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Using an artificial neural network to enhance the spatial resolution of satellite soil moisture products based on soil thermal inertia

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Abstract: High resolution soil moisture information is vital for a number of environmental applications including hydrologic and climatic modelling. However, the available point-scale field measurements and coarse spatial resolution satellite soil moisture products (~10s of km) are unable to provide the spatial resolution requirements for many of these applications, especially at regional scales. Downscaling the L-band satellite soil moisture products appears to be a viable solution for this problem. Many research teams have tested methods and algorithms to downscale the satellite soil moisture retrievals, yet there is no universally applicable model. Among those methods, thermal data based downscaling models have shown promising results over arid and semi-arid regions.

The downscaling approach, based on the soil thermal inertia relationship between the diurnal temperature difference (ΔT) and the daily mean soil moisture (μ_{SM}), is one of the thermal data-based downscaling methods tested in the United States and Australia. These studies have used this method by building regressions between ΔT and μ_{SM} modulated by the vegetation density. However, there are a number of possible factors affecting the linearity of this regression model. Therefore, this study employed a machine learning model to build a more complex algorithm between ΔT, μ_{SM} and vegetation density. The Global Land Data Assimilation System (GLDAS) derived 25 km resolution ΔT values (from 2000 to 2017) and aggregated Moderate Resolution Imaging Spectroradiometer (MODIS) derived Normalized Difference Vegetation Index (NDVI) values were used as inputs, whereas GLDAS derived μ_{SM} values were used as targets to train an artificial neural network (ANN). The Levenberg-Marquardt algorithm with 50 hidden neurons was used as the network architecture in building this model. Thereafter, 1 km resolution MODIS derived ΔT and NDVI values of November 2005 were input into the model to estimate soil moisture at high spatial resolution (1 km). The estimated soil moisture values were then used to downscale aggregated NAFE'05 airborne soil moisture retrievals. The downscaled soil moisture products were compared with the 1 km resolution soil moisture retrievals from the National Airborne Field Experiment 2005 (NAFE'05). This study has been conducted over two medium-scale catchments, Krui and Merriwa River, located in the Upper Hunter region of the south-eastern Australia.

The comparison between downscaled and airborne soil moisture showed root mean square errors (RMSE) of 0.088, 0.072 and 0.058 cm^3/cm^3 on 7[th], 14[th] and 21[st] November 2005, respectively. The downscaled soil moisture products were able to capture the detailed spatial patterns of soil moisture over the study area, showing a good match with the airborne retrievals. However, the algorithm performed better under dry catchment conditions compared to wet catchment conditions.

Keywords: *Artificial neural network, downscaling, soil moisture, Levenberg-Marquardt algorithm, machine learning*

1. INTRODUCTION

Soil moisture is a key variable in a number of environmental processes. Therefore, soil moisture information is important for hydrologic, climatic and agricultural applications. Soil moisture information is obtained mainly by the point-scale field measurements and coarse resolution (10s of km) satellite retrievals. However, due to the limitations involved with scale, spacing and resolution, these available soil moisture measurements are unable to capture the spatial and temporal variability of soil moisture as required by many of these applications, especially at regional scales. This has caused uncertainties in the model outputs making an increasing demand for reliable high resolution soil moisture information. Therefore, researchers have attempted different methods to estimate soil moisture at high spatial resolutions. Among those attempts, disaggregating coarse spatial resolution (10s of km) L-band microwave satellite soil moisture products appears to be a viable option in estimating near surface (~0-5 cm) soil moisture at high spatial resolutions (Peng et al. 2017). Such downscaling approaches were tested more often after the launch of the European Satellite Agency's (ESA) Soil Moisture Ocean Salinity (SMOS) mission (Kerr et al. 2010) in 2009, and the National Aeronautics and Space Administration's (NASA) Soil Moisture Active Passive (SMAP) mission (Entekhabi et al. 2010) in 2015.

The active-passive fusion methods (Das et al. 2011, 2014) and microwave and optical/thermal data fusion methods (Chauhan et al. 2003; Piles et al. 2014) are two satellite data based downscaling streams tested by a number of research teams. Among those, methods based on the thermal remote sensing data have shown promising results over arid and semi-arid regions over the world (Peng et al. 2017). Therefore, such methods have a good potential over most of the Australian land mass in estimating near surface soil moisture at high spatial resolution. Downscaling models developed based on the triangular ('universal triangle') (Carlson et al. 1994) or slightly trapezoidal feature space (Moran et al. 1994; Merlin et al. 2013) between surface temperature and vegetation index, has been investigated and improved by the researchers over the past couple of decades to disaggregate satellite soil moisture retrievals using optical/thermal datasets (Chauhan et al. 2003; Merlin et al. 2008; Piles et al. 2011). Among such methods, DisPATCh (Disaggregation based on Physical and Theoretical scale Change (Merlin et al. 2012) was tested over a number of soil moisture monitoring fields I Australia and abroad (Merlin et al. 2012, 2013, 2015). A disaggregation method based on the soil thermal inertia relationship between the diurnal temperature difference (ΔT) and the daily mean soil moisture (μ_{SM}) was developed by (Fang et al. 2013; Fang and Lakshmi 2014) using North American Land Data Assimilation System (NLDAS) modelled datasets. They have used vegetation density, as a modulating factor in their model considering its influence for the ΔT- μ_{SM} relationship. Senanayake et al. (2017 and 2019) developed a similar model to downscale SMAP and SMOS soil moisture retrievals over south-east Australian catchment using a long-term in-situ dataset. In addition, Senanayake et al. (2018) have tested a model based on the soil thermal inertia using Global Land Data Assimilation System (GLDAS) dataset. In these models a regression tree models between ΔT and μ_{SM} were developed by categorizing based on modulating factors such as season, vegetation density and soil texture.

1.1 Research hypothesis

Thermal inertia is the resistance of an object to the changes in its surrounding temperature (Sellers, 1965). Thermal inertia is proportional to the square root of the product of bulk density, specific heat capacity and the thermal conductivity of the material (Wang et al., 2010). Since water has a high specific heat capacity, it exhibits high thermal inertia. Accordingly, wet soils shows high thermal inertia compared to the dry soils, hence, lower ΔT compared to the dry soils. In other words, μ_{SM} shows an inverse relationship with ΔT. This relationship was used in the studies carried out by Fang et al. (2013), Fang and Lakshmi (2014), Senanayake et al. (2017, 2018 and 2019) to build the regression models to disaggregate coarse resolution satellite soil moisture products. However, this relationship is modulated by a number of factors such as vegetation density, soil texture, topography, daily mean temperature, etc., affecting the linearity of the regression model.

Therefore, in this study, we made an attempt to build a more complex relationship between ΔT, μ_{SM} and vegetation density through a machine learning approach by using an artificial neural network (ANN) to downscale satellite soil moisture products given the fact that ANNs show a good potential in fitting functions. Here, the model was trained by using coarse resolution inputs and targets. The trained model was used to make soil moisture predictions at higher resolution (1 km) by employing 1 km spatial resolution inputs.

2. STUDY AREA

The study area includes two sub-catchments located in the northern part of the Goulburn River catchment, namely, Krui (562 km^2) and Merriwa (651 km^2) River. The study area is located in the Upper Hunter Region of NSW, Australia, about 150 km northwest to Sydney (Figure 1 a). The catchments exhibits temperate, semi-arid climate and most of the land area is cleared for grazing and cropping (Figure 1 b). The southernmost part of the Merriwa River catchment consist of dense vegetation cover. The northern halves of the catchments consist of clayey soils, whereas the southern halves show high sand contents (Figure 1 c and 1 d). This area was instrumented for measuring soil moisture and soil temperature along with other auxiliary data from 2002 under the Scaling and Assimilation of Soil Moisture and Streamflow (SASMAS) project (Rüdiger et al. 2003 and 2007). Therefore, the area has been evaluated for soil moisture variability by a number of research studies (Martinez et al. 2007; Chen et al. 2014; Senanayake et al. 2017, 2018, 2019). This includes a high resolution airborne campaign, National Airborne Field Experiment 2005 (NAFE'05) (Panciera et al. 2008), which was conducted on 4 consecutive Mondays, (31st October, 7th, 14th and 21st November 2005) over a 40 × 40 km land area covering Krui and Merriwa River catchments using an L-band radiometer (Panciera et al. 2008).

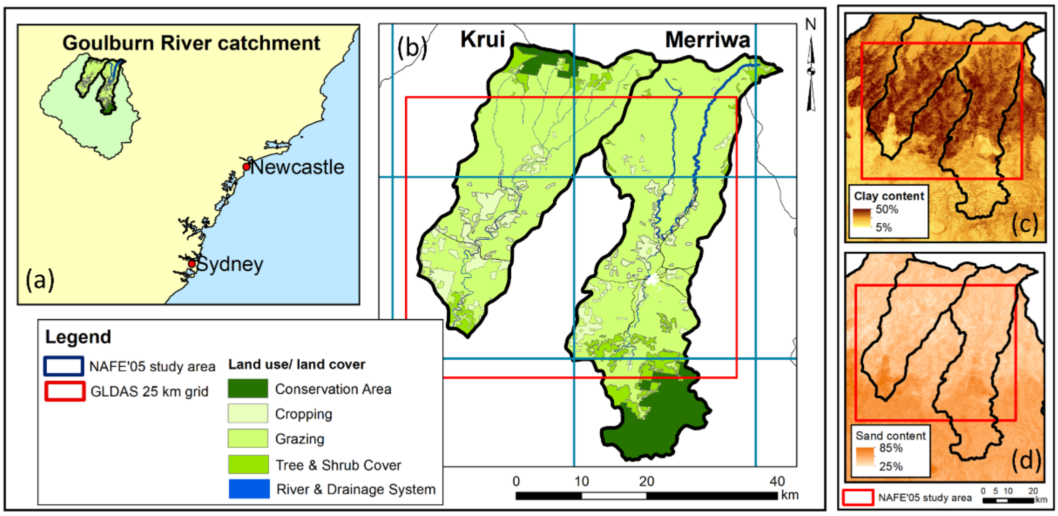

Figure 1. (a) The location of the study area, Krui and Merriwa River catchments, (b) land cover/land use of the Krui and Merriwa River catchments (Source: The Department of Environment and Climate Change, NSW) with GLDAS grid and the area of the NAFE'05 airborne campaign, (c) clay content over the study area, and (d) sand content over the study area (Source: National Soil and Landscape Grid, Australia).

3. METHODOLOGY

3.1 Datasets

The input ΔT and target μ_{SM} values were calculated from the 3-hour interval soil moisture and soil temperature estimates of the top 10 cm soil profile from the 'GLDAS Noah Land Surface Model L4 3 hourly 0.25 x 0.25 degree V2.1' (GLDAS_NOAH025_3H.2.1) (~25 km spatial resolution) from 2000 to 2017 over the study area. Only the datasets for Austral Spring (i.e. September to November) were used in this study to train the ANN since the dataset used for validation, the NAFE'05 airborne dataset, was available for November 2005. MODIS (Moderate Resolution Imaging Spectroradiometer) Aqua 16-day 1 km Normalized Difference Vegetation Index (NDVI) data (MYD13A2) were aggregated into the 25 km GLDAS grid over the study area and used as an input dataset for the model. The 16-day MODIS NDVI data were temporally interpolated over a daily window to estimate daily NDVI values. Airborne soil moisture retrievals (1 km spatial resolution) from the NAFE'05 (Panciera et al. 2008) was used both for downscaling and for validation in this study, i.e. the aggregated NAFE'05 soil moisture over the 40 × 40 km area were used as simulated coarse resolution satellite soil moisture product, while the 1 km resolution NAFE'05 soil moisture retrievals were used for validation of the downscaled products.

3.2 Training the neural network

Matlab 2017b Neural Network Fitting Toolbox was employed in developing the downscaling model. The 25 km spatial resolution ΔT estimates from GLDAS along with the aggregated MODIS NDVI products were used as the inputs and the GLDAS based μ_{SM} values were used as targets in training the network. Here, datasets from September to November (i.e. Austral Spring) over the period of 2000 to 2017, in the study area, were employed. If any of these datasets were not available on a particular day, the record was removed. Accordingly, 6152 data records were used to create the network after cleaning the dataset.

The model was run with a large number of trial and errors processes using three different network architectures available in the Matlab 2017b Neural Network Fitting Toolbox (i.e. Levenberg-Marquardt, Bayesian Regularization and Scaled Conjugate Gradient algorithms). During this process 70% of data was randomly selected for training, 15% for validation and 15% for testing. The best results were obtained by the Levenberg-Marquardt algorithm with 50 hidden neurons with 10 iterations. Typically, Levenberg-Marquardt algorithm requires more memory, but less time. The selection of the algorithm and number of hidden neurons were entirely based on trial and error process. The error histogram of the model and the regressions of the model validation are shown in Figure 2 and 3, respectively.

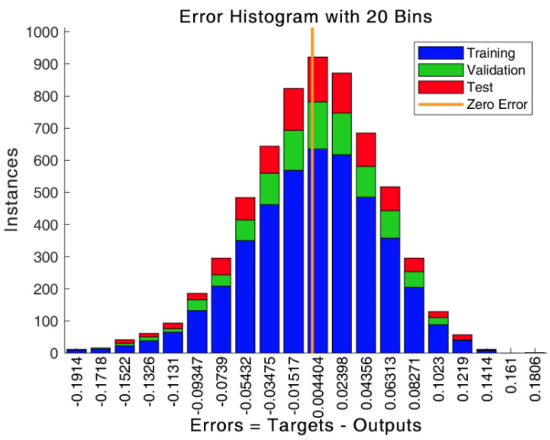

Figure 2. Error histogram of the model

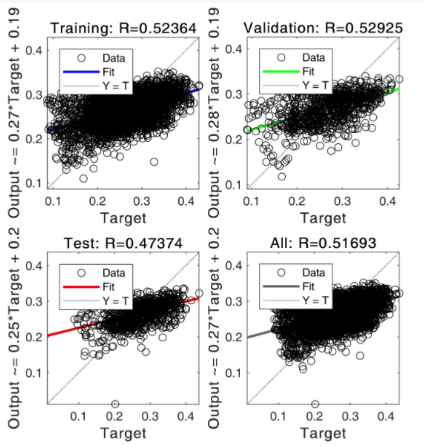

Figure 3. Regressions of the model validation

3.3 Estimating soil moisture at 1 km spatial resolution

MODIS derived 1 km ΔT and NDVI values over the 40 x 40 km NAFE'05 study area were input to the ANN model to predict soil moisture at 1 km resolution (SM_{est}). The predictions were made over November 2005 to facilitate validation of the downscaled products using the 1 km resolution NAFE'05 airborne soil moisture estimates.

3.4 Downscaling satellite soil moisture simulates

The aggregated NAFE'05 soil moisture retrievals provided a good representation of 40 km coarse resolution satellite soil moisture pixel. Aggregated airborne soil moisture retrievals on 7th, 14th and 21st November 2005 were used for downscaling. Data from 31st October 2005 was excluded from this analysis due to high cloud cover on this day, which has caused significant data gaps in MODIS Land Surface Temperature (LST) data. Afterwards, following equation was used to downscale the coarse resolution satellite soil moisture simulates.

$$SM_{ds,p} = SM_{est,p} + \left[SM_{SAT} - \frac{1}{n}\sum_{i=1}^{n} SM_{est,i}\right] \quad (1)$$

where $SM_{ds,p}$ is the downscaled soil moisture at 1 km pixel p, $SM_{est,p}$ is the soil moisture value estimated by the ANN model (section 3.3), SM_{SAT} is the value of the 40 km resolution satellite soil moisture simulate, n is the number of 1 km pixels (i) within the SM_{SAT} pixel and $SM_{est,i}$ is the soil moisture value estimated by the ANN model at 1 km pixel i, $(i=1:n)$. In simple terms, the estimated soil moisture values (1 km resolution) were bias corrected using the difference between the satellite soil moisture simulate and the spatial average of the estimated soil moisture over the coarse resolution (40 km) pixel.

3.5 validation of the downscaled soil moisture estimates

The downscaled soil moisture estimates on 7th, 14th and 21st November 2005 were compared with the 1 km resolution L-band soil moisture retrievals from the NAFE'05 airborne campaign.

4. RESULTS

A comparison between the spatial patterns of the downscaled and airborne soil moisture products on7th, 14th and 21st November 2005 are shown in Figure 4. The absolute error between the two datasets over these three days are shown in Figure 5. The study area show an increasing soil moisture gradient towards north driven by the rainfall pattern and the soil texture. This northward increasing gradient of soil moisture has been captured successfully by both airborne and the downscaled soil moisture products (Figure 4). The contribution of the soil texture for the spatial variability of soil moisture over the study area is evident when comparing the clay content (Figure 1 c) and soil moisture variability (Figure 4). The catchments demonstrated a drying condition from the beginning to the end of NAFE’05 campaign (Panciera et al. 2008). Figure 5 shows that the algorithm has performed better during the dry conditions compared to the wet conditions. However, few constantly saturated soil moisture pixels in the NAFE’05 datasets can be seen, which affects the range of soil moisture. The comparison between NAFE’05 and downscaled soil moisture products over the three days show an average root mean square error (RMSE) of 0.079 cm^3/cm^3 (i.e. RMSEs of 0.088, 0.072 and 0.058 cm^3/cm^3 for November 7th, 14th and 21st, respectively) (Figure 6).

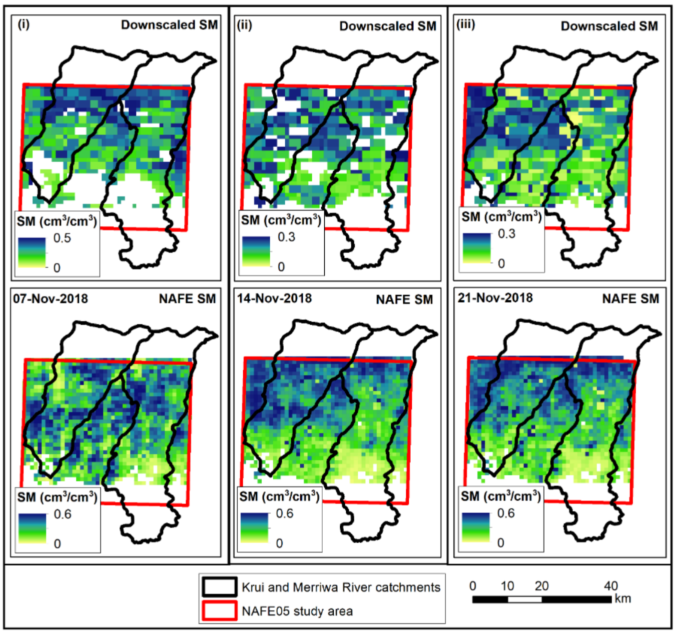

Figure 4. Spatial variability of soil moisture as capture by the NAFE’05 airborne soil moisture retrievals and the downscaled soil moisture products on 7th, 14th and 21st November 2005.

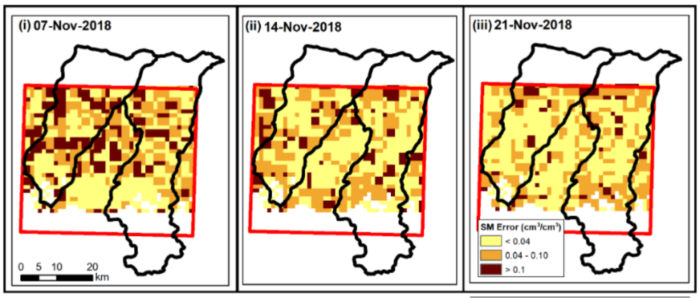

Figure 5. Absolute error between NAFE’05 and downscaled soil moisture products on 7th, 14th and 21st November 2005.

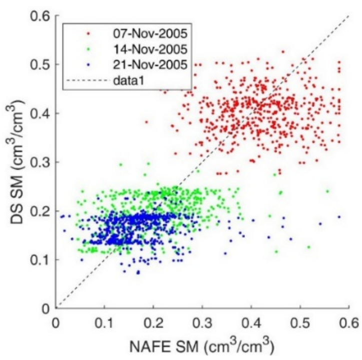

Figure 6. Comparison between the NAFE’05 and the downscaled soil moisture products.

5. DISCUSSION AND CONCLUSIONS

This study investigated an ANN to downscaled coarse-resolution satellite soil moisture products based on the soil thermal inertia. The network was trained by using 25 km GLDAS data and aggregated MODIS NDVI products. MODIS derived 1 km resolution ΔT and NDVI values were input to the ANN model to estimate soil moisture at 1 km spatial resolution. The estimated soil moisture were used to downscale satellite soil moisture simulates. Thereafter, the downscaled products were validated with soil moisture retrievals from a high spatial resolution airborne soil moisture campaign, NAFE'05. The results show that the downscaled products were able to capture the spatial patterns of soil moisture in more detail with an average RMSE of 0.079 cm^3/cm^3. The model has worked better during the dry catchment conditions compared to the wet catchment conditions. The average error is slightly higher than the error observed when comparing the NAFE'05 soil moisture retrievals with the downscaled soil moisture products obtained from the regression tree models over the same study area by Senanayake et al. (2018 and 2019), which is RMSE of 0.07 cm^3/cm^3.

The mismatch between the depth of GLDAS estimates (i.e. 10 cm) and L-band soil moisture products (~ 5 cm) can be one of the error sources in this study. Also, the coarser spatial resolution of GLDAS estimates (~25 km) can moderate the land surface temperatures and vegetation information over a larger area. Simulated datasets often carry uncertainties. Therefore, the uncertainties in both the GLDAS soil temperature and soil moisture estimates can affect the accuracy of the model. Another, major problem with the thermal data based methods is the data gaps caused by the cloud cover. Inability to understand the process within the ANN is another limitation when adapting the model over a different region.

In future work, it would be worth testing this method by training the ANN by using a long-term in-situ dataset. Including other influencing factors such as soil texture and topography has a high potential of improving the model. An improved downscaling model will auger well in developing a long-term time record of soil moisture in the south eastern Australia by downscaling SMOS and SMAP satellite soil moisture products.

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REFERENCES

Carlson, T. N., Gillies, R. R. and Perry, E. M. (1994). A method to make use of thermal infrared temperature and NDVI measurements to infer surface soil water content and fractional vegetation cover. *Remote sensing reviews*, 9(1-2), 161-173.

Chauhan, N., Miller, S. and Ardanuy, P. (2003). Spaceborne soil moisture estimation at high resolution: a microwave-optical/IR synergistic approach. *International Journal of Remote Sensing*, 24(22), 4599-4622.

Chen, M., Willgoose, G. R. and Saco, P. M. (2014). Spatial prediction of temporal soil moisture dynamics using HYDRUS-1D. *Hydrological processes*, 28(2), 171-185.

Das, N. N., Entekhabi, D. and Njoku, E. G. (2011). An algorithm for merging SMAP radiometer and radar data for high-resolution soil-moisture retrieval. *IEEE Transactions on Geoscience and Remote Sensing*, 49(5), 1504-1512.

Das, N. N., Entekhabi, D., Njoku, E. G., Shi, J. J., Johnson, J. T. and Colliander, A. (2014). Tests of the SMAP combined radar and radiometer algorithm using airborne field campaign observations and simulated data. *IEEE Transactions on Geoscience and Remote Sensing*, 52(4), 2018-2028.

Entekhabi, Dara, Njoku, E.G., O'Neill, P.E., Kellogg, K.H., Crow, W.T., Edelstein, W.N., Entin, J.K., Goodman, S.D., Jackson, T.J., Johnson, J., Kimball, J., Piepmeier, J.R., Koster, R.D., Martin, N., McDonald, K.C., Moghaddam, M., Moran, S., Reichle, R., Shi, J.C., Spencer, M.W., Thurman, S.W., Tsang, L. and Van Zyl, J. (2010). The soil moisture active passive (SMAP) mission. *Proceedings of the IEEE*, 98(5), 704-716.

Fang, B. and Lakshmi, V. (2014). Soil moisture at watershed scale: Remote sensing techniques. *Journal of Hydrology*, 516, 258-272.

Fang, B., Lakshmi, V., Bindlish, R., Jackson, T. J., Cosh, M. and Basara, J. (2013). Passive microwave soil moisture downscaling using vegetation index and skin surface temperature. *Vadose Zone Journal*, 12(3).

Kerr, Y. H., Waldteufel, P., Wigneron, J.-P., Delwart, S., Cabot, F., Boutin, J., Escorihuela, M.J., Font, ,J., Reul, N. and Gruhier, C. (2010). The SMOS mission: New tool for monitoring key elements of the global water cycle. *Proceedings of the IEEE*, 98(5), 666-687.

Martinez, C., Hancock, G., Kalma, J. and Wells, T. (2007). Spatio-temporal distribution of near-surface and root zone soil moisture at the catchment scale. *Hydrological processes*, 22(14), 2699-2714.

Merlin, O., Escorihuela, M. J., Mayoral, M. A., Hagolle, O., Al Bitar, A. and Kerr, Y. (2013). Self-calibrated evaporation-based disaggregation of SMOS soil moisture: An evaluation study at 3 km and 100 m resolution in Catalunya, Spain. *Remote Sensing of Environment*, 130, 25-38.

Merlin, O., Malbéteau, Y., Notfi, Y., Bacon, S., Khabba, S. and Jarlan, L. (2015). Performance metrics for soil moisture downscaling methods: Application to DISPATCH data in central Morocco. *Remote Sensing*, 7(4), 3783-3807.

Merlin, O., Rudiger, C., Al Bitar, A., Richaume, P., Walker, J. P. and Kerr, Y. H. (2012). Disaggregation of SMOS soil moisture in Southeastern Australia. *IEEE Transactions on Geoscience and Remote Sensing*, 50(5), 1556-1571.

Merlin, O., Walker, J. P., Chehbouni, A. and Kerr, Y. (2008). Towards deterministic downscaling of SMOS soil moisture using MODIS derived soil evaporative efficiency. *Remote Sensing of Environment*, 112(10), 3935-3946.

Moran, M., Clarke, T., Inoue, Y. and Vidal, A. (1994). Estimating crop water deficit using the relation between surface-air temperature and spectral vegetation index. *Remote Sensing of Environment*, 49(3), 246-263.

Panciera, R., Walker, J.P., Kalma, J.D., Kim, E.J., Hacker, J.M., Merlin, O., Berger, M. and Skou, N. (2008). The NAFE'05/CoSMOS data set: Toward SMOS soil moisture retrieval, downscaling, and assimilation. *IEEE Transactions on Geoscience and Remote Sensing*, 46(3), 736-745.

Peng, J., Loew, A., Merlin, O. and Verhoest, N. E. (2017). A review of spatial downscaling of satellite remotely-sensed soil moisture. *Reviews of Geophysics*, 55, 341-366.

Piles, M., Camps, A., Vall-Llossera, M., Corbella, I., Panciera, R., Rüdiger, C., Kerr, Y.H. and Walker, J. (2011). Downscaling SMOS-derived soil moisture using MODIS visible/infrared data. *IEEE Transactions on Geoscience and Remote Sensing*, 49(9), 3156-3166.

Rüdiger, C., Davidson, R., Hemakumara, H., Walker, J., Kalma, J., Willgoose, G. and Houser, P. (2003). Catchment monitoring for scaling and assimilation of soil moisture and streamflow. *Proceedings of the International Congress on Modelling and Simulation (MODSIM2003)*, Townsville, 386-391.

Rüdiger, C., Hancock, G., Hemakumara, H. M., Jacobs, B., Kalma, J. D., Martinez, C., Thyer, M., Walker, J.P., Wells, T. and Willgoose, G.R. (2007). Goulburn River experimental catchment data set. *Water Resources Research*, 43(10), W10403.

Sellers, W. D. (1965). Physical climment atology, University of Chicago Press, Chicago, Illinois, United States.

Senanayake, I., Yeo, I., Tangdamrongsub, N., Willgoose, G., Hancock, G., Wells, T., Fang, B. and Lakshmi, V. (2017). Downscaling SMAP and SMOS soil moisture retrievals over the Goulburn River Catchment, Australia. *Proceedings of the 22nd International Congress on Modelling and Simulation (MODSIM2017), Hobart, Tasmania*, 1055-1061.

Senanayake, I., Yeo, I., Willgoose, G. and Hancock, G. (2018). Towards sub-catchment scale soil moisture prediction: A combined remote sensing and land surface modelling approach. *Proceedings of the Hydrology and Water Resources Symposium (HWRS 2018): Water and Communities*, Melbourne, 950-962.

Senanayake, I., Yeo, I.-Y., Tangdamrongsub, N., Willgoose, G., Hancock, G., Wells, T., Fang, B., Lakshmi, V. and Walker, J. (2019). An in-situ data based model to downscale radiometric satellite soil moisture products in the Upper Hunter Region of NSW, Australia. *Journal of Hydrology*, 572, 820-838.

Wang, J., Bras, R., Sivandran, G. and Knox, R. (2010). A simple method for the estimation of thermal inertia. *Geophysical Research Letters*, 37 (5), L05404.