Development of a transferrable hybrid retrieval model for mapping sweet potato chlorophyll at matured growth stage using ultra high-resolution UAV data

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Abstract

Smallholder farmers play a critical role in the growing of underutilized crops, such as sweet potato. Obtaining accurate maps of sweet potato biophysical variables is essential for farmers to assess and monitor crop health at different growth stages. Integrating radiative transfer model (RTM) data with vegetation indices (VIs) based on unmanned aerial vehicle (UAV) data, may have the potential for accurately estimating leaf chlorophyll concentration (LCC) across multiple crop varieties. Firstly, in this paper we developed and tested varying hybrid retrieval models by combining PROSAIL RTMs with broadband, narrowband and leaf-pigment VIs applied to 2-cm resolution UAV imagery, to retrieve LCC over 20 sweet potato varieties at 120 days i.e. matured growth stage. Secondly, the best hybrid retrieval model was transferred to a different site which contain similar sweet potato varieties at matured growth stage for the estimation of sweet potato LCC. Results show that the most accurate retrievals of LCC were achieved by integrating a larger database containing 11000 PROSAIL simulated reflectance samples with broadband indices, particularly the enhanced vegetation index (EVI) with coefficient of determination (R^2) of 0.85, root mean squared error (RMSE) of 5.93 µg/cm^2, and relative RMSE (RRMSE) of 9.87%. Furthermore, when transferred to a different site containing similar sweet potato varieties at matured growth stage, this model achieved 60% agreement with field LCC measurements and responded fairly well by capturing LCC variability. These findings have significant implications in sweet potato breeding programmes for developing new cultivars.

1. Introduction

Smallholder farmers play a critical role in the growing of underutilized crops which have the potential address food security and sustainable rural development (Ndlovu et al., 2025). Sweet potato (*Ipomoea batatas L.*) is one of the essential crops that are regarded as globally underutilized. Given its high nutritional value in comparison to staple crops such as maize and wheat, it has the potential to address (i) malnutrition in vulnerable populations and (ii) the urgency for sustainable food supply which is at risk from climate change. Furthermore, the Food and Agriculture Organization (FAO) envisions the global population to reach 9.7 billion by 2050, and this may require about 1.7 times more food than today (Kim et al., 2018). Sweet potato as a climate-resilient and nutrient-dense crop (Mounika et al., 2025) could aid in addressing food, energy and environmental challenges which supports Sustainable Development Goals 1 (No Poverty), 2 (Zero Hunger) and 13 (climate action) (Afzal et al., 2021). In recent years, the production and consumption of sweet potato has been on the rise, and therefore, precision agriculture will ensure that productivity is increased in an efficient and effective way (Sishodia et al., 2020).

The retrieval of plant biophysical variables such as chlorophyll and leaf area index (LAI) could assist farmers in assessing and monitoring crops at different growth stages (Yin et al., 2023, Li et al., 2024). In particular, the accurate retrieval of chlorophyll is critical for understanding crop health condition and growth, and thus can provide an indirect measure of the crop nutrient status. Remote sensing with unmanned aerial vehicles (UAVs) can replace laborious, costly, and destructive on-the-ground surveys. This technique provides high-resolution imagery with adjustable scheduling, which is ideal for assessing and mapping crop biophysical parameters such as the leaf chlorophyll content (LCC) in breeding and field trial plots (Li et al., 2024).

The retrieval of plant biophysical variables from remotely sensed data, is carried out using two approaches, namely statistical and physically-based models. In particular, statistical modelling involve the use of parametric and/or non-parametric methods. This involves for example, the fitting of a linear or non-linear function to explore the relationship between the target variable of interest and UAV or satellite-derived measurements. However, statistical (also called empirical) models are known to be site, season and data specific, and normally requires a lot of *in-situ* data.

In contrast, physically-based models also known as radiative transfer models (RTMs) have low dependence on ground-based measurements because they rely on physical laws to model canopy reflectance spectra accurately, as a function of viewing and illumination geometries, leaf, canopy and soil background characteristics (Jacquemoud et al., 2009). Given the excessive

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costs associated with *in-situ* data collection for obtaining extensive training sets, RTMs are regarded as better alternatives for developing transferrable models across different geographic sites for retrieving and mapping vegetation biophysical parameters.

Numerous studies have explored the integrated use of RTMs with machine learning algorithms and vegetation indices (VIs) on UAV imagery for the estimation of crop biophysical variables (Li et al., 2024, Chakhvashvili et al., 2022, Jay et al., 2019, Duan et al., 2014). However, these studies primarily focused on crops like maize, wheat, sugar beet, potato, and sunflower, and typically examined only one cultivar or a very limited number of cultivars or varieties per crop. There is very few emerging studies based on statistical modelling for sweet potato phenotyping and yield prediction (Ramírez et al., 2023, Tedesco et al., 2021). Based on reviewed literature thus far, there is no study that explored the aforementioned integration approach to develop a transferrable hybrid retrieval model for mapping sweet potato chlorophyll at matured growth stage using ultra high-resolution UAV data.

The aim of this study was to develop a transferrable hybrid model based on integrating PROSAIL RTM data with VIs using drone-based multispectral data to estimate LCC over 20 sweet potato varieties and their replicates at a matured growth stage (120 days after planting). Furthermore, the specific objectives of this study were to: (i) generate PROSAIL databases containing varying synthetic reflectance samples i.e. of 1500, 5000, 9000 and 11000 to determine the optimal size for LCC inversion, (ii) Combine PROSAIL simulations with broadband, narrowband and leaf pigment VIs for the estimation of sweet potato LCC, (iii) determine the best performing RTM VI-based model for accurately retrieving LCC in site-one, and (vi) test model robustness by transferring it to a different site for retrieving LCC.

Overall, this study hypothesises that hybrid retrieval schemes based on RTMs and VIs can provide adequate accuracies when transferred across different sites for the estimation of crop biophysical variables.

2. Study area

The main study area (Figure 1) covered an area of approximately 500 m^2 located between 28°15'36.07"E, 25°44'59.43"S and 28°15'37.39"E, 25°44'59.83"S at the experimental farm at Innovation Africa within the University of Pretoria, South Africa. This study site, also referred to as site-one is represented by a drone composite image showing the 20 sweet potato breeding lines per highlighted row with three replicates, which makes a total of 60 sweet potato varieties.

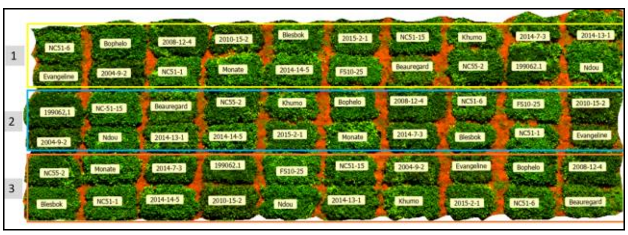

Figure 1. True colour UAV composite image captured at matured stage (120 days after planting).

3. Data sets used

3.1 Chlorophyll measurements

LCC field measurements of the sweet potato breeding lines were taken using the SPAD 502 Plus chlorophyll meter on 27 May 2024 at a matured growth stage (Table 1).

Table 1. Summary statistics of the field LCC (µg.cm^{-2}) over 20 sweet potato varieties planted in 60 compartments at the experimental farm. The variable ‘StDev’ denotes the standard deviation.

Data collection date	Number of samples	Min.	Max.	Ave.	StDev
27 May 2024	60	42.85	125.15	59.90	14.75

The SPAD unitless readings were converted into µg.cm^{-2} by applying the following empirical calibration method proposed by Cerovic et al. (2012):

$$LCC = \frac{99 \times SPAD}{144 - SPAD} \quad (1)$$

where SPAD denotes the leaf chlorophyll reading taken using the SPAD meter, and LCC denotes the converted chlorophyll in µg.cm^{-2}.

3.2 UAV data and pre-processing

Multispectral imagery of the sweet potato field was captured on 27 May 2024 using a DJI Matrice 300 drone equipped with a Micasense RedEdge-P camera and a Downwelling Light Sensor 2 (DLS-2). (Figure 2). The Micasense RedEdge-P sensor records data in 5 multispectral bands and 1 panchromatic band, though the panchromatic band was omitted from the analysis. The camera has a resolution of 1456 x 1088 (i.e. 1.58 megapixels per multispectral band) coupled with a horizontal and vertical field of view of 49.6° x 38.3° respectively. In this study, it was flown at an altitude above ground (AGL) of 30 m covering a ground sampling distance (GSD) of 1.9 cm.

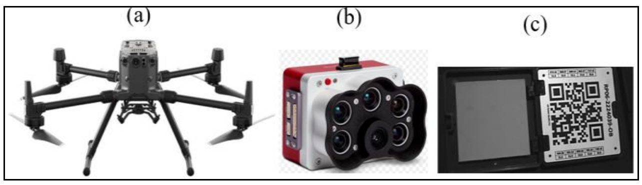

Figure 2. The instruments employed for UAV multispectral imagery acquisition were: (a) DJI Matrice 300 UAV, (b) Micasense RedEdge-P camera, and (c) MicaSense Calibrated Reflectance Panel..

Prior the flight, the UAV was connected to the DJI D-RTK 2 Mobile Station which provides the UAV with real-time differential corrections for generating sub-centimeter level positioning data. The UAV flight mission was carried out on a clear day during 11:30 a.m.–12:30 p.m., selected as the optimal period for reduced shadows and stable solar illumination. The multispectral camera was used to capture images of the MicaSense Calibrated Reflectance Panel (CRP) immediately before and after the UAV flight mission. These images were later used in Agisoft software to calibrate the reflectance of the multispectral data (Figure 3).

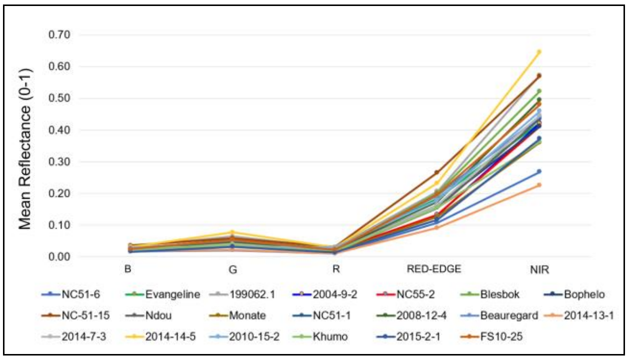

Figure 3. Mean reflectance spectra of 20 sweet potato varieties at maturity stage, obtained from the 27 May 2024 UAV image corresponding to 120 days post-planting.

4. Methods used

4.1 Methodology overview

A summary of the methodology implemented in this study is presented in Figure 4 and discussed in various sections of this paper.

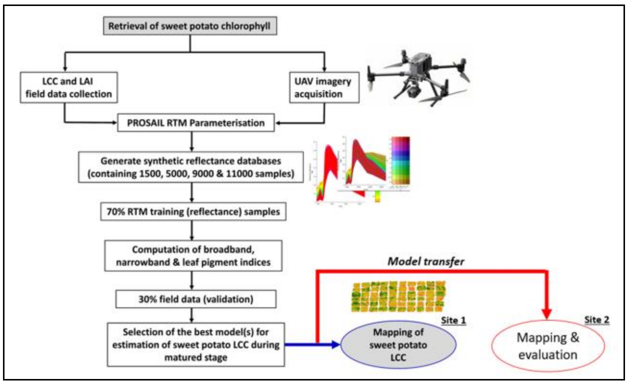

Figure 4. Overview of the methodology for developing a transferrable hybrid retrieval model for mapping sweet potato chlorophyll.

4.2 PROSAIL parameterization and synthetic spectral databases

The PROSPECT and SAIL (hereafter PROSAIL) RTM models (Jacquemoud et al., 2009) as well as the Spectral Index (SI) assessment toolbox are available in Automated Radiative Transfer Models Operator (ARTMO) (https://artmotoolbox.com/) which can be excuted in Matlab. Synthetic reflectance samples for the sweet potato varieties were generated using PROSAIL in ARTMO, with model parameters largely based on site-specific inputs. For example, during parameterisation, the range values for LCC and LAI were based on actual field measurements (Table 1). During the UAV flight, parameters describing sun-target-sensor geometry such as solar zenith angle and sensor viewing angle, were computed during UAV flight time.

Furthermore, the range values for the remaining PROSAIL parameters were obtained by conducting in-field observations and taking samples to the lab. For example, dry matter content was measured by considering the difference between the original and dry weights of the sweet potato leaves. The equivalent water thickness (EWT) was estimated using the following expression by Féret et al. (2019):

$$\mathrm{EWT} = \frac{\mathrm{FW} - \mathrm{DW}}{\mathrm{A}} \tag{2}$$

where FW denotes leaf fresh mass, DW denotes leaf dry mass and the denominator A represents leaf area (cm).

Moreover, soil brightness coefficient values were calculated from the UAV’s red and green bands via the soil brightness index equation described in Marques et al. (2020). Comprehensive details on the PROSAIL parameterisation is reported in Tsele et al. (2025). PROSAIL databases containing varying synthetic reflectance samples i.e. of 1500, 5000, 9000 and 11000 were generated to determine the optimal size for LCC inversion, as well as to assess their influence on LCC retrieval performance.

4.3 Vegetation indices, fitting functions, training and validation

Ten commonly used vegetation indices (VIs) in assessing crop vigour were chosen (Rivera et al., 2014). They were tested on different PROSAIL simulation databases for the estimation of sweet potato LCC. The VIs considered for evaluation in this study are categorised as follows:

(i) Broadband VIs which comprised simple ratio (SR), normalized difference vegetation index (NDVI), enhanced vegetation index (EVI) and green NDVI (GNDVI);
(ii) Narrowband VIs which included the modified normalized vegetation index (mNDVI), greenness index (GI) and green vegetation index (GVI). In particular, the mNDVI uses the red-edge, near-infrared and blue bands in its mathematical expression; whereas the latter two indices uses the green and red bands only;
(iii) Leaf pigment VIs which consists of the anthocyanin reflectance index (ARI), blue-green pigment index (BGI) and blue-red pigment index (BRI).

In particular, 70% of the RTM reflectance data (from each database separately) was used for training the VI-based models coupled with varying fitting functions such as linear, logarithmic and polynomial. In particular, this random selection of 70% of RTM data from each PROSAIL database led to synthetic reflectance samples of 1050, 3500, 6300 and 7700 that were available for training and optimizing the retrieval performance of the VIs. It is worth mentioning, the idea of selecting 70% of RTM data for training was due to the challenge of RTM data known to have redundant and potentially outlying samples which do not improve on the prediction accuracy of the resulting regression model (Verrelst et al., 2016).

Furthermore, 30% of the field LCC data (Table 1) was used to validate the performance of the VI-based retrieval models. The best performing RTM VI-based model was used to estimate LCC in site-one (Figure 1), and subsequently transferred to a different site to test the robustness of the model.

5. Results and discussion

5.1 LCC retrieval performance across broadband indices and four PROSAIL simulation databases

Results in Table 2 reveal varying retrievals accuracies of sweet potato LCC when each of the four broadband indices were applied to four PROSAIL simulation databases, through different fitting functions i.e. linear, logarithmic and polynomial$_2$. The retrieval accuracies are summarised in-terms of the minimum and maximum values of R^2, RMSE and RRMSE under each simulation database.

The most accurate retrievals of LCC over the heterogeneous sweet potato canopy during matured growth stage, were achieved by integrating larger (11000) PROSAIL simulations with EVI coupled with non-linear fitting models. Integrating lesser PROSAIL simulations (i.e., of 1500, 5000, and 9000 reflectance samples) with the EVI, SR, NDVI and GNDVI showed deteriorating LCC retrieval performance (Table 2).

Table 2. Summary of the LCC retrieval performance across four broadband indices.

Metric (min - max)	PROSAIL Simulations			
	1500	5000	9000	11000
R^2	0.57 – 0.59	0.72 – 0.78	0.75 – 0.83	0.7 – 0.85
RMSE (µg.cm^{-2})	8.74 – 10.16	7.12 – 7.74	6.22 – 7.27	5.93 – 7.25
RRMSE (%)	14.71 – 17.11	11.94 – 12.98	10.40 – 12.15	9.87 – 12.09

Table 3. Best model based on EVI and 11000 PROSAIL simulations.

Index	Coefficients	R^2	RMSE (µg.cm^{-2})	RRMSE (%)
EVI	a_2 = 6736.45; a_1 = 1057.63; a_0 = 81.40	0.85	5.93	9.87

Furthermore, during the matured stage (in 120 days) the highest LCC retrieval accuracy was found with an R^2 of 0.85, RMSE of 5.93 µg.cm^{-2} and RRMSE of 9.87% (Table 3). The polynomial$_2$ fitting function provided higher regression accuracy relative to the linear and logarithmic curve-fitting models. These findings suggest that EVI works well in a dense sweet potato field and is resistant to saturation unlike other broadband indices.

5.2 LCC retrieval performance across narrowband indices and four PROSAIL simulation databases

Table 4 show varying retrievals accuracies of sweet potato LCC when each of the three narrowband indices (mNDVI, GI and GVI) were applied to four PROSAIL simulation databases, through different fitting functions i.e. linear, logarithmic and polynomial$_2$. The retrieval accuracies are summarised in-terms of the minimum and maximum values of R^2, RMSE and RRMSE under each simulation database.

Table 4. Summary of the LCC retrieval performance across four narrowband indices.

Metric (min - max)	PROSAIL Simulations			
	1500	5000	9000	11000
R^2	0.57 – 0.63	0.72 – 0.79	0.75 – 0.82	0.76 – 0.84
RMSE (µg.cm^{-2})	8.64 – 9.58	6.72 – 7.74	6.19 – 7.27	5.95 – 7.25
RRMSE (%)	14.54 – 16.13	11.27 – 12.98	10.34 – 12.15	9.91 – 12.09

The most accurate retrievals of LCC over the 20 sweet potato varieties during matured growth stage, were achieved by integrating larger (11000) PROSAIL simulations with mNDVI coupled with a polynomial$_2$ fitting function (Table 4). A higher LCC retrieval accuracy was found with an R^2 of 0.84, RMSE of 5.95 µg.cm^{-2} and RRMSE of 9.91% (Table 5). In addition, the polynomial$_2$ curve-fitting model contributed to the aforementioned regression accuracy better than the linear and logarithmic fitting models.

Table 5. Best model based on mNDVI and 11000 PROSAIL simulations.

Index	Coefficients	R^2	RMSE (µg.cm^{-2})	RRMSE (%)
mNDVI	a_2 = 2174.82; a_1 = 1376.25; a_0 = 260.22	0.84	5.95	9.91

An attempt to integrate lesser PROSAIL simulations i.e. below 11000 synthetic reflectance samples with the mNDVI, GI and GVI showed deteriorating LCC retrieval performance over 20 sweet potato varieties during matured growth stages. These findings demonstrated the sensitivity of the red-edge based mNDVI to increased sweet potato foliage and canopy density (Table 5).

5.3 LCC retrieval performance across leaf pigment indices and four PROSAIL simulation databases

Similar trend is observed in Table 6 where larger (11000) PROSAIL simulations yielded higher retrieval accuracies for all three leaf pigment indices i.e. ARI, BGI and BRI. The non-linear curve-fitting models (especially logarithmic and polynomial$_2$) largely contributed to the aforementioned retrieval accuracies better than the linear model. All PROSAIL simulations below 11000 showed declining LCC retrieval performance.

Table 6. Summary of the LCC retrieval performance across three leaf pigment indices.

Metric (min - max)	PROSAIL Simulations			
	1500	5000	9000	11000
R^2	0.36 – 0.59	0.49 – 0.77	0.50 – 0.81	0.51 – 0.83
RMSE (µg.cm^{-2})	9.18 – 11.01	7.12 – 10.39	6.39 – 10.26	6.18 – 10.36
RRMSE	15.46 –	11.94 –	10.68 –	10.30 –

(%)	18.54	17.43	17.16	17.26

Table 7. Best model based on BGI and 11000 PROSAIL simulations.

Index	Coefficients	R^2	RMSE ($\mu g.cm^{-2}$)	RRMSE (%)
BGI	a_2 = 713.91; a_1 = -861.76; a_0= 303.74	0.83	6.18	10.30

In all three leaf pigment indices, the BGI yielded the best LCC retrieval accuracy with an R^2 of 0.83, RMSE of 6.18 $\mu g.cm^{-2}$ and RRMSE of 10.30% (Table 7). The polynomial$_2$ fitting function provided higher regression accuracy compared to both linear and logarithmic curve-fitting models (Table 7).

5.4 Spatial prediction of sweet potato LCC in site-one

The top performing hybrid retrieval model (Table 3) for LCC over 20 sweet potato varieties during the matured growth is expressed as follows:

$$LCC_{120days} = 6736.45 \times EVI^2 + 1057.63 \times EVI + 81.40 \quad (3)$$

This model was used to spatially predict LCC in site-one over multiple sweet potato varieties (Figure 5). In particular, the model captured more variability as shown by the spatial distribution of LCC across the varieties.

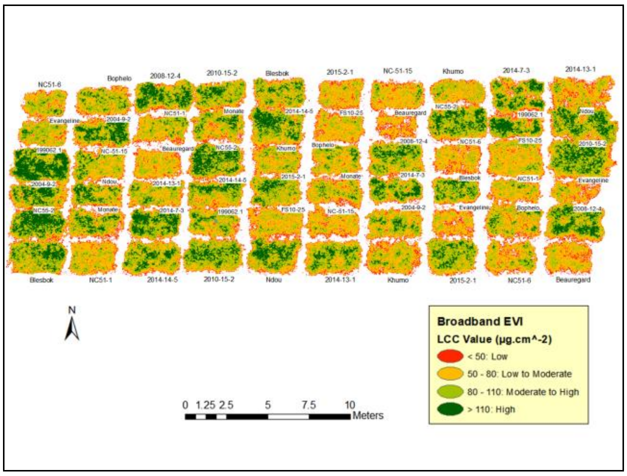

Figure 5. Spatial prediction of LCC in site-one during matured stage over 20 sweet potato varieties and their replicates.

For example, the model consistently predicted low LCC, mostly for low lying leaves along the edges of the sweet potato blocks, possibly due to their little to non-exposure to direct sunlight. The model prediction of moderate-to-high LCC, to a large extent appeared to be consistent across the different varieties and their replicates such as Blesbok, Beauregard, Evangeline, Khumo, Ndou, NC-51-15, NC55-2, FS10-25 and 199062.1 (Figure 5). Overall, prediction map of site-one showed realistic patterns of LCC variability over the sweet potato varieties at matured growth stage.

5.5 Model transferability performance

The site-one EVI-based model presented in section 5.4 was transferred to site-two (Figure 6) for prediction of LCC over similar sweet potato varieties also at matured growth stage.

Figure 6. UAV image of site-two captured on 09 May 2025 during matured growth stage.

Site-two is situated about 25 km north of site-one, and is located between 28°21'55.05"E, 25°36'2.55"S and 28°21'54.73"E, 25°36'3.79"S at the Vegetable, Industrial and Medicinal Plant (VIMP) Roodeplaat campus of the Agricultural Research Council in South Africa (Figure 6).

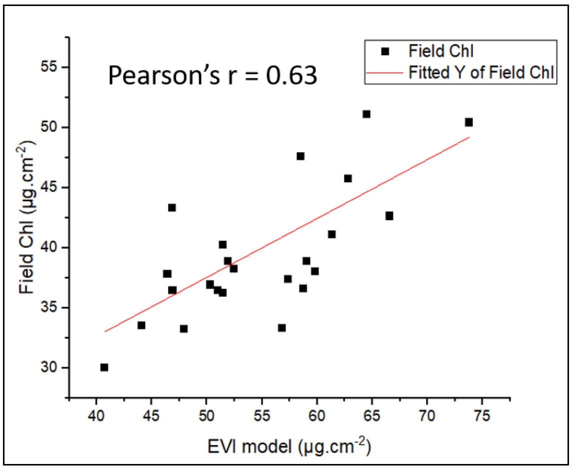

Figure 7. Comparison between field measured and model predicted LCC in site-two.

The model transferability results show that the estimated LCC had about 63% agreement with field chlorophyll data in site-two (Figure 7). Furthermore, there was a notable trend of agreement between the fluctuating estimates of LCC and field data across all sweet potato varieties (Figure 8). The agreement was strongest for the 199062.1 and 2004-9-2 varieties followed by the 2018-1-2, FS10-25, 2018-9-2 and Beauregard varieties.

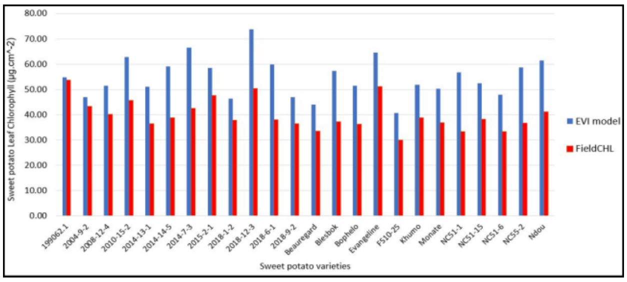

Figure 8. Histogram showing the trends in agreement between the predicted LCC (EVI model) and field LCC (FieldCHL) in site-two across the 20 sweet potato varieties and their replicates.

These findings suggests that the model responded fairly well by capturing LCC variability across the sweet-potato varieties in site-two. Furthermore, this hybrid retrieval model based on the integration of RTMs, VIs and UAV imagery can potentially provide adequate accuracies when transferred across different sites for the estimation of sweet potato chlorophyll at matured growth stage.

6. Conclusion

Overall, our findings demonstrated that the integration of larger PROSAIL simulation reflectance samples with VIs on UAV imagery may be appropriate for the accurate retrieval and monitoring of multi-variety sweet potato LCC, especially during the matured growth stage. Furthermore, the developed hybrid retrieval model in this study could provide adequate accuracies when transferred to a different site for the estimation of sweet potato LCC. This robust performance was partly due to the RTM local parameterization efforts undertaken in this study. This is an important aspect to consider in order to simulate the reflectance of a heterogeneous canopy accurately (Atzberger et al., 2015). Development of transferable models for vegetation biophysical parameter estimation are important, because gathering large training datasets in the field is prohibitively expensive. (Tsele et al., 2023).

Recommendations to improve the obtained results may entail exploring (i) various broadband, narrowband and leaf pigment-based VIs and (ii) more recent versions of the PROSPECT model e.g. PROSPECT-5 and PROSPECT-D, and incorporating lab-based sweet potato measurements such as carotenoids and anthocyanin into the parameterization of PROSAIL RTM. This work has significant implications for use in sweet potato breeding programmes, and precise mapping of sweet potato biophysical variables needed to monitor crop development at various growth stages.

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