Estimating Leaf Water Content using Remotely Sensed Hyperspectral Data

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1. Introduction

Plant water stress may occur due to the limited availability of water to the roots/soil or due to increased transpiration. These factors adversely affect plant physiology and photosynthetic ability to the extent that it has been shown to have inhibitory effects in both growth and yield [18]. Early identification of plant water stress status enables suitable corrective measures to be applied to obtain the expected crop yield. Further, improving crop yield through precision agriculture methods is a key component of climate policy and the UN sustainable development goals [1]. Leaf water content (LWC) is a measure that can be used to estimate water content and identify stressed plants. LWC during the early crop growth stages is an important indicator of plant productivity and yield. The effect of water stress can be instantaneous [15], affecting gaseous exchange or long-term, significantly reducing yield [9, 18, 22]. It is thus necessary to identify potential plant water stress during the early stages of growth [15] to introduce corrective irrigation and alleviate stress. LWC is also useful for identifying plant genotypes that are tolerant to water stress and salinity by measuring the stability of LWC even under artificially induced water stress [18, 25]. Such experiments generally employ destructive procedures to obtain the LWC, which is time-consuming and labor intensive. Accordingly, this research has developed a non-destructive methodology to estimate LWC from UAV-based hyperspectral data.

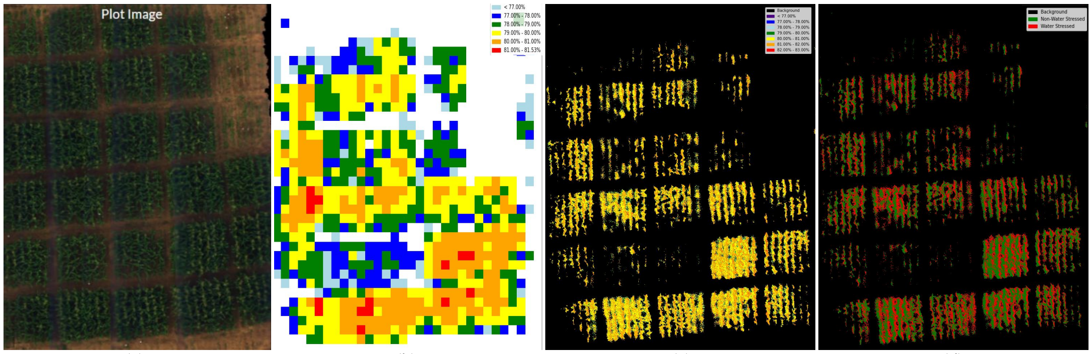
2. Related Work

Previous works have explored water sensitive wavelengths [11, 17] and indices [13] for estimating LWC. However, most of the work is done with 400-2500 nm data. These sensors are expensive and arduous to maintain. [14] discuss the differences between greenhouse and real-world outdoor monitoring with UAVs, and show drought prediction from spectral band data and general vegetative indices (NDVI, PRI, etc.). Recent works [10, 29] present methods for classification using Hyperspectral images (HSI). [16] shows that the spatial variability of chlorophyll from HSI may correlate with LWC. Several works [28, 30, 32] describe methods to estimate water and nitrogen levels in the crop using non-destructive means. However, very few of them have used cross-sensor data modeling. Accordingly, this work investigates water-sensitive indices from hand-held spectroradiometer data that affect water content and train ensemble regressors to compute LWC. A threshold of 79% [15] is used to classify the water stress status of each pixel in the UAV-captured hyperspectral image based on the LWC estimation for the six-leaf growth stage. Further, this work also presents qualitative results for temporal variation of LWC during various stages of crop growth for water stress forecasting. This is the first work to estimate LWC by identifying pure-pixel water-sensitive indices in the 400-1000nm range of the spectroradiometer data to train ensemble methods that generalize for UAV-captured hyperspectral images in real-world outdoor environments.

3. Methodology

Dataset. The experimental farmland consists of 27 specialized treatment plots with varying levels of fertilizer and water provided at regular intervals. The data collected includes hyperspectral data recorded from a hand-held spectroradiometer and a UAV-based Hyperspectral camera to capture HSI of the entire farmland at various stages of growth. The spectroradiometer data consists of 483 data points each with 382 Hyperspectral band data, DAS (Days After Sowing), Nitrogen, Carbon, CNRatio and LWC. The LWC ground-truth value is obtained from destructive distillation of the leaves from the respective plots.

Water-sensitive Indices. Water absorption wavelengths in the 400-1000nm range are more practical to collect due to minimal overhead in maintenance and cost of the sensors. Previous works [21, 27] show that there is a secondary set of water-sensitive wavelengths in the 400-1000nm range. Thus, this work uses the s range for data collection and conduct 400-1000nm range correlation analysis to identify water-sensitive indices. The indices used are tabulated in Table 1. NDVI has been shown to correlate with water stress [4, 5, 8] and is also a common indicator of crop health [2]. The differences in water treatment in the 27 specialized treatment plots may lead to variations in foliage



(a) (b) (c) (d)

Figure 1. Pixel-wise Crop Water Stress Prediction for 20 Nov 2018 (DAS=36) data. (a) Aerial image of plot, (b) Super-pixel $1m \times 1m$ plot computed using Raj *et al*. [20] method used as pseudo ground-truth for LWC estimation, (c) The LWC estimation plot with an NDVI threshold of 0.7 for the proposed method using GBM, (d) Water stress classification using 79% threshold.

Table 1. The indices used to estimate leaf water content.

INDICES	FORMULA
NDVI	$(\rho_{\text{NIR}} - \rho_{\text{RED}})/(\rho_{\text{NIR}} + \rho_{\text{RED}})$
GREEN NDVI	$(\rho_{\text{NIR}} - \rho_{\text{GREEN}})/(\rho_{\text{NIR}} + \rho_{\text{GREEN}})$
RDVI	$(\rho_{\text{NIR}} - \rho_{\text{RED}})/(\rho_{\text{NIR}} + \rho_{\text{RED}})^{1/2}$
MTVI2	$\frac{1.5\times(1.2\times(\rho_{\text{NIR}}-\rho_{\text{GREEN}})-2.5\times(\rho_{red}-\rho_{green})]}{[(2\times\rho_{\text{NIR}}+1)^2-(6\times\rho_{\text{NIR}}-5\times\rho_{red}^{1/2})-0.5]^{1/2}}$
WATER INDEX	ρ_{900}/ρ_{970}
NPCI	$(\rho_{680} - \rho_{430})/(\rho_{680} + \rho_{430})$
OSAVI	$[1.16 * (\rho_{800} - \rho_{670})]/(\rho_{800} + \rho_{670} + 0.16)$
RED EDGE	ρ_{750}/ρ_{710}
NIR1	$(\rho_{800} - \rho_{847})/(\rho_{800} + \rho_{847})$
REDBLUE	$(\rho_{660} - \rho_{420})/(\rho_{660} + \rho_{420})$
WATER BAND	$(\rho_{791} - \rho_{970})/(\rho_{791} + \rho_{970})$

color, and under these conditions the green and red normalized indices [3] are more water-sensitive than NDVI [4, 12], hence the Green NDVI and Red Edge [31] indices have been used in this work. There exist secondary water-sensitive bands at 950-970nm [3, 8, 26] and several works [3, 12, 21, 27] show the direct decrease in Water Index (WI) with water stress. The Renormalized DVI indices (RDVI) [24] and Optimized Soil Adjusted Vegetation Index (OSAVI) [19, 23] have shown to be good predictors of LWC. Further, rigorous analytic experiments show a strong correlation (coefficient: 0.84) among MTVI2, OSAVI and RDVI. This work builds on the findings in [20] to identify NIR1, RedBlue and WaterBand indices to have a strong correlation with LWC.

Estimating Leaf Water Content. Ensemble methods and regressors were trained on the handheld spectroradiometer data (see Table 2). Note that the experiment with three indices corresponds to using NIR1, RedBlue and WaterBand indices, and eight indices correspond to the remaining indices listed in Table 1. The Gradient Boosting [6, 7] method demonstrated the best RMSE and R^2 metrics for the eleven indices experiment (see Table 2). The trained Gradient Boost method is used for the inference stage on the geotagged UAV-captured high-resolution hyperspectral images (HSI). The performance is compared with the super-pixel 1m x 1m plot computed by Raj *et al*. [20] as psuedo ground truth for the surrounding pixels. As discussed in Sec.(2), the threshold of 79% water content during the six-leaf stage DAS=36 (DAS: Days After Sowing) of the crop to classify the water stress status. Fig.(1) shows LWC inference and stress prediction on the UAV-captured hyperspectral images for DAS=36 compared with the $1m \times 1m$ super-pixel plot.

REGRESSION ALGORITHM	8 INDICES RMSE	8 INDICES R^2	3 INDICES RMSE	3 INDICES R^2	11 INDICES RMSE	11 INDICES R^2
GRADIENT BOOST	0.0344	0.641	**0.0158**	**0.925**	**0.0153**	**0.930**
LASSO CROSS-VAL	0.0361	0.610	0.0172	0.911	0.0171	0.912
RANDOM FOREST	0.0354	0.622	0.0165	0.918	0.0161	0.922
STACKED METHODS	**0.0338**	**0.658**	0.0162	0.921	0.0154	0.929

Table 2. Comparing LWC estimation prediction with different subset of indices. We report the corresponding RMSE and R^2 metrics.

4. Conclusion

This work identifies indices that are correlated with leaf water content and water stress. First, the values of the indices from the spectral bands of the hand-held spectroradiometer data are computed. Then, ensemble methods are trained on this dataset with high-quality LWC ground truth values and the $1m \times 1m$ super-pixel pseudo ground truth verifying the improvement in RMSE and R^2 metric using the proposed set of eleven indices. The trained model is evaluated on UAV-captured hyperspectral images for varying stages of growth and DAS to compute pixel-level LWC statistics for each treatment plot. The comparison between the mean predictions on the HSI with the psuedo ground truth mean water content values for each plot verify the performance of the method in estimating LWC effectively.

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