Journal of Experimental Agriculture International

Volume 46, Issue 1, Page 48-61, 2024; Article no.JEAI.109007
ISSN: 2457-0591
(Past name: American Journal of Experimental Agriculture, Past ISSN: 2231-0606)

Hyperspectral Imaging of Soil and Crop: A Review

C. Vairavan [a*], B. M. Kamble [a], A. G. Durgude [a], Snehal R. Ingle [a] and K. Pugazenthi [b]

[a] Department of Soil Science, Mahatma Phule Krishi Vidyapeeth, Rahuri, Maharashtra, India.
[b] Agro Climate Research Centre, Tamil Nadu Agricultural University, Coimbatore, Tamil Nadu, India.

Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

Article Information

DOI: 10.9734/JEAI/2024/v46i12290

Open Peer Review History:
This journal follows the Advanced Open Peer Review policy. Identity of the Reviewers, Editor(s) and additional Reviewers, peer review comments, different versions of the manuscript, comments of the editors, etc are available here: https://www.sdiarticle5.com/review-history/109007

Review Article

Received: 15/09/2023
Accepted: 20/11/2023
Published: 17/01/2024

ABSTRACT

The remote sensing is one of the precision technologies, can be used to monitor and assess the target area or object such as soil, crop, and water. Hyperspectral imaging (HSI), also known as imaging spectrometry or hyperspectral remote sensing, is a combined technique of spectroscopy and imaging system for sensing spectral information of an area or object. It involves capturing images of an object using multiple distinct optical bands that cover a wide range of the electromagnetic spectrum (350-2500 nm). The hyperspectral bands are continuous, narrow, and contagious and contain hundreds and thousands of numbers. Hyperspectral remote sensing is particularly valuable for gathering precise and up-to-date information necessary for agricultural planning and precision farming. HSI technology is the employment of hyperspectral sensors aids in analyzing soil physical (bulk density, texture, water content), chemical (pH, EC, SOC, and macro and micro nutrients), biological (SOM) properties and helps to categorize different crop varieties, identify pests and diseases, and assess crop yield and water stress in plants. The spectral reflectance of soil is affected by its properties such as mineral composition (Fe oxides), organic

**Corresponding author: E-mail: vairavanc99@gmail.com;*

matter, soil moisture, and texture. For example, the spectral reflectance will be more if soil has less organic matter. The chemical bonds of soil molecules interact with the electromagnetic spectrum, and produce distinct pattern of reflectance. But the data collected from hyperspectral imaging are required big storage due to its large amount of data and finding the most appropriate hyperspectral image classification algorithm is a challenging task. So, these problems should be solved in future and national soil spectral library is needed for calibration of models which helps for efficient use of hyperspectral imaging technology.

Keywords: Hyperspectral imaging technology; crop yields; climate change; precision agriculture.

1. INTRODUCTION

Agriculture is the foundation of human civilization, as it has allowed us to produce enough food to support large populations [1]. The face of agriculture has changed as a result of technological advancements during the past century, such as the Green Revolution [2]. The Green Revolution was a period of agricultural development that began in the 1940s and 1950s. It involved the introduction of new, high-yielding crop varieties, as well as the use of synthetic fertilizers and pesticides. These new technologies led to a significant increase in crop yields, which helped to ensure food security, particularly in developing countries [3]. Currently, the climate change and population growth are putting a strain on global food production. In that, the world's population is expected to grow by 2 billion people by 2050 and the total demand for food will rise between 50 and 60 percent between 2019 and 2050 [4]. However, if crop yields decline due to climate change, it will be more difficult to meet this demand [5].

To meet the increasing demand for food as the world's population grows, intensive agriculture is a method of farming that uses large amounts of resources to produce more food on a smaller area of land. If current trends of agricultural intensification in richer nations and land clearing in poorer nations continue, we could lose 1 billion hectares of land globally by 2050. This would lead to an increase in greenhouse gas emissions of 3 gigatons per year and nitrogen use of 250 million tons per year. Human activities, such as intensive agriculture, overgrazing, deforestation, water pollution, and the overuse of fertilizers and pesticides have had a significant negative impact on arable land, with over 35% of it being degraded in the past 6-7 decades. This degradation has led to increased salinization, loss of fertility, soil erosion, and desertification. In order to create a production system that is environmentally sustainable as well as economically feasible, we need to develop new techniques that can increase crop yields while using fewer resources and reducing pollution. Precision agriculture is one of the techniques that helps us to develop reliable models of water and nutrient movement in soil, manage resources efficiently, and protect the environment by accurately estimating the spatial variability of soil properties.

Precision agriculture, also known as precision farming or smart farming, refers to the use of technology and data analytics to optimize agricultural practices and inputs and increase productivity while minimizing waste. Precision agriculture (PA) plays a crucial role in establishing sustainable agricultural systems in the 21st century. PA uses a variety of technologies, such as Global Positioning System, Geographic Information System, Remote Sensing, sensors, and data analysis, to collect data about crop conditions and soil variability. This data can then be used to make more informed decisions about how to apply inputs, such as water, fertilizer, and pesticides. For example, PA can be used to map the nutrient levels in a field. This information can then be used to apply fertilizer only where it is needed, which can help reduce nutrient runoff and pollution. In that, Remote sensing systems, which use information and communication technologies, typically generate a large amount of spectral data due to the high spatial, spectral, radiometric, and temporal resolutions required for precision agriculture applications. Remote sensing is defined as “the science and art of obtaining information about an object, area or phenomenon through the analysis of data acquired by a device that is not in contact with the object, area and phenomenon in the investigation” (Lillsand and Kiefer, 1992). Remote sensing technology, such as satellites, manned aircraft, and unmanned aerial vehicles (UAVs), are employed in the process of agricultural remote sensing to systematically observe and analyse agricultural multi-factors [6].

Agricultural remote sensing is a newer technology that has quickly become a valuable tool for farmers and agricultural researchers. It uses satellite imagery and other data to collect information about crops and fields, such as crop health, soil moisture, and pest infestations. This information can be used to make more informed decisions about crop management, such as when to irrigate or apply pesticides. The use of agricultural remote sensing is growing rapidly, as it offers several advantages over traditional methods of agricultural monitoring, such as being faster, more precise, and less labor-intensive [7]. Remote sensing (RS) of soils and crop plants are the use of satellite imagery to collect data about soil and plant properties from a distance. There has been tremendous progress in both data acquisition technology and data processing techniques, which has made RS of soils and plants a more powerful and versatile tool.

2. HYPERSPECTRAL REMOTE SENSING

The human eye can only see a narrow range of the electromagnetic spectrum, but multispectral imaging sensors can capture images in a wider range. This allows us to identify materials based on their unique spectral signatures. Most multispectral imaging systems use only 3 to 6 spectral bands, which limits the amount of information that can be gathered. However, recent advances in hyperspectral sensing have made it possible to capture hundreds of spectral bands in a single acquisition. This allows for much more detailed analysis of materials. Hyperspectral imaging is a powerful tool for agriculture, as it can be used to identify crop varieties, pests, diseases, and water stress. It can also be used to assess soil characteristics such as composition, physical properties, humidity, and nutrient levels.

Hyperspectral imaging, also known as imaging spectrometry, is a technique for sensing spectral information. It involves capturing images of an object using multiple distinct optical bands that cover a wide range of the electromagnetic spectrum. Hyperspectral remote sensing is particularly valuable for gathering precise and up-to-date information necessary for agricultural planning and precision farming. It employs a well-designed instrument that captures complete images comprising hundreds of spectral bands of the observed objects. By analyzing the spectral signatures extracted from the hyperspectral image, it becomes possible to classify or identify various features within the displayed area. Hyperspectral imaging detectors typically detect light within the range of 400-2500 nm, which encompasses the visible, near-infrared (NIR), and short-wave infrared (SWIR) frequency bands. Hyperspectral imaging technology is widely utilized in agriculture, specifically for precision farming and agricultural advancement. An example of this technology is the employment of hyperspectral sensors to categorize different crop varieties, identify pests and diseases, and assess crop yield and water stress. It also aids in analyzing soil properties such as shape, composition, physical attributes, moisture levels, and nutrient content. This article provides an overview of the technology and its applications in remote sensing imagery for soil analysis and crop growth evaluation.

3. HISTORY

The concept of "hyperspectral imaging" was initially introduced in the field of remote sensing, which involves observing a target without physical contact. The term was first mentioned by Goetz *et al*. in 1985, referring to the use of imaging to directly identify surface materials. The era of hyperspectral imaging began in the late 1970s and early 1980s when airborne mineral mapping became possible. A crucial advancement in hyperspectral technology was the invention of the first CCDs (charge-coupled devices) by George Smith and Willard Boyle in 1969. This invention played a significant role in advancing hyperspectral imaging. Substantial progress in hyperspectral imaging systems occurred throughout the 1980s and 1990s, requiring extensive development efforts in electronics, hardware, computing, and software.

Starting in the 1980s, the origins of hyperspectral imaging can be traced back to the airborne imaging spectrometer (AIS), which was developed by Alexander Goetz and his colleagues at NASA's Jet Propulsion Laboratory (JPL), California Institute of Technology, in Pasadena, California. Subsequently, in 1983, JPL proposed and created the hyperspectral Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) to extend the capabilities of ground-based spectrometers to aerial platforms. In 1987, AVIRIS captured its first spectral images, becoming the first imaging spectrometer to measure the solar reflected spectrum from 400 nm to 2500 nm at 10 nm intervals [8]. Following the success of AVIRIS, significant advancements in sensor technology, calibration techniques, and data systems have led to the development of various multispectral and hyperspectral instruments, both ground-based and airborne. While initially designed for remote sensing applications, hyperspectral imaging has since found diverse applications in areas such as agriculture [9], environmental studies [10], geology [11], pharmaceuticals [12], medicine, and food quality and safety [13], [14], [15], [16]. Hyperspectral imaging operates on the fundamental principle that different materials exhibit unique patterns of reflecting, scattering, absorbing, and emitting electromagnetic energy at specific wavelengths due to variations in their chemical composition and physical structure. These distinctive patterns, known as spectral signatures or spectral fingerprints, can be represented as curves showing the percentage of reflectance, absorbance, or transmittance at different wavelengths for a particular material. By analyzing these spectral signatures, it is possible to characterize, identify, and differentiate between different types of materials present in each pixel of an image. The processed hyperspectral data allows for automatic identification of features with specific spectral signatures and mapping of attributes' spatial distribution.

Hyperspectral imaging is commonly defined as the simultaneous capture of spatial images in numerous contiguous spectral bands from a remote platform. This unique imaging technique combines the capabilities of imaging and spectroscopy, enabling the extraction of physical and geometric properties (such as shape, size, appearance, and color) as well as the chemical composition of the imaged object through spectral analysis. It is important to note that hyperspectral imaging is one type of spectral imaging, alongside multispectral and ultraspectral imaging. Each type involves capturing a stack of images of the same object, with each image representing a different narrowband of the spectrum. The distinction lies in the number of bands and the form of the obtained spectrum. Ultraspectral imaging is commonly used for systems with very fine spectral resolution, while hyperspectral imaging systems are characterized by many contiguous and regularly spaced bands. On the other hand, multispectral imaging systems typically have only a few spectral bands (usually less than 10), and each pixel does not provide a complete spectrum. In contrast, every pixel in a hyperspectral image contains a full spectrum. This abundance of data in hyperspectral images offers highly detailed information about the physical and chemical composition of the imaged objects. However, processing this extensive data requires more advanced methods and techniques.

The terms "Hypercube," "spectral cube," "data cube," or "spectral volume" are all used interchangeably to describe the structure of a hyperspectral image. A hyperspectral image is a three-dimensional (3D) block of data that consists of a series of two-dimensional images stacked together, each representing a different wavelength. This 3D block includes two spatial dimensions (rows and columns) and one spectral dimension (wavelengths). The hyperspectral image, denoted as **I** (x, y, λ), can be perceived either as an image I (x, y) at each specific wavelength λ or as a spectrum **I** (λ) at each individual pixel (x, y). The individual elements in the hypercube **I** (x, y, λ) are referred to as "voxels," while in the two-dimensional image I (x, y) at a single wavelength, they are called "pixels." However, in the context of this paper, both terms (pixel or voxel) are used interchangeably. The values of reflectance or absorbance of a voxel or a set of voxels (as a region of interest, ROI) at all wavelengths are simply referred to as the "spectrum." Each pixel in the possesses a unique spectral signature, representing a specific point in the image. Additionally, the complete spatial characteristics of the objects under examination can be observed in individual grayscale images at different wavelengths, demonstrating how the object exhibits varying intensity values based on its chemical composition. Consequently, an image can be analyzed by considering individual wavelengths or combinations thereof.

In the hypercube, images taken at adjacent wavelengths tend to be similar, while images captured at distant wavelengths can differ significantly and may contain independent information. Furthermore, no single wavelength image provides sufficient information to fully describe the object, which elucidates the utility of hyperspectral imaging in object analysis [17].

4. HYPERSPECTRAL IMAGING OF SOILS

The effectiveness of precision agriculture (PA) relies heavily on an efficient and precise approach to determine soil properties within the field. This information is crucial for farmers to accurately calculate the optimal number of inputs for achieving the best crop performance while minimizing negative environmental impacts. The conventional method of grid sampling, which explores soil variation within the field, is no longer considered suitable due to its labor-intensive and time-consuming nature, as well as its limited spatial coverage. However, remote sensing (RS) offers a new and advantageous tool for gathering information in PA, as it is cost-effective, rapid, and provides relatively high spatial resolution. Significant advancements have been made in utilizing RS to determine various agriculturally significant soil properties.

A wide range of soil properties, such as textures, organic and inorganic carbon content, macro- and micro-nutrients, moisture content, cation exchange capacity, electrical conductivity, pH, and iron, have been successfully quantified using RS to different extents. These applications have varied from analyzing soil samples in a laboratory setting using a bench-top spectrometer to creating soil maps at a larger scale using satellite hyper-spectral imagery. The visible and near-infrared regions are the most employed for inferring soil properties, while the ultraviolet, mid-infrared, and thermal-infrared regions have been occasionally utilized. In terms of data analysis techniques, multiple linear regression (MLR), principal component regression (PCR), and partial least squares regression (PLSR) are the three most widely employed methods.

a) Soil Texture

The composition of soil particles, including sand, silt, and clay, determines soil texture. This environmental factor is highly significant as it influences soil degradation, water movement, and ultimately, soil quality and productivity [18]. Understanding the variability in soil texture is essential for implementing targeted farming strategies that optimize the use of resources such as water and fertilizers, leading to cost reduction and minimized environmental impact [19]. Traditional approaches to mapping soil texture require extensive collection and analysis of numerous soil samples to accurately assess its spatial variation [20], which can be expensive and time-consuming.

To address these challenges, researchers are increasingly exploring indirect estimation methods that utilize proximal and remote sensors, including ground-based or airborne reflectance spectroscopy [21], [22]. Numerous studies have assessed the potential of high-resolution spectroscopy (HRS) for estimating soil texture, with laboratory and airborne imaging spectroscopy. However, the direct determination of soil texture from satellite hyperspectral imagery is still limited to a few studies. Estimating soil texture from spaceborne systems is more complex due to atmospheric distortions, as well as the low spatial and spectral resolution of the sensors [23]. To fully utilize data from future hyperspectral satellites, additional information is needed regarding sensor resolution, range, calibration, and validation. Developing more physically-based models would be a significant advancement in generalizing estimation approaches. However, this objective remains challenging at present [24].

b) Soil Moisture

Soil moisture is important to plant development, contributes to climate change by participates in carbon formation and controls evaporation rates, filtering, drought monitoring, overflow. The conventional methods of soil moisture measurement such as thermogravimetric method, heat flux soil sensors, time domain reflectometry (TDR), microelectromechanical system are time consuming approaches and it predicts in small scale. But hyperspectral imaging technology helps to estimate the soil moisture over a large-scale area. Wang *et al*. (2023) compared prediction efficiency of Random Forest (RF) along with eight other algorithms to predict soil moisture (SM) in Tibetan grasslands [25]. Under climate change scenario, authors used temperature, precipitation, radiation data and normalized differentiation vegetation index (NDVI) to predict spatiotemporal variability of actual SM (SM_a) and potential soil moisture (SM_p). Their developed model predicted SM with higher prediction efficiency of 94% when using RF than other algorithms.

In the past, there have been numerous studies conducted to understand the relationship between soil moisture and its reflectance. These studies were primarily carried out in controlled laboratory settings or outdoor environments. While recent research has shown that assimilating data from high-resolution satellites (HRS) into hydrological models can effectively estimate profile soil moisture, these findings only serve as case studies. They provide a starting point for other HRS users to create quantitative soil moisture maps. However, this innovative approach has not been thoroughly investigated or developed in this specific direction. Nevertheless, it shows promise and is necessary because several challenges, such as low signal-to-noise ratios, unreliable spectral band response, atmospheric interference with raw data, the requirement to position samples on the ground, and the absence of pixel-based physical or chemical models related to soil moisture content, remain unresolved.

c) Soil Nutrient Prediction

Soil nutrients are crucial for soil fertility, agricultural productivity, food security, and sustainable agriculture [26]. Mapping soil nutrients accurately and in a timely manner can help reduce nutrient loss and improve agricultural fertilization management. Traditional methods of monitoring soil nutrients in farmlands involve field sampling and laboratory analysis, which are inefficient and time-consuming. However, hyperspectral remote sensing (HRS) technology has the capability to detect even the slightest spectral changes in soil nutrients, making it a valuable source of information for modeling soil nutrients.

Based on available records from the Web of Science, only a limited number of studies have focused on monitoring soil nutrients using HRS information. For instance, Song *et al*. conducted a study in Zengcheng, north of the Pearl River Delta, China. They collected 1,297 soil samples and measured the content of soil total nitrogen (TN), soil available phosphorus (AP), and soil available potassium (AK). In their research, they used hyperspectral images (115 bands) obtained from the Chinese Environmental 1A (HJ1A) satellite as auxiliary variables. These images were processed using reduce-dimension techniques such as Pearson correlation analysis and principal component analysis. The study compared different prediction models, including simple linear regression, support vector machine (SVM), random forest, and back-propagation neural network (BPNN). All models were trained using both field samples and preprocessed HRS variables. Model validations were based on 324 independent data points. The study concluded that the most efficient method for mapping and monitoring soil nutrients at a regional scale was the application of hyperspectral imaging data with a BPNN model [27].

Another study by Yu *et al*. focused on soil property modeling using HRS in Shenzha County of the Qiangtang Plateau, located in the northwestern Qinghai-Tibet Plateau, where alpine grasslands are the predominant land cover. The research involved collecting hyperspectral data at 67 sample points and obtaining soil samples at those locations to measure properties such as organic carbon, TN, total potassium, and total phosphorus. The study analyzed the correlations between soil properties and original bands as well as enhanced spectral variables derived from both field and satellite hyperspectral data. Regression models were developed to map the soil properties based on the relationships observed. The results showed significant correlations between the soil properties and vis_NIR bands, particularly the wavelengths of 1720-1738 nm. The stepwise regression models using enhanced spectral variables derived from satellite hyperspectral imaging produced reasonable spatial distributions of soil properties. The relative root mean square error values were 68.9% for soil organic carbon, 46.3% for TN, 31.4% for total phosphorus, and 45.5% for total potassium. This study indicated that the method based on hyperspectral data had great potential for predicting soil properties and could be applied to assess the growth conditions of the alpine grassland species Stipa purpurea [28].

The number of published papers on using HRS technology for monitoring soil nutrient elements is limited, and most of these publications are recent, suggesting that this aspect of HRS is still in its early stages. There are various types of hyperspectral sensors available, and further studies need to be conducted in different areas and for different land cover species to explore the full potential of HRS in monitoring soil nutrients.

d) Soil Organic Carbon

The role of soil organic carbon (SOC) is crucial for various chemical and physical processes in soil environments. It serves as a primary nutrient source for plants, aids in particle aggregation, contributes to soil structure development, enhances water storage capacity, and provides a habitat for soil organisms. Understanding the spatial distribution of SOC concentration in the topsoil is vital for effective crop management, guiding fertilizer, and chemical applications. Traditionally, mapping SOC concentration involved laborious methods such as collecting and analyzing numerous soil samples, calibrating spatial prediction models, and interpolating the results over the entire study area. These methods are expensive and time-consuming due to the high spatial variability of SOC.

In recent years, hyperspectral remote sensing (HRS) technology has emerged as a powerful tool for rapid and multiscale monitoring of SOC. Ground, airborne, and spaceborne hyperspectral sensors have been tested for this purpose. However, the application of spaceborne hyperspectral sensors is less frequent compared to airborne sensors, despite the advantages of synoptic view and repetitive coverage offered by satellite data. Consequently, exploring the potential of satellite hyperspectral data for SOC prediction has become a critical focus in the development of digital soil mapping. It should be noted that the use of airborne and satellite hyperspectral sensors for SOC estimation has mainly been limited to small agricultural or bare soil areas and is still in the testing phase. Moreover, most studies have relied on simple statistical methods for SOC prediction, which have limitations in terms of physical interpretation of results and the transferability of models across different sensors. These drawbacks have been pointed out by previous researchers [29].

e) Soil Salinity

Soil salinity has been a significant and widespread issue causing land degradation for a considerable period, greatly limiting crop productivity [30]. It is crucial to accurately map and monitor salt-affected soils in order to make informed decisions promptly, such as adjusting management practices or undertaking reclamation and rehabilitation efforts [31]. However, the conventional techniques currently available for identifying and monitoring these salt-affected soils are costly, time-consuming, and require extensive sampling to capture spatial variations [32]. High-Resolution Spectroscopy (HRS) technology plays a vital role in the detection, mapping, and monitoring of salt-affected surface features by offering rapid, timely, relatively inexpensive, and repeatable data.

Numerous airborne and spaceborne hyperspectral sensors have been tested to assess the potential of HRS in salinity mapping, with positive outcomes. HRS has been widely employed to identify and map areas affected by salt, and several studies have demonstrated that hyperspectral data can be utilized to quantify the characteristics of saline soils at different scales. However, these studies primarily focused on identifying and mapping salt-affected soils, lacking a comprehensive characterization of their severity. Furthermore, most of these studies have remained in the experimental stage, with few evident practical application examples. Moreover, a variety of linear, nonlinear regression, and remote sensing image classification methods have been employed to identify and map soil salinity, causing confusion when selecting appropriate models or methods. These challenges underscore the need to explore universal quantitative models and methods and extensively apply them in practical settings to assess their true effectiveness.

5. HYPERSPECTRAL IMAGING OF CROPS

The use of remote sensing is an effective method for monitoring changes in the physical characteristics and health of crops, as well as for supporting precision agriculture practices [33]. Traditional approaches to detect and monitor important crop parameters require extensive sampling, time, and costly laboratory analyses, which are not feasible or environmentally sustainable on a large scale [34]. In contrast, remote sensing allows for the collection of information across large areas more quickly and at a lower cost per unit area compared to field sampling [35].

However, the use of multispectral remote sensors for crop analysis has limitations in accurately detecting crop changes due to their coarse spectral resolutions, which obscure detailed information about crop parameters [36]. Early multispectral images are hindered by spectral resolution issues, affecting the accuracy of variable retrieval and the ability to timely and effectively detect early signs of crop stress [37].

To overcome these limitations, hyperspectral remote sensing (HRS), also known as imaging spectroscopy or hyperspectral imaging (HSI), utilizes hundreds of narrow spectral bands that are sensitive to distinct biophysical and biochemical characteristics, providing a more detailed understanding of crops [38 and 39]. As a result, advancements in HRS offer opportunities for comprehensive mapping, modeling, and characterization of crop properties [40], particularly in detecting subtle changes in ground cover and its temporal variations.

HRS can effectively address the aforementioned challenges and enable more accurate and timely detection of crop health. Ongoing research focuses on conducting hyperspectral measurements in the field and laboratory to monitor agriculture and vegetation, retrieving plant traits from hyperspectral data in both leaf and canopy layers [41 and 42]. Additionally, efforts are being made to calibrate hyperspectral sensors, validate their products for agriculture and vegetation monitoring, and ensure the quality of retrieved information [43]. Statistical and computational methods are being developed to enhance agricultural and vegetation monitoring, while studies are exploring the impact of agricultural and vegetation environments on microbial load and the presence of surrounding species [44].

6. APPLICATION IN CROP MONITORING

HRS, or hyperspectral remote sensing, offers an efficient method to extract plant parameters [45]. It has been widely utilized for various crop-related purposes, including the retrieval of water content [46], weed management [47], estimation of evapotranspiration [48], yield prediction [49], detection of heavy metals [50], assessment of bioenergy potential [51], determination of stand density [52], measurement of crop residue [53], evaluation of gross photosynthesis [54] diagnosis of diseases [55], derivation of phenology [56], identification of species [57], estimation of nutrient concentration, assessment of biomass, and quantification of pigment content [58]. In general, pigment content and nutrient concentration have been the most studied aspects of HRS in crop monitoring for many years. However, the applications of HRS in crop monitoring have expanded over time, with more diverse and quantitative content. Particularly in recent years, there has been a focus on emerging agricultural research areas, such as the detection of heavy metals and retrieval of water content. It should be noted that most of the studies conducted on HRS were based on ground remote sensing platforms, with very few utilizing airborne or spaceborne remote sensing platforms.

a) High Throughput Phenotyping (HTP) in the Field

The continuous advancement of new technologies is crucial in order to effectively incorporate diverse data from various phenotyping systems. These systems should be consistent, automatic, multifunctional, and capable of high-throughput processing. It is important to focus on developing high-performance, cost-effective technologies. Multifunctional devices for phenotyping generate large volumes of sensor data and images. However, the field of crop high-throughput phenotyping encounters fresh challenges in terms of storing, managing, and analyzing this data [59]. In recent times, high-throughput phenotyping or phenomics technologies have proven beneficial for plant breeding and crop production purposes. Researchers have worked on creating and testing different sensors, platforms, and algorithms for processing images in field-based phenotyping [60].

b) Chlorophyll Content

Hyperspectral remote sensing with high spatial resolution can be used to estimate the amount of chlorophyll present. Accurate assessment of canopy chlorophyll content is crucial for measuring both biotic and abiotic stresses, as emphasized by Yang *et al*. Their research demonstrates the reliability of using hyperspectral remote sensing images to determine chlorophyll content at both the leaf and canopy levels. Moreover, utilizing chlorophyll content for evaluating forest growth stages and diseases can be advantageous [61].

Hyperspectral imaging enables the detection of modified spectral signatures caused by fungal infection. By analyzing chlorophyll fluorescence, which is influenced by the reduced physiological activity of tissues due to Fusarium, it becomes possible to identify the symptoms of this disease easily [62].

To obtain the average spectra of millet leaves, researchers intelligently extracted the region of interest and employed hyperspectral imaging to collect spectral and image information at various stages of millet leaf development. Maria and Xiaoyan (2020) demonstrated the efficiency of the CNN model in estimating the chlorophyll content of millet leaves. This model can effectively extract the intrinsic features of spectral data and simplify preprocessing [63].

c) Fungal Diseases Detection

Hyperspectral imaging can identify fungal contamination by observing alterations in the spectral features, which also helps minimize the impact of Fusarium effects on the tissue's physiological activity. These effects form the basis for the analysis of chlorophyll fluorescence imaging [64].

d) Drought Stress Detection

Hyperspectral imaging is a technique that captures detailed information from plants without causing any harm. Various methods of data analysis exist to recognize both environmental and biological pressures on plants [65]. These methods primarily focus on distinguishing between healthy and diseased plants, assessing the severity of diseases, and identifying early signs of stress [66]. Hyperspectral imaging is becoming increasingly popular as a reliable tool, both in proximity and from a distance, to detect drought stress in agriculture [67]. Notably, a significant finding was that the standard deviations of multiple indices consistently increased as the water availability worsened. The dry treatment and plants experiencing repeated drought events showed noticeable enhancements [68].

e) Weeds Detection and Management

The application of deep learning in automated weed control is a novel and advanced approach that offers superior precision compared to other methods. Deep learning has the potential to be employed across various crops to identify weeds [69] and automate the application of herbicides, addressing a research gap [70]. Khan *et al*. introduced a conceptual segmentation technique using a cascaded encoder-decoder network to detect weeds in crops. Current systems for categorizing weeds and crops are highly complex, involving numerous variables that require extensive training time [71]. To overcome these limitations, the researchers suggested using micro training networks in a cascade, generating coarse-to-fine predictions that can be combined to obtain the outcome [72].

f) Crop Classification

The utilization of hyperspectral remote sensing enables the extraction and categorization of crop characteristics. Remote sensing data is disorganized, but the effective handling of unstructured data can be achieved using convolutional neural networks (CNNs) [73]. With their multiple bands, abundant spectral information, and sensitivity to subtle spectral variations among objects on the ground, hyperspectral data has successfully identified crop types, varieties, and obtained spatial distribution maps and planting structure information of crops. However, due to its high dimensionality and the extensive effort required for data processing, hyperspectral data is not suitable for accurate crop classification in large-scale regions. Therefore, it is crucial to develop a strategy for dimension reduction and a classifier capable of accelerating the processing of hyperspectral data for future precise crop classification using hyperspectral remote sensing over broad regional areas [74].

7. KEY PROBLEMS AND CHALLENGES

A) Limitation of Standard Datasets and Experiment Analysis

Datasets play a crucial role in assessing and studying various subjects. It has been observed that there is a scarcity of publicly accessible benchmark hyperspectral datasets. Additionally, researchers may not employ the appropriate methodology for tackling challenging tasks if they deviate from the conventional evaluation approach in real-world scenarios. Different researchers have generated diverse datasets by modifying experimental parameters, which makes it improbable to replicate real-time situations and hinders comparative analysis between two techniques [75]. Techniques that prove effective on these limited and small-scale images can be easily extrapolated to larger real-world images. Considering these factors, it is important for the hyperspectral remote sensing community to develop new open datasets [76].

b) Dimensionality Problem

The challenge of dealing with the high dimensionality of hyperspectral data in remote sensing has been extensively studied. The term "virtual dimensionality" (VD) originally referred to the number of distinct spectral signatures present in hyperspectral data. In the past, VD was commonly used to determine the number of end members. Compared to intrinsic dimensionality, virtual dimensionality is a relatively new concept that, if properly understood, can significantly impact the processing of hyperspectral data [76].

HSI data, with its high number of dimensions, exhibits various artifacts that lead to misclassification. Like very high-resolution (VHR) images, HSI data demonstrates significant intraclass variability due to uncontrollable variations in the reflectance detected by the spectrometer. These variations are often caused by changes in atmospheric conditions, the presence of clouds causing occlusions, fluctuations in illumination, and other environmental factors [77].

c) Deep Learning Limitations

A deep learning system that operates without supervision is considered the most effective approach for analyzing hyperspectral data. It leverages large amounts of labeled images that are already available. On the other hand, supervised deep learning relies on extensive datasets. Previous studies have explored the transferability of unsupervised features learned from different types of images. Deep generative models such as generative adversarial networks (GANs) and variational autoencoders (VAs) show great potential in modeling unlabeled hyperspectral data. These models can simulate the generation of spectra and be utilized to quantify spectral variability. However, the computational requirements and memory demands of deep models with numerous variables are substantial. Researchers need to carefully choose the most suitable models that align with the characteristics of hyperspectral imaging (HSI) data while considering the inherent challenges of the HSI dataset and the limitations of deep models. To reduce computation time, it is crucial to select appropriate architectures, learning methods, and procedures that are well-suited for the data.

d) Mixed Pixel Classification

The primary issue faced by hyperspectral imaging is the lack of labeled data. In comparison to multispectral remote sensing sensors like Sentinel or Landsat, there are limited numbers of active space-borne spectrometers capturing images, and the resulting data is often not publicly available. Additionally, airborne spectrometers cover a smaller area compared to satellite-based sensors. The availability of hyperspectral (HIS) datasets is also relatively limited [77]. Hyperspectral images contain many pixels, making it challenging to manually select the optimal spectra for vegetation and bare soil. Consequently, unsupervised approaches for extracting end members can perform better than supervised methods. However, the unmixing techniques [78] used are based on linear mixture models, and they may not effectively handle areas with significant nonlinear effects [79]. These effects present interesting opportunities for further exploration and processing.

8. CONCLUSION

Due to the abundance of spectrum information sensitive to many biophysical and biochemical characteristics of plants and soil, hyperspectral imaging offers enormous promise for applications in agriculture, particularly precision agriculture. In recent years, a variety of platforms, including satellites, aircraft, unmanned aerial vehicles (UAVs), and close-range platforms, have become more readily accessible for gathering hyperspectral images with various spatial, temporal, and spectral resolutions. Regarding the amount of space covered, the length of the flight, flexibility, operational complexity, and cost, these platforms likewise have different advantages and disadvantages. When selecting imaging platforms for particular research aims, these elements must be taken into account. To get beyond some of the restrictions, such as the limited battery life of UAV operations and the expensive price of hyperspectral sensors, more technology advancements are also required.

Numerous agricultural applications of hyperspectral imaging have been successful, including estimating crop biochemical and biophysical properties, assessing crop nutrient and stress status, categorizing or detecting crop types, weeds, and diseases, and examining soil characteristics.

Previous studies did not thoroughly assess crop status and growth-limiting factors since they only covered one or two of the many variables affecting crop growth performance and output. To get a better knowledge of these components' interactions and to ensure the best crop production and environmental preservation, it is crucial to integrate them.

COMPETING INTERESTS

Authors have declared that no competing interests exist

REFERENCES

1. Awokuse TO, Xie R. Does agriculture really matter for economic growth in developing countries?. Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie. 2015; 63(1):77-99.
2. Patel R. The long green revolution. The Journal of Peasant Studies. 2013;40(1):1-63.
3. John DA, Babu GR. Lessons from the aftermaths of green revolution on food system and health. Frontiers in sustainable food systems. 2021;5:644559.

4. Falcon WP, Naylor RL, Shankar ND. Rethinking Global Food Demand for 2050. Population and Development Review. 2022;48(4):921-957.
5. Navath S. What to Expect in the Next Green Revolution?. Journal of Green Chemistry and Chemical Engineering. 2022;1(1):12-13.
6. Wang D, Shao Q, Yue H. Surveying wild animals from satellites, manned aircraft and unmanned aerial systems (UASs): A review. Remote Sensing. 2019;11(11):1308.
7. Huajun T. Progress and prospect of agricultural remote sensing research. Journal of Agriculture. 2018;8(1):175.
8. Goetz AFH. Imaging spectrometry for remote sensing, Vision of reality in 15 years, Proceedings of SPIE. 1995;2480:2–13.
9. Lawrence KC, Windham WR, Park B, Buhr RJ. Hyperspectral imaging system for identification of faecal and ingesta contamination on poultry carcasses. Journal of Near Infrared Spectroscopy. 2003;11(4):269–281.
10. Clark CD, Tipley HT, Green EP, Edwards AJ, Mumby PJ. Mapping and measurement of tropical coastal environment with hyperspectral and high spatial resolution data. International Journal of Remote Sensing. 1997;18(2):237–242.
11. Resmini RG, Kappus ME, Aldrich WS, Harsanyi JC, Anderson M. Mineral mapping withhyperspectral digital imagery collection experiment (HYDICE) sensor data at Cuprite, Nevada, USA. International Journal of Remote Sensing. 1997;18(7):1553–1570.
12. Ravn C, Skibsted E, Bro R. Near-infrared chemical imaging (NIR-CI) on pharmaceutical solid dosage forms—comparing common calibration approaches. Journal of Pharmaceutical and Biomedical Analysis. 2008 Nov 4;48(3):554-61.
13. Mehl PM, Chen YR, Kim MS, Chan DE. Development of hyperspectral imaging technique for the detection of apple surface defects and contaminations. Journal of food engineering. 2004 Jan 1;61(1):67-81.
14. Naganathan GK, Grimes lM, Subbiah J, Calkins CR, Samal A, Meyer GE. Visible/near-infrared hyperspectral imaging for beef tenderness prediction. Computers and Electronics in Agriculture. 2008;64:225–233.
15. Qiao J, Ngadi MO, Wang N, Gariépy C, Prasher SO. Pork quality and marbling level assessment using a hyperspectral imaging system. Journal of Food Engineering. 2007 Nov 1;83(1):10-6.
16. Liu M, Zhang L, Guo E. Hyperspectral Laser-induced fluorescence imaging for non destructive assessing soluble solids content of orange. Computer and Computing Technologies in Agriculture. 2008;1:51–59.
17. Kim IN, Kim MS, Chen YR, Kong SG. Detection of skin tumors on chicken carcasses using hyperspectral fluorescence imaging. Transactions of the ASAE. 2004;47(5):1785-92.
18. Blume HP, Brümmer G, Horn R, Kandeler E, Kögel-Knabner I, Kretzschmar R, et al., Scheffer/Schachtschabel Lehrbuch der Bodenkunde, sixteenth ed. Spektrum Akademischer Verlag, Heidelberg; 2010.
19. Castaldi F, Palombo A, Pascucci S, Pignatti S, Santini F, Casa R. Reducing the influence of soil moisture on the estimation of clay from hyperspectral data: a case study using simulated PRISMA data. Remote Sensing. 2015;7:15561-15582.
20. Curcio D, Ciraolo G, Asaro FD, Minacapilli M. Prediction of soil texture distributions using VNIR-SWIR reflectance spectroscopy. Procedia Environment Science. 2013;19:494-503.
21. Brown DJ, Shepherd KD, Walsh MG, Mays MD, Reinsch TG. Global soil characterization with VNIR diffuse reflectance spectroscopy. Geoderma. 2006;132:273-290.
22. Ben-Dor E, Chabrillat S, Demattê JAM, Taylor GR, Hill J, Whiting ML, et al., Using imaging spectroscopy to study soil properties. Remote Sensing of Environment. 2009;113:38-55.
23. Mulder VL, de Bruin S, Schaepman ME, Mayr TR. The use of remote sensing in soil and terrain mapping—a review. Geoderma. 2011;162:1-19.
24. Casa R, Castaldi F, Pascucci S, Palombo A, Pignatti S. A comparison of sensor resolution and calibration strategies for soil texture estimation from hyperspectral remote sensing. Geoderma. 2013 Apr 1;197:17-26.
25. Wang S, Fu G. Modelling soil moisture using climate data and normalized

difference vegetation index based on nine algorithms in alpine grasslands. Frontiers in Environmental Science. 2023 Feb 10;11:1130448.
26. Nowak B, Nesme T, David C, Pellerin S. Nutrient recycling in organic farming is related to diversity in farm types at the local level. Agriculture, Ecosystems & Environment. 2015 Jun 1;204:17-26.
27. Song YQ, Zhao X, Su HY, Li B, Hu YM, Cui XS. Predicting spatial variations in soil nutrients with hyperspectral remote sensing at regional scale. Sensors. 2018 Sep 13;18(9):3086.
28. Yu H, Kong B, Wang G, Du R, Qie G. Prediction of soil properties using a hyperspectral remote sensing method. Archives of Agronomy and Soil Science. 2018 Mar 21;64(4):546-59.
29. Peón J, Fernández S, Recondo C, Calleja JF. Evaluation of the spectral characteristics of five hyperspectral and multispectral sensors for soil organic carbon estimation in burned areas. International Journal of Wildland Fire. 2017 Feb 28;26(3):230-9.
30. Epstein E, Norlyn JD, Rush DW, Kingsbury RW, Kelley DB, Cunningham GA, Wrona AF. Saline culture of crops: a genetic approach. Science. 1980 Oct 24;210(4468):399-404.
31. Metternicht GI, Zinck JA. Remote sensing of soil salinity: potentials and constraints. Remote sensing of Environment. 2003 Apr 25;85(1):1-20.
32. Shepherd KD, Walsh MG. Development of reflectance spectral libraries for characterization of soil properties. Soil science society of America journal. 2002 May;66(3):988-98.
33. Lu B, Dao PD, Liu J, He Y, Shang J. Recent advances of hyperspectral imaging technology and applications in agriculture. Remote Sensing. 2020 Aug 18;12(16):2659.
34. Mahajan GR, Pandey RN, Sahoo RN, Gupta VK, Datta SC, Kumar D. Monitoring nitrogen, phosphorus and sulphur in hybrid rice (*Oryza sativa* L.) using hyperspectral remote sensing. Precision agriculture. 2017 Oct;18:736-61.
35. Flynn KC, Frazier AE, Admas S. Nutrient prediction for tef (*Eragrostis* tef) plant and grain with hyperspectral data and partial least squares regression: Replicating methods and results across environments. Remote Sensing. 2020 Sep 4;12(18):2867.
36. Hong G, Abd El-Hamid HT. Hyperspectral imaging using multivariate analysis for simulation and prediction of agricultural crops in Ningxia, China. Computers and Electronics in Agriculture. 2020;172.
37. Ang LM, Seng J. Big data and machine learning with hyperspectral information in agriculture. IEEE Access. 2021;1–1.
38. Gao J, Meng B, Liang T, Feng Q, Ge J, Yin J, Wu C, Cui X, Hou M, Liu J, Xie H. Modeling alpine grassland forage phosphorus based on hyperspectral remote sensing and a multi-factor machine learning algorithm in the east of Tibetan Plateau, China. ISPRS Journal of Photogrammetry and Remote Sensing. 2019;147:104–117.
39. Meivel S, Maheswari S. Remote sensing analysis of agricultural drone. Journal of the Indian Society of Remote Sensing. 2021;49:689–701.
40. Nidamanuri RR, Zbell B. Transferring spectral libraries of canopy reflectance for crop classification using hyperspectral remote sensing data. Biosystems Engineering. 2011;110:231–246.
41. Berger K, Verrelst J, Feret JB, Wang Z, Wocher M, Strathmann M, Hank T. Crop nitrogen monitoring: recent progress and principal developments in the context of imaging spectroscopy missions. Remote Sensing of Environment. 2020;242.
42. Dobrota CT, Carpa R, Butiuc-Keul A. Analysis of designs used in monitoring crop growth based on remote sensing methods. Turkish Journal of Agriculture and Forestry. 2021;45:730–742.
43. Fahey T, Hai P, Gardi A, Sabatini R, Lamb DW. Active and passive electro-optical sensors for health assessment in food crops. Sensors. 2020;21:171.
44. Santos-Rufo A, Mesas-Carrascosa FJ, Garcia-Ferrer A, Merono-Larriva JE. Wavelength selection method based on partial least square from hyperspectral unmanned aerial vehicle orthomosaic of irrigated Olive Orchards. Remote Sensing. 2020;12(20):3426.
45. Millan VG, Azofeifa SA. Quantifying changes on forest succession in a dry tropical forest using angularhyperspectral remote sensing. Remote Sensing. 2018;10:1865.
46. Chou S, Chen JM, Yu H, Chen B, Zhang XY, Croft H, Khalid S, Li M, Shi Q. Canopy-level photochemical reflectance index from hyperspectral remote sensing

and leaf-level non-photochemical quenching as early indicators of water stress in maize. Remote Sensing. 2017;9:794.
47. Huang YB, Lee MA, Thomson SJ, Reddy KN. Ground-based hyperspectral remote sensing for weed management in crop production. International Journal of Agricultural and Biological Engineering. 2016;9:98–109.
48. Marshall M, Thenkabail P, Biggs T, Post K. Hyperspectral narrowband and multispectral broadband indices for remote sensing of crop evapotranspiration and its components (transpiration and soil evaporation) Agricultural and Forest Meteorology 218–219. 2016;122–134.
49. Elsayed S, Darwish W. Hyperspectral remote sensing to assess the water status, biomass, and yield of maize cultivars under salinity and water stress. Bragantia. 2017;76:62–72.
50. Zhou WH, Zhang JJ, Zou MM, Liu XQ, Du XL, Wang Q, Liu YY, Liu Y, ad Li J.L. Prediction of cadmium concentration in brown rice before harvest by hyperspectral remote sensing. Environmental Science and Pollution Research. 2019;26:1848–1856.
51. Offermann R, Seidenberger T, Thrän D, Kaltschmitt M, Zinoviev S, Miertus S. Assessment of global bioenergy potentials. Mitigation and adaptation strategies for global change. 2011 Jan;16:103-15.
52. Udelhoven T, Delfosse P, Bossung C, Ronellenfitsch F, Mayer F, Schlerf M, Machwitz M, Hoffmann L. Retrieving the bioenergy potential from maize crops using hyperspectral remote sensing. Remote Sensing. 2013;5:254–273.
53. Pacheco A, Bannari A, Staenz K, McNairn H. Deriving percent crop cover over agriculture canopies using hyperspectral remote sensing. Canadian Journal of Remote Sensing. 2008;34:110-123.
54. Chi J, Crawford MM. Spectral unmixing-based crop residue estimation using hyperspectral remote sensing data: A case study at Purdue University. IEEE Journal of Selected Topicsin Applied Earth Observations and Remote Sensing. 2014;7:2531–2539.
55. Yuan H, Yang G, Li C, Wang Y, Liu J, Yu H, Feng H, Xu B, Zhao X, Yang X. Retrieving soybean leaf area index from unmanned aerial vehicle hyperspectral remote sensing: Analysis of RF, ANN, and SVM regression models. Remote Sensing. 2017 Mar 25;9(4):309.
56. Prasannakumar NR, Chander S, Sahoo RN. Characterization of brown planthopper damage on rice crops through hyperspectral remote sensing under field conditions. Phytoparasitica. 2014 Jul;42:387-95.
57. Lausch A, Salbach C, Schmidt A, Doktor D, Merbach I, Pause M. Deriving phenology of barley with imaging hyperspectral remote sensing. Ecological Modelling. 2015 Jan 10;295:123-35.
58. Moreno R, Corona F, Lendasse A, Graña M, Galvão LS. Extreme learning machines for soybean classification in remote sensing hyperspectral images. Neurocomputing. 2014 Mar 27;128:207-16.
59. Inoue Y, Guerif M, Baret F, Skidmore A, Gitelson A, Schlerf M, Darvishzadeh R, Olioso A. Simple and robust methods for remote sensing of canopy chlorophyll content: a comparative analysis of hyperspectral data for different types of vegetation. Plant Cell and Environment. 2016;39:2609–2623.
60. Shakoor N, Lee S, Mockler TC. High throughput phenotyping to accelerate crop breeding and monitoring of diseases in the field. Current opinion in plant biology. 2017 Aug 1;38:184-92.
61. Zhang C, Marzougui A, Sankaran S. High-resolution satellite imagery applications in crop phenotyping: an overview. Computers and Electronics in Agriculture. 2020 Aug 1;175:105584.
62. Yang X, Yu Y, Fan W. Chlorophyll content retrieval from hyperspectral remote sensing imagery. Environmental monitoring and assessment. 2015 Jul;187:1-3.
63. England JR, Cheng PM. Artificial intelligence for medical image analysis: a guide for authors and reviewers. American journal of roentgenology. 2019 Mar;212(3):513-9.
64. Maria S, Xiaoyan W. Chlorophyll Content for Millet Leaf using Hyperspectral Imaging and an Attention- Convolutional Neural Network. 2020;1–12.
65. Bauriegel E, Herppich WB. Hyperspectral and chlorophyll fluorescence imaging for early detection of plant diseases, with special reference to fusarium spec. Infect. Wheat. 2014;32–57.

66. Sahoo RN, Ray SS, Manjunath KR. Hyperspectral remote sensing of agriculture. 2015;108(5).
67. Lowe A, Harrison N, French AP. Hyperspectral image analysis techniques for the detection and classification of the early onset of plant disease and stress. Plant Methods. 2017;1–12.
68. Gerhards M, Schlerf M, Mallick K. Challenges and Future Perspectives of Multi-/ Hyperspectral Thermal Infrared Remote Sensing for Crop Water-Stress Detection: A Review; 2019.
69. Zelanzny. Drought Stress Detection in Juvenile Oilseed Rape Using Hyperspectral Imaging with a Focus on Spectra Variability; 2020.
70. Knoll FJ, Czymmek V, Poczihoski S, Holtorf T, Hussmann S. Improving efficiency of organic farming by using a deep learning classification approach. Computers and electronics in agriculture. 2018 Oct 1;153:347-56.
71. Moazzam SI. A Review of Application of Deep Learning for Weeds and Crops Classification in Agriculture. 2019;1-6.
72. Khan A, Ilyas T, Umraiz M, Mannan ZI, Kim H. Ced-net: crops and weeds segmentation for smart farming using a small cascaded encoder-decoder architecture. Electronics. 2020 Oct 1;9(10):1602.
73. Bhosle K, Musande V. Evaluation of CNN model by comparing with convolutional autoencoder and deep neural network for crop classification on hyperspectral imagery. Geocarto Int. 2020;0 (0):1–15.
74. Zhang Y, Wang D, Zhou Q. Advances in crop fine classification based on Hyperspectral Remote Sensing. 8th Int Conf Agro-Geoinformatics. 2019;1–6.
75. Babu MCG, Padma MC. A efficient solution for classification of crops using hyper spectral satellite images. Int J Innov Technol Explor Eng. 2019;9 (2):5204–5211.
76. Gewali UB, Monteiro ST, Saber E. Machine Learning based Hyperspectral Image Analysis: A Survey; 2018.
77. Paoletti ME, Haut JM, Plaza J, Plaza A. ISPRS J. Photogr. Rem. Sens. Deep Learning Classifiers for Hypersp. Imaging: A Rev. 2019;158 (September):279–317.
78. Bioucas-dias JM. Hyperspectral Remote Sensing Data Analysis and Future Challenges. IEEE Geoscience and remote sensing magazine. 2013;1(2):6-36.
79. Wei Q, Chen M, Tourneret JY, Godsill S. Unsupervised nonlinear spectral unmixing based on a multilinear mixing model. IEEE Transactions on Geoscience and Remote Sensing. 2017 May 25;55(8):4534-44.

Peer-review history:
The peer review history for this paper can be accessed here:
https://www.sdiarticle5.com/review-history/109007