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Estimation of Water Contents from Vegetation Using Hyperspectral Indices

Rupali R. Surase, Karbhari V. Kale, Amrsinh B. Varpe, Amol D. Vibhute, Hanumant R. Gite, Mahesh M. Solankar, Sandeep Gaikwad and Dhananjay B. Nalawade

Abstract This paper outlines the research objectives to investigate the approaches for assessment of vegetation water contents using hyperspectral remote sensing and moisture sensor. Water contents of crops monitor crop health for precision farming and monitoring. In the present research, spectral indices with some chemical extraction procedures were identified for estimation of water contents of crops. The investigated crop species, namely Vigna Radiata, Vigna Mungo, Pearl Millet, and Sorghum were collected from Aurangabad region of Maharashtra, India. Spectral reflectance curve of crop growth patterns was measured using ASD field Spec 4 Spectroradiometer and 150 Soil moisture sensor including healthy, diseased, and dry leaves with standard laboratory environment. It is found that there was a positive correlation between WI and Soil moisture sensor with 0.99, 0.76, and 0.97 accuracy.

R. R. Surase · K. V. Kale · A. B. Varpe (✉) · A. D. Vibhute · H. R. Gite · M. M. Solankar
S. Gaikwad · D. B. Nalawade
Geospatial Technology Research Laboratory, Department of Computer Science and IT,
Dr. Babasaheb Ambedkar Marathwada University, Aurangabad 431004, Maharashtra, India
e-mail: varpeamarsinh@gmail.com

R. R. Surase
e-mail: rupalisurase13@gmail.com

K. V. Kale
e-mail: kvkale91@gmail.com

A. D. Vibhute
e-mail: amolvibhute2011@gmail.com

H. R. Gite
e-mail: hanumantgitecsit@gmail.com

M. M. Solankar
e-mail: mmsolankar13@gmail.com

S. Gaikwad
e-mail: sandeep.gaikwad22@gmail.com

D. B. Nalawade
e-mail: dhananjay.bamu@gmail.com

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The research work was implemented using Python open source software. In the conclusion, water estimation from crops may be useful in irrigation mapping and drought risk modeling.

Keywords Spectral reflectance · Coefficient of correlation · Crop analysis
Spectral indices

1 Introduction

Estimation of water stress level of vegetation plays the vital role in precision farming and agricultural monitoring system. Crop water stress monitoring maintains crop health for irrigation of crop scheduling process [1]. Large-scale spatial areas are not feasible for mapping and assessing field measurements with limited samples. To overcome such pitfalls, remote sensing techniques offer alternatives to nondestructive methods. The environmental study recognized that lack of water availability impacts on plant growth process with a decrease in crop productivity and field [2]. Water bands absorb reflected radiant energy through Short-Wave Infrared (SWIR) region ranging from 1.3 to 2.7 μm and some of the bands centered at near-infrared from 0.72 to 1.3 μm. The literature [3] reveals the details about the complete absorption peak at 0.9 and 0.97 μm wavebands for analysis. The remote sensing technology offers the measurements of leaf and its canopies for estimation of water contents from the leaves. Reflectance spectra of vegetation's collected from the field investigation produce the somewhat lacuna due to canopy coverage, whereas it provides the minute details about water stress measured reflectance spectra at controlled laboratory environment. Field investigation comes with canopy spectral response with some lacuna for water stress estimation alternatively laboratory measurement on single leaves with standard environment provides instantaneous effects [4]. The spectral response curve varies as per the crop leaves from thin to thick physiological parameters. The leaf water contents matching faces challenge by a varying leaves physiological structure of cells, its thickness reflectance affects plant to plant. The literature assumed that chlorophyll contents of leaves may discriminate crop growth stages but chlorophyll stress pattern depends on the availability of water contents. Particularly, the wavelength range from 1530 to 1720 seems to be more appropriate for water estimation [5]. In the SWIR wavelength region, 1400–2500 nm, measurements have shown considerable changes to this section of the scale resulting from changes in the water content of plants leaves [6].

The paper reports on an experimental method to acquire reflectance signature of crop species and for analysis of crop growth stages water stress level. This paper contains four sections including an introduction to background knowledge of crops and significance of the promoted research. Section 2 contains details about study sites and data collection methods. All comparative discussion about results with the analysis is in Sect. 3. Finally, the conclusions are summarized in the last section.

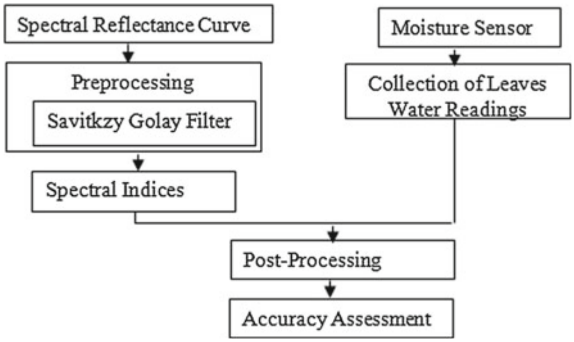

Fig. 1 Methodology of water contents estimation study

2 Experimental Setup

This section enlights location of the study area with instrument details with the characteristics of non-imaging hyperspectral instrument.

2.1 Study Site and Experimental Setup

All the experimental data selected for crop study have been obtained during the growing season of summer and winter 2017 at Aurangabad region (19054′3.7944 N latitude and 75021′8.9208 E) Maharashtra, India [7]. It covers annual precipitation 725.8 mm, means annual temperature 17–33 °C. Four main types of crop species were selected as objectives of investigation planted using black soil. A total of 30 samples each species were measured using ASD Field Spec 4 Spectroradiometer. The four species had collected 480 spectral responses for analysis (namely, Vigna Radiata, Pearl Millet, Sorghum, and Vigna Mungo). Figure 1 shows the proposed work of succeeding section for the estimation of water contents.

2.2 Instrumentation and Measurement

Spectral signatures were taken using Field Spec 4 (Analytical Spectral Devices, Boulder, CO, USA) high-resolution field portable spectroradiometer with spectral range located in the VIS, NIR, and SWIR regions (350–2500 nm). Instrument sampling intervals of ASD are (1.4 and 2 nm) with the 1 nm linear spacing interval. All the spectral responses were collected under the 450° and Field of View (FOV) lamp angle. Tungsten halogen quartz lamp with 1,000 W under the standard darkroom controlled condition. White reference panel measurements were collected to the standardized instrument and calibrate for database collection. The spectral responses were

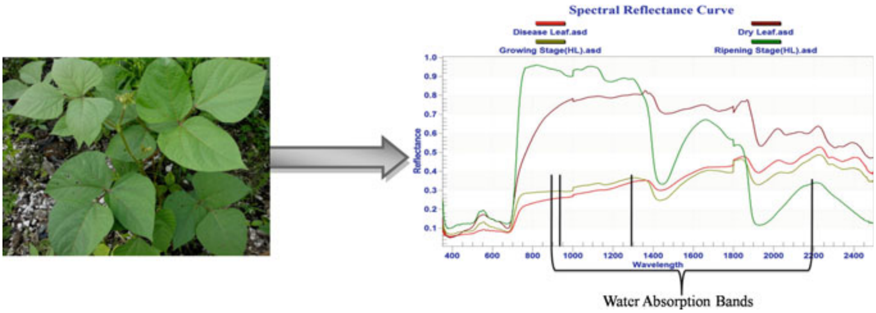

Fig. 2 Spectral response curve of Vigna Radiata crop with four growth stages captured during the 2017 experiment setup

collected throughout experiment between 11:30 a.m. and 2:00 p.m. to avoid bidirectional reflections. Each reflectance curve was measured as an average of 10 spectral measurements with slightly varying locations of samples [8]. The 8° FOV along with fiber optic cable is used for spectra collection using RS3 which is inbuilt software tool calibrated with the instrument. The following Fig. 2 provides the leaf samples and generated spectral response curve ranging from 350 to 2500 nm using spectroradiometer in a closed indoor environment. The spectra were collected in crop growth stages including healthy leaves, diseased leaves, and dry leaves for water contents estimation. The X-axis represents wavelength spectrum and the Y-axis represents reflectance of observed samples.

2.3 Soil Moisture Sensor Data Collection

The SM 150 soil moisture sensor measures moisture available in soil but we had tried to place the tip of the sensor within leaves for measurement of water contents. The instrument is wrapped with the plastic body and attached to two sensor tips with the gun for measuring display. The output reading was internally captured in DC voltage and then converted to readable units for user [9]. The following Fig. 3 signifies samples collection procedure of 150 soil moisture sensor using crop leaves.

3 Data Processing Techniques

This section contains filtering algorithm to remove noise from collected spectral response curve and analysis techniques.

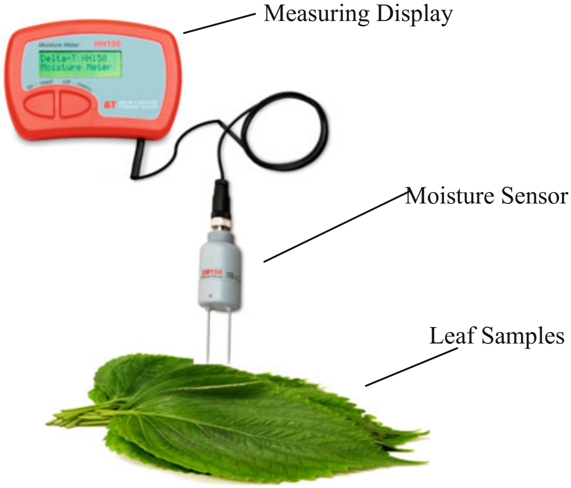

Fig. 3 Moisture sensor for detection of water contents from crop species leaves

3.1 Savitkzy Golay Filtering (SGF)

Spectroradiometer generates spectral response curve of crop species with noise in some detectors. The measured spectra of crop species are usually slowly varying and corrupted by random noise. The purpose of smoothing technique is to reduce the level of noise keeping spectrum details. SGF was designed to analyze the absorption peaks in noisy spectra. SGF works with advantages in the form of preserving the area of the spectrum, the position of bands, and width of spectral peaks which may be useful for some forms of statistical analysis. The absorption peaks suggest which chemical elements are presented in the tested objects [10]. The given formula signifies Savitzky-Golay Filtering with polynomial order 2 in Eq. (1).

$$Savitzky\ Golay\ Filter = \sum_{n}^{1} C_n S_i + n \tag{1}$$

where C_n are weight coefficients computed in a moving window, S_i is finite impulse response filter used for a linear combination of neighbor values of spectral bands, and n is the number of spectral sample points.

3.2 Spectral Indices

Remote sensing research works with the bunch of spectral indices based on objectives of researchers. Water index is one of the well-calibrated algorithms for estimation of water contents of crop samples [11]. WI works with the spectrum ranging in SWIR region including reflectance of 900 and reflectance of 970 nm wavelengths.

$$Water\ Index = R900/R970 \tag{2}$$

Here, R denotes Reflectance of *n*th band wavelength.

3.3 Analysis of Variance

Analysis of variance (ANOVA) method applies for testing where the hypothesis founds to be there is no difference between two or more population means considering spectral response value and soil moisture readings. ANOVA test works, if there is no difference in a number of treatments of samples [12]. ANOVA test assumes P value significant for more accurate results.

$$SS^2 = n \sum_{i=1}^{I} \frac{(\overline{X}i - \overline{X})^2}{I - 1} \tag{3}$$

where n is a total number of samples, $\overline{X}$ is mean of all spectral indices categories, and I is the samples size of the group as shown in Eq. (3).

3.4 Coefficient of Correlation

The coefficient of correlation (CC) gives the summary of a degree of association within two or more variables. CC varies from positive (+1) and negative (−1) based on the relationship with a number of variables correlated [13].

$$R = \frac{N \sum XYZ - (\sum X)(\sum Y)(\sum Z)}{\sqrt{[N \sum X^2 - (\sum X^2)] - [N \sum Y^2 - (\sum Y^2)] - [N \sum Z^2 - (\sum Z^2)]}} \tag{4}$$

where N is a number of pairs of samples, the sum of products of paired scores with two categories, $\sum X$ is the sum of x scores, $\sum Y$, and is the sum of Y scores, $\sum Z$ as per healthy, diseased, and dry leaves in Eq. (4).

4 Result and Discussion

Four crops were selected for study including Vigna Radiata, Vigna Mungo, Pearl Millet, and Sorghum for estimation of water contents with their families. Data were analyzed in two aspects for a comparative study of spectroradiometer and moisture sensor. Table 1 provides statistically measured for crops with varying stages including healthy leaves, diseased leaves, and dry leaves samples. Preprocessed reflectance

Table 1 Coefficient of correlation between spectral response curve and 150 soil moisture sensor for four crops

Crop species	Family	ASD field spec 4			Moisture sensor			ANOVA (SS)
		Average of 10 samples						
		HL	DL	Dry L	HL	DL	Dry L	$\alpha = 0.05$
Pearl Millet	Poaceae	1.023	0.969	0.612	1.02	0.96	0.61	0.197
Sorghum	Gramineae	1.012	0.943	0.679	1.01	0.93	0.68	0.15
Vigna Radiata	Fabaceae	1.11	0.979	0.720	1.10	0.96	0.70	0.16
Vigna Mungo	Fabaceae	1.131	0.98	0.707	1.11	0.99	0.69	0.18

Table 2 Coefficient of correlation with crop growth pattern and R^2 values

Correlation analysis	Equation	R residual value
Healthy leaves	$Y = 0.860x + 0.140$	0.99
Disease leaves	$Y = 1.245x + 0.246$	0.76
Dry leaves	$Y = 0.836 + 0.102$	0.97

spectra were considered for further analysis with average of 10 samples of each crop species within 3 categories for calibration and one-way ANOVA followed by a sum of squares prediction, where alpha = 0.05, alpha with 0.05 works well for determining the differences according to null hypothesis with respect to spectrum population in the form of bands. Herewith varying alpha values tried for implementing ANOVA but only 0.05 is stated as significant for sum of residual (SS). The ANOVA for healthy leaves ranging from 1.01 to 1.131 based on spectroradiometer and 1.02 to 1.11 using moisture detection sensors. The result shows for diseased leaves indicates from 0.943 to 0.98 and 0.93 to 0.99, respectively. Dry leaves resultant values were ranging from 0.612 to 0.720 and for soil moisture sensor 0.61 to 0.70. The sum of squares (SS) in ANOVA consists of 0.197, 0.15, 0.16, and 0.18 to analysis crop identification. Average values signify that diseased leaves range within 0.61 to 0.702 consist water level stress as per the diseases.

Table 2 shows R^2, root means square error (RMSE) of spectroradiometer and 150 soil moisture sensor with the strong positive correlation between HL, i.e., 0.99, DL, i.e., 0.76, and Dry leaves with 0.97.

As per the objectives of our research, the correlation signifies that both of procedure meets the positive results. HL was correlated better with accuracy 0.99, dry leaves give 0.97 accuracy, and disease leaves give less because of disease variation affects water stress level with 0.76 accuracies. This research analyzes that; soil moisture sensor also provides details of water level from leaves with accurate readings.

5 Conclusion and Future Scope

Hyperspectral reflectance data (350–2500 nm) for four different crop species demonstrated significant responses of crops reflectance characteristics with growth conditions. Temporal data was also collected using 150 soil moisture sensor. Current research signifies that crops water contents were estimated using soil moisture sensor compared with a spectroradiometer. Water content estimation helps to monitor crop stress for precision farming and monitoring. This research also signifies that SWIR alone can manage water stress level with leaves reflectance. The overall estimates had shown HL with accuracy 99%, dry leaves accuracy 0.97%, and disease leaves accuracy with 0.76%. The research work is implemented using Python software. Future directions for current research will be correlation study of photosynthetic pigments with water contents based on spectral response curves and chemical extraction process will be validated for more analysis to minimize time and cost using remote sensing approach.

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