Downscaling satellite-derived soil moisture products based on soil thermal inertia: a comparison of three models over a semi-arid catchment in south-eastern Australia

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Abstract

High spatial resolution soil moisture information is important for regional–scale hydrologic, climatic and agricultural applications. However, available point-scale in-situ measurements and coarse-scale (~10s of km) satellite soil moisture retrievals are unable to capture hillslope to sub-catchment level spatial variability of soil moisture as required by many of these applications. Downscaling L-band satellite soil moisture retrievals appears to be a viable technique in estimating near surface (~ top 5 cm) soil moisture at a high spatial resolution. Among different downscaling approaches, thermal data based methods exhibits a good potential over arid and semi-arid regions, i.e. in many parts of Australia. This study investigates three downscaling approaches based on soil thermal inertia to estimate near surface soil moisture at high spatial resolution (1 km) over Krui and Merriwa River catchments in the Upper Hunter region of New South Wales, Australia. These methods are based upon the relationship between the diurnal soil temperature difference (ΔT) and daily mean soil moisture content (µSM). Regression tree models between ΔT and µSM were developed by using in-situ observations (in the first approach) and using land surface model (LSM) based estimates (in the second approach). The relationship between ΔT and µSM was modulated by the vegetation density and the Austral season. In the in-situ data based approach, soil texture was also employed as a modulating factor. These in-situ datasets were obtained from the Scaling and Assimilation of Soil Moisture and Streamflow (SASMAS) network and model-based estimates from the Global Land Data Assimilation System (GLDAS). Moderate Resolution Imaging Spectroradiometer (MODIS) derived Normalized Difference Vegetation Index (NDVI) products were used to define vegetation density. An ensemble machine-learning model was employed in the third approach using ΔT, NDVI and Austral season as predictors and µsm values as responses. Aggregated airborne soil moisture retrievals were used as the coarse resolution soil moisture products. These coarse resolution soil moisture simulations were downscaled to 1 km by employing the above three approaches using MODIS-derived ΔT and NDVI values. The results from the three downscaling methods were compared against the 1 km soil moisture retrievals from the National Airborne Field Experiment 2005 (NAFE'05) over 3 days in November 2005. The results from both in-situ data and GLDAS-based regression tree models show RMSEs of 0.07 cm3/cm3 when compared against the high resolution NAFE'05 airborne soil moisture observations. The GLDAS-based model can be applied over a larger extent, whereas the in-situ data based model is catchment specific. These results were compared with the results from the machine-learnt model. A combination of these methods with additional forcing factors such as topography, meteorology, etc. can be utilized to develop an improved downscaling model. Such a mod

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1. INTRODUCTION

- High spatial resolution soil moisture information is important for regional–scale hydrologic, climatic and agricultural applications.
- Available point-scale in-situ measurements and coarse-scale (~10s of km) satellite soil moisture products are unable to capture hillslope to sub-catchment level spatial variability of soil moisture as required by many of these applications.
- Downscaling L-band satellite soil moisture retrievals appears to be a viable technique in estimating near surface (~ top 5 cm) soil moisture at a high spatial resolution.
- Among different downscaling approaches, thermal data based methods exhibit a good potential over arid and semi-arid regions, i.e. in many parts of Australia.

Fig 1: Soil moisture is a key variable in a number of environmental processes *(Image source: NASA)*.

2. OBJECTIVES

- This study investigates three downscaling models based on soil thermal inertia relationship between the diurnal soil temperature difference *(ΔT)* and daily mean soil moisture content *(θμ)* to estimate near surface soil moisture at high spatial resolution (1 km) over two sub-catchments in the Upper Hunter region of south-eastern Australia.

3. THEORY

- The relationship between the diurnal soil temperature difference (*ΔT*) and the daily mean soil moisture content (*θμ*) has been used in this work to develop the downscaling model.
- Thermal inertia (*TI*) is a property that characterizes the degree of resistance of a body to the changes in its surrounding temperature.
- $TI = \sqrt{\rho.K.c}$ where *ρ*, *K* and *c* are the density, thermal conductivity and specific heat capacity of the material [1].
- Water has a high specific heat capacity, hence high thermal inertia, compared to dry soil.
- Therefore, Presence of moisture increases the thermal inertia of soil, i.e. higher the soil moisture content, lesser the diurnal temperature difference of soil (*ΔT*) [2, 3].
- This relationship between *θμ* and *ΔT* has been employed in this study to estimate soil moisture at high spatial resolution.

4. DATA

- **SASMAS in-situ data (2003-2015) [4, 5]**
  - Daily mean soil moisture (*θμ*) *(0-5 cm soil profile)*
  - Diurnal soil temperature difference (*ΔT*) *(0-5 cm soil profile)*
  ($\Delta T = T_{13:30} - T_{01:30}$) *http://www.eng.newcastle.edu.au/sasmas/SASMAS/sasmas.htm*
- **NAFE'05 airborne soil moisture retrievals [6]**
  - Soil Moisture (1 km resolution) 30th Oct, 7th, 14th and 21st Nov 2005.
  www.nafe.monash.edu
- **MODIS (MYD11A1) data (2015)**
  - Day and Night Land Surface Temperature (LST) data (1 km resolution)
  Land Processes Distributed Active Archive Center (LP DAAC)
- **MODIS (MYD13A2) data (2003-2015)**
  - 16-Day Normalized Difference Vegetation Index (NDVI) data (1 km resolution)
  Land Processes Distributed Active Archive Center (LP DAAC)
- **National Soil and Landscape Grid**
  - Clay content (90 m resolution)
  Commonwealth Scientific and Industrial Research Organisation (CSIRO)
- **Global Land Data Assimilation System (GLDAS)**
  - *θμ and ΔT (0-10 cm soil profile)* *https://disc.gsfc.nasa.gov*

5. STUDY AREA

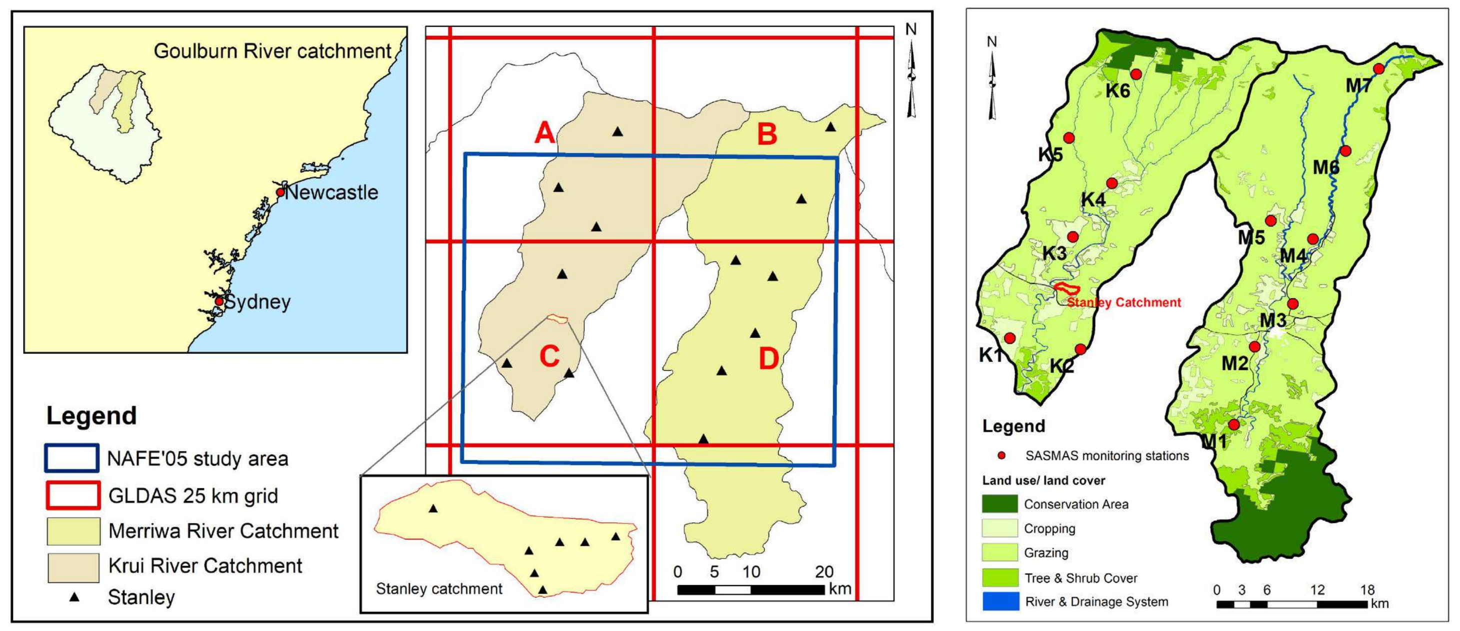

Fig. 2: (a) Krui and Merriwa River catchments and SASMAS soil moisture monitoring stations along with the NAFE'05 study area (40×40 km) and GLDAS (25 km) grids. The GLDAS pixels used for model building are labelled as A-D. (b) Land use/land cover of Krui and Merriwa River catchments.

- The study area, Goulburn River catchment (~7000 km²), is located in the Upper-Hunter region of south-eastern Australia (in NSW).
- The two focus catchments, Krui (~562 km²) and Merriwa River (~651 km²), are located in the northern half of the Goulburn River catchment. These two sub-catchments are mostly cleared for cropping and grazing.
- Under the Scaling and Assimilation of Soil Moisture and Streamflow (SASMAS) project, 26 monitoring stations have been established across the Goulburn River catchment to monitor soil moisture and soil temperature (Fig. 1) [4, 5]. Soil moisture and soil temperature of 0-5 cm soil layer is measured by using Steven's Water HydraProbes at these monitoring stations.
- Soil moisture over a 40×40 km area over the Krui and Merriwa River catchments were recorded at 1 km spatial resolution under the regional airborne campaign of the National Airborne Field Experiment 2005 (NAFE'05) on 31st Oct, 7th, 14th and 21st November 2005 [6].

6. METHODS

6. 1 Model development

MODEL 1
ΔT – θμ Regression Model [7, 8]
(in-situ data based ΔT and θμ)

Inputs
- SASMAS in-situ data (ΔT and θμ)

Modulated by:
- Season: Austral spring (Sep-Nov)
- NDVI: (NDVI<0.4, 0.4-0.6 and >0.6)
- Soil clay content: Clay<35% and >35%

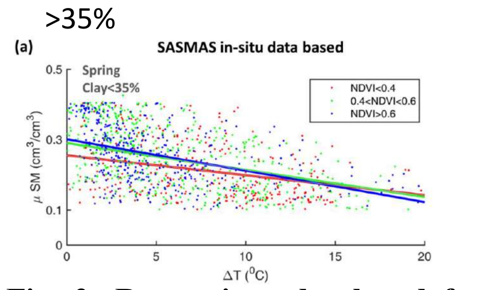

Fig. 3: Regressions developed for Austral spring, clay content <35% using SASMAS in-situ data.

MODEL 2
ΔT – θμ Regression Model [9]
(Model based ΔT and θμ)

Inputs
- GLDAS land surface model (LSM) based ΔT and θμ

Modulated by:
- Season: Austral spring
- NDVI: (NDVI<0.4, 0.4-0.6 and >0.6)

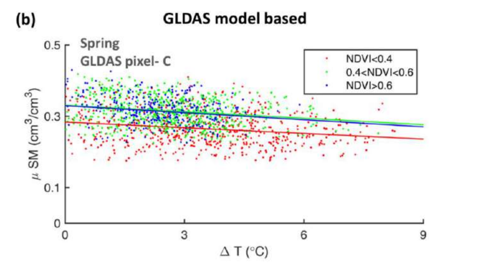

Fig. 4: Regressions developed for Austral spring, at GLDAS pixel-C using GLDAS model-based data.

MODEL 3
Artificial Neural Network (ANN)
(Model based ΔT and θμ)

- Levenberg-Marquardt algorithm with 50 hidden neurons (by trial and error)
- Matlab 2017b Neural Network Fitting Toolbox

Inputs
- GLDAS model based ΔT and θμ of Austral spring
- NDVI

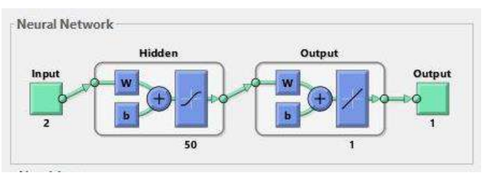

Fig. 5: Levenberg-Marquardt algorithm with 50 hidden neurons with GLDAS-based inputs.

6. 2 Estimating soil moisture at a high spatial resolution

- Calculating ΔT values using MODIS LST products.
- Estimating at 1 km spatial resolution by fitting ΔT values into the regression tree models and to the ANN.
- Downscaling simulated coarse resolution satellite soil moisture products.

6. 3 Validation

- Validation with NAFE'05 soil moisture retrievals.

7. RESULTS

NAFE'05 Soil Moisture

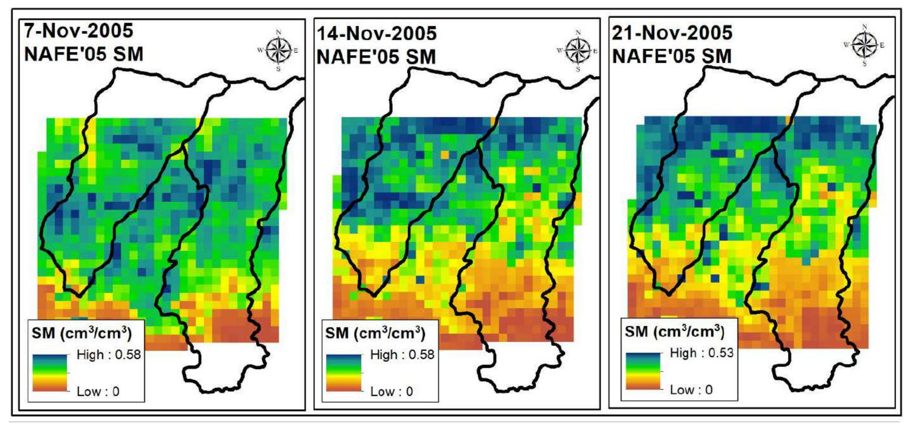

Fig. 6: High spatial resolution (1 km) airborne soil moisture retrievals from NAFE'05 on 7th, 14th 21st November 2005.

- Due to the high cloud cover, 31st Oct 2005 was omitted from this analysis.
- NAFE'05 dataset shows mean soil moisture of 0.36, 0.16 and 0.14 cm³/cm³ on 7th, 14th and 21st November 2005. This implies a drying trend towards the end of November.
- Error maps (Fig. 7b, 8b and 9 b) show the absolute difference of soil moisture between NAFE'05 datasets and downscaled soil moisture.
- A Root Mean Square Errors (RMSE) of 0.07 cm³/cm³ were observed with downscaled soil moisture from in-situ and LSM-based ΔT – θμ regressions, and an RMSE of 0.08 cm³/cm³ was observed with downscaled soil moisture from Neural Network based model, when compared with NAFE'05 soil moisture data.
- A high error was observed with the Artificial Neural Network compared to the in-situ and modelled data based ΔT – θμ regression models

MODEL 1 – In-situ data based *ΔT – θμ* Regression Model

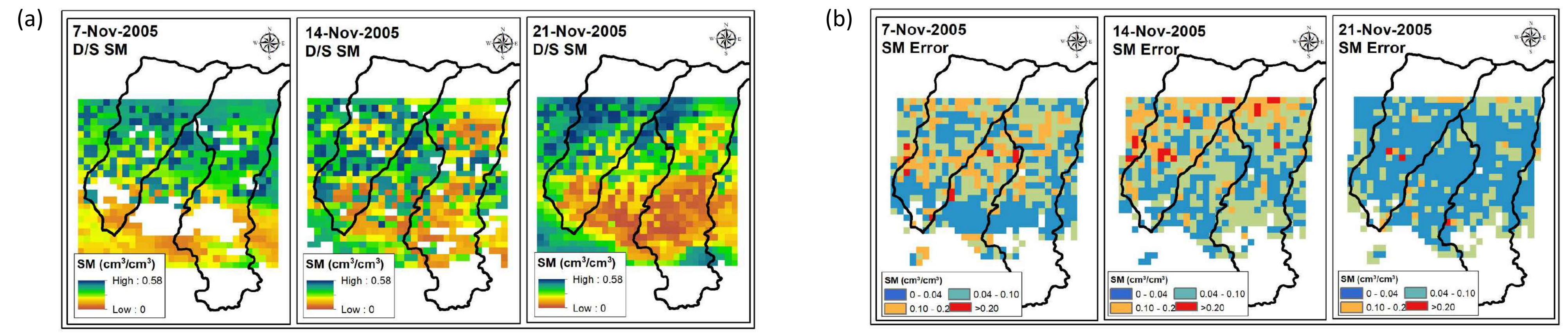

Fig. 7: (a) Downscaled soil moisture and, (b) soil moisture error, for in-situ data based *ΔT – θμ* regression model on 7th, 14th 21st November 2005.

MODEL 2 – LSM derived estimates based *ΔT – θμ* Regression Model

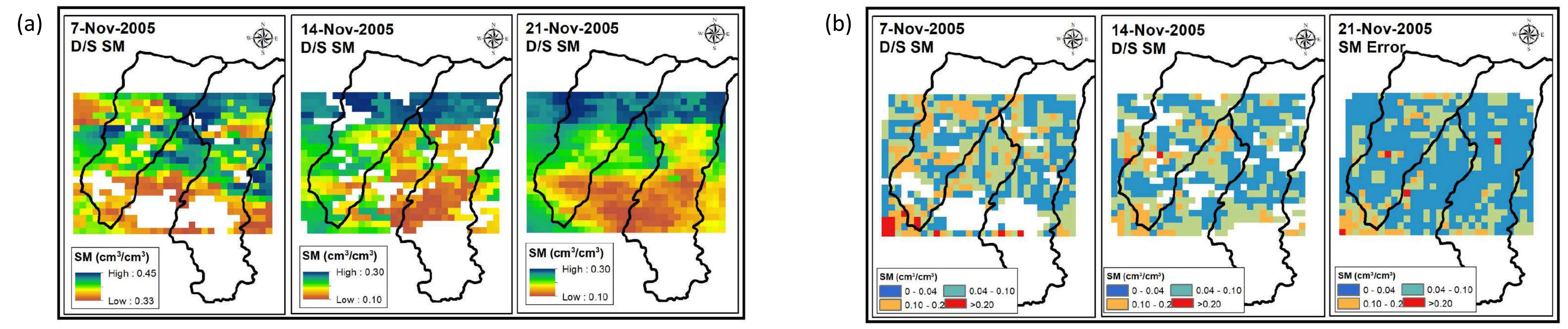

Fig. 8: (a) Downscaled soil moisture and, (b) soil moisture error, for GLDAS data based *ΔT – θμ* regression model on 7th, 14th 21st November 2005.

MODEL 3 – Ensemble Machine Learning Model (Artificial Neural Network)

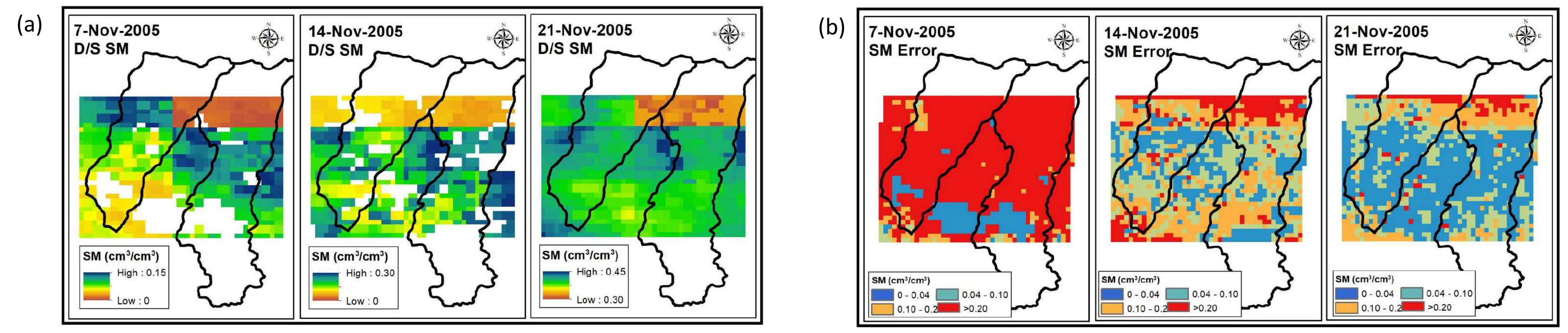

Fig. 9: (a) Downscaled soil moisture and, (b) soil moisture error, for Neural Network based model on 7th, 14th 21st November 2005.

8. CONCLUSION

- Downscaled soil moisture from *ΔT – θμ* regression models, based on both (i) in-situ and (ii) GLDAS LSM based data, showed RMSEs of 0.07 cm³/cm³. Downscaled soil moisture from Artificial Neural Network based model shows RMSE of 0.08 cm³/cm³.
- Soil thermal inertia based models showed better performance during dry catchment conditions.
- Both, in-situ and LSM based regression models show promising results in estimating high spatial resolution soil moisture using satellite data.
- Neural Network based model should be further improved using in-situ data and other factors affecting *ΔT – θμ* relationship.

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