Remote and retrospective calibration of soil moisture probes

QM Amir [a], TFA Bishop[a], FF Van Ogtrop [a]

[a]*Precision Agriculture, Hydrology & Geoinformation Science Laboratory, The University of Sydney, 1 Central Avenue, Eveleigh, NSW 2015*
Email: muqeet.amir@sydney.edu.au

Abstract: Soil moisture probe measurements are sensitive to soil texture, salinity, and temperature, which can lead to inaccuracies if the probe does not account for these site-specific soil conditions (Zreda et al., 2008; Adla et al., 2024). Calibrating soil moisture probes to site-specific conditions requires multiple measurements of soil moisture through time, that in most situations will be geographically, financially, and logistically unfeasible across a probe network. In this study we test a pedotransfer-based (PTF) calibration method, referred to in this study as PTF scaling, introduced by Gasch et al. (2017), which may be applied to datasets without the measurements of soil moisture needed to calibrate through conventional methods. This method is based on scaling soil moisture measurements to the bounds of PTF-estimated crop lower limit (CLL) and drained upper limit (DUL).

We conduct two experiments to test the viability of PTF scaling for calibrating soil moisture probes. In ex-periment A we PTF scale and conventionally calibrate soil moisture measurements from six sites across the Muttama creek catchment, NSW, and compare them to field-measured volumetric water content measure-ments. We found the PTF scaling to be more accurate than the conventional calibration at 4 out of 6 sites (RMSE below 4.8 %VWC). The sites where conventional calibration performed better were located in close proximity to each other, and the PTF scaling differed by at most 1 %VWC from the conventional calibration at these sites. In experiment B we compared PTF scaled soil moisture measurements to conventionally cali-brated soil moisture measurements from the Murrimbidgee Soil Monitoring Network and the 6 conventionally calibrated sites from experiment A. Using various PTFs, we summarised our analysis by land use, and found grazing sites to be more accurately calibrated than cropping sites. Many sites could be PTF scaled to an accu-racy under 5 %VWC, depending on PTF choice. However some sites were PTF scaled to accuracies as poor as 24 %VWC.

Keywords: *Soil water, soil moisture probe networks, Australia*

1. INTRODUCTION

Soil moisture probes allow growers to improve irrigation decisions, forecast yield, monitor crop stress, and reduce water-related diseases (Mgendi, 2024). These probes employ various mechanisms to indirectly measure soil moisture. The most commonly used probes are dielectric based probes, which propagate electromagnetic waves through the soil and measure reflection frequency, intensity, period, or charge-storage capacity (Mane et al., 2025). The sensor response fluctuates due to changes in dielectric permittivity, which is a function of the pore space occupied by water. The signal response is converted to dielectric permittivity and then converted to volumetric soil moisture using an equation such as the Topp equation (Gasch et al., 2017). However, these relationships are empirical and do not account for the soil composition and structure at the point of measurement (Adla et al., 2024). Therefore, they are not able to capture the true soil-water interactions in a profile, and without adjustment, report erroneous values (Zreda et al., 2008).

Soil moisture probes are typically calibrated by fitting a regression model to field measurements of soil mois-ture and their corresponding probe measurements (hereby known as conventional calibration). To calibrate a network this way, soil samples need to be taken at every probe site over multiple measurements, depths, and times, which can be logistically unfeasible. Additionally, soil sampling is invasive and can disrupt the true soil-water dynamics at a sampling point, leading to inaccurate readings of soil moisture. The impracticality of calibrating probes through this conventional method can contribute to low adoption of probe technology, as cost and operational feasibility are key considerations for potential users (Maya Moreshwar Meshram et al., 2024).

With the development of pedo-transfer functions (PTFs) for Australian soils and the availability of mapped soil property data products, a more reproducible and less intrusive calibration method can be implemented for the calibration of soil moisture probes. Gasch et al. (2017) introduced a method for calibrating soil moisture probes (hereby referred to as PTF scaling), by transforming probe measurements to their theoretical physical bounds of the crop lower limit (CLL) and drained upper limit (DUL). The CLL refers to the amount of water remaining in a soil after a crop has extracted all water available to it. The DUL refers to the amount of water a soil can hold against gravity (Gajurel et al., 2024).

In this study we aim to assess the accuracy of PTF scaling in comparison to conventional calibration to demon-strate its suitability for calibrating Australian soil moisture probes. While Australia has multiple soil moisture probe networks, many of them are uncalibrated (Weir and Dahlhaus, 2024). This study is motivated by the potential for greater utilisation of soil moisture data by growers and the scientific community provided a more viable and standardised calibration technique.

2. DATA

2.1. Murrumbidgee Soil Moisture Monitoring Network

The Murrumbidgee Soil Moisture Monitoring Network (MSMMN) is a dataset composed of 38 soil moisture monitoring sites across the Murrumbidgee River catchment in New South Wales (Smith et al., 2012). The dataset consists of Campbell Scientific CS615 and CS16 dielectric based probes that measure soil moisture at three depth intervals: 0-30, 30-60, and 60-90 cm. The MSMMN probes are calibrated using temperature-based conversion equations of Ru¨diger (2006), at three different levels: site-specific, texture-specific, and proximity (Yeoh et al., 2008). In this study we make use of seventeen of these sites, with selection based on completeness of data and the availability of calibrated data. We resample the temporal frequency to daily to impose a standardised frequency across sites, and to normalise any anomalous 20/30-minute observations.

2.2. The University of Sydney soil moisture network

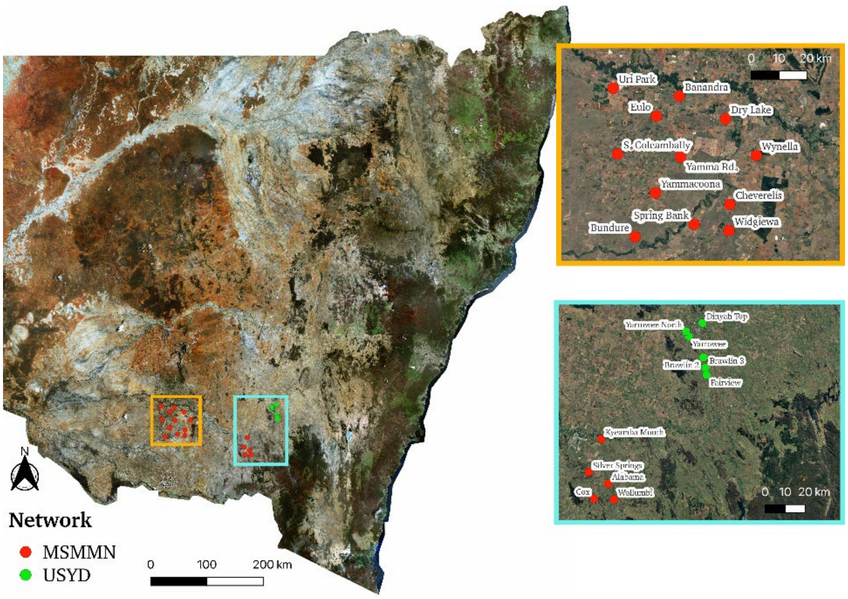

Figure 1 Situes used in this study (relative to New South Wales)

The University of Sydney soil moisture monitoring network (here by, USYD) consists of 15 soil moisture Sentek Drill & Drop di-electric based probes across the Muttama creek catchment within the Murrumbidgee River catchment, in New South Wales. The probes record data at 10 cm intervals from 30 – 110 cm at a 15 minute temporal resolution. We resample the temporal frequency to daily to impose a standardised frequency across sites, and to normalise any anomalous 15-minute observations. The USYD soil moisture measurements are uncalibrated; however, six sites have lab measured soil properties and volumetric water content across the profile at various dates from 2018-2022. Soil samples were taken at the probe sites and transported for lab measurements of volumetric water content (%VWC), sand, silt, and clay fractions (%), organic carbon (%), and bulk density (g/cm^3) at depths ranging from 25 cm to 55 cm. These six sites are considered in this study, and are calibrated conventionally and through PTF scaling in Experiment A below.

3. PEDOTRANSFER FUNCTIONS

A variety of pedotransfer functions (PTFs) were considered for this study, each with different modes, inputs, and validation data.

NK. NK is an unpublished PTF based on a Random Forest model trained on 364 APSoil database plant available water retention field measurements across Australia (Hoskin et al., 2025; Dalgliesh et al., 2012). The model is used to predict DUL and CLL at a given depth by taking sand (%), silt (%), clay (%), rocks (%), organic carbon (%), and depth (cm).

JA & JB. In this study JA and JB are two sets of PTFs developed by Padarian (2014). Each set uses a unique function for DUL, but the same function for CLL. JA and JB are validated on field measurements of DUL and CLL through the APSoil database (Dalgliesh et al., 2012). The equations for JA and JB are provided below:

$$JA_{DUL} = 0.374 + (0.01182 \times BD) + (0.00365 \times Clay) + (6.09 \times 10^{-5} \times Sand \times Clay) - (0.00192 \times BD^2 \times Clay) - (0.00339 \times Sand);$$

$$JB_{DUL} = 0.2082 + (0.02757 \times OC) + (0.002666 \times Clay) - (1.73 \times 10^{-7} \times Sand^3);$$

$$JA_{CLL} \ \& \ JB_{CLL} = 0.1476 + (9.002 \times 10^{-5} \times Clay^2) - (0.00115 \times Sand) - (9.75210^{-7} \times Clay^3);$$

where sand, silt, clay are their relative fraction measures (%), BD is bulk density (g/cm^3), and OC is organic carbon (%).

CSIRO. The CSIRO PTF employs equations developed by Searle and Somarathna (2022) using 1190 labo-ratory measurements of DUL and CLL from The National Soil Site Collation (NSSC) database. The equations for the CSIRO DUL and CLL are below:

$$CSIRO_{DUL} = 48.98 - (21.86 \times BD) + (0.36 \times Clay) - (0.06 \times Sand) - (0.19 \times \sqrt{Silt}) + (2.9 \times \sqrt{OC});$$

$$CSIRO_{CLL} = 17.40 - (10.05 \times BD) + (0.34 \times Clay) - (0.02 \times Sand) + (0.18 \times Silt);$$

where sand, silt, clay are their relative fraction measures (%), BD is bulk density (g/cm^3), and OC is organic carbon (%).

SLGA. The SLGA PTF is produced from a Cubist machine learning model that is trained on CSIRO PTF-estimated CLL and DUL with soil attribute inputs from NSSC. This model is used to map CLL and DUL across the entirety of Australia at 6 depths at a 90 m resolution (Searle and Somarathna, 2022).

Site	RMSE (%VWC)			
	Uncalibrated	Conventional	PTF Scaling	Best PTF
Brawlin 2	19.94	7.82	4.82	NK
Brawlin 3	5.41	5.88	3.83	NK
Yarrowee	9.65	4.81	5.63	JA
Yarrowee North	8.85	5.7	5.94	JA
Fairview	13.26	5.54	1.48	CSIRO
Dinyah Top	9.76	7.96	6.4	SLGA

(a) Site-wise

Depth (cm)	RMSE (%VWC)			
	Uncalibrated	Conventional	PTF Scaling	Best PTF
30	7.19	6.42	4.7	SLGA
40	11.04	6.8	6.5	SLGA
50	14.09	7.31	6.76	SLGA
60	14.22	5.67	4.74	NK
70	13.13	4.3	4.73	JA
80	12.64	6	5.01	JA
90	11.69	7.89	4.1	JA

(b) Depth-wise

Figure 2. Accuracy of calibration methods for USYD network

4. PTF SCALING

PTF scaling involves scaling the uncalibrated soil moisture measurements to the crop lower limit (CLL) and drained upper limit (DUL). For this study we source the required inputs for each PTFfrom the Soil Landscape Grid Australia (Malone et al., 2025). To account for the DUL and CLL not being representative of the true minimum and maximum soil water storage capacity, scaling percentiles (s) are included to scale the data inclusive of water being stored above the drained upper limit and below the crop lower limit. In particular, soils with high storage abilities (e.g. clayey soils) can retain water for longer above the DUL (de Jong van Lier, 2017). Conversely, soils that experience swelling and cracking (e.g. Vertosols) can often drain below the CLL at depth through evaporation due to surface exposure (Li et al., 2020). The soil moisture probe measurements are scaled to the bounds of the CLL and DUL through the following equation:

$$\theta_{PTF\,scaled} = \left(\frac{\theta_t - \theta_{max}}{\theta_{max} - \theta_{min}} \times (\theta_{(100-s)_p} - \theta_{(s)_p})\right) + \theta_{(100-s)_p};$$

where θ_t is probe measured volumetric soil moisture at time t (%VWC), $\theta_{(s)_p}$ is the sth percentile of the probe measured volumetric soil moisture. For example, $s = 5$ entails scaling the 5th and 95th percentiles of the probe measured soil moisture to the CLL and DUL, respectively.

Validation. We validated the performance of the PTF scaled measurements to lab measured and pre-calibrated soil water measurements using the Root Mean Square Error (RMSE). The RMSE is in units of the response (%VWC) and an RMSE of 0 indicates no difference between the two measurements. The RMSE is defined as below:

$$RMSE = \sqrt{\frac{\sum(x_i - o_i)^2}{n}};$$

where n is the number of observations, x_i is the PTF scaled measurement at index i, and o_i the true/observed soil water measurement at index i.

5. RESULTS

5.1. Experiment A

In Experiment A, PTF scaled, conventionally calibrated, and uncalibrated measurements were compared to their corresponding measured volumetric water content, for the USYD network. Conventional calibration was performed by fitting a multiple linear regression model with covariates: measured soil properties, probe measurements, and depth of measurement. The combination of covariates with the lowest AIC was selected for the regression. The multiple linear regression model was fit to all the measured data across all sites, depths, and times to produce a network-wide calibration. The following form was found to have the lowest AIC and was used as the conventional calibration equation for the USYD network:

$\theta_{calibrated} = 23.92 - (0.47 \times \mathit{Depth}) - (29.03 \times \mathit{SOC}) + (0.14 \times \mathit{Probe}) + (0.99 \times \mathit{Depth} \times \mathit{SOC}) + (0.01 \times \mathit{Depth} \times \mathit{Probe})$;

where Probe is the probe measurement (%VWC), Depth is the depth of measurement (cm), and SOC is soil organic carbon (%).

The difference between each method was highlighted per site and measurement depth to more precisely analyse the accuracy of each method (Figure 2a). The PTF with the highest accuracy was reported for each level of comparison. We benchmark the accuracy of our calibration methods to 5 %VWC, where an RMSE below this benchmark is considered satisfactory. Yeoh et al. (2008) establish this performance benchmark, in the context of the MSMMN data, on the basis of the accuracy of their recommended conventional calibration model.

At every site, with the exception of Yarrowee and Yarrowee North, the PTF scaling is the most accurate calibration method. At these sites, the PTF scaling is within 1 %VWC of the conventional calibration. The PTF scaling is always below, or very near the 5 %VWC benchmark, affirming high confidence in its applicability at these sites. The most accurate PTF is variable across sites, however, is the same for sites on the same farm, such as in Brawlin and Yarrowee.

The PTF scaling is generally the most accurate method across all depths, excepting 70 cm (Figure 2b). The conventional calibration is least accurate at 50 cm and 90 cm, showing no clear performance patterns with depth. The PTF scaling performs its poorest in the 40 and 50 cm range, however, unlike the conventional calibration, is adequately able to calibrate measurements at deeper depths. The choice of PTF shows a distinct patten of SLGA performing the best at shallower depths, and JA at deeper depths.

5.2. Experiment B

Experiment B was conducted to understand the accuracy of the PTF scaling method with respect to PTF choice, scaling percentile, land use type, and depth against conventionally calibrated measurements. In this experiment we assume conventional calibration measurements represent the true soil moisture, as conventional calibration is the most common technique, and for many networks are the only published point of truth data available. We apply PTF scaling on the MSMMN and USYD data and compare it to their original calibrated measurements. In theory, an accurate PTF scaling should minimally differ from its original calibrated soil moisture. With this principle at the centre, the probe measurements at each site are scaled using each PTF with various scaling percentiles applied. We assess the accuracy of the PTF scaling in depth ranges of 0-30 cm, 30-60 cm, and 60-90 cm, as these ranges are the coarsest depth discretisation amongst our data (native depth resolution of MSMMN). We study cropping and grazing sites separately in this experiment as their differences in surface cover, rooting depth, and vegetation type all creates differing soil-water mechanics that should be accounted for. Furthermore, our conclusions from the performance of each PTF in either category can be effectively extrapolated to other agricultural sites that will likely fall into one of these two categories. There are 15 grazing and 8 cropping sites used in this experiment. We compare the difference between the original and PTF scaled data using the Root Mean Square Error. We benchmark the accuracy of our PTF scaling at 5%VWC (Yeoh et al., 2008). Here, a PTF scaling with an RMSE less than or equal to 5 %VWC is considered to be as accurate as a conventionally calibrated measurement at a given site.

As seen in Figure 3, cropping sites exhibit greater variability than grazing sites with respect to PTF choice across all depths. In the 0-30 cm interval, the median RMSE of NK is below the benchmark, and the range of accuracies across sites is not notably better than other PTFs. At the 30-60 cm interval, JB and SLGA exhibit the lowest median RMSE. While the NK PTF is slightly less accurate at this depth, the range of accuracy across sites is narrower, indicating an arguably better overall performance. Similarly at 60-90 cm, while CSIRO scales with the lowest median scaling accuracy, its range is very high, indicating low reliability in scaling a new site. In selecting a PTF to scale a new cropping site, while the highest accuracy may not necessarily be through NK and JA, as their median RMSEs are poorer than others, their narrow range makes them a more reliable choice of PTF.

Grazing sites are more accurately calibrated than the cropping sites as is indicated by the lower median RMSE for the grazing sites across all PTFs and depths (Figure 4). With NK, the median RMSEs across all scaling percentiles and depths at grazing sites are below the 5 %VWC benchmark. While the median RMSE across all combinations is generally below the benchmark or within 1 %VWC of it, some sites are predicted to an accuracy above the threshold, and up to 20 % VWC. The grazing sites show a general tendency to scale measurements most accurately with a scaling percentile of 0, however while the median RMSE is typically lowest, the overall range of accuracy is similar across scaling percentiles. JA and SLGA both exhibit accuracies in proximity of the 5 %VWC benchmark, with JA outperforming SLGA at the deepest depth, but SLGA being a suitable option at the shallower 0-30 cm depth. The function modes of SLGA and JA being a gridded product and an equation, respectively, are advantageous as their ease of application is greater than NK (Random Forest model).

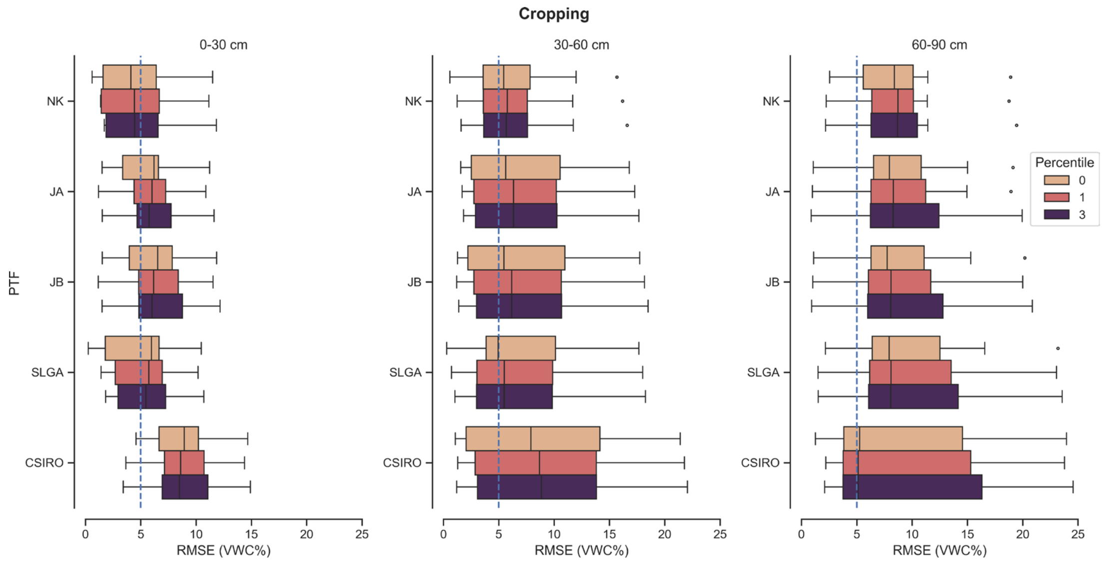

Figure 3. Accuracy of PTF scaling at cropping sites

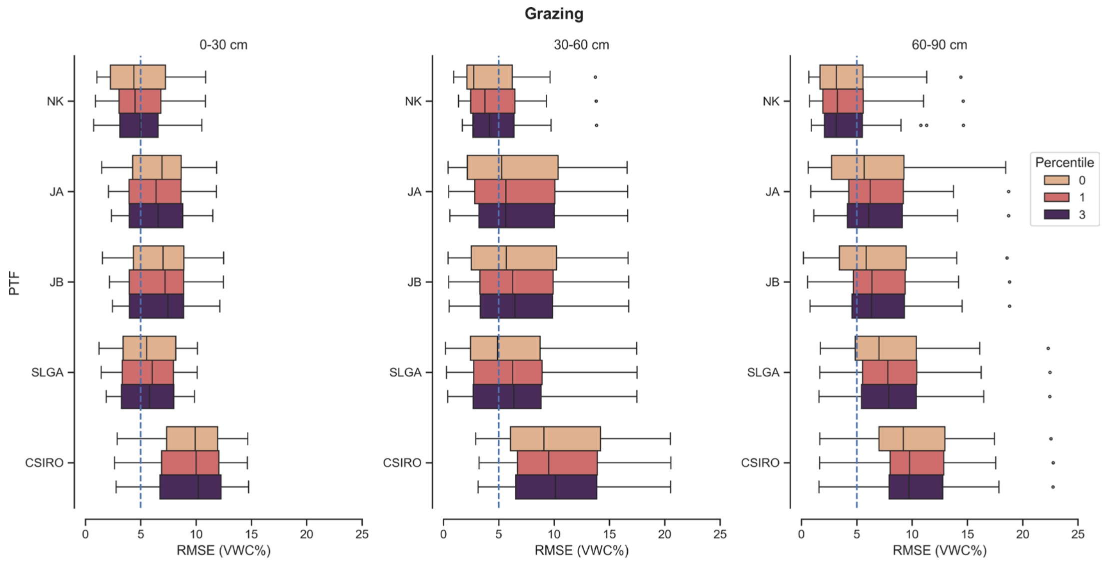

Figure 4. Accuracy of PTF scaling at grazing sites

5.3. Experiment C

The accuracy of the PTF scaling at a given site, in theory, is dependent on the CLL and DUL being matched to the long-term minimum and maximum soil moisture measurement, respectively. Due to variations in rain-fall, surface temperature, and root uptake, the recorded soil moisture extrema change over time. However, the global minimum and maximum need to be matched to the CLL and DUL, respectively, to ensure the measure-ments are scaled to the correct bounds. For example, matching a local maximum to the DUL is problematic as any subsequent periods of exceedance of that local maximum result in PTF scaled soil moisture measure-ments greater than the DUL, which in theory is not possible. Understanding the frequency in global extremum occurrences and the sensitivity of PTF scaling accuracy to changes in the extremum are necessary in validat-ing a PTF-scaled measurement. Figure shows the number of years each probe measurement record takes to reach its global maximum (or within 0.5 %VWC below it). The 0.5 %VWC buffer is added to account for measurements within a reasonable rounding error of the CLL or DUL. The depth ranges differ for the USYD and MSMMN dataset as both probe networks record soil moisture at different depth ranges; MSMMN records at 0-30 cm, 30-60 cm, and 60-90 cm, and USYD at 30-60 cm, 60-90 cm, and 90-110 cm.

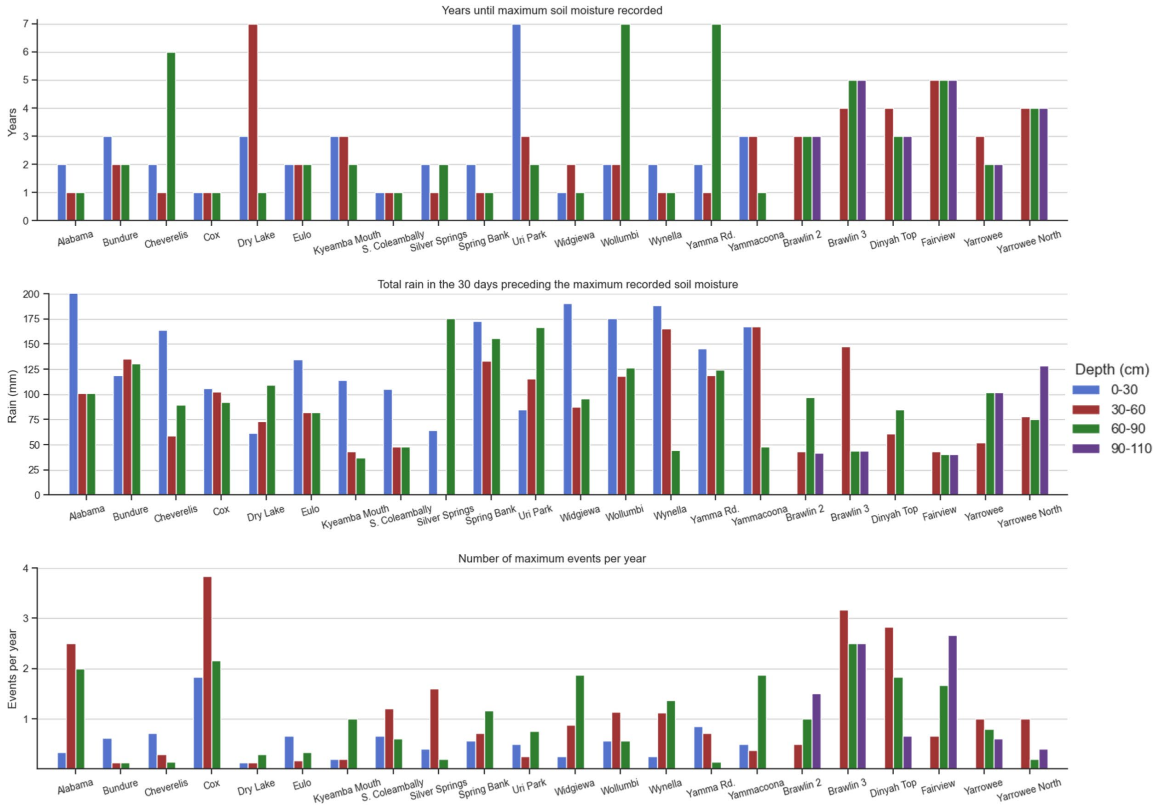

Figure 5. (a) Years until maximum soil moisture recorded. (b) Total rain the 30 days preceding the maximum long-term recorded soil moisture. (c) Number of maximum events per year.

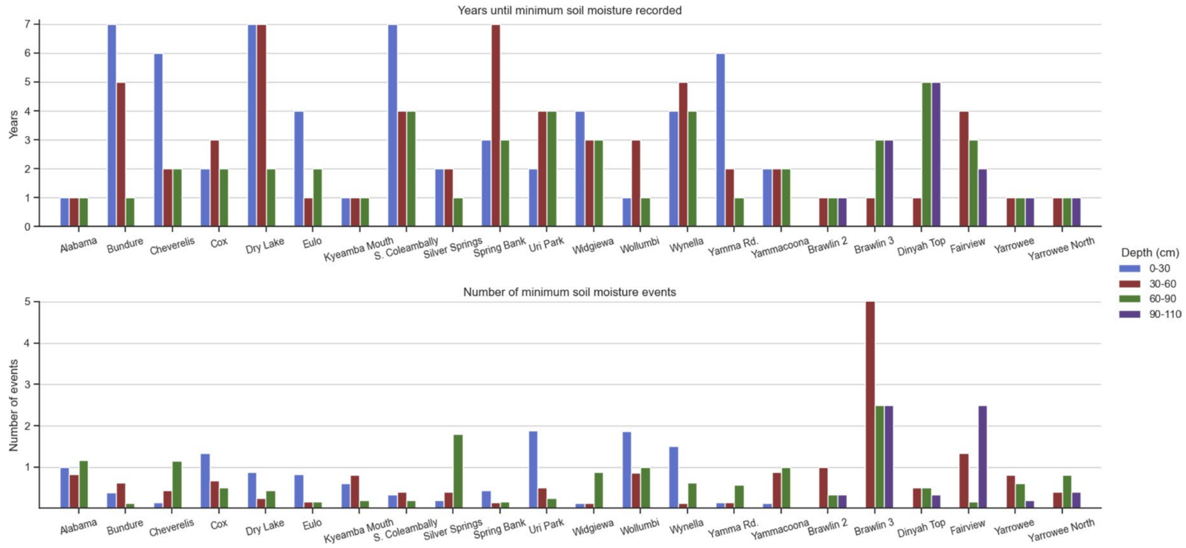

Figure 6. (a) Years until long-term soil moisture recorded. (b) Number of minimum events per year.

15 out of the 22 sites considered for this study reached their global maximum within the first 4 years of their record. Across the MSMMN sites, located in the Murrumbidgee catchment, the deepest depth interval (60-90 cm) was the most variable with regard to time taken to record the long-term maximum soil moisture, in contrast to the other depths at a given site. The long-term maximum soil moisture in the 60-90 cm depth interval was recorded within two years at 13 of these sites, and or after at least 6 years at three of them. With the exception of Uri Park and Dry Lake, the 0-30 cm and 30-60 cm intervals record the long-term maximum within at most 3 years. The Muttama sites (USYD network) are less variable across depth. At a given site, the depth intervals differ by at most 1 year, and these sites generally need at least 4 years to calibrate at all depths. The deeper intervals, 60-90 cm and 90-110 cm, experience the long-term maximum within the same year at every USYD site.

With regards to rainfall, Figure shows the amount of rainfall in the 30 days preceding the first maximum soil moisture event. This was done to understand how much rainfall a soil typically needs to experience before a global maximum can be assumed to have been recorded. The sites with incomplete/missing rainfall data are not included in this figure (Silver Springs, & Dinyah Top). Of MSMMN sites, the 0-30 cm depth interval required the most rainfall of all depths to reach its maximum point. This can be expected due to the larger pore sizes in the topsoil, making it more susceptible to water loss through ET (SOURCE). The 30-60 cm and 60-90 cm intervals experienced relatively less rainfall before a maximum event, and experience similar amounts of rainfall preceding a maximum event. The MSMMN sites exhibit no clear minimum rainfall amount before a particular interval can be determined as having reached its DUL. However, as a general guideline, 80% of all depths across all sites recorded a maximum soil moisture reading after 150 mm rain in the preceding 30 days. The USYD sites show less consistency with the maximum being reached and rainfall. However generally 100 mm of rain in a month is an ample amount of rain to sufficiently wet the soil enough for the long-term maximum to have been recorded.

With regards to the likelihood of recording a maximum event in a year, and the frequency of calibration, Figure shows that the number of maximum events (VWC within 0.5 %VWC of the maximum soil moisture). The 0-30 cm interval in the Murrumbidgee sites typically reach their maximum less than once a year, meaning at least multiple years of data are needed before assuming a long-term maximum has been recorded. The deeper intervals wet up more often, and at many sites can exceed once a year. The Muttama sites wet up more regularly, as at most sites at least two of the depth intervals experience a wetting event at least once a year.

The minimum soil moisture is highly variable across sites and depth intervals. The sites which took the longest for the 0-30 cm depth to reach minimum (Bundure, Cheverelis, Dry Lake, S. Coleambally, Yamma Rd.) were the sites with the above average clay percentage across all sites (clay ¿ 40%) and with total recorded rainfall greater than average (¿4377 mm). These sites can be expected to take longer than others to reach the CLL as clay is able hold water well, and these have experienced more rainfall and hence are expected to take more time before reaching the CLL. In theory, cropping sites should experience more drying events than grazing sites due to deeper rooting depth in grains than grasses and due to more frequent tilling of the soil during harvest. However, there are no notable difference in cropping and grazing sites amongst frequency of drying periods.

Experiment C we used the minimum and maximum of each subsequently added year of soil moisture to scale the entire profile. The general trend across all sites is the accuracy improves as the range of years for the min-max are considered is expanded. Some sites experience a greater improvement with accuracy over time than others. However, the recording of the maximum is not critical as in some instances the accuracy is greatly improved before the long-term maximum has been recorded. For example, at Yarrowee North and Fairview, the accuracies greatly improve by using the min-max over two years, while their min-max limits are not recorded for at least 3 years. This indicates the min-max was near their long-term values but getting near greatly in the first place greatly improved their accuracy. A similar trend is seen at Brawlin 2 and Brawlin 3. This affirms the capability of the PTF scaling in accurately scaling the data even without hitting the min-max limits but nearing them. The sites with low gradients indicate a small shift in the min-max over time, such as at Uri Park where the 0-30 cm maximum is recorded after 7 years, however the accuracy improves with a low gradient over time, until it reaches its highest accuracy at 7 years. While accuracy per depth interval deviate from each other at every site, they stabilise typically after 3 years. Experiment C shows that generally including 3 years of data before PTF-scaling a probe is recommended, however subsequently updating the min-max limits yearly can provide incremental but notable improvements over time.

6. CONCLUSIONS

Retrospective calibrations provide a feasible solution to the complexity of sampling logistics for conventional calibration. We find the use of PTF scaling to be an appropriate substitution, under the correct selection of PTF and scaling percentile depending on land use and region. Our calibration of the USYD network exhibited the ability for PTF scaling to be a suitable alternative to conventional calibration. From Experiment B we can note that grazing sites are generally more accurately calibrated than cropping sites (relative to conventionally calibrated measurements). However, considering the conventionally calibrated data exhibited upto 8 %VWC error for the USYD network and Yeoh et al. (2008) report up to 5 %VWC error for the MSMMN dataset, the accuracy of the PTF scaling may in fact be closer to the true volumetric water content than can be noted from the results of Experiment B. With regard to PTF selection, NK was the most reliably accurate PTF across every region, land use and depth. It is the most suited PTF for a singular calibration across a widespread multi-land use network. However, considering land use and depth, JA is a reliable choice for cropping sites, especially at deeper depths. Both PTFs are best suited for higher scaling percentiles (e.g. s = 3) at grazing sites, and the lowest scaling percentile (s = 0) at cropping sites.

A limitation of this study is the lack of publicly available collocated measured volumetric water content and probe measurements. This leads to our results being more applicable to our study area or certain soil types over others. For example, of the 23 soils tested in this study, 19 are Chromosols and 4 are Vertosols (Raymond Isbell, 2002). However, considering the consistency in performance across the various regions and land uses within NSW, the soil type skew is unlikely to be critical in applying PTF scaling to other regions.

With the PTF recommendations from our experiments, uncalibrated soil moisture probes across Australia can be calibrated remotely to reasonable accuracy.

REFERENCES

Adla, S., Bruckmaier, F., Arias-Rodriguez, L.F., Tripathi, S., Pande, S., Disse, M., 2024. Impact of cali-brating a low-cost capacitance-based soil moisture sensor on AquaCrop model performance. *Journal of Environmental Management 353*, 120248. doi:10.1016/j.jenvman.2024.120248.

Dalgliesh, N., Cocks, B., Horan, H., 2012. APSoil-providing soils information to consultants, farmers and researchers. .

Gajurel, S., Lai, Y., Lobsey, C., Pembleton, K.G., 2024. A cost-effective approach to estimate plant available water capacity. *Geoderma 442*, 116794. doi:10.1016/j.geoderma.2024.116794.

Gasch, C.K., Brown, D.J., Brooks, E.S., Yourek, M., Poggio, M., Cobos, D.R., Campbell, C.S., 2017. A pragmatic, automated approach for retroactive calibration of soil moisture sensors using a two-step, soil-specific correction. *Computers and Electronics in Agriculture 137*, 29–40. doi:10.1016/j.compag. 2017.03.018.

Hoskin, N., Filippi, P., Bishop, T.F.A., 2025. Unpublished article .

Li, Z., Vanderborght, J., Smits, K.M., 2020. The effect of the top soil layer on moisture and evaporation dynamics. *Vadose Zone Journal 19*, e20049. doi:10.1002/vzj2.20049.

de Jong van Lier, Q., 2017. Field capacity, a valid upper limit of crop available water? *Agricultural Water Management 193*, 214–220. doi:10.1016/j.agwat.2017.08.017.

Malone, B.P., Searle, R., Stenson, M., McJannet, D., Zund, P., Roma´n Dobarco, M., Wadoux, A.M.J.C., Minasny, B., McBratney, A., Grundy, M., 2025. Update and expansion of the soil and landscape grid of Australia. *Geoderma 455*, 117226. doi:10.1016/j.geoderma.2025.117226.

Mane, S., Singh, G., Das, N.N., Kanungo, A., Nagpal, N., Cosh, M., Dong, Y., 2025. Development of low-cost handheld soil moisture sensor for farmers and citizen scientists. *Frontiers in Environmental Science Volume 13 - 2025*. doi:10.3389/fenvs.2025.1590662.

Maya Moreshwar Meshram, S., Adla, S., Jourdin, L., Pande, S., 2024. Review of low-cost, off-grid, biodegrad-able in situ autonomous soil moisture sensing systems: Is there a perfect solution? *Computers and Elec-tronics in Agriculture 225*, 109289. doi:10.1016/j.compag.2024.109289.

Mgendi, G., 2024. Unlocking the potential of precision agriculture for sustainable farming. *Discover Agricul-ture 2*, 87. doi:10.1007/s44279-024-00078-3.

Padarian, J.S., 2014. Provision of soil information for biophysical modelling .

Raymond Isbell, 2002. The Australian Soil Classification. CSIRO Publishing. URL: https://ebooks.publish.csiro.au/content/9780643069817/9780643069817, doi:10.1071/9780643069817.

Ru¨diger, C., 2006. Streamflow Data Assimilation for Soil Moisture Prediction. Ph.D. thesis.

Searle, R., Somarathna, P., 2022. Soil and Landscape Grid National Soil Attribute Maps - Drained Upper Limit Volumetric Water Content (Percent) (3 arc second resolution) Version 1. v4. CSIRO. Data Collection. URL: https://data.csiro.au/collection/csiro%3A56704v4, doi:10.25919/JNVD-3A26.

Smith, A.B., Walker, J.P., Western, A.W., Young, R.I., Ellett, K.M., Pipunic, R.C., Grayson, R.B., Siriwardena, L., Chiew, F.H.S., Richter, H., 2012. The Murrumbidgee soil moisture monitoring network data set. *Water Resources Research 48*. doi:10.1029/2012WR011976.

Weir, P., Dahlhaus, P., 2024. Beyond soil moisture probes: improving field scale soil moisture mapping. *Discover Soil 1*, 25. doi:10.1007/s44378-024-00025-0.

Yeoh, N., Walker, J., Young, R., Ru¨diger, C., Smith, A., Ellett, K., Pipunic, R., 2008. Calibration of the Murrumbidgee Monitoring Network CS616 Soil Moisture Sensors.

Zreda, M., Desilets, D., Ferre´, T.P.A., Scott, R.L., 2008. Measuring soil moisture content non-invasively at intermediate spatial scale using cosmic-ray neutrons. *Geophysical Research Letters 35*. doi:10.1029/2008GL035655.

