

ABSTRACT

Hyperspectral (HS) sensors are essential for measuring minute changes in vegetation spectra, making it a useful tool to study vegetation parameters, for monitoring crop. Leaf Chlorophyll Content (LCC) indicate plant growth, stress, and nutrient availability, its detailed information is required in precision agriculture. Leaf Area Index (LAI), a biophysical vegetation parameter which indicates shadow imprint and density of vegetation. Hence, scientists must determine its precise quantity for monitoring of vegetation healthy growth.

Every object emits light in range of electromagnetic spectrum, in order to study such emissions and absorption HS sensors are required. These sensors acquire images in hundreds of bands with very high spectral resolution (as high as 5nm) making it a very useful tool to study any subjects that require information of very low spectral width. The parameters of interest in the present study are LCC and LAI.

HS images are not freely available, but multispectral images with low spectral resolution are widely available. The part of work in the thesis attempts to create AVIRIS-NG, a hyperspectral image, using Sentinel-2 image and a linear unmixing method called Universal Pattern Decomposition Method (UPDM), it decomposes each image pixel as a linear combination of many classes. Since, the image is reconstructed with three major classes present in the study site, so there is some information loss while simulation because there could be more than three classes present in the area. Ground-based LCC observations from a chlorophyll meter (Soil Plant Analysis Development (SPAD)) confirmed that the simulated AVIRIS-NG could calculate LCC efficiently. Further, generated image's wavelength range depends on the number of

multispectral bands, but its spatial resolution is the same as the base image (multispectral image). Thus, an image from RedEdge MX installed on an Unmanned Aerial Vehicle (UAV), was used to simulate a half-range AVIRIS- NG image. The generated image was utilised to create a LAI and LCC map, which compared well to in-situ LAI and LCC.

Furthermore, denoising the vegetation spectra of diverse agricultural species using AVIRIS-NG imagery using different types of wavelets was used to improve LCC estimation accuracy. After noise removal, several Feature Selection Methods (FSMs) were employed to choose absorption bands relevant to chlorophyll content such as Recursive Feature Elimination (RFE), Regularised Random Forest (RRF), Least Absolute Shrinkage and Selection Operator (LASSO), and Partial Least Square (PLS). These FSMs selected the top three absorption bands to create new LCC retrieval Vegetation Indices (VIs). These VI indicators are used to form linear regression models for LCC mapping. PLS-based LCC retrieval model performed the best, whereas LASSO-generated chlorophyll model performed the least.

Another study used PLS's (Variable Importance in Projection) VIP score to select important VIs for LCC and LAI retrieval of various agricultural crops under different treatments such as fertilizers and irrigation. Twenty-Five hyperspectral VIs for LCC and seven canopy VIs for LAI assessment were tested using Support Vector Regression (SVR with linear, radial, and polynomial kernels), Partial Least Square Regression (PLSR), Hybrid neural fuzzy inference system (HyFIS), and Random Forest Regression (RFR). VIP from PLS and R^2 were determined for each VI to find the most sensitive information for vegetation parameters.

LAI was found to be most sensitive in red-edge reflectance region. The green, red, and red-edge VIs indices were responsive to lentil and maize crop bed temporal LCC values. However, for Mustard the temporal LCC values were sensitive to VIs generated from green, red, and NIR bands. Top three indices with the highest VIP and R^2 values were used as ideal inputs to create different machine learning models. SVR-Rad generated model gave the best estimation among others.

Conclusively, the work shows a successful attempt in generating models for LAI and LCC estimation, using different remote sensing technique such as from a simulated hyperspectral image, denoised hyperspectral image, and from a spectroradiometer data.