Effect of multi-level and multi-scale spectral data source on vineyard state assessment.

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Abstract

Leaf water potential (LWP) is widely used to assess plant water status. Also, pigment concentration work as a proxy for the canopy's water status. Spectral data methods have been applied to monitor and evaluate crops' biophysical variables. This work developed a model to predict LWP using a UAS equipped with a VIS-NIR multispectral camera and trained artificial neural network (ANN) represents a good and relatively cheap solution to assess plant status spatial information to predict LWP and obtain canopy and foliar reflectance on three dates in 2020 and two ways of validation; a pressure chamber to measure and geophysics survey of the electronic conductivity (EC). Two modeling approaches, combining spectral data and spectral vegetation indices, were used to estimate LWP in a commercial vineyard in the Tufo Wine Region. The first approach predicts LWP through vine's canopy reflectance; reconstructed (from 5 bands to 21bands) dataset using a conventional neural network (CNN) the several vegetation indices (VIs) were computed and selected. The second modeling approach is based only on the (CNN) reconstructed dataset. Both approaches predicted LWP-based Vls and spectral data classified from high to low; the results were consistent in direct proportion to the laboratory results and performed the best results for both modeling approaches.

Introduction

Currently, the main goal of agriculture is to promote the resilience of agricultural systems in a sustainable way (SDGs United Nations, Green Deal EU strategy) improve the use efficiency of farm resources, increase crop yield and quality under climate change (CC) conditions.
This last has a direct influence on the suitability of current agricultural areas for food production, undermining the resilience of agriculture systems and in particular of those rainfed, as the viticultural sector is(Bonfante *et al.*, 2017) .
In this context, the monitoring of spatial behavior of grapevine, and in particular the plant water status during the growing season, represents an opportunity to face the effects of CC sustainably, supporting the improvement of plant management and then winegrowers' incomes.
Plant water status can be evaluated using leaf water potential (LWP) measurements realized with the pressure chamber technique(Scholander *et al.*, 1965). These types of measurements are punctual and can be spatially distributed to represent the vineyard's spatial behavior, but their usage in the field has the disadvantages of being invasive, demanding hermetical handling, and being time-consuming, then they hardly adapt to routine monitoring (farm's field monitoring). Therefore, alternative accurate and user-friendly methodologies are needed to assess the spatial vineyard plant water status.
A drone equipped with a VIS-NIR multispectral camera (blue, green, red, red-edge, and NIR) approach is a good and relatively cheap solution to assess plant status spatial information in the vineyard (using a limited set

of spectral vegetation indices), representing important support in precision agriculture management during the growing season.

Even though the multispectral cameras are highly suited for drought stress detection, pathogen detection, and estimation of nutrients the application of vegetational indices from the literature is not enough to represent the plant water stress as described by LWP measurements.

In this work, we use ANN models that are composed of a complex and nonlinear network of neurons like the actual brain. Han and others showed that ANN is more effective than random forest regression in calculating maize above-ground biomass(Han *et al.*, 2019). Zhang used four structure vegetation indices, narrowband vegetation indices, and multivariate approaches regression to estimate the forest canopy using spectral data from a spaceborne hyperspectral image to determine sugarcane canopy nitrogen concentration spatial variation using ML algorithms(Zhang *et al.*, 2021). Xu used regression algorithms, including ANN, to assess the yield using UAV- with multispectral camera data in vineyard crops(Xu *et al.*, 2020).

The aim of this contribution is to apply new modeling approaches, combining spectral data and spectral vegetation indices, which were used to estimate LWP in a commercial vineyard in the Tufo Wine Region.

The first approach predicts LWP through vine's canopy reflectance; reconstructed (from 5 bands to 21bands) dataset using a conventional neural network (Brook et al.,2020) the several vegetation indices (VIs) were computed and selected. The second modeling approach is based only on the (CNN) reconstructed dataset. Both approaches predicted LWP-based Vls and spectral. This research work has been realized within the GREASE regional project of the Campania region (Southern Italy), Sustainable models of cultivation of the Greco grapevine: efficiency of use of resources and application of 'Footprint family' indicators" –PSR Campania 2014-2020; Measure 16 - Sub-measure 16.1.2.

Materials and methods

The methodology consists of four steps:

1. *Field data acquisition:*
   - a- UAS multispectral camera (5 bands: Blue, Green, Red, Red-edge and NIR) imagery during the grown season (flowering, ripening, and harvesting; 14 flight over two growing seasons : 2020-2021).
   - b- Leaf water potential (LWP) acquired using a pressure bomb (Scholander chamber method, Scholander et al., 1965).
   - c- The data were acquired in an experimental vineyard of Feudi di San Gregorio winery in southern Italy (Avellino, Campania region). Here the autochthonous grape variety 'Greco' (Vitis vinifera L. subsp. vinifera) is cultivated grafted on a 420A rootstock, since 2008, and trained at double guyot and double arched canes.

2. *Preprocessing data:*
   - a- Building photogrammetry models based on the UAS multispectral camera imagery using Pix4Dmapper software.
   - b- Reconstruction of the high-resolution photogrammetry models based on multispectral imagery (5bands to 21 bands across 445-840nm) through the Convolutional Neural Network (CNN) approach proposed by Brook et al., 2020.
   - c- Calculation of Vegetation indices based on the photogrammetry models database (Vls list: DVI, EVI, GARI, GCI, GDVI, GLI, GNDVI, GOSAVI, GRVI, GSAVI, IPVI, LAI, MNLI, MSAVI2, MSR, NDVI, NLI, OSAVI, RDV, SAVI, SR, TDVI, TGI, VARI, WDRVI.)
   - d- Organization of four datasets: i) Vls models maps based on 5 bands, ii) Vls models maps based on 21 bands, iii) orthomosaics maps based on 5 bands, and iv) orthomosaics maps based on 21 bands.
   - e- orginazing data tables the leaf water potential (LWP) based on the field pressure bomb measurements.

3. *Data processing using the artificial neural network (ANN) algorithm;*
   - a- Training models with the Input of four datasets and LWP tables (training 70%, 15 testing, and validation 15%).
   - b- Predicting LWP with ANN models and creating a series of thematic maps

Artificial Neural Networks (ANN) is a system modeled on the human brain. It consists of large number of interconnected processing nodes called neurons, structured in different layers of varying numbers, enabling the system to process multiple inputs from external sources. The heuristic approach was adopted for multi-layer perceptron. It has been used for back-propagation training of feed-forward neural networks, utilized in several real-life applications such as prediction and estimation. Feed-forward back-propagation networks were developed with the using the Levenberg–Marquardt and Bayesian regularization training functions. A grid search with two tuning parameters (the number of nodes in the hidden layer from 3 to 20, and the decay of weight at each iteration set at 0.01, 0.05, and 0.1) was used to select the model with the lowest RMSEP values.

Results and discussion

Four datasets were designed for the processing stage: i) Vls models maps based on 5 bands of UAS-based multispectral imagery, ii) Vls models maps based on 21 reconstructed spectral bands, iii) orthomosaics maps based on 5 bands of UAS-based multispectral imagery, and iv) orthomosaics maps based on 21 reconstructed spectral bands.
The influence of training set size (50% - 90%) on the performance of ANN once the default (MATLAB2022a) hyper-parameters on 21 reconstructed spectral bands were implemented. The average R2-value on the training set was increased from 0.78 to 0.91 when the training set size was increased from 50% to 70% and after it was slightly decreased. Similarly, the average R2-value on the testing was increased to 70%, followed by a slight decrease. The training set size on ANN performance with default hyperparameters gives us better performances in the training phase than in the testing phase.

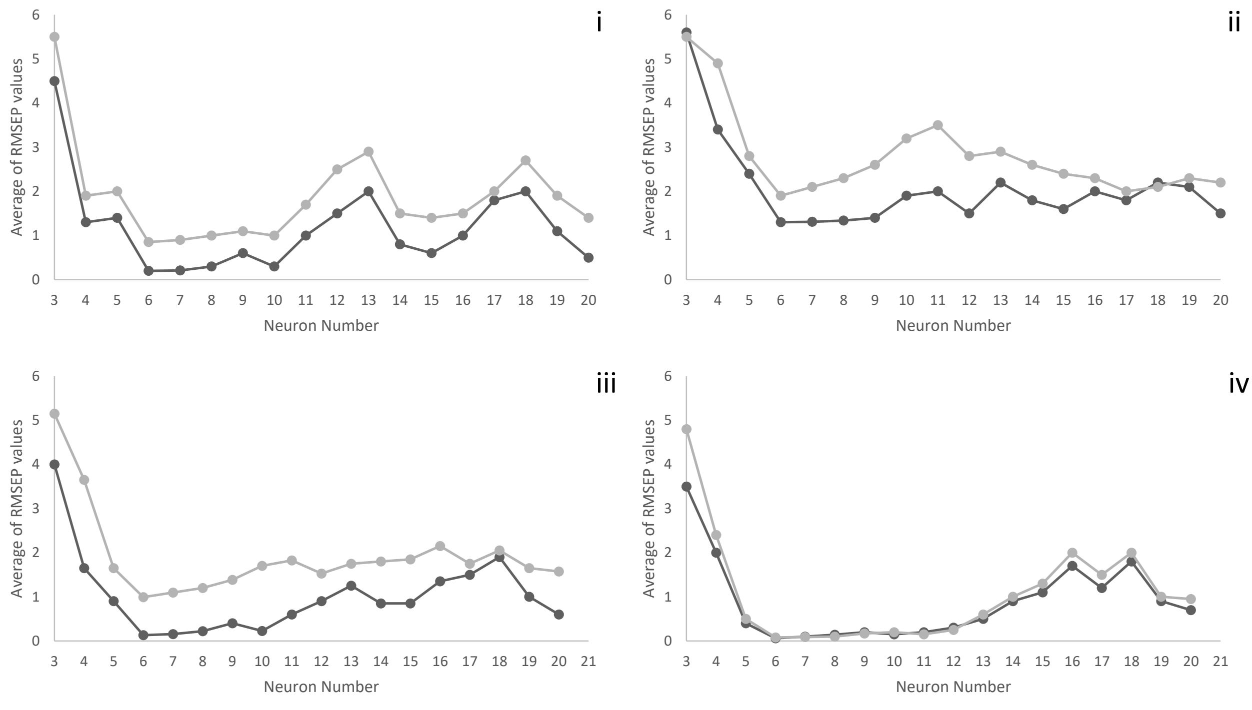

Figure 1. Average RMSE prediction values using LWP estimations from**.** i) Vls models maps based on 5 bands UAS-based multispectral imagery, ii) Vls models maps based on 21 reconstructed spectral bands, iii) orthomosaics maps based on 5 bands UAS-based multispectral imagery, and iv) orthomosaics maps based on 21 reconstructed spectral bands, input to ANN with Levenberg–Marquardt (bright grey plot) and Bayesian regularization (dark grey plot) models.

The average of the summed RMSE was recorded for each neuron, and the model with the lowest RMSE value (Fig. 1) was considered the best. The aforementioned steps in ANN were carried out using the Levenberg–Marquardt and Bayesian regularization training functions to find out which one was better suited for this purpose. The results show that networks with 3 to 5 neurons performed poorly, and the addition of a 6th neuron greatly improved the models. Adding more neurons was beneficial until the network had 9-10. The error of the models slightly increased at the 10 neuron threshold, implying that 6 neurons were sufficient for LWP content prediction, with more neurons producing overfitted models. The performance of the Levenberg–Marquardt-

based ANNs was inferior to the Bayesian regularization models for all examined criteria. Despite the longer time needed to train the Bayesian regularization models, the use of the Levenberg–Marquardt model remains unjustified.
The application of each trained and validated ANN model produces maps of the LWP of the field of experiment on the dates where UAV images were collected or on the reconstructed Orthomosaic(21bands).
In this contribution, an example of a map realized with the ANN model trained on the data set of the vegetation indices that got the best performance is reported in Figure 1.
Because the models were trained and validated on punctual LWP measurements over the field, we decided to investigate the ability of the model to represent the spatial variability of the plant response.

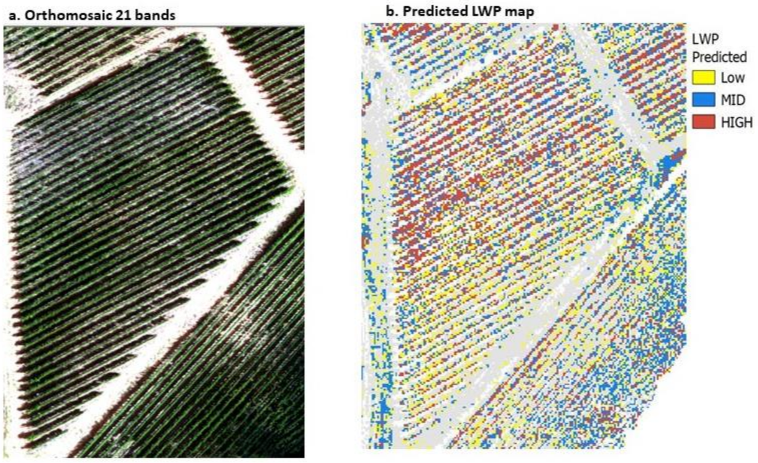

Figure 2. (b) The predicted LWP map in the 20.07.2021 produced by the ANN trained model based on (a) the reconstructed Orthomosaic(21bands) of the same date.

Conclusion

This study explored a brand-new sensing method for predicting the leaf water potential of a vineyard, and it can be very effective when the vineyard is under certain conditions encountered in dry summers, the equations of classical water balance models can be simplified. Results indicated that the methods used in this work can be a new technology and has great potential for evaluating the status of the vineyard. Compared with the traditional detection methods, UAS multispectral camera trained with an ML model has great potential in leaf water potential prediction. With the rapid development of drone cameras for precision agriculture use manufacture, portable and contactless detection will be realized shortly. As this development continues, it is expected to gain more and new insight into the water dynamics of plants in a way that has not been possible before with previous technologies. However, further studies should be made to improve detection accuracy when determining the leaf water potential based on multispectral photogrammetry and trained ML models in the future.

References

Bonfante, A. *et al.* (2017) 'Evaluation of the effects of future climate change on grape quality through a physically based model application: a case study for the Aglianico grapevine in Campania region, Italy', *Agricultural Systems*. doi: 10.1016/j.agsy.2016.12.009.

Brook, A., De Micco, V., Battipaglia, G., Erbaggio, A., Ludeno, G., Catapano, I. and Bonfante, A., 2020. A smart multiple spatial and temporal resolution system to support precision agriculture from satellite images: Proof of concept on Aglianico vineyard. Remote Sensing of Environment, 240, p.111679.Han, L. *et al.* (2019) 'Modeling maize above-ground biomass based on machine learning approaches using UAV remote-sensing data', *Plant Methods*. doi: 10.1186/s13007-019-0394-z.

Scholander, P. F. *et al.* (1965) 'Sap pressure in vascular plants', *Science*. doi: 10.1126/science.148.3668.339.

Xu, J. X. *et al.* (2020) 'Estimation of sugarcane yield using a machine learning approach based on uav-lidar data', *Remote Sensing*. doi: 10.3390/rs12172823.

Zhang, L. *et al.* (2021) 'Evaluating the sensitivity of water stressed maize chlorophyll and structure based on UAV derived vegetation indices', *Computers and Electronics in Agriculture*. doi: 10.1016/j.compag.2021.106174.