words, the spectral similarity between two pixels vectors is measured by SID based on the discrepancy between their corresponding spectral signature-derived probability distribution. SID is one such measure which measures the distance between the probability distributions produced by the spectral signatures of two pixel vectors.

Two probability vectors $p = (p_1, p_2, \ldots\ldots p_L)^T$ and $q = (q_1, q_2, \ldots\ldots q_L)^T$ for the spectral signatures of two pixel vectors s_i and s_j where $p_k = s_{ik} / \sum_{l=1}^{L} s_{il}$ and $q_k = s_{jk} / \sum_{l=1}^{L} s_{jl}$. So, the self-information provided by $\mathbf{r}_j$ (pixel vector) for band l is defined by (4) and given by

$$I_l(r_j) = -\log q_l \quad (4)$$

Using (3) and (4), $D_l(r_i \| r_j)$ can be defined which is the discrepancy in the self-information of band l in $\mathbf{r}_j$ relative to the self-information of band l in $\mathbf{r}_i$ (Cover and Thomas, 1991) by,

$$D_l(r_i \| r_j) = I_l(r_j) - I_l(r_i) = (-\log q_l) - (-\log p_l) = \log(p_l / q_l) \quad (5)$$

Averaging $D_l(r_i \| r_j)$ in (5) overall bands $1 \le l \le L$ with respect to r_i results in

$$D(r_i \| r_j) = \sum_{l=1}^{L} p_l D_l(r_i \| r_j) = \sum_{l=1}^{L} p_l (I_l(r_j) - I_l(r_i)) = \sum_{l=1}^{L} p_l \log(p_l/q_l) \quad (6)$$

Where $D(r_i \| r_j)$ is the average discrepancy in the self-information of $\mathbf{r}_j$ relative to the self-information of $\mathbf{r}_i$. In context of information theory $D(r_i \| r_j)$ in (6) is called the relative entropy of $\mathbf{r}_j$ with respect to $\mathbf{r}_i$ which is also known as Kullback-Leibler information measure, directed divergence or cross entropy [9]. Similarly, average discrepancy in the self-information of $\mathbf{r}_j$ relative to the self-information of $\mathbf{r}_i$ by

$$D(r_j \| r_i) = \sum_{l=1}^{L} q_l D_l(r_j \| r_i) = \sum_{l=1}^{L} q_l (I_l(r_i) - I_l(r_j)) = \sum_{l=1}^{L} q_l \log(q_l/p_l) \quad (7)$$

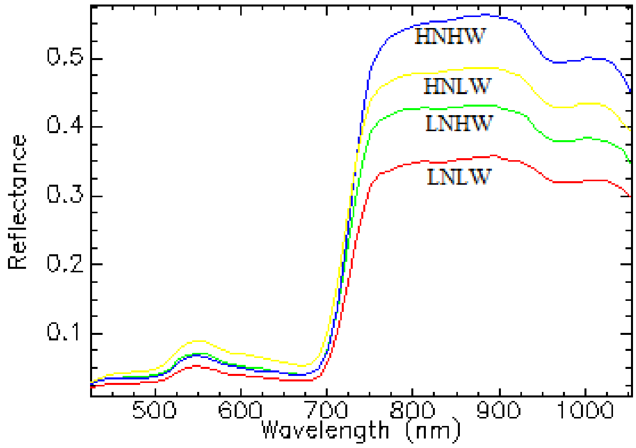
Summing (6) and (7) yields spectral information divergence (SID) defined by,

$$\mathrm{SID}(\mathbf{r}_i, \mathbf{r}_j) = D(r_i \| r_j) + D(r_j \| r_i) \quad (8)$$

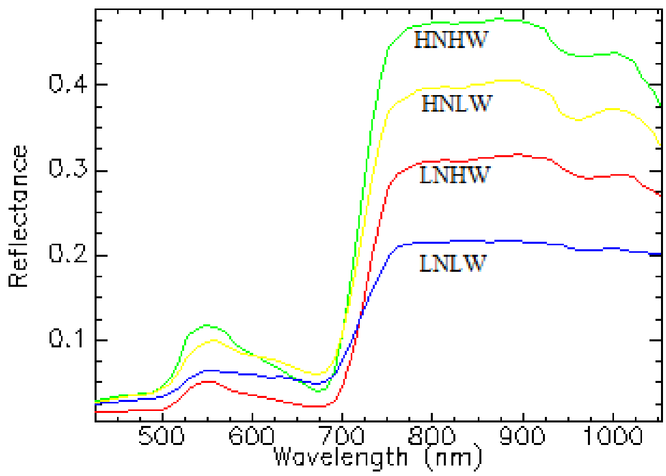
Equation (8) can be used to measure the spectral similarity between two pixel vectors $\mathbf{r}_i$ and $\mathbf{r}_j$. It should be noted that while SID $(\mathbf{r}_i \| \mathbf{r}_j)$ is symmetric, $D(r_i \| r_j)$ is not. This is because $\mathrm{SID}(\mathbf{r}_i, \mathbf{r}_j) = \mathrm{SID}(r_j, r_i)$ but $D(r_i \| r_j) \neq D(r_j \| r_i)$.

4. RESULTS AND DISCUSSION

Major four groups: HNHW (High Nitrogen High Water), HNLW (High Nitrogen Low Water), LNHW (Low Nitrogen High Water) and LNLW (Low Nitrogen Low Water) was formed to study the problem of deficiency in Nitrogen and water applied. Differences in vegetation vigor, resulting from variation in nitrogen and water applied, are especially evident when Near Infrared imagery or data are used. Stress is indicated by progressive decrease in Near-IR reflectance. Collected spectra for four conditions of crops i.e. HNHW, HNLW, LNHW and LNLW are as shown in figure 2.



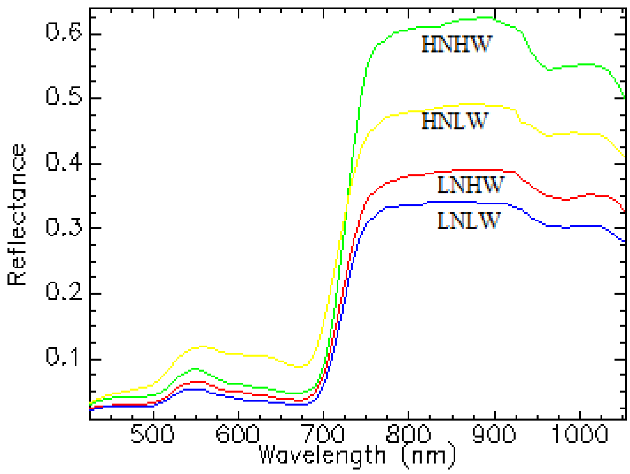
(a)



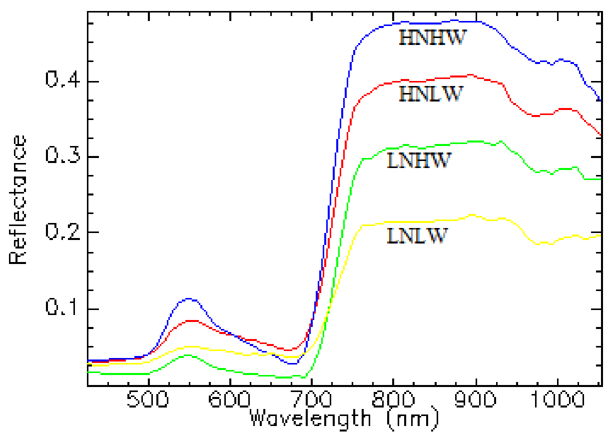
(b)

Figure 2: Crop Spectra , a) Chickpea, and b) Wheat for four condition HNHW (High Nitrogen High Water), HNLW (High Nitrogen Low Water), LNHW(Low Nitrogen High Water) and LNLW (Low Nitrogen Low Water) in controlled nitrogen (as fertilizer) and water applied conditions

Spectral similarity analysis using SID is carried out between the collected field spectra and spectra collected in controlled condition of nitrogen and water applied. Similarity values were computed among various spectra of controlled crop conditions as HNHW, HNLW, LNHW and LNLW and all collected field spectra of study area for a specific crop. Field spectra of the crops were assigned to a controlled crop spectrum of a specific condition where close match has been observed. Separately for both crops this analysis was carried out. Based on matching of coefficient of correlation and spectral similarity values, a spectra is assigned to specific health condition which produce very close match. Similarity results are tabulated in table 1. Table:1 shows very close match between coefficient of correlation and SID value equivalent to coefficient of correlation derived for crop spectral library generated in controlled conditions and uncontrolled (study area) conditions. Build spectral library for variation in nitrogen and water for uncontrolled (study area) conditions is as shown in figure 3. Hence spectral similarity based crop health analysis provides an effective and possible alternative to quantify field crop condition based on knowledge derived from controlled field conditions.



(a)



(b)

Figure 3: Field Crop Spectra of, a) Chickpea and b) Wheat for four condition HNHW (High Nitrogen High Water), HNLW (High Nitrogen Low Water), LNHW (Low Nitrogen High Water) and LNLW (Low Nitrogen Low Water) developed based on spectral similarity with controlled field conditions.

Table1: Coefficient of Correlation and SID spectral similarity value between crop spectra for controlled and uncontrolled (study area) field conditions for Nitrogen and Water variations

Closeness Measure / Crops	Crop Condition	Coefficient of Correlation	SID Value (Distance Measure Value)	SID Value Equivalent to Coefficient of Correlation
Chickpea	HNHW	0.9998	0.0003	0.9997
	HNLW	0.9978	0.0063	0.9937
	LNHW	0.9995	0.0003	0.9997
	LNLW	0.9992	0.0004	0.9996
Wheat	HNHW	0.9968	0.0025	0.9975
	HNLW	0.9974	0.0157	0.9843
	LNHW	0.9967	0.0042	0.9958
	LNLW	0.9978	0.0022	0.9978

*SID Value equivalent to Coefficent of Correlation = 1- Distance Measure Value

5. CONCLUSION

It was quite difficult to develop crop spectra for nitrogen and water variations for actual field conditions as there is large variations in nitrogen (as fertilizer) and water applied. During field visit it was found that crop growth was not uniform in the study area even though local conditions were same. Development of crop spectra for nitrogen and water variations for uncontrolled (study area) field conditions based on spectral similarity analysis with controlled field conditions provides a fresh opportunity to develop and evaluate the crop spectra for nitrogen and water variations for real time applications.

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