77. Exploring the potential of hyperspectral imaging and machine learning to assess biophysical traits of tomato crops

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Abstract

This study examined the application of hyperspectral imaging (HSI) and machine learning (ML) in agricultural research to assess biophysical traits of tomato crops in the Mediterranean region. The research was conducted at the DATI project experimental field in Italy, using a DJI M600 Pro UAV equipped with a Headwall Nano-Hyperspec® camera. The results showed that irrigation deficiency significantly increased the content of chlorophyll and flavonoids in tomato leaves but had no effect on anthocyanin. The best prediction models were obtained with HS wavelength of 715 nm and the transformed chlorophyll absorbance reflectance index (TCARI) performing the best.

Keywords: hyperspectral, tomato, unmanned aerial vehicles (UAV), vegetation indices (VI)

Introduction

The integration of hyperspectral imaging (HSI) and machine learning (ML) in agricultural research has gained considerably attention in recent years. The effectiveness of both techniques in retrieving crop biophysical parameters via UAVs has been reviewed, but only few consistent results have been found among similar studies, especially when applied to low-value crops. The main questions addressed have been whether HSI could have an added value over alternatives such as multispectral imaging in assessing crop biophysical parameters, though the cost of complex instrumentation, data processing and analyses. Moreover, the large volume of data often led to redundancy and inconsistency in determining universally appropriate wavelengths. Machine learning has been identified as having strengths such as narrowing research focus through bands selection, reducing data dimensionality and minimizing the burden of data collection. However, there has been no consistent indications that these methods are superior to classical statistical approaches (Matese *et al.*, 2024).
Tomatoes (*Solanum Lycopersicum* L.) are among the most widely consumed vegetables worldwide, with a global production of 186 Mt in 2022 (FAOSTAT, 2024). Tomato crops are drought-sensitive and require significant water amounts, especially in hot, dry Mediterranean climates. Rising temperatures are shortening the growing season and impacting yields (Cammarano *et al.*, 2020; Saadi *et al.*, 2015;). Water stress significantly affects yield, size, and quality, with variable impacts depending on the phenological stage (Ripoll *et al.*, 2016). Traditional methods for assessing water stress include soil and plant-based techniques, such as soil moisture analysis and leaf water potential, which are reliable but labor-intensive (González-Dugo *et al.*, 2006). Remote sensing technologies, particularly drone-mounted sensors (UAVs), have emerged as a non-destructive alternative, offering enhanced spatial and temporal monitoring capabilities (Gago *et al.*, 2015; Matese *et al.*, 2024). UAVs equipped with hyperspectral and multispectral cameras enable precise measurement of vegetation indices, aiding in water stress detection, yield prediction, and nutrient status assessment (Bagherian *et al.*, 2023). Combining UAV imaging with ground-based measurements has proven effective in optimizing tomato phenotyping, improving understanding of physiological responses to water stress, and enhancing water-use efficiency under varying environmental conditions (Di Gennaro *et al*, 2024; Enciso *et al.*, 2019; Fullana-Pericàs *et al.*, 2022). This study aimed to monitor

crop growth and biophysical traits of tomato plants grown under different irrigation regimes using UAV-mounted hyperspectral cameras combined with ground-based measurements. The research considered extensive data acquisition conducted over three years under changing environmental conditions to better understand the physiological response of tomato plants to water stress and the dynamic changes occurring between the plant and the environment.

Materials and methods

The experiment was conducted at the DATI experimental field (Figure 1) located at Regione Toscana experimental farm in Italy from May to August in 2021, 2022 and 2023, with 18 experimental blocks. Three irrigation treatments have been set, of which T1 represents 100% compared to the traditional irrigation practice in that area, while the other two treatments are a reduction of 75 % (T2) and 50 % (T3) of that value (T1). A DJI M600 Pro UAV was equipped with a Headwall Nano-Hyperspec® camera to capture hyperspectral imagery data in the range of 400–1000 nm, with 273 bands and 2 nm spectral resolution. Conversion from radiance to reflectance was carried out using reference reflectance panels and the empirical line method (Matese *et al.*, 2022). Pixels were aggregated to work at a canopy level avoiding soil and shadows pixels.

Several vegetation indices commonly used for crop growth monitoring were calculated from the hyperspectral dataset. Ground data, including leaf chlorophyll (Chl), flavonoid (Flav), and anthocyanin (Anth) content, were measured using the Dualex® leaf-clip meter. Dualex measures chlorophyll by analyzing the light transmitted through the leaf at specific wavelengths. The chlorophyll content is given as an absolute value in μg/cm². Measurements were performed in 2021, 2022 and 2023 from late June to early August at three growth stages: flowering-early fruit set (DOY 174–186), fruit development (DOY 192–201) and fruit ripening (DOY 207–215). The experimental design was characterized by 18 blocks where 3 plants per block were chosen for

Figure 1. Experimental field during the growing season.

ground measurements. The collected data were then integrated with hyperspectral bands and indices to develop accurate prediction models capable of estimating these ground measurements for tomatoes under water-stressed conditions. First, a correlation matrix was calculated using the hyperspectral indices. Then, the dataset was divided, with 70% allocated for training and 30% for testing. The training dataset was divided into two partitions: training and validation. This train-validation split was repeated multiple times, each time reserving a different portion of the data for evaluation through a process known as cross-validation. In our case, this was implemented using ten-fold cross-validation, repeated 10 times. Five machine learning algorithms, including multiple linear regression (LM), random forest (RF), support vector machine (SVM), k-nearest neighbours (KNN), and partial least squares (PLS) regression, were evaluated to predict ground parameters based on hyperspectral reflectance. A preprocessing step was applied for dimensionality reduction and feature selection using the recursive feature elimination (RFE) method (Zhu *et al*, 2020), which improves model efficiency by eliminating less important bands/indices before modelling. In this study, the coefficient of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE) were utilized as accuracy evaluation metrics for the predictive models.

Results and discussion

Figure 2 showed correlation matrix of tomato Dualex indices (CHL, chlorophyll content; FLAV, flavonoids content; ANTH, anthocyanin content) and hyperspectral (HS) indices from 2021 to 2023. The CHL content revealed good correlation coefficients with most of the HS indices, including GRVI (r=0.75), LCI (r=0.73), NDRE and SR5 (r=0.72). ANTH showed a high correlation value of 0.89 with GNDVI, NDVI and SR4, while mainly negative correlations were observed for FLAV, which had the strongest negative correlation of -0.66 with VARI.
The evaluation of ML prediction models was performed based on the RMSE, R^2 and MAE values of the training and testing dataset shown in Table 1.

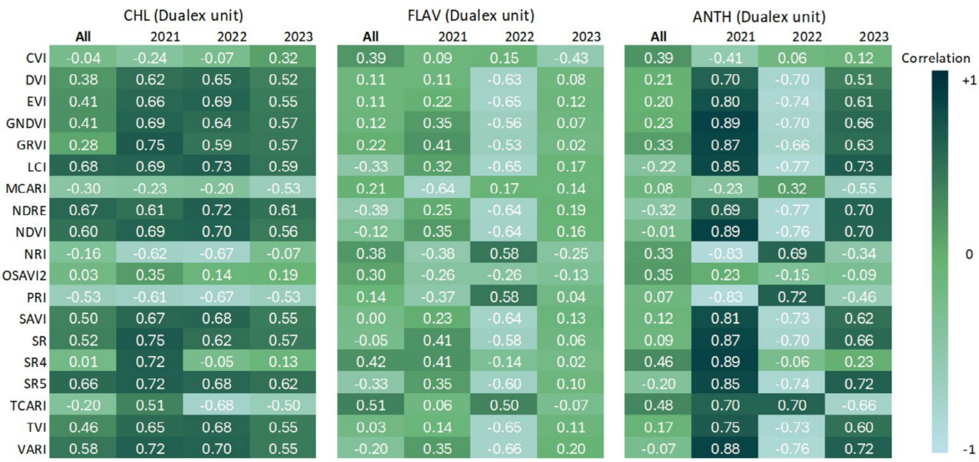

Figure 2. Correlogram of tomato Dualex indices (CHL, FLAV and ANTH) and HS indices from 2021 to 2023. Correlation coefficients were calculated for total and single seasons.

Table 1. Results of the machine learning algorithm in predicting ground parameters.

Parameter	Model	Training dataset			Test dataset		
		RMSE	R^2	MAE	RMSE	R^2	MAE
HS bands							
CHL	LM	2.76	0.57	2.27	3.28	0.56	2.57
	RF	3.07	0.48	2.50	3.45	0.48	2.59
	SVM	3.02	0.55	2.40	2.68	0.55	2.29
	KNN	3.22	0.48	2.60	3.01	0.47	2.45
	PLS	2.90	0.55	2.38	3.18	0.52	2.35
FLAV	LM	0.25	0.57	0.20	0.26	0.57	0.21
	RF	0.28	0.46	0.23	0.30	0.44	0.22
	SVM	0.29	0.43	0.23	0.28	0.42	0.23
	KNN	0.30	0.44	0.24	0.28	0.43	0.21
	PLS	0.30	0.42	0.24	0.29	0.41	0.22
ANTH	LM	0.05	0.63	0.04	0.05	0.63	0.04
	RF	0.06	0.45	0.05	0.06	0.41	0.05
	SVM	0.06	0.44	0.05	0.06	0.43	0.05
	KNN	0.06	0.36	0.05	0.07	0.36	0.05
	PLS	0.06	0.36	0.05	0.06	0.36	0.05
HS indices							
CHL	LM	3.00	0.55	2.44	2.95	0.54	2.29
	RF	2.93	0.53	2.32	3.24	0.52	2.57
	SVM	2.77	0.58	2.25	3.19	0.53	2.59
	KNN	2.96	0.52	2.43	3.23	0.51	2.62
	PLS	3.16	0.50	2.61	3.04	0.48	2.51
FLAV	LM	0.29	0.49	0.23	0.26	0.49	0.20
	RF	0.26	0.53	0.21	0.25	0.53	0.18
	SVM	0.29	0.48	0.22	0.30	0.46	0.24
	KNN	0.26	0.58	0.20	0.24	0.53	0.18
	PLS	0.32	0.39	0.25	0.31	0.37	0.24
ANTH	LM	0.06	0.45	0.04	0.06	0.44	0.05
	RF	0.05	0.54	0.04	0.05	0.52	0.04
	SVM	0.07	0.38	0.05	0.06	0.36	0.05
	KNN	0.06	0.37	0.05	0.07	0.35	0.06
	PLS	0.07	0.32	0.06	0.06	0.30	0.05

The best prediction models of quality parameters with HS bands were obtained by LM with relative R^2 of 0.57 for CHL and FLAV and 0.63 for ANTH, corresponding to RMSE of 2.76, 0.25 and 0.05, respectively. Predictions using HS indices showed better performance with SVM for CHL (R^2=0.58; RMSE=2.77), KNN for FLAV (R^2=0.58; RMSE=0.26) and RF for ANTH (R^2=0.54; RMSE=0.05).

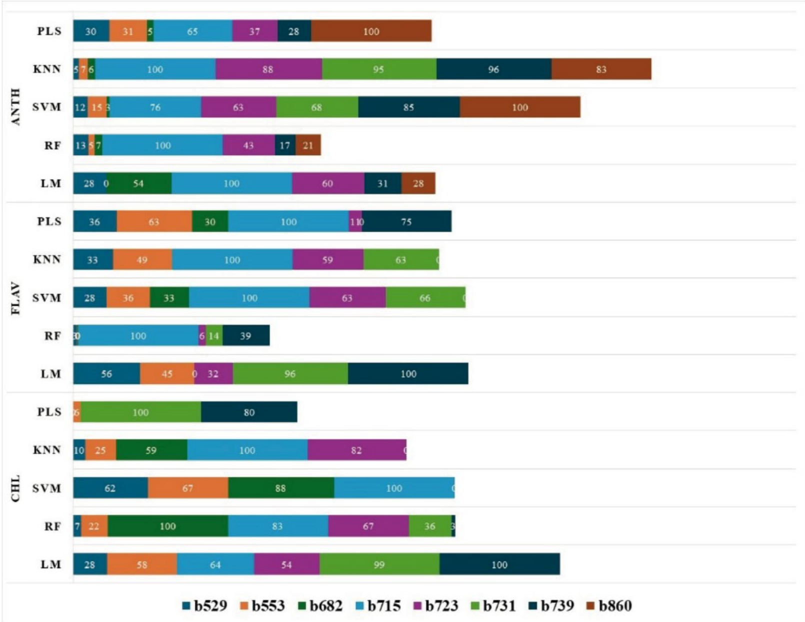

Figure 3. Variable importance of predictors for models scaled from 0 to 100 of best HS bands.

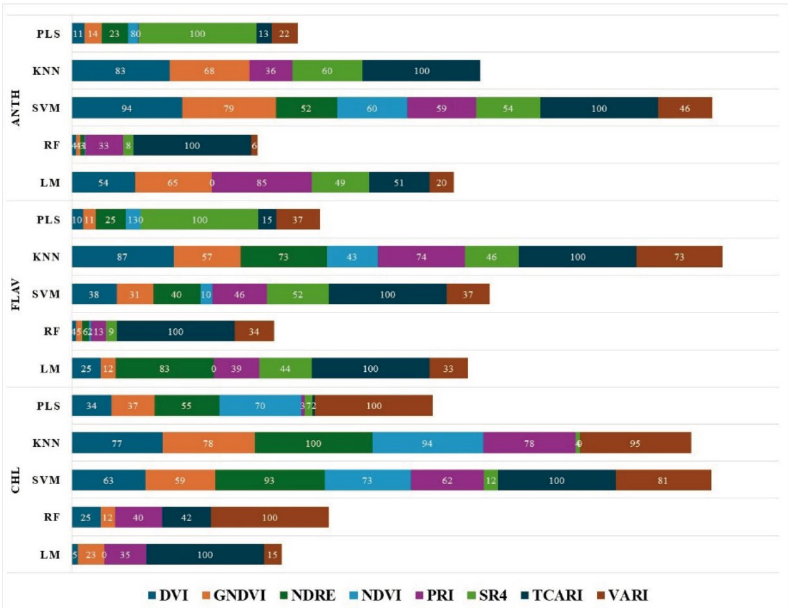

Figure 4. Variable importance of predictors for models scaled from 0 to 100 of best HS indices.

Performance of models (PLS, KNN, SVM, RF, LM) across the three ground parameters (ANTH, FLAV, CHL), with colours indicating specific HS bands in Figure 3 and HS indices in Figure 4. Variable importance scores were computed. Values were scaled from 0 to 100 with larger values indicating higher contribution in the model.

Overall, it can be clearly seen that the band 715 nm was dominating most of the generated models across the different parameters. Regarding ANTH, the models KNN, RF and LM were headed by the band 715 nm with an importance value of 100, while PLS and SVM were dominated by the band 860 nm. FLAV was also led by the band 715 nm with all the ML models, except for LM, where the most important bands were 739 and 731 nm, corresponding to an importance value of 100 and 96, respectively. For the CHL, differences were observed across the models, with KNN and SVM being fronted by the band 715 nm, while PLS by 731, RF by 682 nm, and LM by 739 and 731 nm.

Regarding the HS indices, TCARI seemed to be the most important index across the developed models. KNN, SVM, and RF were dominated by TCARI, while PLS and LM by SR4 and PRI, respectively. TCARI had also the highest value of importance (100) for all ML models generated for FLAV, except for PLS, which was fronted by SR4. In parallel with HS bands, CHL also had variations across the indices-based models, with TCARI being the most important HS index selected by SVM and LM, while VARI was the dominant index for PLS and RF, and NDRE for KNN model.

Prior research has shown that integrated indices such as MCARI/OSAVI and TCARI/OSAVI outperform TCARI and MCARI alone, mitigating background effects (Daughtry *et al.*, 2000). Angel and McCabe (2022) demonstrated that a linear SVR model performed optimally when using 272 reflectance bands as predictors but reached poorer results when the predictor was reduced to 60 bands. Limited research has examined SPAD-based chlorophyll retrieval using vegetation index models derived from hyperspectral datasets. For instance, studies using linear regressions (Qi *et al.*, 2020) and random forests (Shah *et al.*, 2019) combined with various VIs have achieved more accurate results compared to using single bands.

It is important to note that most VIs rely on red and near-infrared wavelengths. As crops mature, reproductive growth intensifies while vegetative growth declines, leading to increased biomass but reduced chlorophyll concentration. This increases red spectral reflectance, while decreased turgor and the collapse of spongy mesophyll reduce near-infrared reflectance, weakening the correlation between VIs and the biophysical traits of plants. The most relevant features are typically found within the 400–500 nm and 700–800 nm wavelength ranges, which are sensitive to nitrogen (Thenkabail *et al.*, 2000).

Applying these ML methods to the entire hyperspectral data may reduce the biological or physical interpretability of the model, complicating result understanding (Jin & Wang, 2019). Although training the model with all hyperspectral variables resulted in higher accuracy than using vegetation indices, multiple factors, such as accuracy, reliability, and practicality, must be considered when selecting variables for model development. While accuracy is typically a primary goal, it is crucial to recognize that maximum accuracy may not always align with the model's specific objectives (Jia *et al.*, 2019).

Conclusions

The findings suggest that the integration of hyperspectral imaging techniques with machine learning is of great importance in improving agricultural management. Reliance on ML approaches may reduce replicability, reproducibility and generalization. This study highlights the potential of hyperspectral (HS) data and machine learning (ML) for precision agriculture. Strong correlations were observed between HS indices and plant traits, with CHL and ANTH closely linked to GRVI, LCI, NDRE, and NDVI, while FLAV showed a negative association with VARI. Among ML models, SVM, KNN, and RF delivered the best predictive performance, particularly when using HS indices over individual bands. The 715 nm wavelength and TCARI index emerged as key predictive features.

These findings underscore the value of integrating HS imaging and ML to enhance tomato crop quality assessment, calling for further refinement in feature selection and model scalability.

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