Ph.D. Synopsis

Title of Thesis: Understanding of Quality Issues in Hyperspectral Data for Vegetation Assessment.

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Remote sensing applications are playing pivotal role for societal benefits in numerous areas since a few decades. Started with the broadband observations, remote sensing applications are now seeking for better quality data with improved spatial, spectral and radiometric resolutions. This is because broad band data cannot harness the information from several distinctive absorption troughs as well as from the reflectance characteristics including the 'red edge'. Application of broadband data is limited for species level discrimination (Anderson et al., 1976; Clark et al., 2005; Fairweather et al., 2012), for ruling out pests and disease infestation in vegetation (Ranjitha & Srinivasan, 2014), crop residue discrimination (Singh et al., 2013), weed detection (Sobhan, 2007) etc. Thus improvement, especially with regards to spectral domain has led to the evolution of hyperspectral remote sensing (Clark et al., 1995; Clark et al., 2003; Shippert, 2004; Bannari et al., 2015; Singh et al, 2015; Ballanti et al., 2016; Adao et al., 2017). The main differences between multispectral and hyperspectral data lie in large number of contiguous bands and narrow bandwidth (~10nm). Since, most natural Earth surface materials have diagnostic absorption features within 400 –2500nm range of the electromagnetic spectrum, this information can be used as a tool to identify the differences in materials at a sufficiently high resolution and that too at pixel level.

When vegetation is observed from a remote hyperspectral instrument, the integrated effect of vegetation as a whole is recorded. The general shape of reflectance and transmittance curves for green leaves is similar for all species with some peaks and troughs corresponding to specific pigments and the cellular structure of the leaf tissue (Ustin et al, 1999). In the optical part of the spectrum, the leaf's radiation regime, shape, size, internal structure, pigment concentration, water content and dry matter content modulates the nature and amount of reflection. This leads to the characteristic reflectance curves for different vegetation species, and thus forms the fundamental for hyperspectral remote sensing of vegetation.

Hyperspectral data, especially the airborne and spaceborne sensors, have quality issues mainly due to sensor artefacts and erroneous calibration leading to issues such as smile/frown, keystone, banding, low Signal to Noise Ratio (SNR) etc. Moreover, the type of sensing technique used places severe demands upon image processing systems, analysis algorithms etc. These issues need to be addressed beforehand so as to maximize the full potential of hyperspectral data (Staenz,; Khurshid et al., 2006). For instance, smile effect may result into insufficient atmospheric correction (Moran et al., 1992), leading to a noisy reflectance product; consequently, the spectra-based results like classification may be erroneous (Dadon et al, 2010), although hyperspectral data classification is a challenging task due to the presence of a large number of bands (Luo & Chanussot, 2009). The conventionally used classification techniques hold little significance here because they require a large number of training samples. Moreover, many bands are spectrally correlated. This means a large number of bands have redundant data which curtail their profitable use (Zhang et al, 2007). It calls for the reduction in the number of features without a significant loss of information (Fukunaga, 1990; Tan et al., 2014).

As regards to noise, its level is usually higher in hyperspectral data because narrow bandwidth can only capture very little energy, which, at times, is less than the system noise itself. Additionally, physical disturbances like changes in light illumination and atmospheric states make the situation worse. Hyperspectral image analysis can be improved by effective noise estimation and removal as was demonstrated by Nicholson et al (2013).

While designing hyperspectral sensors there always exist a tradeoff between spatial resolution, spectral resolution and SNR. Finer spatial resolution implies that the radiation reaching the sensor corresponding to one pixel comes from smaller area and thus has less energy. The same is true for finer spectral resolution. If the spectrum is divided into a number of bands, the total energy stays equal but a single band contains less energy. It may happen that the energy due to sensor noise equals the energy of the signal. Therefore, hyperspectral sensors have often coarser spatial resolution (Landgrebe, 2003), which has been considered as a major drawback. Several studies related to vegetation classification have reported hyperspectral spatial resolution as a major limiting factor (Siegmann et al., 2015; Rogge et al., 2014; Christian et al., 2009).

Besides this, hyperspectral data, too, can be affected by band mis-registration, interpretation errors, image distortion, experimental errors etc. All of these result in poor data interpretation.

The above-mentioned factors render understanding of data quality issues especially for vegetation assessment. Simultaneously, it is important to establish optimum sensor specifications for future Hyperspectral missions focusing vegetation.

Consequently, the broad objectives of the thesis were formulated as follows:

1) Understanding data quality pertaining to inherent issues, interpretation issues, data redundancy, image classification and atmospheric correction.

2) Establishing optimum spatial and spectral specifications for future hyperspectral sensors with regards to vegetation studies

Thus, the thesis following this synopsis will cover the following in detail:

Chapter 1 will comprise of an introduction to the topic of remote sensing with special emphasis on hyperspectral remote sensing and its evolution. It would point out the advantages and limitations of hyperspectral sensors in addition to providing an insight to the current applications of hyperspectral data in the field of vegetation studies. It would provide a detailed overview as well as literature survey of the inherent quality issues of the hyperspectral data like band shift, noise, poor band-to-band registration etc. Additionally, it would address the important concerns that adversely affect vegetation assessment like atmospheric interferences, band redundancy, use of conventional classifiers etc.

Chapter2 will consist of a detailed discussion on the inherent quality issues, with special reference to detection of smile effect, band-to-band registration, scene noise, image distortion, standard range of radiance values, sources of experimental errors including variation with exposure time, effect of inappropriate sampling, effect of leaf stacking, effect of phenology and species and effect of saturation radiance. A few of the outcomes of this chapter are:

1)	Smile effect can lead to deviation of ostensible band position to as much as 3nm, as can be seen from figure 1.

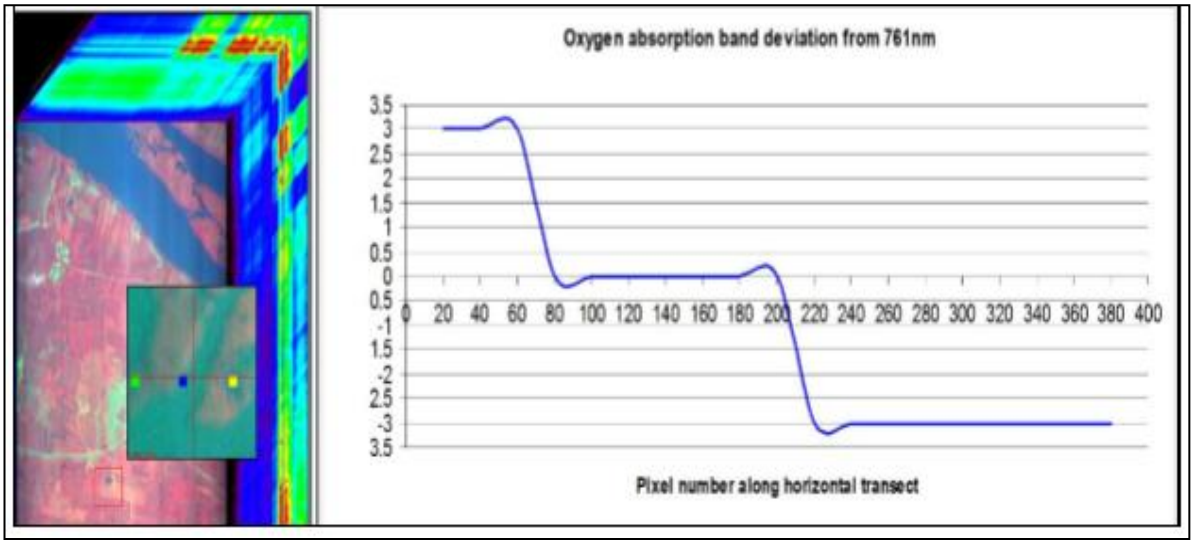

Figure 1: Deviation from typical Oxygen absorption channel across-track in Airborne Imaging Spectrometer data

2)	Out of band response shields characteristic absorption features (figure 2)

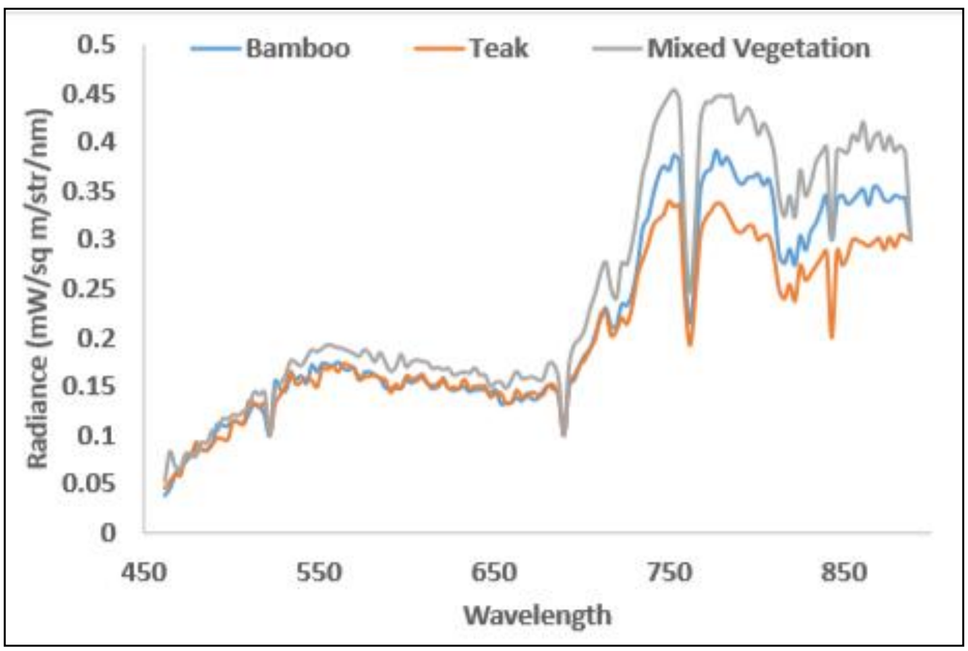

Figure 2: Out of band response shielding characteristic absorption features responsible for target discrimination

3) Change in phenological stage of the target under study may cause mis-interpretation and identification of the target under study (figure 3).

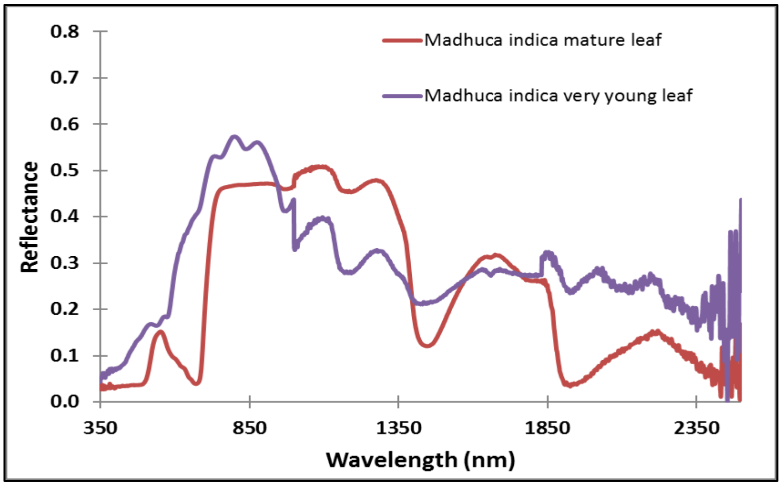

Figure 3: Spectral plots of the two growth stages of *Madhuca indica*

Chapter 3 would include a discussion on the relative and absolute atmospheric correction methods and what effect they create on the vegetation spectra. The effect of hyperspectral data redundancy on vegetation analysis is discussed through a number of methods. This understanding was drawn on the basis of classification accuracy. Here, conventional classifiers vs hyperspectral-centric classifiers would be studied and reported. Additionally, it would show the novel technique developed for feature extraction based on image texture (figure 4).

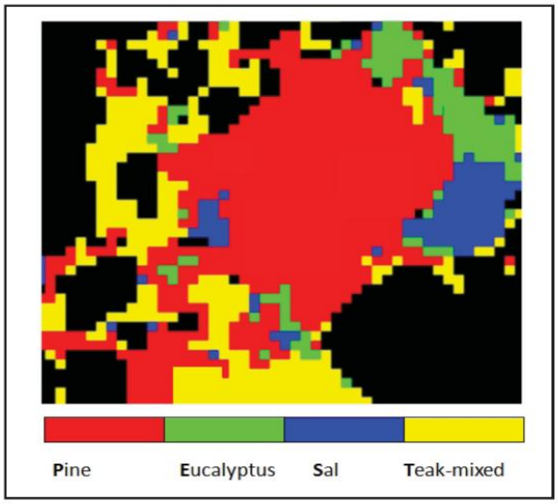

Figure 4: Figure showing vegetation classification based on image texture based feature extraction method

Chapter 4 would include the effect of spatial resolution (e.g. figure 5) on vegetation image interpretation. It would also include the effect of spectral resolution (e.g. figure 6) on the identification of various kinds of vegetation. Based on this study, optimum sensor definition parameters for vegetation assessment are defined and discussed.

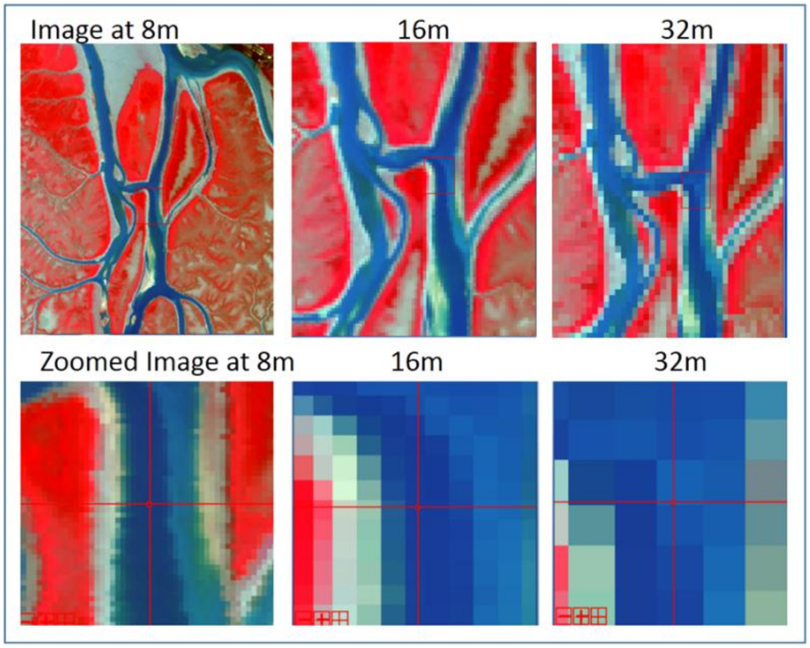

Figure 5: Figure showing effect of degrading spatial resolution on visual interpretation

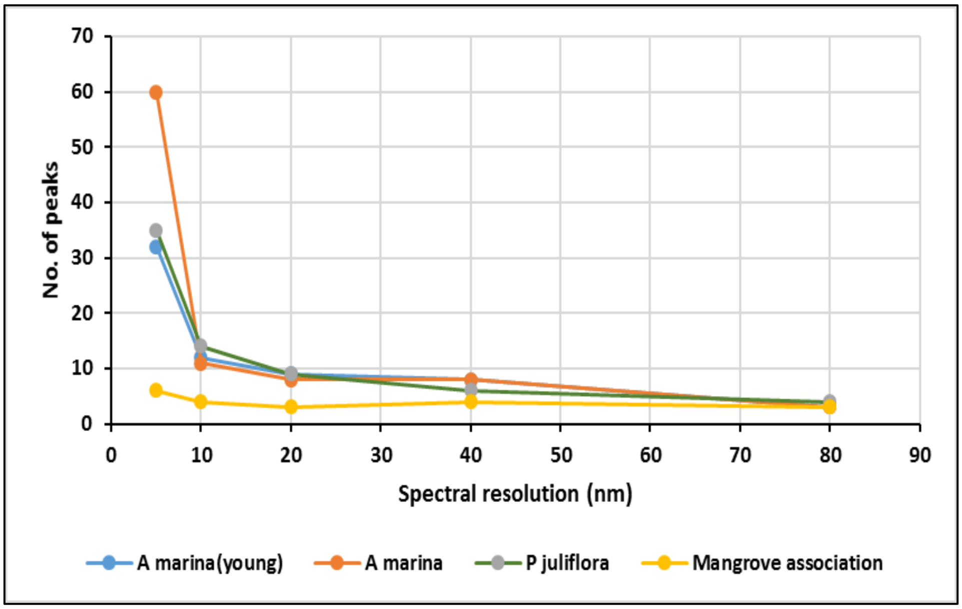

Figure 6: Figure showing effect of degrading spectral resolution on discrimination of vegetation

Chapter 5 would consist of conclusions derived from the entire study. It would also mention the scope for future work in this field.

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