

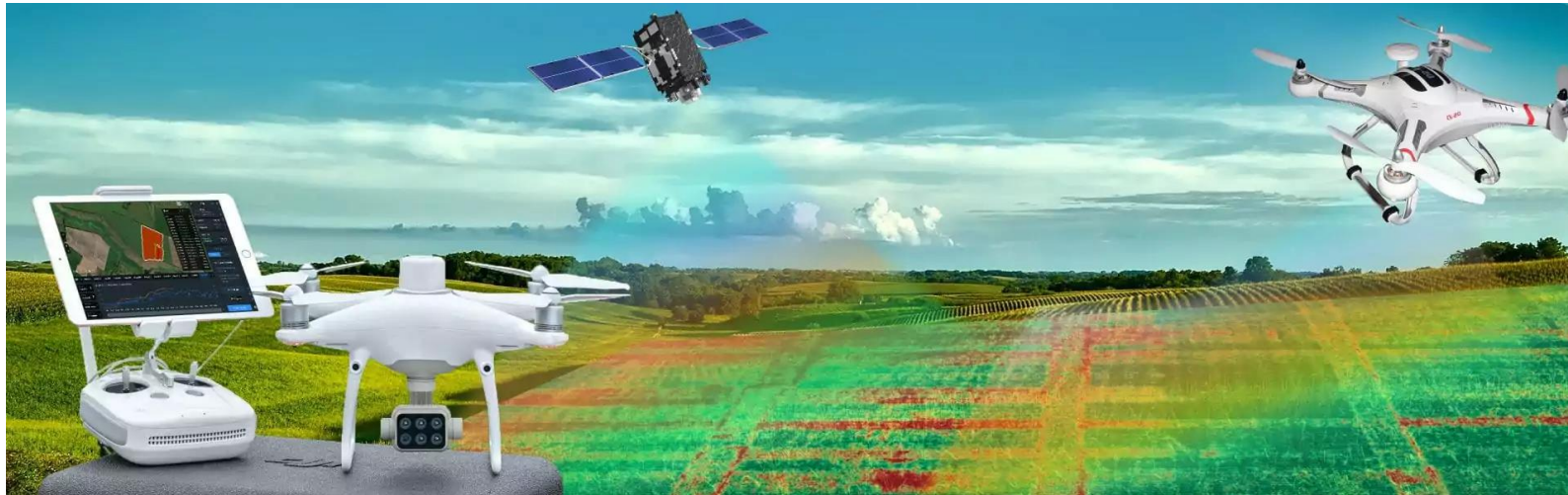
# AST 426 :Remote Sensing in Agriculture I

Instructor: **Pappu Kumar Yadav, Ph.D.**  
Department of Agricultural & Biosystems Engineering  
Machine Vision & Optical Sensors Laboratory  
South Dakota State University  
Fall 2024



# Remote Sensing

- Remote sensing is the acquisition of information about an object or phenomenon **without physical contact**, typically via **satellite** or **airborne sensors/drone-mounted sensors**
- Provides real-time, large-scale data on crop health, soil conditions, and climate factors
- Key to **precision agriculture**, enabling more efficient resource management



<https://eos.com/blog/drones-vs-satellites/>

# History of Aerial Photography

- First known aerial photograph was taken in **1858** by French photographer and balloonist, **Gaspar Felix Tournachon**, known as "**Nadar**"



(left) Nadar "elevating photography to the condition of art", caricature by Honoré Daunier. Published in Le Boulevard 25th May, 1862.



(center) Nadar's earliest surviving aerial image, taken above Paris in 1866.



(right) Boston from a tethered balloon, 13th October, 1860, by James Wallace Black.

History of Aerial Photography - Professional Aerial Photographers Association Intl ([clubexpress.com](http://clubexpress.com))

# History of Aerial Photography

## Kites, Pigeons and Rockets



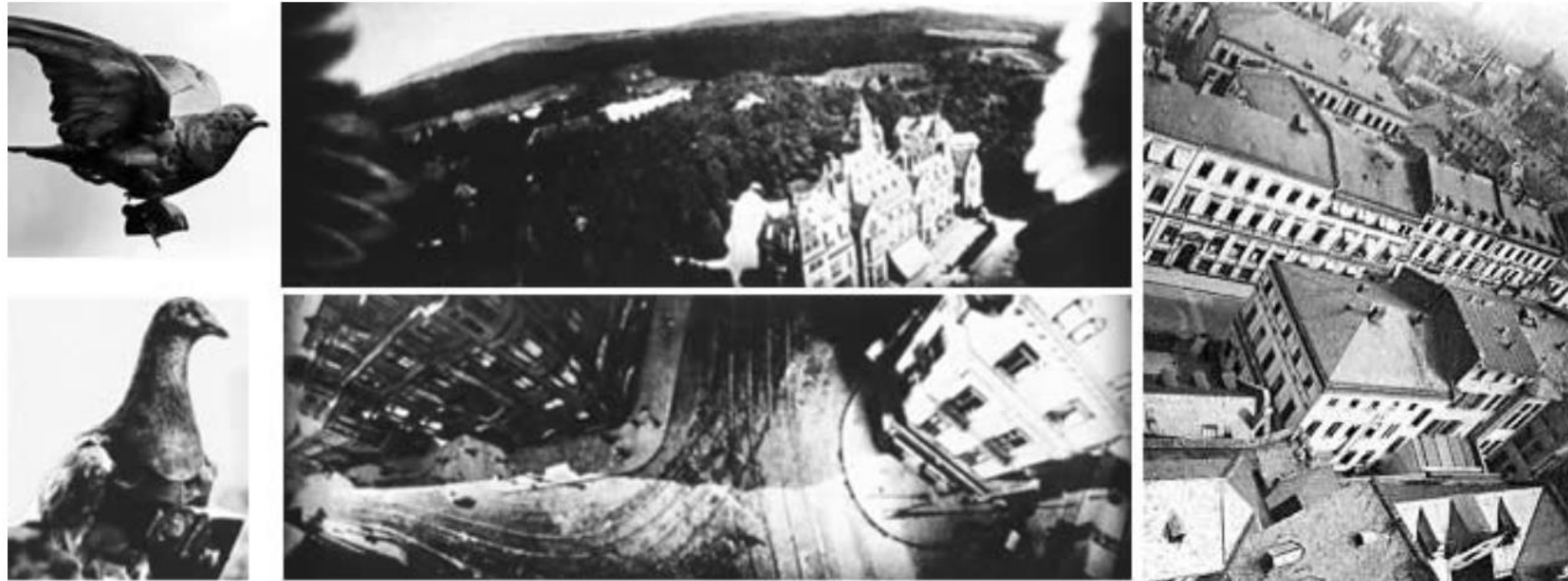
*(left) Batut's kite, and (center top) his photograph of Labrugiere  
(right) Lawrence's kites, and (center bottom) one of his panoramas of San Francisco after the earthquake and fire*

History of Aerial Photography - Professional Aerial Photographers Association Intl ([clubexpress.com](http://clubexpress.com))



# History of Aerial Photography

## Kites, Pigeons and Rockets



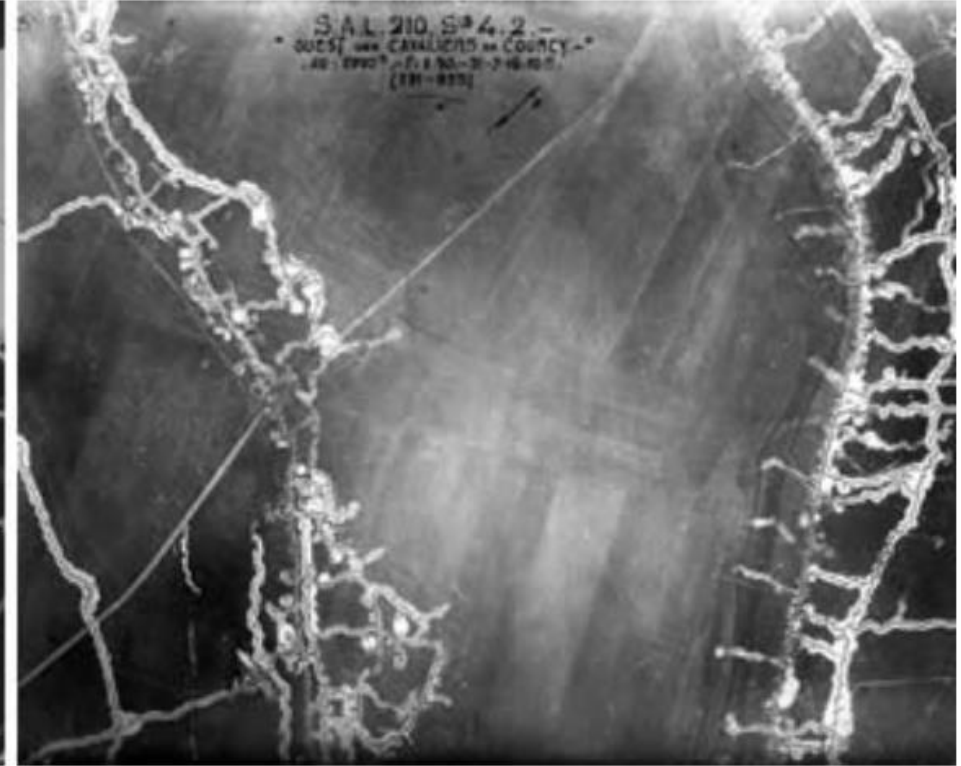
*(left) Neubrunner's pigeon mounted camera*

*(center and right) Aerial photographs taken on pigeon photo flights. Note the wingtips showing in the center top image of the castle.*

History of Aerial Photography - Professional Aerial Photographers Association Intl ([clubexpress.com](http://clubexpress.com))

# History of Aerial Photography

# Aerial Photography from Airplanes



(left) Military aerial observer/photographer during World War I  
(right) Vertical aerial photograph of trenches in 1916

History of Aerial Photography - Professional Aerial Photographers Association Intl (clubexpress.com)

# History of Aerial Photography

## Business of Aerial Photography



*(left) Fairchild's camera became the standard for aerial photography*

*(center) Lower Manhattan Island, constructed from 100 aerial photographs taken by Fairchild Aerial Camera Corporation at an altitude of 10,000 feet on August 4, 1921*

*(right) Ocean City, New Jersey, part of an aerial survey of the New Jersey coast in 1920, believed to be by the Fairchild Aerial Camera Company.*

[History of Aerial Photography - Professional Aerial Photographers Association Intl \(clubexpress.com\)](http://clubexpress.com)



**SOUTH DAKOTA  
STATE UNIVERSITY**  
College of Agriculture, Food  
and Environmental Sciences

AST 426 :Technology Applications for Precision Agriculture

7





# Modern Remote Sensing Technologies



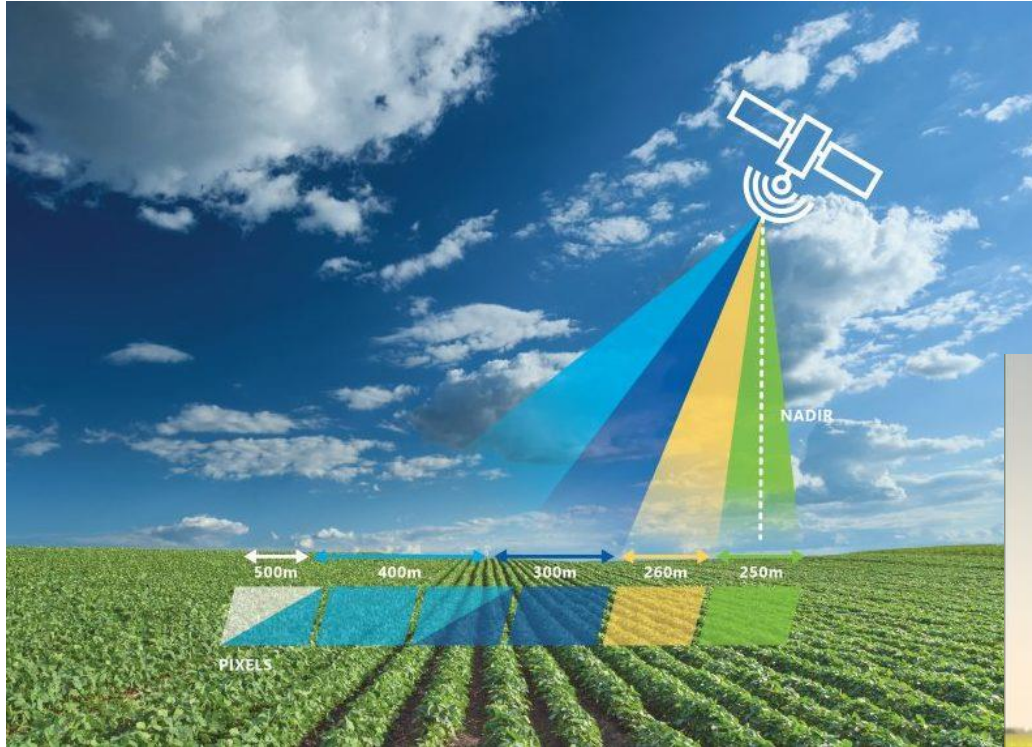
- Modern remote sensing technologies use drone-based Imagery for modern farm management practices



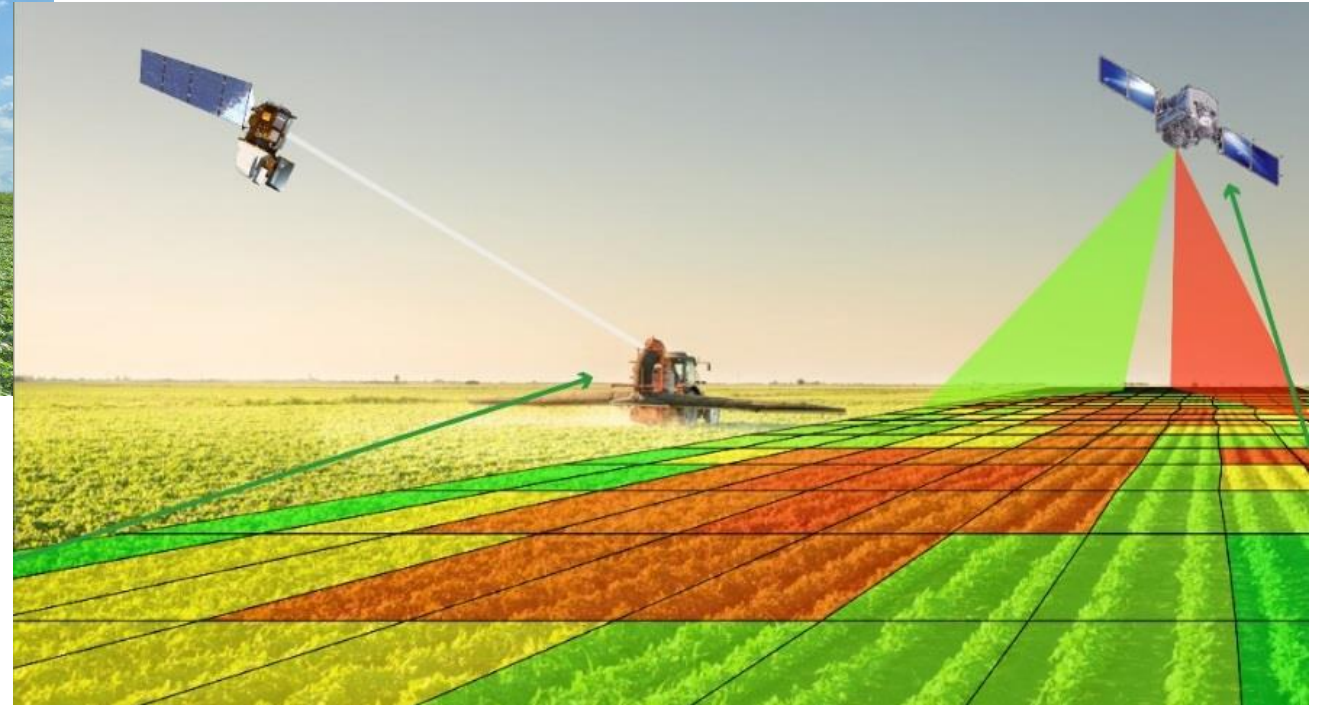
- The imaging platform as well as imaging sensors have improved a lot over the period in terms of spatial resolution, ease of use, speed of image capture, number of bands, etc.



# Modern Remote Sensing Technologies



- Modern remote sensing technologies also use satellite-based Imagery for modern farm management practices



- The imaging platform as well as imaging sensors have improved a lot over the period in terms of spatial resolution, temporal resolution, number of bands, etc.

# Key Application Areas in Precision Agriculture

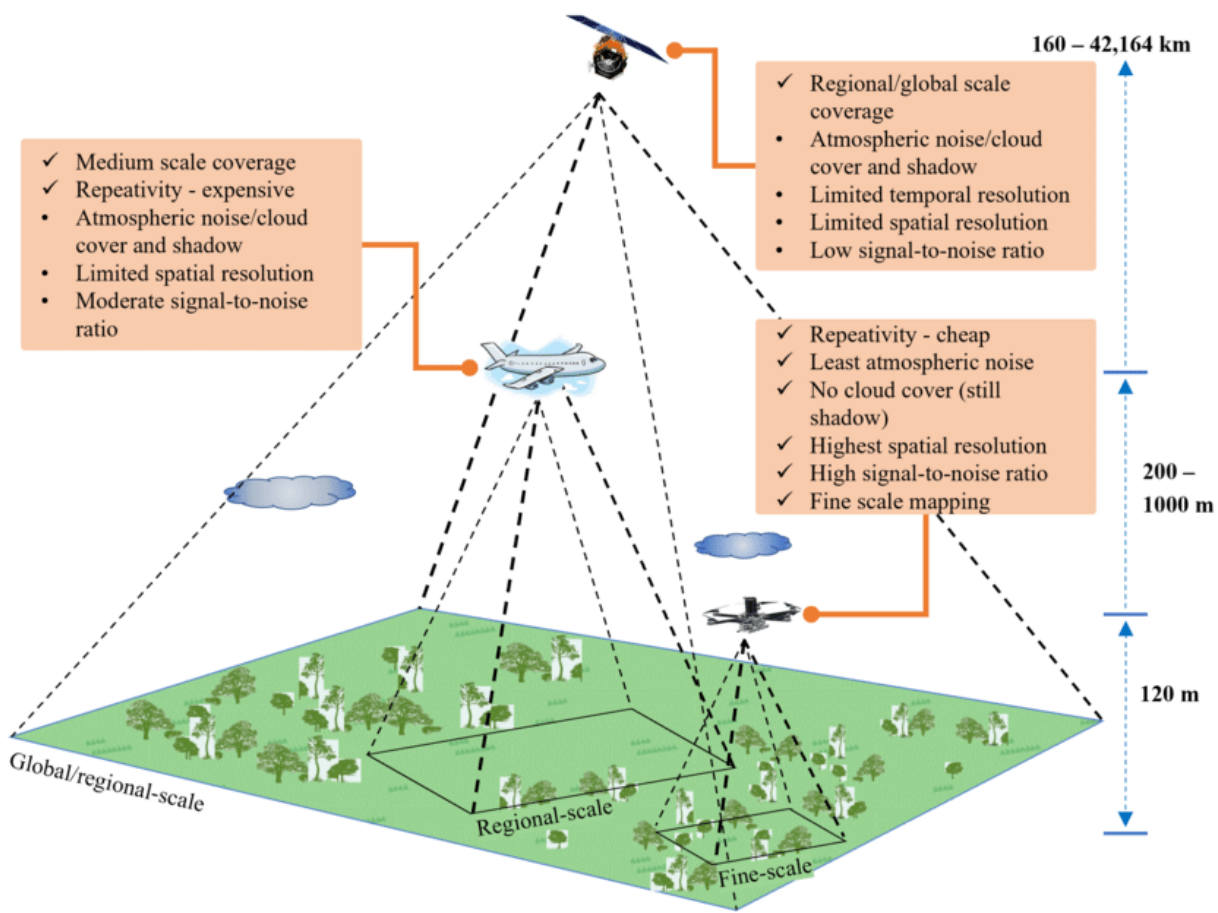
- Crop monitoring
- Crop Disease Detection
- Crop stress detection
- Yield estimation
- Soil moisture detection
- Mapping of water resources
- Irrigation Management
- Fertilization Management
- Etc.





# Satellite vs. Drone-Based Remote Sensing

	Satellite	Drone
Resolution	Down to 30 cm, with 50 cm being a sweet spot	Down to mms, with 1 cm being a sweet spot
Sensors	Optical, SAR (can capture images through clouds and at night)	Lidar, Optical, Thermal
Flight time	Unlimited	Up to 60-90 minutes
Initiation time	As quickly as the client provides asset geolocation	As quickly as drones are physically brought to the monitoring area
Acquisition time	1-2 days	Within the same day
Process time	A few weeks	A few months
Affected by weather, season, time of the day	Not for SAR	Yes. For instance, it's impossible to deploy drones for disaster response during wildfires or hurricanes
Geospatial restrictions	No	Yes
Privacy restrictions	No	Partially yes
Cost	Satellite images may be available for free, archived ones available at reduced price or tasked at full price.	No free service is available



<https://spottitt.com/industry-news/satellites-drones-geospatial-data-collection-comparative-analysis/>  
 Banerjee, Bikram & Raval, Simit. (2022). Mapping Sensitive Vegetation Communities in Mining Eco-space using UAV-LiDAR. International Journal of Coal Science & Technology. 9. 10.1007/s40789-022-00509-w.



## scientific reports



OPEN

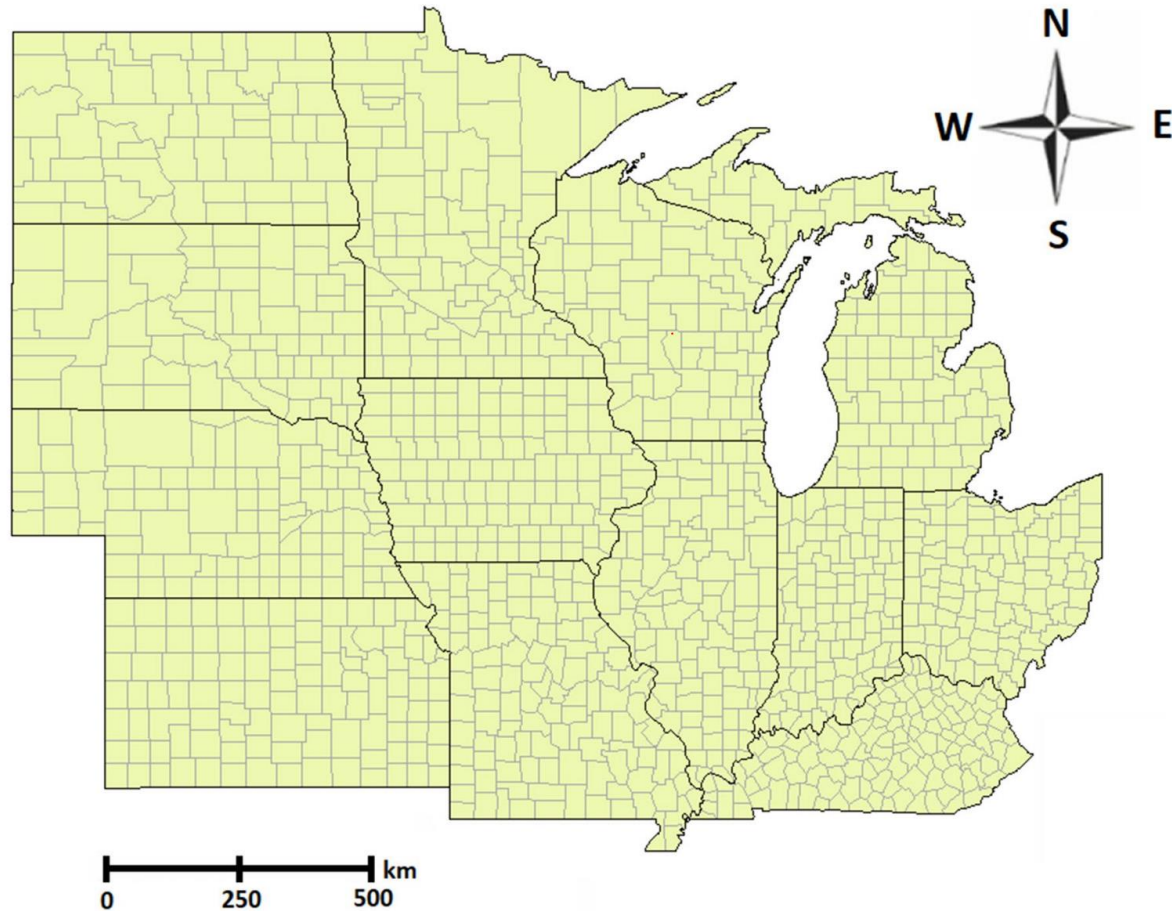
### Simultaneous corn and soybean yield prediction from remote sensing data using deep transfer learning

Saeed Khaki<sup>1✉</sup>, Hieu Pham<sup>2</sup> & Lizhi Wang<sup>1</sup>

Large-scale crop yield estimation is, in part, made possible due to the availability of remote sensing data allowing for the continuous monitoring of crops throughout their growth cycle. Having this information allows stakeholders the ability to make real-time decisions to maximize yield potential. Although various models exist that predict yield from remote sensing data, there currently does not exist an approach that can estimate yield for multiple crops simultaneously, and thus leads to more accurate predictions. A model that predicts the yield of multiple crops and concurrently considers the interaction between multiple crop yields. We propose a new convolutional neural network model called YieldNet which utilizes a novel deep learning framework that uses transfer learning between corn and soybean yield predictions by sharing the weights of the backbone feature extractor. Additionally, to consider the multi-target response variable, we propose a new loss function. We conduct our experiment using data from 1132 counties for corn and 1076 counties for soybean across the United States. Numerical results demonstrate that our proposed method accurately predicts corn and soybean yield from one to four months before the harvest with an MAE being 8.74% and 8.70% of the average yield, respectively, and is competitive to other state-of-the-art approaches.

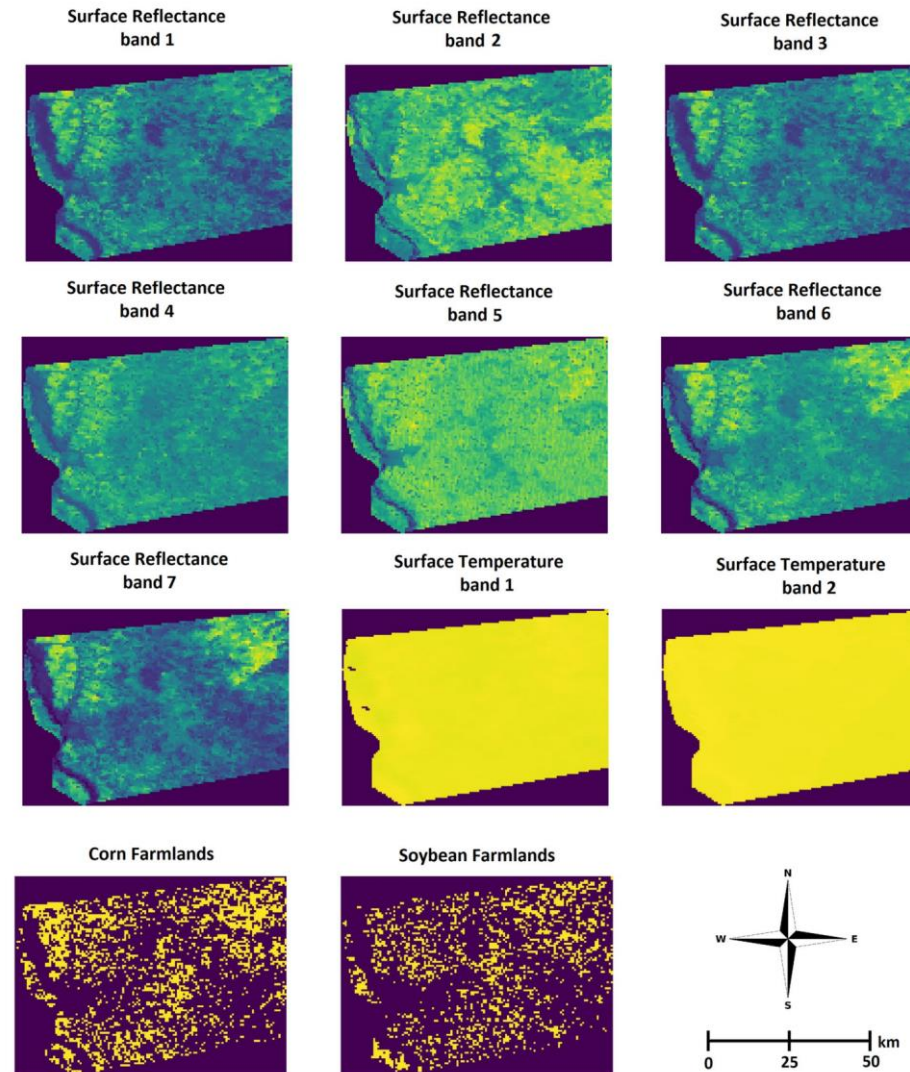
# Case Study of Satellite Remote Sensing

## Map of US Corn Belt



Summary statistics	Corn	Soybean
Year range	2004–2018	2004–2018
Average yield	146.68	45.02
Standard deviation of yield	36.03	10.08
Minimum yield	18.3	9.3
Maximum yield	246.7	82.3
Number of locations	1132	1076
Number of observations	13,992	12,502

# Case Study of Satellite Remote Sensing





## What is Root Mean Square Error?

- Root mean square error or root mean square deviation is one of the most commonly used measures for evaluating the quality of predictions.
- It shows how far predictions fall from measured true values.
- **Example:**
  - If you predicted a plant's height to be 50 cm but it's actually 45 cm, the **error is 5 cm** ( $50 - 45 = 5$ ).
  - Next, square each error. **This makes all the errors positive** and gives more weight to larger mistakes.
  - Then, take the average (mean) of all these squared errors. This tells you, **on average, how big the squared errors are.**
  - Finally, **take the square root of that average.** This **brings the error back to the original units** (like centimeters, instead of squared centimeters) and gives you the RMSE.

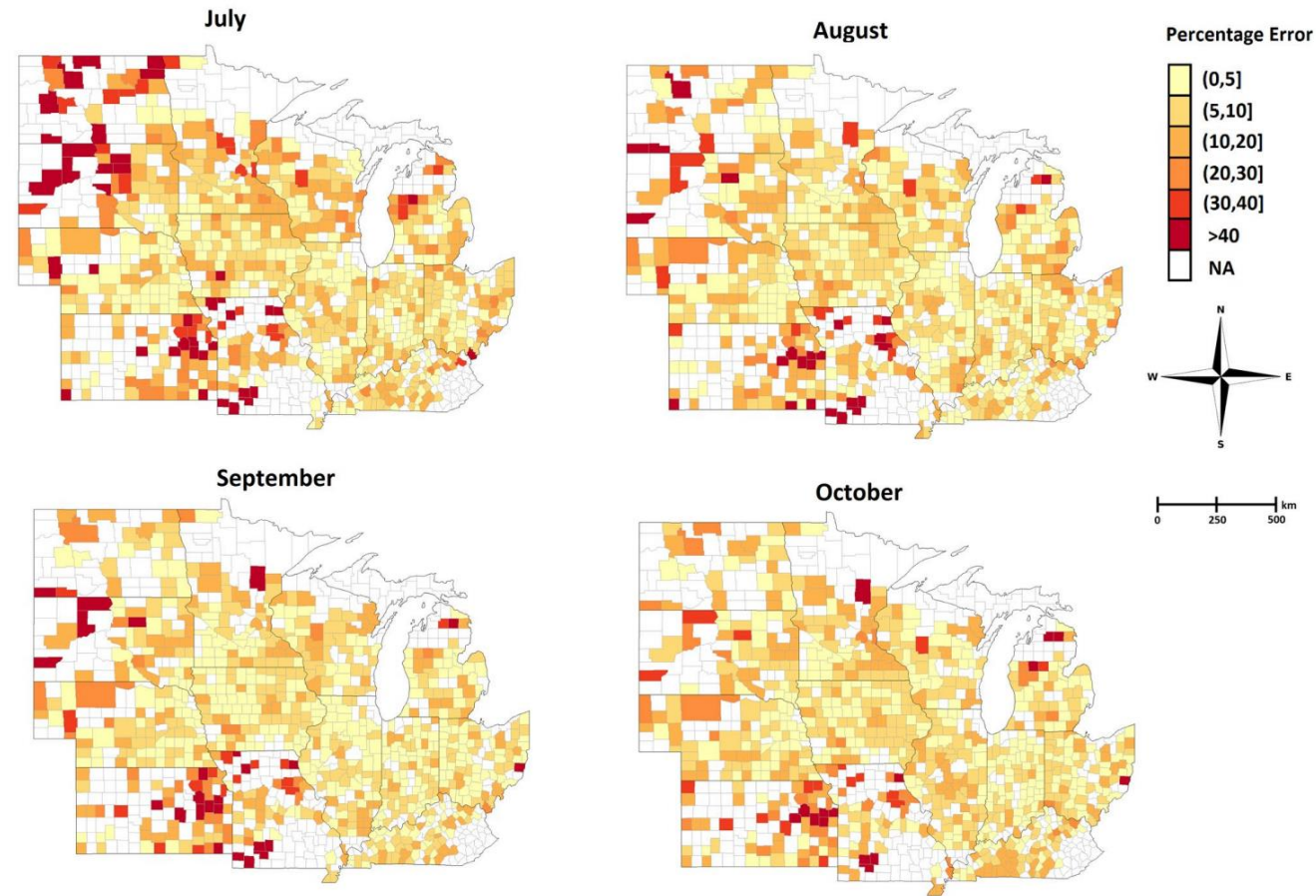
# Case Study of Satellite Remote Sensing

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	<b>18.73</b>
	August	23.16	19.68	20.95	20.48	29.16	<b>15.25</b>	15.76
	September	24.53	20.6	21.23	21.04	29.31	16.55	<b>15.96</b>
	October	24.93	21.05	21.15	20.74	27.96	16.65	<b>15.85</b>
2017	July	30.55	27.53	26.61	26.40	33.64	22.50	<b>20.88</b>
	August	25.16	22.27	22.25	20.85	28.02	<b>16.60</b>	17.74
	September	24.15	21.5	21.99	19.21	26.8	15.71	<b>15.53</b>
	October	25.73	20.94	22.14	18.90	26.78	15.69	<b>15.40</b>
2018	July	27.51	21.21	22.38	22.85	27.69	<b>20.64</b>	22.08
	August	24.5	19.46	21.52	21.14	29.34	18.81	<b>18.25</b>
	September	25.1	18.69	21.7	20.57	28.91	17.58	<b>16.89</b>
	October	32.5	19.2	22.28	21.63	28.9	17.72	<b>16.75</b>
Average		25.91	21.10	22.22	21.33	28.83	17.71	<b>17.49</b>

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

# Case Study of Satellite Remote Sensing

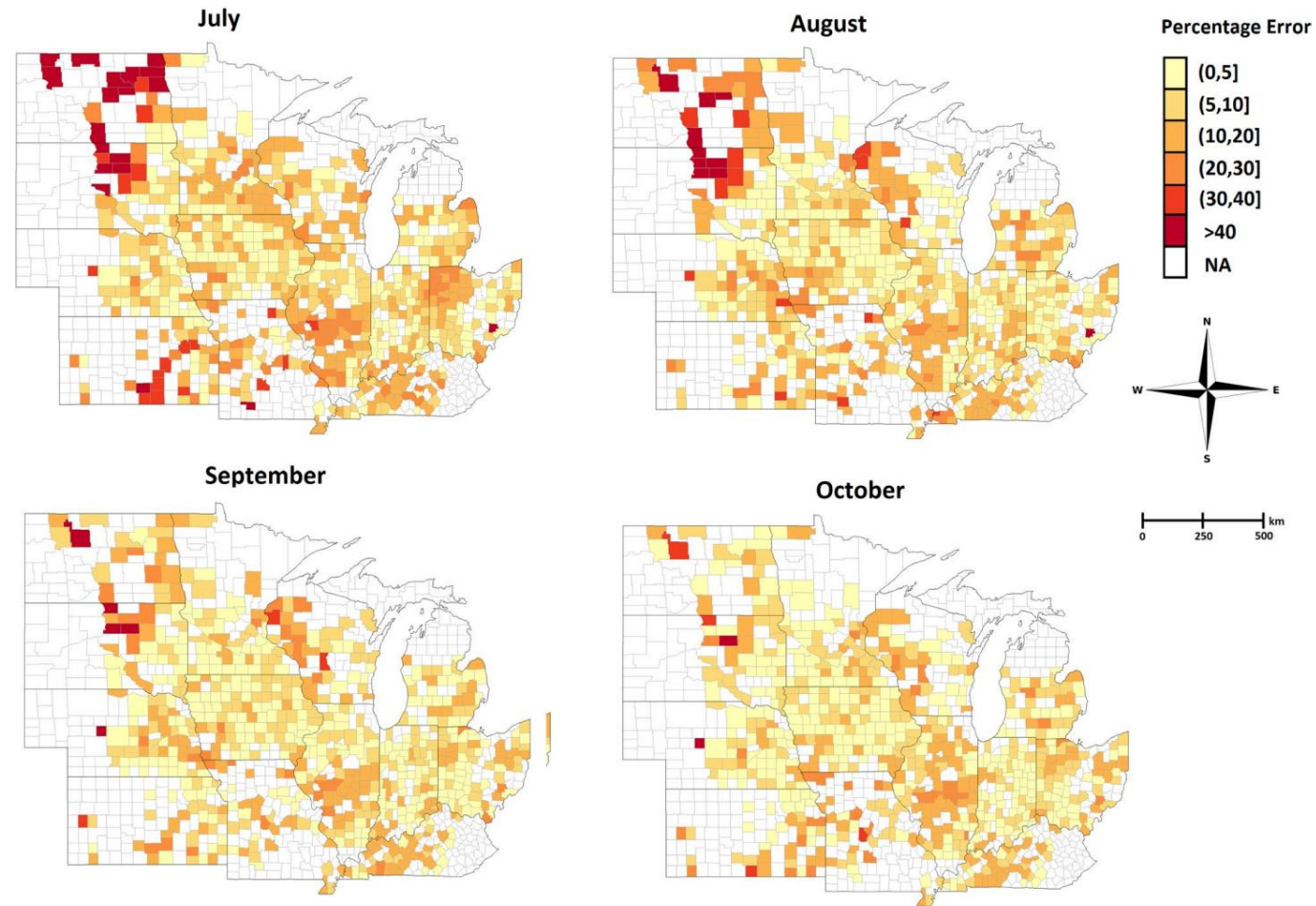
## The error percentage maps for the 2018 corn yield prediction





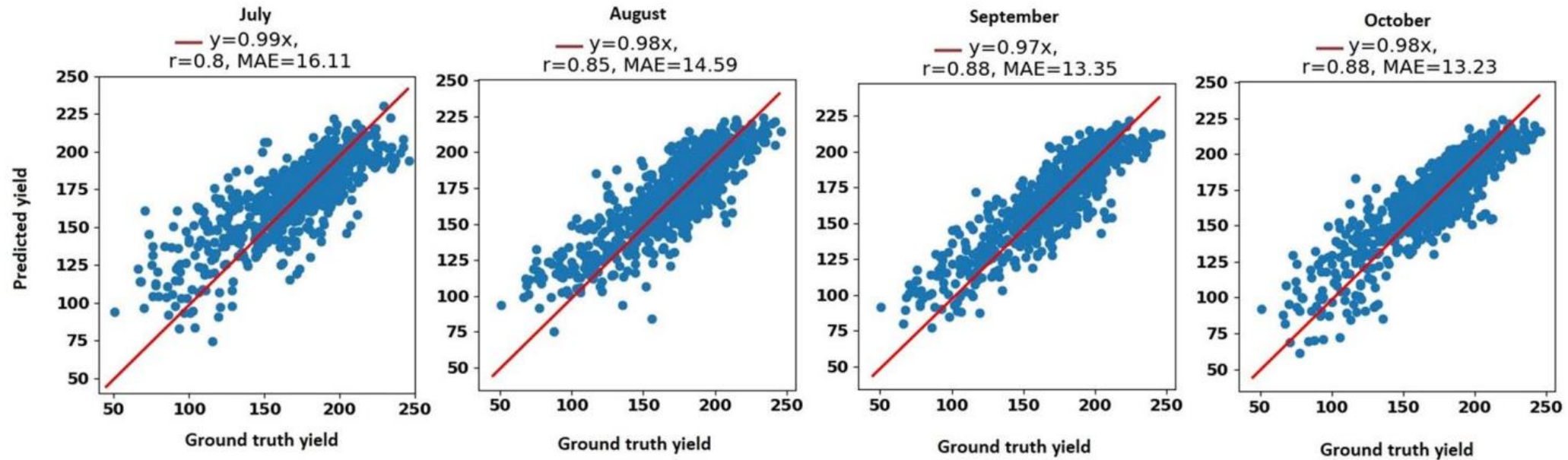
# Case Study of Satellite Remote Sensing

## The error percentage maps for the 2018 soybean yield prediction



# Case Study of Satellite Remote Sensing

## The scatter plots for the 2018 corn yield prediction



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

MAE = mean absolute error

$y_i$  = prediction

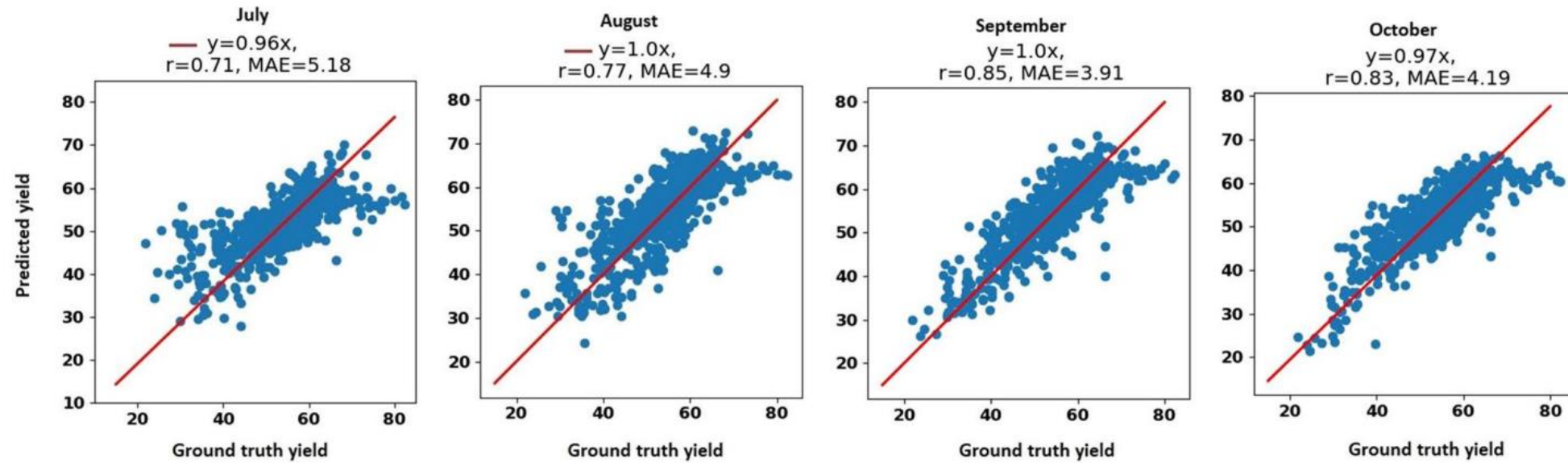
$x_i$  = true value

$n$  = 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**.

# Case Study of Satellite Remote Sensing

## The scatter plots for the 2018 soybean yield prediction



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

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**.



# Next Lecture

## Remote Sensing in Agriculture II

