

Imaging Alfalfa to Predict Yield & Quality & Impacts of Water Deficits Using Innovative Overhead Irrigation Systems

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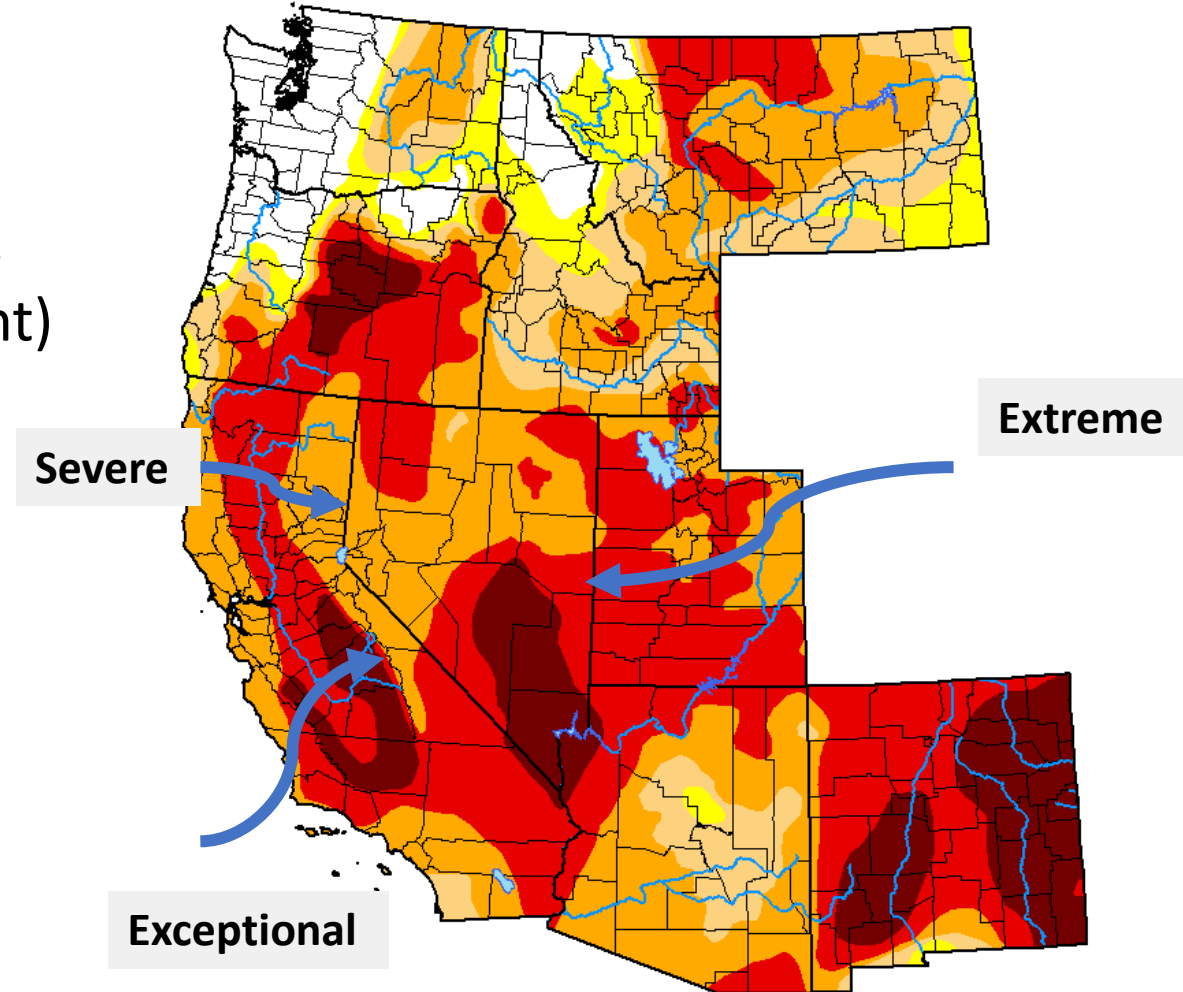




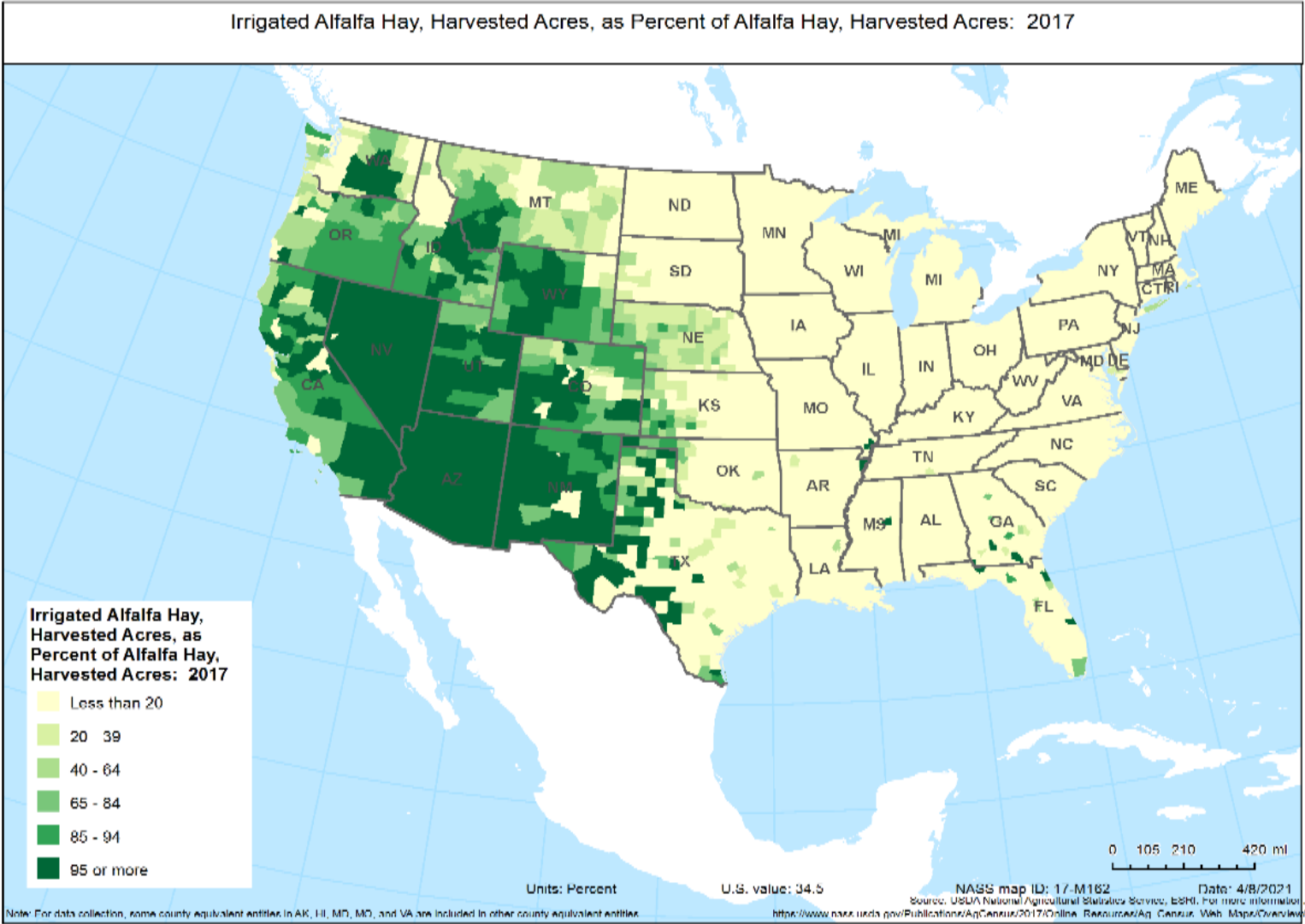
Context:

- Severe challenges:
 - ‘Exceptional’ Drought –water supply limits
 - Competition for Water (crops, environment)
 - Water Transfers to other users
 - Long term coping with deficits
- Strategies to Cope:
 - ‘Triage’ (leaving old fields behind)
 - Abandoned fields
 - Deficit Irrigation
 - Technology Improvements

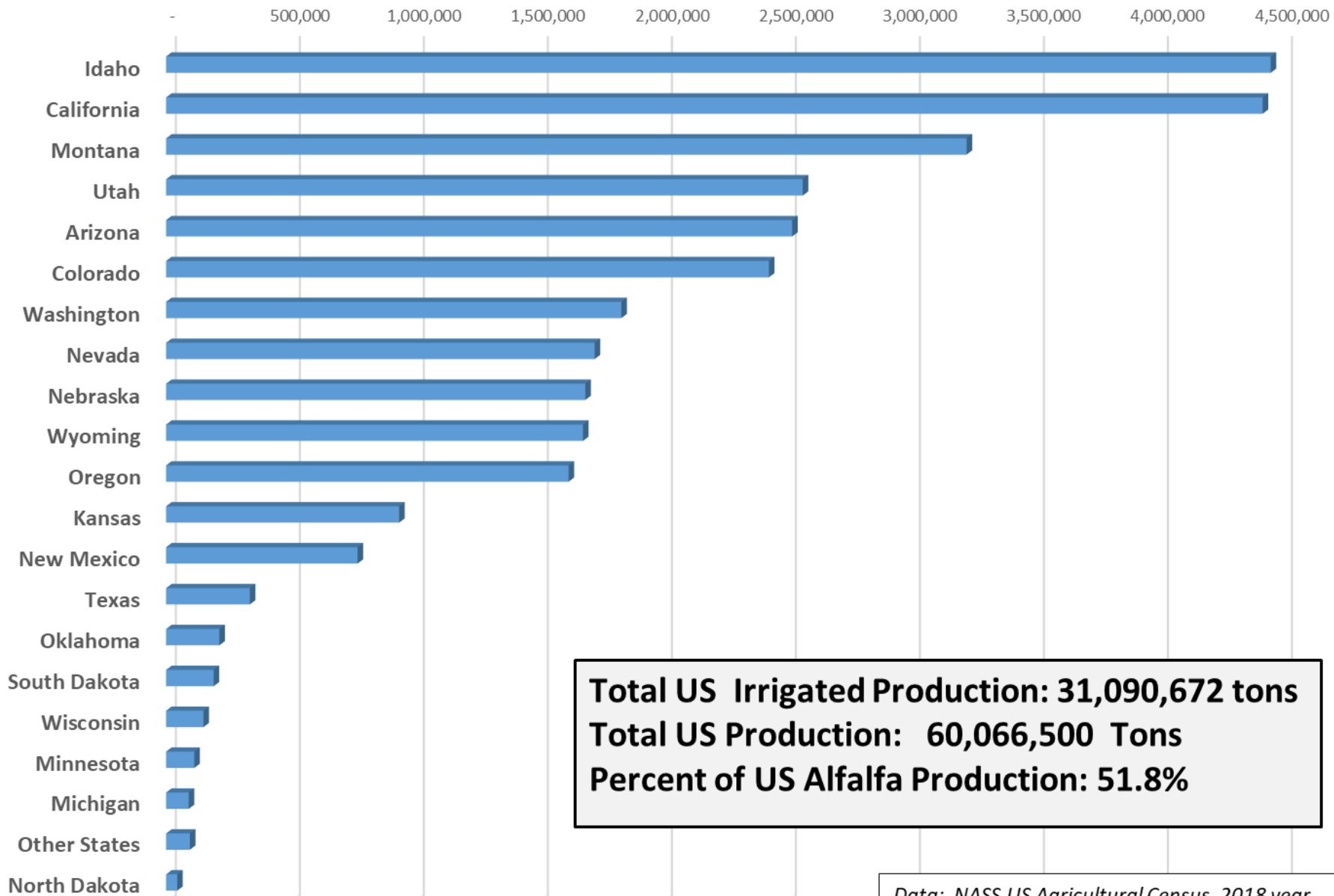
Current Situation (June 2, 2022)



Irrigated Alfalfa



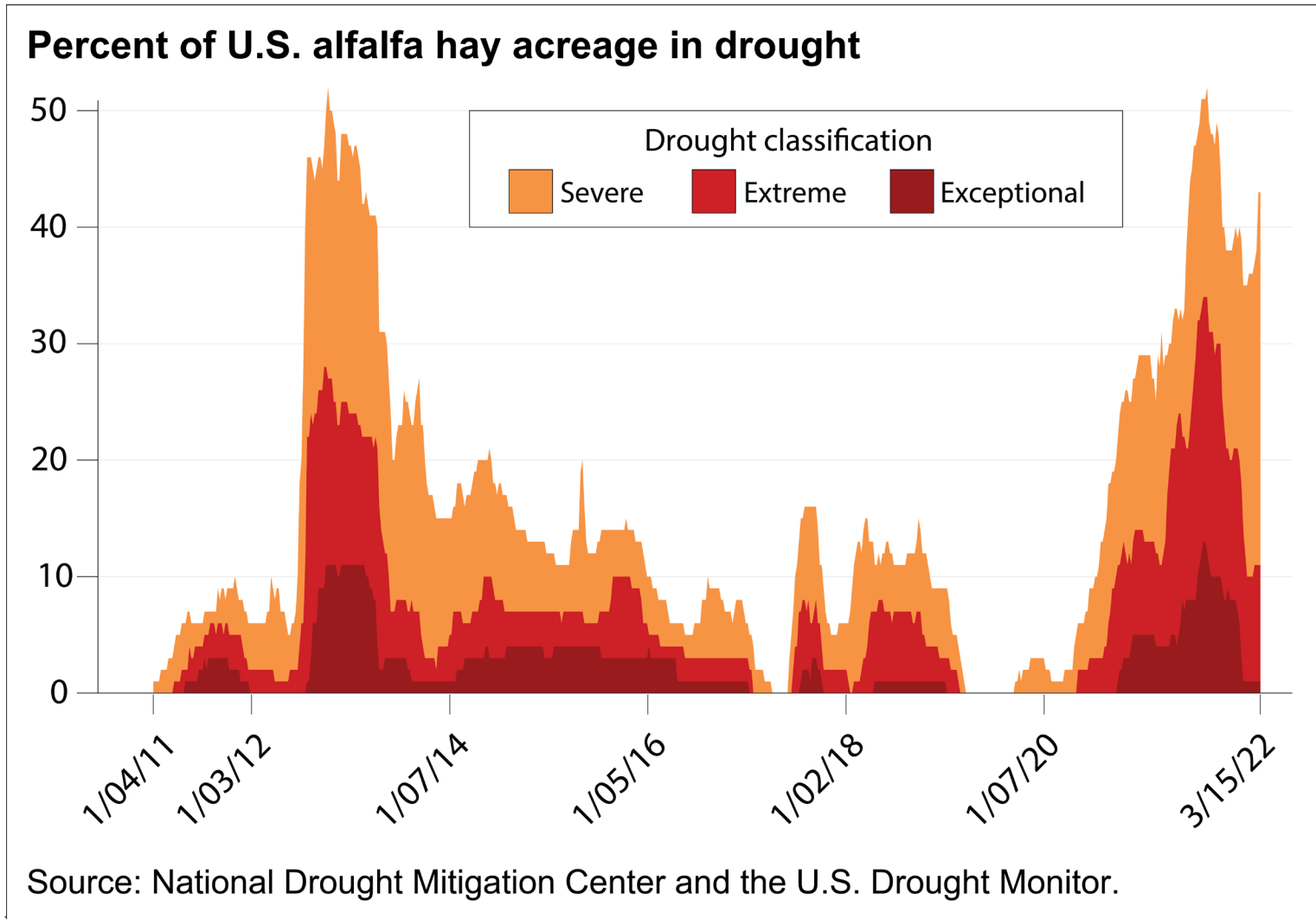
Production of Irrigated Alfalfa Hay, Greenchop, Silage - 2018 (tons)



Data: NASS US Agricultural Census, 2018 year



Percent US Alfalfa impacted by drought



**>50% of Hay acres (US),
spring/summer of 2022
(NDMC, and ERS). (April, 2022)**



Response to Water Limits in Irrigated Alfalfa:

- Need for Innovative techniques to improve water-application efficiency (Overhead Systems, Pivots, Linears, Subsurface Drip, Automated Surface Systems)
- LESA/LEPA (Low Elevation, Low Pressure, Low losses)- nozzling systems & close spacings.
- Deficit Irrigation (How to do partial season applications when not enough water).
- Imaging/Monitoring. Effects of drought and deficits on yields. Estimating ET and yield impacts remotely.
- Water transfers to other users (credits to farmers)



Linear Overhead Irrigation



Objectives:

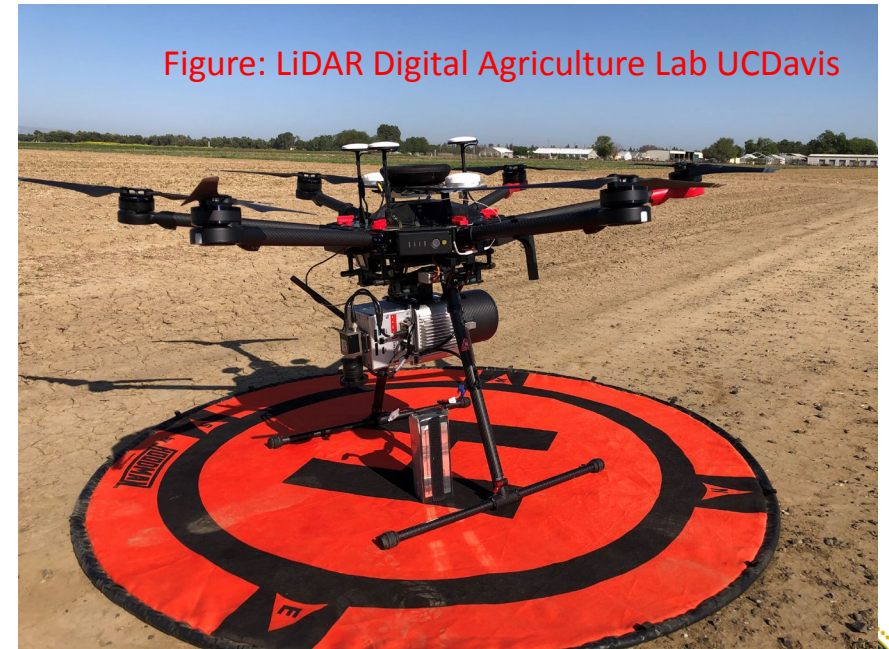
- Yield response to deficits
- Develop an image to yield relationship using multispectral and LiDAR imagery for alfalfa
- Create a yield and quality map for understanding spatial temporal variability
- Identify the best models to estimate alfalfa yield and quality



Crop Imaging:

- Analysis of Yield Limitations in fields (field diagnostic tool) to understand the variability in yield due to abiotic stresses.
- Less labor involved as compared with traditional sampling methods.
- The results may be provided in short time for field management

Figure: LiDAR Digital Agriculture Lab UC Davis



Source: Chandel et al., 2021, Dvorak et al., 2021, Tang et al., 2021



Material and Methods: (Year 2019 and 2020)

Source: Gull et. al., 2021

LESA/LEPA

100% ET Full

60% ET-Cutoff

60% ET-Gradual

40% ET-Gradual

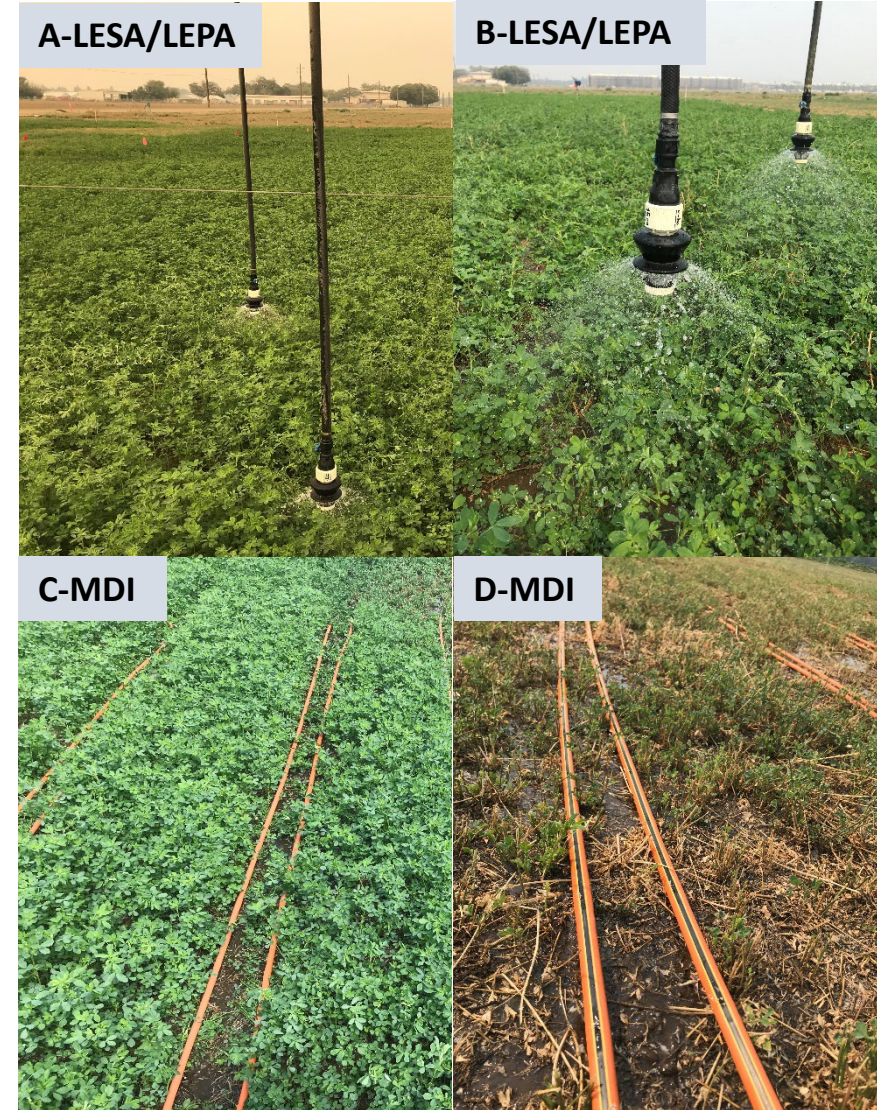
MDI

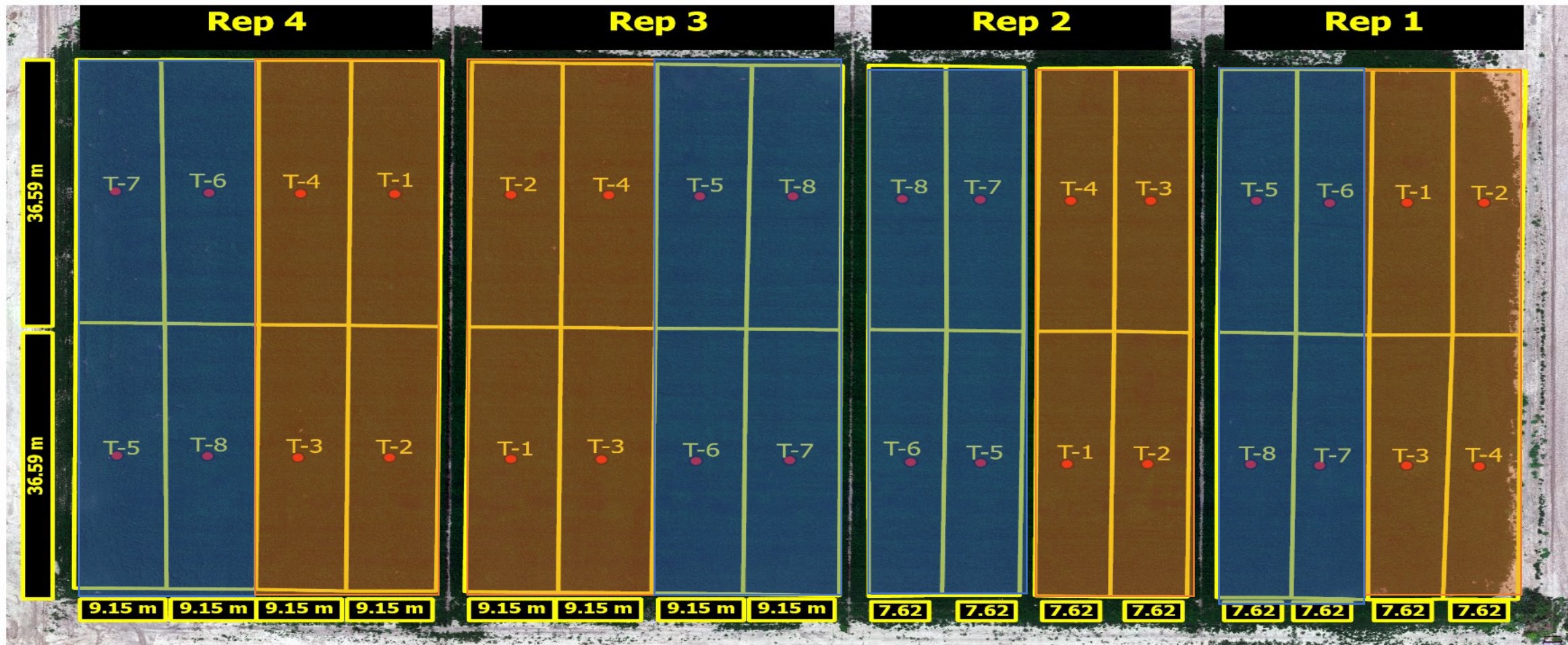
100% ET Full

60% ET-Cutoff

60% ET-Gradual

40% ET-Gradual





Treatments

- T1- LESA 100% ET Full
- T2- LESA 60% ET- Cutoff
- T3- LESA 60% ET-Gradual
- T4- LESA 40% ET-Gradual

- T5- MDI 100% ET Full
- T6- MDI 60% ET-Cutoff
- T7- MDI 60% ET-Gradual
- T8- MDI 40% ET-Gradual

● Neutron Probe

LESA

MDI



Advantages and Disadvantages

Chapter 2:

LESA/LEPA

Low Elevation Spray Application
Low Energy Precision Application

- Close to the ground
- Efficiency ~ 88% and 97%
- Wind Losses minimum
- 18% reduced pumping cost

MDI

Mobile Drip Irrigation

- Travelling trickle irrigation
- Reduced wind losses
- Less soil evaporation (35%)
- Minimum repair costs

Source: Peters et al., 2016; Kisekka et al., 2017; O'Shaughnessy and Colaizzi, 2017; Oker et al., 2018; Aguilar et al., 2019; Reynolds et al., 2020



Monitoring Soil Water Status

Neutron Probe

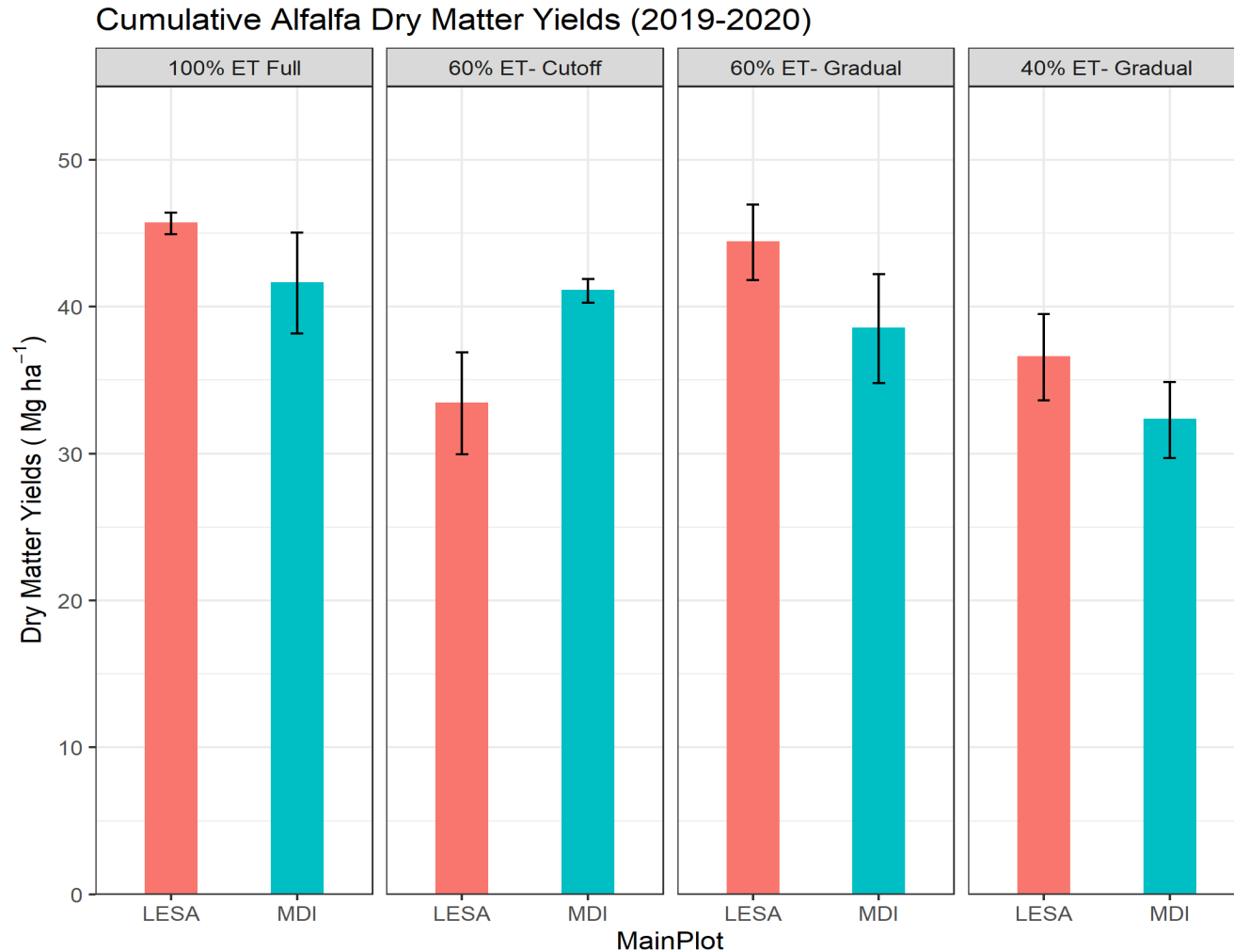


EM38 Calibration



Source: Gull et. al., 2021

Yield Response to Deficits:



Imaging Material and Methods:

Table 1. Image acquisition details using Micasense Rededge and LiDAR in alfalfa during 2020

Harvest Date	Flight Date	Sensor Used
23-Apr-20	-----	-----
28-May-20	26-May-20	Micasense Rededge
	27-May-20	LiDAR
25-Jun-20	24-Jun-20	Micasense Rededge
23-Jul-20	22-Jul-20	Micasense Rededge
	21-Jul-20	LiDAR
20-Aug-20	19-Aug-20	Micasense Rededge
17-Sep-20	16-Sep-20	Micasense Rededge
	16-Sep-20	LiDAR
22-Oct-20	20-Oct-20	Micasense Rededge
	20-Oct-20	LiDAR

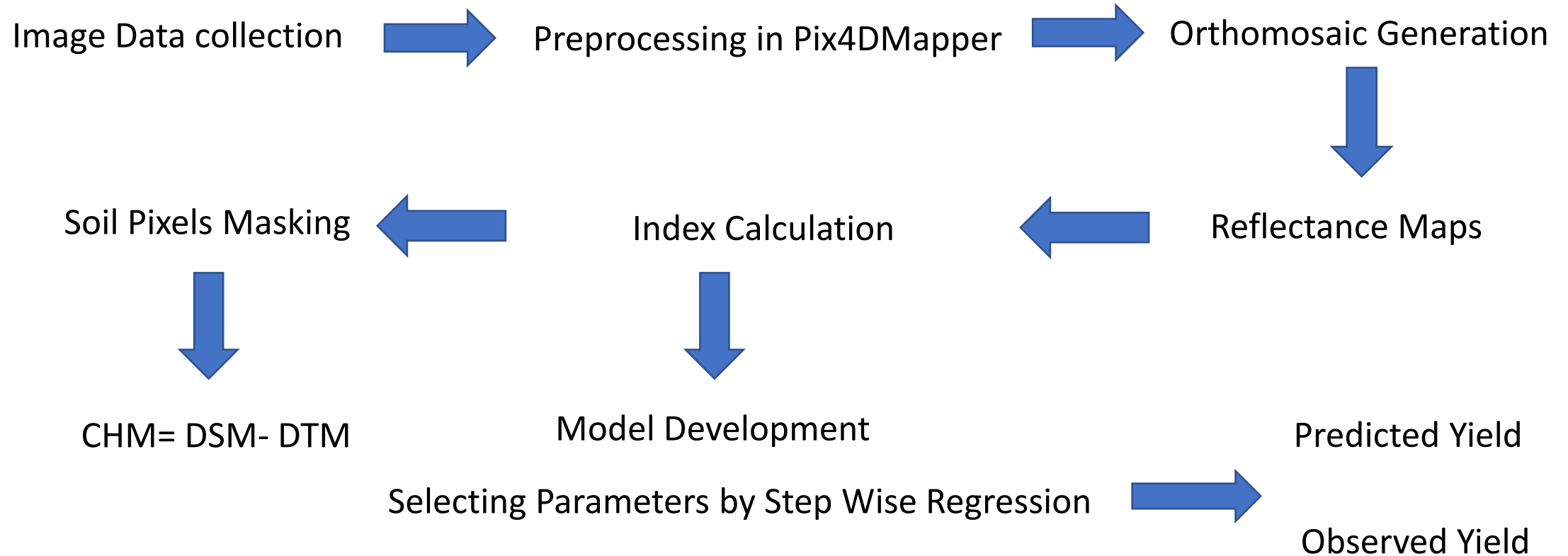
Source: Gull et. al., 2021



Source: MicaSense

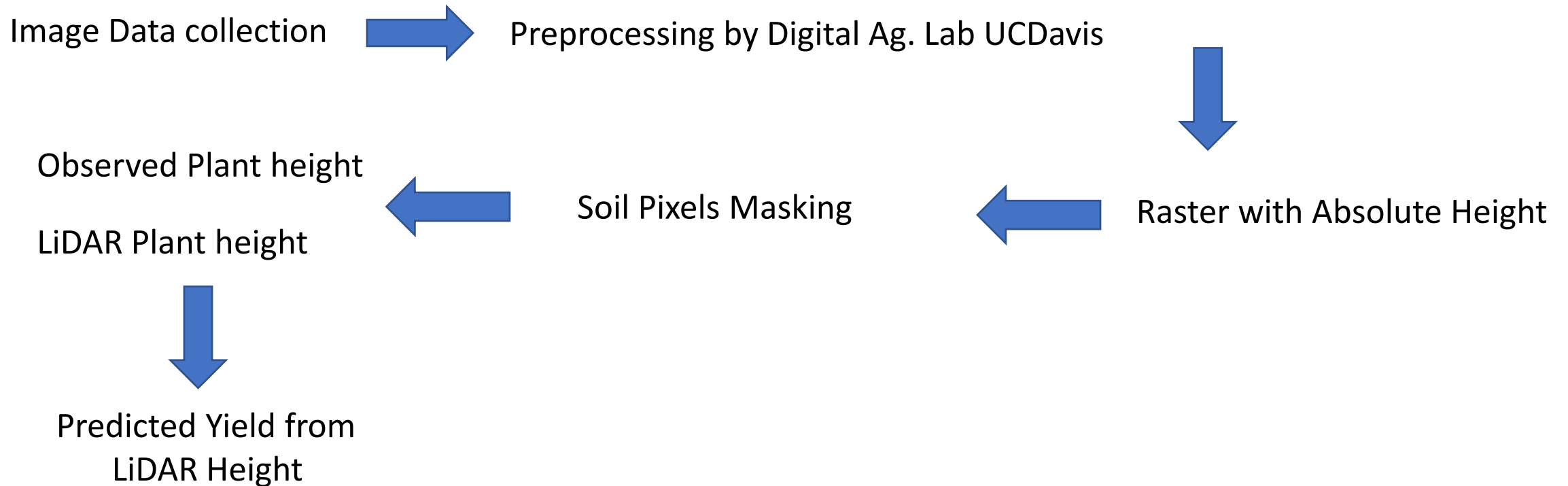


Multispectral Processing Steps:



Source: Gull et. al., 2021

LiDAR Processing Steps:



Source: Gull et. al., 2021



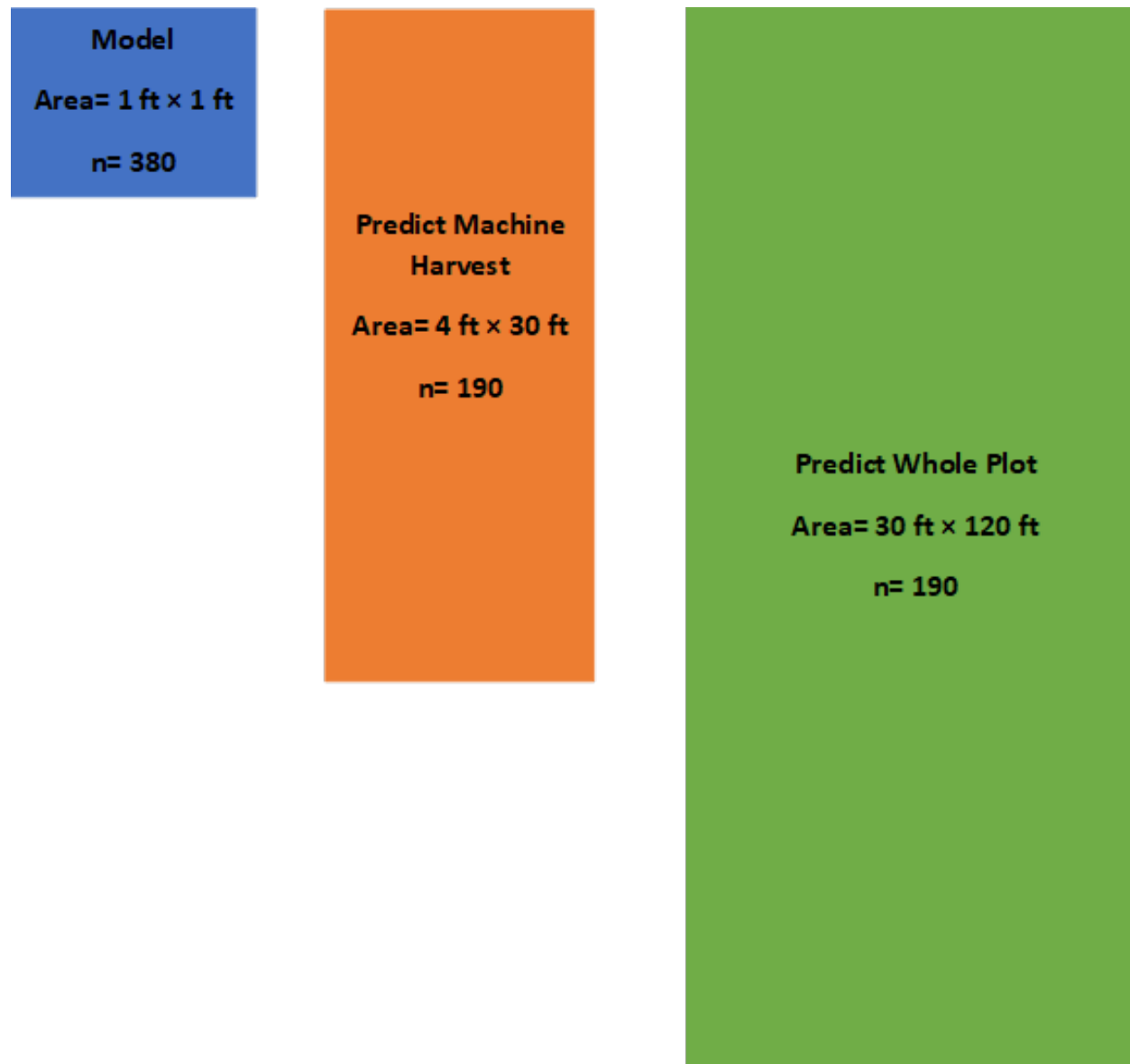


Figure 1. An illustration of observed data collected from 0.09 m² (blue square), 11.15 m² (orange rectangle) and estimated whole plot 334.45 m² (green rectangle).

Source: Gull et. al., 2021

Table 2. Vegetation indices used in the present study were adopted from Tang et al., 2021 for developing the model.

Source: Gull et. al., 2021

Indices	Abbreviation	Formula
Chlorophyll Index of Green	CI _{Green}	$(\text{NIR}-\text{Green})/(\text{Green})$
Chlorophyll Index of Red Edge	CI _{Re}	$\text{NIR}-\text{RedEdge}/\text{RedEdge}$
Chlorophyll Vegetation Index	CVI	$(\text{NIR}*\text{Red})/(\text{Green}*\text{Green})$
Enhanced Vegetation Index	EVI ₂	$2.5*(\text{NIR}-\text{Red})/(\text{NIR}+(6*\text{Red})-(7.5*\text{Blue})+1)$
Excess Green	ExG	$2*\text{Green}-\text{Red}-\text{Blue}$
Green Leaf Index	GLI	$(2*\text{Green}-\text{Red}-\text{Blue})/(2*\text{Green}+\text{Red}+\text{Blue})$
Green Normalized Difference Vegetation Index	GNDVI	$(\text{NIR}-\text{Green})/(\text{NIR}+\text{Green})$
Green Red Blue Vegetation Index	GRBVI	$((\text{Green}^2)-(\text{Blue}*\text{Red}))/((\text{Green}^2)+(\text{Blue}*\text{Red}))$
Green Ratio Vegetation Index	GRVI	NIR/Green
Leaf Chlorophyll Index	LCI	$(\text{NIR}-\text{RedEdge})/(\text{NIR}-\text{Red})$
Modified Chlorophyll Absorption in Reflectance Index	MCARI	$((\text{RedEdge}-\text{Red})-0.2*(\text{RedEdge}-\text{Green}))*(\text{RedEdge}/\text{Red})$
Normalized Difference Red Edge Index	NDRE	$(\text{NIR}-\text{RedEdge})/(\text{NIR}+\text{RedEdge})$
Normalized Difference of Vegetation Index	NDVI	$(\text{NIR}-\text{Red})/(\text{NIR}+\text{Red})$
Normalized Green-Red Difference Index	NGRDI	$((\text{Green}-\text{Red}))/((\text{Green}+\text{Red}))$
Ratio Vegetation Index	RVI	(Red/NIR)
Simple Ratio	SR	(NIR/Red)
Triangular Vegetation Index	TVI	$60*(\text{NIR}-\text{Red})-100*(\text{Red}-\text{Green})$
Visible Atmospherically Resistant Index	VARI	$(\text{Green}-\text{Red})/(\text{Green}+\text{Red}-\text{Blue})$
Wide Dynamic Range Vegetation Index	WDRVI	$(0.1*\text{NIR}-\text{Red})/(0.1*\text{NIR}+\text{Red})$
Predicted Plant Height	PH	Relationship between Observed and UAV



Statistical Analysis:

- Mostly conducted in R with following packages
- Caret (Kuhn, 2021), raster (Hijmans, 2020),
- sf (Pebesma, 2018), rgdal (Bivand et al., 2021), Hmisc (Harrell Jr et al., 2021).
- HydroGOF (Bigiarini, 2020),
- Corrplot (Wei and Simko, 2017).
- Ggplot (Wickham, 2016).

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (Predicted - Observed)^2}{n}}$$

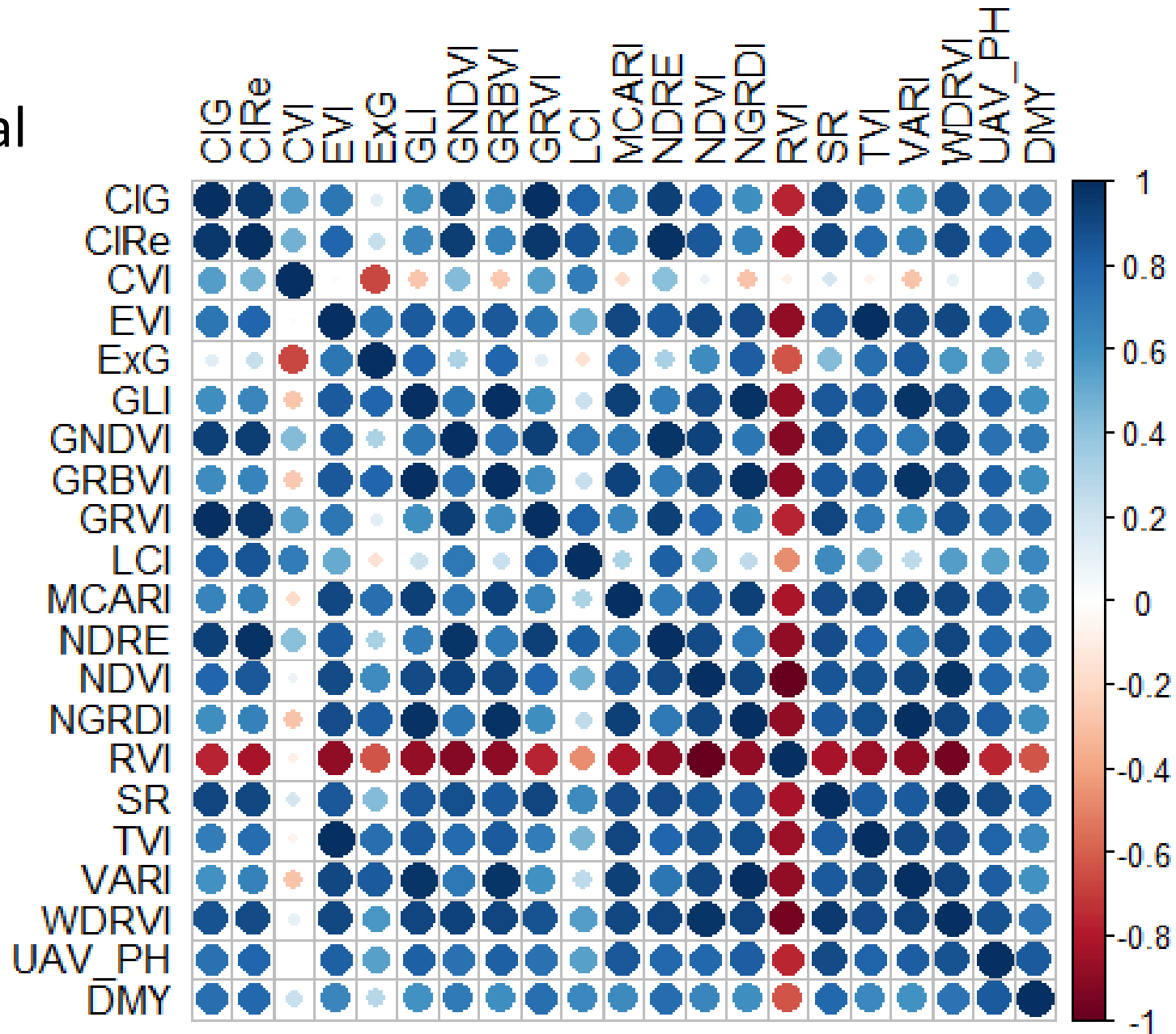
$$MAE = \frac{\sum_{i=1}^n |Predicted - Observed|}{n}$$

$$nRMSE = \frac{RMSE}{sd(observed)}$$

Source: Gull et. al., 2021



- Multispectral



Model
Area= 1 ft × 1 ft
n= 380

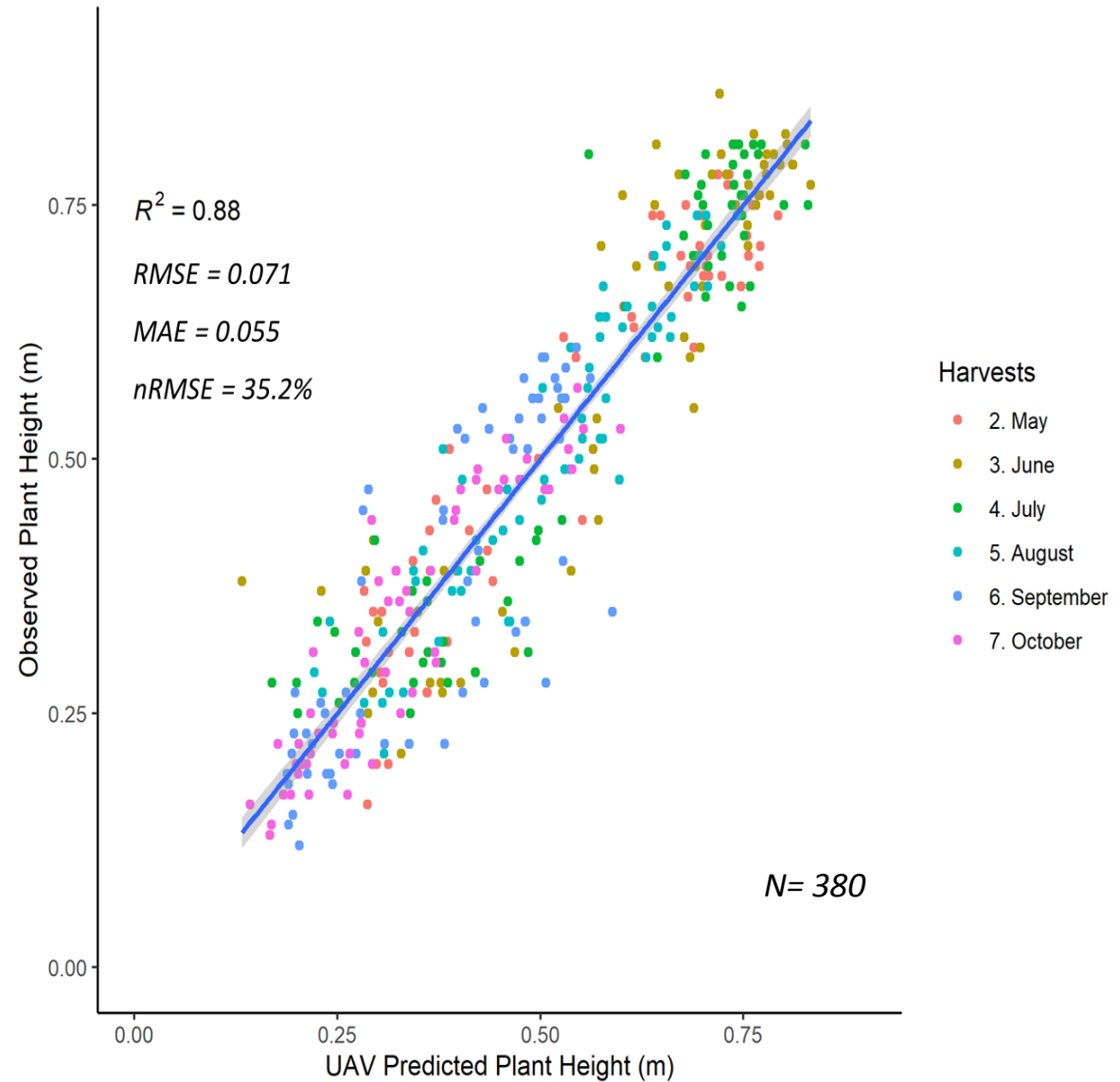
Source: Gull et al., 2021



Plant Height

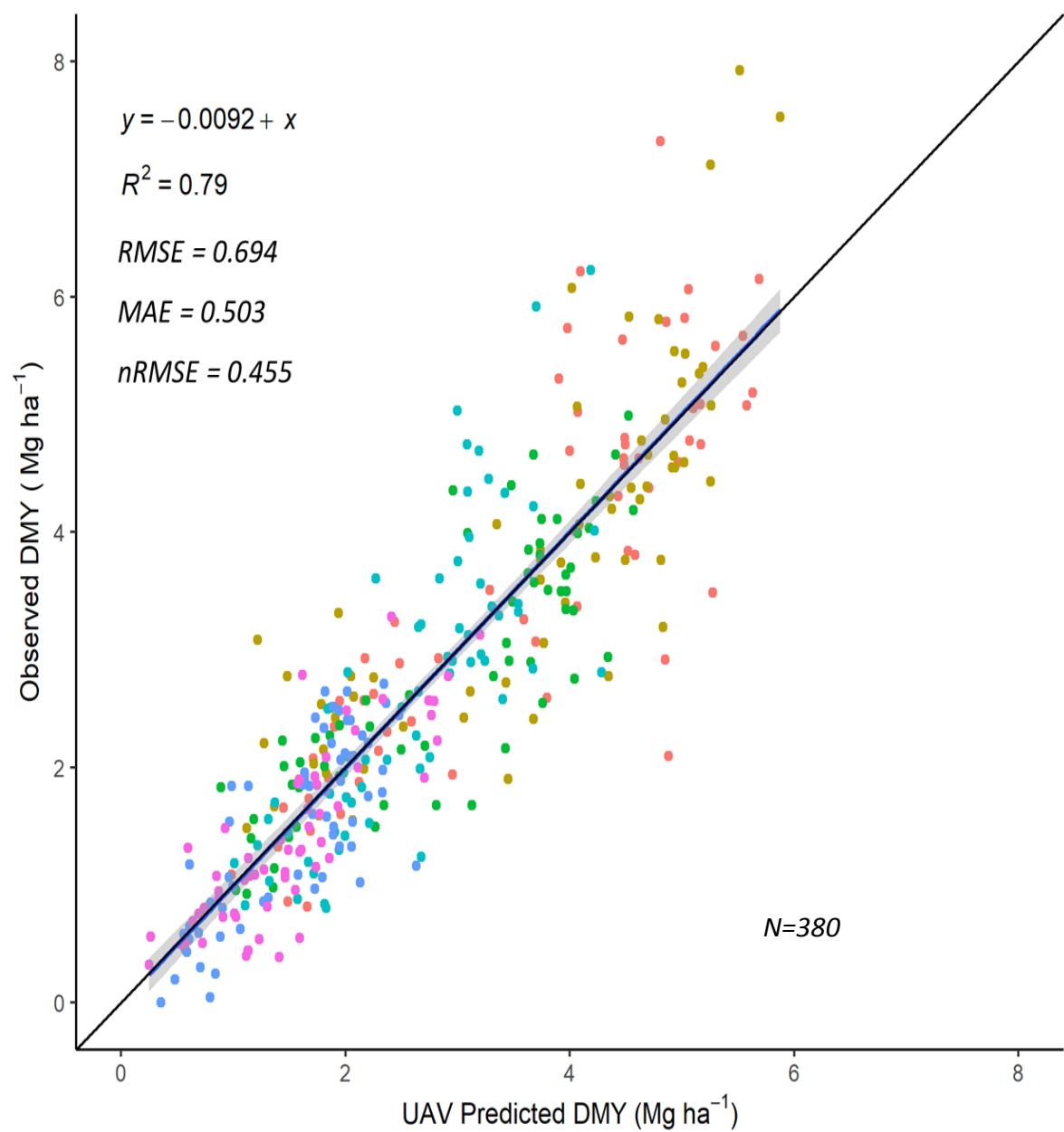
- Multispectral

Model
Area= 1 ft × 1 ft
n= 380



Source: Gull et. al., 2021





Model
Area= 1 ft × 1 ft
n= 380

- Multispectral

$$\text{Yield (Mg/ha)} = -35.772 - 0.660 * \text{ClGreen}$$

$$+ 8.188 * \text{ClRe} + 19.242 * \text{GLI} - 18.275 *$$

$$\text{GNDVI} + 58.159 * \text{LCI} - 4.921 * \text{MCARI}$$

$$- 115.297 * \text{NDRE} + 58.406 * \text{NDVI} -$$

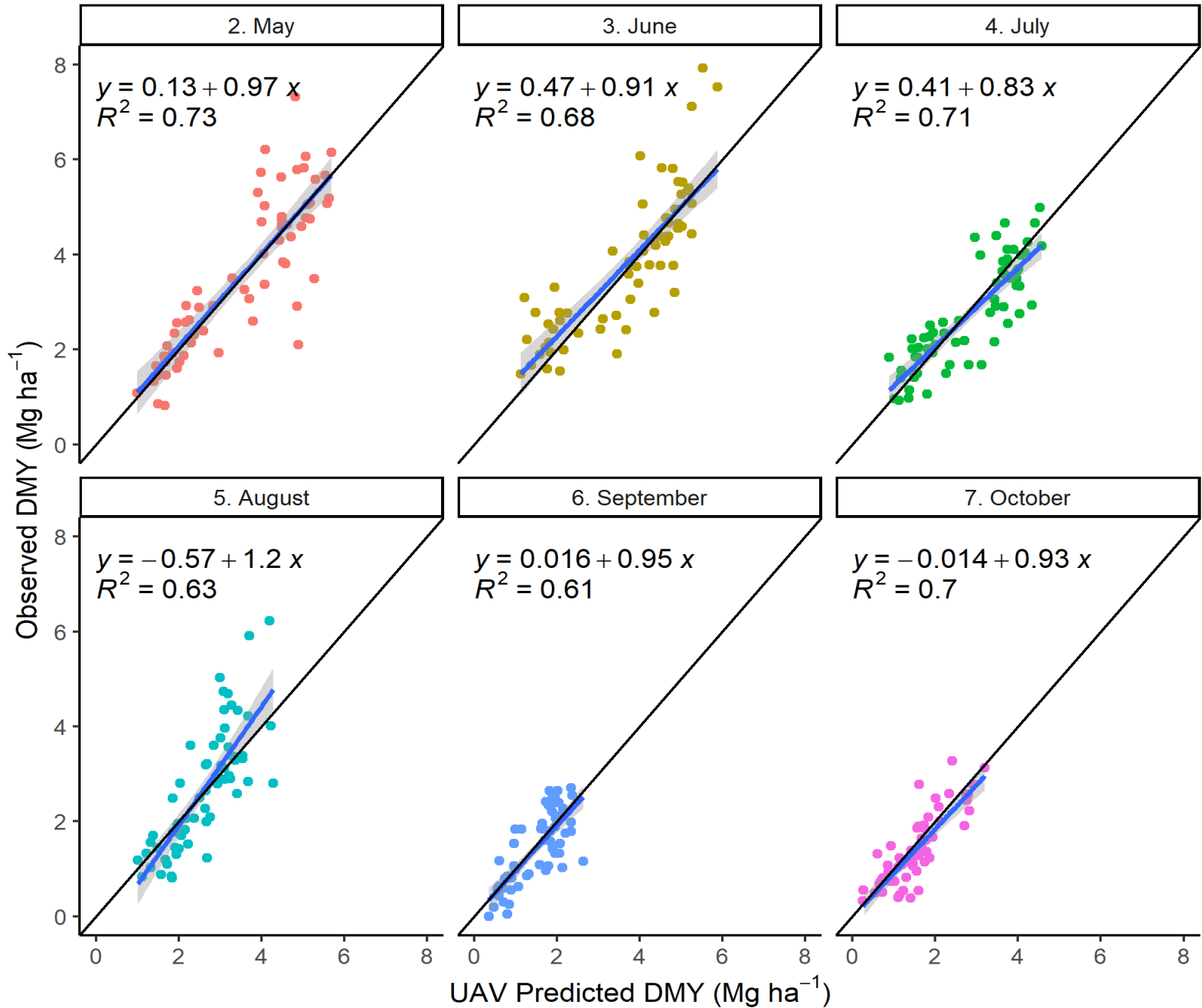
$$29.124 * \text{NGRDI} + 0.334 * \text{SR} + 0.118 * \text{TVI}$$

$$+ 5.942 * \text{PH}$$

MAY DELETE IT

Source: Gull et. al., 2021





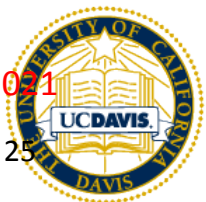
• Multispectral

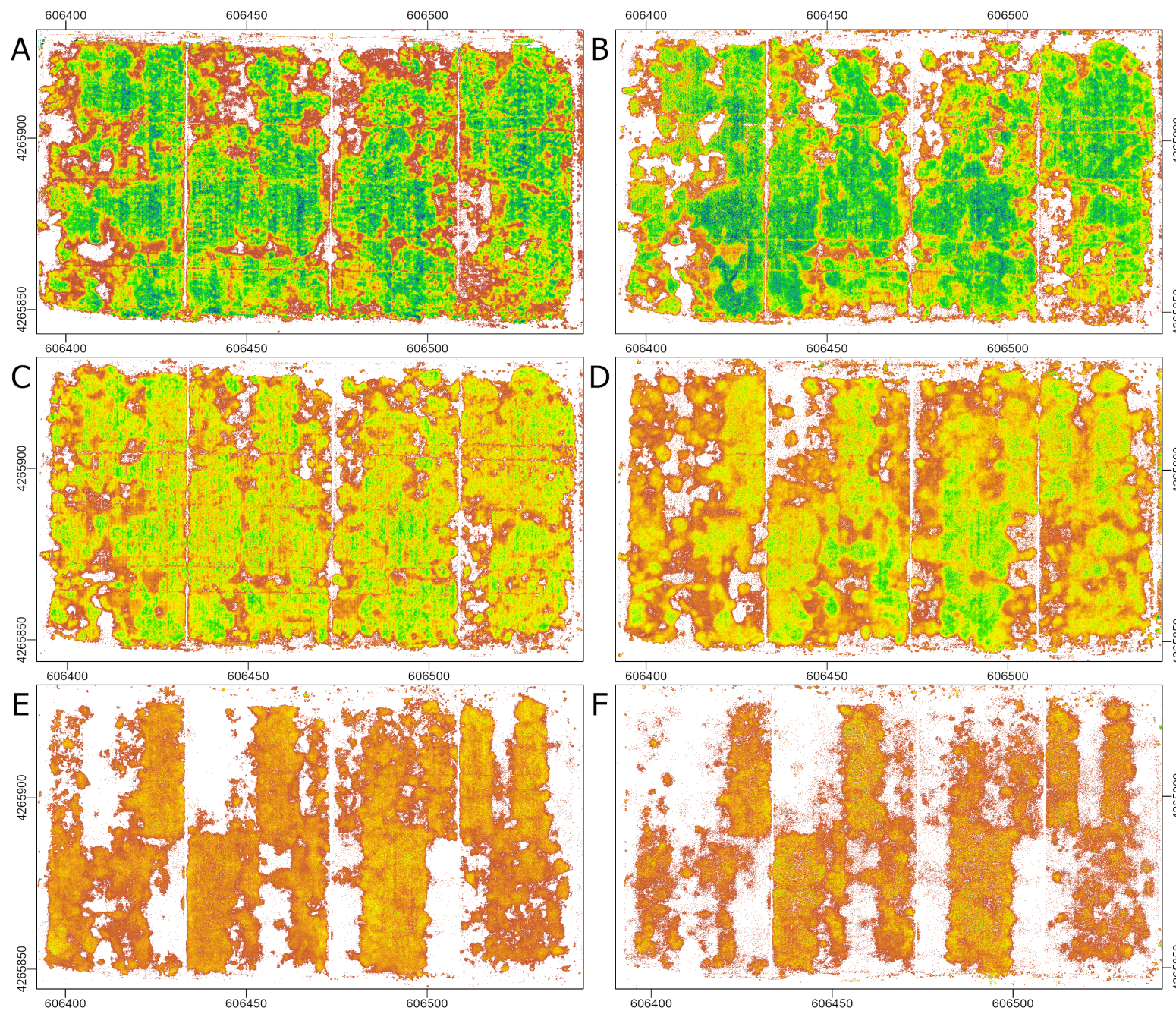
Harvests

- 2. May
- 3. June
- 4. July
- 5. August
- 6. September
- 7. October

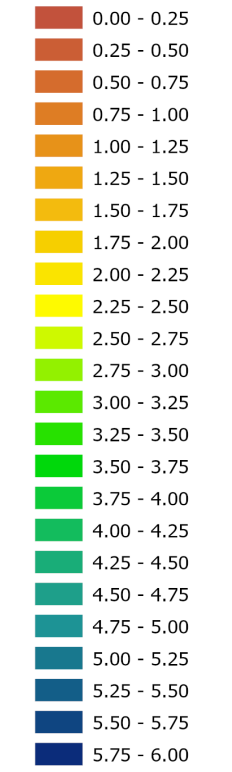
Model
 Area= 1 ft × 1 ft
 n= 380

Source: Gull et. al., 2021

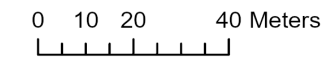




Yield Mg/ha



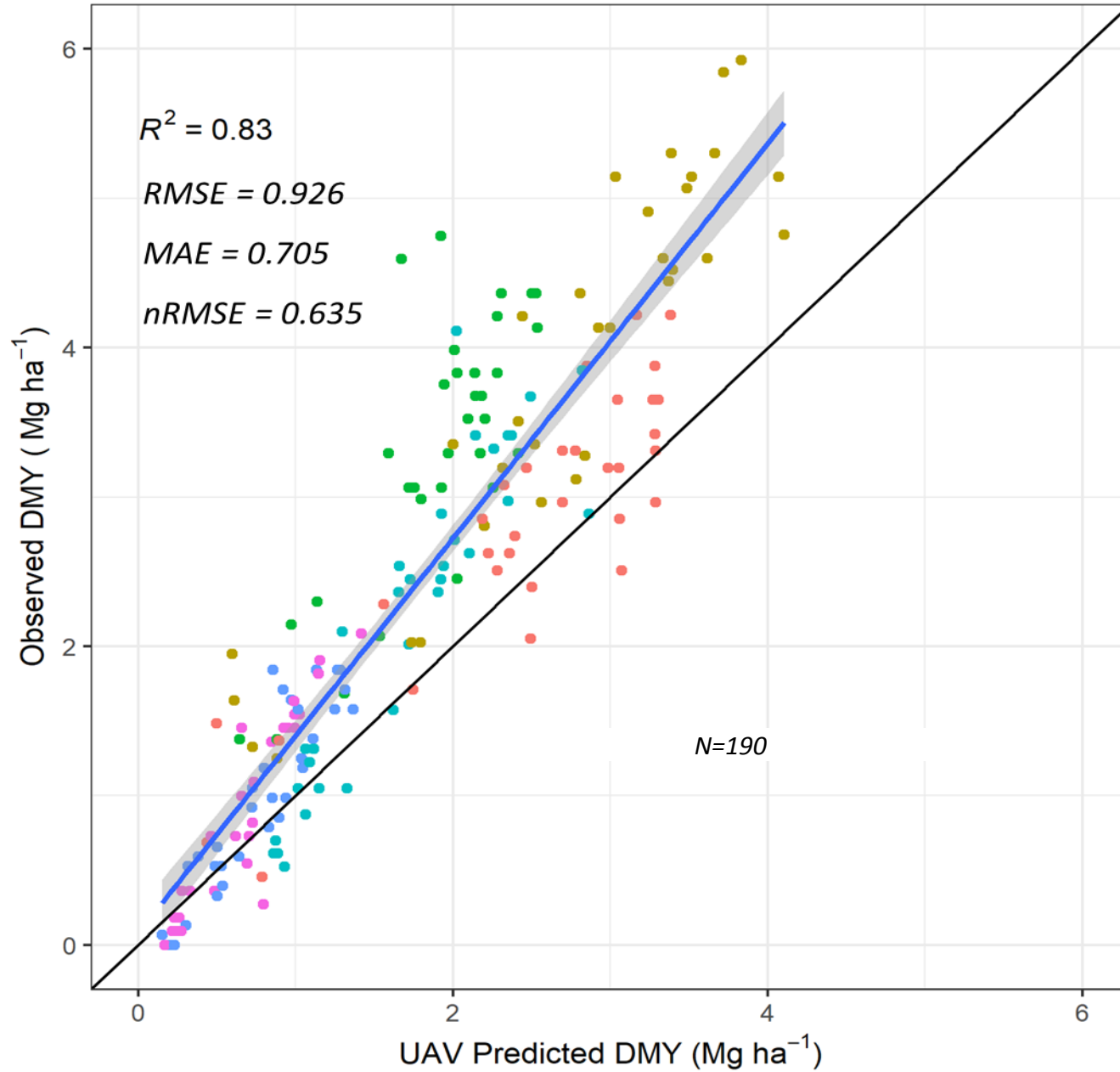
Source: Gull et. al., 2021



• Multispectral



Predicted vs. Observed DMY 2020



- Multispectral

Harvests

- 2. May
- 3. June
- 4. July
- 5. August
- 6. September
- 7. October

Predict Machine Harvest
Area= 4 ft × 30 ft
n= 190

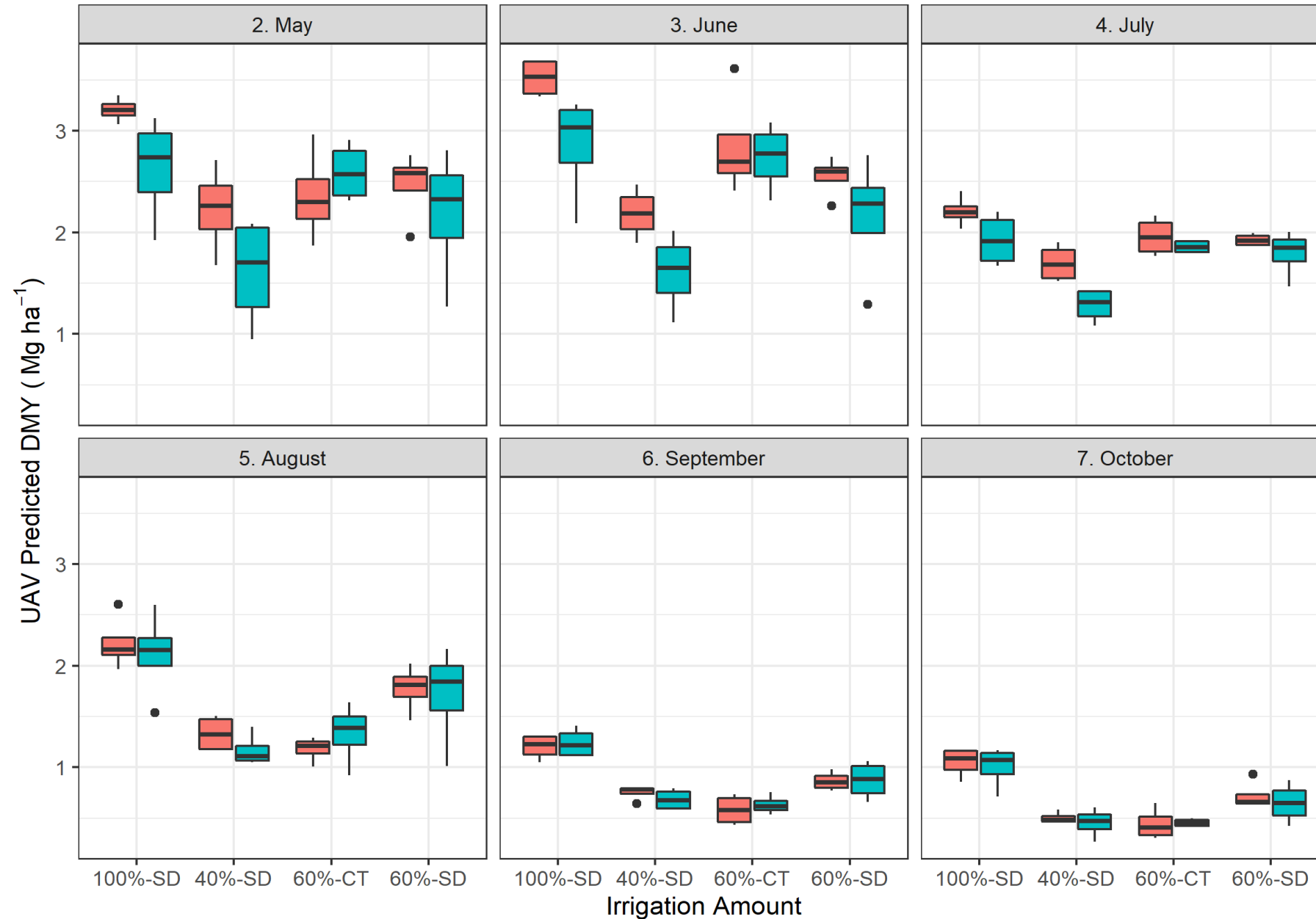
Source: Gull et. al., 2021



• Multispectral

Irrigation Amount under LESA & MDI

Source: Gull et. al., 2021



MainPlot

LESA

MDI

Predict Whole Plot

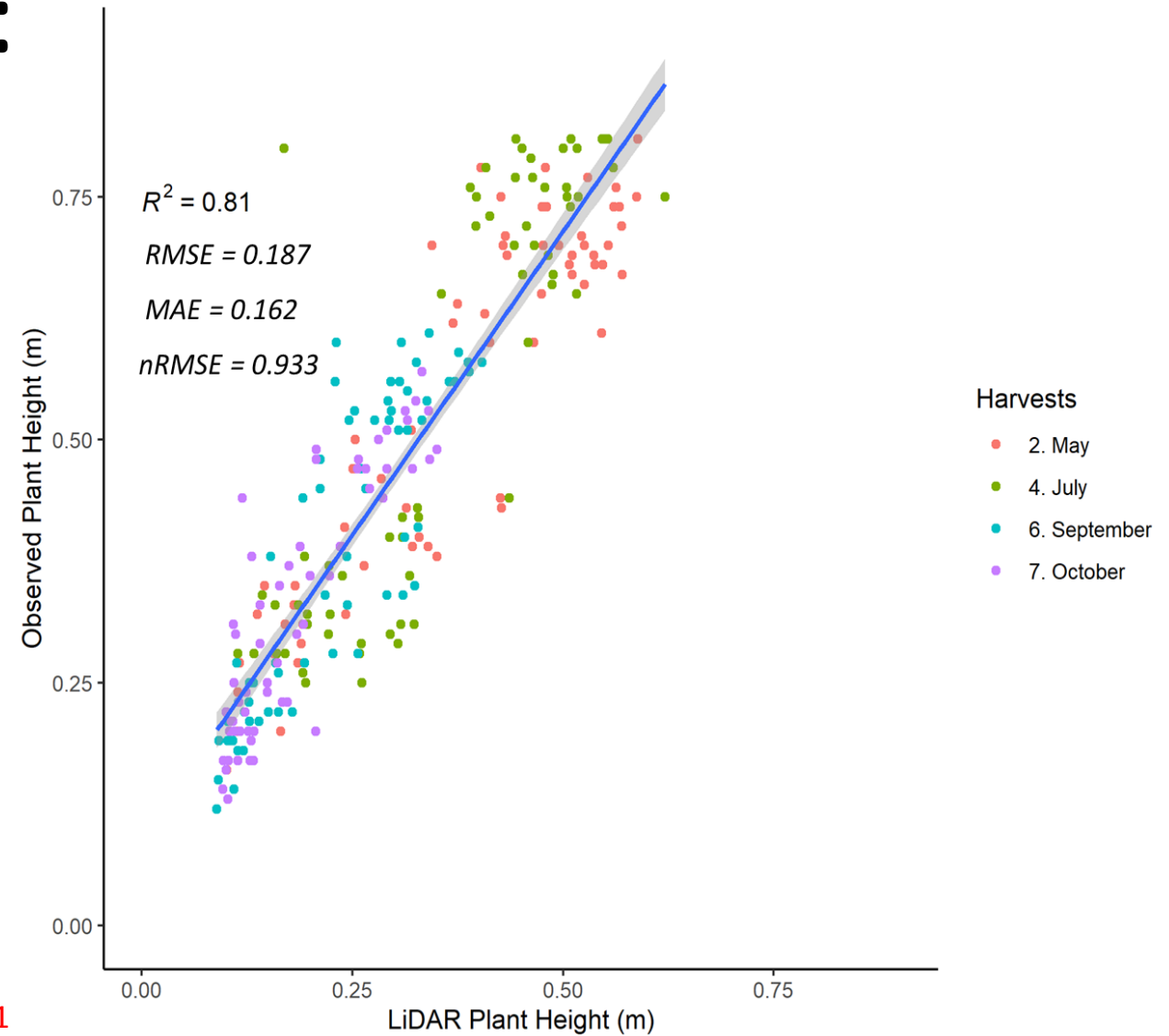
Area= 30 ft × 120 ft

n= 190

Results and Discussion:

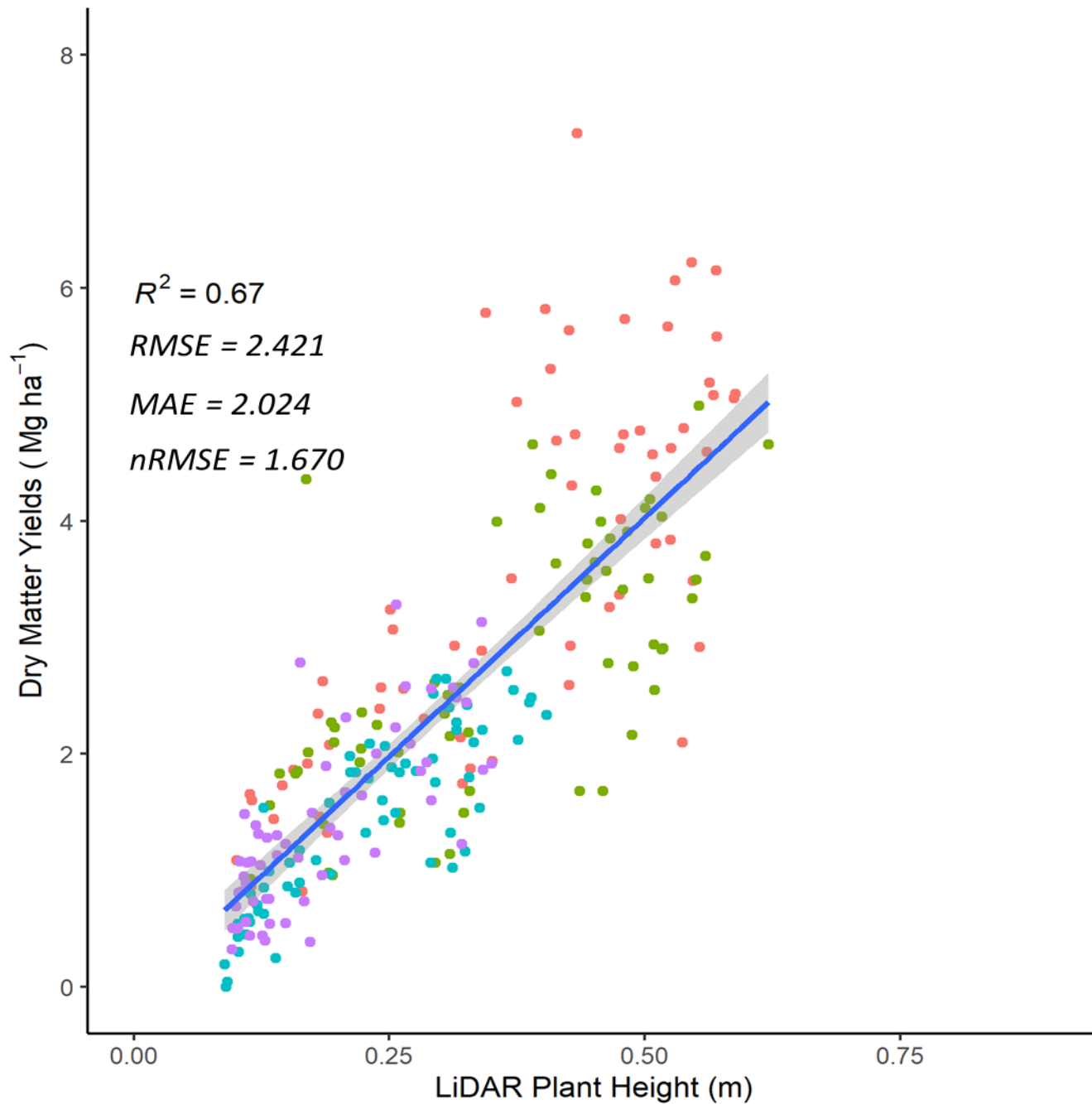
- LiDAR

Model
Area= 1 ft × 1 ft
n= 252



Source: Gull et. al., 2021





• LiDAR

- Harvests
- 2. May
 - 4. July
 - 6. September
 - 7. October

Source: Gull et. al., 2021

Model
 Area= 1 ft × 1 ft
 n= 252

Yield (Mg/ha) = $-0.071 + 8.198 * PH$



A- May

B- July

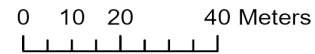
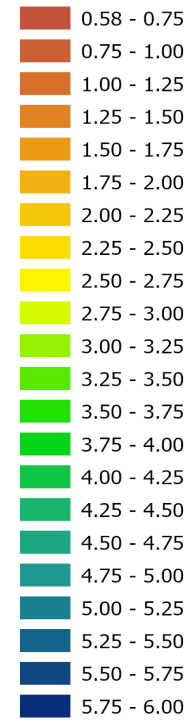
C- September

D- October

• LiDAR



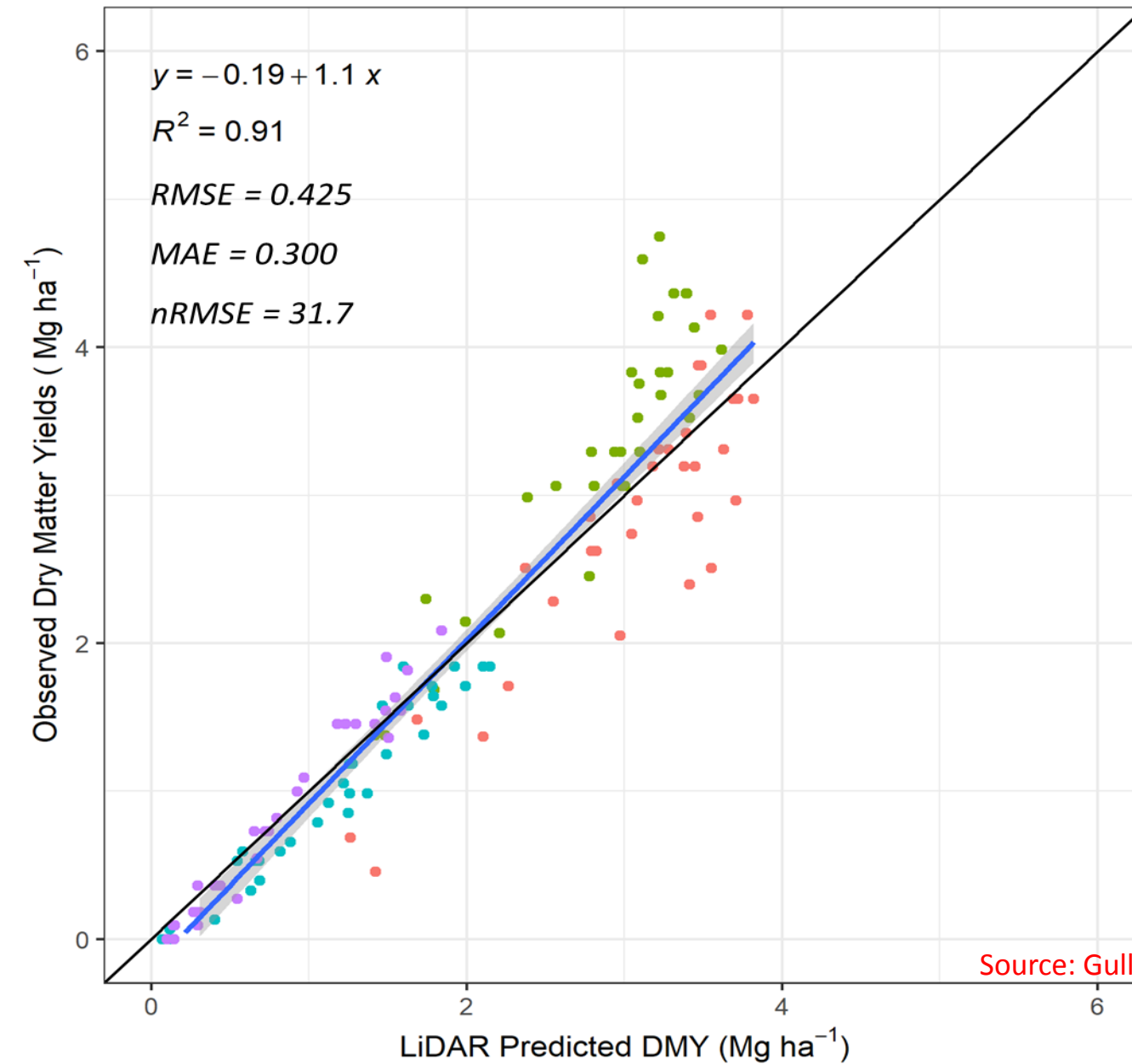
Yield Mg/ha



Source: Gull et. al., 2021



LiDAR Predicted vs. Observed DMY 2020



Source: Gull et. al., 2021

• LiDAR

Predict Machine Harvest

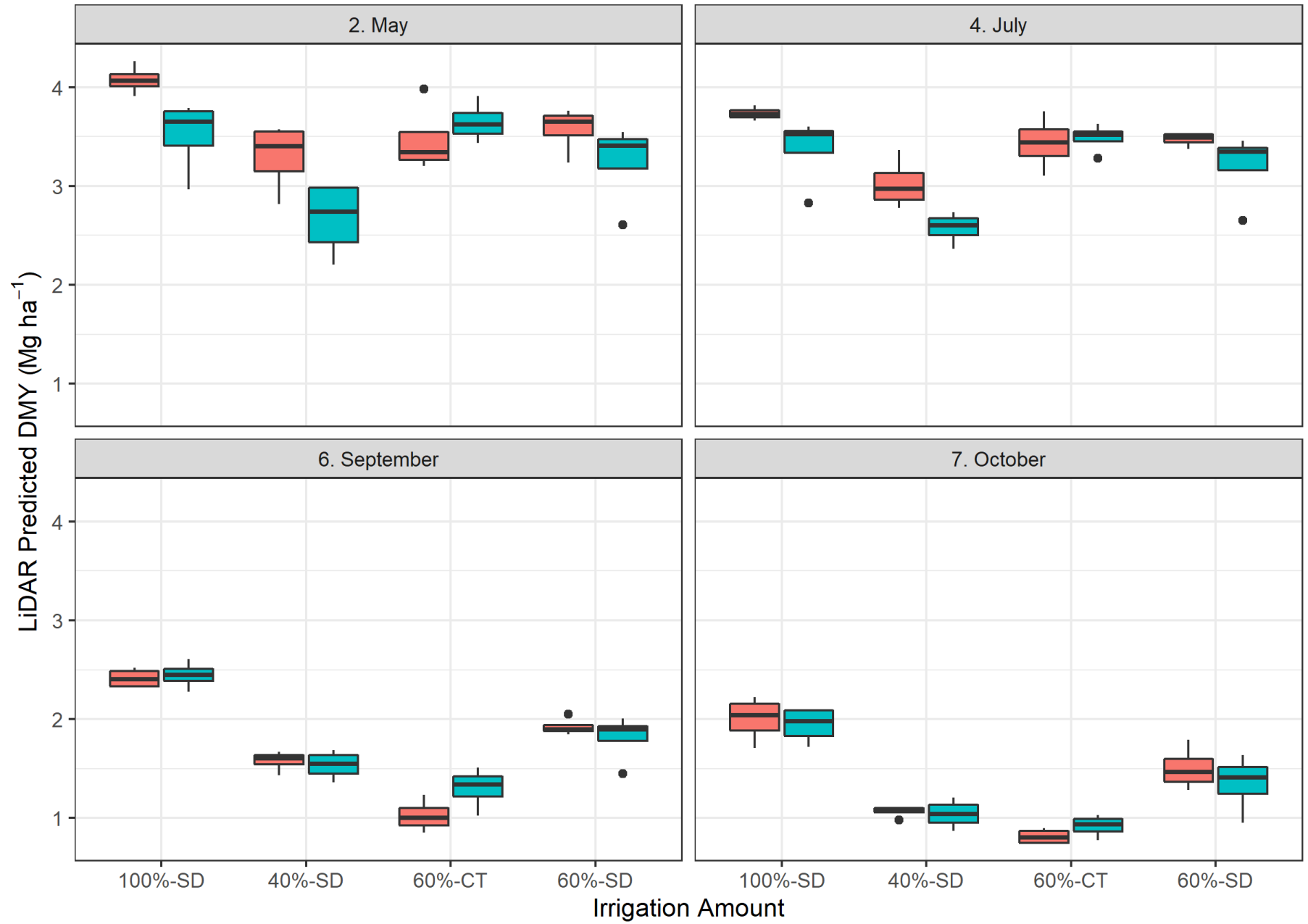
Area= 4 ft × 30 ft

n= 124



• LiDAR

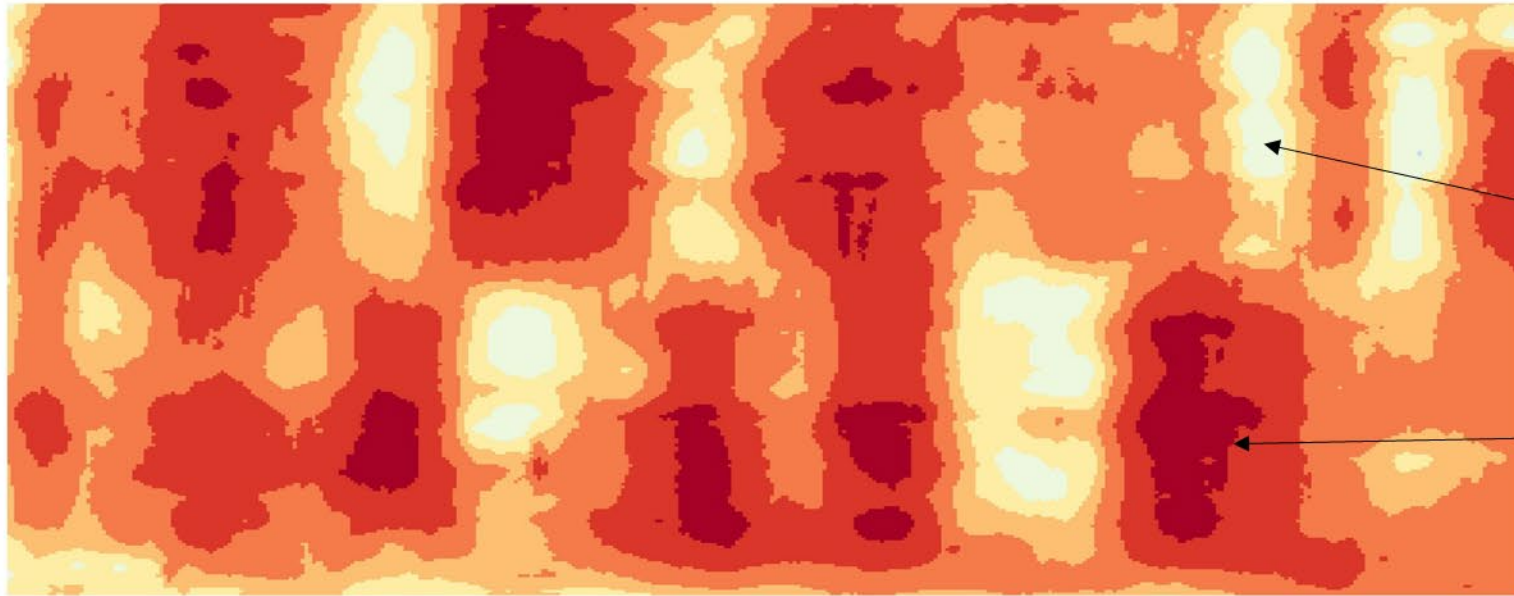
Irrigation Amount under LESA & MDI



Source: Gull et. al., 2021

Predict Whole Plot
Area= 30 ft × 120 ft
n= 190

Davis Alfalfa Soil Water Content

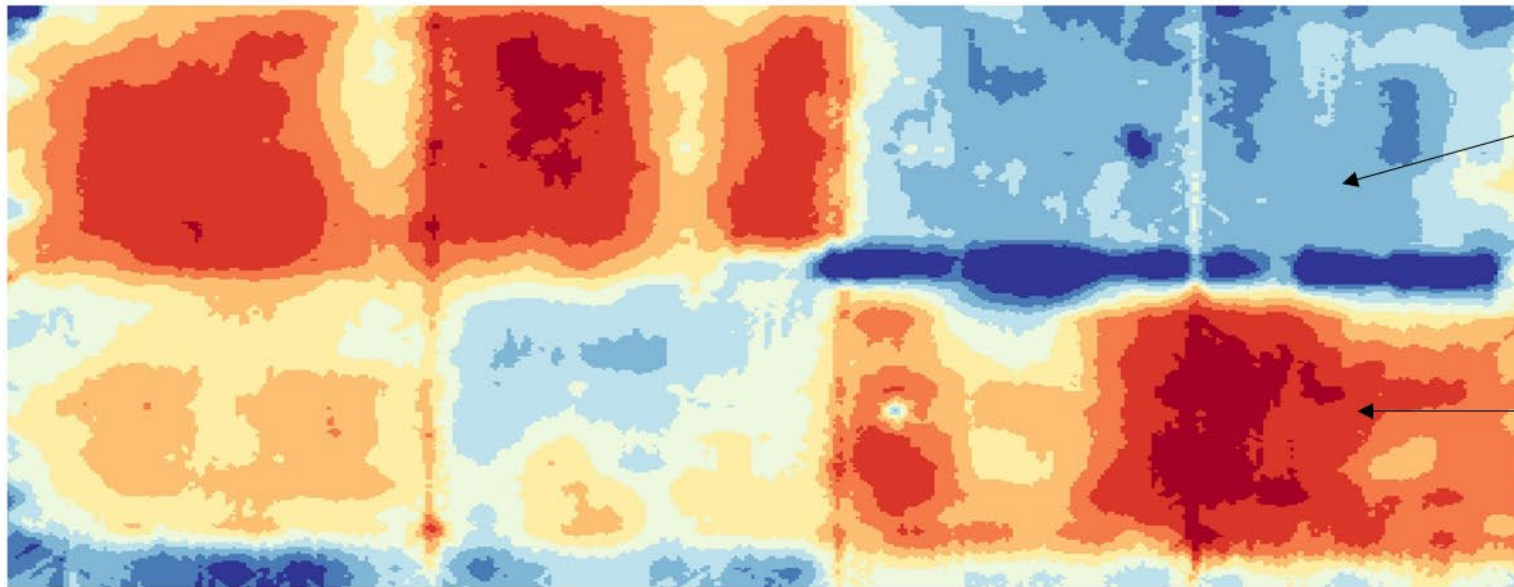
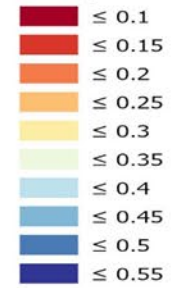


Full ET_c

September 2020

Deficit Plots

Soil Moisture
cm³/cm³



Winter Flooding

February 2021

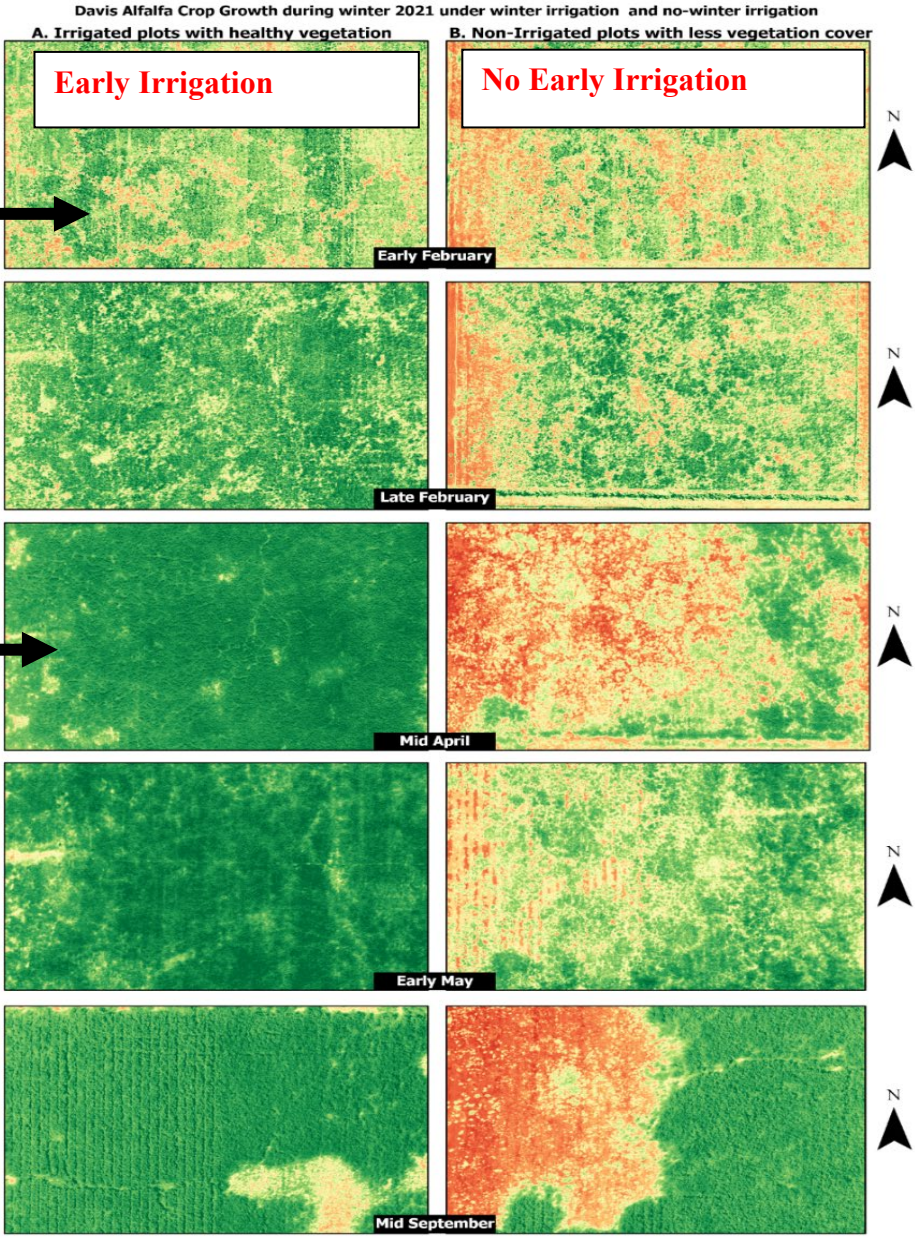
No-Winter Flooding



Importance of Early Irrigation:

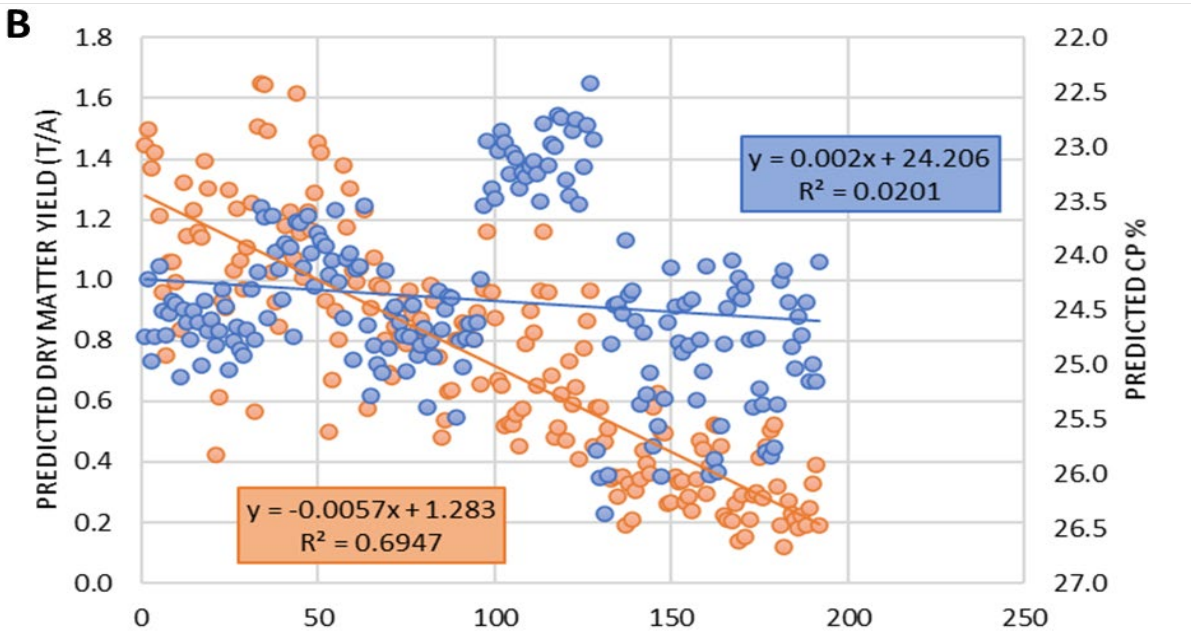
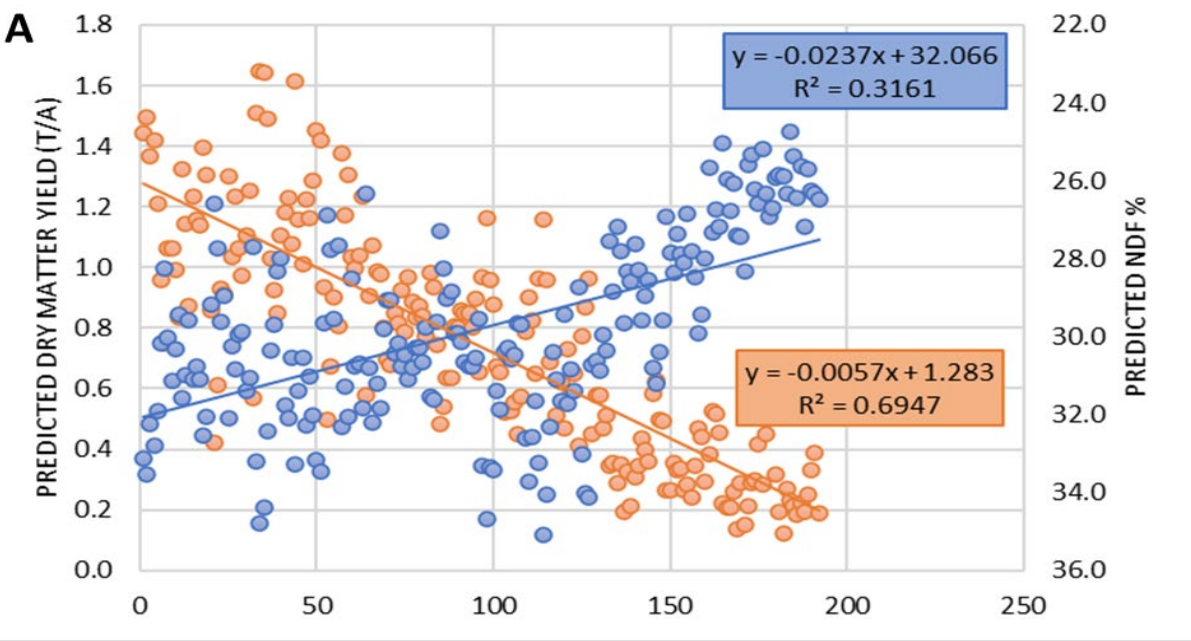
Irrigation:

Irrigation:



Forage Quality

- Multispectral



Source: Gull et. al., 2021



Conclusions:

- Both LEPA/LESA sprinklers and Mobile Drip Systems have the capability of improving WUE of alfalfa. MDI Improved subsoil infiltration.
- Deficits targeting 40% of ET_c resulted in yields 78-80% of full irrigation.
- Both multispectral cameras and LiDAR have the capability of spatially predicting alfalfa yield.
- Less accuracy in prediction of quality.
- Vigorous tested equations could predict yield effects over larger areas, taking into account sources of field variation
 - Traffic effects
 - Soil Variation
 - Imprecise irrigation techniques
 - Pest Impacts
- Utility: diagnosing problems, more vigorous yield evaluations of varieties in larger areas



Acknowledgments:



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Resources



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UCDAVIS

DEPARTMENT OF PLANT SCIENCES

College of Agricultural and Environmental Sciences



University of
AGRICULTURE
Faisalabad-Pakistan



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