Detection of chlorophyll and leaf area index dynamics from sub-weekly hyperspectral imagery

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ABSTRACT

Temporally rich hyperspectral time-series can provide unique time critical information on within-field variations in vegetation health and distribution needed by farmers to effectively optimize crop production. In this study, a dense time-series of images were acquired from the Earth Observing-1 (EO-1) Hyperion sensor over an intensive farming area in the center of Saudi Arabia. After correction for atmospheric effects, optimal links between carefully selected explanatory hyperspectral vegetation indices and target vegetation characteristics were established using a machine learning approach. A dataset of in-situ measured leaf chlorophyll (Chl) and leaf area index (LAI), collected during five intensive field campaigns over a variety of crop types, were used to train the rule-based predictive models. The ability of the narrow-band hyperspectral reflectance information to robustly assess and discriminate dynamics in foliar biochemistry and biomass through empirical relationships were investigated. This also involved evaluations of the generalization and reproducibility of the predictions beyond the conditions of the training dataset. The very high temporal resolution of the satellite retrievals constituted a specifically intriguing feature that facilitated detection of total canopy Chl and LAI dynamics down to sub-weekly intervals. The study advocates the benefits associated with the availability of optimum spectral and temporal resolution spaceborne observations for agricultural management purposes.

Keywords: LAI, Total canopy chlorophyll, Cubist, Hyperion, Hyperspectral, Dryland, Vegetation indices

1. INTRODUCTION

Enhancements in the spectral, spatial and temporal resolution of space observations have significantly advanced the capacity to monitor and model the state and function of vegetation canopies¹. Hyperspectral sensing (i.e., involving data acquisition in several narrow (<10 nm) contiguous spectral bands) has proven particularly useful for quantifying plant pigments^{2,3}, assessing crop growth and vegetation density^{4,5}, crop type discrimination⁶, and monitoring of light-use-efficiency and plant productivity⁷, using unique spectral features in narrow bands distributed across the electromagnetic spectrum. The same retrieval robustness and capability is rarely achievable by standard broadband multi-spectral systems such as Landsat due to limitations in the spectral information content⁸. However the advancement of hyperspectral techniques for vegetation monitoring and characterization over space and time domains has been hindered by the lack of an operational hyperspectral satellite mission distributing high-resolution data over the entire surface of the earth.

Hyperion onboard the Earth Observing-1 (EO-1) satellite launched in 2000 represents the first spaceborne hyperspectral imager that remains in operation to this day despite an impressive 15 years of operation. Hyperion has made important contributions to the advancement of science and has been instrumental in the development of future global imaging spectrometers⁹. The availability of repeatable high spatial resolution (i.e., 30 m) imagery over large regions is constrained by its revisit capability and narrow scene swaths (~7.5 km), which limit acquisitions to relatively few target sites via the instruments tasking capability. The frequency and large area availability of hyperspectral observations will improve substantially with the prospective launch of the Environmental Mapping and Analysis Program (ENMAP; www.enmap.org) hyperspectral satellite mission in 2018, and the Hyperspectral Infrared Imager (HyspIRI; <https://hyspiri.jpl.nasa.gov>) around 2022. ENMAP will provide full spectrum (420 to 2450 nm) data in 30 km swaths at 30 m resolution over a globally distributed network of regional target sites with a 4-day revisit frequency by exploiting the off-nadir ($\pm 30^\circ$) pointing capability¹⁰. The wider scene swath (i.e., 150 km) of HyspIRI would ensure a global revisit of 19 days. If realized, these initiatives would constitute a hyperspectral revolution with far reaching opportunities for

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Figure 1. (a) The Tawdeehiya farm in Saudi Arabia with indication of sites with intensive measurements during the five field campaigns in 2015. The background image is a natural color representation of 5 m resolution RapidEye data collected on May 31st. (b) Natural color (RGB) representations of the five Hyperion images collected in proximity to the field campaigns. The changing viewing geometry of the acquisitions (see Table 1) result in variations in the farm coverage as indicated in (a).

high spatial resolution vegetation monitoring¹. Hyperion remains attractive as a preparatory platform for researching and demonstrating the enhanced utility to be offered by these future hyperspectral sensing platforms^{11,12}.

With the exciting prospect of a substantial increase in the availability and frequency of hyperspectral imagery in the near future, the development of advanced techniques to fully utilize the vast information content present in hyperspectral data streams is imminent. In this contribution, high frequency Hyperion images acquired over an intensive farming site in the desert of Saudi Arabia (see Figure 1) were used to infer the spatial and temporal dynamics in leaf area index (LAI) and total canopy chlorophyll (TChl) based on an empirical data mining approach. The availability of hyperspectral observations at both high spatial (30 m) and high temporal (~weekly) resolution over an extended period is unique and an opportunity to investigate the benefits of a near-optimum resolution (i.e., spectral, spatial, and temporal) dataset for monitoring vegetation health and growth at sub-field scales.

2. MATERIAL AND METHODS

2.1 Study site

The Hydrology, Agriculture and Land Observation (HALO) group at King Abdullah University of Science and Technology (hydrology.kaust.edu.sa) has established a state-of-the-art observatory at the Tawdeehiya Arable Farm (24.174 °N, 48.015 °E) located in a desert region southeast of the capitol Riyadh in Saudi Arabia (Figure 1). Flux and meteorological towers have been deployed at the farm and ancillary information on soil and vegetation characteristics are collected regularly during intensive field campaigns. The farm operates center-pivot irrigation systems on 47 fields that grow alfalfa, Rhodes grass, maize, or vegetables. The climate is arid with the bulk of the annual precipitation (~95 mm) concentrated between the months of December through April¹³. Despite a predominance of clear skies, desert dust and relatively strong winds often result in hazy field conditions¹⁴.

Table 1. Dates of the field campaigns, number of in-situ samples (n), and the average values (and stddev) of LAI and Chl_i during each campaign. Characteristics associated with the Hyperion scenes acquired within a few days (HYP DOY) of the field campaign dates are also given.

Campaign dates (2015)	DOY	n	LAI	Chl _i	HYP DOY	Time	τ_{550}	θ_{sz} [°]	θ_{vz} [°]	θ_{saz} [°]	θ_{sataz} [°]
Feb 16-18 28	47-49	16/15	1.9±1.1	60±16	50	9:15	0.13	54.0	26.4	126.4	98.0
March 23-24	82-83	18/17	3.6±0.9	54±20	90	8:55	0.41	47.1	6.0	108.2	278.0
April 13-15	103-105	25/19	2.8±1.8	43±18	106	8:46	0.58	45.4	20.5	100.2	278.0
June 1-3	152-154	13/13	4.2±1.3	46±9	152	8:43	0.31	41.7	18.2	83.5	278.0
Oct 6-8	279-281	4/3	2.6±1.9	51±13	282	8:29	0.40	54.5	21.9	117.6	278.0

2.2 In-situ measurements

This study used data collected during five field campaigns (Table 1). Measurements of leaf area index (LAI), defined as one-sided green leaf area per unit horizontal ground area [$\text{m}^2 \text{m}^{-2}$], and leaf chlorophyll (Chl_i), defined as the total chlorophyll *a* plus chlorophyll *b* content on a one-sided leaf area basis [$\mu\text{g cm}^{-2}$], were conducted within rectangular sampling units (30 x 30 m) comprised of 13 measurement plots. The measurement at each plot was averaged to produce a representative value for the specific sampling unit. A total of 76 (LAI) and 67 (Chl_i) samples were collected over the duration of the five campaigns (Table 1) within the domain of the satellite acquisitions (Figure 1). LAI was measured on clear days with a LAI-2200C plant canopy analyzer (LICOR, U.S.A) and corrected for light scattering¹⁴. Chl_i was measured near-simultaneously with a portable SPAD-502 meter (Konica Minolta, Inc., Osaka, Japan), except in the carrot fields where the leaves were too narrow to accurately measure Chl_i. The detailed measurement protocol and conversion of the SPAD units to leaf chlorophyll content [$\mu\text{g cm}^{-2}$] is described in Houborg and McCabe¹⁴. Total canopy chlorophyll (TChl) in units of g m^{-2} was derived by multiplication of Chl_i with LAI and division by 100.

2.3 HYPERION data

The Hyperion hyperspectral imager is part of the Earth Observing-1 (EO-1) satellite mission launched in November 2000⁹. Hyperion acquires continuous narrow-band (10 nm) data over the visible to shortwave infrared domain (400 to 2500 nm), providing 196 calibrated spectral bands with a 30 m nadir ground resolution. Hyperion data collections are programmable which facilitates targeted and potentially frequent monitoring in narrow swaths (Figure 1). The off-nadir viewing capability (i.e., $\pm 22^\circ$ roll angle) facilitates up to five image acquisitions during a 16-day period¹⁵. For the present study, a total of 42 scenes were acquired over the Tawdeehiya farm during 2015. The imagery is provided radiometrically corrected in at-sensor radiance units and has been resampled for geometric correction and georeferenced using a digital elevation model¹⁶. Atmospheric correction to surface reflectance was performed using the Fast Line-of-Sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) algorithm^{17,18}. Precipitable water vapor was retrieved using bands around the 1135 nm water vapor band and information on aerosol optical depth at 550 nm (τ_{550}), was acquired from the Terra MODIS aerosol product (MOD04). The atmospheric correction also included corrections for adjacency effects, which are particularly important for high spatial resolution observations in regions with large contrasts in surface reflectance¹⁹. The horizontal range of the adjacency effect was defined via an aerosol scale height of 2 km. Finally minimum noise fraction transformation²⁰ was applied to reduce striping effects and smooth reflectance profiles.

Each of the intensive field campaigns was associated with a satellite acquisition within a few days of the in-situ observations (Figure 1 and Table 1). Hyperion acquisitions occur in the mornings (around 9 am) and image capture may occur in both forward and back scattering directions with variable viewing angles (Table 1).

Table 2. List of vegetation indices (VI) used as explanatory variables in the Cubist regression modeling. The band designations of the original indices have been adjusted to match the center bandwidths of the 10 nm wide Hyperion sensor bands. The first 12 VIs represent Landsat-like indices.

Name	Vegetation index	Reference
Normalized Difference Vegetation Index	$NDVI = (R_{872} - R_{661}) / (R_{872} + R_{661})$	21
Enhanced Vegetation Index	$EVI = 2.5 \cdot \frac{R_{872} - R_{661}}{R_{872} + 6 \cdot R_{661} - 7.5 \cdot R_{488} + 1}$	22
Soil Adjusted Vegetation Index	$SAVI = [1.5 \cdot (R_{872} - R_{661})] / (R_{872} + R_{661} + 0.5)$	23
Non-Linear Index	$NLI = (R_{872}^2 - R_{661}) / (R_{872}^2 + R_{661})$	24
Simple Ratio	$SR = R_{872} / R_{661}$	25
Renormalized Difference Vegetation Index	$RNDVI = (R_{872} - R_{661}) / (\sqrt{(R_{872} + R_{661})})$	26
Green Normalized Difference Vegetation Index	$GNDVI = (R_{872} - R_{559}) / (R_{872} + R_{559})$	27
Green Ratio Vegetation Index	$GRVI = R_{872} / R_{559}$	28
Modified Triangular Vegetation Index – Improved	$MTVI2 = \frac{1.5[1.2(R_{803} - R_{549}) - 2.5(R_{671} - R_{549})]}{\sqrt{(2 \cdot R_{803} + 1)^2 - (6 \cdot R_{803} - 5 \cdot \sqrt{R_{671}}) - 0.5}}$	4
Atmospherically Resistant Vegetation Index	$ARVI = \frac{R_{872} - [R_{661} - (R_{488} - R_{661})]}{R_{872} + [R_{661} - (R_{488} - R_{661})]}$	29
Green Atmospherically Resistant Index	$GARI = \frac{R_{872} - [R_{559} - (R_{488} - R_{661})]}{R_{872} + [R_{559} - (R_{488} - R_{661})]}$	30
Visible Atmospherically Resistant Index	$VARI = (R_{559} - R_{661}) / (R_{559} + R_{661} - R_{488})$	31
Modified Chlorophyll Absorption Ratio Index	$MCARI = [(R_{702} - R_{671}) - 0.2 \cdot (R_{702} - R_{549})] \cdot (R_{702} / R_{671})$	32
Modified Chlorophyll Absorption Ratio Index Improved	$MCARI2 = \frac{1.5[2.5(R_{803} - R_{671}) - 1.3(R_{803} - R_{549})]}{\sqrt{(2 \cdot R_{803} + 1)^2 - (6 \cdot R_{803} - 5 \cdot \sqrt{R_{671}}) - 0.5}}$	4
Red Edge Normalized Difference Vegetation Index	$RENDVI = (R_{752} - R_{702}) / (R_{752} + R_{702})$	33
Modified Red Edge Normalized Difference Vegetation Index	$MRENDVI = (R_{752} - R_{702}) / (R_{752} + R_{702} - 2 \cdot R_{447})$	33
Red-edge Simple Ratio	$RSR = R_{872} / R_{712}$	34
Vogelmann Red Edge Index 1	$VREI1 = R_{742} / R_{722}$	35
Vogelmann Red Edge Index 2	$VREI2 = (R_{732} - R_{752}) / (R_{712} + R_{722})$	35
Photochemical Reflectance Index	$PRI = (R_{529} - R_{569}) / (R_{529} + R_{569})$	36
Structure Insensitive Pigment Index	$SIPI = (R_{803} - R_{447}) / (R_{803} - R_{681})$	37
MERIS Terrestrial Chlorophyll Index	$MTCI = (R_{742} - R_{702}) / (R_{702} - R_{661})$	38
Anthocyanin Reflectance Index 2	$ARI2 = R_{803} [1/R_{549} - 1/R_{702}]$	39
Carotenoid Reflectance Index 1	$CRI1 = 1/R_{508} - 1/R_{549}$	40
Carotenoid Reflectance Index 2	$CRI2 = 1/R_{508} - 1/R_{702}$	40
Red Green Ratio Index	$RGRI = \left(\sum_{i=600}^{691} R_i \right) / \left(\sum_{j=498}^{599} R_j \right)$	41

2.4 Cubist regression approach

Empirical associations between target vegetation characteristics (i.e., LAI and TChl) measured in-situ and the Hyperion spectral observations were established on the basis of the Cubist (RuleQuest; www.rulequest.com) data mining technique. Cubist adopts a model tree approach^{42,43} for building a set of rules each represented by a multi-variate linear regression model. The LAI and TChl predictive models were trained on the basis of the in-situ collected data paired with explanatory data values from a wide range of Vegetation Indices (VIs) extracted from the hyperspectral imagery at each sampling unit. The squared form of each VI was also added as input to the model training. The list of selected VIs (Table 2) encompasses indices previously reported in the literature and with known sensitivities to the target variables. The band designations of the original indices were adjusted to conform to the center bandwidths of the 10 nm wide Hyperion bands (Table 2).

The benefit of Cubist lies in its ability to efficiently identify and organize the optimal combination of VIs in a set of rules based on a large training dataset. The full training dataset was used to build the predictive regression models that were subsequently applied to the full suite of Hyperion images in order to map LAI and TChl over the duration of the study period. Given the fairly limited number of in-situ sampling units (Section 2.2), the number of maximum rules was set to 2. This will reduce the risk of disrupting the spatial value continuity in LAI and TChl when applying the models on unseen data⁴⁴. Model regressions were also constructed using standard Landsat-like VIs (i.e., the first 12 indices in Table 2) as input to Cubist. These were constructed using the Hyperion bands that most closely match the band designations of the Landsat-8 blue (488 nm), green (559 nm), red (661 nm), and near-infrared (872 nm) bands. The results of these model predictions were compared to the results utilizing the full suite of VIs (Table 2) in order to investigate the potential benefit of the enhanced hyperspectral information content for characterizing vegetation canopies. The predictabilities were assessed using standard statistics including the coefficient of determination (R^2), and the relative Mean Absolute Deviation (MAD) and Mean Bias Deviation (MBD) calculated by dividing the deviations with the mean of the in-situ measurements.

3. RESULTS AND DISCUSSION

3.1 Cubist regression results

For LAI, Cubist defined two separate model regressions (i.e., rules) for describing the variability of the in-situ LAI observed during the five campaigns (LAI ranging between 0 and 5.87 m²m⁻²):

$$LAI = -0.1547642 + 50.5 \cdot SAVI^2 + 26.58 \cdot NDVI^2 \quad (1)$$

$$LAI = -1.2568875 + 44.1 \cdot SAVI^2 - 22.3 \cdot GNDVI^2 - 14.9 \cdot MTVI2^2 + 6.62 \cdot NLI + 3.52 \cdot VREI1^2 - 7.61 \cdot NDVI^2 - 8.8 \cdot VARI + 27 \cdot PRI^2 \quad (2)$$

The first model is used when $SAVI \leq 0.213$ (i.e., low vegetation densities) and incorporates normalized difference VIs (i.e., NDVI, SAVI) based on standard bands in the red and near-infrared domain (Table 2). The second model is used when $SAVI > 0.213$ and also includes a simple ratio (i.e., VREI1) based on bands in the red-edge region, in addition to the normalized difference between leaf reflectance on either side of the green reflectance peak (i.e., PRI) (Table 2). The red-edge is highly sensitive to variations in LAI and has shown to provide improved predictability over dense vegetation^{5,14}. The PRI signal responds to vegetation stress and correlates with the efficiency of photosynthetic activity⁴⁵, which will be related to the greenness, health and density of the vegetation canopy. These hyperspectral models yield an R^2 of 0.94 and a relative MAD of 10.4% when using the same dataset for training and validation (Figure 2a). The level of agreement decreases ($R^2=0.89$, MAD=14.6%) when only Landsat-like VIs are used in Cubist (Figure 2b). With that setup, Cubist also defined two rules (with similar rule conditions as stated for Eq. 1 and 2), combining SAVI, NDVI, EVI and NDVI in rule 1, and GARI, ARVI, VARI, NDVI, EVI, GNDVI and GRVI in rule 2 (not shown).

The resulting model regressions for TChl, based on the full spectrum suite of VIs, predominantly consist of indices using bands in the red-edge region (i.e., VREI1, RSR, RENDVI, MRENDVI, MCARI, CRI2):

$$TChl = 10.57968 + 11.51 \cdot VREI1^2 - 24.52 \cdot VREI1 - 0.8 \cdot RSR^2 + 0.482 \cdot SR + 4.53 \cdot RGRI + 7.39 \cdot RNDVI^2 - 1.7RGRI^2 - 2.17 \cdot RENDVI - 1.63 \cdot MRENDVI^2 + 1.46 \cdot EVI - 129.34 \cdot MCARI^2 \quad (3)$$

$$TChl = 35.14363 - 41.49 \cdot VREI1 + 14.97 \cdot VREI1^2 + 13.8 \cdot RGRI^2 - 20.42 \cdot RGRI + 13.01 \cdot RNDVI^2 - 0.00357 \cdot CRI2^2 - 0.291 \cdot RSR^2 - 31.88 \cdot MCARI^2 \quad (4)$$

These rules are valid over the observed range in TChl (0 to 3.6 g m⁻²). Rule one (Eq. 3) is used when RGRI>1.173 whereas rule two (Eq. 4) applies when RGRI≤1.173. Verification against the training data yields an R² of 0.83 and a relative MAD of 22% (Figure 2c). When the spectral information is reduced to the Landsat-like VIs, the majority of the in-situ data points are defined by a single rule that relies on indices based on the green band (i.e., GARI, ARVI, VAI, GNDVI, GRVI) in addition to indices responding predominantly to vegetation density (i.e., NDVI, EVI). While the green band contains valuable information for the assessment of chlorophyll dynamics^{34,46}, red-edge information is recognized as key for improving the robustness of chlorophyll retrieval^{47,48} due to enhanced sensitivity at high ranges and lower atmospheric correction uncertainties¹⁴. Accordingly, validation results based solely on the Landsat-like VIs yield a reduced correlation (R²=0.69) and a higher MAD (26.8%) (Figure 2d). As demonstrated above, the enhanced hyperspectral information content serves to more robustly reproduce the LAI and TChl dynamics observed during the five field campaigns (Figure 2).

Figure 2. Validation of the Cubist-based LAI (a, b) and TChl (c, d) predictions against the in-situ observations (the error bars represent the stddev of the measurements within each sampling unit). In (a) and (c) the full suite of hyperspectral VIs (Table 2) was used as input to Cubist. In (b) and (d) only Landsat-like VIs were used as input to Cubist. The model performance is indicated by standard statistic metrics.

3.2 Time-series of LAI and TChl

The model regressions described and validated above (Eq. 1 to 4) were applied to the full suite of available Hyperion images. Figure 3a showcases resulting spatial features in LAI and TChl for a single Hyperion acquisition whereas Figure 3b (middle and bottom panels) demonstrates the temporal dynamics for three crop-specific (i.e., alfalfa, maize, grass) pixel locations. The overall spatial features in LAI and TChl are similar with dense crop pivots generally associated with the highest canopy chlorophyll contents (Figure 3a). However the magnitudes in TChl may differ significantly between crop classes as a result of variations in the characteristic leaf chlorophyll (Chl_l) level of each crop species. For instance, the Rhodes grass fields at the farm (e.g. P3) have substantially lower Chl_l values than the alfalfa fields (e.g. P1)¹⁴, which result in large differences in the TChl level between the densely vegetated grass and alfalfa pivots (Figure 3a). Variations in the behavior of LAI and TChl are also evident at the sub-field scale, which may result from intra-field variations in growing conditions (e.g., nutrients and water availability, plant physiological condition and photosynthetic performance) that will affect the canopy density and leaf chlorophyll content differently⁴⁹.

The LAI time-series demonstrate the characteristic phenology of alfalfa (P1) with multiple relatively short growing cycles and an abrupt decline due to harvest at peak vegetation densities (Figure 3b). The harvest and re-growth of the alfalfa crop is not captured by the satellite imagery between DOY 180 and 208 due to a pause in the tasked acquisitions

Figure 3. (a) LAI and TChl predictions on DOY 282 based on Eq. 1 – 4. (b) Time-series of scene-wide MODIS-derived τ_{550} (top panel), and Hyperion-based LAI (middle panel) and TChl (bottom panel) for selected pixel locations.

during this time interval. Maize (P2) is characterized by two growing cycles with planting dates in the early spring and early fall, respectively (Figure 3b). Maize is harvested before senescence sets in as evidenced by the sharp decline in LAI between DOY 171 and 179. The phenology of the grass field (P3) indicates multiple growing cycles similar to alfalfa, but the harvesting schedule varied and the activity of the grass center-pivot irrigation system was significantly more sporadic over the course of the field campaigns¹⁴. The TChl and LAI temporal dynamics are strongly associated, particularly over the alfalfa ($R^2=0.88$) and maize ($R^2=0.94$) pixel locations, which are expected in fields with sufficient water and nutrient availability⁵⁰. The inter-correlation is lower for the grass location ($R^2=0.64$), which may be the result of non-optimal growing conditions during periods with sporadic activity of the irrigation system.

The time-series of both LAI and TChl sometimes depict unrealistic behavior, which may result from uncertainties introduced by the atmospheric correction process, view-angle effects from the use of off-nadir Hyperion acquisitions⁵¹, and issues related to the transferability of empirically based model regressions⁵². While the spectral stability of Hyperion surface reflectance time-series has been shown to consistently range between 2.5 – 5%¹², the atmospheric correction is particularly challenged over these dryland agricultural regions due to high aerosol loadings (Figure 3b) and substantial adjacency effects resulting from high contrast surface reflectance surfaces (i.e., bright desert versus dark vegetated surfaces)¹⁴. These issues will need further consideration in order to accurately detect subtle temporal dynamics in LAI and chlorophyll from sub-weekly Hyperion acquisitions.

4. CONCLUSIONS

Hyperspectral sensing offers significant potential for advancing the capacity to retrieve vegetation characteristics through novel uses of the vast spectral information content. This study demonstrated the utility of a unique high-frequency time-series of Hyperion images for leaf area index (LAI) and total canopy chlorophyll (TChl) estimation over a dryland agricultural landscape. A data mining approach was used to establish optimal links between in-situ measurements of the target variables and a wide range of explanatory hyperspectral vegetation indices. The established multi-variate model regressions provided robust assessments of the dynamics in LAI and TChl observed over five intensive field campaigns, and out-performed the predictability achieved when only Landsat-like vegetation indices were used to train the regression models. Application of the developed models to the full suite of Hyperion images realistically reproduced the general phenological features of the dominant crops. However the detection of more subtle spatial and temporal dynamics resulting from short-term variations in vegetation condition remains a key challenge due to uncertainties introduced by the atmospheric correction and significant sensor view-angle effects. In addition, the validity of the empirical regressions beyond the training data will need further investigation. A key objective of ongoing work is to fully utilize the rich information content of the hyperspectral data streams by complementing the existing list of explanatory spectral indices (Table 2) with additional hyperspectral metrics, such as those based on continuum removal^{12,53,54}.

ACKNOWLEDGEMENTS

Research reported in this publication was supported by the King Abdullah University of Science and Technology (KAUST). We greatly appreciate the logistical, equipment and scientific support offered to our team by Mr Jack King, Mr Alan King and employees of the Tawdeehiya Farm in Al Kharj, Saudi Arabia, without whom this research would not have been possible.

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