Hyperspectral remote sensing of agriculture

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Remote sensing is being increasingly used in different agricultural applications. Hyperspectral remote sensing in large continuous narrow wavebands provides significant advancement in understanding the subtle changes in biochemical and biophysical attributes of the crop plants and their different physiological processes, which otherwise are indistinct in multispectral remote sensing. This article describes spectral properties of vegetation both in the optical and thermal range of the electromagnetic spectrum as affected by its attributes. Different methods have been discussed to reduce data dimension and minimize the information redundancy. Potential applications of hyperspectral remote sensing in agriculture, i.e. spectral discrimination of crops and their genotypes, quantitative estimation of different biophysical and biochemical parameters through empirical and physical modelling, assessing abiotic and biotic stresses as developed by different researchers in India and abroad are described.

Keywords: Agriculture, biotic and abiotic stress, hyperspectral remote sensing, spectral reflectance.

Introduction

CROP growth studies require quantification and monitoring of biochemical and biophysical attributes. Estimates of foliar biochemicals such as the levels of chlorophyll and nitrogen provide us indicators of plant productivity, stress and the availability of nutrients. Compared to direct field techniques, remote sensing techniques have been shown to be timely, non-destructive and provide spatial estimates for quantifying and monitoring these vegetation attributes. However, multispectral broadband-based remote sensing has limitation for quantitative estimation of biochemical properties primarily because of the low spectral resolution. A major limitation of broadband remote sensing is that it uses average spectral information over broadband widths resulting in loss of critical information available in specific narrow bands, e.g. absorption features[1,2]. In the 1970s, realization of the limitations of the multispectral approach when faced with the diversity and complexity of spectral signatures found on the surface of the Earth led to the concept of an imaging spectroscopy. Hyperspectral remote sensing is based on the examination of many contiguous narrowly defined spectral channels[3] and has been found to be superior to conventional broadband remote sensing in spectral information. Hyperspectral (narrow band) indices have been shown to be crucial for providing additional information with significant improvements over broadbands, in characterizing, mapping and quantifying biophysical and biochemical parameters of agricultural crops. Recent advances in hyperspectral remote sensing demonstrate great utility for a variety of crop monitoring applications. The reflectance and absorption features in narrow bands are related to specific crop characteristics such as biochemical composition[4], physical structure, water content[5] and plant ecophysical status[6]. There are many studies supporting this, conducted on a wide array of crops and their biophysical and biochemical variables such as yield[7,8], chlorophyll content[9], nitrogen content[10,11], carotenoid pigment[1], plant biotic stress[12,13], plant moisture[14] and other biophysical variables[15]. The development of spectral library using hyperspectral data is another emerging component[16]. This fairly detailed list, though not exhaustive, gives a measure of the current, proven experimental capabilities and operational applications, and stimulates investigations of new and ambitious applications.

Spectral properties of vegetation

The spectral properties of vegetation are strongly determined by their biophysical and biochemical attributes such as leaf area index (LAI), the amount live and senesced biomass, pigment and moisture content and spatial arrangement of cells and structures[17]. Leaves represent the main surfaces of plant canopies where energy and gas are exchanged. Hence, knowledge of their optical properties is essential to understand the transport of photons within vegetation[18]. The general shape of reflectance and transmittance curves for green leaves is similar for all species. It is controlled by absorption features of specific molecules and the cellular structure of the leaf tissue[19]. Three distinguished spectral domains of vegetation reflectance are defined based on the effect of biophysical and biochemical attributes on reflectance properties of vegetation (Figure 1).

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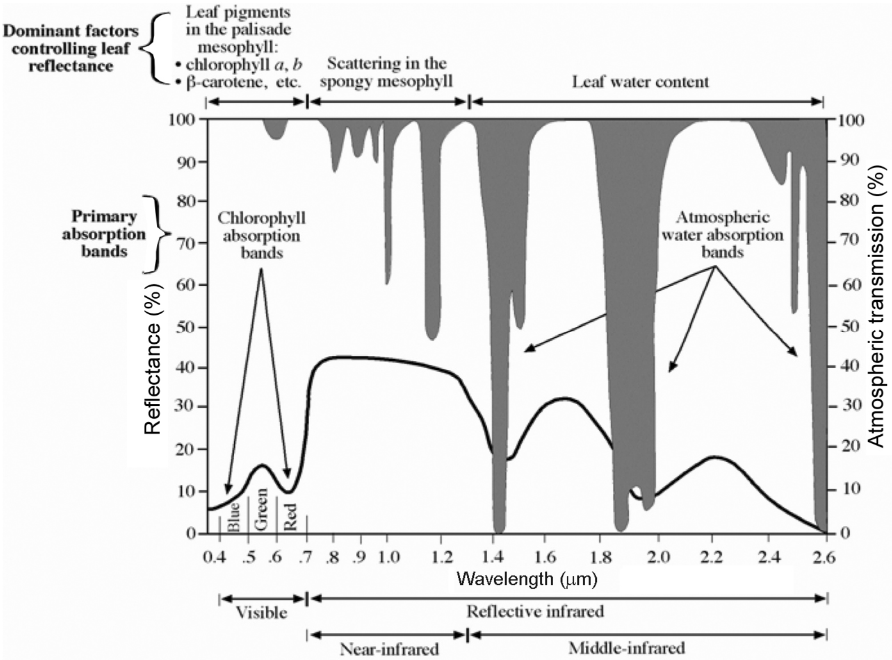

Figure 1. Typical reflectance pattern of leaf (source: Jensen[20]).

In the visible domain (400–700 nm), absorption by leaf pigments is the most important process leading to low reflectance and transmittance values. The main light-absorbing pigments are chlorophyll *a* and *b*, carotenoids, xanthophylls and polyphenols, and all pigments have overlapping absorption features. Chlorophyll *a* (Chl *a*) is the major pigment of higher plants and together with chlorophyll *b* (Chl *b*) accounts for 65% of the total pigments. Chl *a* displays maximum absorption in the 410–430 and 600–690 nm regions, whereas Chl *b* shows maximum absorption in the 450–470 nm range. These strong absorption bands induce a reflectance peak in the green domain at about 550 nm. Carotenoids absorb most efficiently between 440 and 480 nm. Polyphenols (brown pigments) absorb with decreasing intensity from the blue to the red and appear when the leaf is dead[20]. In the foliage of many canopy species, Chl *b* dominates the overall absorption spectrum at shorter and longer wavelengths in the visible spectrum, whereas carotenoids can be a major contributor at slightly longer wavelengths.

In the near-infrared domain (near-IR: 700–1300 nm) leaf pigments and cellulose are almost transparent, so that absorption is very low and reflectance and transmittance reach their maximum values. This is caused by internal scattering at the air–cell–water interfaces within the leaves[14]. The level of reflectance on the near-IR plateau increases with increasing number of inter-cell spaces, cell layers and cell size. Scattering occurs mainly due to multiple refractions and reflections at the boundary between the hydrated cellular walls and air spaces[21]. In the mid-infrared domain (mid-IR: 1300–2500 nm), also called shortwave-infrared (SWIR), leaf optical properties are mainly affected by water and other foliar constituents. The major water absorption bands occur at 1450, 1940 and 2700 nm and secondary features at 960, 1120, 1540 1670 and 2200 nm (ref. 19). Water largely influences the overall reflectance in the mid-IR domain effectively trapping the radiation, resulting in absorption that exceeds scattering processes and also has an indirect effect on the visible and near-IR reflectances. Protein, cellulose, lignin and starch also influence leaf reflectance in the mid-IR. However, the absorption peaks of these organic substances are rather weak as they result from overtones or combinations related to fundamental molecular absorptions in the region 5–8 μm (ref. 22). Absorption features of different foliar chemical parameters are listed in Curran[22]. In fresh leaves, spectral features related to organic substances are masked by the leaf water, so that estimation of leaf constituents is difficult[20].

Vegetation canopies reflect radiation anisotropically and hence sensor measurements strongly depend on both position of the Sun and the sensor relative to the Sun[23]. Anisotropy calculations are based on directional reflectance measurements of a target, called collectively as bi-directional reflectance distribution function (BRDF)[24]. A BRDF can be assessed using a spectrometer mounted on a goniometer that is capable of measuring varying viewing and illumination geometries around a target material. It is constructed from reflectance measurements repeated at certain angular intervals both in the azimuth and elevation directions. The bidirectional reflectance is not only a function of relative geometry of illumination and observation, but also physical and morphological properties of the observed surface[25]. Empirical and theoretical investigations have treated the BRDF both as a source of noise for remote sensing systems and as a possible source of information about vegetation and soil surfaces[26,27]. The directional nature of reflectance can also be exploited as a source of useful information relating to canopy architecture, and sun and sensor position by analysis of BRDF data.

Spectral features of plant species in the visible to SWIR (0.4–2.5 μm) region have been studied extensively, but scanty attention has been given to plant thermal infrared (TIR: 4–14 μm) properties. Emissivity spectra collected for the first time in India using a FTIR (Fourier transform infrared) field spectroradiometer working in 2–14 μm for agricultural crops like rice and wheat[28] and eight common agricultural crops and grass species[29] were analysed to relate to the leaf chemical constituents, such as cellulose and xylan (hemicellulose) and structural aspects of leaf surface like abundance of trichomes and texture. Generally plants were assumed to be featureless in the TIR. This notion continued in the remote sensing community because of several factors as discussed by Ribeiro da Luz and Crowley[30]. First, few equipment are available that facilitate measurements of the TIR emissivity spectra of plants. Second, the genesis of spectral emissivity features of plants is quite complex and involves details of plant physiology and biochemistry that are not familiar to many remote sensing researchers. Third, in order to observe proper TIR spectral variations in plants, sensors onboard airplane or satellite must have high signal-to-noise ratio as well as very high spatial and spectral resolution. There is considerable potential in remote sensing for discriminating vegetation characteristics with TIR sensors having high spectral resolution[31]. Moreover recent TIR sensor designs[32] have begun to achieve the necessary data quality for discerning TIR spectral features in plants.

Hyperspectral remote sensing data analysis for agricultural crops

Hyperspectral data collected over a large number of narrow bands in continuous spectral coverage are voluminous and more complex than multispectral data posing great challenges in data handling and analysis[33]. It demands methods and techniques be advanced and developed to handle high-dimensional datasets. The most common issue is redundancy in information due to inter-band correlation, which requires knowledge of application-specific 'optimal bands' that may capture most of the information of crop characteristics[34,35]. It has also been shown that 96% of the variability in the data could be explained using four principal components derived from 76 bands[36]. Apart from this, hyperspectral spectra are generally noisier compared to the controlled laboratory conditions. This is because their narrow bandwidth can only capture very little energy that may be overcome by the self-generated noise inside the sensors. Moreover, the Sun's variable illumination greatly reduces the incoming signal. It is required to smoothen the reflectance spectra collected in the field using spectroradiometer or from remotely sensed images before further analysis. Optimal bandwidth selection needs to be followed preserving absorption features and keeping intact local minima or maxima and inflection points[36]. Very narrow bandwidth may have lower signal-to-noise ratio. Keeping a bandwidth of 5–10 nm will ensure that optimal information on a particular feature is captured rather than average conditions captured in broadbands. Ray *et al.*[36] suggested optimum bandwidths of 5–10 nm in red edge and early NIR region, and 25 nm in 500–700 and 800–900 nm regions for crop stress studies. Experimental results by different workers suggest a nominal bandwidth of 5–10 nm for all wavebands[35].

An innovative lambda (λ_1 = 350–2500 nm) by lambda (λ_2 = 350–2500 nm) plot of R^2 values is used to determine (a) redundant bands and (b) unique bands[28]. Figure 2 shows inter-band correlation of rice crop using 216 bands (in 350–2500 nm at 10 nm interval) plotted as lambda 1 versus lambda 2. The least redundant bands (R^2 values of <0.1) are shown in white. Therefore, it will be suffice to select least correlated bands for further hyperspectral analysis mining of all redundant bands.

Other methods used for selecting optimal bands are: (i) principal component analysis (PCA) based on high factor loadings or eigen vectors[37], (ii) uniform feature design (UMD) through reducing dimensionality of dataset retaining spectral shape information[38], (iii) wavelet transforms, analysing data at different scales, and specially suited for crop phenology studies[39] and (iv) artificial neural network (ANN)[40]. All these methods have advantages and disadvantages. As reported by many researchers, lamda versus lambda plotting is found to be the best band reduction approach that still provides optimal information by

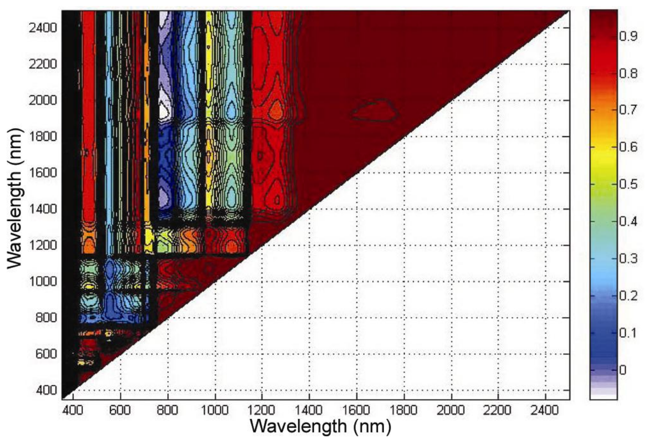

Figure 2. Lambda by lambda plot indicating redundant and distinctly unique bands (source: Sahoo *et al.*[28]).

retaining key bands[34]. The main advantage is in retaining the identity of the original bands that can be linked to biophysical and biochemical attributes and physical basis of sensitivity of these variables to wavebands are clearly explained.

Optimal number of hyperspectral narrow bands in the study of crops is determined based on an exhaustive review of the literature that includes: (a) identifying redundant bands, (b) modelling by linking crop biophysical and biochemical variables with hyperspectral indices and bands, (c) establishing wavebands that best help separate crops and genotypes, (d) establishing classification accuracies of crop classes and identifying bands that best help enhance these accuracies. Based on frequency of occurrence, Ray *et al.*[36] found 13 optimal bands in the VNIR (400–1050 nm) region for crop discrimination using stepwise discriminant analysis (SDA). Miglani *et al.*[41] carried out optimal band selection of Hyperion sensors having 220 wavebands using PCA, band-to-band correlation and analysis of frequency of occurrence of each band. They found 26 bands which could be considered significant for the study of leaf or plant and their physical (i.e. biomass, LAI), biochemical (chlorophyll, nitrogen) and physiological properties (canopy structure, growth stage, and growth condition and stress level; Table 1).

Hyperspectral (narrow band) vegetation indices (HVI) have been shown to be crucial for providing additional information with significant improvements over broadbands, in quantifying biophysical characteristics of agricultural crops, especially those related to crop physiology and stress due to weeds, water and nitrogen. Broadband vegetation indices have two limitations: (i) saturation at high vegetation coverage, and (ii) a few number of broadband indices and do not explain large proportion of variability in modelling biophysical and biochemical properties. These limitations are overcome in the case of HVIs. HVIs can be used for finding a right index for a particular variable of vegetation. HVIs have greater dynamic range to better model the plant variables and to explain a significantly higher proportion of their variability[10,42,43]. Four types of HVIs are suggested for agricultural crop studies – (i) hyperspectral two-band vegetation index[28,37], (ii) hyperspectral multiple band models[35,44,45], (iii) hyperspectral derivative greenness vegetation indices[10,46] and (iv) hyperspectral hybrid vegetation indices[47,48]. Sahoo *et al.*[49] developed a 1D index called total information content index from *n*-dimensional bands for characterization of different natural features based on Shannon's information theory and found potential use in hyperspectral data with respect to dimension reduction and cluster analysis.

There are other methods of hyperspectral data analysis for studying biophysical and biochemical properties of agricultural crops, including (i) independent component analysis which is an unsupervized temporal unmixing methodology mainly found useful in both time profile and area distribution of different crop types[50]; (ii) minimum nosie fraction transformation; (iii) spectral unmixing analysis; (iv) continuous continuum definition and removal factor[51] and (iv) radiative transfer modelling[15].

Hyperspectral remote sensing applications in agriculture in India

Spectral characterization and discrimination of crops

The high spectral resolution of hyperspectral data has an advantage of capturing and discriminating subtle differences among crop types, but it also contains redundant information at the band level, which makes computation difficult. Band/feature selection is the most commonly used practice to reduce the number of wavebands and highest discriminant bands are selected using discriminant statistics such as PCA and SDA. Many researchers[35,52–54] have successfully used these methods to select informative bands in hyperspectral data and discriminate vegetation types or species.

Manjunath *et al.*[55] used SDA technique to select optimum bands and discriminate among pulses, cole crops and ornamental plants using ground-based hyperspectral data. The analysis showed that the best four bands for pulse crop discrimination lie mostly in NIR and early MIR regions, i.e. 750, 800, 940 and 960 nm. Within cole crops discrimination is primarily determined by the green, red and NIR bands of 550, 690, 740, 770 and 980 nm. The separability study showed that the bands 420, 470, 480, 570, 730, 740, 940, 950, 970, 1030 nm are useful for discriminating flowers.

Sahoo *et al.*[56] explored possibility of discrimination of 70 wheat genotypes from proximal hyperspectral reflectance data (350–2500 nm at 10 nm interval) using SDA as the feature selection method and Jeffries–Matusita (J–M) distance[40] as a separability index. Threshold of $\geq$1.90 for squared J–M distance was considered for spectral separability of two genotypes. The study revealed that even though the 70 wheat genotypes are statistically different at all ranges of hyperspectral bands (400–2500 nm) with a 1% level of significance in the ANOVA test, only 2037 out of 2415 genotype pairs were found to be separable. Hierarchical agglomerative clustering analysis was also done to find out well-separable groups of wheat genotypes with an objective to maximize the homogeneity of genotypes within the clusters based on a set of characteristics while also maximizing the heterogeneity between clusters. They could find six clusters and all the 15 cluster pairs were separable.

Kumar *et al.*[57] carried out field hyperspectral data analysis for discriminating spectral behaviour of tea plantations with respect to type, age of plantation, growth

Table 1. List of the 26 best bands selected from PCA and band-to-band correlation for agricultural studies (source: Miglani *et al.*[41])

Hyperion band no.	Region of electromagnetic spectrum	Central wavelength (nm)	Frequency of occurrence	Agricultural importance (according to Thenkabail *et al.*[35])
9	Visible	436.99	2	Blue absorption peak; sensitive to senescing, chlorophyll *a*
25		599.80	2	Absorption pre-maxima; sensitive to biomass, soil background
26		609.97	2	
27		620.15	2	
29		640.50	2	
30		650.67	2	
32		671.02	2	Absorption maxima; maximum chlorophyll absorption, greatest soil crop contrast
33		681.20	2	
39	Red edge	742.25	2	Red edge region, sensitive to vegetation stress and dynamics
40		752.43	2	
42	NIR	772.78	4	Early NIR; more sensitive to changes in chlorophyll content than a broad NIR band
43		782.95	2	
44		793.13	2	
45		803.30	2	Centre of NIR shoulder; strong correlation with total chlorophyll
50		854.18	2	
52		874.53	3	Correlation with biomass, LAI
86	Moisture sensitive	1003.30	2	Rapid reflectance rising spectra after moisture absorption; sensitive to plant moisture status, biomass and LAI
87	NIR (MSNIR)	1013.30	2	
88		1023.40	2	
89		1033.50	2	
90		1043.59	2	
91		1053.69	2	
92		1063.79	2	Post-reflectance peak in NIR; sensitive to biomass and LAI
94		1083.99	2	
159	Early MIR (EMIR)	1739.69	2	Reflectance post-peak in EMIR; sensitive to biomass, cellulose and lignin
185	Far MIR (FMIR)	2002.06	2	Moisture absorption trough in FMIR; sensitive to plant moisture

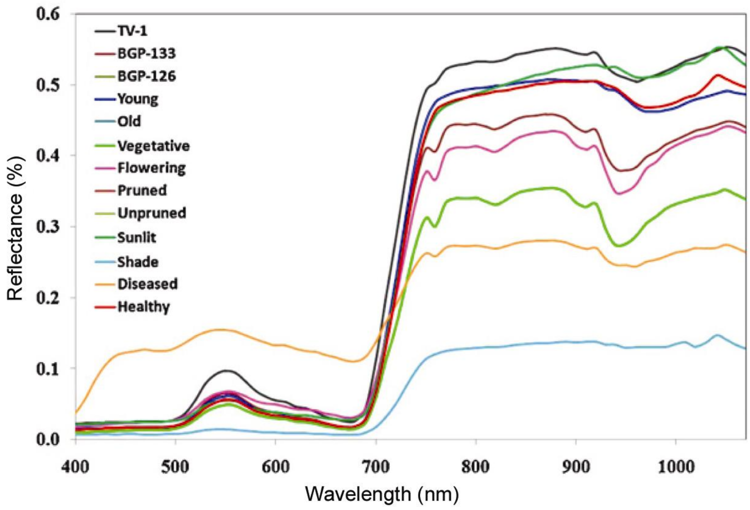

Figure 3. Spectral signature of tea grown under various management practices.

stage, pruning status, light conditions and disease incidence (Figure 3). Stepwise discriminant analysis and principal component analysis were conducted to identify the appropriate bands for accessing the above mentioned factors. The green region followed by NIR region was found to be the most appropriate band for discriminating different types of tea plants, and tea in sunlit and shade conditions. For discriminating age of plantation, growth stage of tea, and diseased and healthy bush, the blue region was the most appropriate. The red and NIR regions were the best bands to discriminate pruned and unpruned tea.

Antony *et al.*[58] used multi-angular, narrow-band, compact, high-resolution imaging spectrometer (CHRIS) on-board the project for on-board autonomy (PROBA) experimental hyperspectral image data (410–1050 nm) of the European Space Agency to discriminate three stages (mainly ear head, grain formation and milking stage) of wheat crop grown in Suratgarh farm, Rajasthan, India and used normalized distance between means[59] as a measure of separability. They could find five optimum narrow bands for wheat discrimination, namely 630, 660, 674, 705 and 712 nm, irrespective of sensor viewpoints. Miglani *et al.*[41] evaluated hyperspectral remote sensing satellite data of Hyperion (of EO1) classifying different winter crops such as wheat (and its phenostages), sugarcane, mustard, sorghum and potato using principal component analysis and band-to-band correlation analysis as the feature selection step. In the crop spectra, chlorophyll absorption near 690 nm, a steep slope in the red edge region (700–750 nm) and leaf water absorption near 940 and 1104 nm were remarkably evident. Spectral curves generated for different crops in the *Rabi* season (wheat, sugarcane, mustard, sorghum and potato) showed the diversity in reflectance pattern depending on the crop characteristics and growth stage of the crop. All the stages of wheat were distinctly different in the NIR (780–870 nm) and SWIR (1000–1080 nm) regions. Wheat at mature stage had lowest radiance values, while the crop in grain-fill stage showed highest values. This showed that Hyperion could offer possibilities for separating crop phenological categories using specific narrow bands or by analysis of the whole 450–2350 nm spectral range.

Anisotropicity study of crops using BRDF data

Anisotropicity of two contrasting crop types such as wheat as erectophile[60] and soybean as planophile[61] in nature was studied using BRDF data collected from field portable spectroradiometer with 10° FOV mounted on a goniometer. Two indices, namely anisotropy factor (ANIF) and anisotropy index (ANIX) proposed by Sandmeire *et al.*[24] were used. ANIF describes the portion of radiation reflected into a specific view direction relative to the nadir reflectance, whereas ANIX gives the amplitude of the bidirectional reflectance variation for a given spectral band for a defined view azimuth plane or relative azimuth. It was found that optical properties and architecture of crop exert a strong influence on anisotropy. Multiple scattered radiation in the NIR region smoothens the BRDF anisotropy, whereas high absorption in the visible region increases BRDF anisotropy which results in higher NAIX and NAIF in the visible range 560–700 nm compared to the NIR region. ANIF and ANIX of wheat crop (erectophile) was higher compared to soybean (planophile) crop, evidently revealing the effect of plant geometry on BRDF. Anisotropy index has the potential for crop discrimination and also for understanding spectral variability with varying biophysical and biochemical attributes of crops. Antony *et al.*[58], studied the importance of different view angles in discriminating wheat crop stages using CHRIS/PROBA image data. The results showed that off-nadir view angles performed better than nadir viewing in discriminating three wheat stages, i.e. ear head, grain formation and milking stage based on individual band analysis. However, this study does indicate that a combination of bands and view angles can potentially give a better discrimination capability. Thus, it emphasizes the usefulness of multi-angular narrow-band data for crop-stage discrimination. Further exploration of the utility of off-nadir viewing for crop phenology characterization is required. High spatial and spectral resolution satellite data with multi-viewing capability may thus prove to be useful for operational crop monitoring. This could be realized with the future addition of new instruments that provide data with similar characteristics.

Estimation of biophysical and biochemical variables of crops

LAI is a key variable used by crop physiologists and modellers for estimating foliage cover, as well as forecasting crop growth and yield. Because LAI is functionally linked to the canopy spectral reflectance[62] and narrow band indices perform better than broadband indices for LAI estimation[31,63], hyperspectral sensor can be used as a valuable tool for implementation of remote sensing-based precision agriculture. Ray *et al.*[36] carried out a study to compare different hyperspectral vegetation indices for estimation of LAI of potato crop, using ratio indices, principal components and derivative indices. Among various band combinations, the indices (NDVI, SAVI, RVI) based on reflectance at 780 and 680 nm showed maximum correlation to LAI. Other narrow-band indices, which were highly correlated to LAI, included three-band ratio (TBR), maximum of second derivative reflectance in the red edge (ddRE-680) and normalized difference of maximum of first derivative reflectance in the green and minimum of first derivative reflectance in the green (GGFN). None of the principal components (PCs) showed significant correlation with LAI. This might be due to the fact that the PCs provide only statistical measures, whereas the other indices are based on a priori knowledge of the connections between specific physiological and reflectance features. Optimum narrow bands suitable for discriminating between different irrigation treatments were 540, 610, 630, 700 and 1000 nm which were in green, red, red-edge and moisture-sensitive

NIR region. It was concluded that hyperspectral indices were more efficient than LAI to detect the differences among crops under different irrigation treatments.

Hyperspectral remote sensing is an automatic, quick and non-destructive method of assessing plant growth parameters and nutrient levels in crop plants[64–66]. But, the major fact associated with this is its limited use in prediction of nitrogen and biomass development[67,68]. The technique can potentially assist in the monitoring of growth parameters as well as plant N status and recommending fertilization strategy, which leads to minimizing the environmental risks of excess N rates and maximizing the N use-efficiency in crop production[69]. Ranjan *et al.*[10] evaluated 35 hyperspectral vegetation indices for quantification of plant N status in terms of leaf nitrogen concentration (LNC) and plant nitrogen accumulation (PNA), and validated the prediction accuracy of the best selected predictive equations in wheat crop. They observed maximum differences in reflectance due to varied degrees of N stress at the booting stage of wheat crop. The spectral ranges 350–710 and 740–1100 nm depicted maximum discrimination in the spectral response, indicating their suitability to quantify the degree of N stress. Based on the analysis of the quantitative relationships between LNC and PNA and various hyperspectral indices, five indices, i.e. green normalized difference vegetative index (GNDVI), normalized difference chlorophyll index (NDCI), normalized difference$_{705}$ (ND$_{705}$), ratio index-1dB (RI-1dB) and Vogelman index a (VOGa) for LNC, and five indices, i.e. the simple ratio pigment index (SRPI), modified simple ratio$_{705}$ (mSR$_{705}$), photochemical reflectance index (PRI), normalized pigment chlorophyll index (NPCI) and modified normalized difference$_{705}$ (mND$_{705}$) for PNA were found most suitable. Jain *et al.*[69] monitored the effect of nitrogen application on potato using 512-channel spectroradiometer with a range 395–1075 nm, and identified reflectance ratio at red edge (R740/720) and the structure-insensitive pigment index (SIPI) and optimal four bands, i.e. 560, 650, 730 and 760 nm suitable for discriminating different N rate-treated potato crops. Mahajan *et al.*[11] developed prediction models for monitoring nitrogen (N), phosphrous (P), potassium (K) and sulphur (S) in wheat crop using multiple regression equations of wavelengths selected from correlation analysis of nutrient concentration and leaf and canopy reflectances and evaluated. Existing as well as newly developed indices were calculated for prediction of N, P and S concentration using spectral reflectance data. Two newly proposed vegetation indices P_670_1092 and P_670_1260 for P and only one index S_670_1090 for S prediction appeared most robust with high and significant prediction accuracies. Regressive models for dry biomass and nutrient (N, P, S and K) content showed improvement in accuracy of retrieval when biomass-based nutrient status was considered over concentration-based nutrient status. Prediction accuracy of linear regressive models improved when biomass-based nutrient contents were considered rather than concentration. Newly developed and validated spectral algorithms specific to N, P, S and K can further be used for monitoring a wheat crop in order to undertake site-specific management.

Spectral reflectance of a plant leaf or canopy particularly beyond the visible range is mainly governed by leaf water content. Therefore, it can be used indirectly for non-destructive *in situ* assessment of plant water-deficit. Researchers[70] have identified a number of different spectral bands for water absorption sensitivity at wavelengths 950–970, 1150–1260, 1450, 1950 and 2250 nm. These water absorption bands result from the absorption of electromagnetic energy by atmospheric water vapour content and are dominant in the MIR and SWIR range of the spectrum and can help in the estimation of the plant water content. Many water-sensitive spectral indices have been developed over the years – water band index (WBI, R970/R900)[71], normalized difference water index (NDWI; (R860 – R1240)/(R860 + R1240))[72], normalized difference infrared index (NDII; (R820 – R1600)/(R820 + R1600))[73] and double ratio spectral index (DRSI)[74]. Kokaly and Clark[51] developed an approach for continuum removal and band depth analysis at specific absorption bands, which was found to be highly correlated to various biochemical and morphological characteristics of the plants. Pargal *et al.*[75] evaluated all the above-mentioned indices, including band depth analysis and continuum removal for quantitative estimation of relative water content of different rice genotypes as an alternate non-invasive method for water stress monitoring in laboratory, pot and field experimental conditions. It was observed that the model using band depths approach was best suited for estimation of relative water content with coefficient of determination $R^2 = 0.9$. Spectral indices-based monitoring of differential response of 11 rice genotypes to different water stress levels could help identify suitable water stress susceptible or resistant genotypes. The protocols developed are in use for phenomics study of rice crop for water stress.

Bandyopadhyay *et al.*[76] studied the optimum growth stage of wheat crop and suitable water stress indices which correlated well with wheat grain and biomass yield for developing prediction models. Spectral water indices at milking stage of wheat crop was found to be significantly negatively correlated with the grain and biomass yield of wheat. Validation of empirical models based on spectral indices could account up to 87.5% and 89.2% variation in the observed grain and biomass yield of wheat respectively.

All the above studies showed quantitative estimation of plant biophysical and biochemical properties based on empirical approaches. Simplicity and computational efficiency of empirical approaches makes these highly desirable for large-scale remote sensing applications. However, limitations of this approach are obvious, such as the limited amount of spectral information, the diversified empirical equations used and their sensitivity to non-vegetation factors and lack of generality. Since canopy reflectance depends on the complex interaction of several internal and external factors that may vary significantly in time and space and from one crop type to another, spectral reflectance empirical relationships will be site-, time- and crop-specific, making the use of a single relationship for an entire region unfeasible[77–79]. Alternately, the analytical/physically based models have proven to be promising alternatives as they describe the transfer and interaction of radiation inside the canopy based on physical laws and thus provide an explicit connection between the biophysical variables and canopy reflectance[77]. A number of canopy radiative transfer models (RTMs) of different complexities have been reported in the literature, which simulate the bi-directional reflectance as function of canopy characteristics[78]. Among all the RTMs, PROSAIL is the most popular model that is widely applied and describes both the spectral and directional variations of canopy reflectance as a function of leaf biochemistry and canopy architecture[15]. So the inversion of bi-directional canopy reflectance models has emerged as a promising alternative for retrieval of biophysical parameters[80,81].

Model inversion, however, requires significant computational resources which are slow on large datasets. This problem is also due to a complex description of the radiative field within the canopy and from the inversion method itself. Different inversion techniques have been proposed for physical models, including numerical optimization methods[82], look-up table (LUT) approaches[25,83,84], artificial neural networks[85], genetic algorithm (GA)[86,87], principal component inversion technique[88] and support vector machines regression[89]. A number of studies have been carried out in India for calibrating and evaluating the PROSAIL model for crops like wheat, mustard, maize and soybean with BRDF collected through field experimentation and spectral data collected at farmers' field covering the spectral range 350–2500 nm. Model inversion was done using LUT, ANN and GA for estimation of mainly leaf area index, total chlorophyll content and equivalent water thickness of these crops at experimental and farmers' field scale using proximal reflectance and satellite data[25,40,88]. Further derived parameters were used to develop a composite crop health index for monitoring crop conditions at spatio-temporal scale[83].

Monitoring biotic stress

Plants respond to biotic and abiotic stresses in a number of ways, including leaf curling, wilting, chlorosis or necrosis of photosynthetically active parts, stunted growth, or in some cases reduction in leaf area due to severe defoliation. Many of these plant responses are difficult to quantify visually with acceptable levels of precision and promptness. However, these responses also affect the amount and quality of electromagnetic radiation reflected from plant canopies. Based on the assumption that stresses interfere with photosynthesis and physical structure of the plants and affect absorption of light energy and reflectance spectrum of plants, hyperspectral remote sensing was found to be able to identify different stresses[90]. Besides, this technique provides a better means to objectively quantify crop stress than visual methods, as it can be repeatedly used to collect sample measurements non-destructively[91]. Use of non-destructive methods to detect crop stress at an early stage of its development holds great promise for pest and disease management in commercially important agricultural crops[92]. However, spectral characteristics and damage symptoms need to be aptly correlated based on ground truth prior to development of pest management schemes[93]. It is thus imperative to develop and differentiate spectral signatures due to common biotic and abiotic crop stresses to facilitate quick detection of stress depicted in satellite imageries[94]. Some of the studies on the use hyperspectral remote sensing for different pest and disease monitoring in international scenarios are brown soft scale insect in citrus, strawberry spider mite in cotton, net blotch in barley, glume blotch in winter wheat[91], greenbug stress in wheat[95], etc.

Most of the studies on assessing crop stress due to pests and diseases in India are based on proximal reflectance measurements. Prabhakar *et al.*[13] observed that the reflectance from healthy and leafhopper infested cotton plants was significantly different in both VIS and NIR regions and also demonstrated the potential use of indices for detection of leaf hopper severity in cotton by developing novel indices, viz. leaf hopper index 2 and leaf hopper index 4.

Kumar *et al.*[96] found that the spectral reflectance of aphid-infested canopy and healthy canopy of mustard crop had significant difference in the NIR region. The most significant spectral bands for assessing aphid infestation in mustard were found to be in the VIS (550–560 nm) and the NIR regions (700–1250 and 1950–2450 nm). Different levels of aphid infestation could be identified in 1950–2450 nm spectral regions. Spectral indices, viz. NDVI, ratio vegetation index (RVI), aphid index (AI) and structure insensitive pigment index (SIPI) could be found having significant correlation with aphid infestation. Prasannakumar *et al.*[12] assessed brown plant hopper (BPH) damage in rice plant using proximal hyperspectral reflectance. Correlation between plant reflectance and BPH damage, when plotted against wavelength, enabled us to identify four sensitive wavelengths at 1986, 665, 1792 and 500 nm, in relation to BPH stress on rice plants. Three new brown plant hopper spectral indices (BPHI) were formulated by combining two or more of these sensitive wavelengths. Using rice plant reflectance corresponding to the sensitive wavelengths, a multiple–linear regression model was developed and validated, which would facilitate assessment of BPH damage-based on rice plant reflectance, thereby ensuring prompt fore-warning to stakeholders. Ray *et al.*[97] investigated the utility of hyperspectral reflectance data for potato late blight disease detection. The differences between the vegetation indices for plants at different levels of disease infestation were found highly significant. The optimal hyperspectral wavebands to discriminate the healthy from disease-infested plants were 540, 610, 620, 700, 710, 730, 780 and 1040 nm, whereas up to 25% infestation could be discriminated using reflectance at 710, 720 and 750 nm. Das *et al.*[98] examined changes in spectral reflectance of soybean leaves induced by yellow mosaic virus (YMV) infection to monitor and assess YMV in the field. Sensitivity analysis indicated that reflectance at wavelengths ~642, ~686 and ~750 nm is sensitive to YMV infection, whereas for yellow leaves induced due to nitrogen deficiency the sensitive wavelength was ~589 nm. Red edge parameter was valuable for the assessment of YMV grades as the red edge peak (λ_{re}) was a good indicator to discriminate yellowing of leaves due to nitrogen deficiency from YMV infection. Nagaraja *et al.*[99] used red edge technique (i.e. red edge position and red edge value) along with other hyperspectral indices to successfully discriminate healthy and malformed mango panicles both under field and laboratory conditions. Sahoo *et al.*[100] assessed yellow rust disease in wheat crop using hyperspectral reflectance data collected in farmers' fields in northwest India and also laboratory conditions. They found four sensitive wavelengths at 675, 695, 727 and 935 nm, to study yellow rust stress and proposed two spectral disease indices based on reflectance of the above bands. In validation analysis of newly developed indices, the regression coefficient between the disease observed and predicted severity was found to be as high as 0.92.

Conclusion

Hyperspectral remote sensing studies have shown a variety of applications including varietal discrimination, moisture stress, parameter retrieval, pest and diseases assessment, etc. A large part of hyperspectral data may be redundant in agricultural application studies. It is important to identify and remove the redundant bands from further analysis to ensure most effective and efficient use of hyperspectral data in agriculture. However, some of the redundant bands in one application may be useful in some other application and this must be taken into consideration while data mining methods are used. Selection of optimum wavebands to study different agricultural applications is a consensus view based on a broad range of the literature reported. Advances in application of whole spectral analysis through spectral matching techniques would require well-characterized and well-understood spectral libraries of the features of interest. Acquisition and understanding of the basic spectral signatures of plants in the TIR is a major gap area. Thus, looking at the gap area and new technological developments in the TIR sensor designs make it worthwhile to investigate plant TIR emissivity characteristics and explore the potential use of TIR remote sensing information in vegetation studies. Also, there is a need to develop specific advanced tools for handling hypespectral application-specific utilities. The day is not far for realizing the operationalization of hyperspectral applications. The strength of hyperspectral data in biophysical and biochemical characterization of crops is well known. However, LIDAR and thermal data need to be considered in future for hyperspectral remote sensing.

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