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Brightness-Shape-Moisture Radiative Transfer Model Improves Soil Moisture Estimation from Sentinel-2 Imagery

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ABSTRACT

Soil moisture is the main water source for plants, affecting everything from germination to nutrient absorption. The physics-informed brightness-shape-moisture (BSM) radiative transfer model can be used in the inverse direction for accurate soil moisture estimation from high-resolution spectra. However, this accuracy is not maintained once spectra are resampled to fewer-band multispectral resolutions. By coupling a simulated BSM look-up table, resampled to Sentinel-2 response spectra, with gradient boosting regression, the authors developed a transferable method capable of estimating soil moisture from Sentinel-2 imagery, achieving high accuracy on simulated data ($R^2 = 0.96$) and moderate accuracy on real-world data ($R^2 = 0.51$), while avoiding the poorer generalization typically associated with empirical, field-calibrated models. This approach shows strong potential for operational, long-term soil moisture monitoring across Southern Africa.

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Africa; radiative transfer model; Sentinel-2; soil science; brightness-shape-moisture

Introduction

The mapping of soil biophysical and moisture characteristics is useful for ecosystem and environmental monitoring and is important for water management. These properties can be mapped through various geostatistical methods using representative soil samples. However, this is sometimes impractical or inconsiderate, because it is destructive, expensive, and consumes too much time and labor. Remote sensing is an alternative to such analysis and is a faster and cheaper means to retrieve soil measurements within a desired area. Remote sensing leverages either ratio-based empirical methods or physically based radiative transfer modeling (RTM) to gauge soil measurements from spectral signatures.

Most existing literature has estimated soil properties through empirical methods when Sentinel-2 imagery was utilized. For example, Gholizadeh et al. (2018), Castaldi et al. (2019) and Lin et al. (2020) used Sentinel-2 spectra to estimate soil organic content using empirical methods. However, the subtropical soils in the semi-arid landscapes of southern Africa have not been analyzed in detail.

Soil RTMs implemented in the inverse direction are used to gauge soil characteristics from available soil spectra. One beam tracing RTM, called the multilayer radiative transfer model of soil reflectance (MARMIT), was used by Eon and Bachmann (2021) for estimating bare dunes' moisture levels from aerial sensor spectral signatures. The brightness-shape-moisture (BSM) RTM (Yang et al. 2020, 2021) was also developed to simulate soil reflectances based on physical soil and brightness parameters, which are then spectrally adjusted based on soil moisture content. Bayat et al. (2020) used the BSM

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within a multi-layer RTM implementation for the retrieval of drought-time land characteristics from Landsat imagery. Prikaziuk et al. (2022) applied the Soil Canopy Observation, Photochemistry and Energy fluxes (SCOPE) model in the inverse direction on potato fields' soil to retrieve BSM inputs. Bonnet et al. (2024) used the BSM model in the inverse direction to retrieve distributions of soil characteristics, including soil moisture, for the semi-arid regions within Southern Africa using archived Hyperion data. However, Bonnet et al.'s results were limited to a spatial resolution of 30 m, further clustered into superpixels, and were also dependent on archived data, since the Earth Observing-1 satellite mission with Hyperion ended in March 2017, meaning that the obtained results cannot be used for ongoing monitoring.

It therefore remains to find a mechanism to measure soil moisture on an ongoing basis using regularly available data streams with finer spatial resolutions, such as Sentinel-2.

Thus, the research poses the question of whether the BSM model can be useful in multispectral remote sensing estimation of soil moisture, given that it was designed for hyperspectral data simulation and retrieval.

Data collection

Study site

Soil samples were obtained from two maize farms near the Vlakplaas/Vanderbijlpark area in the south of Gauteng, South Africa, as well as from two canola farms in Bathurst and Sakhisizwe in South Africa's Eastern Cape (Figure 1). The first two farms fall within the Highveld bioregion, which follows subtropical highland conditions. This region has a mean annual precipitation of ca. 659 mm with high variability. Most of the rainfall occurs between November and February, while May to August is the driest period (Hlahane 2018). The area under study is relatively flat, with sandy, acidic soil and is primarily utilized for maize cultivation (Naidoo et al. 2022). The farm is rain-irrigated, but fertilizers and herbicides are regularly applied for nutrient and weed control. The weeds that primarily invade these farms include *Richardia brasiliensis*, *Chenopodium album*, *Cyperus esculentus*, and *Megathyrus maximus* (Mkhize et al. 2024). The Bathurst site is at an altitude of around 250 m and demonstrates a milder subtropical climate. Average temperatures fluctuate between a minimum of 17°C and a maximum of 26°C in summer, and between 10°C and 21°C in winter. Rainfall is highly unpredictable, with annual averages of around 720 mm (Puttick et al. 2011). Intermittent droughts occur in line with the characteristics of the broader Eastern Cape climate (Jury and Levey 1993). Annual rainfall shows a bimodal distribution with maxima in autumn and spring (Kopke 1988). The second site in the Eastern Cape is in the Sakhisizwe region, which, being more inland and at a higher elevation (1390 m above sea level), has a different climate than Bathurst. This zone is characterized by warm, moist summers and cold, dry winters. The mean annual precipitation is between 200 mm and 300 mm, with 70–80% of rainfall occurring in summer (Sakhisizwe Local Municipality 2024). Temperatures vary between 3°C and 16°C in winter and between 12°C and 24°C in summer (World Weather Online 2025).

Sampling

The data collection campaigns for the Vanderbijlpark and Vlakplaas farms were carried out on 26 November 2019 to collect soil samples. This coincided with the tillage phase of the farming cycles, so samples were taken from a mixture of tilled and untilled portions. Another campaign was conducted on 18 December 2020 at the Vlakplaas farm, where some germination had already taken place in the sampled field however, only bare areas were sampled. Sampling was done randomly throughout the farm's fields. This was performed by taking three sub-samples using a gouge auger up to 10 cm deep per point, which corresponded to a single 10 m × 10 m Sentinel-2 pixel. In total, 41 soil samples (i.e., 123 sub-samples) were collected and weighed. Afterward these were oven-dried for 24 hr

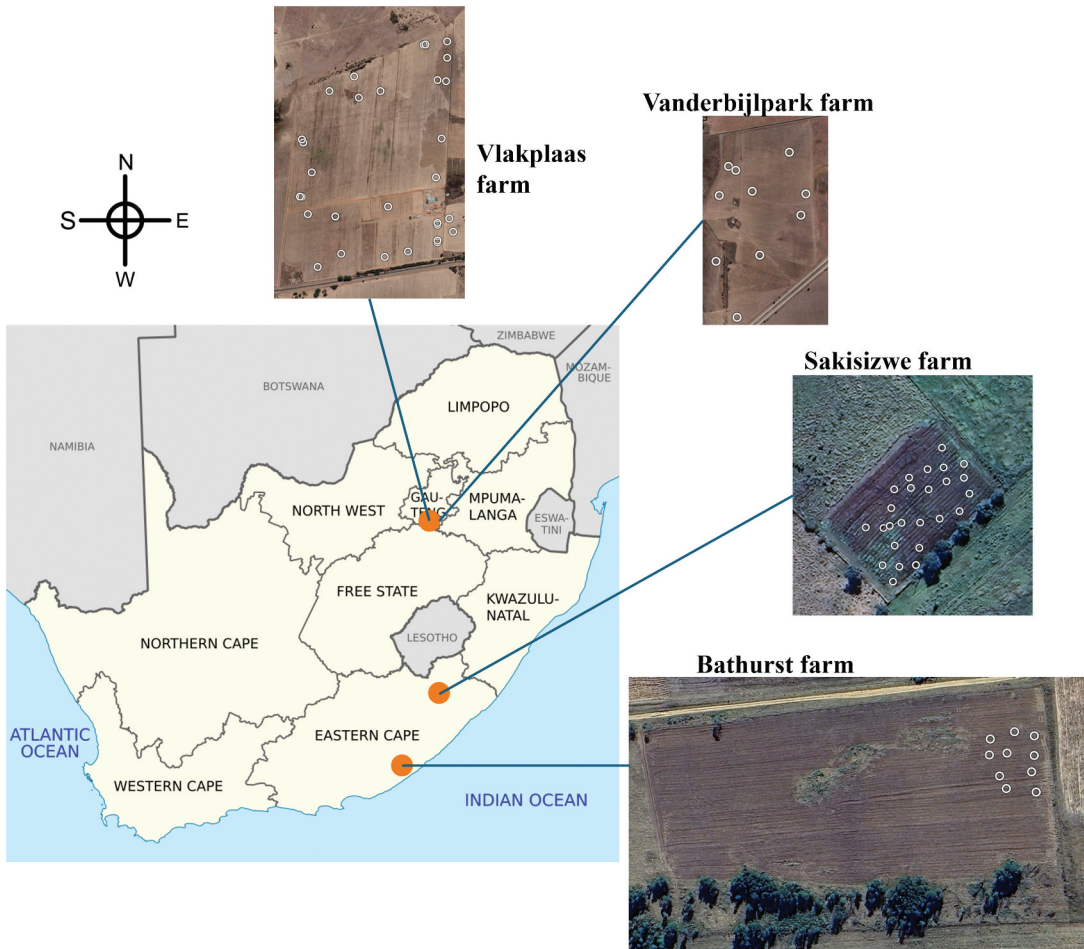


Figure 1. Four farms of soil collection in South Africa with 75 sample points.

at 80°C and weighed again to gauge the soil moisture content lost through drying. Volumetric soil moisture content was then calculated based on the wet and dry soil sample weights and the relative densities of the soils and water.

In contrast, soil moisture measurements for the Eastern Cape farms were carried out on 19 August 2024 at Sakhisizwe and on 22 August 2024 at Bathurst. Forty measurements were taken using a handheld SMT-100 soil moisture and temperature probe operated at a depth of 5 cm. This device records soil temperatures and volumetric soil moisture content. Coordinates for the measurements were recorded using a GPS. As demonstrated by Nieberding et al. (2023), the SMT-100's volumetric soil moisture readings generally remain within a 3% margin of true volumetric water content. Therefore, these volumetric weight readings can be used analogously to the true values from the first two sites.

Image acquisition and preprocessing

The research utilized 12-band Sentinel-2 sensor multispectral data. This imagery provides four bands (490 nm, 560 nm, 665 nm, and 842 nm) at a 10 m resolution, six bands (704 nm, 740 nm, 783 nm, 865 nm, 1610 nm, and 2200 nm) at a 20 m resolution, and three bands (442 nm, 943 nm, and 1374 nm) at a 60 m resolution. Sentinel-2 imagery with no cloud cover was obtained from the

Copernicus browser <https://browser.dataspace.copernicus.eu/> for the Vanderbijlpark/Vlakteplaas region for the dates 28 November 2019 and 20 December 2020. The same was done for the Bathurst region on 23 August 2024 and for the Sakhisizwe region on 19 August 2024. All of these images correspond to dates within 2 days of the field campaigns detailed in the previous section. The imagery was atmospherically corrected to top-of-canopy reflectances using the iCOR (image correction for atmospheric effects) algorithm available as a plugin within the SNAP (SentiNel Application Platform) toolbox. This correction uses a Moderate Resolution Atmospheric Transmission 5 (MODTRAN-5) look-up table (Berk et al. 2005) to perform its corrections. The Sentinel-2 imagery's metadata is used to retrieve the relevant MODTRAN-5 information such as the solar and viewing azimuth and zenith angles and the scene elevation (De Keukelaere et al. 2018). After this atmospheric correction, all bands were pansharpened to a $10\text{ m} \times 10\text{ m}$ resolution using the nearest neighbor tool in the ENVI 4.8 software.

Methodology

This study explores how accurately the BSM model can invert soil moisture content from Sentinel-2 spectra and their associated ratios using gradient boosting regression. Specifically, BSM spectra are simulated from specified parameter distributions, which are resampled to Sentinel-2 responses. All possible bands and pairwise ratios between bands are considered as the array of predictor variables. It is explored how well these predictor variables can be related to the BSM soil moisture content parameter through a gradient boosting regression method. The gradient boosting model is then applied to actual Sentinel-2 imagery to predict field-measured soil moisture levels, demonstrating the ratio's real-world tractability.

Brightness-shape-moisture model simulation

BSM spectra from 400 to 2400 nm were simulated for 20 000 model parameterizations $\Theta = [B, \varphi, \lambda]^T$ in line with the grassland parameter distribution suggested by Bonnet et al. (2024) as:

$$\hat{\Theta}_{\text{grassland}} \sim \mathcal{N}\left(\begin{bmatrix} 0.498 \\ -2.50 \\ 85.0 \end{bmatrix}, \begin{bmatrix} 0.012 & -0.077 & -0.112 \\ -0.077 & 6.38 & -0.724 \\ -0.112 & -0.724 & 17.6 \end{bmatrix}\right), \quad (1)$$

where B denotes the brightness parameter and φ and λ denote the soil spectral shape latitude and longitude parameters. Soil moisture content values SMp are randomly chosen from a uniform distribution between 0% and 20% soil moisture.

The simulated spectra generated by the parameters were resampled to the Sentinel-2B spectral bands using the Copernicus response function. This means the data are reduced to 12 spectral bands in line with true, atmospherically corrected bottom-of-atmosphere Sentinel-2 imagery.

Gradient boosting regression

Gradient boosting is a powerful technique for combining multiple base classifiers into an ensemble. The method was originally developed by Freund and Schapire (1996) for binary classification problems. This method utilizes AdaBoost (a blended word derived from 'adaptive boosting'), which can provide strong results even when base classifiers perform only slightly better than random guessing. Unlike normal committee methods such as bagging, gradient boosting differs in that the base classifiers are trained in sequence. Furthermore, weighting coefficients of the data points depend on the performance of previously run classifiers (Bishop and Nasrabadi 2006). In particular, previously misclassified points are given greater weight in the training of the next classifier in the sequence. Once

all the classifiers have been trained, their predictions are then combined through a weighted majority voting scheme.

Four parameters must be optimized to provide the lowest testing error. The number of boosting stages must be chosen to provide high accuracies without overspecification. The maximum depth is then chosen as the depth of the individual regression estimators or decision nodes in the tree, and the maximum number of features to be considered per decision is also optimized. Lastly, a learning rate is chosen as a step size to ensure numerical convergence to the minimized error rate.

Results

Testing accuracies were maximized via a grid search method using seven trees grown to a maximum depth of eight and three features per split, with a learning rate of 0.13. The simulated BSM table gives a coefficient of determination R^2 of 0.96 between simulated and modeled soil moisture contents.

When this same modeled gradient boosting predictor is applied to the field data, it is found that the coefficient of determination R^2 is 0.51 between the predicted and the field-measured soil moisture contents.

The gradient boosting results compared well to alternative estimation methods. Some of these are listed:

- A linear regression model trained on the simulated data yielded R^2 values of 0.988 and 0.013 for the simulated and real-world soil moisture content values. This is indicative of extreme over-specification. If the identified relevant predictor set $\left\{ \frac{B8}{B12}, \frac{B8A}{B12}, \frac{B11}{B12}, \frac{B12}{B8A}, \frac{B12}{B11}, B12 \right\}$ is used, these R^2 values become 0.94 and 0.159, respectively.
- A support vector machine was tried, optimized to a radial basis function kernel with $\gamma = 0.01$, $C = 1$, and $\epsilon = 6.3$. It yielded R^2 values of 0.82 and 0.44 for the simulated and real-world moisture contents. This too indicates some overspecification.
- A random forest regressor was optimized to 33 trees, pruned to a maximum depth of 4 nodes, and an uncapped number of features per node. This estimator yielded R^2 values of 0.80 and 0.47 against the simulated and real-world moisture contents.
- Two thousand linear regression models trained on 50 points of the field data yielded average training R^2 values of 0.9 and average testing R^2 values of 0.04. This changed to 0.55 and 0.34 using the best predictor set $\left\{ \frac{B6}{B12}, \frac{B7}{B12}, \frac{B8}{B12}, \frac{B8A}{B12}, \frac{B11}{B12}, \frac{B12}{B6}, \frac{B12}{B7}, \frac{B12}{B8}, \frac{B12}{B8A}, \frac{B12}{B11} \right\}$.

Figure 2 shows soil moisture content estimations linearly regressed from predicted values for BSM-simulated and actual Sentinel-2 spectra. These are plotted against the soil moisture content values in

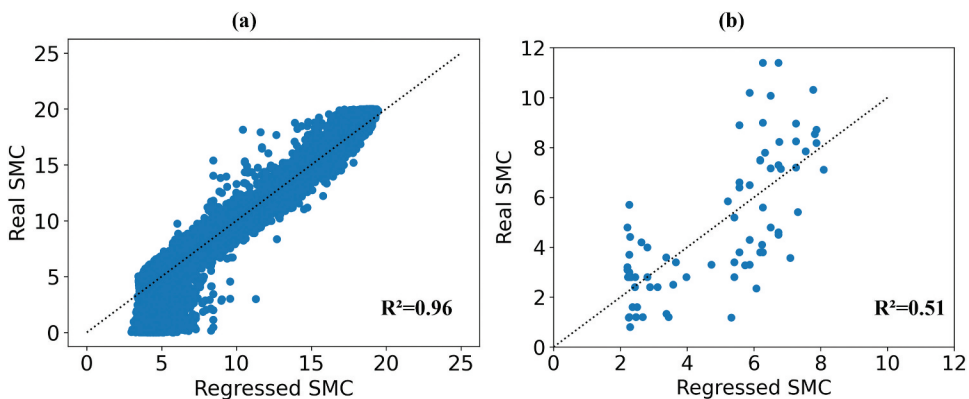


Figure 2. Regressed vs actual soil moisture content: (a) BSM-simulated Sentinel-2 spectra, and (b) actual Sentinel-2 spectra.

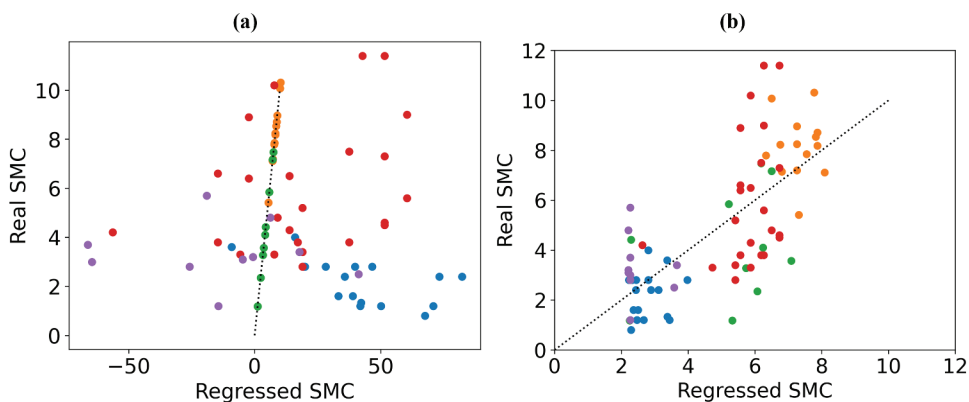


Figure 3. Regressed vs actual soil moisture content for points from different campaigns: (a) trained on the 2019 farm-sampled data, and (b) trained with BSM.

the simulated and field data cases. It is evident that a pattern exists between the regressed and the true soil moisture contents for both the simulated and real-world cases. This result is in line with the simulated and real correlation coefficients obtained above.

Figure 3 shows the linearly regressed soil moisture content estimations against the points categorized by the campaign. The model (a) is trained on in-field data from the 28 November 2019 campaign and the model (b) on the BSM model. Figure 3(a) demonstrates a model trained to perfect accuracy and collinearity from the training data (points appearing on the dotted line). However, the model did not hold for samples from other areas or even the same areas in a different season (other points). The BSM-trained model does not show this limitation, since the model is trained independently of field data, as can be seen in Figure 4 (b).

Outputted maps for soil moisture estimation are shown in Figure 4 for the different farms considered in this study. All farms showed soil moisture content levels between 0% and 9%. This

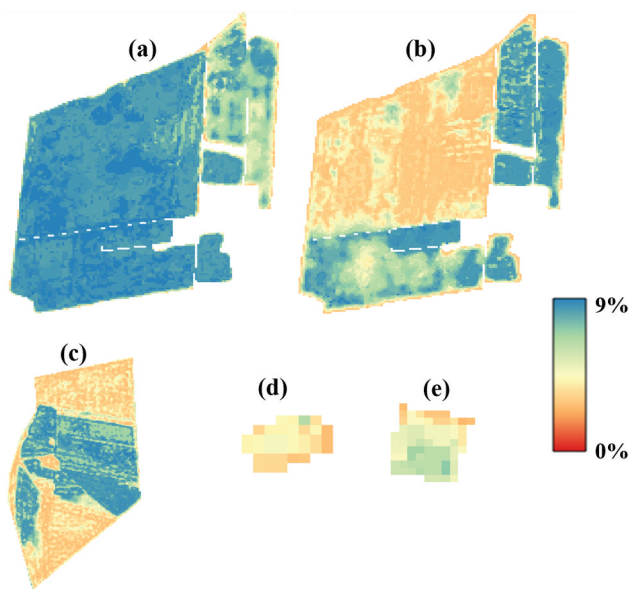


Figure 4. Derived soil moisture maps for farms: (a) Vlakplaas farm 2019, (b) Vlakplaas farm 2020, (c) Vanderbijlpark farm, (d) Bathurst farm, and (e) Sakhisizwe farm.

demonstrates that the model yielded values within a reasonable range of soil moistures. Zones within the Vanderbijlpark farm in 2019 and in the Vlakplaas farm in 2020, known to be vegetated, yielded soil moisture levels below 4 %. These are shown as the yellow and orange portions within the images. The accuracy of vegetation-covered readings may not be reliable, since the model does not yet account for the case where vegetation cover is present. Elsewhere, bare soils showed moistures of over 8%, in line with images captured within the wet season. This is especially visible in the western and southern fields of the Vlakplaas farm and in the central field of the Vanderbijlpark farm. The Sakhisizwe and Bathurst farms, which are unvegetated, showed soil moisture contents between 2.6 and 7.2 % and between 2.7 and 6.5 %, respectively, corresponding to the low moisture levels within the dry season.

Discussion

This research assessed the use of a BSM radiative transfer model look-up table, resampled to Sentinel-2 band returns, in predicting soil moisture content. A gradient boosting regression predictor was used to predict soil moisture content based on ratios of BSM-simulated bands. A coefficient of determination R^2 of 0.96 was achieved between parameterized BSM moisture content levels and the simulated spectra. The same predictor was utilized on true Sentinel-2 responses for testing against field-measured soil moisture content measurements. The results were found to transfer well to real-world Sentinel-2 data, with a coefficient of determination R^2 of 0.51. This means that a Pearson's correlation coefficient of over 0.7 is obtained, indicating a moderate-to-strong relationship between the predictions and the true moisture contents.

The gradient boosting regression predictor demonstrated favorable results compared to alternative methods. Higher R^2 values were obtained than those of support vector regression and random forest regression methods. The R^2 values were also shown to improve on the regression model trained on random samples from the field data.

The results compare favorably in their transferability against those of field-calibrated models. The model trained on data from one field campaign did not transfer to other sites or to the same site at a different time, despite being trained to perfect collinearity. This demonstrates the limitations of using empirical ratio-based models for soils and plants, which are generally not as robust across time and space (Darvishzadeh et al. 2008; Li et al. 2018; He et al. 2023).

However, the drop in the correlation coefficient when using simulated or field-measured Sentinel-2 data remains notable for all implemented algorithms. A number of geometric or spectral factors could be the cause. Field-measured spectra can be altered by differing sun-sensor-surface geometries (Jafarbiglu and Pourreza 2023). Else, aerosols or airborne particles may impair the spectral purity (Joshi et al. 2020). Sentinel-2's lower 10 m to 60 m spatial resolution and spatial resolution mismatches between the bands will also lead to mixed pixel effects (Recanatesi et al. 2025). Spatial resolution mismatches are particularly material in this context, due to the method's reliance on band ratios.

Soil moisture content maps could be created from Sentinel-2 imagery for the farms from which the soil samples were taken. Although these images were captured very far apart and on vastly different dates and seasons, the model rendered similar, reasonable soil moisture content values.

The estimation of soil properties using Sentinel-2 has previously been explored in the literature. For example, Gholizadeh et al. (2018), Castaldi et al. (2019) and Lin et al. (2020) have explored soil organic content estimation. However, the subtropical soils within southern Africa have not been explored in this manner.

This soil moisture estimation mechanism uses only a Sentinel-2 resampled look-up table as its input. Since Sentinel-2 data are readily available in line with satellite overpasses, soil moisture can be effectively mapped on an ongoing basis. RTM methods are also transferable, and the BSM model is constructed from soil spectra gathered all over the world. Therefore, the methodology can be scaled to

larger regions or zones and can be replicated for any biome if suitable BSM parameterizations can be found.

The accuracy of soil moisture content estimation for broader regions has not been assessed, which may include built-up areas or water bodies within the landscape. Added to this, simulations were only made for entirely bare soils without crop or vegetation cover. This is not an accurate representation of most landscapes worldwide, since it is likely that some cover would be present. This limitation is already apparent in [Figure 4\(b,c\)](#), where soil moisture estimations are warped due to vegetation cover. The BSM model has already been demonstrated to integrate well with the PROSAIL canopy RTM in South African vegetated canopy simulations (Bonnet et al. 2026), so the estimation of soil moisture content under vegetation cover simulated through the PROSAIL canopy model would represent a good opportunity for subsequent research.

Conclusion

In this study, a grassland-specific BSM radiative transfer model look-up table, resampled to Sentinel-2 band returns, was used to predict soil moisture content. A gradient boosting regression predictor was applied to the simulated bands' ratios to provide a predictor of soil moisture content. The key findings were as follows:

- Gradient boosting regression could be applied to the simulated Sentinel-2 spectra for soil moisture estimation. A coefficient of determination of 0.96 was achieved against BSM input values.
- The gradient boosting model was found to be transferable to real-world Sentinel-2 data. A correlation coefficient of 0.51 was obtained between the model outputs and measured soil moisture contents.
- The gradient boosting model's results compared favorably against other prediction methods such as linear regression, support vector regression, and random forest predictors.
- A realistic representation of soil moisture levels on the sampled farms could be created based on the gradient boosting model outputs for non-vegetated areas.

The results demonstrate the utility of the BSM model in defining soil moisture content estimators. A gradient boosting model has also been proposed without requiring calibration to in-field data. These insights will prove valuable for the advancement of ongoing remotely sensed soil monitoring and management through its alignment to an ongoing data source.

Author contributions

CRedit: **Wessel Bonnet**: Conceptualization, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing; **Moses Azong Cho**: Conceptualization, Investigation, Methodology, Project administration, Resources, Supervision, Writing – original draft; **Yonwaba Atyosi**: Data curation, Investigation; **Nobuhle Patience Majozi**: Data curation, Investigation; **Paxie Wanangwa Chirwa**: Supervision.

Nomenclature

AdaBoost	Adaptive Boosting
BSM	Brightness-Shape-Moisture
iCOR	image correction for atmospheric effects
MODTRAN	Moderate Resolution Atmospheric Transmission
RTM	Radiative Transfer Model
SCOPE	Soil Canopy Observation, Photochemistry and Energy fluxes

B	Soil brightness parameter
φ	Soil spectral shape latitude parameter
λ	Soil spectral shape longitude parameter
Θ	Brightness-Shape-Moisture parameter vector $[B, \varphi, \lambda]^T$
$\Theta_{\text{grassland}}$	Θ parameterization for the Southern African grassland biome

Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability statement

The data that support the study's findings are available upon reasonable request from the authors.

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