general model to downscale SMAP soil moisture data in semi-arid regions using multiple variables.

1 Introduction

Soil moisture is a key factor in controlling a number of environmental processes, especially in arid and semi-arid environments. Therefore, soil moisture information at regional and global scales are important as an input variable in many of the climatic and hydrological modelling approaches (Koster et al., 2004; Western et al., 2002). Two common approaches to measure the soil moisture are ground-based methods and space-borne sensors.

The in situ soil moisture measurements are the most effective, but only available at point scale. This limits their ability to represent the spatial and temporal variabilities of regional or global scale soil moisture (Brocca et al., 2010). Satellite remote sensing technique is an alternative, which has showed promising results in measuring soil moisture at large scales as required by climatologists, hydrologists and agrologists (Engman and Chauhan, 1995). Microwave

remote sensing emerges as an important technique in providing surface soil moisture estimates of approximately the top 5 cm of soil (Ulaby et al., 1981).

The NASA's Soil Moisture Active/Passive Mission (SMAP), launched on 31st January 2015, consisted of a microwave radiometer and a high-resolution radar to measure the surface soil moisture and freeze-thaw state. The revisit time of SMAP is typically 3 days. The spatial gridding for passive, active and active-passive soil moisture products are 36 km, 3 km and 9 km respectively (Entekhabi et al., 2014). The SMAP radar failed after about 11 weeks of operation and is out of service (Colliander et al., 2017). The SMAP radiometer is providing passive soil moisture retrievals successfully since April 2015.

The scale which soil moisture information is acquired is not often readily applicable for hydrological models since the interactions between soil, atmosphere and vegetation are variable over both spatial and temporal domains. Therefore, both aggregation of point scale measurements to larger scales and disaggregation of satellite or model derived soil moisture data to sub-pixel levels is often required (Hemakumara, 2007).

The study presented here assesses the ability of disaggregating SMAP Passive (radiometric) 36 km soil moisture data at catchment scale using the thermal inertia relationship between diurnal temperature difference and daily mean soil moisture (ΔT–$\theta\mu$). Further, the applicability of ΔT–$\theta\mu$ regressions developed for one catchment into another catchment with similar characteristics was evaluated in this study.

1.1 Study area

The study area, Goulburn River catchment, is located in the southeast region of Australia and has an area of approximately 7000 km^2. The catchment can be generally described as a temperate and semiarid region (Chen et al., 2014). The northern part of the catchment mainly consists of basalt-derived soils while in the southern part the soils are mainly sandstone derived. The northern part comprises of undulating hills and the average elevation ranges from 300 to 500 m. The southern region of the catchment shows different topographic characteristics with steep hills, cliffs and gorges. The average annual precipitation of the catchment is 700 mm, yet is variable across the catchment from 500 mm to 1100 mm at higher altitudes. Monthly mean maximum temperature of the catchment in summer and winter are 30^{0}C and 17^{0}C, with minimum values of 16^{0}C and 3^{0}C respectively (Rudiger et al., 2003). The southern part of the catchment is covered by dense vegetation while the northern part is mostly covered by cleared grassland grazing (Chen et al., 2014).

1.2 The Scaling and Assimilation of Soil Moisture and Streamflow (SASMAS) project

Twenty-six soil moisture profile and temperature monitoring stations were established within the Goulburn River catchment (Figure 1) commencing from 2002 under the Scaling and Assimilation of Soil Moisture and Streamflow (SASMAS) project and has undergone several enhancements to the original installations in the subsequent years. Representativeness in soil moisture monitoring within the sub-catchments has been considered as a factor in choosing the locations when establishing the monitoring stations. Three Campbell Scientific CS616 water content reflectometers have been vertically installed at each of the soil moisture monitoring stations over the soil depths of 0-300, 300-600 and 600-900 mm. The number of reflectometers installed was determined by the depth to the bedrock, which is less than 900 mm at some of the stations. The sensors record the soil moisture at one-minute intervals and log at every 20 min interval. Campbell Scientific T107 temperature sensors were vertically installed to measure the temperature of 0-300 mm soil profile by aligning their mid points at 150 mm below the surface. During an upgrade, sites were installed with Stevens water HydraProbes to measure the soil moisture and temperature at 0-50 mm and at 25 mm soil depths respectively (Rudiger et al., 2007). However, the soil moisture and temperature data in 2015 at 0-50 mm depth are not yet available at most of the stations.

The Goulburn River catchment comprises two intensively monitored sub-catchments, Krui and Merriwa River catchments, located in the northern region. Six soil moisture monitoring stations (denoted by K1 to K6) are located in 562 km^2 Krui and seven stations (denoted by M1 to M7) in 651 km^2 Merriwa sub-catchments (Rudiger et al., 2007). Both Krui and Merriwa catchments have similar climatic and topographic characteristics and are mostly covered by croplands or grazing. Furthermore, a micro-catchment, Stanley (~150 ha), located in the southern half of the Krui River catchment (Figure 1) is densely monitored with seven soil moisture monitoring stations (Martinez et al., 2008). The calibrated version 3 dataset of SASMAS monitoring stations (Rudiger et al., 2010) were used in this study.

2 Theory

The SMAP soil moisture downscaling method employed in this study is based on the relationship between thermal inertia and soil moisture modulated by the vegetation cover and clay content. Thermal inertia is the resistance of a

body to change its temperature. Thermal inertia is proportional to the thermal conductivity, density and specific heat capacity of an object. The temperature of a material with low thermal inertia changes more rapidly compared to a material with high thermal inertia. Since water has a high specific heat capacity compared to dry soils, the dry soil temperature varies more rapidly than the temperature of the wet soils. This phenomenon can be used to estimate soil moisture by developing a regression model for the relationship between daily mean soil moisture ($\theta\mu$) and the daily difference of the soil temperature (ΔT). The background of this work extends to the past studies of Fang and Lakshmi (2014) and Fang et al. (2013), where AMSR-E soil moisture retrievals were downscaled using MODIS LSTs modulated by the NDVI. In our study, clay content has also been considered as a modulating factor based on the impact of soil type on soil thermal conductivity. Further, we evaluated the applicability of using the ΔT–$\theta\mu$ regressions built at one catchment into another with similar characteristics to downscale satellite soil moisture data.
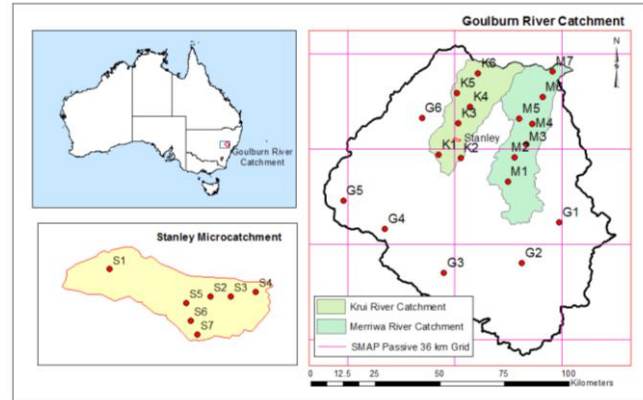

Figure 1: SASMAS Soil moisture monitoring stations located in the Goulburn River catchment.

3 Methodology and results

3.1 Developing ΔT–$\theta\mu$ regression equations

Hourly surface temperature data and daily mean soil moisture data acquired in the year 2015 from the SASMAS – Krui River catchment in situ dataset were used to develop ΔT–$\theta\mu$ regressions in this study. ΔT can be defined as the difference between the daily maximum and minimum temperatures (Fang et al., 2013). The diurnal hourly temperature data at the Krui catchment monitoring stations depict that surface temperature difference between MODIS Aqua and Terra overpass times provides fair approximations of ΔT. The approximate MODIS Terra and Aqua daytime overpass times are 10:30 and 13:30 respectively in local time. Soil moisture and temperature data at 0-50 mm soil profile were unavailable in 2015 at the Krui catchment stations except at K3. However, the soil moisture and temperature at 0-50 mm and 0-300 mm soil profiles are closely identical at the Krui catchment. Therefore, the daily mean soil moisture and soil temperature of 0-300 mm soil profile were used to build linear regressions fits.

The ΔT–$\theta\mu$ relationship is seasonally varying and modulated by vegetation cover (Fang and Lakshmi, 2013). Additionally, we considered soil type as another variable modulating ΔT–$\theta\mu$ relationship considering the effect of soil type in soil thermal conductivity. Therefore, the ΔT–$\theta\mu$ relationships were developed for each weather season in the year 2015 and further classified into six classes based on NDVI and clay content as shown in the Table 1. The seasonal average NDVI values of Krui catchment stations were calculated by using MODIS 16-day NDVI composites (MYD13A2). The clay content of each station was extracted from the Soil and Landscape Grid National Soil Attributes Maps. Figure 2 shows the linear regression fits built between ΔT and $\theta\mu$ at the Krui River catchment monitoring stations for autumn-2015, classified based on the NDVI and clay content as per Table 1.

3.2 Estimating 1 km soil moisture using ΔT–$\theta\mu$ regressions

Thereafter, the daily LST maps of Krui River catchment area were prepared by using MODIS Terra (MOD11A1) and Aqua (MYD11A1) daytime LST datasets over the period of SMAP data availability in the year 2015. MODIS derived LST values were calibrated based on the SASMAS in situ soil temperature data. Afterwards, the daily 1 km resolution ΔT maps of Krui River catchment area were developed by calculating the difference between the adjusted MODIS Aqua and Terra LST datasets of each day.

Thereafter, the seasonal average NDVI values and clay content at each 1 km MODIS LST pixel over the Krui River catchment were calculated by using MODIS 16-day NDVI composites and Soil and Landscape Grid National Soil

Attributes Maps respectively. Based on NDVI values and clay content, the ΔT data were classified into the regression classes as per Table 1. Subsequently, the daily 1 km soil moisture maps were generated by applying the respective ΔT–θμ regression equations to the ΔT values, modulated by the weather season, NDVI and clay content.

Table 1: Classification of seasonal ΔT–θμ relationships based on NDVI and clay content.

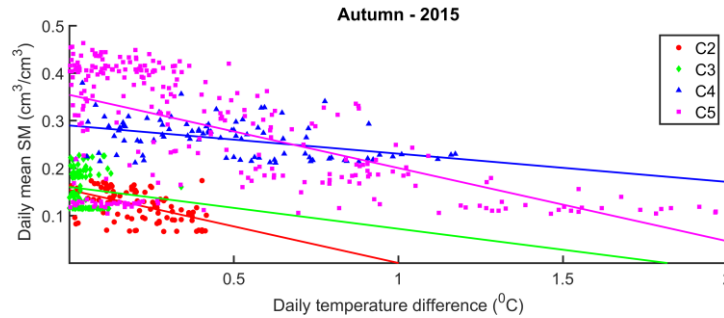| Clay content	NDVI	Class
Clay<25%	NDVI<0.4	1
Clay <25%	0.4<NDVI<0.6	2
Clay <25%	NDVI>0.6	3
Clay>25%	NDVI<0.4	4
Clay>25%	0.4<NDVI<0.6	5
Clay>25%	NDVI>0.6	6

Figure 2: ΔT–θμ regression fits developed for Krui River catchment soil moisture monitoring stations using SASMAS field data collected in autumn - 2015.

3.3 Disaggregating SMAP 36 km soil moisture data

Thereafter, the SMAP radiometric 36 km data were disaggregated by using the estimated 1 km soil moisture values through the following equation (modified from Fang and Lakshmi, 2014; Fang et al., 2013);

$$\theta_{adj}(x,y) = \theta_{est}(x,y) + [\theta_{SMAP} - \frac{1}{N}\sum_{x,y}\theta_{est}(x,y)] \qquad (2)$$

where, $\theta_{adj}(x,y)$ is the disaggregated SMAP soil moisture at the 1 km pixel x,y, $\theta_{est}(x,y)$ is the 1 km soil moisture estimated from ΔT–θμ relationship at x,y, θ_{SMAP} is the soil moisture derived from SMAP 36 km radiometric data corresponding to the pixel at x,y and N is the number of 1 km $\theta_{est}(x,y)$ pixels within the respective 36 km SMAP pixel. The spatial data gaps caused due to cloud contamination in MODIS LST data were excluded in this calculation.

3.4 Applying pre-defined regression fits to estimate soil moisture at a catchment with similar characteristics

Thereafter, the capability of applying the ΔT–θμ regression equations built at Krui River catchment to estimate the soil moisture at Merriwa River catchment was evaluated. The daily 1 km ΔT values were calculated for Merriwa catchment using MODIS Terra and Aqua daytime LST data. The respective class values (Table 1) of each 1 km pixel at Merriwa catchment was calculated by using MODIS 16-day NDVI composites and Soil and Landscape Grid National Soil Attributes Maps. Subsequently, the 1 km resolution θμ values over the Merriwa catchment was estimated by fitting the ΔT values into the regression equations developed at Krui River catchment. Thereafter, the SMAP 36 km radiometric data covering the Merriwa River catchment were disaggregated by using equation 2.

3.5 Verification of disaggregated soil moisture data

The disaggregated data of Krui and Merriwa River catchments were verified with SASMAS in situ soil moisture observations. Figure 3 shows a comparison between in situ and disaggregated SMAP soil moisture data in Krui and Merriwa catchments. K5 and M4 were excluded from verification due to data irregularities. In situ data from S5, a station from Stanley catchment, was also employed in the verification at Krui catchment. The RMSEs between in situ and disaggregated soil moisture data are 0.136 and 0.146 cm³/cm³ at Krui and Merriwa catchments respectively.

Figure 4 shows the agreement between in situ and disaggregated soil moisture data at M1 monitoring station. A comparison of disaggregated soil moisture maps of Merriwa River catchment on 31st August and 30th November 2015 are shown in Figure 5 a and b, along with the variability of daily mean soil moisture at SASMAS - Merriwa River catchment monitoring stations over the year 2015 in Figure 5 c.
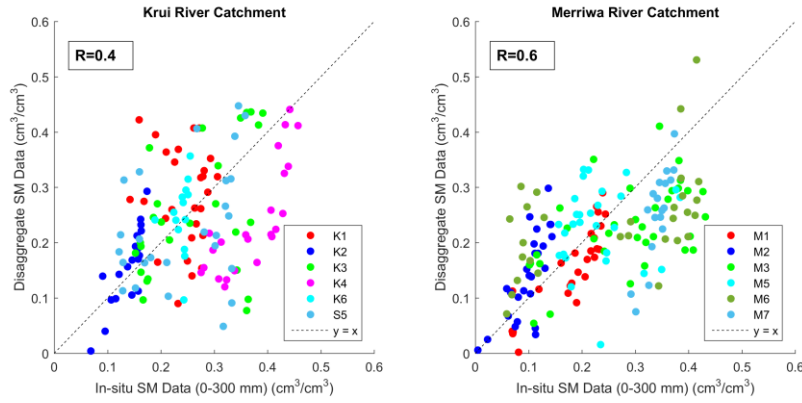
Figure 3: Comparison of disaggregated and in situ soil moisture measurements at Krui and Merriwa River catchments.
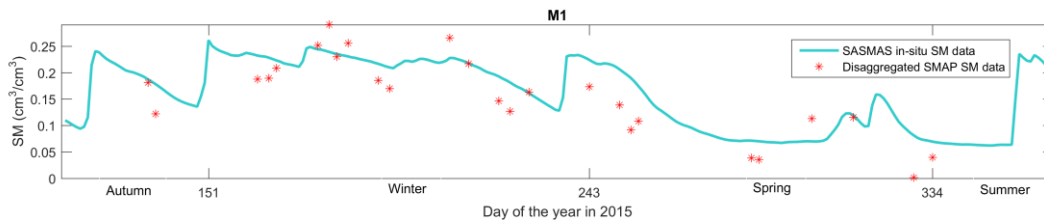

Figure 4: Agreement of disaggregated SMAP soil moisture data and in situ data at M1 station.
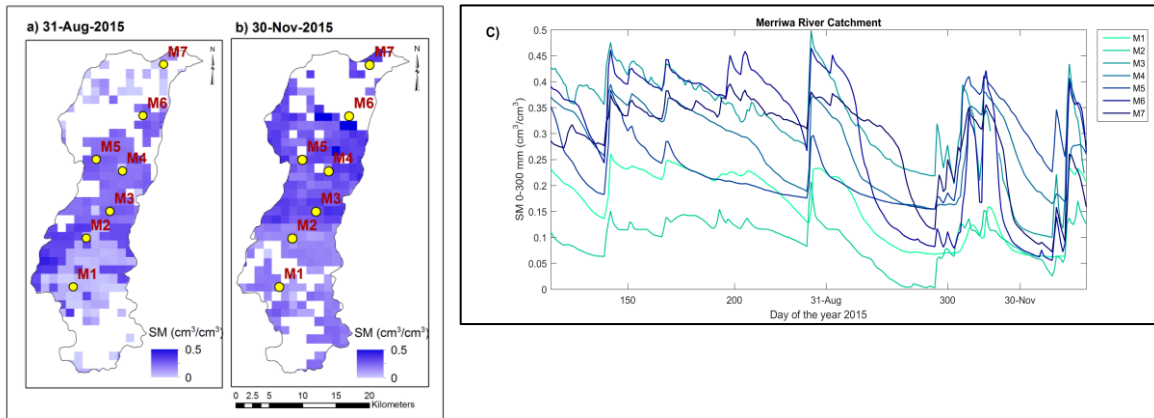

Figure 5: Disaggregated soil moisture at Merriwa River catchment on a) 31st August 2015 and b) 30th November 2015, c) Variability of daily mean soil moisture at Merriwa River catchment SASMAS monitoring stations from 14th April to 31st December 2015.

4 Discussion and Conclusions

The results at the Merriwa River catchment show a good potential in applying the ΔT–θμ algorithms built at one catchment to another with similar climatic, vegetation, topographic and soil conditions. The approach provided in this study delivers a reasonable agreement between in situ and disaggregated soil moisture values. The disaggregated SMAP soil moisture maps have successfully captured the wet and dry conditions at Merriwa River catchment on 31st August and 30th November 2015. In addition, the approach was able to capture the increasing spatial variation of soil moisture towards northern part of the catchment. These results provide promising prospects in developing a general model to estimate soil moisture through thermal inertia theory by employing multiple modulating variables and subsequently downscaling satellite soil moisture retrievals in semi-arid regions.

The spatial and temporal data gaps can be identified as one of the main limitations of using MODIS LST data caused mainly by the cloud contamination. Both SMAP soil moisture data and MODIS derived ΔT data over a study

area of a particular day is required to successfully apply this method to obtain downscaled soil moisture maps. Both spatial and temporal gaps in remotely sensed data causes null pixels in results.

MODIS LSTs retrieved at their overpass times do not necessarily represent the daily maximum and minimum temperatures over a location. Replacing MODIS LSTs with the LST data derived from a geostationary satellite has a potential in providing better ΔT values since they can capture the daily minimum and maximum LSTs. Distortions in satellite data from dense vegetation cover can also be identified as another cause leading to erroneous results. The disparities between the skin surface temperatures provided by MODIS LST data and the in situ temperature measurements over a 0-300 mm top soil profile can be shown as another error source in this study.

The accuracy of the regressions and class values (Table 1) could be significantly improved by using a dataset with increased number of data locations. Less number of data points results gaps in class values defined at Table 1. Disaggregating SMAP soil moisture data by using $\Delta T-\theta\mu$ regressions developed using soil moisture and temperature difference data derived by surface models such as JULES, CABLE and HYDRUS, and comparing the results with the results presented in this study will provide further insights on improving the accuracy of the results.

Acknowledgments

5   References

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