

SOIL MOISTURE PREDICTION WITH MULTISPECTRAL VISIBLE AND NIR REMOTE SENSING

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ABSTRACT:

Water is a valuable resource and an understanding of soil moisture dynamics is critical in many land management, agricultural and engineering applications. Satellite and UAV remote sensing platforms present an opportunity for rapid, cost-efficient data collection; however, soil moisture remote sensing presents unique challenges. Specifically, spectral bands near 1400nm and 1900nm associated with water are typically avoided in remote sensing data products due to strong interference by atmospheric moisture. Using soil reflectance data collected in the lab, this paper presents a number of linear equations which maybe be applied to predict soil moisture content from Landsat 5 MSS, 7 TM and 9 data, as well as other NIR sensors collecting data at 1720, 1782, 2140 and 2240nm.

1. INTRODUCTION

Accurate measurements of soil moisture are valuable in numerous disciplines, including land management, agriculture and engineering (Ahlmer et al., 2018). As a dynamic and spatially erratic variable, soil moisture measurements are most valuable when they are up-to-date, accurate, and available in high spatial resolution. With the rapidly expanding capabilities of satellite and UAV remote sensing platforms and sensors, it could be assumed that there is an opportunity to perform soil moisture measurements of high spatial and temporal resolution with remote sensing technologies.

Soil moisture remote sensing presents unique challenges, however, as instrument design and atmospheric moisture (i.e humidity) interfere with spectral measurements of moisture on the land surface. Water molecules, comprised of two O – H bonds, vibrate and strongly absorb energy near ~1400nm and ~1900nm in the NIR (Viscarra Rossel et al., 2006). As the water content of the atmosphere is significant, and highly variable, it is common-place to exclude wavelengths ~1400nm and ~1900nm from remote sensing data products due to exceptionally strong absorption at these wavelengths by atmospheric moisture (He et al., 2004). This means that NIR reflectance data associated with O – H absorption bands, which might be used to predict soil moisture content, are not available in most remote sensing data products and cannot be collected by most sensors designed for remote sensing platforms (Figure 1).

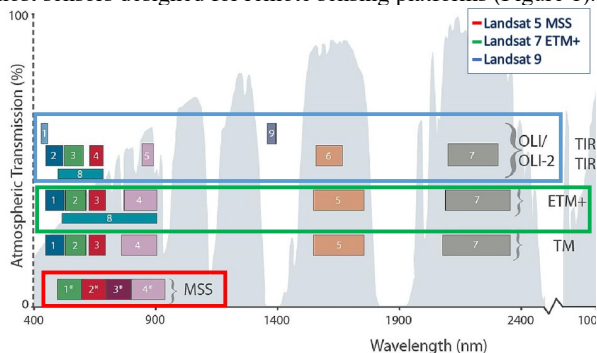


Figure 1. Landsat 5 MSS, Landsat 7 ETM+ and Landsat 9 sensors avoid absorption bands ~1400nm and 1900nm. Modified from Wulder et al. (2019).

A number of studies have examined the relationship between soil moisture content (MC) and reflectance at visible and NIR wavelengths. However, none of the studies known to us explicitly quantified the domain of the relationship or the equation for the line of best fit. Bowers and Hanks (1965) refer to earlier studies which record a decrease in reflectance with increasing moisture content, while also presenting foundational results which describe the effects of moisture on soil reflectance. Results presented by Bowers and Hanks (1965) demonstrate that the absorption intensity of soil moisture is wavelength dependent, that the presence of soil moisture inhibits prediction of the soil organic matter content, that soil moisture generates two large absorption features near ~1400nm and 1900nm and masks the absorption feature near ~2200nm, which is not associated with water (Dematte et al., 2004; Gomez et al., 2008). A number of these broad trends are also recorded and reported by Bogrekcı and Lee (2006), Lobell (2002) and Minasny et al. (2011).

A number of other authors examining the relationship between soil reflectance and MC mention a ‘moisture threshold’ (Liu et al., 2009; Whiting et al., 2004) or ‘critical point’ in the relationship (Weidong et al., 2002), but do not provide detail regarding the position or conditions of this threshold. Hong et al. (2018) claim the presence of a clear differentiation in the relationship between visible-NIR (400–2500nm) soil reflectance and MC at exactly 17.66% MC. The nature of the reported relationships is also inconsistent, with varied reports of linear (Condit, 1972) and non-linear (Liu et al., 2009; Weidong et al., 2002; Whiting et al., 2004) relationships, as well as some claims that no relationship exists (Stenberg et al., 2010).

The presence of soil moisture also causes problems for the prediction of other soil properties from remotely-sensed and other soil reflectance data (Jiang et al., 2016; Stenberg et al., 2010). A number of approaches have been trialled to remove the effects of soil moisture from soil reflectance data (without knowledge of the relationship between soil reflectance and MC) for the purpose of improving model predictions of other soil properties. These alternative approaches include: classifying samples into groups based on their moisture content (Dematté et al., 2004; Mouazen et al., 2006), estimating soil moisture content from the organic carbon content of a sample (Nocita et al., 2013), analysing data transformed with the first derivative

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(Wu et al., 2009), or applying an external parameter orthogonalization algorithm (Minasny et al., 2011).

In this study, the relationships between soil reflectance and moisture content are explicitly quantified using experimental data. Equations which represent the line of best fit and describe the relationship between soil reflectance and MC, are calculated from high-resolution soil reflectance data collected at >20 moisture levels. Equations describing the relationship between soil MC and reflectance averaged over the Landsat 5 MSS (multi-spectral scanner), Landsat 7 TM (thematic mapper) and Landsat 9 bands (Figure 1) and other wavelengths are then presented.

2. METHODS

2.1 Soil samples

Soil reflectance data was collected from ten surface soil samples from Muttama, NSW, Australia. All samples were collected from the same grazing paddock, with an approximate area of 45ha. Samples were dried at 40°C after collection in 2019 and stored in plastic, screw-top jars in a temperature-controlled environment until reflectance data collection in May 2021. The clay, silt, sand, soil texture, organic matter and bulk density characteristics of the samples are detailed in Table 1.

Table 1: PSD, soil texture, bulk density and OM content of Muttama soil samples at time of collection.

Sample	Clay %	Silt %	Sand %	Soil texture	Organic Matter	Bulk Density
ISS10A	25.41	18.65	55.93	CL	3.86	1.30
ISS11A	25.21	19.35	55.44	CL	4.55	1.26
ISS14A	22.11	17.05	60.83	L	3.19	1.36
ISS17A	25.06	20.89	54.05	CL	4.38	1.27
ISS20A	21.10	25.83	53.07	ZL	2.24	1.41
ISS25A	27.19	15.86	56.95	CL	3.48	1.33
ISS26A	18.28	28.56	53.16	ZL	4.26	1.27
ISS27A	20.24	6.83	72.93	SCL	3.71	1.34
ISS28A	18.55	26.02	55.43	ZL	2.83	1.38
ISS36A	14.47	27.58	57.94	ZL	3.91	1.30

2.2 Soil preparation and drying

50.0g of each sample was measured out into a glass petrie dish. Samples were dried to 0% MC by placing the petrie dishes in an oven at 105°C for 48–60 hours. This drying procedure is recommended by OEH (1990) to bring the soil moisture content to 0%.

2.3 Moisture addition

Water was added to each sample with a pipette, to increase the gravimetric MC by the desired 1% or 5% MC interval. The amount of water added to reach the desired SM content was calculated using the following equation (OEH, 1990):

$$\text{Soil water content (\%)} = \frac{\text{mass of moist soil (g)} - \text{mass of oven-dried soil (g)}}{\text{mass of oven-dried soil (g)}} \times 100 \quad (1)$$

In detail, 2.5ml of water was added and mixed in with a clean spoon to increase the SM content by 5%, while 0.5ml of water was added and mixed in to increase the SM content by 1%. Reasonable efforts were made not to crush soil aggregates or apply excessive force during mixing.

2.4 Spectrometer calibration, data collection and software

An ASD FieldSpec visible-NIR spectroradiometer was used to collect soil reflectance data in the range of 400–2500nm at 1nm resolution. The ASD includes a backlit, handheld, contact probe, connected to the spectrometer by a hard-wearing cable containing optical fibres. The contact probe is held against the soil surface during data collection, eliminating atmospheric absorption.

Data were exported to a csv file using the ASD software package *Indico Pro*. A Spectralon-branded reflectance tile was used to calibrate reflectance measurement between each sample and each MC. Python libraries including *pandas*, *numpy*, *matplotlib* and *seaborn* were utilised for data cleaning, visualisation and analysis. The *lmfit* library was used to fit linear models and *scipy* utilised to generate fit-statistics. Models presented in Figures 2 to 8 were generated with soil reflectance data averaged across all ten soil samples.

3. RESULTS

When soil reflectance is averaged across the visible and NIR Landsat 5 MSS wavelengths, a monotonic relationship between soil MC and reflectance (Figure 2a) below 25% MC is apparent. Between 5 and 25% MC the relationship is linear (Figure 2b). Beyond 25% MC, reflectance is a poor indicator of MC.

The relationship between soil MC in the domain of 5–25% MC, and reflectance averaged across the visible and NIR Landsat 5 wavelengths can be described by the following equation:

$$y = -0.60x + 26.78 \quad (2)$$

A linear regression model fitted to this relationship returns an R^2 value of 0.99, a standard error (SE) of 0.02, and a reduced chi-square of 0.20

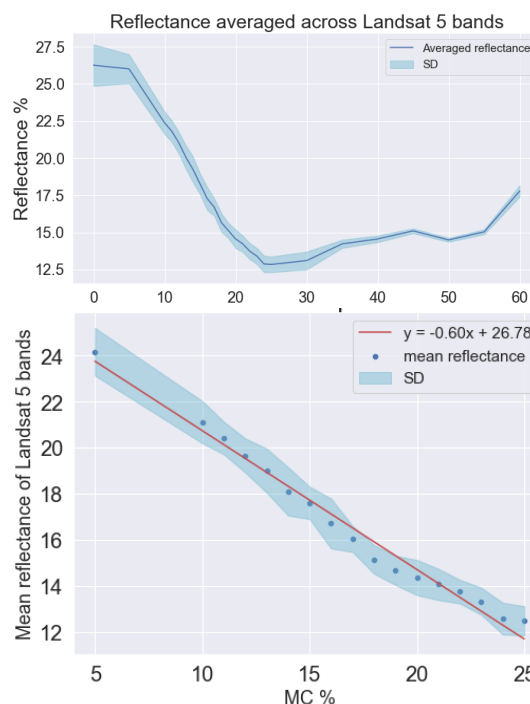


Figure 2(a & b). A monotonic relationship between soil MC and reflectance averaged across all the vis-NIR Landsat 5 wavelengths is apparent below 25% MC. Between 5–25% MC, the relationship is linear. (Note SD is the standard deviation.)

When reflectance data averaged across the Landsat 7 ETM+ and Landsat 9 wavelengths are considered as a function of MC, the monotonic decrease in reflectance continues to 30% MC, however the decrease is not linear beyond 25% MC. Linear models fit to reflectance data averaged across the Landsat 7 ETM+ (Figure 3a) and Landsat 9 (Figure 4a) wavelengths returns an excellent fit in the 5–25% MC domain, with an R^2 of 1.00, SE of 0.02, reduced chi-square of 0.14 (Figure 3b), and R^2 of 1.00, SE of 0.01, reduced chi-square of 0.11 (Figure 4b), respectively.

The equation for the line of best fit between soil MC and reflectance averaged across the Landsat 7 ETM+ wavelengths is:

$$y = -0.83x + 34.71 \quad (3)$$

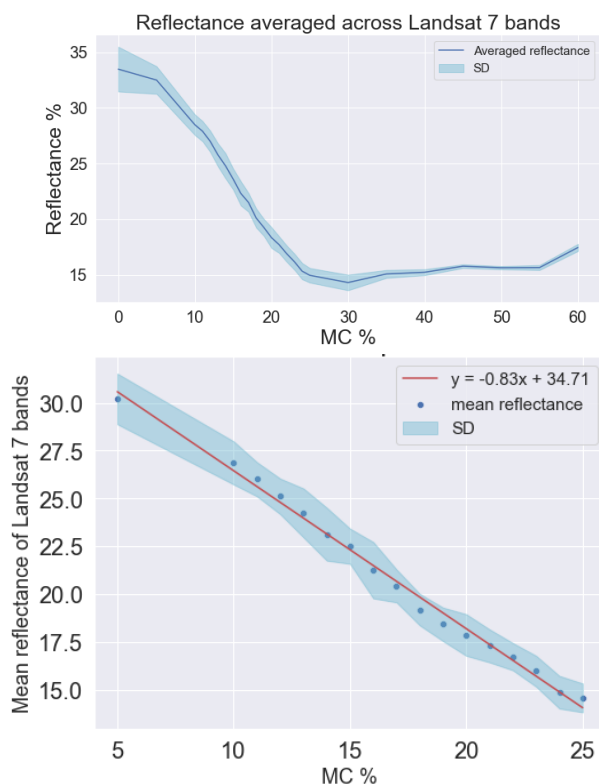


Figure 3(a & b). A linear regression model between soil reflectance averaged across the Landsat 7 wavelengths and MC returns an excellent fit for the domain of 5 to 25% MC.

The equation for the line of best fit between soil MC and reflectance averaged across the Landsat 9 wavelengths is:

$$y = -0.73x + 30.97 \quad (4)$$

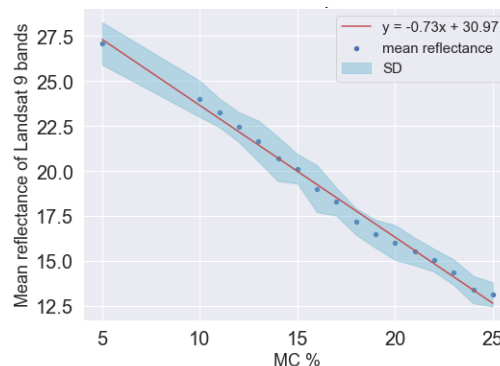
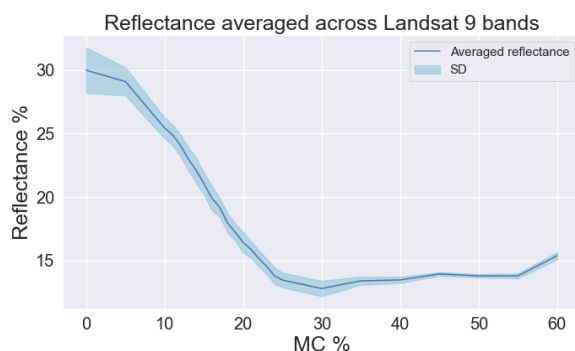


Figure 4(a & b). A linear regression model fitted to reflectance data averaged across the Landsat 9 wavelengths, returns an excellent fit in the domain of 5–25% MC.

Strong linear relationships between soil reflectance and MC are also apparent for other NIR wavelength combinations when basic addition or subtraction transformations are applied.

Reflectance data from individual wavelengths can also be used in a number of ways to predict soil moisture content. For example, the sum of reflectance values at 2140 and 2240nm (Figure 5a) can be accurately described with an inverse linear relationship between 5 and 25% MC (Figure 5b) (R^2 of 1.00, SE of 0.01, reduced chi-square of 0.21). The relationship should not be applied beyond this domain, however, as the linear relationship disappears (becomes “saturated”) above 25% MC (Figure 5a) and does not continue to 0% MC. The equation for the line of best fit for the linear relationship is:

$$y = -2.41x + 95.67 \quad (5)$$

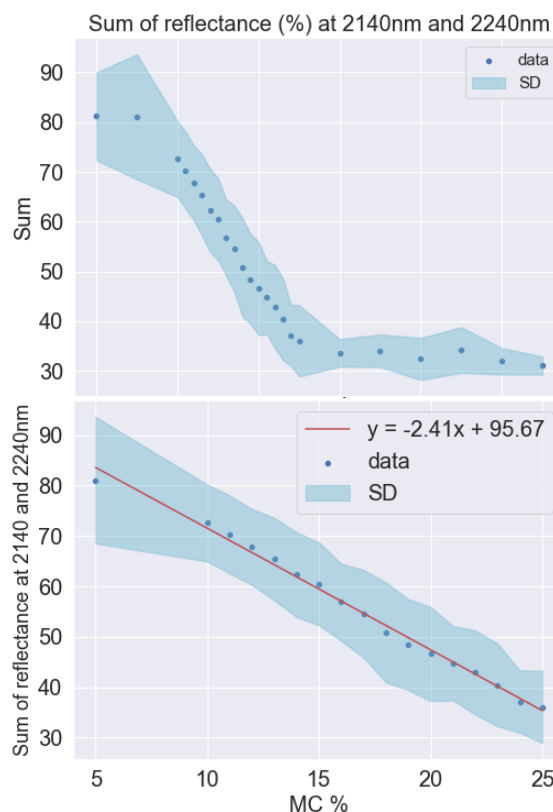


Figure 5(a & b). There is a linear relationship between the sum of soil reflectance at 2140 & 2240nm and MC between 5 and 25% MC.

A linear model with very low error (R^2 of 1.00, SE of 0.16, reduced chi-square of 0.24) can also be used to describe the relationship between soil MC and the difference between reflectance values at 2140 and 2240nm (Figure 6a & b).

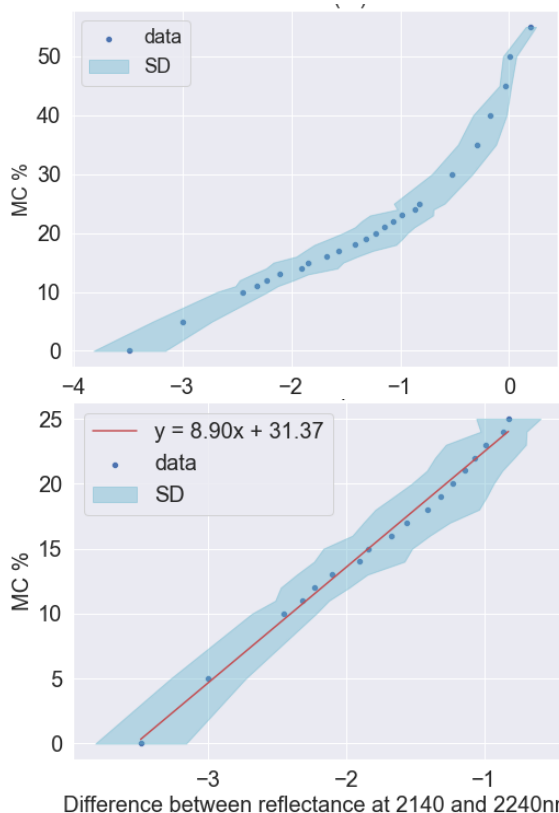


Figure 6(a & b). A linear model best describes the relationship between soil MC and the difference x between reflectance values at 2140 and 2240nm between 5 – 25% MC.

Though the relationship shown in Figure 6a appears non-linear for the domain 0–55% MC, a linear model (Figure 6b) best describes the relationship at low MC’s from 0–25% MC. The equation for the line of best fit is for this domain is:

$$y = 8.90x + 31.37 \quad (6)$$

Reflectance data from 1720nm and 1782nm can be analysed in a similar way to identify linear relationships between soil moisture content and reflectance below 25% MC. When the sum of reflectance values at 1720 and 1782nm are added together and considered as a function of MC (Figure 7a & b), a linear relationship between 5–25% MC becomes apparent.

In this case, the linear regression model fitted to this relationship returns an R^2 value of 1.00, a SE of 0.01 and a reduced chi-square of 0.24.

The equation of the line of best fit for this relationship is:

$$y = -2.18x + 95.57 \quad (7)$$

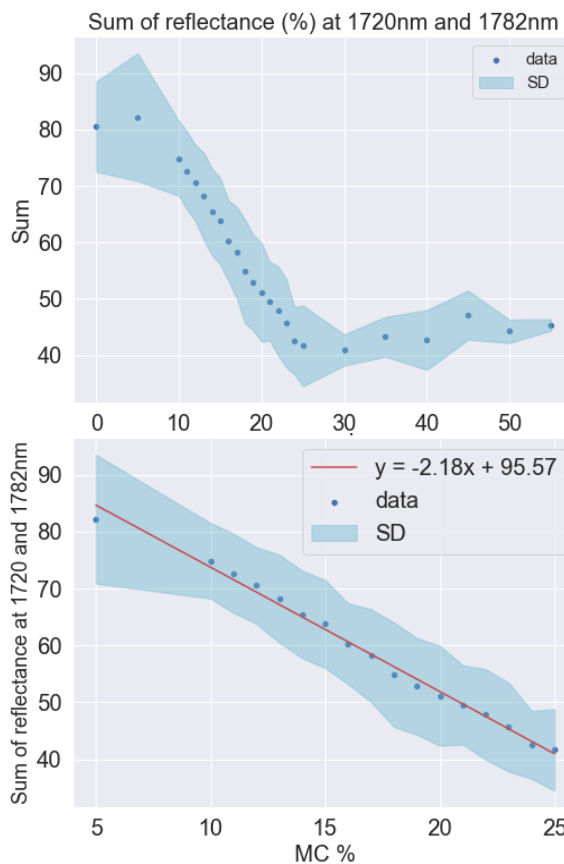
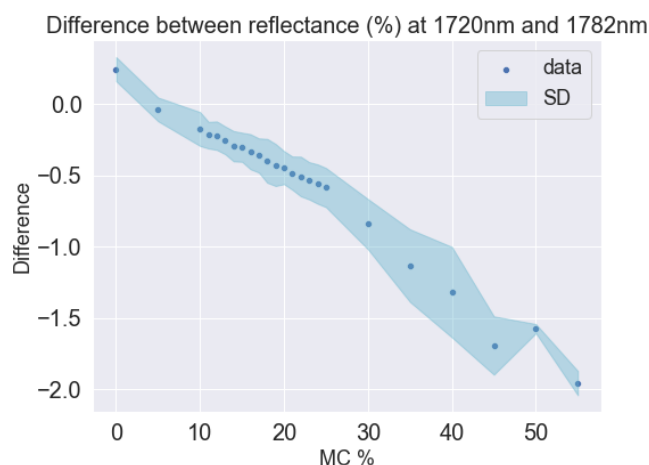


Figure 7(a & b). There is a linear relationship between soil moisture content (y) in the domain of 5–25% MC and the sum (x) of reflectance at 1720 and 1782nm.

Similarly, when the difference between reflectance values at 1720 and 1782nm is compared to soil MC (Figure 8a & b), a linear relationship is also apparent in the domain of 5–25% MC. The line of best fit describing this relationship has the equation:

$$y = -0.03x + 0.10 \quad (8)$$

This linear regression model returns an R^2 value of 1.00, a SE of 0.42 and a reduced chi-square of 0.07.



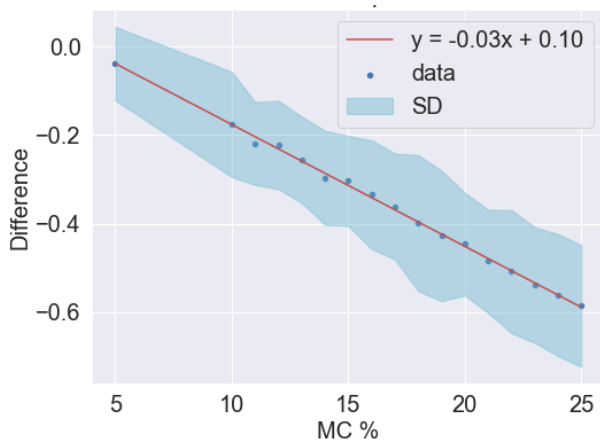


Figure 8(a & b). There is a linear relationship between soil MC and the difference between reflectance at 1720 and 1782nm.

The simple transformations presented in Figures 5 to 8 and corresponding lines of best fit (Equations 5 to 8) demonstrate opportunity for soil moisture prediction from a variety of NIR wavelengths.

4. DISCUSSION

The results presented in this paper demonstrate strong linear relationships between soil MC and the reflectance of our soil samples at wavelengths corresponding to the Landsat bands and other NIR wavelength combinations. The results suggest that simple, linear algorithms could be applied to Landsat 5, 7, or 9, or other select NIR data for the purpose of soil MC prediction. All models and wavelength combinations proposed are practical for application to remote sensing data, as they avoid spectral bands around 1400 and 1900nm, the NIR bands most strongly affected by atmospheric moisture absorption.

It is, however, important to recognise that there is a limit to the domain of the relationships presented in Figures 2 - 8. Therefore, equations 2 - 8 should only be applied when soil MC is expected to be in the range of 5 - 25% MC, with the exception of equation 6, which may be applied to the 0 - 25% MC range. Approximations of soil MC (used to determine the models' applicability) may be determined with the Australian Landscape Water Balance (ALWB) tool (BOM, 2022).

In the future, our models could be applied to remotely sensed surface reflectance data and tested against data from in-situ soil moisture probes. If the models perform well, it may be possible to improve the resolution and performance of the ALWB tool by integrating remote sensing data classified with the moisture content prediction models presented in this study. The ALWB tool relies upon local rainfall data and evapotranspiration, runoff, and deep drainage models to provide predictions of surface soil MC across Australia. In addition to testing the ALWB against our models and in situ MC data, the combination of the ALWB and soil MC models could also be used inversely to predict surface reflectance, a useful dataset for the correction of some remote sensing data products.

The linear relationships shown in this paper are for a set of 10 soil samples from a single Australian paddock. It might be questioned how universal these results are. Importantly, similar linear relationships are found in very similar MC domains when each soil sample is analysed separately, although precise relationships differ; for example see Figure 9(a & b).

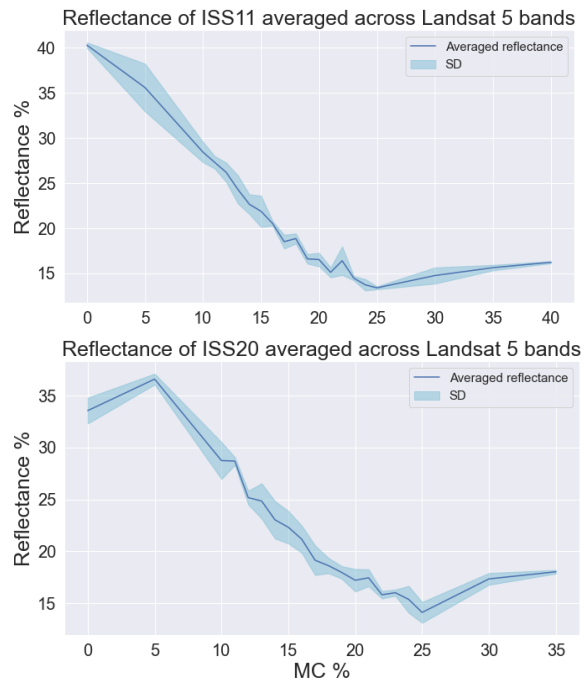


Figure 9(a & b). The reflectance of single samples e.g. ISS11(a) and ISS20(b) averaged across the Landsat 5 bands, decrease in a monotonic, linear fashion, as MC increases. The domain of the relationship varies slightly between soil types, but was typically recorded as 5 - 25% MC or 0 - 25% MC.

Moreover, these samples were chosen essentially at random, in the sense that we used samples collected for independent projects by others which were available to us. These points suggest that most, if not all, soils will have linear relationships between MC in the approximate domain of 5-25% and the reflectance averaged over suitable domains of visible-NIR wavelengths. If so, then for any given soil (or set of averaged soils) it appears that measurements of the averaged reflectance at two different MC's in the domain of 5-25% are sufficient to determine the relevant linear relationship and permit its use for remote sensing analyses.

The presence of soil moisture is a significant impediment to the prediction of other soil properties (Angelopoulou et al. 2019; Soriano-Disla et al. 2014; Stenberg et al. 2002; Yaron et al., 2019): for example, organic carbon, calcium, magnesium or clay content, cation exchange capacity (CEC), Fe content, pH and microbial activity. This is due to water's strong absorbance characteristics throughout the visible and NIR spectrum (Bowers and Hanks, 1965; Jiang et al., 2016). Recognising that soil moisture is a highly variable parameter across landscapes and causes significant absorption in the visible and NIR wavelengths (Yaron et al., 2019), it is recommended that professionals applying remote sensing data consider the effects of soil moisture when interpreting, correcting and considering the application of remote sensing data.

Most 'analysis-ready' remote sensing data products are not corrected for the effects of soil moisture. Hence, temporal analyses employing time-series data are likely to be affected by varying levels of absorption by the soil, likely linearly proportional to the soil moisture content in the domain of 5 - 25% MC as shown here. Other soil components such as soil organic matter also include O - H bonds, with concentration predictions known to be impacted by water in the soil (Stenberg et al., 2002), especially in cases where the soil moisture content

is significantly higher than the organic matter content. In these, and numerous other circumstances, the prediction of land-surface properties and temporal variability could be improved by correction of remotely sensed data for the effects of soil moisture.

5. CONCLUSION

Linear relationships between soil reflectance and MC are demonstrated for a number of Landsat band combinations and selected wavelengths at 1720, 1782, 2140 and 2240nm for a set of 10 soil samples, averaged together, from a single Australian paddock. Similar relationships exist for all the individual soil samples tested. Linear relationships are typically found in the domain 5–25% MC, but sometimes extend to 0% MC. Beyond 25% MC, linear relations are not found for our samples and analyses. Importantly, below 25% MC, there are multiple wavelength domains for which linear relationships exist, which can be utilised to generate linear models for soil MC prediction. Linear models with R^2 of ≥ 0.99 , standard error of <0.5 , and reduced chi squared between 0 and 0.66 could be fit to all relationships presented. Though extensive work has been undertaken previously for the purposes of predicting soil moisture content and removing the effects of soil moisture from remotely sensed data, this study provides clarity on the nature of the relationship (linear), demonstrates the necessity to constrain a linear correction algorithm to an appropriate domain (5 – 25% MC in most cases), and provides equations which can be used to correct remote sensing data for the effects of soil moisture at commonly measured wavelengths. The existence of linear relations is expected to be robust, based on such relations existing for the individual soil samples, and when averaged over the set of 10, and considering the essential randomness of the choice of samples which were analysed. However, calibration for the precise soils of interest may be necessary, with measurements of the reflectance at two MCs (in the domain of 5 – 25% MC) is required to quantify the relationship within the available error bars.

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