Summary

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 artifacts 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

Consequent to the studies corresponding to the above mentioned objectives, following is the summary of each chapter, the details of which are discussed within the chapters.

Chapter 1 begins with a brief overview of remote sensing fundamentals and then moves onto the topic of hyperspectral remote sensing where the concept of spectral signatures with regards to vegetation is thoroughly discussed. The issues of hyperspectral sensors causing limitation in their widespread use are discussed in detail. Literature survey comprising of inherent issues like smile, noise, flaws in experiment design etc. is presented here. Also included is the literature survey concerning data redundancy, atmospheric correction and image classification. In context to specifications needed for future hyperspectral remote sensor for vegetation assessment, literature survey pertaining to spatial and spectral resolutions is also presented. Based on this chapter, the objectives of this work are mentioned at the end.

Chapter 2 starts with the account of data and software used in the study. It also mentions about the study areas for which the spectral observations were made. Then, it consists of a detailed discussion on the inherent quality issues with special reference to the following- Understanding the influence of smile effect, band-to-band registration and noise in data over vegetation assessment. It includes how the judgment of radiance values for vegetation lead to addressing and improvement in response of the airborne hyperspectral sensor. It also includes the understanding based upon the studies pertaining to the effect of exposure time on vegetation's radiance values, saturation radiance, insufficient sampling, presence of stacks of leaves, phenological stage, species and variety of vegetation through studying the vegetation spectra. The thorough analysis of the hyperspectral data revealed that for vegetation, the shift in bands is of higher significance especially in the VNIR range because this may lead to wrong identification of the vegetation type and poor assessment of its condition. Regarding smile effect, it was found that it can be present in variable proportions, its deviation from the ostensible band positions can be positive or negative and the deviation does not follow any particular order. It was also found that the quantitative assessment helps in identifying band-to-band mis-registration when qualitative assessment fails. Furthermore, scene SNR was identified as an important tool in identifying the noisy bands at pre-processing levels. In addition to this, optimum exposure time and optimum number of samples required for generating representative spectral profile were also identified.

Chapter 3- While analyzing remote sensing data in order to derive meaningful interpretation, atmospheric correction and image classification form the two essential steps. However, when the data is hyperspectral data, one more step becomes essential and that is removal of redundant bands. Thus, this chapter comprises of the discussions regarding these three aspects. At the onset is the hyperspectral data analysis for atmospheric correction. The two kinds of techniques, namely-relative and absolute are discussed here in connection to their effect on vegetation assessment. As regards to data redundancy, feature extraction as well as reduction techniques are discussed. Their success is measured through the improvement in classification accuracy owed to them. Furthermore, due to very large number of bands conventional classifiers are not suitable, so hyperspectral-centric classifiers are discussed. This has led to the identification of the feature extraction/reduction method and classifier which yield the best classification accuracy while using hyperspectral data in various domains of vegetation assessment. The analysis of relative and absolute methods of atmospheric correction revealed that relative methods may give 'vegetation like spectra' where the pseudo reflectance values don't owe any real significance but they do emphasize upon the important absorption features. These methods may help in objectives like classification, but are not suitable for quantitative studies like biochemical parameter estimation. In using absolute methods of atmospheric correction, water vapor retrieval is important. In case of phytoplankton studies, the effect of change in zenith angle revealed that the surface radiance increases by 4-5 times with increase in zenith angle. As regards to hyperspectral data classification, a novel technique based on image texture is developed.

Chapter 4- While designing hyperspectral sensors, it becomes important to have suitable spatial and spectral resolutions as well as an idea about the dynamic range of values so that appropriate SNR can be defined. This chapter defines the optimum spectral resolutions for three broad cases of vegetation assessment -Species discrimination, Crop residue and for Phytoplankton. The optimum spatial resolution is also defined by showing the reduction in contrast with coarsing spatial resolutions. Dynamic range of radiance is defined and based upon it the requirements for SNR are also discussed. Concerning optimum spatial and spectral resolution, the studies were conducted which yielded that beyond 10nm, species level identification of vegetation as well as for phytoplankton studies is not possible. For discriminating crop residue from other farm components, the optimum spectral resolution is 10nm although spectral resolution up to 100nm can work. There is a continuous decrease in the contrast ratio as the spatial resolution becomes coarser, indicating mixing of pixels, resulting in lesser information. In addition to this, the dynamic range of the sensors should be wide enough to capture the low as well as high albedo targets. But, in both the cases the SNR should be separately defined.

Chapter 5 consists of conclusions derived from the entire study. It also mentions the scope for future work in this field.

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