Data-Driven Estimation of Actual Evapotranspiration to Support Irrigation Management

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Abstract

Recent advances in remote sensing and machine learning show potential for improving irrigation efficiency. In this study, two independent methods to determine the irrigation dose in processing tomatoes were tested in an irrigation experiment. The first method used multispectral imagery acquired from an unmanned aerial aircraft (UAV) to estimate the FAO-56 crop coefficient (K_C). The second method used an Artificial Neural Network (ANN) to predict latent heat fluxes using meteorological variables from a nearby meteorological station. An irrigation experiment was conducted, where the farmer was instructed through a mobile application with updated irrigation recommendations. Both methods were compared against an expert guided control treatment. Yields, water use efficiency, and Brix levels were measured, and showed to be on par with the control. Additionally, both methods estimated ET at a near-perfect agreement with best-practice irrigation. These results demonstrate the potential of machine learning techniques and aerial remote sensing to quantify crop water consumption and support irrigation management.

Introduction & Related Work

Water demand is expected to increase by 55% globally between 2000 and 2050, mainly for manufacturing, electricity, and domestic use (Kitamori et al. 2012). This will leave a small margin to increase water use in agriculture, and therefore, it is imperative to optimize the irrigation process. A precise estimation of crop water consumption, or evapotranspiration (ET_C), can improve irrigation management and lead to similar yields while reducing water usage throughout the growing season. Tomato *(Lycopersicon esculentum Mill)* is one of the most important vegetable crops globally, with production estimated by 180 million tons in 2017 (FAO 2019). It is also one of the most demanding in water (Peet 2008). Accordingly, improvement in tomato irrigation could result in significant water savings. Therefore, tomato is a suitable model crop for the evaluation of irrigation strategies.

The FAO-56 crop coefficient approach is one of the most commonly applied irrigation management methods (Allen et al. 1998). Using this approach, ET_C is estimated based on the reference evapotranspiration from a hypothetical crop (ET_0) and is given by $ET_C = K_C \times ET_0$, where ET_0 is commonly derived using the Penman-Monteith method, while K_C for specific crops in specific environments is empirically determined in water consumption experiments to isolate the atmospheric evaporative demand from the plant reaction. Standard K_C tables based on such experiments may not be sufficiently accurate when the regular crop development is inhibited by stress factors or irregular weather conditions. Therefore, remote sensing estimations of K_C based on vegetation indices that reflect the ground cover and crop development level in near-real-time, can serve as surrogates of K_C that overcome this limitation (Rozenstein et al. 2018, 2019).

In a previous study (Kaplan et al. 2021), K_C estimation models were developed for processing tomatoes based on Sentinel-2 imagery that is available at a frequency of 5 days at 10–20m spatial resolution, and Venμs imagery that are available at a frequency of 2 days at 5–10m spatial resolution (Manivasagam, Kaplan, and Rozenstein 2019). This development facilitates estimating K_C at a high enough temporal resolution for irrigation decisions that well capture within-field variability. However, in cloudy environments, even such a high revisit time may not be enough to support near-real-time estimations of K_C from optical satellite imagery. In addition, satellite pixels are too coarse to properly estimate K_C in narrow experimental plots. However, low flying Unmanned Aerial Vehicles (UAV) can overcome such limitations. An UAV can capture imagery on days not covered by satellite overpass, and even under clouds (Tmušić et al. 2020). Moreover, the spatial resolution of imagery from low altitude remote sensing is better suited for small plots (Aasen et al. 2018). K_C estimations from UAVs equipped with multispectral cameras have been previously used.

In parallel with the increased use of UAV, in recent years there is an upsurge in the use of machine learning for system modeling, not only for remote sensing data but also for irrigation management (e.g., Ohana-Levi et al. (2019); Romero et al. (2018)). Recently, (Reichstein et al. 2019) highlighted the potential of using deep learning techniques in geoscience for modeling dynamic time series. Wide research was done on prediction of reference evapotranspiration using machine learning (Kumar, Raghuwanshi, and Singh (2011) and references therein), but few on actual evapotranspiration measurements over agricultural crops. Some of the work focused on using Multi-Layer-Perceptrons (MLPs) to gap in ET_C time series (Papale and Valentini 2003; Coutinho et al. 2018; Richard et al. 2020). However, here we want to make running predictions of the ET_C values. This is significantly harder as we do not have access to the past or future ET_C values. A key issue when trying to estimate running crop's ET_C values is that as the crop grows, its evapotranspiration increases as well. This means that we need to learn two things: The impact of the meteorological variable on the crop evapotranspiration, and how to model the plant growth.

This paper outlines the performance of two novel approaches to determine the irrigation dose in processing tomatoes. Specifically, the estimation of K_C from UAV multispectral imagery, and the application of an ANN trained to predict latent heat fluxes based on meteorological data. These methods were tested against the current best practice in processing tomato irrigation and were shown to perform as well while being cheaper and simpler to use.

Proposed Methods

In this work, we evaluated different methods aimed at maximizing tomato yield by irrigation management. To do so, we developed two original methods and built a mobile application to instructs farmers with irrigation recommendations based on our models. The different methods used are detailed in the following sub-sections.

Irrigation estimation from UAV

The first method we present here consists of flying a UAV equipped with a multispectral camera to acquire images and estimate K_C to compute the required irrigation dose. The K_C estimation model developed for Sentinel-2 (Kaplan et al. 2021) was applied to multispectral imagery acquired with a Micasense[1] RedEdge-MX Sensor. This work by Kaplan et al. (2021) used eddy covariance measurements of the actual crop water consumption during three growing seasons to calculate the actual K_C and model it using spectral vegetation indices derived from spaceborne multispectral imagery. To apply this model to imagery acquired by the RedEdge-MX Sensor, a relative calibration between Sentinel-2 Level-2A products and RedEdge-MX imagery was carried out. we used co-acquired imagery of agricultural fields from four different dates and crops. UAV imagery was processed into orthomosaics using Pix4Dmapper (Pix4D S.A., Prilly, Switzerland). Satellite and UAV images were then resampled to 10 m resolution, and the area of the field was masked. Subsequently, linear regression models were fitted for overlapping pixels of Sentinel-2 and RedEdge-MX bands with similar central wavelengths. The result was transformation equations from Sentinel-2 to RedEdge-MX reflectance values for which the K_C estimation models could be applied to.

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UAV flights took place at the irrigation experiment site in Gadash Farm in the Hula Valley (33°10'55"N 35°34'57"E) every 5-10 days during the 2020 growing season from an altitude of 50 m above the ground, with front and side overlap was 85% to facilitate the generation of a good equality orthomosaic. The average K_C value in UAV-treatment replicates together with ET_0 data from a nearby meteorological station (Kavul station; 33°06'03"N35°36'34"E) was used to calculate the actual ET_C in this experimental treatment and to instruct the grower with an irrigation recommendation via the mobile application.

Irrigation estimation from ANN

The second method consists in using an ANN to predict the ET_C. To do so, the ANN used meteorological variables collected from local weather stations, and the average Leaf Area Index (LAI) of the control treatment. The LAI is measured on a fortnightly basis while the weather variables can be acquired at a ten-minute sampling rate or higher. Since the irrigation was applied every day, we first needed to build an algorithm capable of forecasting the LAI while taking into account past measurements.

Given that we only had LAI recordings from four past experiments, we chose to use a K-Nearest-Neighbour (KNN) algorithm to predict future LAI values with a two days sampling rate. This meant that at the beginning, the LAI was modeled as the mean of all the past measurements, and then as we started collecting measurements, the extrapolated points followed the growth curve of the most similar examples in the database. To interpolate between the predicted points we fitted a spline on top of them, relaxing the shape of the predicted curve, and making the sampling process more convenient.

To estimate the daily irrigation dose, we trained a neural-network to predict the latent-heat-flux, a common proxy for ET_C. To do so, we used the LAI, acquired with the method outlined above, in combination of the following variables: the net-radiation, the temperature, the humidity, the wind speed, the time-of-the-day, and the days since germination. These variables are acquired by scrapping data from local weather stations, while the latent-heat-flux was measered using the eddy-covariance method during in previous collection campaigns in the region. We sampled all these variables at a 30 minutes rate and used them to train an MLP. This MLP was composed of two dense layers with 48 neurons each, and a last dense layer with a single neuron. To minimize overfitting, we added dropout layers in-between each dense layer. All layers used leaky-relus activations (Maas et al. 2013), except for the last layer which had no activation. The network weights were regressed using the adam optimizer, with a learning rate of 1e-5, and the drop rate was set to 0.3. Regarding the optimization function, we used a huber-loss as it made the training less rigid, and allowed to account for the inaccuracies in the variables fed to the network. To make our training more efficient we also relied on a Prioritized Experience Replay (PER) training scheme (Schaul et al. 2015). In the end this models allowed us to predict the ET_C at a half-hourly rate. To get the daily treatment recommendation we integrated the predicted val-

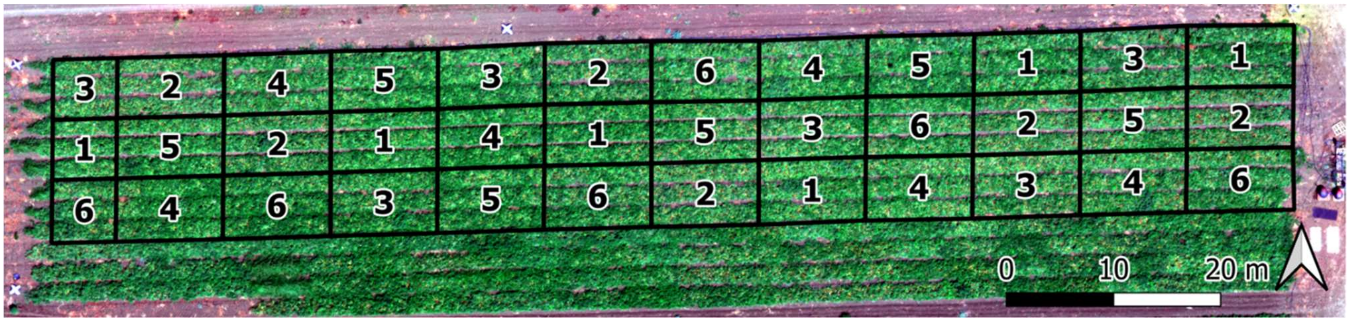


Figure 1: An overhead imagery of our experimental field and the different plots corresponding to each treatment.

ues over a whole day.

Baseline, Experiment & Evaluation

Baseline

To compare our methods we used the current best-practice irrigation in Israel. This control treatment consisted of an expert relying on a set of soil tensiometers to determine the irrigation dose. The water tension in three depths was used as feedback to confirm the correct irrigation; if a desired water tension threshold was not reached, the next irrigation could be supplemented to reach the target value. Three more treatments were derived from the control treatment as ratios of 50%, 75%, and 125% of the control irrigation dose.

Experiment

To evaluate the different methods we conducted an irrigation trial in an experimental crop-farm close to some of our previous data-collection campaigns (33°10'55"N 35°34'57"E). We selected the processing tomato cultivar H-4107 and transplanted them with a plant density of 2500 plant/dunam. After transplanting, the entire field was irrigated with 30mm water in order to fill the soil profile. Then it was irrigated according to the irrigation expert guidance for two months after which the irrigation trial began. In total we tested six different irrigation treatments: 1) "Control" – the 'best-practice' irrigation, our baseline. 2) 50% of the control. 3) 75% of the control. 4) 125% of the control. 5) "ANN" – irrigation based on the trained machine learning model. 6) "UAV" - the irrigation based on the K_c estimated from the UAV. The main assumption in this experiment was that the natural variability, which originates in environmental conditions, genetic material, equipment and management, is considerably smaller than the differences from the different irrigation treatments. Each treatment had six repetitions as can be seen in Fig. 1 where each repetition was comprised of three 10 m by 2 m rows (60 m^2). The effects of the environmental conditions were also be mitigated by the scattering of the different repetitions across the field.

Evaluation

To evaluate the performance of the different methods we used three evaluation metrics: the yield, water use efficiency, and brix. The yield is the most important metric, it is a measure of the fresh biomass of harvested tomato fruit per unit of area (e.g., ton / dunam).

This metric is supplemented by the water use efficiency, calculated by dividing the total yield (kg) with the total applied irrigation (m^3) in each treatment. The overall goal of the irrigation experiment was to maximize the yield while maximizing the water use efficiency at the same time. However, the optimization of the water use efficiency should not be done to the detriment of the yield. Hence, for now, having a higher yield is more desirable than having a higher water use efficiency.

Finally, Degrees Brix is a measure of the sugar content in an aqueous solution. One brix degree corresponds to one gram of sugar for 100 grams of liquid. In the case of the Tomatoes, the brix level is a common way to quantify their quality; higher is better, but there is usually a trade-off between quality and quantity. In general, less irrigation typically results in higher Brix but lower yield.

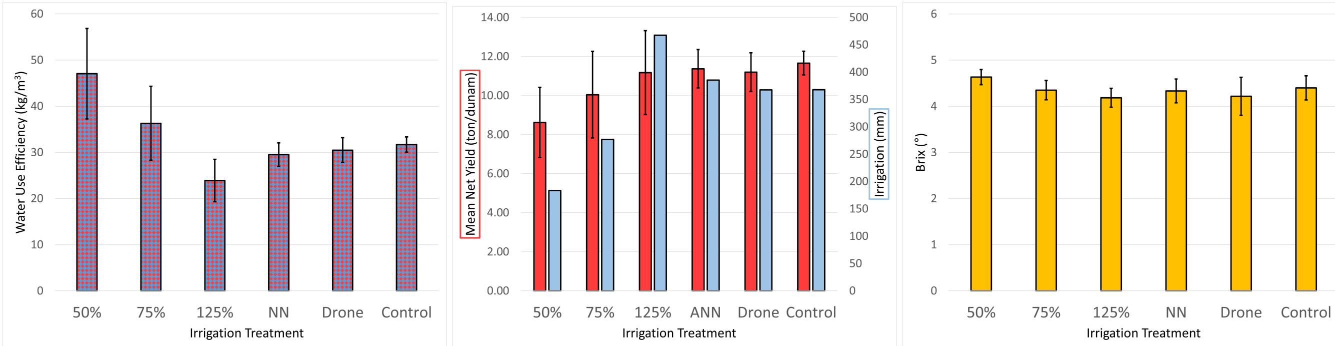
Results & Discussion

Results

In this section we compare the different treatments using the metrics defined earlier. Fig. 2, shows the metrics for each method throughout the season. The histograms show both the average performance of the treatments across the six repetitions and their standard deviation.

As can be seen on fig. 2b, the control, the ANN, and the UAV, all achieve a similar yield, around 12 tons/dunam. The 125% treatment achieves the highest yield, while the 50% treatment achieves the lowest yield, 8.5 ton/dunam. On the same graph, we can also see that the 125% treatment consumed a lot more water than the control, while its yield was not significantly higher than the other methods. This shows, that our methods and the control are performing near the optimal yield/irrigation ratio. At the same time, the 50% treatment and 75% treatment consumed much less water but their yield is drastically reduced.

The same pattern can be seen in fig. 2a, the 50% and 75% treatment both have a high water use efficiency but this comes at the cost of the yield, which is not desirable as we are first and foremost interested in the yield. On the other side of the spectrum, we can see that the 125% treatment has the lowest water use efficiency while it does not have



(a) Water use efficiency, higher is better.

(b) Yield against irrigation. Red, higher is better; blue, lower is better.

(c) Brix, higher is better.

Figure 2: Results of the different treatments over the whole season.

a significantly better yield than the other treatments. In the end, we can see that from the irrigation and yield perspective our methods performed as well as the best-practice irrigation (control).

The brix measurement shown in fig. 2c, displayed very large variance across the different repetitions of each treatment. The 50% treatment was slightly higher then the rest but this difference was not statistically significant.

Overall, this experiment, in which we delivered live recommendation to the farmer, was successful. The whole of the pipeline, from data-scrapping, to predicting, and sending the prediction worked reliably for the full summer season. This allowed us to show that the irrigation recommendation from the ANN and the UAV almost perfectly agreed with the best practice, both in the total amount and rate of irrigation throughout the season. Moreover, they resulted in a similar yield and brix levels.

Discussion

In this experiment, we showed that methods based on ANN could be used to achieve expert level irrigation. The main advantage of this method compared to the baseline resides in its low running cost, and ease of use. However, this method is timely to set-up as it requires careful calibration of the system. This calibration is unique to the area and crop-type, which means it has to done again for every new locations. Yet, once set up, this method requires neither in-field sensor nor experts. Furthermore, it requires no supervision and is transparent to use. This makes it particularly interesting in developing countries, where the cost of advanced equipment and the availability of domain experts remain a key limitation to a wider adoption of efficient irrigation methods.

The other method, the UAV, is more expensive to run but does not require region-specific calibration and allows for highly accurate irrigation recommendation. It can be used anywhere on earth, deployed quickly, and does not need expert supervision.

Conclusion

Both novel approaches to determine the irrigation dose in processing tomatoes were found to perform equally to the control treatment of best common practice for processing tomato irrigation. While the control treatment relied on an experienced agronomist specialized in vegetable crops cultivation that had the benefit of feedback from soil tensiometers, the experimental approaches, the estimation of K_C from an UAV, and the ANN, did not. This makes these methods particularly interesting as they alleviate the need of crop experts and hence make efficient irrigation more affordable, which is crucial to broader the usage of high precision irrigation techniques. In our experiments, the multispectral imagery-based K_C estimation model, originally calibrated for Sentinel-2, was successfully transferred to work from a UAV with a multispectral camera payload. The trained ANN model demonstrated its validity by estimating ET accurately. There were no significant differences in the yield quality and quantity between the approaches in the irrigation experiment. Although the study included only one irrigation experiment, the results illustrate the capacity and ease-of-implementation of novel techniques based on UAVs and ANNs for irrigation management.

Future work will focus on replicating this experiment at a larger scale to further establish the experimental approach for irrigation management. Furthermore, we will explore bayesian and evidential deep-learning to estimate the uncertainty on the neural-network predictions. This would enable the detection out-of-distribution samples, and allow the end-user to discard or adapt these predictions.

Acknowledgments

This research was supported by grants from the Chief Scientist of the Ministry of Agriculture, Israel (grant number 20-21-0006), the Ministry of Science & Technology, Israel (grant number 3-15830), the Ministry of Europe and Foreign Affairs (MEAE) and the Ministry of Higher Education, Research and Innovation (MESRI) of France.We also thank all the growers for their assistance in the field measurements that contributed to the development of the models.

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