Hyperspectral Variable Band Selection Methodology to Assess Soil Salinity

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ABSTRACT

The high spectral resolution of hyperspectral data helps in discovering minor differences in narrow-band reflectance caused by soil types and characteristics, which are not detectable with multispectral data. Much of the information provided by hyperspectral data is, however, redundant due to spatial and spectral correlations between individual bands. Remotely sensed hyperspectral data serve as promising measures to assess the reclamation levels of saline soil, as opposed to time-consuming field investigations. The main objective of this research is to determine the best hyperspectral wavebands in the study of soil salinity over the spectral range of 400-2500 nm. The band selection techniques that are commonly used in remote sensing image processing are generally image-based approaches. Here, an algorithm based on Hierarchical band selection procedure using mixed statistics metrics is attempted. In first level, all the bands are ordered according to their entropy measure (contains more information). Second level is based on divergence measure to reduce the redundancy.

1. INTRODUCTION

Soil degradation including soil salinity, erosion and water logging are among the main factors of desertification. Soil salinity is considered as an environmental hazard and one of the factors in desertification in arid, semiarid and dry sub-humid areas both dry and irrigated regions. It causes decreasing or losing agricultural productivity. Salt affected soils occupy an area of 953 Mha covering 120 countries and reducing 7–8% of the productive capacity of the land surface of the world (Szabolcs 1992). In India, salt affected soils cover 2% of the geographical area of the country, located primarily in arid and semiarid regions and coastal areas (Dwivedi and Sreenivas 1998).

For planning reclamation and management, a database capable of handling spatial and attribute datasets in multiple layers in electronic format is required (Mandal and Sharma 2009). Remote sensing techniques have reduced field work to a considerable extent and soil boundaries are more precisely delineated than in conventional methods. (Manchanda 2002).

A number of studies have been done using coarse spectral resolution data such as LANDSAT TM and IRS LISS III to map salt affected soil. But this coarse spectral resolution is insufficient to study soil salinity of moderately and slightly saline areas. Hyperspectral sensors have the potential to significantly reduce the cost of mapping and monitoring the extent and severity of soil salinity based on the presence of salt tolerant species while maintaining the accuracy of the current field based method.

The main objective of this technical paper is to determine the best hyperspectral wavebands in the study of soil salinity over the spectral range of 400-2500 nm. The selection of suitable bands for assessing soil salinity not only improves classification accuracy but also aid dimensionality reduction that substantially reduces computational time, and hence the costs. The soil salinity information is helpful in planning strategy for their reclamation and optimal utilization for sustainable development.

2. BACKGROUND STUDY

The spectral behaviour of soil and its components is fundamental to deriving information from remote sensing data. Work done at National Remote Sensing Agency (NRSA) indicates that soil spectral characteristic within an area have enough variation for the delineation of soil associations by both image interpretation and computer aided techniques (Venkataratnam 1981).

While studies to date have applied hyperspectral imagery to the mapping of soil and vegetation indicators of irrigation induced salinity at specific sites (Dehaan and Taylor 2002, Anna Dutkiewicz 2006). De Haan and Taylor (2002) have established a number of criteria, based on field-derived spectra of four different soil types, to characterize and discriminate saline areas using hyperspectral data. Their results showed that saline soils have distinctive spectral features in the visible (VIS) and near-infrared (NIR) parts of the electromagnetic spectrum.

Eldieri (2005) showed that, the green band, the near infrared band, and divided by the red band ratio are strongly related to soil salinity. Image transforms like principle components analysis (PCA), ratioing, and image differencing are used for change detection in the spatial extent and distribution of salt-affected soils. (Dwivedi and Sreenivas 1998).

3. MATERIALS AND METHODS

Site Description
The study area is selected between 13°27’ and 13°30’ North latitude and 80°06’ and 80°08’ East longitude which lies in Gummudipundi Taluk, Thiruvallur district, Tamilnadu. Laterite soil is the predominant soil type in Thiruvallur district accounting for 63.2% of the total area under cultivation. Red loam and black soil account for 28% in the district soil map. Over 13.7% of soil suffers from salinity/alkalinity. 13.2% of soil are with problems of water logging and marshy land. Sands, desert/coastal soils account for 3.0%.

Soil Sampling
A reconnaissance survey is made throughout the investigated area in order to gain an appreciation of the different soil types. Field investigations show four classes of soil salinity: high saline soil and moderate saline soil distributed in the near to coastal land. Low saline and non-saline soils are distributed on agriculture lands.

Hand held GPS was used in the field to recognize the locations of the sampling. Soil salinity can be measured by a simple field test. The test is reasonably accurate in indicating if salts may cause yield losses or soil management problems, but is not as accurate as laboratory analysis. In the field, ratio of 1 part soil sample to 5 parts distilled water is used to find the salinity of the soil. The Salt Testr11 (range 0 to 10.00 ppt) is used in the field to assess the salinity level. A total of 10 soil samples are collected (depth<=30 cm) at different locations by considering their variation in soil type and tested for salinity. Out of 10 samples 3 shows the salinity. Sample S2 collected in the agriculture land near the entry to Sunnambukulam village has salinity 0.10ppt(parts per thousand), samples S3 and S4 close to the beach have 2.5ppt and 2.9ppt respectively.

Laboratory Procedure for Spectral Analysis
In this study a Field Spec®Pro Spectrometer (Analytical Spectral Device (ASD), Inc., Boulder, Colorado, USA) with a fibre-optic contact probe is employed for laboratory measurements. The instrument covers the visible to short-wave infrared wavelength range (350 to 2500 nm). Reflectance is calibrated against a white panel of known reflectance (Spectralon Diffuse Reflectance Panel). The collected soil samples are dried and passed through a 1.18-mm sieve to remove large debris and stones. A portion of each sample is used for spectroscopic measurements.

Band Selection Method
Here, an algorithm based on Hierarchical band selection procedure using mixed statistics metrics is attempted. In first level, all the bands are ordered according to their entropy measure (contains more information). Second level is based on divergence measure to reduce the redundancy.

Entropy measure is similar to variance and follows band variance very closely. Although entropy measure accounts for the information content in bands, it fails to consider information redundancy between different bands. Therefore, entropy may not be adequate as a standalone method for band selection and also a suitable method is needed for selecting a set of bands that will provide the best characterization of a given target characteristic without redundancy. Information divergence is used to detect redundancy within the prioritized bands.

Information Entropy
This method is based on evaluating each band separately using the information entropy measure which is defined below.

\[
H(\lambda) = - \sum_{i=1}^{n} p_i \ln p_i
\]

Here, \(H(\lambda)\) is the entropy measure, \(p_i\) is the probability density function of reflectance values in a hyperspectral band and \(n\) is the number of distinct reflectance values. Generally, if the entropy value \(H\) is high then the amount of information in the data is large. Thus, the bands are ranked in the ascending order from the band with the highest entropy value (large amount of information) to the band with the smallest entropy value (small amount of information).

Divergence
According to Chang (1999), divergence performs very well in terms of capturing similarity and dissimilarity between two images and can be used for band subsetting purpose.
The number of bands selected depends upon the threshold value. If the divergence between two bands is below a prescribed threshold, the band with lower priority is removed from the list of bands. The number of selected bands images is entirely dependent on threshold value.

3. RESULTS AND DISCUSSION

Hyperspectral Data
The hyperspectral image data used in this work is collected from EO1 Hyperion sensor on December 2008. The Hyperion is a push-broom imager with 224 bands covering the spectrum from 400 nm - 2400 nm with 10 nm width.

To select the most distinctive but informative bands, water absorption and low SNR bands are need to be pre removed. The removal of bad bands and noise are carried out manually. Due to atmospheric radiation absorption, some bands in the spectral ranges 1,350-1,440 nm; 1,790-1,990 nm; and 2,360-2,500 nm are not considered. Also, data in 350-400 nm are not considered due to spectral inconsistencies.

Results from Band Selection Method
The band selection involves two steps to select the bans with maximum information entropy measure is used and prioritized based on its higher values. Band divergence measure is used to remove highly correlated bands. Choosing a proper threshold becomes crucial. Thus, a good threshold for redundancy reduction should be selected so as to optimally balance feature loss with redundancy.

The results of hierarchical band selection method by varying the threshold value are shown in Table 1. The top 15 bands selected by varying the divergence threshold value shows that 66% of the same bands are selected in all three selections and 100% of same bands in the last two selection.

Table 1: Top 15 Bands Selected by Hierarchical Band Selection Method

<table>
<thead>
<tr>
<th>Threshold Div=100</th>
<th>Threshold Div=500</th>
<th>Threshold Div=1000</th>
</tr>
</thead>
<tbody>
<tr>
<td>B. No</td>
<td>Wavelength (nm)</td>
<td>B. No</td>
</tr>
<tr>
<td>85</td>
<td>993.17</td>
<td>85</td>
</tr>
<tr>
<td>87</td>
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<td>92</td>
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</tr>
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</tr>
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<tr>
<td>45</td>
<td>803.3</td>
<td>48</td>
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</tbody>
</table>

Interpretation of Results
In this experiment, the goal is to select a optimal number of bands by following the methodology in section 3.3, the results of the hierarchal methods are cross verified using reflectance signatures. The reflectance curves for sample soils with different salinity level under laboratory study are plotted in Figure 1. The first derivative of the reflectance curve is plotted in Figure 2 to know the band variation more precisely.

Fig. 1: Reflectance Curves of Soil Samples with Different Salinity Level

The reflectance curves are similar to one another with nine distinct absorption features at 487 nm, 671 nm, 905 nm, 1144 nm, 1416–1447 nm, 1800 nm, 1911–1945 nm, 2203 nm, and 2345 nm. However, the depth of absorption feature varies with the degree of soil salinity. The first order derivative peaks confirm the absorption wavelength. Compared with wavelengths above, broader absorption features are found around 1144 nm and 1800 nm. The increases in absorption intensity at 671 nm, 905 nm, and 1911–1945 nm become more pronounced as salinity level increases. As shown in figure 1, the low and non-saline soils produced weak absorption features at 671 nm, 905 nm, and 1144 nm.

Fig. 2: First Derivative Reflectance of Soil Samples with Different Salinity Level
It is interesting to note that the saline soil samples show slight variation in the spectral curve in the region 550-700 nm and also in 700-800 nm. The wavelength regions 1900-2200 nm and 2200-2350 nm are also playing an important role in categorizing the salinity level. Since contact probe is used for laboratory study the spectral responses in the region 1100 nm to 1800 nm were not considered for analysis of the reflectance curve study.

4. SUMMARY AND CONCLUSION

Band selection on the experimental data demonstrated the process of obtaining the optimal number of bands for soil salinity assessment. The study concluded that there are about 6-8 most informative bands available for the salinity study. The proposed band selection methodology is also applicable to other application domains requiring hyperspectral data analysis. This study is verified based on spectra measured in laboratory. An important point is observed in this study is that most of the spectral features at around 1400 nm and 1900 nm, which are crucial for the discrimination of salt-affected soils, is not available in image data due to the effect of atmospheric water absorption windows. Further study should focus on investigating the possibility of change in the band subset for salinity study using spectral data collected from field.

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REFERENCES


