High-resolution irrigation: A low-cost proximal sensing method for predicting single vine ET

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Introduction and Background

In California, recurrent droughts and widespread water shortages have lead to competition between agricultural, urban, and conservation water needs[1].

Despite these challenges, specialty crop acreage has increased throughout the state, and it now includes over 900,000 acres of vineyards[2].

In vineyards, the status quo is bulk irrigation. This strategy ignores the heterogeneous distribution of water needs, which can be caused by variation in cultivar, topography, soil structure and composition, and many other factors[3]. Furthermore, especially in winegrapes, growers attempt to achieve deficit irrigation to promote grape quality[4].

An irrigation manager's goal is balancing applied water with the plant's needs[5]. But, achieving this goal given water demand variability and complex deficit irrigation strategies can be nearly impossible using existing technology.

To address this gap, we propose HRI: a novel irrigation system that delivers water to each plant according to its specific needs.

High-resolution Irrigation (HRI)

1) Targeted water delivery
2) Understanding plant water needs
   - How much
   - When

HRI demands two fundamental components are addressed: (1) building a delivery system, and (2) understanding the water needs of the plant, which requires knowing *how much* water to apply, and *when* to apply it. The scope of this report is limited to *how much* water to apply, which we define as evapotranspiration (ET) from a single plant.

We developed three models for predicting the mass flow rate of water leaving a single grapevine. Here, we evaluate the utility of each model by comparing ET predictions to ground truth ET.

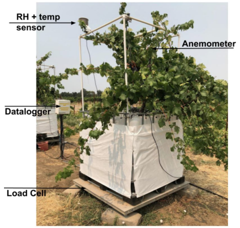
Materials and Methods

Three models for predicting single plant mass transfer flux $\dot{m}_e$

Model	Assumes	
Convective Mass Transfer* (**CMT**)	*Assumes* - ET driven by a pressure gradient - Area Term is total surface area of transpiring leaves	Required biometeorological parameters***: Windspeed $\frac{m}{s}$ Air temperature inside/outside canopy $^\circ C$ Relative humidity inside/outside canopy $\%$
Mass Balance** (**MB**)	*Assumes* - ET driven by a humidity gradient - Area Term is cross sectional area of vine canopy	
Empirical Model (**EM**)	*Assumes* - Enough of variation in crop ET is explained by air temperature and wind speed	

*CMT developed with help from Konrad Miller, PhD; and **MB developed with help from Shayla Nikzad
***Not all parameters required for all models

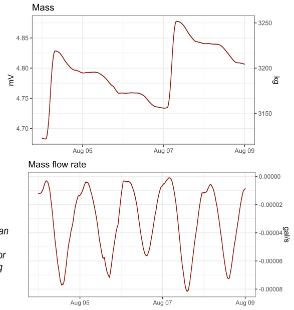
(Left) In HRI, biometeorological sensors measure **windspeed**, **air temperature** and **relative humidity**, then using one of three models that we developed, we estimate **mass transfer flux**. The **CMT** and **MB** models were inspired by first principles describing critical steps in the process of evapotranspiration, and require assumptions about the driving force of this process. The **EM** model, however, was selected statistically from 25 candidate models, using a process that prioritized dimensional reduction and predictive utility via comparison of performance metrics.



(Above) ***Data Collection System****. Four mature, head-trained Zinfandel vines on St. George rootstock, planted in sandy loam in an ~1m^3 plastic container. Each vine is mounted with a sensor suite including a needle* ***anemometer*** *for windspeed and CS HMP60L for* ***air temperature*** *and* ***relative humidity****. Models were tested using* ***ground truth*** *ET data, generated using the* ***load cell****. All data was collected using a Campbell Scientific CR1000 with a custom CR1 program. Data collection was powered using a 30W solar cell and lead acid battery.*

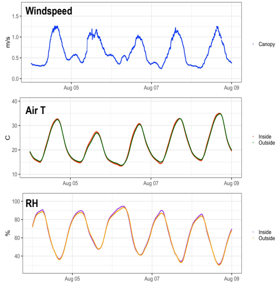
Load Cell Data

→ ET ground truth



Biometeorological Data

→ for ET predictions



Calculating evapotranspiration $\mathbf{ET}$ from mass transfer flux $\dot{m}_e$

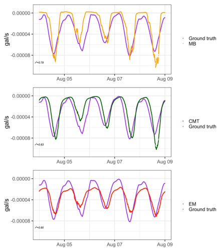
$\mathbf{ET_e}$ is predicted ET from 0 to t
$\mathbf{A_s}$ is the Area Term m^2
$\dot{\mathbf{m}}_e$ predicted mass transfer flux $\frac{g}{s \cdot m^2}$
$\mathbf{t}$ is time s

$$ET_e = A_s \cdot \int_0^t \dot{m}_e \, dt$$

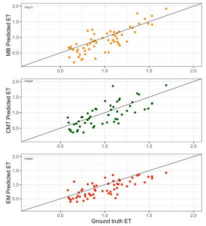
(Left) **Predicted ET (ET_e)** is equal to integral of mass transfer flux over time, and a plant scaling term called the **area term** or **A_s**. The area term relates the predicted mass transfer flux from each of our models to true mass transfer flux. Right now, A_s is determined experimentally at various times during the season, about every 10-14 days. If this parameter could be measured empirically, then HRI would theoretically be **generalizable** to any vine (we will also investigate orchard crops). Based on each model's underlying theory, we suspect this area term will correlate well with some physical aspect of the vine. In an ongoing investigation we are assessing whether several easily measured vine parameters could be used to directly estimate A_s.

Results

Mass Flow Rate: Predictions and Ground Truth



Full Day ET: Predicted v. Ground Truth



(left column) Each figure is a plot of **mass flow rate** of water as determined using the load cell (ground truth) and using each of the three models (**r^2: MB=0.79, CMT=0.83, EM=0.90**) over a 5 day period in August, 2020.

(right column) Each figure shows **full day ET** from 10a-8p with model predicted **ET_e**, and load cell (ground truth) **ET_c** (**r^2: MB=0.71, CMT=0.47, EM=0.61**). Each point represents a single day, with a total of 64 evenly spaced days chosen randomly from mid-May to mid-September, 2020.

Conclusion

After exploring model estimates using the 5-day window in August, 2020, it is clear that ***all three models can predict a significant amount of the variation in mass flow rate and ET_c.***

We observed similar predictions for the rest of the 2019 and 2020 seasons, both during normally irrigated periods and extended periods of drought. In follow-up work, we will compare the models using residuals plots, RMSE, and other metrics to better understand relative performance. With final validation of these three models, using 2021 data, we will begin working towards unraveling the physical meaning of the area term.

References

[1] California Dept. of Water Resources, California's Most Significant Droughts: Comparing Historical and Recent Conditions. (2015).
[2] California Dept. of Food and Ag. in cooperation with USDA National Agricultural Statistics Service, Grape Acreage Report 2019 Crop. (2020).
[3] Bramley et. al., Understanding variability in winegrape production systems 1. Within vineyard variation in yield over several vintages. Australian J of Grape and Wine Research, 10-1, (2008).
[4] Chaves et. al., Deficit irrigation in grapevine improves water-use efficiency while controlling vigour and production quality. Annals of Applied Biology 150-2, (2007).
[5] Van Leeuwan et. al., The concept of terroir in viticulture. Journal of Wine Research 117-1, (2006).