Combining a Crop Model with AI for Enhanced Yield Prediction
Findings from Oyster Cove Potato Farms.

Kinkora, PE
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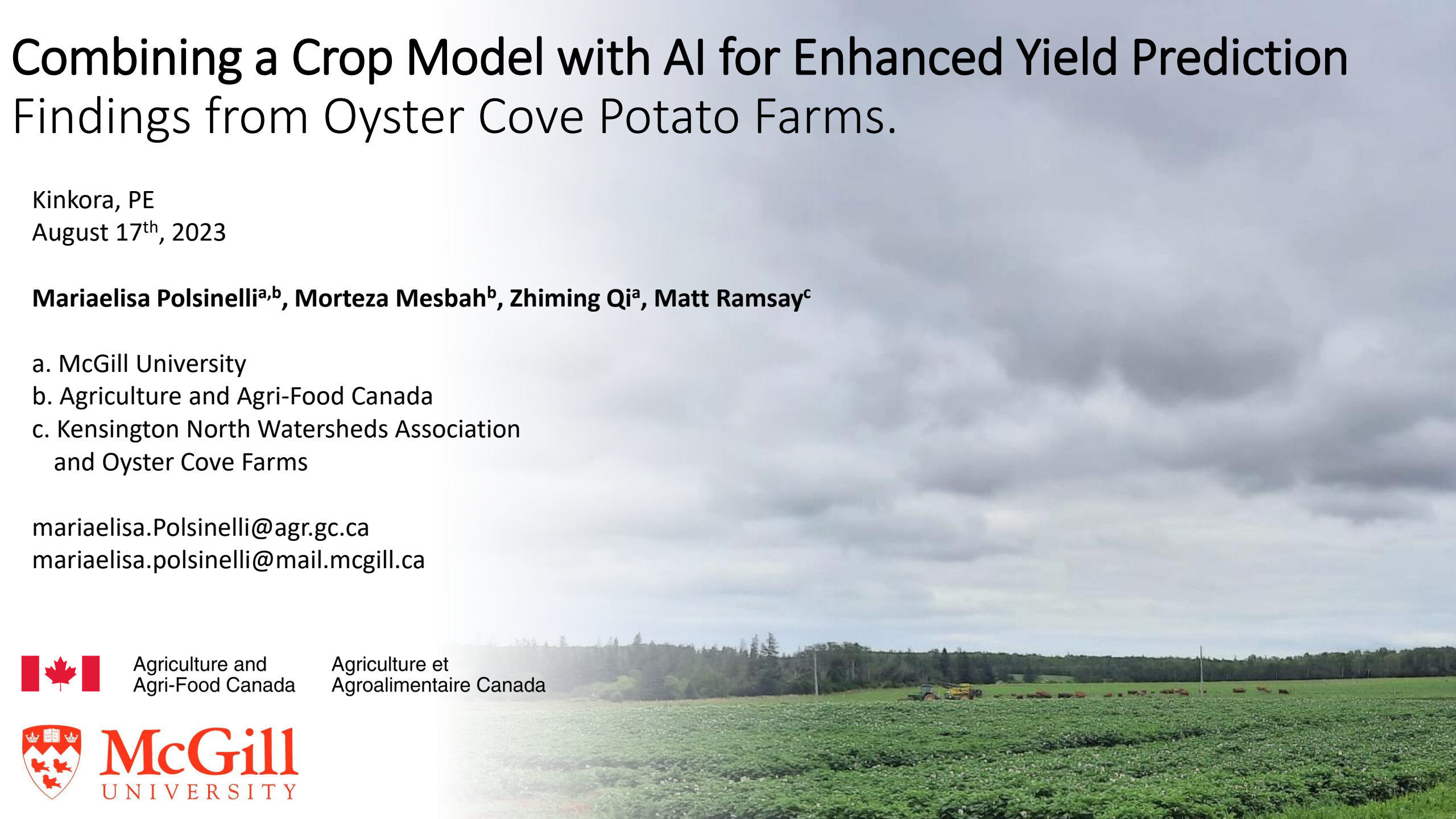
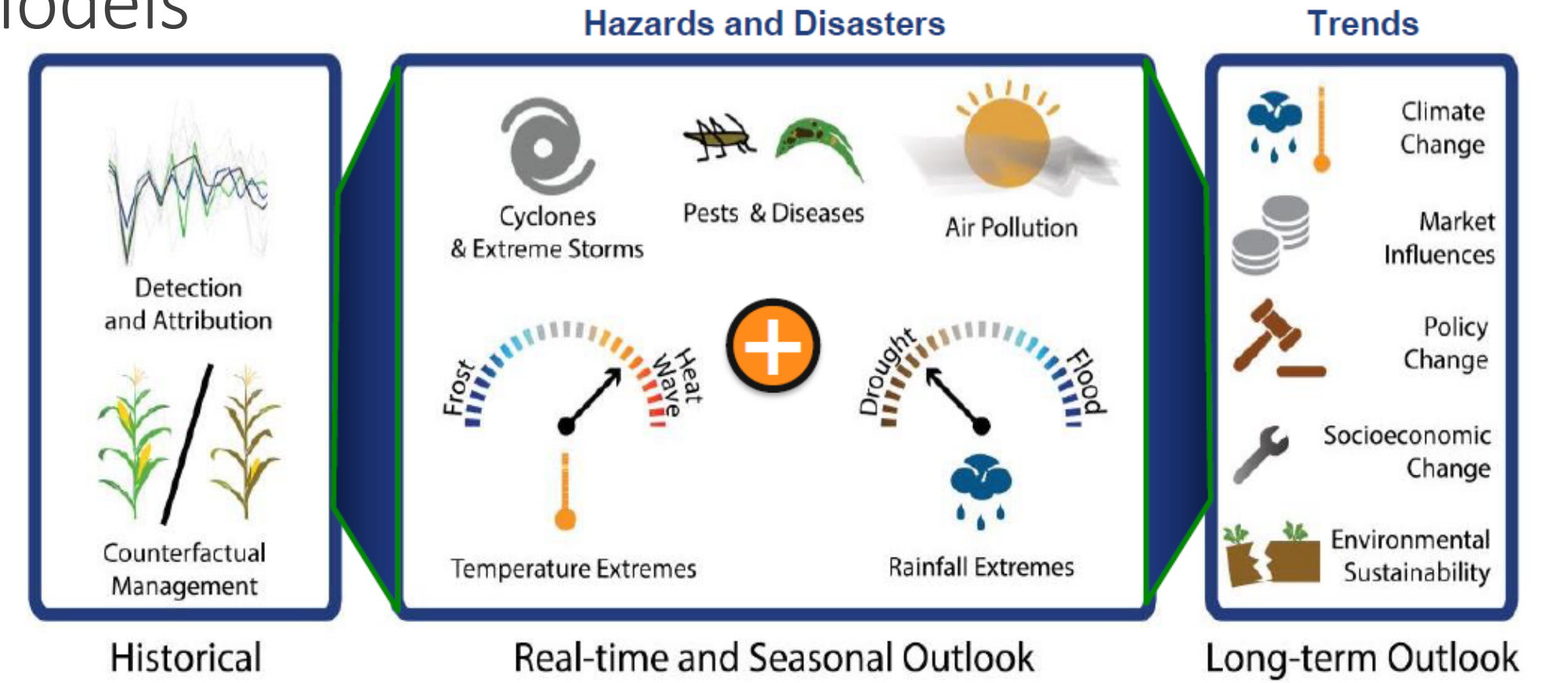
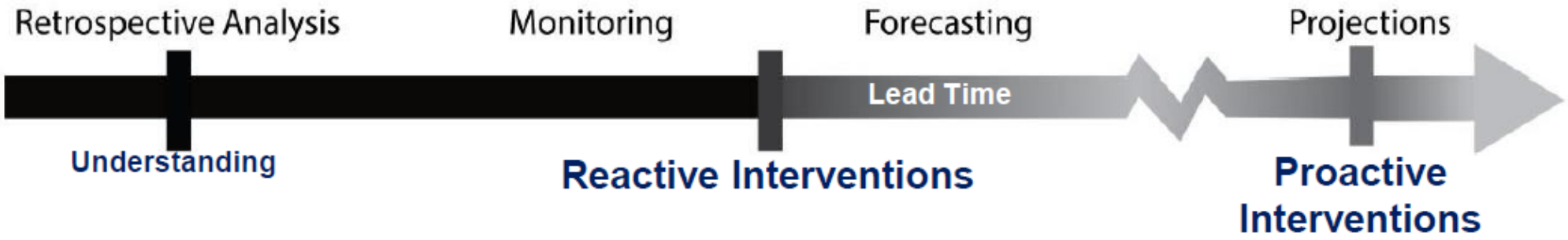


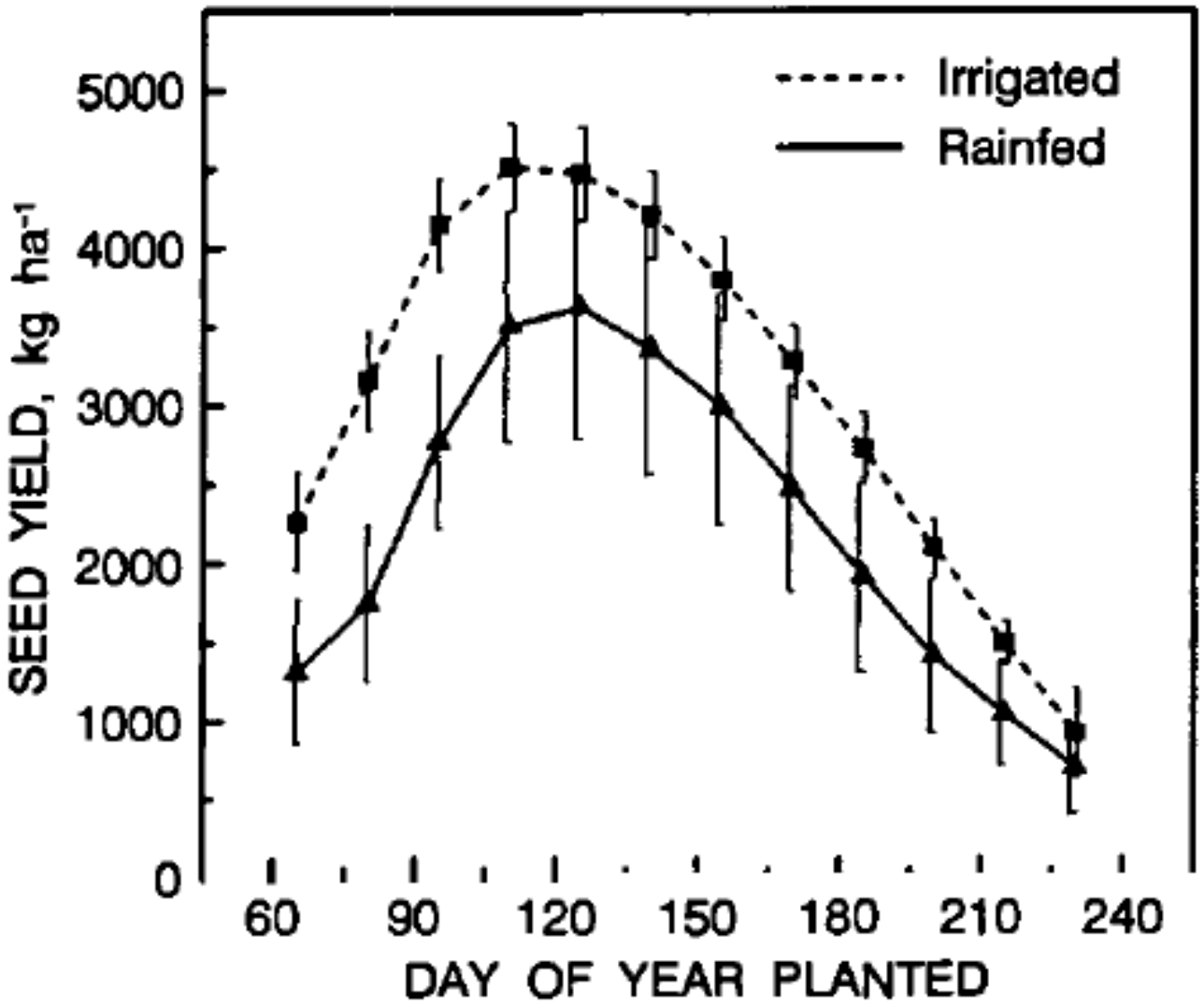
Who Am I

Crop Models

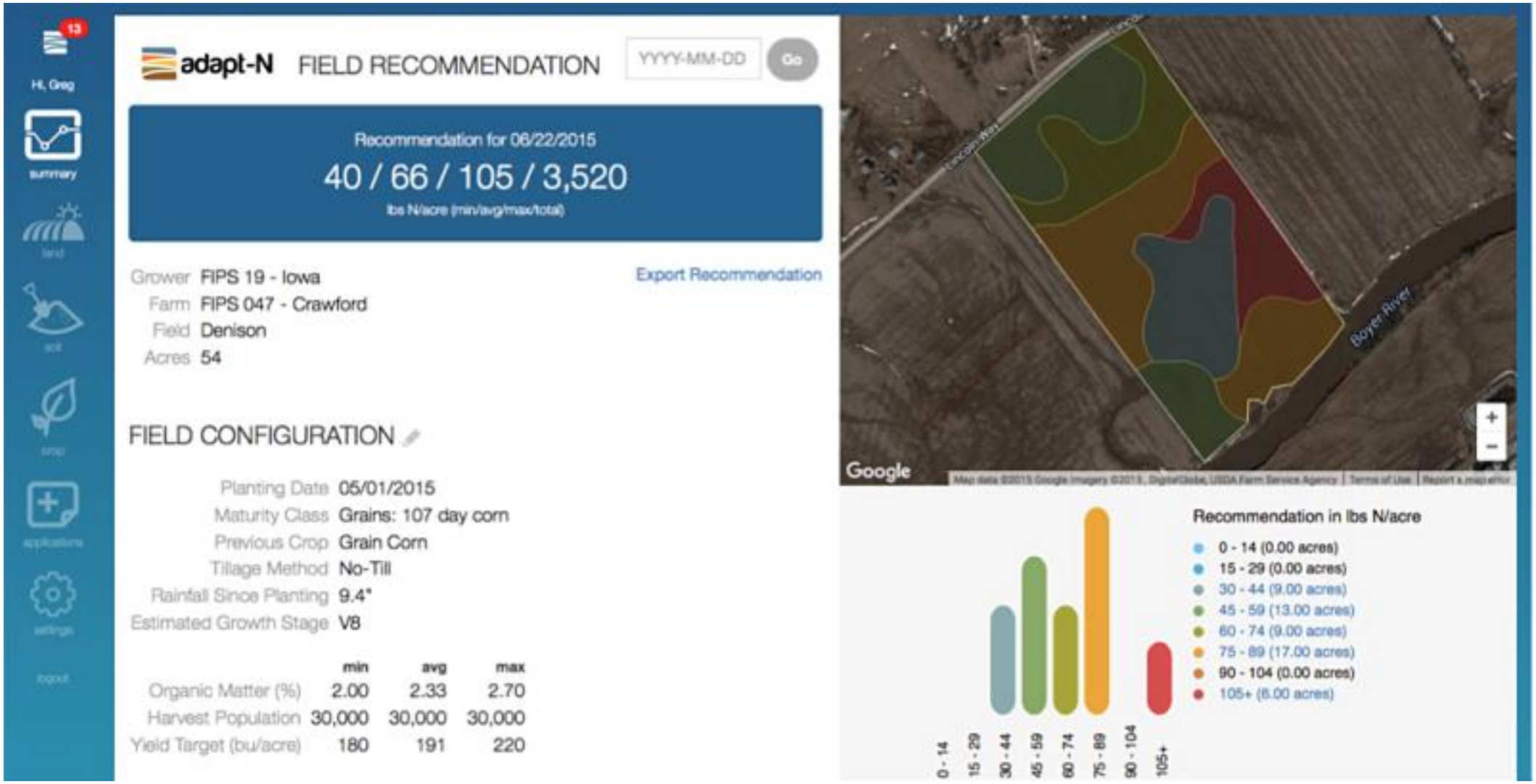




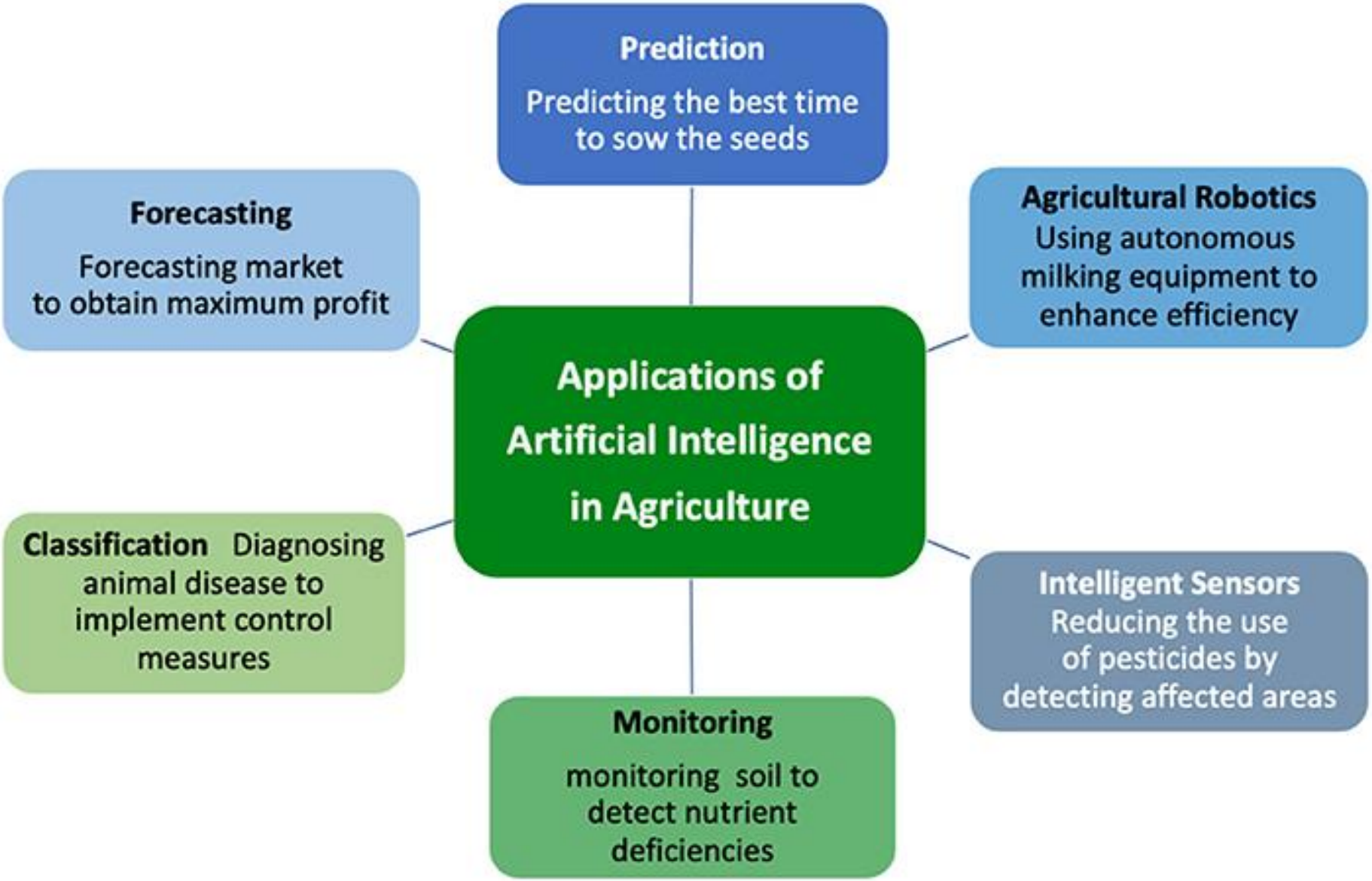
Ruane et al., 2021



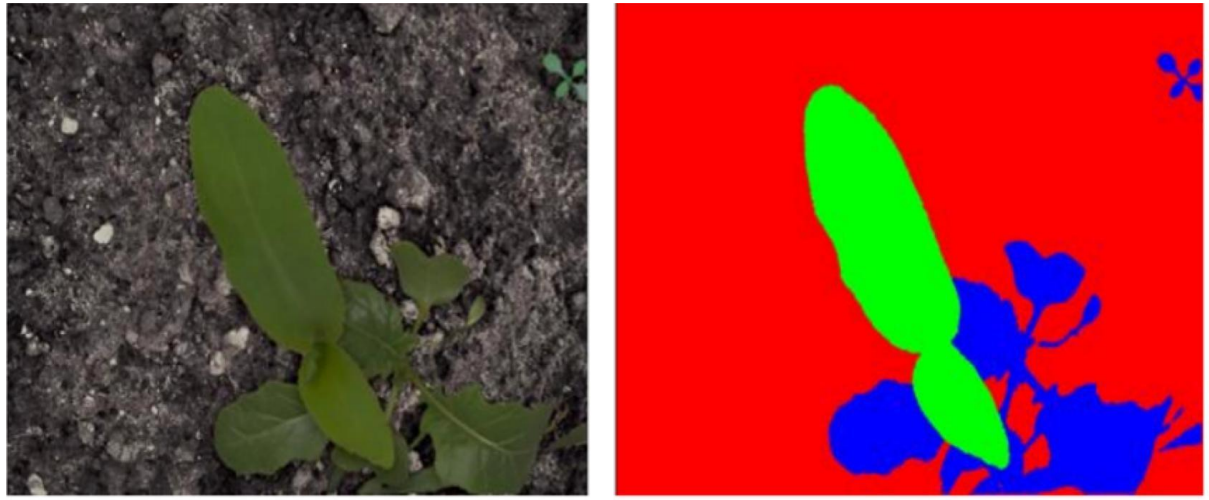
Soybean yield response to planting date simulated for 25 year at Gainesville FL (Boote et al. 1996)



Adapt-N (Moebius-Clune et al. 2013)

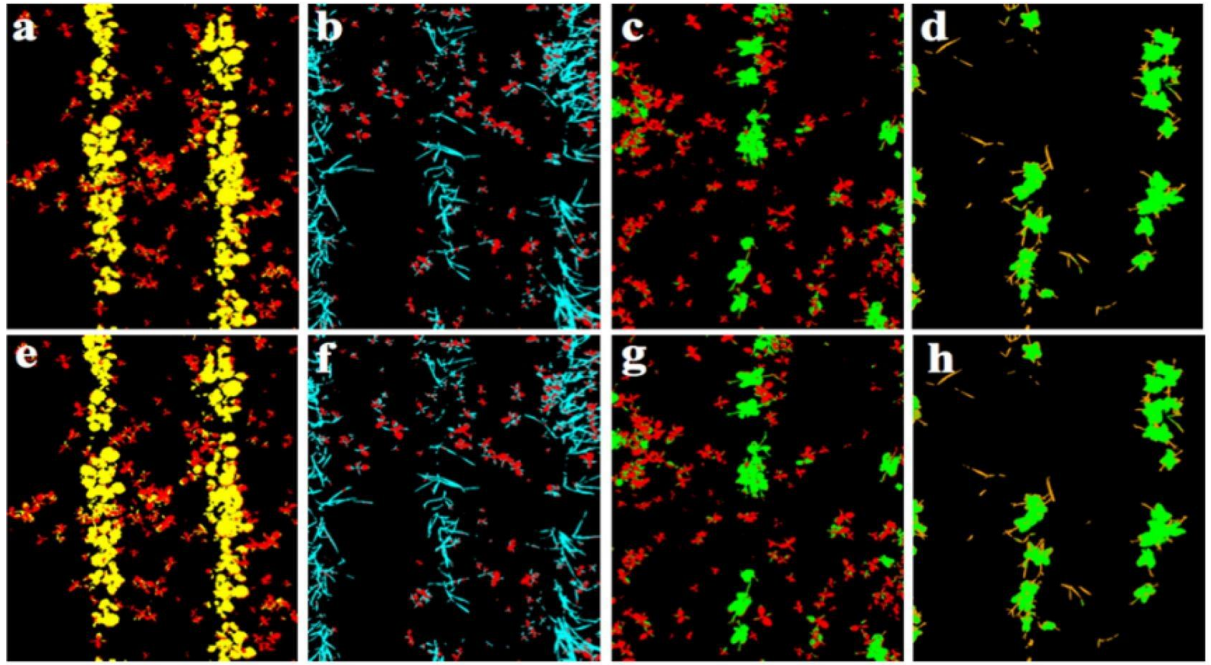


(Dara et al., 2022)

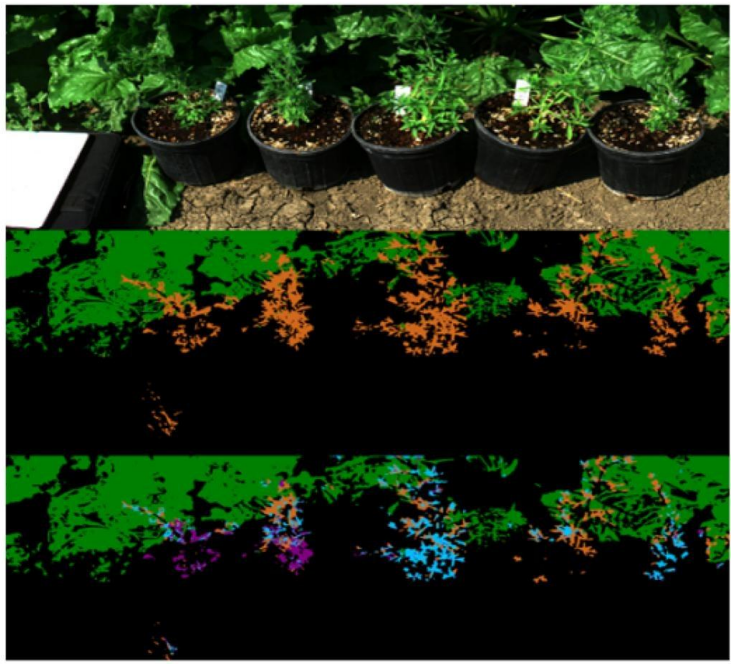


(a) Classified weed (blue) and maize (green)

(b) Weed detection and localization



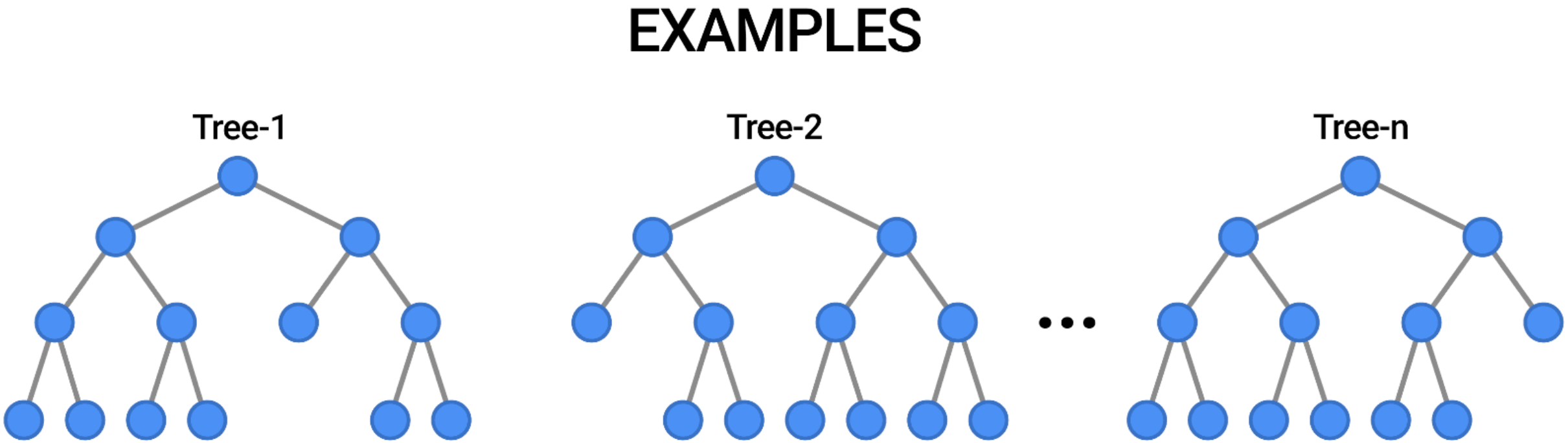
(c) Classified weed in Hyperspectral images (red and orange pixels)



(d) Classified weed species types

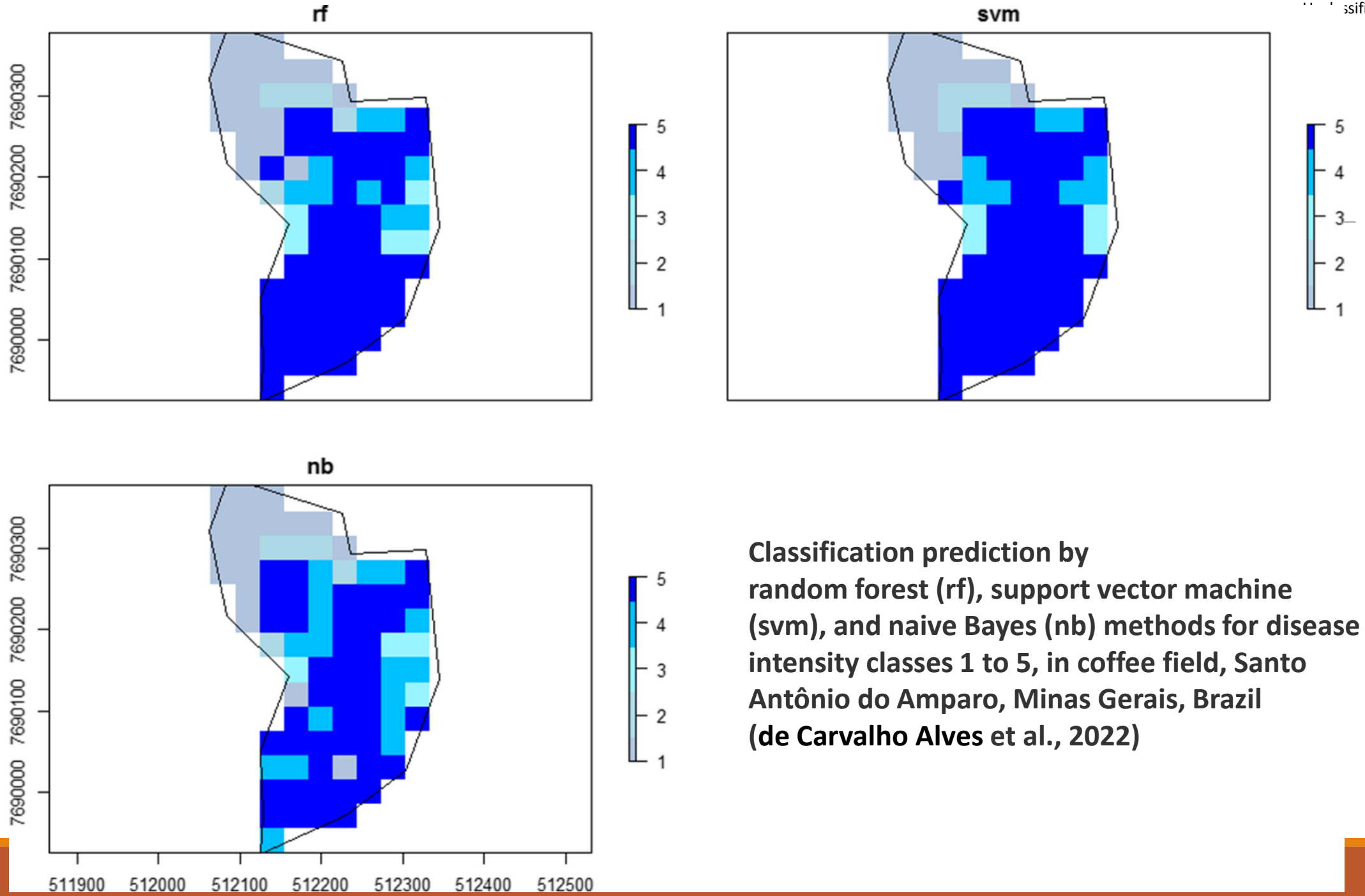
(Rai et al., 2023)

Random Forest (RF)

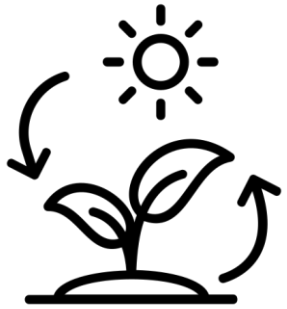


(Breiman, 2001)

Animation Source: https://blog.tensorflow.org/2021/05/introducing-tensorflow-decision-forests.html

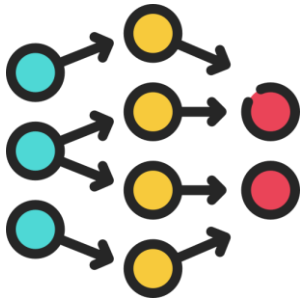


Classification prediction by random forest (rf), support vector machine (svm), and naive Bayes (nb) methods for disease intensity classes 1 to 5, in coffee field, Santo Antônio do Amparo, Minas Gerais, Brazil (de Carvalho Alves et al., 2022)



Process Based

- Need to collect data for many variables
- Expert knowledge to calibrate
- Simulates daily values
- Interpretable

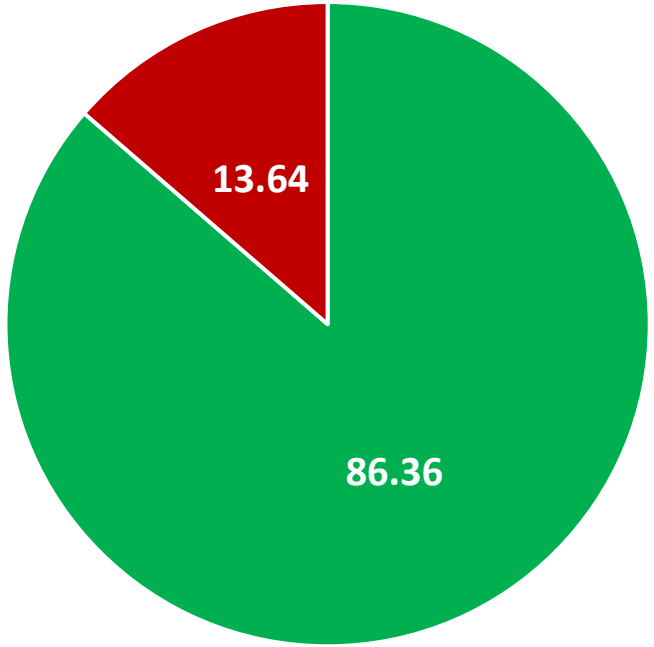


Machine Learning

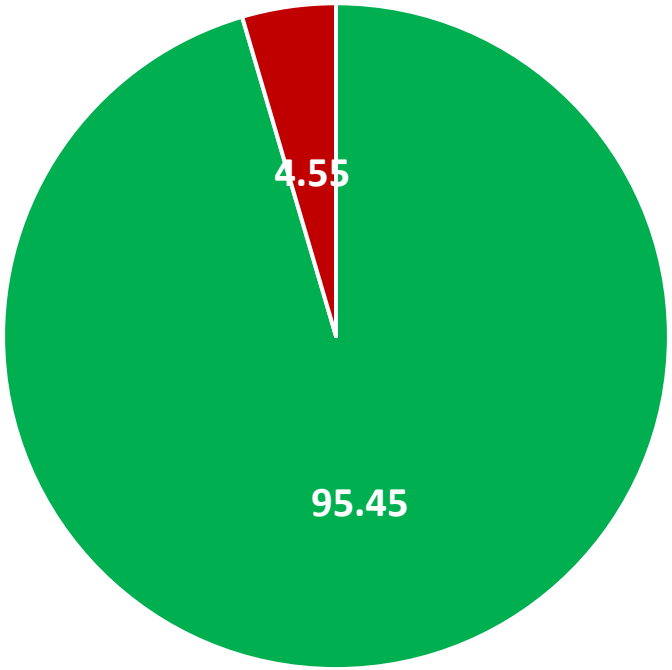
- Easy set up
- Less variables needed
- Needs a lot of data points
- Hard to interpret

Classification Forecast of High or Low Sugarcane Yield

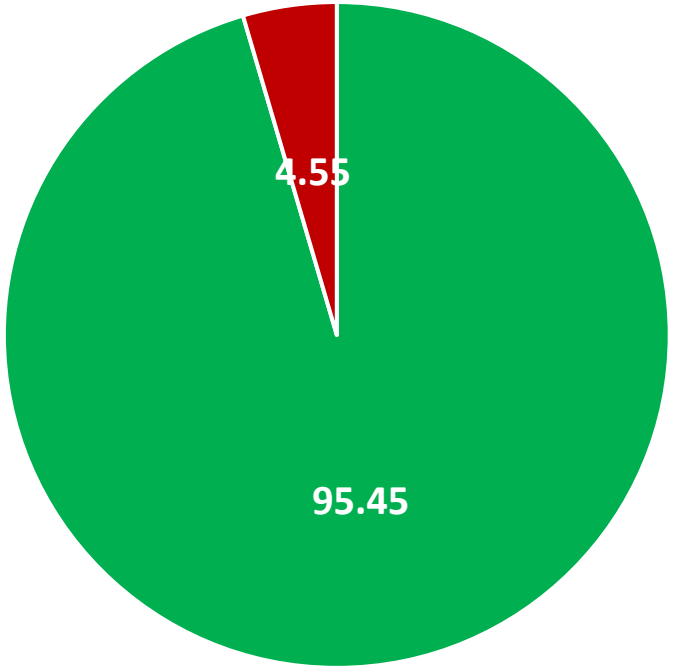
September 1st Year Before Harvest



January 1st Year of Harvest



March 1st Year of Harvest



Correct

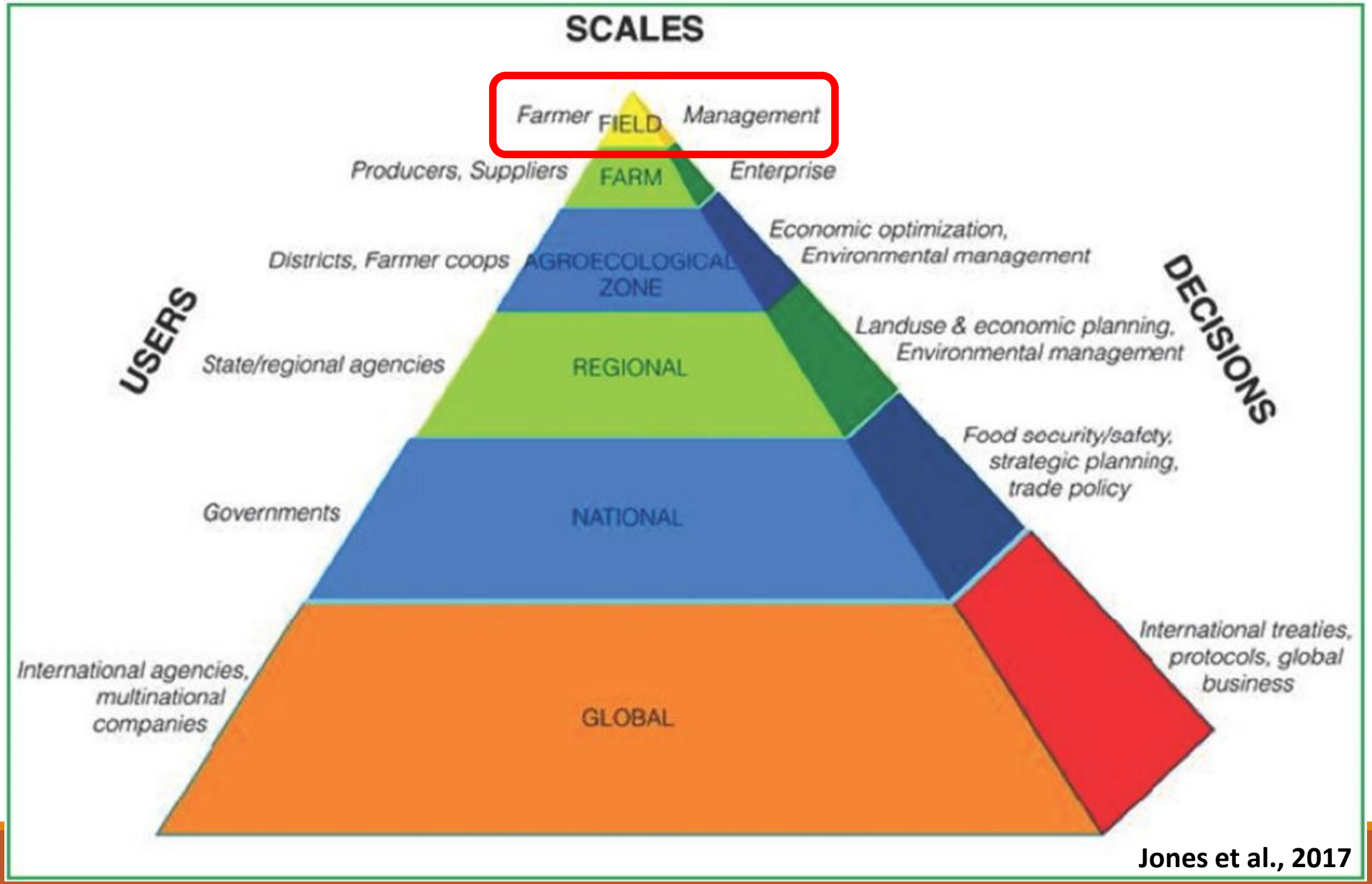
Incorrect

(Everingham et al., 2016)

Hybrid

- Improved Yield Predictions in the US Corn Belt by up to 20%.
  (Shahhosseini et al., 2021)

- Improved Yield Forecasts in southeastern Australian wheat belt.
  (Feng et al., 2020)



Jones et al., 2017

Industrial Farm Data

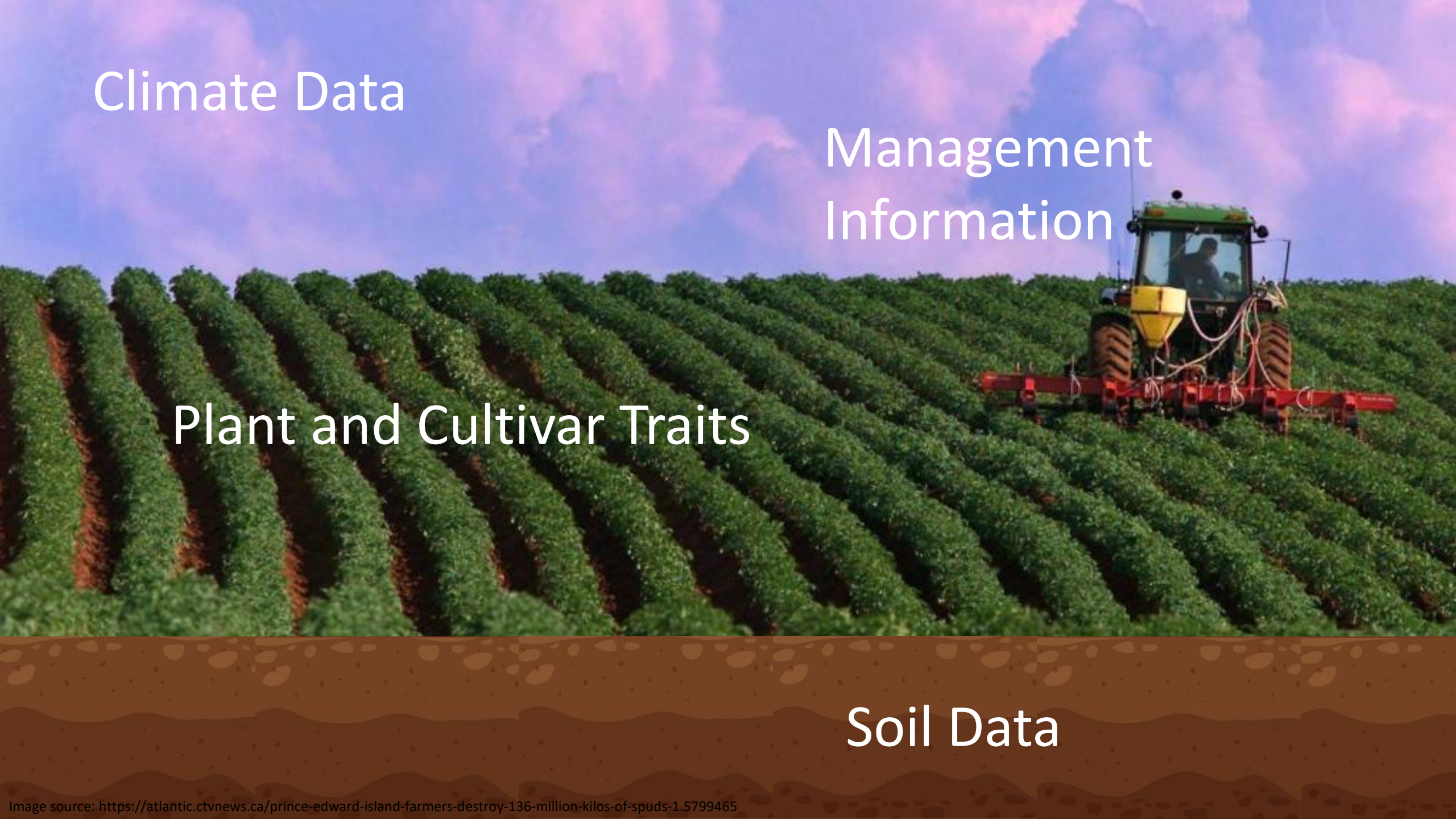
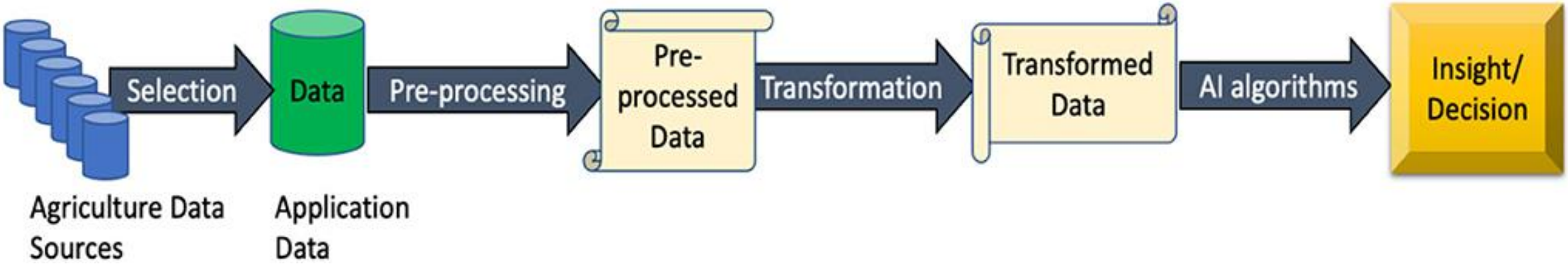


Image source: https://atlantic.ctvnews.ca/prince-edward-island-farmers-destroy-136-million-kilos-of-spuds-1.5799465


Yaeccc Load Cell Scale Sensor
Model:JK-0396
Type:weighing
Material:metal
Rated Load:0-1000kg


0.0 mph
13'
End of Row Approaching
CH.1 Liquid Primary
TARGET
20.0
gal/a
ACTUAL
0.0
gal/a
All
CH.1
Session Quantity
467.95 GAL
Layer Quantity
1073.46 GAL
Applied Rate
0.00 gal/a
System Flow
0.0 GPM
Trimble
RATE
Trimble
FIELD-IQ



(Dara et al., 2022)

Questions

- Can a crop model calibrated on research farm data be used for industrial fields?
- Can Random Forest predict yield for individual field-years?
- Will a hybrid approach improve predictions?
- What if we irrigated according to crop water need?

Model Performance

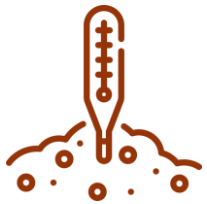
Model	RMSE	nRMSE	nMBE
STICS	54.95 cwt/ac.	**14.30%**	-6.95%
Random Forest	63.60 cwt/ac.	**16.55%**	-1.88%
Hybrid	49.06 cwt/ac.	**12.77%**	0.22%

nRMSE	< 10% Excellent	10 – 20 % Good	21 – 30% Satisfactory	> 30 % Poor

Important Variables

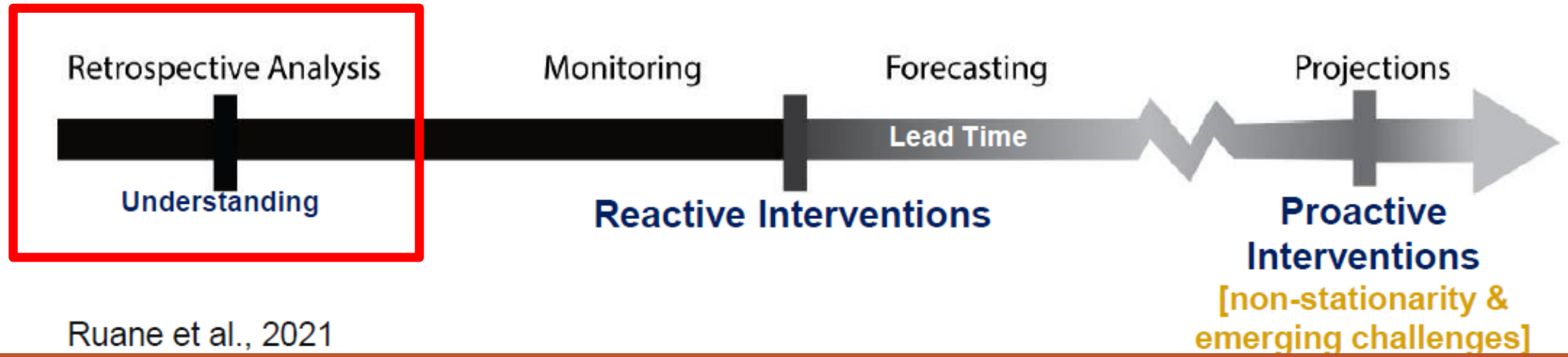
Water stress and evapotranspiration

Nitrogen uptake and loss



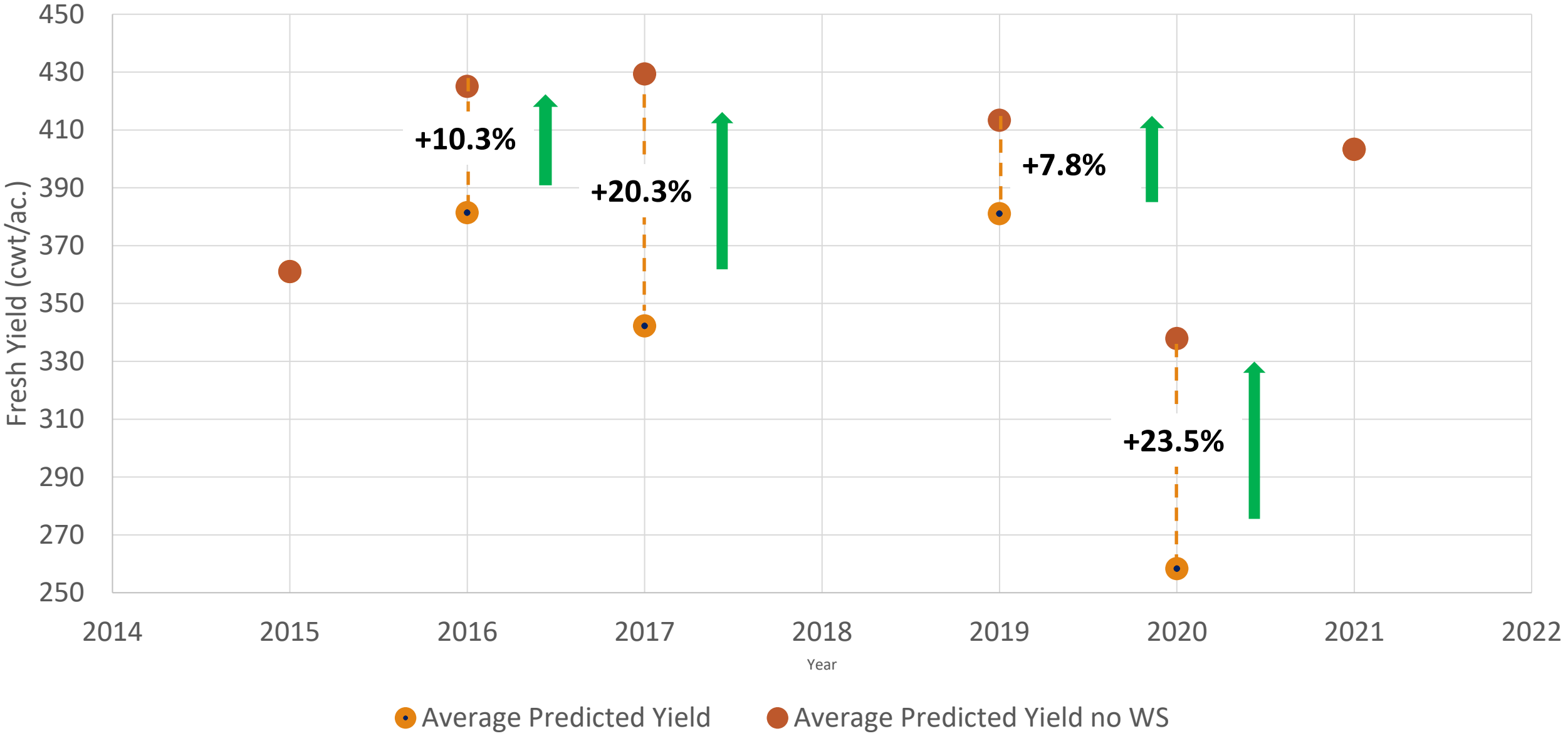
Soil pH

% OM in Soil

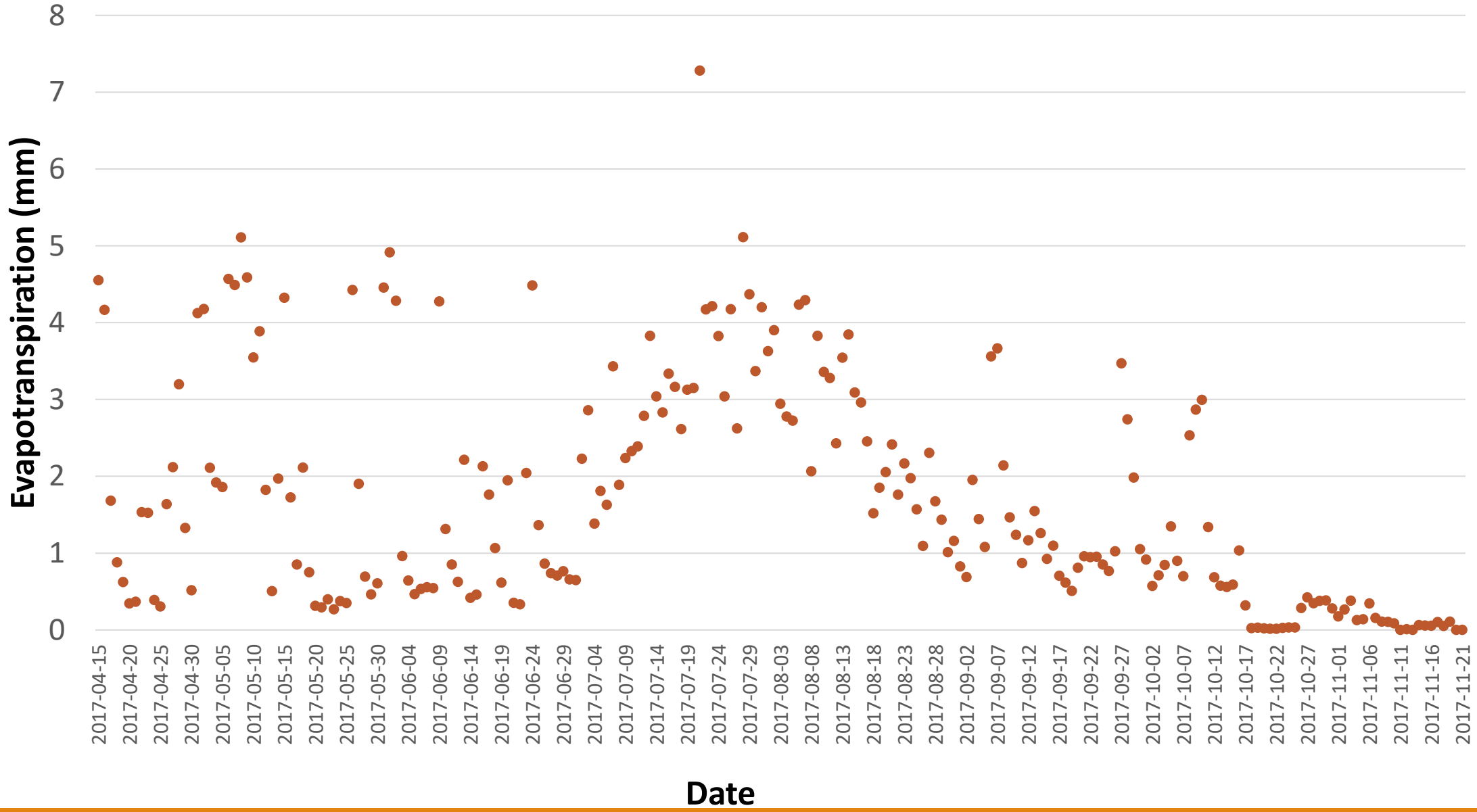


Ruane et al., 2021

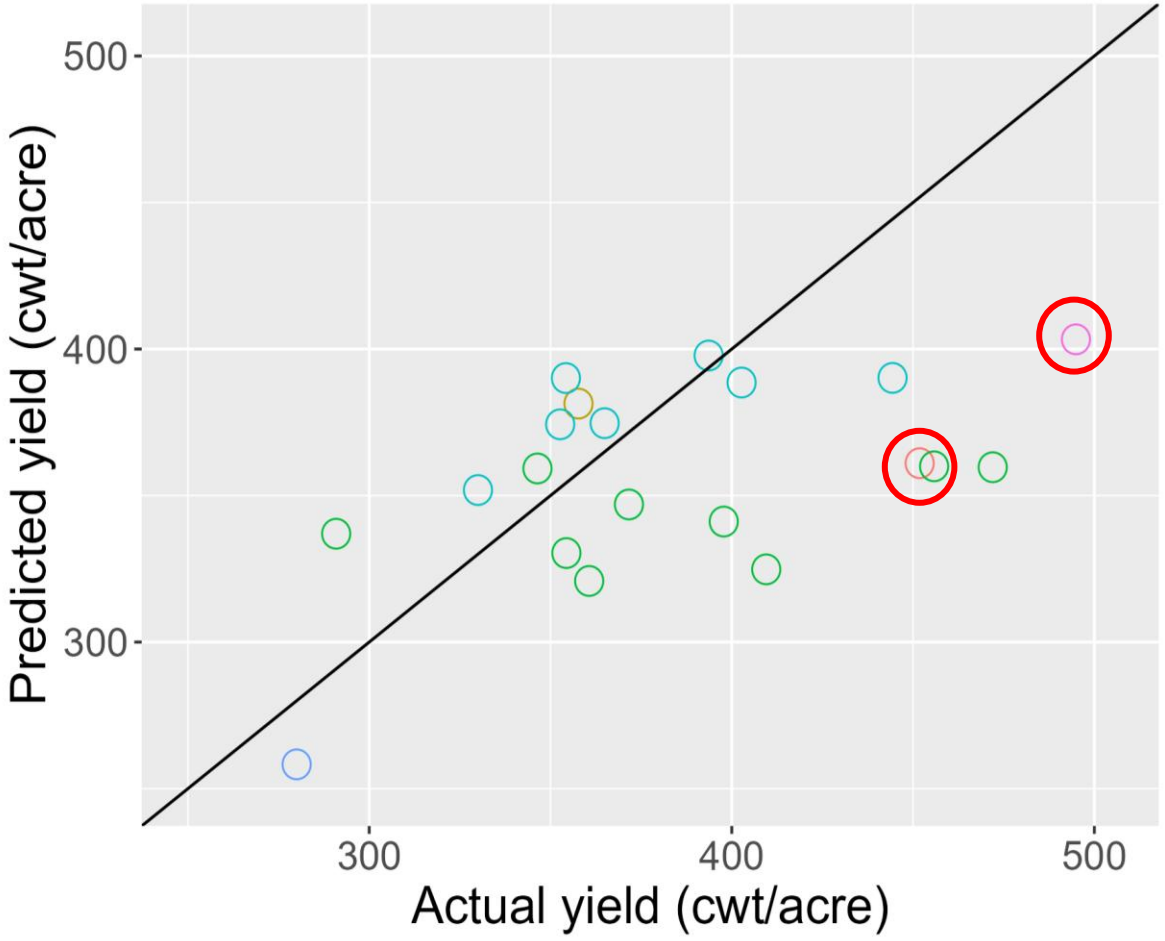
Predicted Average Yield With No Water Stress Vs. Actual Average Yield



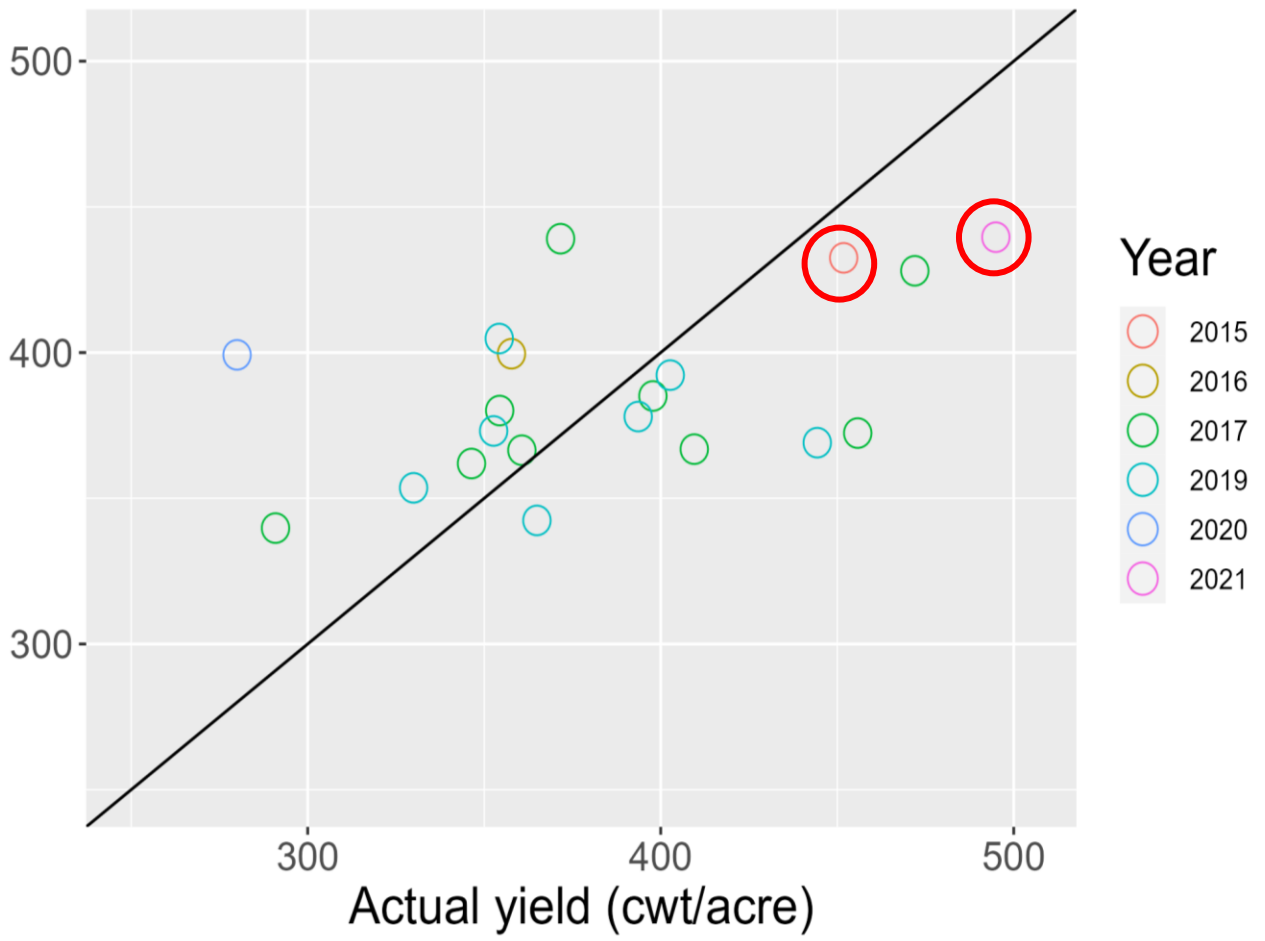
Simulated Daily Evapotranspiration



STICS



Hybrid



Limitations

- Errors in Measured Data
- Errors in Input Data
- Lack of Data
- Incorrectly represented relationships
- Forecasting can be difficult

Take Home Messages

- Crop modelling is continuing to improve
- Combing Process Based Crop Models and ML gives better predictions
- Need more and better-quality data
- Models can be a useful tool

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