AST 426 :Remote Sensing in Agriculture II

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Recap

Case Study of Satellite Remote Sensing

Test date		Models						
Year	**Month**	**Ridge**	**Lasso**	**RF**	**DFNN**	**RT**	**3D-CNN**	**YieldNet**
2016	July	23.12	21.03	22.48	22.16	29.41	18.84	**18.73**
	August	23.16	19.68	20.95	20.48	29.16	**15.25**	15.76
	September	24.53	20.6	21.23	21.04	29.31	16.55	**15.96**
	October	24.93	21.05	21.15	20.74	27.96	16.65	**15.85**
2017	July	30.55	27.53	26.61	26.40	33.64	22.50	**20.88**
	August	25.16	22.27	22.25	20.85	28.02	**16.60**	17.74
	September	24.15	21.5	21.99	19.21	26.8	15.71	**15.53**
	October	25.73	20.94	22.14	18.90	26.78	15.69	**15.40**
2018	July	27.51	21.21	22.38	22.85	27.69	**20.64**	22.08
	August	24.5	19.46	21.52	21.14	29.34	18.81	**18.25**
	September	25.1	18.69	21.7	20.57	28.91	17.58	**16.89**
	October	32.5	19.2	22.28	21.63	28.9	17.72	**16.75**
Average		25.91	21.10	22.22	21.33	28.83	17.71	**17.49**

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$$

Khaki, S., Pham, H., & Wang, L. (2021). Simultaneous corn and soybean yield prediction from remote sensing data using deep transfer learning. Scientific Reports, 11(1), 11132.

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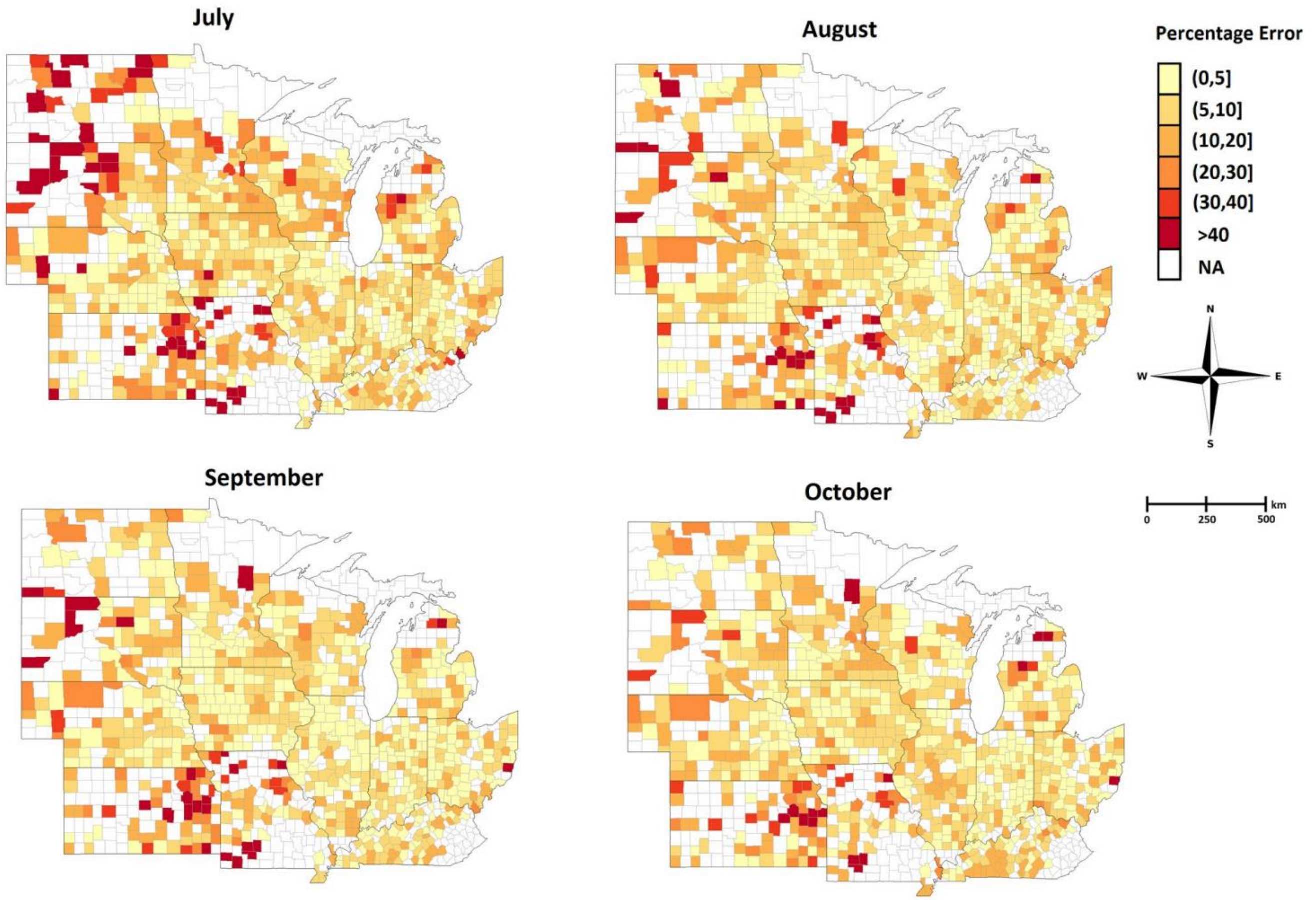
Case Study of Satellite Remote Sensing



The error percentage maps for the 2018 corn yield prediction

Khaki, S., Pham, H., & Wang, L. (2021). Simultaneous corn and soybean yield prediction from remote sensing data using deep transfer learning. Scientific Reports, 11(1), 11132.

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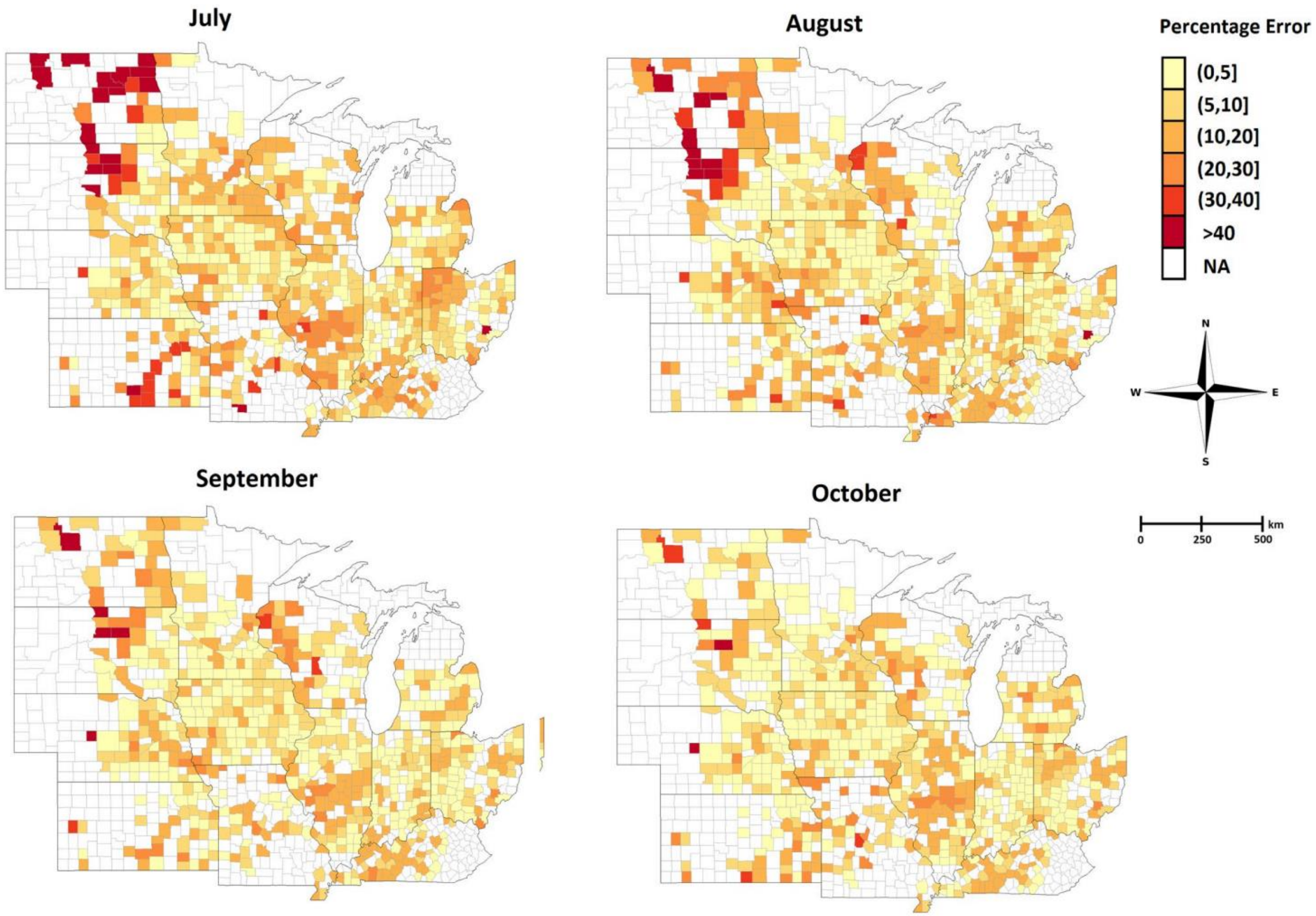

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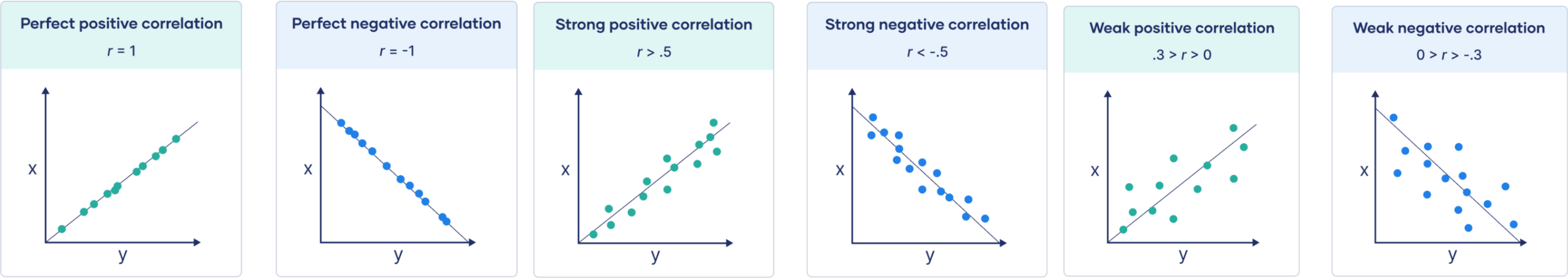
What is the Pearson correlation coefficient? (r)

- The Pearson correlation coefficient (r) is the most widely used correlation coefficient
- Is a descriptive statistic, meaning that it summarizes the characteristics of a dataset
- It describes the **strength and direction** of the **linear relationship between two quantitative variables**.



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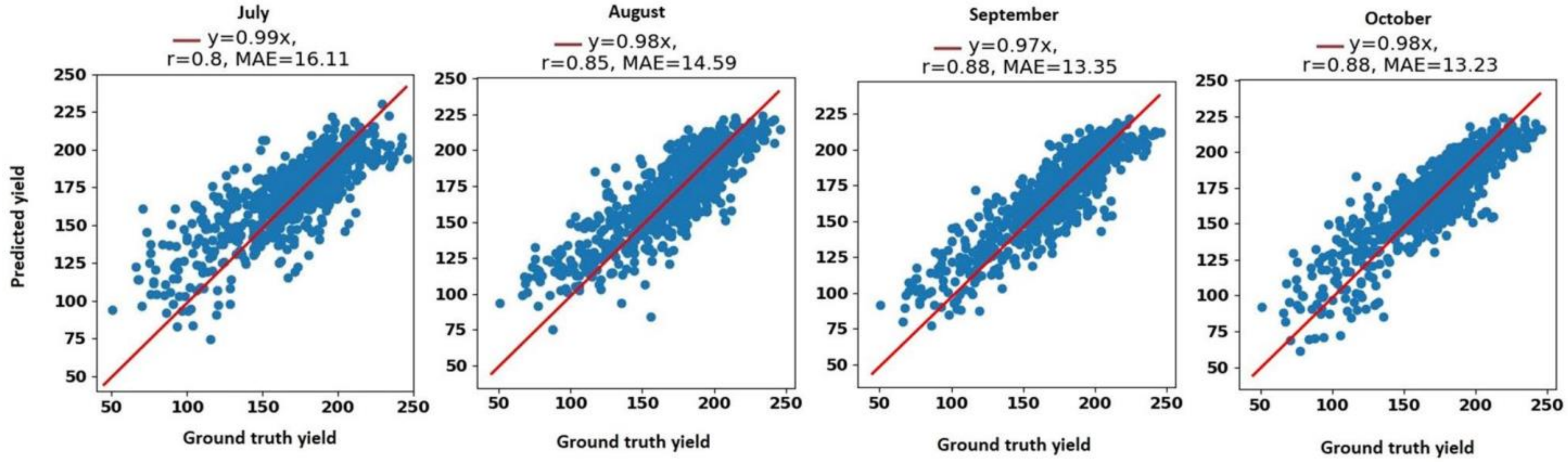

The scatter plots for the 2018 corn yield prediction

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n}$$

MAE = mean absolute error
y_i = prediction
x_i = true value
n = total number of data points

- MAE tells you the **average size of the mistakes your model is making**. It's straightforward and **doesn't give extra weight to larger errors like RMSE** does.

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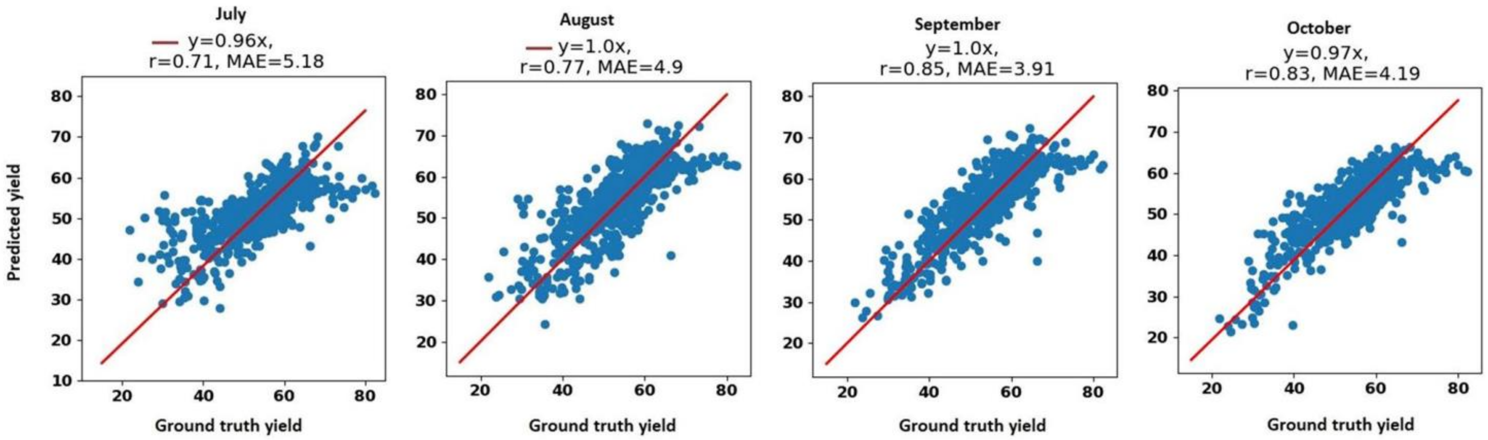

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UAV/Drone Remote Sensing

- **UAVs (Unmanned Aerial Vehicles)** are aircraft systems that fly without an onboard human pilot. They are commonly referred to as **drones**.
- UAVs provide high-resolution, real-time data collection for precision agriculture, allowing farmers to optimize inputs such as water, fertilizers, and pesticides.
- They enable the detection of crop health issues, soil conditions, and water stress much faster than traditional methods.

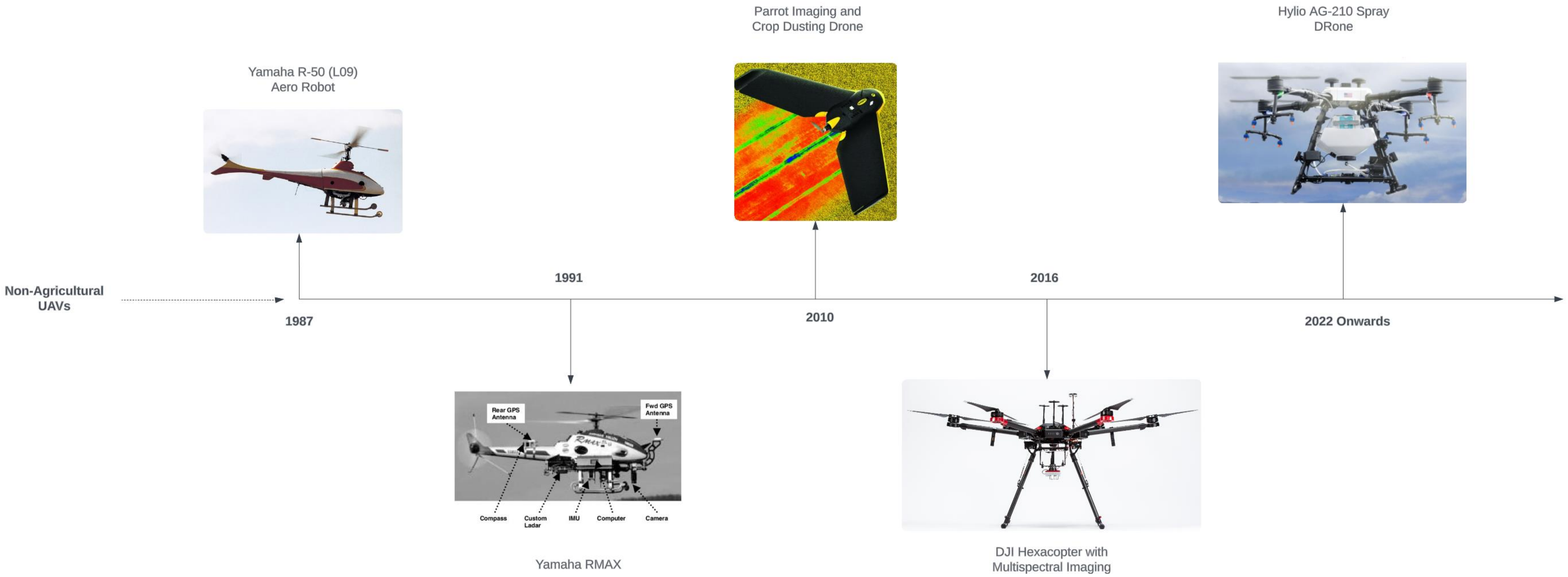
Shi, Y., Thomasson, J. A., Murray, S. C., Pugh, N. A., Rooney, W. L., Shafian, S., ... & Yang, C. (2016). Unmanned aerial vehicles for high-throughput phenotyping and agronomic research. PloS one, 11(7), e0159781.

UAV/Drone Remote Sensing

- Originally developed for **military purposes**, UAVs began to be used for civilian applications like **agriculture** in the the **early 2000s**.
- Introduction of UAVs with RGB cameras for basic visual inspections in early 2010s.
- Development of multispectral and hyperspectral sensors on UAVs, allowing for more detailed vegetation index calculations (e.g., NDVI) in mid 2010s.

https://www.thedroneu.com/blog/history-of-drones-in-agriculture/

Evolution of Agricultural Drone



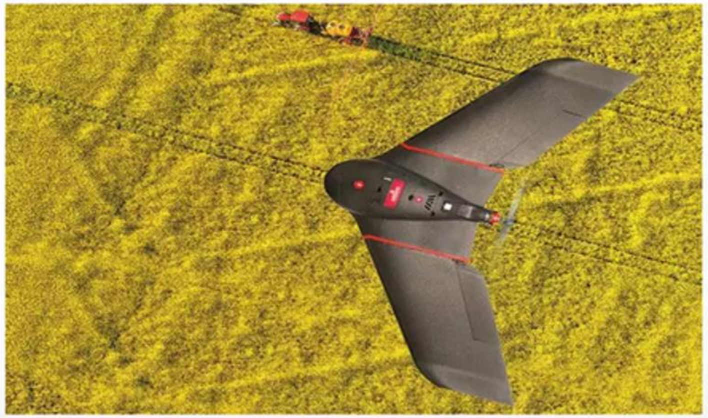
Types of UAVs :Based on form, features and functions

1. Fixed wing drone

- Have two wing design as like aero plane.
- Operate up to the speed of 50km/hr.
- Larger field mapping.
- Transport heavier loads over long distance.
- They cannot takeoff vertically.

2. Single rotor drone

- Have only one rotor.
- Can takeoff and land vertically.
- More efficient than multi rotor drones.
- Used for spraying of agrochemicals.



https://www.slideshare.net/slideshow/use-of-drones-in-agriculturepdf/251696595

Types of UAVs: Based on form, features and functions

3. Multi rotor drone

- ➢Have four rotors or Eight rotors.
- ➢Life time only of 10 to 20 minutes.
- ➢Take off and land vertically.
- ➢Record pictures and transport light cargo.
- ➢Mostly used for spraying of agrochemicals.

4. Hybrid drone

- ➢Equipped with both wings and rotors.
- ➢Can takeoff and land vertically.
- ➢Cover far longer distances.
- ➢carry heavier cargo than multi-rotor drones.

5. Ducted fan drone

- ➢Can take off and land vertically.

Types of UAVs: Based on Maximum Takeoff Weight

1. **Nano:** Less than or equal to 250 grams. (~ 0.55 lb.)
2. **Micro:** Greater than 250 grams and less than or equal to 2 kg. (~ 4.41 lb.)
3. **Small:** Greater than 2 kg and less than or equal to 25 Kg. (~ 55 lb.)
4. **Medium:** Greater than 25 kg and less than or equal to 150 kg. (~ 331 lb.)
5. **Large:** Greater than 150 kg. (> 331 lb.)

Components of UAVs

1. **Sensors**
   i. RGB camera
   ii. Multispectral camera
   iii. Hyperspectral camera
   iv. Thermal camera
   v. LiDAR (Light Detection and Ranging,)
2. **Mechanical**
   i. Frame
   ii. Takeoff and Landing Gears
3. **Electrical**
   i. Motors
   ii. GPS
   iii. Communication System
   iv. Onboard computers
   v. Flight controller

4. **Payloads**
   i. Seeds
   ii. Spray chemicals iii. Sensors




UAV Image Processing

- UAVs collect **large volumes of data that need to be processed** using software for generating maps like NDVI, canopy cover, and yield predictions.
- The process of capturing, analyzing, and **extracting useful information from images** collected by drones (UAVs).
- Use of **AI** and **machine learning** to interpret sensor data and provide actionable insights
- It **provides insights from aerial views** for **decision-making**, improves accuracy, **saves labor**, and **enables real-time monitoring**.

Workflow of Drone Image Processing

1. **Image Capture** : RGB, Multispectral, Hyperspectral, Thermal
2. **Image Preprocessing** : Correcting distortions, georeferencing, aligning images
3. **Image Data Analysis** : Using techniques like **NDVI**, **classification**, or **3D modeling**
4. **Output**: **Maps**, **models**, and **actionable insights**

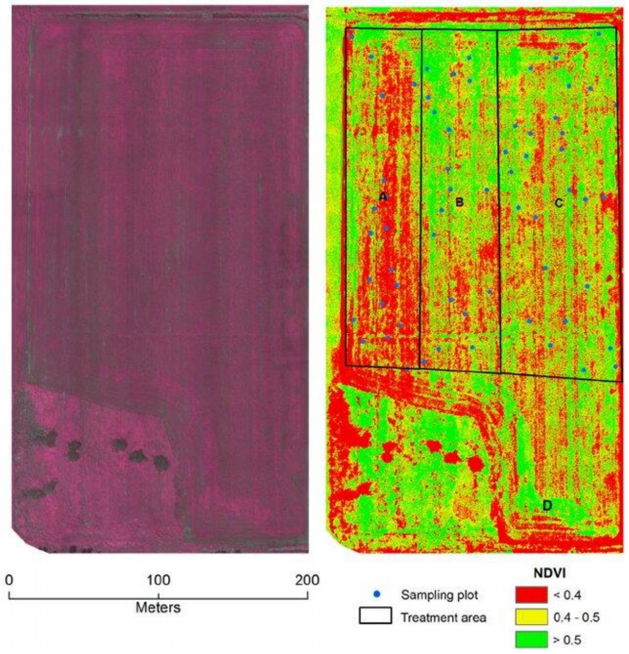
Image Processing Techniques

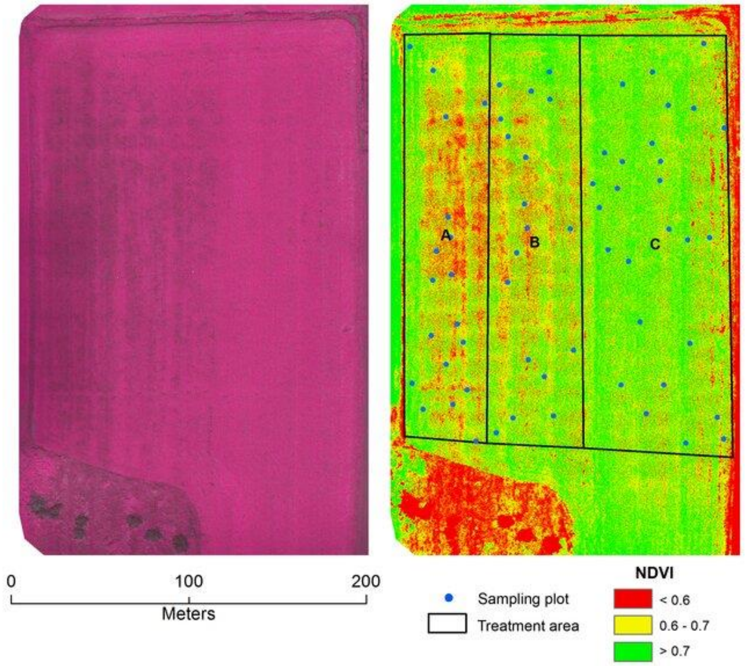
1. **Orthomosaic Generation**
   - Stitching together multiple overlapping images to create a georeferenced map

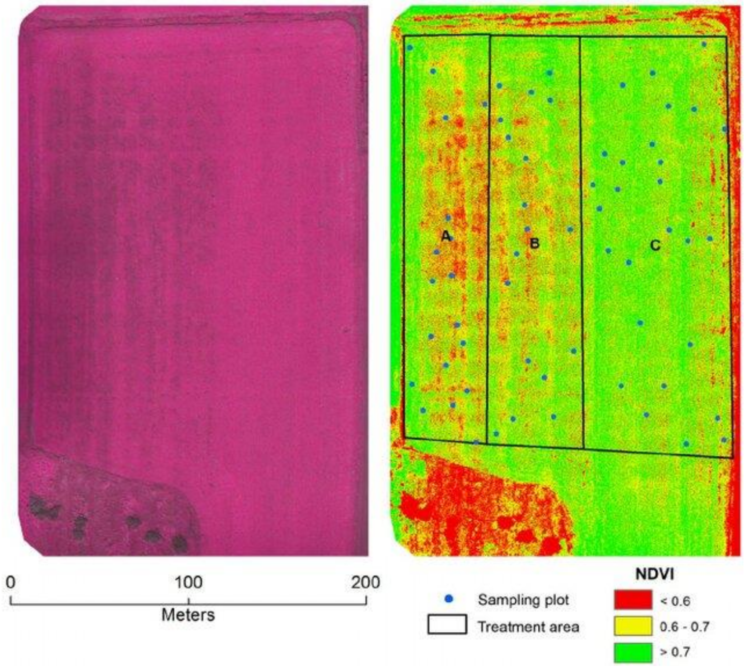
   - Commonly used software for Orthomosaic generation are: **Pix4DMapper**, **Agisoft Metashape**, **DroneDeploy**, **OpenDroneMap**, **ArcGIS Drone2Map**, etc.

Image Processing Techniques

2. Index Maps such as NDVI (Normalized Difference Vegetation Index)

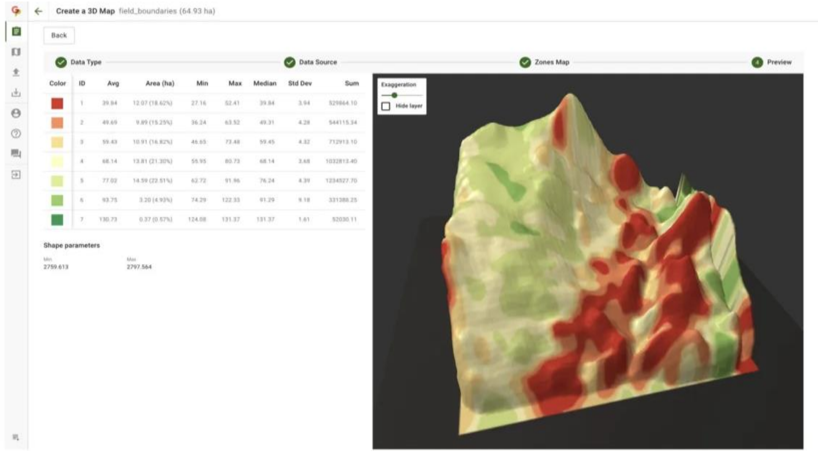


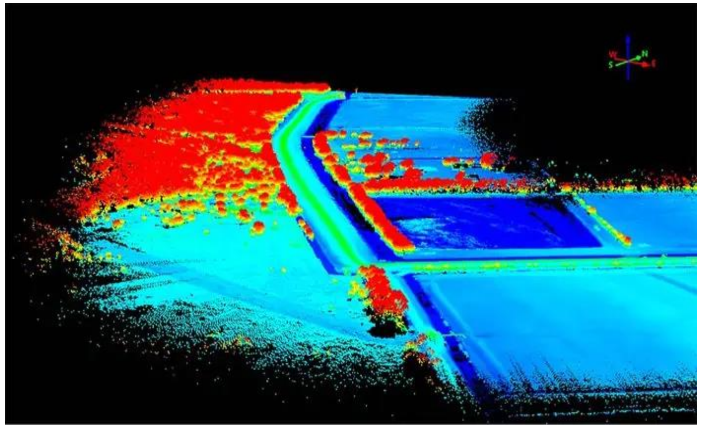


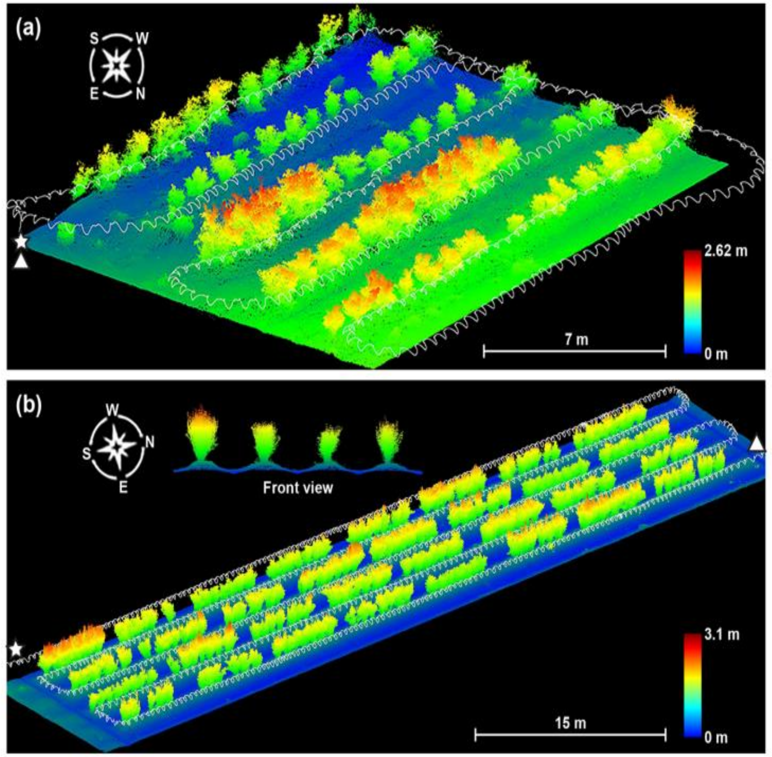


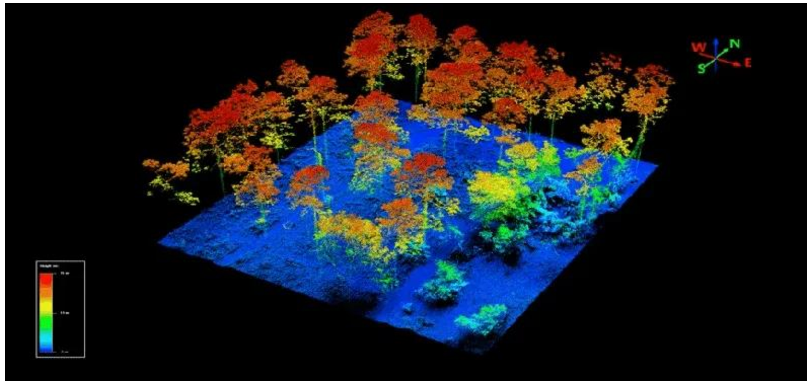
https://www.researchgate.net/publication/268197180_Applications_of_Low_Altitude_Remote_Sensing_in_Agriculture_upon_Farmers%27_Requests-_A_Case_Study_in_Northeastern_Ontario_Canada/figures?lo=1

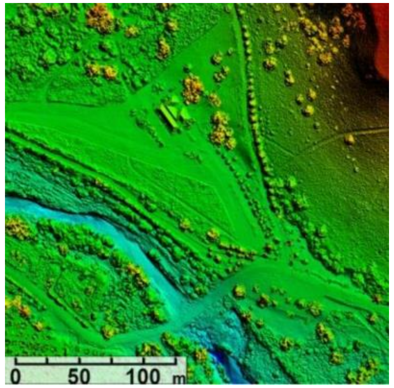
3. 3D Mapping and Modeling











[UAV LiDAR Services | FlyGuys (youtube.com)]

[GeoPard Agriculture - 3d model of a field rendered in a browser (youtube.com)]

Jiang, Y., Li, C., Takeda, F., Kramer, E. A., Ashrafi, H., & Hunter, J. (2019). 3D point cloud data to quantitatively characterize size and shape of shrub crops. Horticulture research, 6.

Image Processing Techniques

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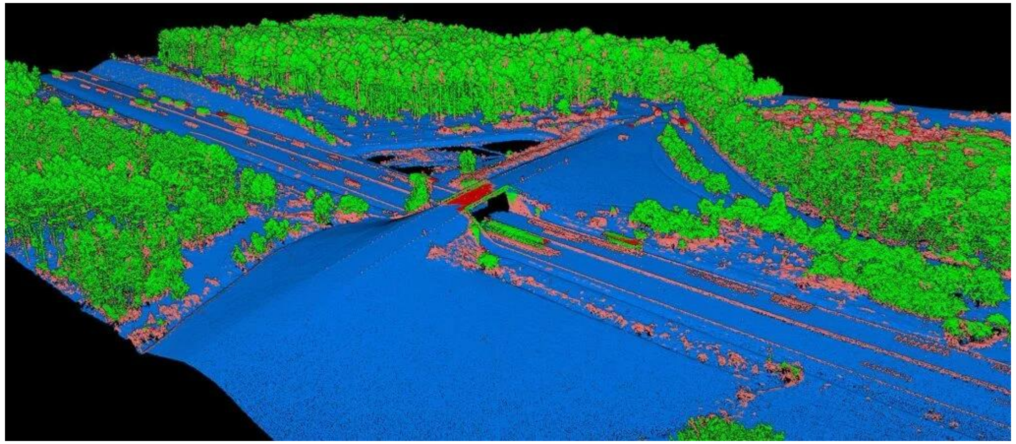
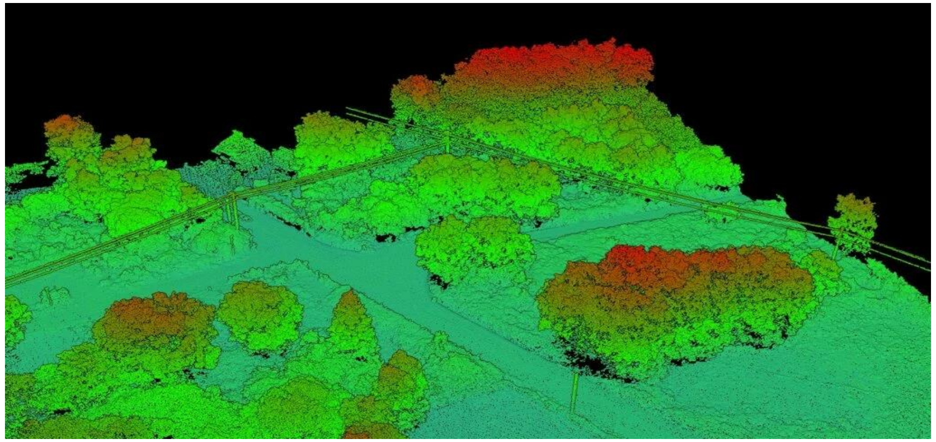
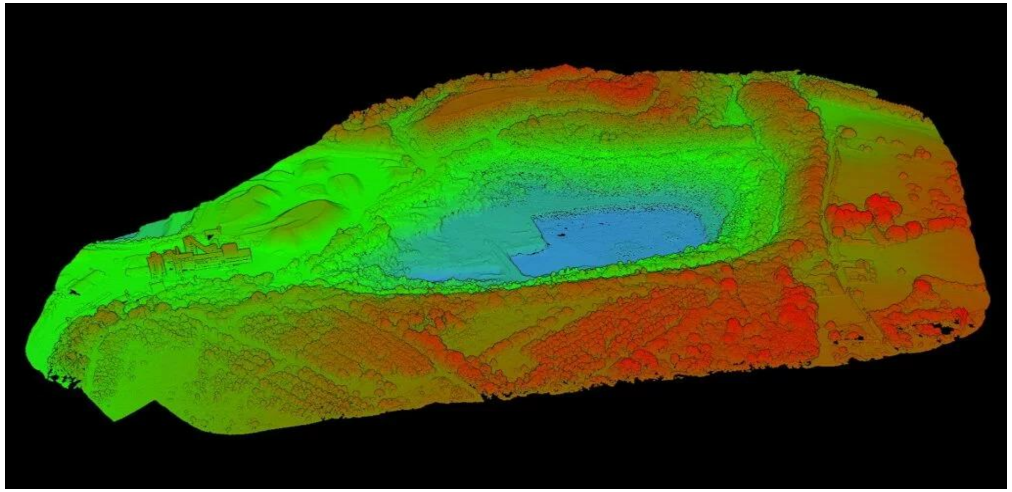






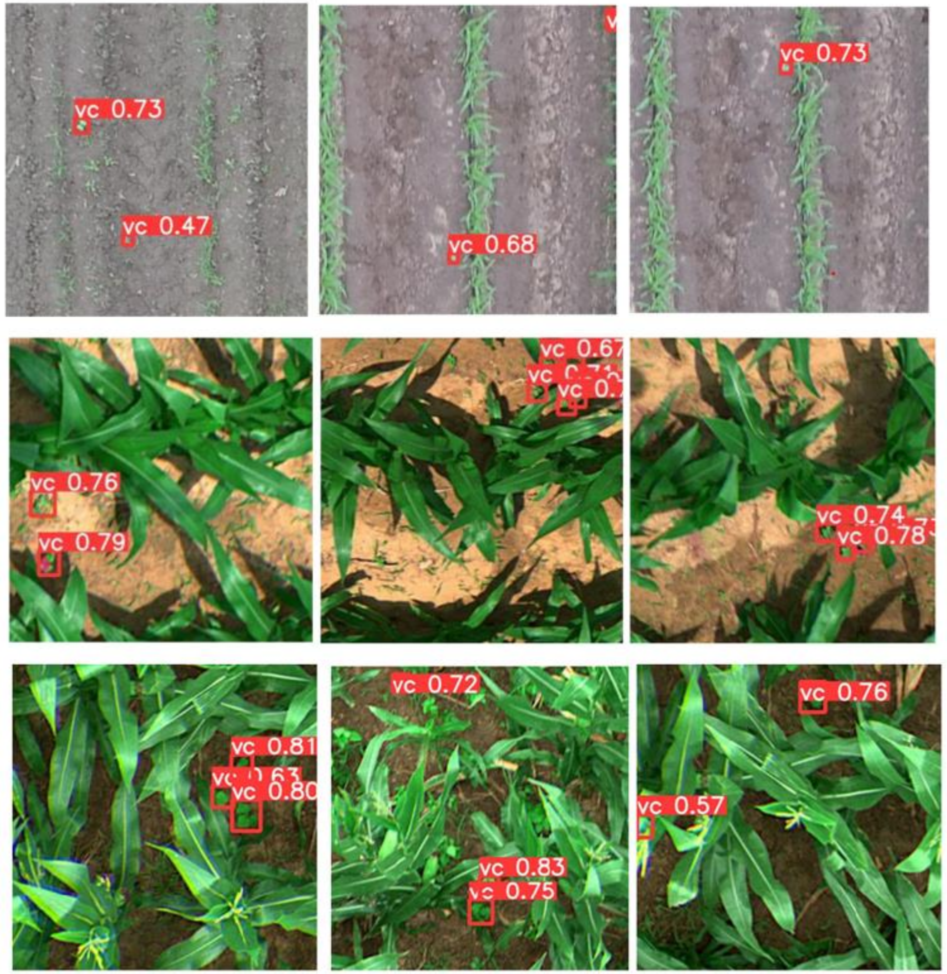
[Point Cloud Tour of Corn Field in Early September (youtube.com)]

https://lidarvisor.com/

[Riding School :30 (youtube.com)]

Machine Learning and AI Techniques

Detecting and classifying specific crops



Yadav, P. K., Thomasson, J. A., Searcy, S. W., Hardin, R. G., Braga-Neto, U., Popescu, S. C., ... & Wang, T. (2022). Assessing the performance of YOLOv5 algorithm for detecting volunteer cotton plants in corn fields at three different growth stages. Artificial intelligence in agriculture, 6, 292-303.

Next Lecture

Guest Lecture by **Skye Brugler, SDSU**