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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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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

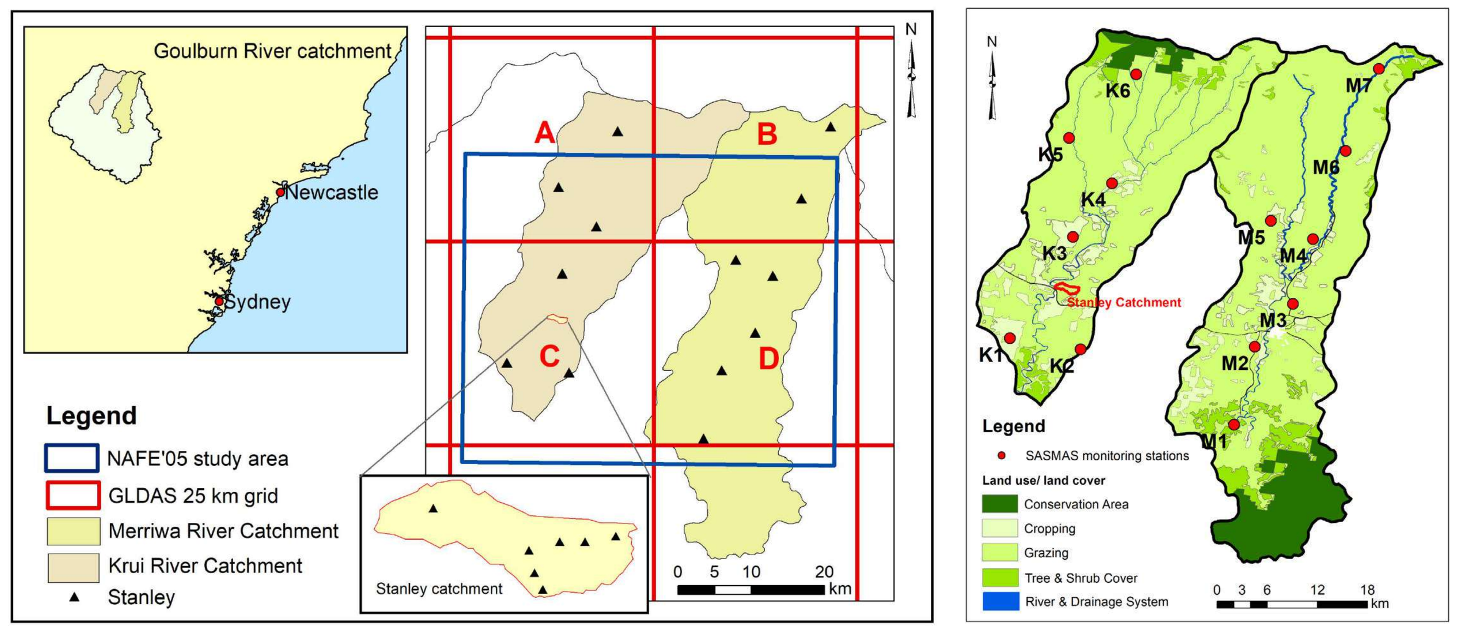

Fig. 2: (a) Krui and Merriwa River catchments and SASMAS soil moisture monitoring stations along with the NAFE'05 study area (40×40 km) and GLDAS (25 km) grids. The GLDAS pixels used for model building are labelled as A-D. (b) Land use/land cover of Krui and Merriwa River catchments.

- The study area, Goulburn River catchment (~7000 km^2), is located in the Upper-Hunter region of south-eastern Australia (in NSW).
- The two focus catchments, Krui (~562 km^2) and Merriwa River (~651 km^2), 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%

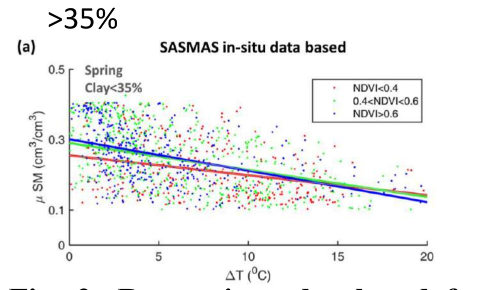

Fig. 3: Regressions developed for Austral spring, clay content <35% using SASMAS in-situ data.

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)

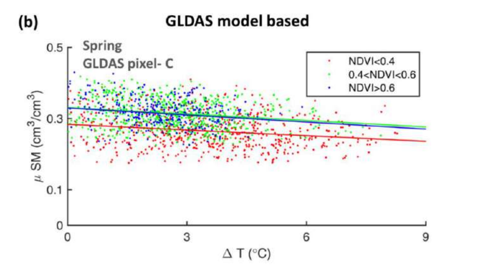

Fig. 4: Regressions developed for Austral spring, at GLDAS pixel-C using GLDAS model-based data.

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

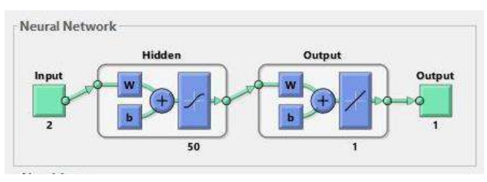

Fig. 5: Levenberg-Marquardt algorithm with 50 hidden neurons with GLDAS-based inputs.

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

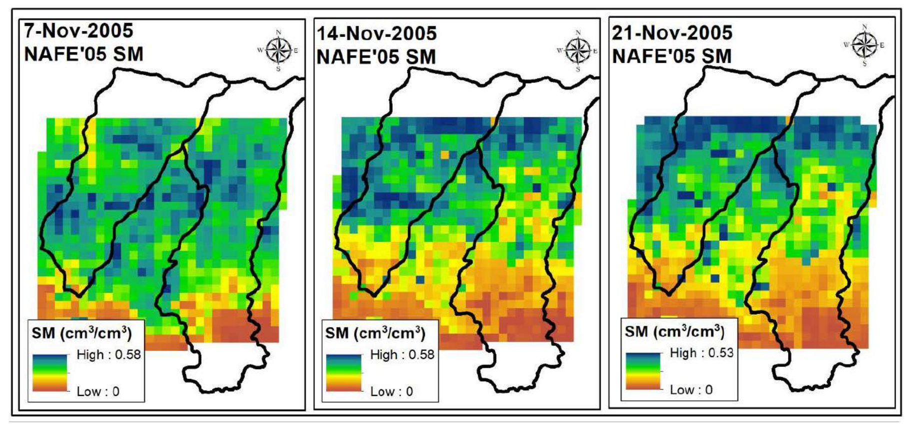

Fig. 6: High spatial resolution (1 km) airborne soil moisture retrievals from NAFE'05 on 7th, 14th 21st November 2005.

- 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 cm^3/cm^3 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 cm^3/cm^3 were observed with downscaled soil moisture from in-situ and LSM-based ΔT – θμ regressions, and an RMSE of 0.08 cm^3/cm^3 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

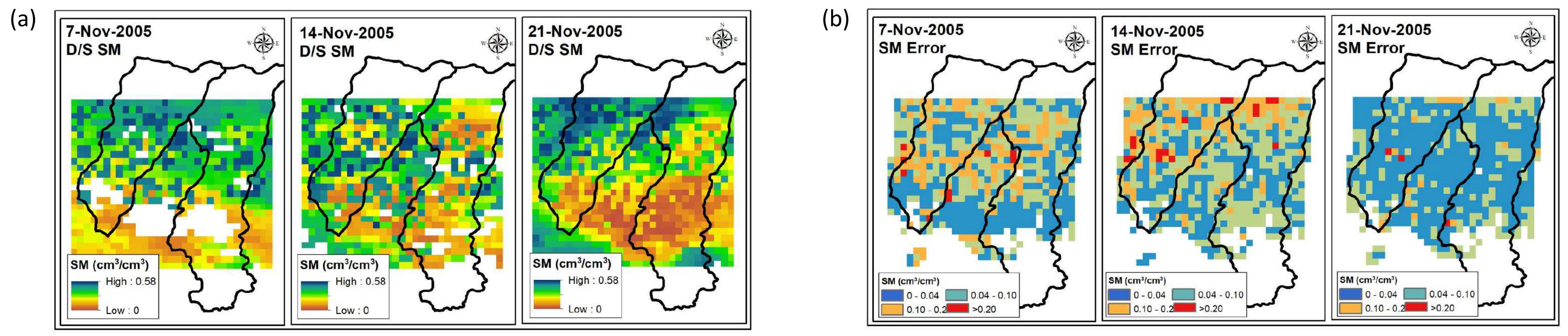

Fig. 7: (a) Downscaled soil moisture and, (b) soil moisture error, for in-situ data based *ΔT – θμ* regression model on 7th, 14th 21st November 2005.

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

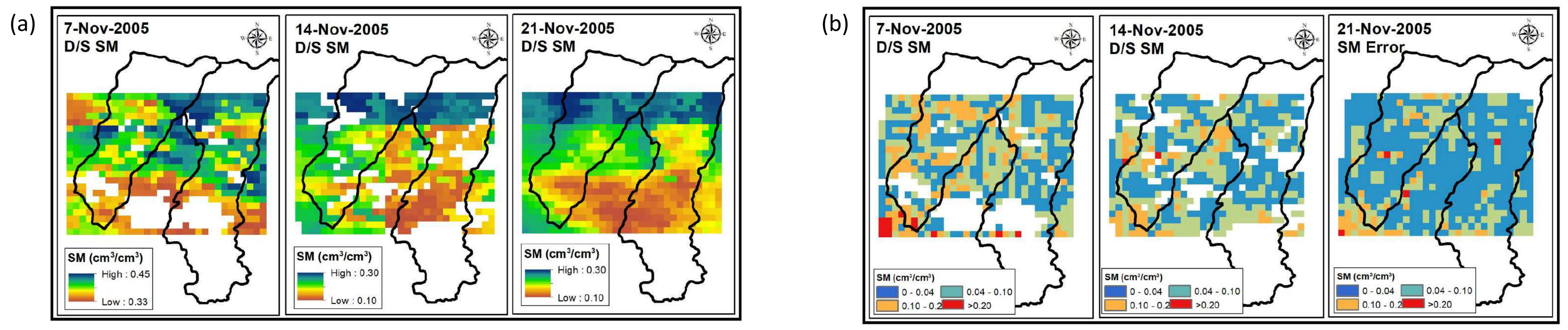

Fig. 8: (a) Downscaled soil moisture and, (b) soil moisture error, for GLDAS data based *ΔT – θμ* regression model on 7th, 14th 21st November 2005.

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

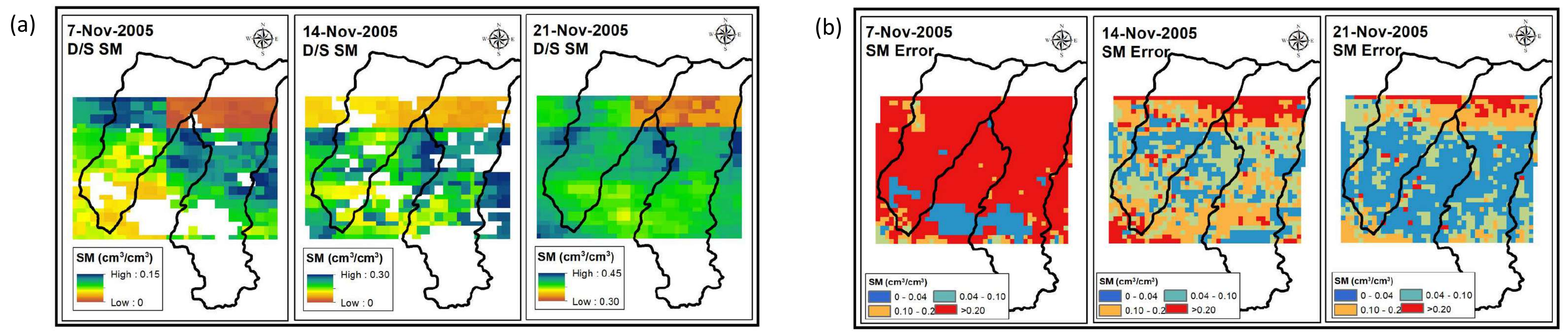

Fig. 9: (a) Downscaled soil moisture and, (b) soil moisture error, for Neural Network based model on 7th, 14th 21st November 2005.

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 cm^3/cm^3. Downscaled soil moisture from Artificial Neural Network based model shows RMSE of 0.08 cm^3/cm^3.
- 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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