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Development of Spectral Signature of Chir Pine Using Hyperion Data

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ABSTRACT

The study was conducted during January, 2023 which aims to map the chir pine forest of the Almora region of Uttarakhand, India using hyperion data and construct a spectral signature. The data was processed using ENVI 4.4 software. For image classification, the Spectral Angle Mapper (SAM) was employed. Many remote sensing projects covering relatively large areas have effectively exploited multispectral data for data extraction and statistical analysis of natural resources. Hyperspectral imagery has seen recent methodological and technological developments that open up new avenues for researching the structure and processes of local ecosystems. Within the realm of sustainability studies, trees are deemed essential for a multitude of ecosystem services that encompass environmental quality, food security, and human health. Species level tree mapping could be one of these prerequisites. Using a reliable method for species-level remote sensing of forest composition will significantly advance our understanding of these dynamics. After the correct match between field spectra and pixel spectra was established, the spectra library of chir pine was created. The result show that the NIR spectral range (700–1300 nm) has higher spectral reflectance than the visible region (400–700 nm). The data indicated a sharp decrease shortly after 1300 and 1700 nm. The library of spectral signature created for the chir pine will serve as the target spectrum for the classification of remote sensing data pertaining to this species. With this knowledge, there may be considerable opportunity to support upcoming initiatives aimed at sustainability in various socio-ecological contexts.

KEYWORDS: Chir pine, hyperion, hyperspectral, remote sensing, spectral signature

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1. INTRODUCTION

Hyperspectral remote sensing which began in early 1980s is one of the most significant breakthroughs in remote sensing. It became apparent that this approach held promise for the spectroscopic and spatial analysis of earth surface minerals. Excellent performance in spectral and radiometric calibration of the data sets is offered by hyperspectral remote sensing. Information can be extracted from this high-performing sensor data and used in a variety of quantitative and qualitative applications. Information is gathered via hyperspectral sensors at intervals of 10 to 20 nm in wavelength bands. The single pixel in hyperspectral data resembles laboratory-quality spectra obtained with a spectro-radiometer, which can be utilized to comprehend the material's spectral properties. It is comparatively easier to identify and distinguish spectrally similar materials using hyperspectral data. The development of improved multispectral and hyperspectral scanners is a result of the growth of space-borne remote sensors (Goodenough et al., 2003). With differing degrees of success, numerous studies have tried to determine the relationship between forest qualities and their multispectral signatures using data from SPOT, Multi-spectral Scanner (MSS), and Landsat Thematic Mapper (TM) (Krohn et al., 1981; Vohland et al., 2007; Cohen et al., 2018; Yu et al., 2018; Sawaiker and Gaonkar, 2020; Pham and Prakash, 2018; Chaware et al., 2021). Due to their limited spectral resolution, multispectral remote sensing scanners have not shown to be reliable in giving species-level information (Asner, 1998), although they have been helpful in producing information on the kind of forest cover (Schriever and Congalton, 1995; Watson and Wilcock, 2001). The majority of natural things may be distinguished from one another by their distinct spectral signatures, many of which are found in a relatively small wavelength range. Therefore, a narrower band sensor must be used in order to understand these narrow features. In order to identify and classify plant species (Underwood et al., 2003; Shwetank and Bhatia, 2010; Haldar et al., 2008), differentiate crop varieties (Rao, 2008), and detect vegetation stress-tasks that are not achievable with multi-spectral data-vegetation scientists are employing hyperspectral imagery. According to Soukupova et al. (2002), the great spectral resolution of hyperspectral imagery enables the identification, quantification, and classification of surface components as well as the inference of chemical and biological activities. A spectral library is a collection of spectrum reflectance measurements made in a lab or on materials and objects, such soil and vegetation. A user can swiftly identify the substance in question, such as rubber tree, by consulting both hyperspectral data and data in the spectral library (Jusoff and Yusoff, 2009). However, there is not much material available and the spectral library for the Indian region is still in its infancy. Consequently, spectral libraries have been created using hyperspectral imaging, and spectral signatures have been employed to categorize the images. Identification of tree species, their canopy, forest products, biogeochemistry, etc. is crucial to comprehending various processes in forestry. The application of a trustworthy technique for species-level remote sensing of forest composition would be a major step forward in our knowledge of these dynamics. While several studies (Woodcock et al., 1994; Gilabert et al., 2000; Leckie et al., 2003) have made significant strides, there are still significant obstacles to overcome and a lack of well-developed standardized methods for producing species-level data that is both temporally and spatially dynamic. Using EO-1 hyperspectral data and mapping of the species, the current study aims to develop the spectral signatures of chir pine (*Pinus roxburghii*), an important forest species in the Uttarakhand state.

2. MATERIALS AND METHODS

2.1. Location of study

The study was conducted during January, 2023 and the selected location was Almora district of the Uttarakhand state lies in the Lesser Himalayan terrain in India (Figure 1). It extends between 29° 32' 30" N to 29° 44' 23" N latitudes and 79° 31' 11" E to 79° 43' 50" E longitudes.

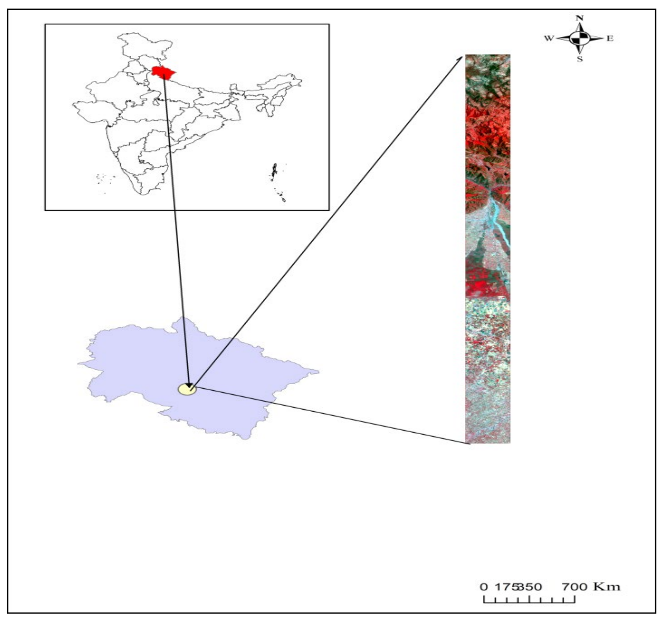

Figure 1: Study area

2.2. Data and software used

2.2.1. Satellite data

Hyperion data onboard EO-1 satellite acquired on 22.12.2003 from USGS website (http://earthexplorer.usgs.gov) was used for this study. Imager with 242 bands of 10 nm covering the spectrum from 400 nm–2400 nm.

2.2.2. Software used

ENVI 4.4 (Environment for Visualizing images Research System, Inc) software was used for processing of Hyperion Data.

2.3. Methodology

2.2.1. Collection of field data

GPS location points of pure patches of chir pine forest areas in Almora district were collected from Forest Research Institute (FRI), Dehradun. Pure patches were selected in order to minimize spectral mixing of other ground objects in a single pixel of hyperion data.

2.2.2. Pre processing of hyperion data

2.2.2.1. Bad bands removal

USGS Hyperion product (L1R) contains 242 bands, of which 131 bands (1–7, 56–82, 98, 120–134, 165–202 and 205) were un-calibrated bands and the remaining 111 bands were selected for further processing as shown in Figure 2(a) and Figure 2(b).

2.2.2.2. Bad column removal

Bad columns were due to the sensors incapability of capturing data over a strip in a band and they contain zero or negative pixel values. Some of the bands in the Hyperion data which contain bad columns were removed (Figure 3).

Atmospheric correction using FLAASH:

Spectral reflectance was extracted from hyper spectral radiance images using ENVI's Fast Line-of-Sight Atmospheric Analysis of Spectral Hyper cubes (FLAASH) module, which is a first-principles atmospheric correction modeling tool. FLAASH is used to adjust for atmospheric effects in hyperspectral data.

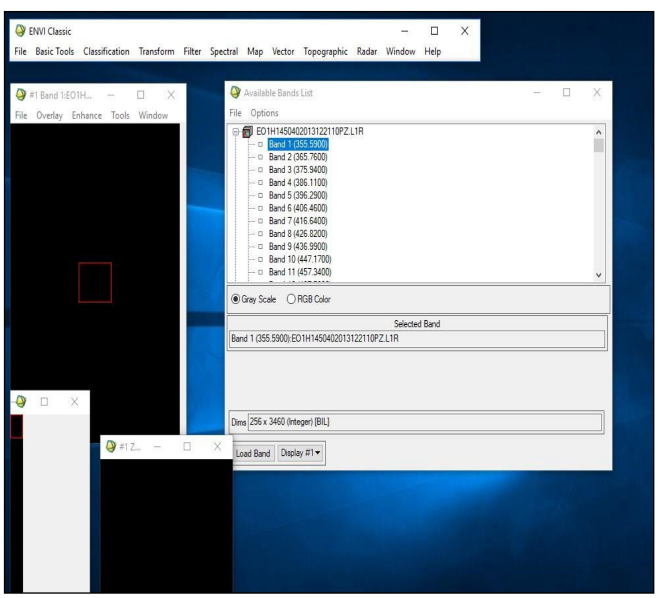

Figure 2(a): Presence of bad bands

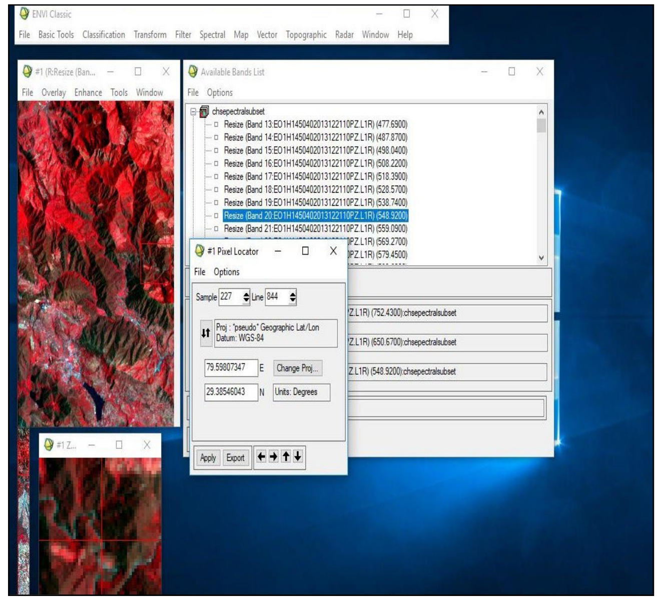

Figure 2(b): Removal of bad bands

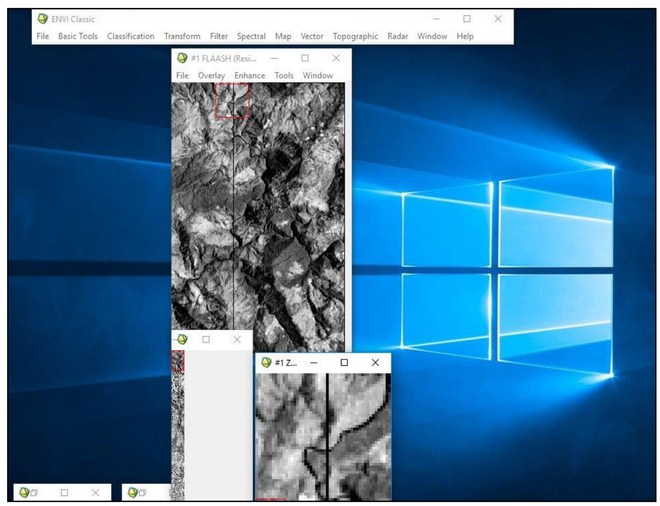

Figure 3: Bad columns removal

2.2.2.3. Minimum noise fraction (MNF)

A linear transform called MNF was used to shorten processing times, eliminate noise, and estimate an image's true dimensions. MNF creates a new space that is divided into two sections using input data (a multidimensional image) as its source: The signal is linked to the first one, whereas noise impacting the image dominates the second. The image is improved in terms of a smaller dimension and a higher signal to noise ratio (SNR) by using only the first subspace of the data. As a result, the clarity of the image produced of the Almora region was improved through this method. MNF Rotation Transforms were used to separate noise in the data, find the intrinsic dimensionality of the image, and lower the processing overhead needed for further processing. The final output MNF of all the good bands is shown in the graph in Figure 4.

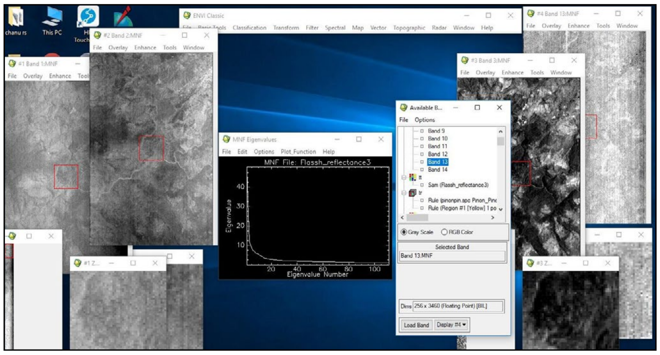

Figure 4: Result of minimum noise fraction

2.2.2.4. Pixel purity index (PPI)

In multi-spectral and hyper-spectral images, PPI was used to identify the pixels that were the most spectrally pure (extreme). Usually, these match mixing endmembers. By repeatedly projecting n-D scatter plots onto a random unit vector, the PPI was calculated (Figure 5).

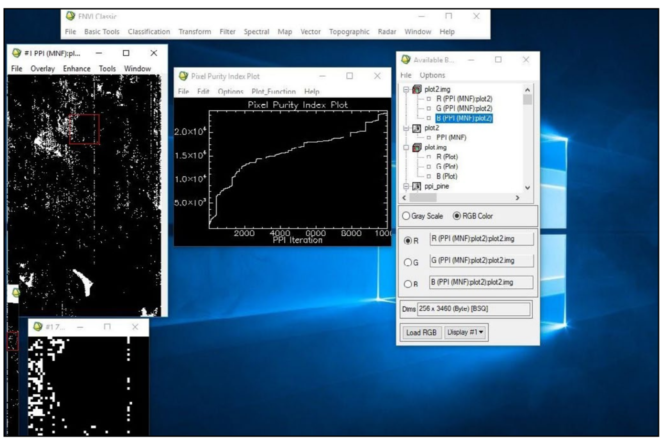

Figure 5: Result of pixel purity index

2.2.2.5. Linear spectral unmixing

Based on the spectral properties of the materials, Linear Spectral Unmixing was used to calculate the relative abundances of the materials that were represented in multi- or hyper-spectral imaging. It is assumed that the reflectance of any material (or endmember) contained in a pixel is a linear combination of its reflectance at each pixel in the image. Therefore, the linear unmixing is solving for the abundance values of each endmember for each pixel given the endmember spectra and the final spectrum (the input data). All of the endmembers in the image must be used, and the number of endmembers cannot exceed the number of spectral bands. The output of spectral unmixing depends heavily on the input endmembers, and altering the endmembers alters the outcome (Figure 6).

2.2.2.6. SAM classification

The hyperspectral images were classified using the Spectral Angle Mapper (SAM) approach as described in ENVI.

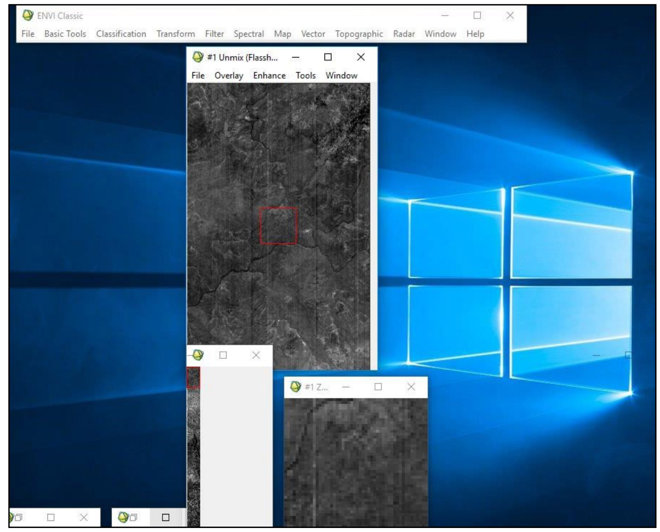

Figure 6: Result of linear spectral unmixing

In reality, SAM calculates the spectral angle between the target and pixel spectra. A discriminating metric is the angle between two spectra. More similar pixel and target spectra are associated with smaller spectral angles (Yuhas et al., 1992). Since the SAM algorithm only considers the vector direction and not the vector length, this approach is insensitive to illumination. The image that displays the best match at each pixel is the outcome of SAM categorization.

3. RESULTS AND DISCUSSION

Spectral signatures created for chir pine using Hyperion data is shown in Figure 7. The middle line displays the mean spectrum, while the bottom and higher lines displayed the minimum and maximum spectra, respectively. The signature plots showed that the NIR spectral range (700–1300 nm) had higher spectral reflectance than the visible region (400–700 nm). The data showed a sharp decline shortly after 1300 and 1700 nm. Using the derived chir pine spectral signature, hyperion data was categorized. SAM, a spectrum matching method, was used to identify and categorize chir pine. For SAM categorization, the pure

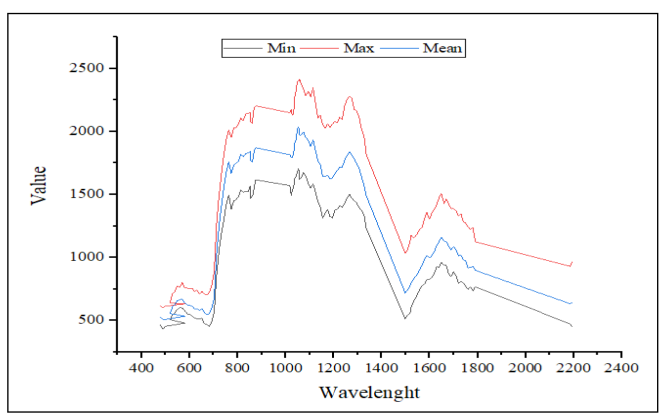

Figure 7: Spectral signature of chir pine

pixel (end members) of chir pine was utilized as the region of interest. The SAM classifier employed three distinct spectrum angles: 0.03, 0.04, and 0.05 radians.

The accuracy of classification was higher in 0.04 radians comparing to other radians. Comparing the result with the base map from Google, it was illustrated that Hyperion data had potential in identifying chir pine (Figure 8). By creating spectral libraries, it was helpful for mapping and identifying the different species of trees. Due to overlap between the VNIR and SWIR focal planes, only 111 of the 242 spectral bands covered by hyperion data had been calibrated. This chir pine-specific library of spectral signatures would serve as target spectra for the classification of remote sensing data pertaining to this species. Hyperion data was utilized by Christian and Krishnayya (2007) and Rizvi et al. (2017) to classify tree species using the SAM classifier. They concluded that there was significant potential for mapping individual tree species in high spectral and spatial resolution data. Such library of spectral signatures developed for chir pine will work as target spectra for classification of remote sensing data for this species.

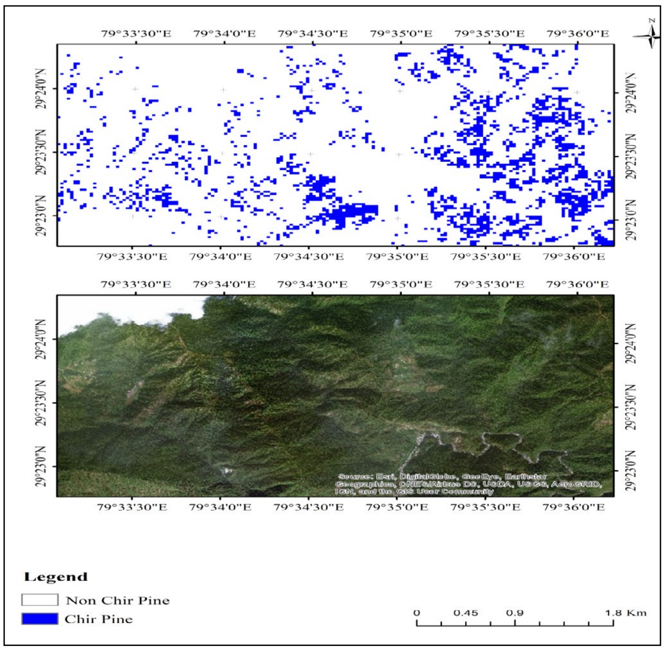

Figure 8: Comparison of chir pine map from SAM with the base map from Google map

4. CONCLUSION

The hyperion data was an effective tool for gathering information for this study. It was observed that that chir pines had distinctive spectral signature that were discernible across a wide range of the spectrum. Multi-seasonal research could be able to more precisely investigate the ideal timeframe for species-level mapping.

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