# Comparison of the Modified Energy Cascade Model Versions' Function and Predictive Capabilities

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## Problem Statement

Controlled environment agriculture (CEA) is an industry that lacks predictive crop models developed for and tested within it's environments. The modified energy cascade (MEC) model meets that need but has multiple versions without proper comparisons of new versions to previous ones. This work aims to carry out these evaluations prior to improving the MECs physiological predictions such as yield and transpiration.

## Research Objectives

1. Using Python, recreate the past MEC versions from Cavazzoni (CAV), Boscheri (BOS), and Amitrano (AMI).
2. Compare each MEC version to the others with data from the indoor vertical farming industry and heat tolerant varieties from University of Florida breeders.
3. Evaluate the value and effect past modifications of the MEC has had on its predictive ability and uncertainty compared to the other versions.
4. Select the best model to move forward with for the improvement of the MEC and developing it as a modular component in larger software systems such as being used to calculate plant growth for functional structural plant models, operational management packages, digital twins or simple yield predictions.

## Methods

◊ The crop being modelled in this work is a variety of green lettuce, Salanova (*Lactuca sativa* var. *capitata*).

◊ For Obj. 1 all models were coded in Python utilizing shared libraries, naming schemes and data structures.

◊ The same experimental data set [3] was used to set model inputs to the same values (Table 1). Constants used in the models were already identical.

◊ Due to differences in design BOS and CAV outputs from 0 days after emergence (DAE) to 40, while the AMI model ranges from 10 (transplant) to 40 DAE.

Table 1: Values of the model inputs used in all three models.

| Model Input | Set Value |
|---|---|
| PPFD | 315 µmol $m^{-2}$ $sec^{-1}$ |
| Photoperiod | 12 hours |
| $CO_2$ | 370 ppm |
| RH | 81% |
| Temperature | 24 °C |

## References

**[1]** J. Cavazzoni, "Using explanatory crop models to develop simple tools for Advanced Life Support system studies," *Advances in Space Research*, vol. 34, no. 7, pp. 1528–1538, Jan. 2004, doi: 10.1016/j.asr.2003.02.073.

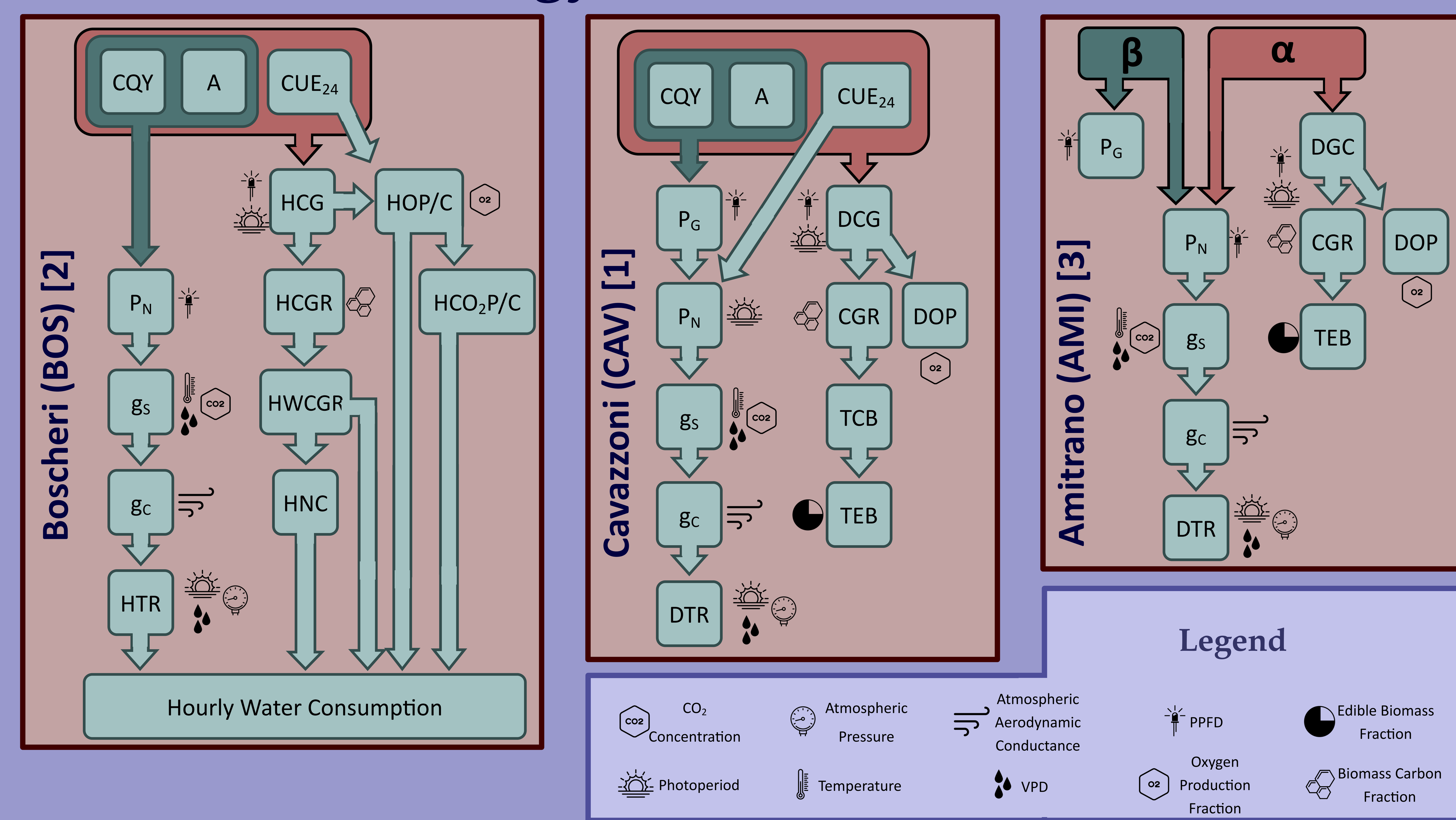
**[2]** G. Boscheri *et al.*, "Modified energy cascade model adapted for a multicrop Lunar greenhouse prototype," *Advances in Space Research*, vol. 50, no. 7, pp. 941–951, Oct. 2012, doi: 10.1016/j.asr.2012.05.025.

**[3]** C. Amitrano, G. B. Chirico, S. De Pascale, Y. Rouphael, and V. De Micco, "Crop Management in Controlled Environment Agriculture (CEA) Systems Using Predictive Mathematical Models," *Sensors*, vol. 20, no. 11, p. 3110, May 2020, doi: 10.3390/s20113110.

## Abbreviations

| | |
|---|---|
| CQY | Canopy Quantum Yield |
| A | Light Absorption |
| $CUE_{24}$ | Carbon Use Efficiency |
| $P_G$ | Gross Photosynthesis |
| α | A*CQY*CUE |
| β | A*CQY |
| $P_N$ | Net Photosynthesis |
| $g_S$ | Stomatal Conductance |
| $g_C$ | Canopy Conductance |
| DTR | Daily Transpiration Rate |
| DCG | Daily Carbon Gain |
| CGR | Crop Growth Rate |
| DOP/C | Daily Oxygen Production/ Consumption |
| $HCO_2$ P/C | Hourly $CO_2$ Production/ Consumption |
| TCB | Total Crop Biomass |
| TEB | Total Edible Biomass |
| HNC | Hourly Nutrient Consumption |

## Modified Energy Cascade Models



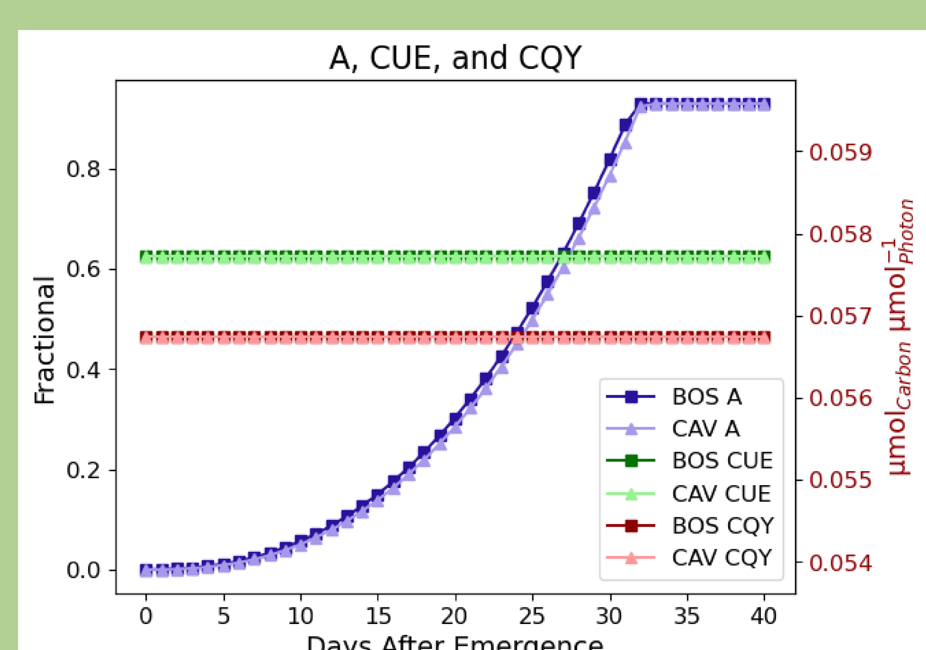




Figure 1: The base parameters of Light Absorption (A), Carbon Use Efficiency (CUE), and Canopy Quantum Yield (CQY). A, and CUE are fractional numbers representing the canopies potential for photosynthesis.

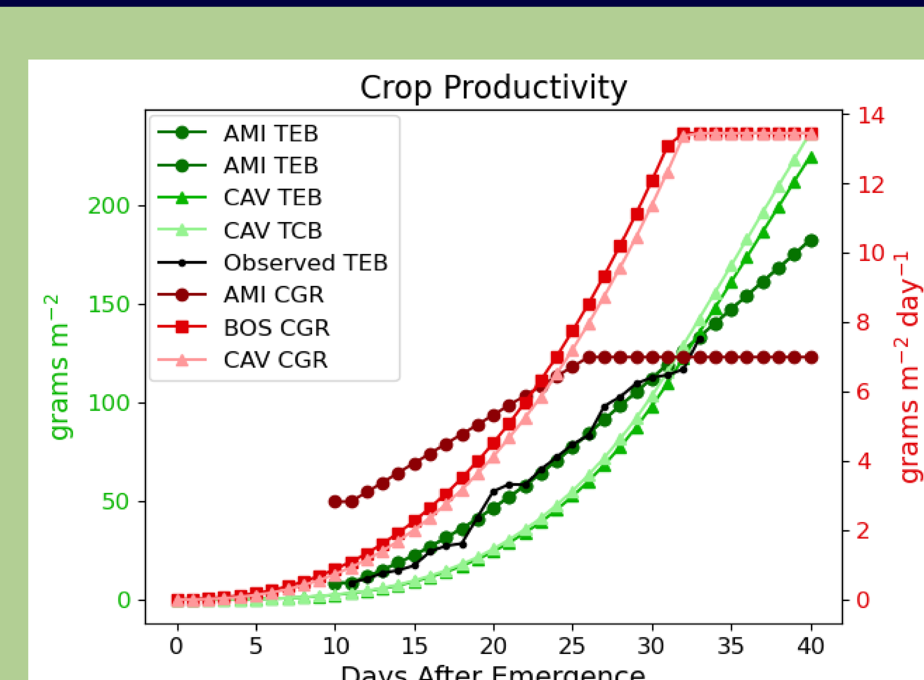



Figure 2: Crop yield in terms of Total Crop Biomass (TCB) and Total Edible Biomass (TEB) in green alongside the Crop Growth Rates (CGR) in red. Boscheri did not report crop TEB or TCB. Observed TEB data from [3].

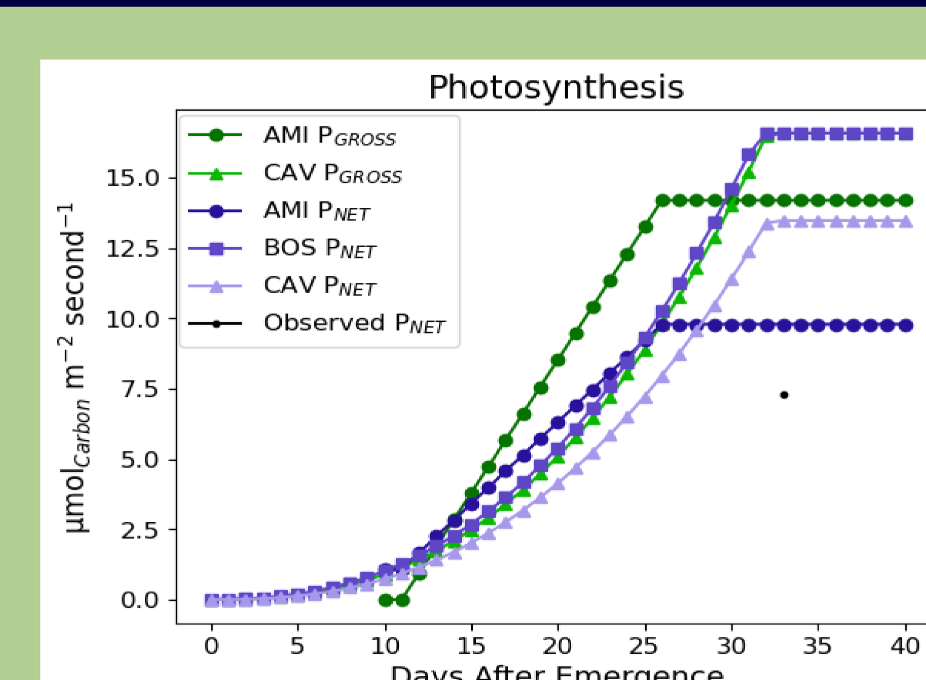



Figure 3: Model outputs of photosynthesis calculations. Boscheri did not include gross photosynthesis ($P_{GROSS}$) in the model. Included is a single measurement for net photosynthesis ($P_{NET}$) [3].

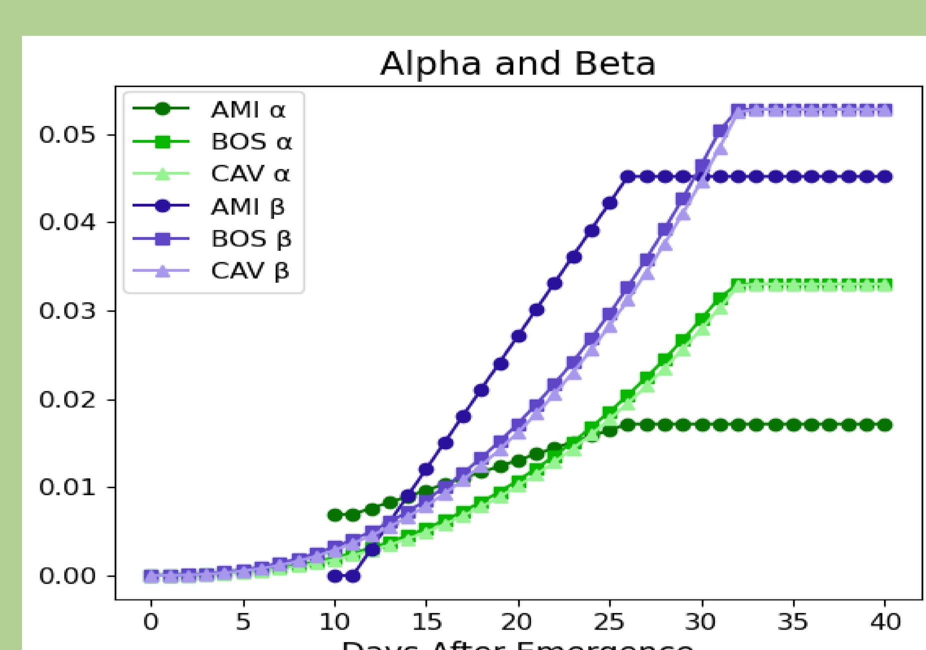



Figure 4: Amitrano's model calculated α and β instead of using A, CUE, and CQY. Here they are calculated for each model as α=A*CUE*CQY and β= A*CQY [3].

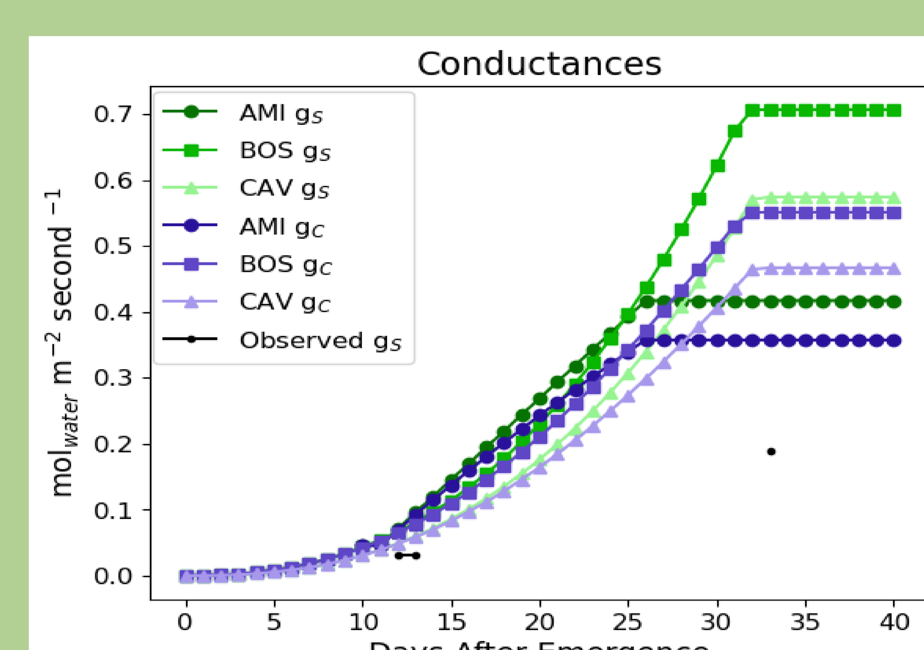



Figure 5: Stomatal conductance ($g_S$) in green and canopy conductance ($g_C$) in blue as predicted for the different models alongside experimental data [3].

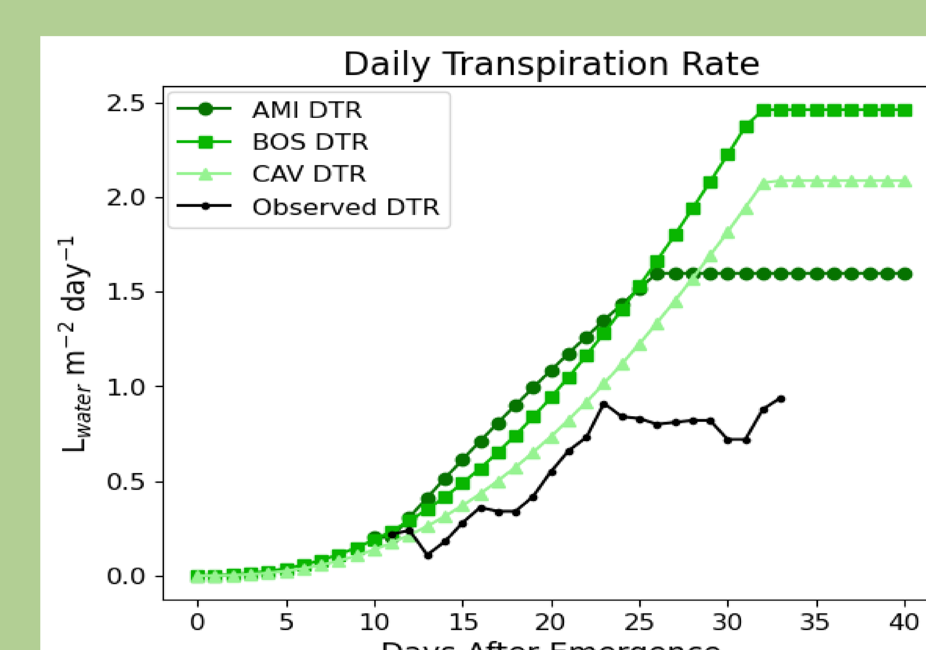



Figure 6: Model outputs from AMI, BOS, and CAV, for daily transpiration rates (DTR) and observed data [3].

## Objective 2 Results

Table 2: Results of RMSE calculations of all three models for outputs which had observational data available at this time.

| | AMI | BOS | CAV |
|---|---|---|---|
| TEB | 4.46 | | 19.28 |
| DTR | 0.59 | 0.85 | 0.59 |
| $g_S$ | 0.14 | 0.30 | 0.22 |
| $P_{NET}$ | 2.49 | 9.29 | 6.18 |

◊ The changes in AMI resulted in a linear estimations that plateaued at 25 DAE compared to others at 30 DAE. Which limits predictive range as the maximums are reduced compared to other models.

◊ BOS $P_{NET}$ and $g_S$ predictions are similar to $P_{GROSS}$ and $g_C$ respectively from CAV and greater than AMI's values (Figures 3, 5). Indicating that not only may $P_{NET}$ be wrong, but downstream calculations may be too.

◊ AMI had the lowest RMSE in all categories evaluated followed by CAV, then BOS (Table 2), implying its linearity did not impact its predictive ability.

## Conclusions

◊ The AMI model is promising to move forward with, especially in regards to the lettuce cultivar Salanova, which it was originally calibrated with.

◊ It will be necessary to use multiple cultivars of lettuce to see if any model consistently outperforms another regardless of cultivar or model inputs.

◊ The BOS model changes may have expanded its outputs but likely sacrificed predictive ability.

◊ The cascading nature with limited feedback within the models make ensuring accuracy in earlier calculations essential.

## Future Work

◊ Obj. 3: Utilize a wider range of data to capture model performance under ideal and non-ideal conditions. Also, conduct global sensitivity and uncertainty analysis to understand how each input affects the outputs

◊ Obj. 4: Conduct experiments with combinations of high heat, low VPD, and High VPD to increase the range of the models applicability.

◊ Obj. 4: Restructuring of the code to an object oriented design to ensure compatibility with other programs

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