Empirical modelling for retrieval of foliar traits in cotton crop using spatial data

Ramandeep Kaur M. Malhi and G. Sandhya Kiran*

Ecophysiology and RS-GIS Lab, Department of Botany, Faculty of Science, The Maharaja Sayajirao University of Baroda, Vadodara 390 002, India

The present study conducted in cotton fields of Vadodara district, Gujarat, India during *kharif* season of 2009–10, aimed at assessing foliar traits, in particular crop leaf area index (LAI) and chlorophyll content (CC) from space-borne optical LANDSAT 5 TM and IRS LISS-IV satellite data. Field measurements of these foliar traits coinciding with the dates of the satellite data for cotton were used for validation of RS-based VI–LAI and VI–CC empirical models developed in the present study. These models developed for LAI estimation in cotton crop showed good correlation with R^2 varying from 0.592 to 0.805, and CC between 0.585 and 0.746 with P at 0.01 level in both cases. It has been observed that the potential of NDVI–LAI and NDVI–CC empirical models was better compared to RVI–LAI and RVI–CC models. The VI–LAI and VI–CC models derived from LISS-IV data were better estimators of LAI compared to LANDSAT. A high R^2 value between ground-measured foliar traits and those predicted using empirical models complemented the validation.

Keywords: Cotton crop, empirical models, foliar trait, spatial data.

AGRICULTURAL, ecological and meteorological applications require an accurate quantitative estimation of canopy foliar traits – in particular vegetation biochemical and biophysical variables[1,2]. Information about the spatial and temporal distribution of these traits provides an important input for various models quantifying the exchange of energy and matter between the land surface and the atmosphere. The knowledge of these traits is of prime interest in many applications related to crop function modelling, evapotranspiration, crop growth modelling and yield prediction. These traits also aid in predicting the soil–vegetation–atmosphere energy transfers. Even at a much smaller scale, as in precision farming and water management, these traits play a critical role to describe the state of crop development and water needs. Measurement of these traits during the growing season also provides an opportunity for improving grain yields and quality by site-specific application of fertilizers. Among the many canopy foliar traits, leaf area index (LAI) and chlorophyll content (CC) are of prime importance.

LAI, an important biophysical parameter characterizing a canopy, is the total one-sided area of leaf tissue per unit ground surface area[3]. It has a key role as one of the surface parameters in climate, weather and ecological studies as it influences vegetation photosynthesis, transpiration and the energy balance of canopies[4]. It serves as an important input to the ecosystem productivity models operating at landscape to global scales[5], and also as an interacting component in general circulation models[6]. Estimation of LAI is critical for understanding and quantitatively analysing many physical and biological processes that are related to vegetation dynamics, global carbon cycle and climate.

Chlorophyll is the earth's most important organic molecule and one of the most important biochemicals in the leaves of plants. The CC within a vegetation canopy is positively related to both vegetation productivity and its health[7]. It holds significance since it controls photosynthetic potential[8] and, consequently, primary production as CC has a dominant control upon the amount of solar radiation absorbed by the leaves[9]. It is also an important indicator of nutritional stress[10–13]. Thus estimation of CC can provide an accurate and indirect estimate of plant nutrient status, especially nitrogen, because the molecular structure of chlorophyll incorporates a large proportion of total leaf nitrogen[14–16]. CC in leaves is an indicator of nitrogen content, as it is dependent on soil nitrogen availability to a great extent and also on crop nitrogen uptake. Hence, this foliar trait in agricultural fields can prove to be of immense use. Estimates of this parameter can help farmers and agronomists make management decisions related to nitrogen supply at critical growth stages.

Undoubtedly conventional methods of estimating LAI and CC are cumbersome, tedious, time-consuming at the global scale. In this context, information regarding these traits extracted from satellite data has better potential[17,18]. Approaches for the estimation of CC and LAI from remotely sensed data are based either on the inversion of physically based models[19–27] or improved relationships between these traits and spectral indices[28–37]. In the former model approach, simulation of canopy reflectance is performed, followed by quantitative relationships between remotely sensed data and canopy attributes for inversion purposes. Approaches using spectral indices rely on the establishment of empirical relationships between ground-measured foliar traits and observed spectral reflectances.

Vegetation index (VI)–LAI and VI–CC models for cotton crop using LANDSAT 5 TM and IRS LISS-IV reflectance data have been developed in the present study.

The study was conducted in the cotton fields of Vadodara district, Gujarat, India (Figure 1). The district lies between 21°45′–22°45′N and 72°48′–74°15′E, having a geographical area of 7550 sq. km. Major part of the

*For correspondence. (e-mail: ecorsgis12@gmail.com)

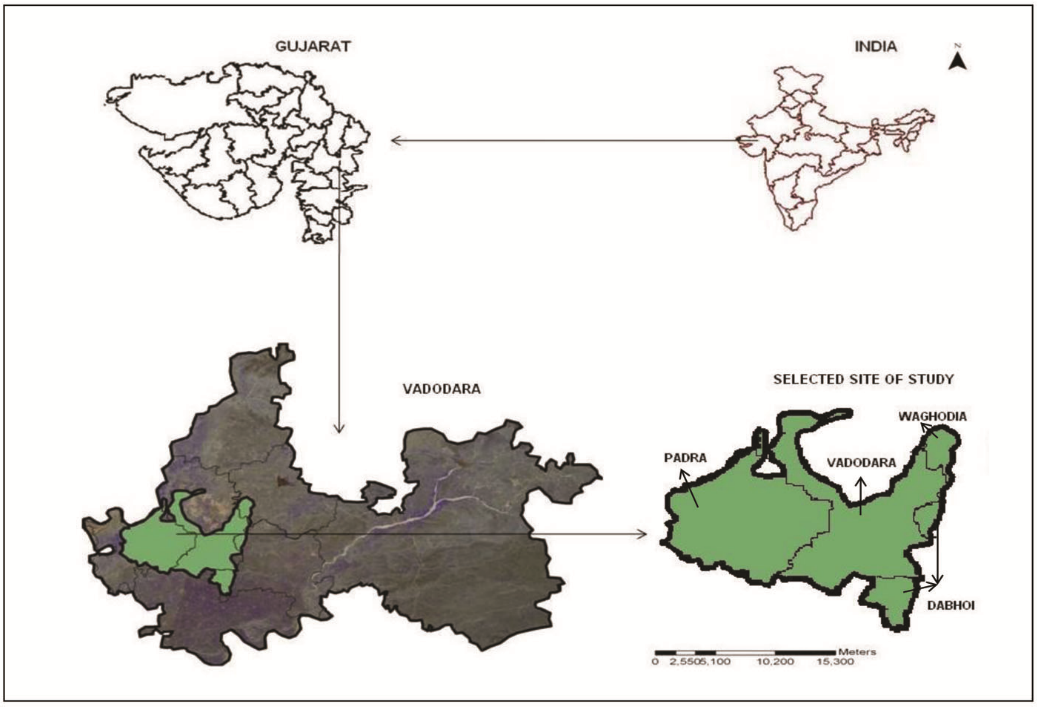

Figure 1. Map showing location of the study area.

study area is covered by alluvial soil which is fertile and thus suitable for agriculture.

Generally, the climate of Vadodara district during major part of the year is characterized by a hot weather and humidity. During winter season, it is not too cold in the district with temperature remaining over 10°C. January is the coldest month of the year, with mean daily maximum and minimum temperature of 30.1°C and 10.8°C respectively. It is hot during March to October, with temperatures hovering over 35°C, with little respite during monsoon in June, which lasts till the end of September. May is the hottest month of the year with mean daily maximum and minimum temperature of 40.7°C and 26.1°C respectively. During the last ten years, average rainfall has been recorded in the range of 1000–1200 mm. October and November are considered as the post-monsoon period.

Based on India Meteorological Department (IMD) data, it was observed that predominant wind direction during winter season (October–April) was from northeast and northwest directions, whereas during summer, it was from west and southwest directions. The general weather conditions were conducive to good agriculture (both *kharif* and *rabi* harvest).

LAI of cotton crop was measured using the plant canopy analyser (LAI-2000; LI COR Inc., Lincoln, NE, USA). This is a portable field instrument that simultaneously measures diffuse radiation using fisheye technique, with the optical sensors arranged in concentric rings in five distinct angular bands, and central zenith angles of 7°, 23°, 38°, 53° and 68°. The basic technique involves measuring sky brightness from a levelled sensor above the canopy and a second measurement below the canopy, with the sensor viewing towards sky[38].

LAI measurements were taken at six random locations within each field, where each observation was the average of six point measurements. The measurements were carried out under uniform clear diffuse skies at low solar elevation to prevent the effects of direct sunlight on the sensor.

A portable chlorophyll meter (SPAD-502; Minolta Corporation, New Jersey, USA) was used to measure leaf CC. However, the instrument does not provide the actual contents of chlorophyll per unit area of leaf tissue; instead it gives data only in arbitrary units. In the present study, a standard method was used for determination CC in leaf samples of cotton crop. Homogenization of the leaf tissue in 80% acetone was carried out and then absorbance at 663 and 645 nm was measured. Then, specific absorption coefficients for chlorophyll *a* and *b*, provided by Arnon[39] were used for the calculation of CC (ref. 40).

LAI and CC measurements were carried out corresponding to the selected satellite pass time.

LANDSAT 5 TM and LISS-IV data were used for the study. The pixel reflectances were extracted in the red and NIR bands within the region of interest (ROI) centred on cotton fields, where LAI and CC measurements were taken. Mean values for red and NIR reflectances for each ROI were computed.

Table 1. Vegetation indices used in the study

Index	Equation	Reference
Normalized difference vegetation index (NDVI)	NDVI = (NIR – red)/(NIR + red)	57
Ratio vegetation index (RVI)	RVI = NIR/red	58

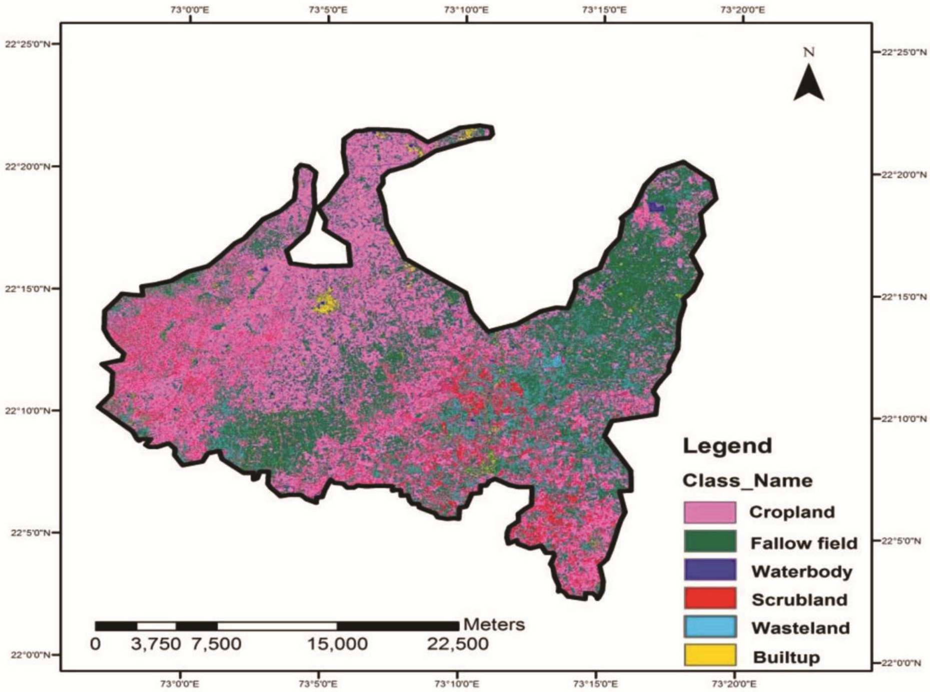

Figure 2. Land-use map generated using LISS-IV data for October 2009.

For retrieval of the foliar traits from optical satellite data, empirical statistical approach was adopted. The methodology involves two steps: (1) Extracting spectral indices from optical satellite images. (2) Establishing relationships between extracted spectral indices and ground-measured foliar traits.

Vegetation indices considered to be good candidates for estimating LAI and CC were tested. These were developed from the reflectance bands of the optical data using ERDAS-9.1. Table 1 shows two vegetation indices computed from the selected optical satellite images.

The gathered datasets of indices and foliar traits (namely LAI and CC) were statistically analysed to determine correlations and derive empirical relationships between crop LAI and VI; and leaf CC and VI. Each calculated VI was linearly related to different LAI values. Similarly, extracted values for each VI were also linearly related to CC. Accuracy assessment and validation of the developed models were also carried out.

To understand overall scenario of the study area, initially land-use classification was carried out which provided a precise information on the total contribution of agricultural land in the study area (Figure 2). The data generated showed 78.7% of land under agriculture, which included both cropland and fallow field categories with an overall accuracy of 93.3% and kappa statistics as 0.89.

Crop-type classification showing cotton area in the entire study region was found to be subtle, despite high resolution due to field heterogeneity resulting into mixing of signatures. Several workers have also reported such difficulties in crop-type classification due to small-scale traditional agricultural holdings, such as the densely populated rural landscapes of India[41,42]. Small agricultural fields and diversity in crop types are the components contributing to subtleness in crop-type classification while mapping large areas.

In situ LAI values in the cotton fields captured the data range 0.2–4.76, around a total mean value of 2.59. CC ranged from 9.07 to 22.47 mg g^{-1}, with mean value of 15.8 mg g^{-1}. NDVI and RVI values for cotton crop extracted from LANDSAT 5 TM and LISS-IV data are shown in Table 2, which serve as an input for the retrieval of cotton foliar traits, viz. LAI and CC.

Linear models developed for the assessment of LAI in cotton crop by correlating it with LANDSAT and LISS-IV-derived NDVI and RVI showed good correlations. Chlorophyll also showed good correlation with the extracted indices. Coefficient of determination (R^2) for

Table 2. Extracted vegetation indices from LANDSAT 5 TM and LISS-IV data

Crop	Satellite data	NDVI Range	NDVI SD	RVI Range	RVI SD
Cotton	Landsat 5 TM	0.11–0.42	0.07	1.0–2.7	0.33
	LISS-IV	0.13–0.45	0.08	1.1–2.7	0.43

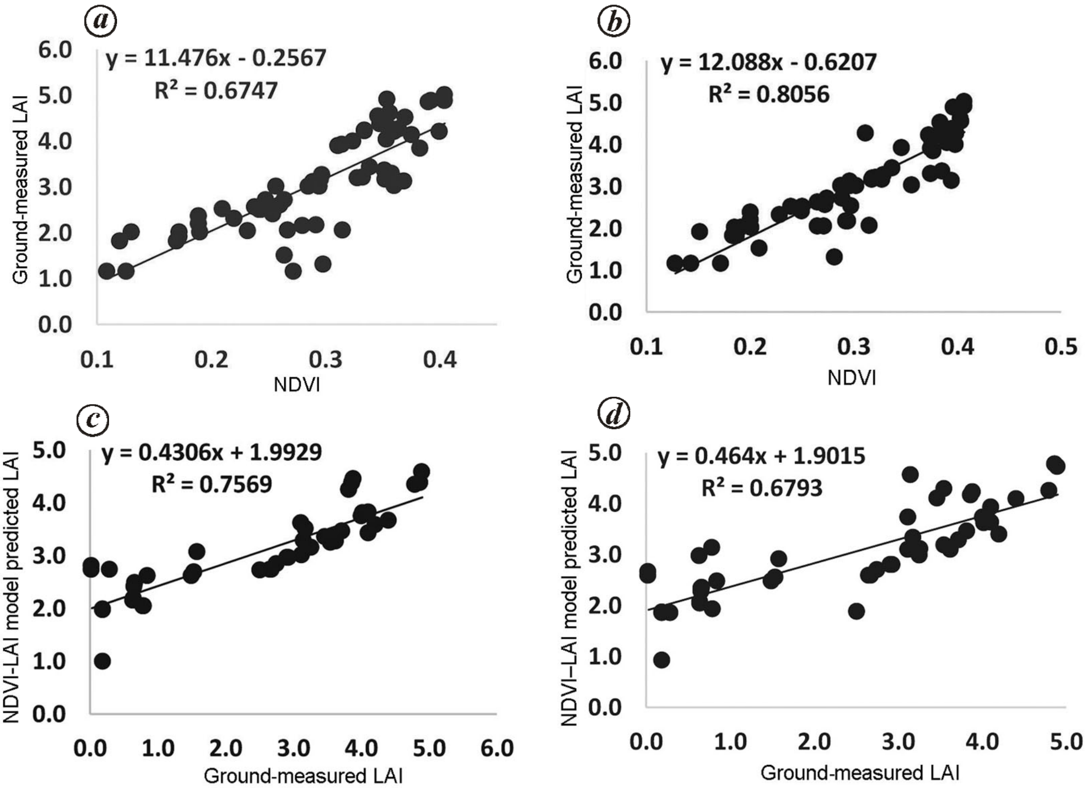

Figure 3. ***a***, Linear relationship between LANDSAT NDVI and cotton leaf area index (LAI); ***b***, Linear relationship between LISS-IV NDVI and cotton LAI; ***c***, Validation of Landsat NDVI–LAI model using ground-measured cotton LAI; ***d***, Validation of LISS-IV NDVI–LAI model using ground measured cotton LAI.

these models varied from 0.585 to 0.805. RS-based empirical models generated from spatial indices for the retrieval of foliar traits have also been reported by earlier researchers[43–45]. They have confirmed that the retrieval of these traits using vegetation indices such as NDVI and RVI can be achieved with an acceptable accuracy.

For any established statistical model, its validation becomes important with respect to algorithm development for large-scale applications[46]. Validation carried out for all the developed models exhibited strong relationship between estimated and predicted foliar traits.

NDVI–LAI model: The correlation of LAI with LISS-IV NDVI was comparatively higher with $R^2 = 0.805$ (Figure 3 *b*) when compared to that with LANDSAT NDVI with $R^2 = 0.674$ (Figure 3 *a* and *b*). The *t*-test conducted for correlation coefficient showed that the results are highly significant at $P = 0.01$ level. Validation of both the LANDSAT NDVI-LAI and LISS-IV NDVI-LAI models showed a good relationship between ground-measured LAI and NDVI–LAI-predicted LAI (for LANDSAT data, $R^2 = 0.756$ and for LISS-IV data $R^2 = 0.679$; Figure 3 *c* and *d*). A good accuracy of 92.7% and 87.8% was observed for the developed LANDSAT and LISS-IV data based biophysical models respectively.

RVI–LAI model: The linear regression relationships established between *in situ* cotton LAI and LANDSAT RVI showed comparatively less but good positive correlation (Figure 4 *a*) ($R^2 = 0.592$) than LISS-IV RVI which showed better correlation with *in situ* LAI (Figure 4 *b*) ($R^2 = 0.696$). Results for these correlations are highly significant ($P = 0.01$ level). Validation carried out for RVI-LAI models showed significant correlation between ground-measured LAI and RVI-LAI model-predicted LAI (Figure 4 *c* and *d*). RVI–LAI model established using LANDSAT

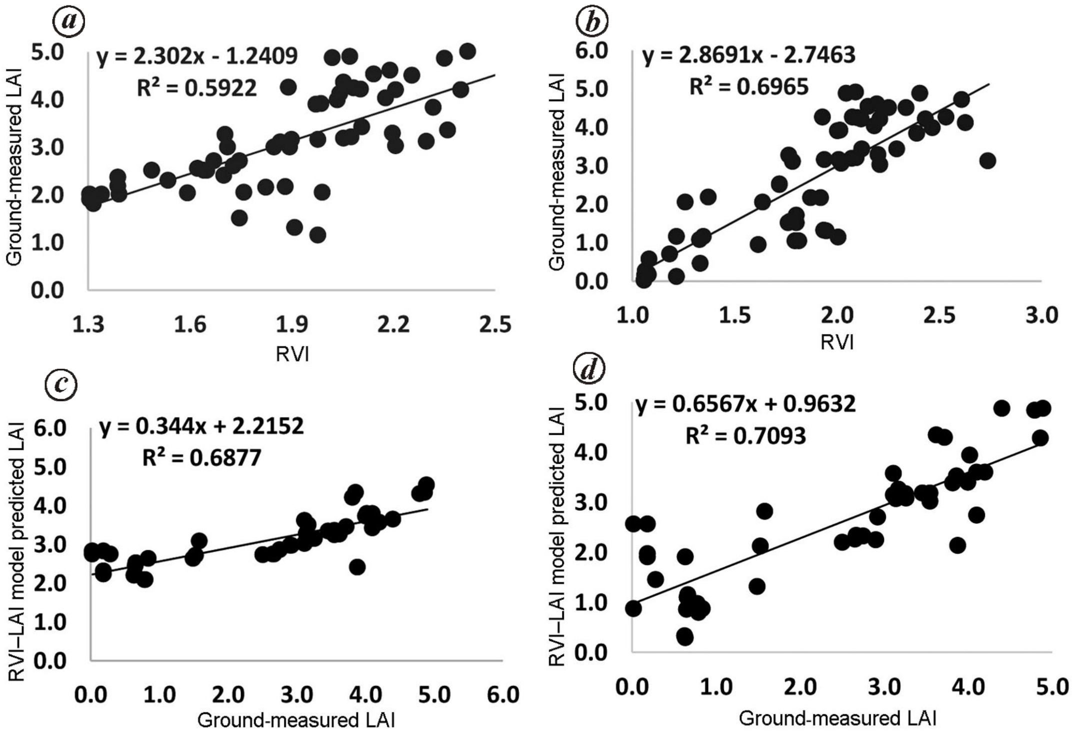

Figure 4. ***a***, Linear relationship between LANDSAT RVI and cotton LAI; ***b***, Linear relationship between LISS-IV RVI and cotton LAI; ***c***, Validation of LANDSAT RVI–LAI model using ground-measured cotton LAI; ***d***, Validation of LISS-IV RVI–LAI model using ground-measured cotton LAI.

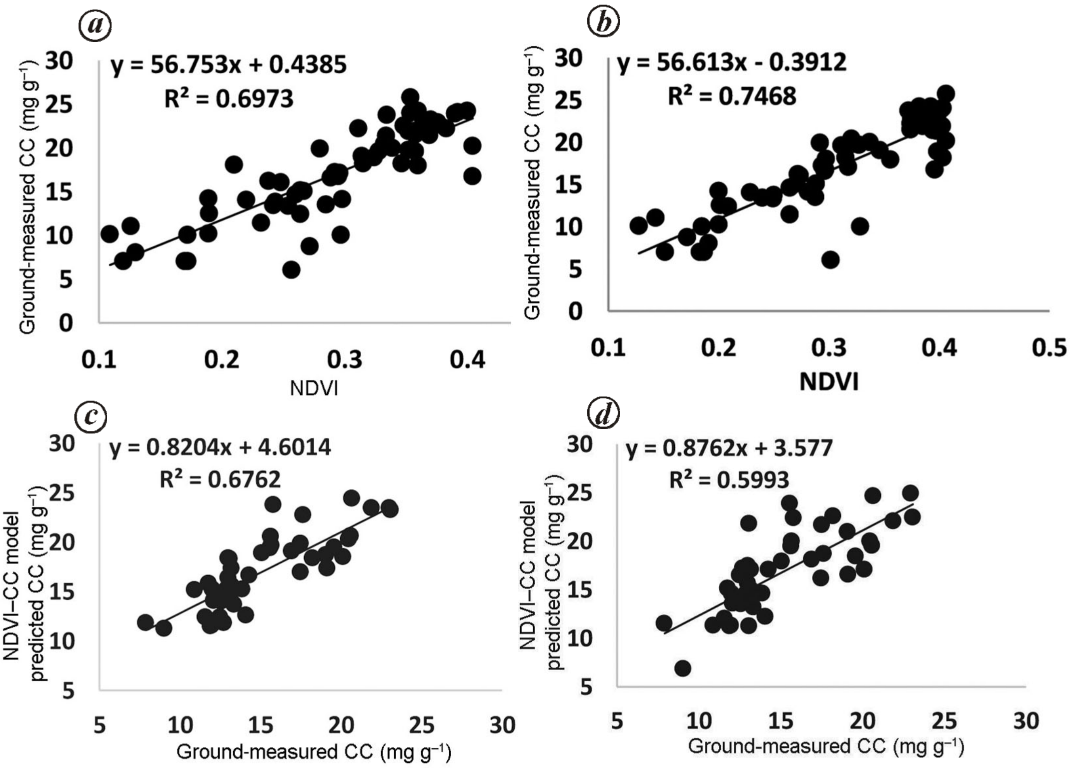

Figure 5. ***a***, Linear relationship between LANDSAT 5 TM NDVI and cotton chlorophyll content (CC); ***b***, Linear relationship between LISS-IV NDVI and cotton CC; ***c***, Validation of LANDSAT NDVI–CC model using ground-measured cotton CC; ***d***, Validation of LISS-IV NDVI–CC model using ground-measured cotton CC.

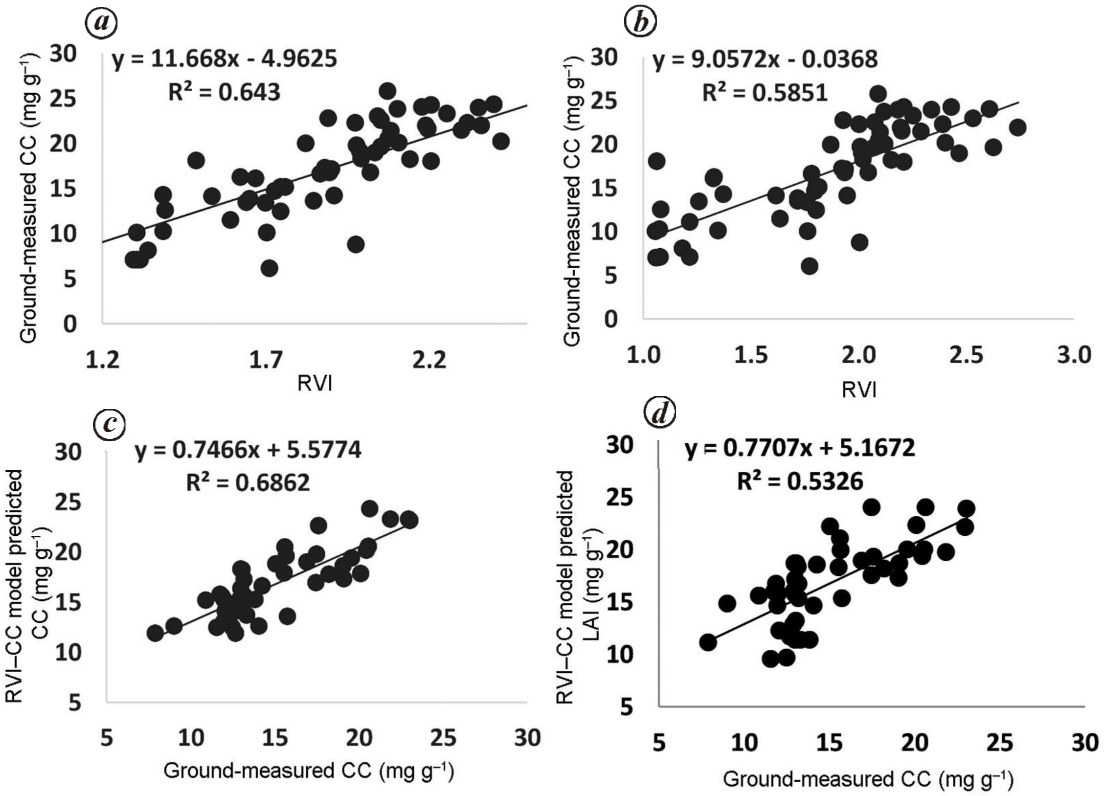

Figure 6. ***a***, Linear relationship between LANDSAT 5 TM-derived RVI and cotton CC; ***b***, Linear relationship between LISS-IV RVI and cotton CC; ***c***, Validation of Landsat RVI–CC model using ground-measured cotton CC; ***d***, Validation of LISS-IV RVI–CC model using ground-measured cotton CC.

Table 3. Empirical–statistical relationships between cotton leaf area index (LAI) and optical RS-derived vegetation indices

Parameter	Index	Satellite data	Fitting formula	R^2
LAI	NDVI	LANDSAT TM	LAI = 11.476NDVI – 0.2567	0.6747
		LISS-IV	LAI = 12.088NDVI – 0.6207	0.8056
	RVI	LANDSAT TM	LAI = 2.302RVI – 1.2409	0.5922
		LISS-IV	LAI = 2.8691RVI – 2.7463	0.6965
Chlorophyll content (CC)	NDVI	LANDSAT TM	CC = 56.753NDVI + 0.4385	0.6973
		LISS-IV	CC = 56.613NDVI – 0.3912	0.7468
	RVI	LANDSAT TM	CC = 11.668RVI – 4.9625	0.643
		LISS-IV	CC = 9.0572RVI – 0.0368	0.5851

data showed an accuracy of 92.6% and that established using LISS-IV data showed an accuracy of 87.8%.

NDVI–CC model: A positive and comparatively higher correlation was obtained between pigment CC and LISS-IV NDVI with $R^2 = 0.746$, when compared to that between leaf CC and LANDSAT NDVI with $R^2 = 0.697$ (Figure 5 *a* and *b*). NDVI-CC models when validated showed good correlation between ground measured CC and predicted CC (Figure 5 *c* and *d*). Accuracies for these models were estimated; for LANDSAT 5 TM data it was 85.4% and for LISS-IV data it was 82.9%.

RVI–CC model: Fitted empirical regression relationships between CC and LANDSAT RVI showed good correlations with $R^2 = 0.643$ (Figure 6 *a*). Fitted regression relationships for CC and LISS-IV RVI emphasized comparatively low correlations with $R^2 = 0.585$ (Figure 6 *b*). Validation for these models showed good relationship between CC estimated on the ground and that predicted using RVI–CC model (Figure 6 *c* and *d*). Accuracy test for these RS-based models was found to be good. For LANDSAT data 90.2% accuracy was obtained while for LISS IV data 65.9% accuracy was obtained.

Based on R^2 values NDVI was seen to be more closely related to CC than RVI, highlighting the potential of the former in the estimation of CC.

LISS-IV data showed better potential for estimation of LAI and CC when compared to LANDSAT 5 TM data, except for LISS-IV RVI-CC model. Comparison of R^2 values between the models revealed that NDVI was slightly superior to RVI in its correlation with crop foliar traits in both LANDSAT 5 TM and LISS-IV data (Table 3). Hence, NDVI–LAI and NDVI–CC models proved to be better for estimation of these traits. This may be due to the relatively lower insensitivity of NDVI to background soil reflectance and greater sensitivity of RVI to this factor[47]. Moreover, NDVI is less affected by atmospheric conditions and topographical variations, while RVI is affected the most by atmospheric haze and topography. A relative disadvantage of NDVI is its saturation at higher LAI values[48–54] compared to RVI, which indicates the inappropriateness of NDVI in the discrimination of crops with high-density cover or LAIs[55,56].

In the present work, NDVI and RVI were used to retrieve foliar traits, viz. LAI and CC by developing empirical models. It is well known that there exists a strong correlation relationship between NDVI and RVI values. A simple linear regression model has been used in this analysis for estimation of crop foliar traits using optical satellite data, as these methods have been found to be fast and easily implementable for the large datasets. The models developed from both LANDSAT 5 TM and LISS-IV data for cotton showed good performance. In terms of indices, NDVI and in terms of data, LISS-IV exhibited better potential in the retrieval of foliar traits.

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