Estimating Crop Coefficients Using Deep Stochastic Configuration Networks (DeepSCNs) and UAV-Based Normalized Difference Vegetation Index (NDVI)

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ABSTRACT

Crop coefficient (Kc) methods have been commonly used for evapotranspiration (ET) estimation. Researchers estimate the Kc as a function of the vegetation index because of the similarities between the Kc curve and the vegetation index curve. A simple linear regression model is usually developed between the Kc and the normalized difference vegetation index (NDVI) derived from satellite imagery. However, the spatial resolution of satellite imagery is in the range of meters, which is often not enough for crops with clumped canopy structures, such as trees, and vines. In this study, Unmanned Aerial Vehicles (UAVs) were used to collect high-resolution images in an experimental pomegranate orchard located at the USDA-ARS, San Joaquin Valley Agricultural Sciences Center, Parlier, CA. The NDVI is derived from UAV images. The Kc is calculated from the data recorded by a weighing lysimeter in the pomegranate field. The relationship between the NDVI and Kc was established by using the linear regression model and the DeepSCNs. Results show that linear regression model Kc(DNV I) = 4.6666NDV I−2.9277 has R^2 and RMSE of 0.975 and 0.05, respectively. The DeepSCNs regression model has R^2 and RMSE of 1 and 0.046, respectively. The DeepSCNs show a much better performance than a simple linear regression model.

OBJECTIVES

The objective of this study is to investigate the UAV-based NDVI to the development of Kc in an experimental pomegranate orchard. The pomegranate is widely grown all over the world, which has drought resistance and high economic value. There are approximately 11,000 ha of pomegranate in the semi-arid and arid areas of California. The spatial and temporal variability of Kc and NDVI are analyzed by using the Deep Stochastic Configuration Networks (DeepSCNs). A regression model is established between the NDVI and Kc. The performance of the new regression model was evaluated by the data collected by the UAVs.

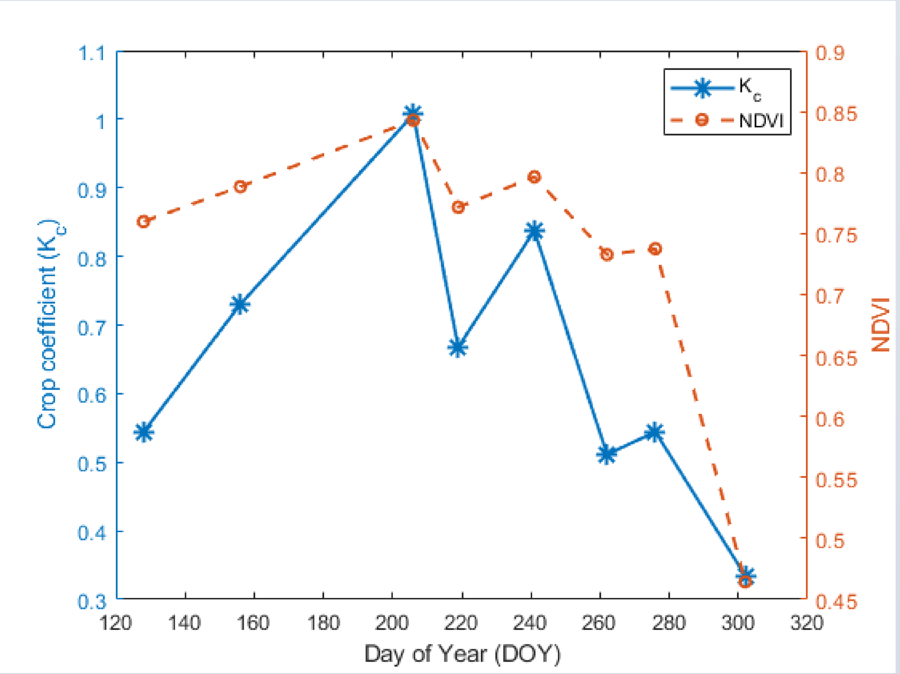

Fig. 1 2019 Seasonal Kc and NDVI

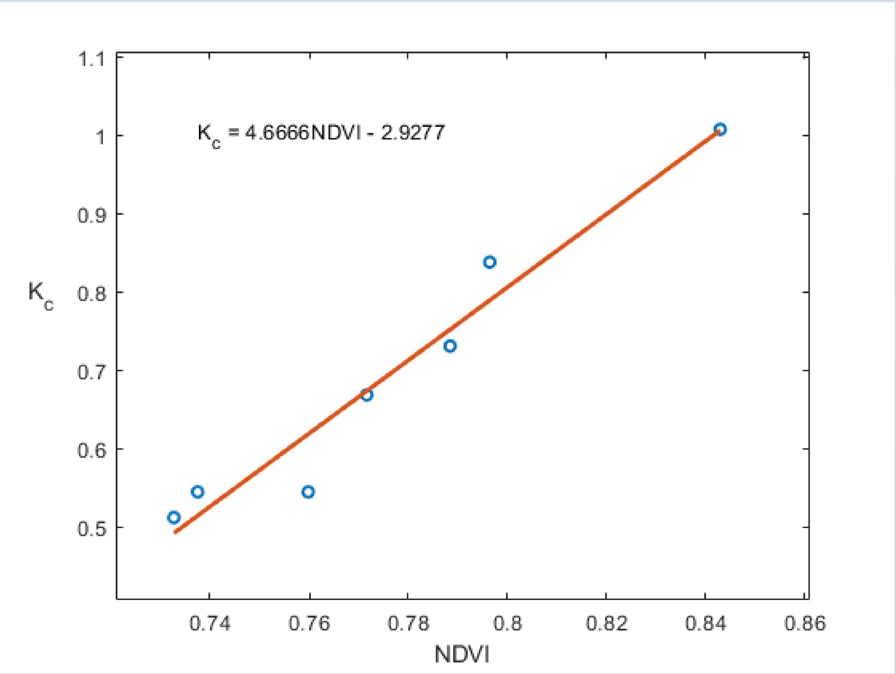

Fig. 2 Linear regression model for Kc and NDVI

MATERIALS & METHODS

As shown in Fig. 3, this study was conducted in an experimental pomegranate orchard at the USDA-ARS, San Joaquin Valley Agricultural Sciences Center (36.594°N, 119.512°W), Parlier, California, 93648, USA. The pomegranate was planted in 2010 with a 5 m spacing between rows and 2.75 m within-row tree spacing in a 1.3ha field. There are two large weighing lysimeters, which are 2m × 4m x 3m deep. The lysimeters have a resolution of 0.1 mm of water loss, which are located in the center of the field, marked in red boxes in Fig. 3.

Lysimeters

Fig. 3 The experimental pomegranate orchard

RESULTS

Deep Stochastic Configuration Networks (DeepSCNs) was first proposed by Wang et al. in 2017. Compared with the known randomized learning algorithms for single hidden layer feed-forward neural networks, the DeepSCNs randomly assign the input weights and biases of the hidden nodes in the light of a supervisory mechanism. The output weights are analytically evaluated in a constructive or selective method. The trained model was used to generate the Kc. For example, the spatial mapping of Kc on September 19th are shown in Fig. 4.

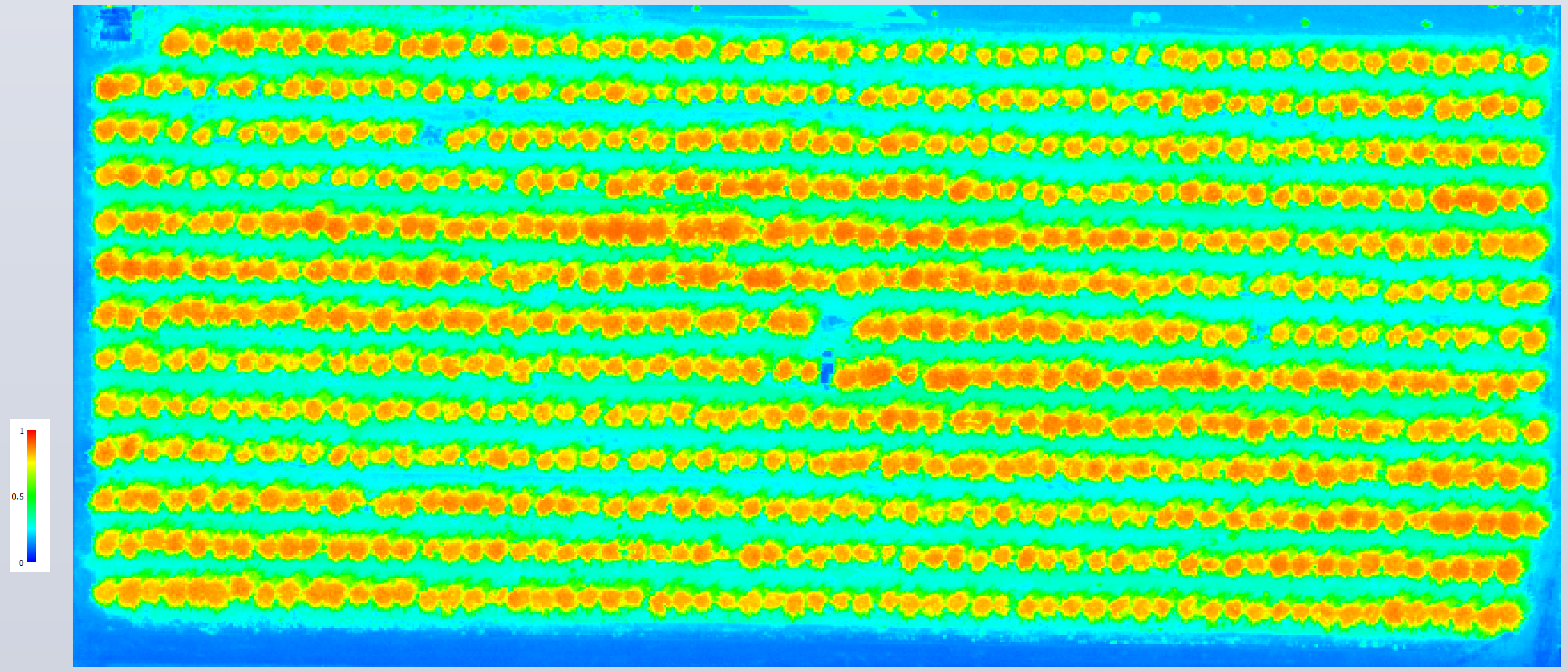

Fig. 4 Kc mapping on Sept. 19th, 2019.

CONCLUSIONS

DeepSCNs performance

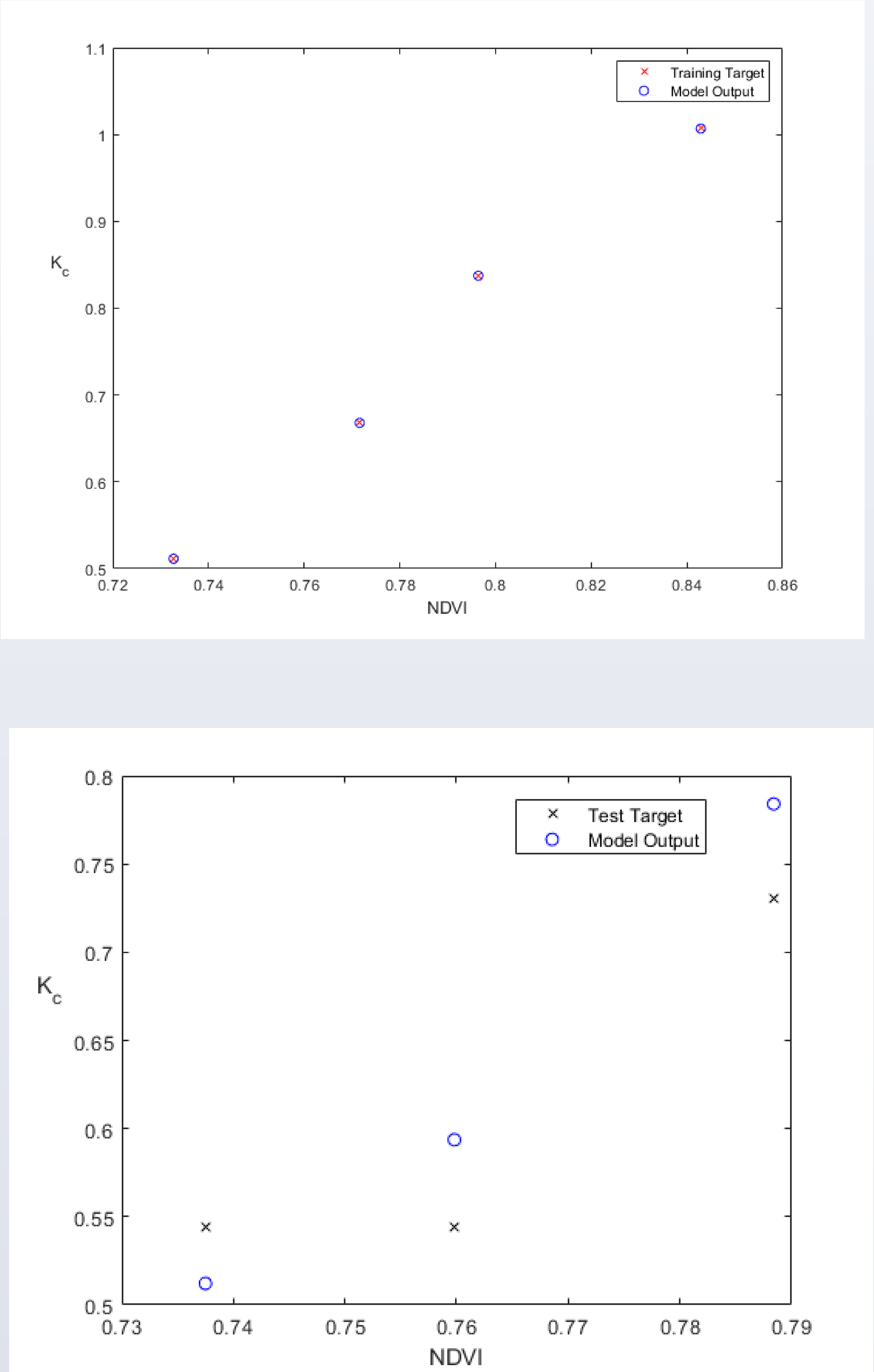

Fig. 5 The DeepSCNs training and testing performance

In this study, UAV flight missions were conducted to collect remote sensing multispectral images in a pomegranate orchard at USDA. Using the NDVI derived from the multi-spectral imagery, we can apply DeepSCNs for a regression model between NDVI and Kc. The Kc represents the actual growth conditions in the field. Therefore, Kc can be used for estimating the ET temporally and spatially in the pomegranate field.

The simple linear regression model is Kc (DNVI) = 4.6666NDVI − 2.9277. Compared with the simple linear regression model, the DeepSCNs model can better fit the data points in the training dataset. The simple linear regression model has R^2 and RMSE of 0.975 and 0.05, respectively. The DeepSCNs regression model has R^2 and RMSE of 1 and 0.046. The DeepSCNs show a better performance than a simple linear regression model.

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