HYPERSPECTRAL REMOTE SENSING AND ITS APPLICATIONS IN AGRICULTURE

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Abstract:

Hyperspectral remote sensing or imaging spectroscopy has provided precise monitoring of land. Improved tools, technology and methods have improved utilization of remotely sensed data. Traditional multispectral remote sensing data have many limitations in providing spectral data and hence it leads to the loss of crucial crop features. Hyperspectral remote sensing provides spectral data from 400 nm to 2700 nm range which provides accurate spectral information which helps precise mapping and quantification. Moreover, techniques based on hyperspectral remote sensing are less time consuming, non-destructive and easy to repeat unlike field survey-based techniques. In country like India, hyperspectral remote sensing has emerged with great possibilities of precision agriculture. With the use of hyperspectral remote sensing data estimation of biophysical and biochemical properties of crops like leaf area index, estimation of chlorophyll a and b, nitrogen, lignin, cellulose has become precise and quick. This paper includes and elaborates advantages of using hyperspectral remote sensing data.

Key Words: Imaging Spectroscopy, leaf area index, multispectral data.

Introduction

Recent technological advancements in hyperspectral remote sensing or imaging spectroscopy has opened new avenues in land monitoring applications. It is now possible to utilize remotely sensed data in a direct and informed manner using improved tools and techniques. Hyperspectral remote sensing is superior to conventional multispectral remote sensing in providing spectral information. Multispectral broadband remote sensing has major limitation as it uses average spectral information over the broad bandwidth which results in loss of critical information which is crucial in quantification and characterization of important crop parameters (Alchanatis and Cohen, 2011; Thenkabail, 2003). Hyperspectral remote sensing captures spectral information in many contiguous narrowly defined spectral bands. Moreover, compared to direct field survey based approach hyperspectral remote sensing techniques are less time consuming and non-destructive which provide spatial estimates for quantification and monitoring of the target. Hyperspectral remote sensing is being increasingly used in many applications of vegetation and agricultural croplands. It has potential applications in crop type discrimination to understand the cropping system of the region, measuring concentration of photosynthetic pigments, detecting abiotic and biotic plant stress, change detection in vegetation cover, accurate quantification and observing subtle changes in biophysical and biochemical parameters such as leaf area index, nitrogen, cellulose and lignin, assessment of moisture content. Hyperspectral remote sensing provides improved and significant basis to characterize, classify, model and map agricultural crops (Alchanatis and Cohen, 2011; Thenkabail, 2003). Occurrence of energy and gas exchange takes place at the main surface of crop canopies which is mainly represented by leaves. To understand the transport of photons within the crops it is essential to understand its optical properties. The reflectance and absorption attributes captured in narrow bands are linked to specific crop characteristics such as biochemical constituents, physical structure, water content and eco-physical status of crops (Thenkabail, Enclona, Ashton, Legg and Van Der Meer, 2004). Mainly, there are three eminent spectral ranges are defined as per the biophysical and biochemical constituents of the crops. In the visible domain (400-700 nm), the most important biological process absorption by leaf pigments takes place and therefore low reflectance and transmittance values are observed. Here, main light absorbing pigments chlorophyll-a, chlorophyll-b, carotenoids, xanthophylls and polyphenols play significant role in the process of absorption (Gitelson, 2011; Gitelson, Gritz, & Merzlyak, 2003). Chlorophyll-a demonstrates maximum absorption in 410-430 nm and 600-690 nm spectral regions whereas chlorophyll-b exhibits maximum absorption in 450-470 nm range. Total chlorophyll-a and chlorophyll-b account for 65% of the total pigment concentration. In the green domain, due to these strong absorption bands a reflectance peak is observed at around 550 nm. Carotenoids and xanthophylls mainly absorb light in blue region and are responsible of various colours of flowers and fruits. Polyphenols absorb light with decreased intensity from blue to red region and usually occur when leaf is dead. In near-infrared region (700-1300 nm), low absorption and highest reflectance and transmittance is observed because leaf pigments and cellulose are mostly transparent in this region. The level of reflectance in this domain is mainly reliant on the number if intercell spaces, cell layers and cell size. Here, scattering takes place due to multiple refractions and reflections at the boundary between hydrated cell walls and air spaces. Leaf water content and foliar constituents have major influence on leaf optical properties in the shortwave infrared (SWIR) region. In this domain, 1450 nm, 1940 nm and 2700 nm are responsible for major water absorption. Additionally, biochemical components like protein, cellulose, lignin and starch also have major impact on the overall reflectance of SWIR region. These organic molecules have weak absorption peak due to molecular absorption and are related to some chemical bonds like C-H, N-H and O-H in the fresh and healthy leaves (Ferrato and Forsythe, 2013; Rahul et al., 2017). Apart from the advantages of hyperspectral remote sensing data there are many challenges associated at various levels of data analysis. Hyperspectral data consist of numerous narrow contiguous spectral bands hence have large volume. Complex and voluminous data pose challenge in order to store, handle and analyze the data. High data dimensionality is one more challenge associated with hyperspectral remote sensing data (Ferrato and Forsythe, 2013; Rahul et al., 2017). The most common issue data redundancy occurs due to inter-band correlation and therefore peculiar knowledge about the application specific optimal bands is necessary to carry out data analysis. This article describes various methods of hyperspectral data analysis and its potential applications in the field of agriculture.

Hyperspectral remote sensing applications in Agriculture

Spectral Characterization and Crop Type Discrimination

Discrimination of subtle differences in various crop types can be accurately captured by narrow contiguous bands of hyperspectral remote sensing data. Although containing crucial information for crop type discrimination it also contains redundant information at band level due to inter-correlation of bands. Hence, Identification and removal of redundant bands is one of the key steps in the hyperspectral data analysis. Band/feature selection is very significant for the ease in data analysis and computation as well as to achieve higher accuracy. Optimal band selection is most commonly used technique to reduce the data redundancy and extraction of optimal bands. Many band discriminant methods like principle component analysis and spectral discriminant analysis are used for band/feature extraction. Crop type discrimination can be achieved by two approaches: 1. Unsupervised classification methods 2. Supervised Classification methods. Unsupervised classification is based on the pattern identification of the target in the image data. These methods do not require training data or prior knowledge of the true classes of the image. These methods are based on clustering, which uses an iterative optimization process to classify the pixel vectors to a number of groups based on a similarity measures. One of the distance measures can be used such as Euclidean distance and Mahalanobis distance to measure the similarities between the pixels. The clustering algorithm can divide pixels into a user specified number of classes using k-mean clustering or to a flexible number of classes within a specified range using ISODATA clustering method. the clustering algorithm will analyze the distance between the cluster means and a pixel vector which needs to be classified and will assign a pixel to the closest cluster. In the first iteration, all the pixels will be assigned to the nearest clusters and in further iterations cluster means will be recalculated (Thenkabail et al., 2000; Thenkabail, Smith & De-Pauw, 2002). This iterative process will be repeated until it meets to the one of the user specified criteria. The number of classes, number of iterations and percentage pixels migrating from one cluster to another are user specified criteria. Supervised classification techniques need training data or ground data hence the first requirement to carry out supervised classification is significant ground or training dataset. Ground data refer to pixels or endmembers within an image with known class labels. Collected ground data is divided into training set and test set. Training set is utilized to train the classification algorithm to identify similar pixels and test set is independently used to validate the performance of the classifier. In the supervised classification techniques, training set of ground data is used for feature extraction. The training of classification algorithm involves parameter estimation used in the particular classification algorithm until one of the user specified criteria is fulfilled. Post classification processing involves classification accuracy estimation using the ground data under the independent validation set to ensure that classification result is of acceptable level (Thenkabail et al., 2000; Thenkabail, Smith & De-Pauw, 2002). The most used hyperspectral data classification methods are spectral angle mapper (SAM), Maximum likelihood classifier (MLC), artificial neural network (ANN)and support vector machine (SVM).

Hyperspectral Vegetation Indices

Accurate estimation of crop biophysical and biochemical parameters is essential for many precision agricultural management practices. Narrow, contiguous hyperspectral bands capture specific information related to crop biophysical and biochemical parameters. These parameters are often measured by converting reflectance spectrum into a single value or vegetation index. Crop parameters measured by hyperspectral vegetation indices are divided into three main categories: 1. Crop structure; 2. Biochemical parameters; 3. Crop physiology/stress estimation.

Crop Structure

Crop structural properties include green leaf biomass, leaf area index (LAI), senesced biomass and fraction absorbed photosynthetically active radiation. Most indices developed for structural analysis were formulated for broadband data but applicable for narrowband hyperspectral data. Structure based vegetation indices mostly depend upon combination of near infrared (NIR) to red reflectance such as NIR to red ratio or simple ratio (SR). Normalized form of SR, normalized difference vegetation index (NDVI) reduces the impact of atmospheric scattering by using a normalized difference between red NIR and red bands. Both SR and NDVI are good predictor of biomass, LAI and fractional cover but NDVI saturates at higher LAI values and varies with viewing geometry (Jollineau & Howarth, 2008). To improve canopy structure and minimize the effect of atmosphere and substrate other indices based on NDVI like soil adjusted vegetation index (SAVI), the atmospherically resistant vegetation index (ARVI) and the enhanced vegetation index (EVI). NDVI is largely replaced by EVI due to improved resistance to the atmosphere and less evidence of saturation at higher values of LAI.

Biochemical parameters

Pigments concentration

Pigments concentration is an important indicator of phenological stages of crop, biotic or abiotic stress in crops. Many indices are developed to measure pigment concentration or to quantify specific pigments in leaves and canopies. Visible reflectance in crop spectra is mainly influenced by three pigments: 1. Chlorophyll a and b; 2. Carotenoids and anthocyanin. Indices developed to quantify chlorophyll concentration include chlorophyll absorption in reflectance index (CARI), modified CARI (MCARI) and chlorophyll red-edge index ($CI_{red\ edge}$). CARI utilizes mathematical difference between 700 and 670 nm reflectance, adjusted by a difference between 700 and 550 nm to recompense for non-photosynthetic material. MCARI further adjusts the soil component by ratio of NIR to red reflectance. $CI_{red\ edge}$ is based on a three band model for quantifying pigments. Here, the concentration of an absorber is quantified as the mathematical difference in reciprocal reflectance within an absorption region and reciprocal reflectance at a second wavelength outside of the main absorption region. This quantity is multiplied by NIR reflectance to compensate for variation in brightness. It shows almost linear relationship to chlorophyll content over diversity of crop types. Anthocyanin plays crucial role in minimizing photoinhibition and increases response to environmental stress (Jollineau & Howarth, 2008). Anthocyanin reflectance index (ARI) is calculated as the difference between reciprocal green reflectance (540-560 nm) and reciprocal red edge reflectance (690-710 nm) is the main index proposed for quantification of anthocyanin. Further, indices red/green ratio (RGRI) and the anthocyanin content index (ACI) calculated as the ratio of green to NIR reflectance are based on SR model. The process of light harvesting for photosynthesis and protect chlorophyll from photooxidation via the reversible conversion of the xanthophylls violaxanthin to zeaxanthin is aided by carotenoids. Photochemical reflectance index is most widely used carotenoids index which captures the shift from violaxanthin to zeaxanthin. Due to this transition subtle decrease occurs at 531 nm and can be quantified using a normalized difference index and 570 nm as the reference band.

Moisture content

Moisture content varies with number of leaves and water content of individual leaves. There many simple ratio and normalized indices proposed to estimate the expression of liquid water bands relative to reference non-absorbing wavelengths. SRs include the moisture stress index (MSI) which is calculated as ratio of SWIR band (1650 nm) to NIR band (830 nm). Normalized difference infrared index (NDII) is the normalized version of MSI. Here, 960 and 1180 nm are found to have the best correlation with tissue water over large range of plant types.

Crop residues

Distinct absorption bands related to proteins, starch, lignin, cellulose are critical for accurate quantification of crop biochemistry like senesced plant material, crop residue, carbon sequestration in the absence of water content and pigment. Out of all the biochemicals lignin and cellulose exhibit distinct absorption features in SWIR region. Cellulose absorption index (CAI) and normalized difference lignin index (NDLI) are most widely used indices to estimate lingo-cellulose content in the crop. CAI is calculated as the difference within a strong cellulose absorption band 2101 nm and average reflectance for two bands outside of this absorption feature, at 2031 and 2211 nm. NDLI utilizes prominent lignin absorption band at 1754 nm.

Crop physiology

Crop physiology significantly impacts overall reflectance spectra. Photochemical reflectance index (PRI) is one of the most effective physiology oriented hyperspectral vegetation index. With increased biotic or abiotic stress in plants, light absorbing capacity decreases and therefore reflectance at 531 nm drops due to shift of violaxanthin to zeaxanthin which produces increasingly negative PRI (Thenkabail, Enclona, Ashton, Legg, et al., 2004). Light use efficiency of crop can be effectively measured by PRI. NDVI and SR responds less effectively to change in FPAR whereas PRI effectively depicts downregulation of photosynthesis.

Pest and Disease Detection

Pest invasion and disease detection can be effectively captured by narrow contiguous bands of hyperspectral remote sensing data. The changes in crop canopy reflectance can provide significant information about the effect of pests and diseases on the crop physiology and biochemistry. Spectral unmixing process can be successfully applied to distinguish healthy crop from pest affected crop. Changes in leaf colour occurs due to occurrence of pest/disease in crops. Hyperspectral data can be useful to detect the change in leaf colour and further pest/disease severity can be measured. Spectral classification such as spectral normalization and nearest neighborhood classification technique and indices based analysis approach can estimate fungal disease severity. Spectral classification approach can be applied to discriminate healthy crop from diseased or pest affected crop to minimize the economic loss. Hyperspectral remote sensing data can be an important data source for pest and disease detection, estimating disease severity and investigating the impact of pest and disease over crops.

Precision Farming

Precision farming involves management of field site specifically based on the local field needs rather than managing entire field as a uniform unit. Precision agricultural practices lead to economic, productive and sustainable farming regime. By adapting precision farming, greater yield than traditional farming with the same or reduced input or the same yield with reduced input can be achieved. Precision agriculture has four important aspects; 1. Field variability sensing and critical information extraction; 2. Decision making based on the information retrieved and data analysis; 3. Precision field control; 4. Operationalization of new methods and approached and result evaluation. Hyperspectral remote sensing from ground or airborne platform can be important tool to extract field information (Thenkabail, Enclona, Ashton, Legg, et al., 2004). Agricultural remote sensing typically utilizes surface reflectance data which provides accurate and fast field specific data. Hyperspectral remote sensing data is captured in narrow contiguous bands hence provides critical information about biomass, crop yield estimation, crop physiology, nutrient stress, water stress, biotic stress (pest and disease infestation), weed control and soil properties. Apart from having major applications of hyperspectral remote sensing, a common issue related to it is spectral mixing of various target components. The implementation of various unmixing techniques, dimensionality reduction techniques help to extract accurate and specific spectral reflectance information for better data analysis. Combination of various techniques can lead to sustainable agricultural management with precision farming approach.

Conclusion

Hyperspectral remote sensing was initially used for detecting and mapping minerals. In recent times, hyperspectral remote sensing techniques are used by many researchers in studies related to vegetation and agriculture allied domains. Hyperspectral remote sensing gathers data in narrow contiguous bands. It is an emerging technology with many applications and provides sustainable solutions to map, model, characterize and quantify vegetation and agricultural crops. Finally, strength of hyperspectral remote sensing has proved in biochemical and biophysical characterization of agricultural crops. In future, integration of hyperspectral data with thermal and LIDAR are envisaged the future of remote sensing.

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