Integration of Sensors, IoT, and Machine Learning (ML) in Precision Irrigation and Nutrient Management

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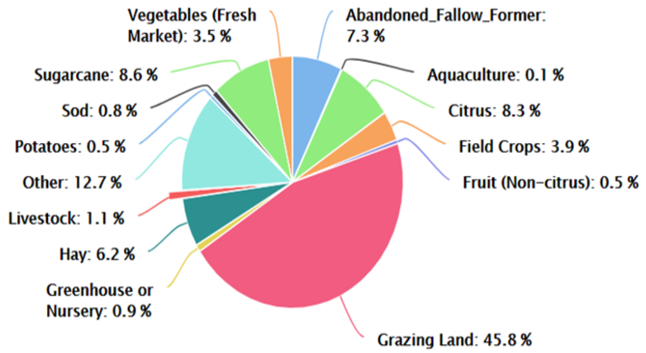
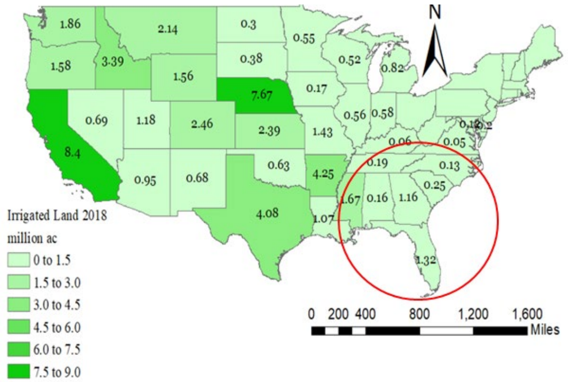
Outline

- Background
- Use of drone and satellite imagery and machine learning model in predicting the crop nitrogen status.
- Design of Physical Model-based Predictive Control System for Adaptive Variable Rate Irrigation
- Development of IoT-based automated irrigation system for strawberry irrigation scheduling.
- Q&A

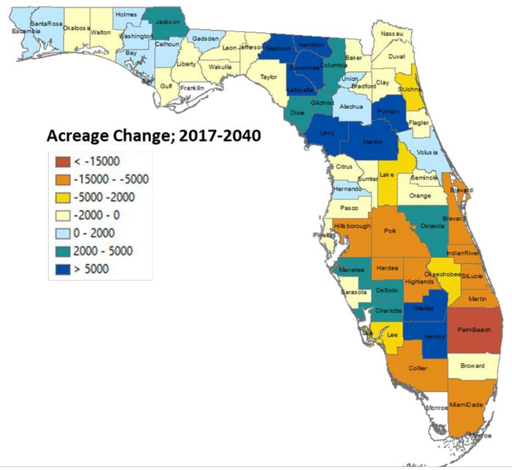
Florida Irrigated Agriculture

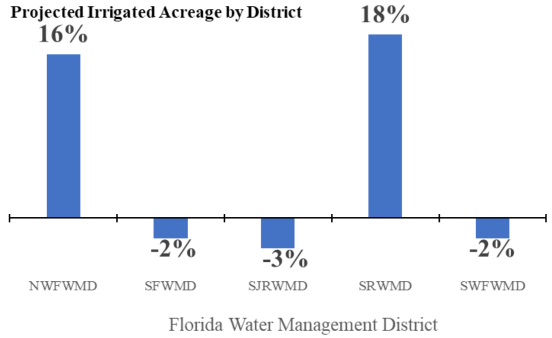
Specialized crops and Irrigated Ag





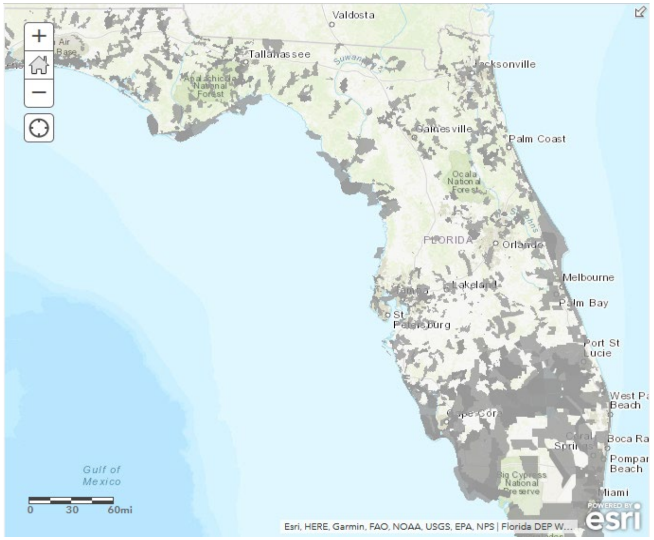
Water Quantity Challenges





4% increase in Florida Water use by 2040

Water Quality Challenges



Increased nitrate-nitrogen (NO^3-N) concentrations, Impaired waterbodies, harmful algal bloom

Extreme year to year variability in irrigation requirements

Source: (NASS, FDACS, FDEP, Springs Eternal Project, by InDepth)

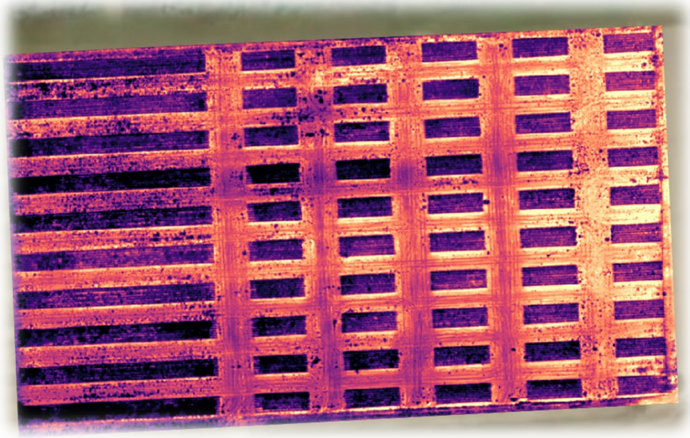
Precision Agriculture

- Successful advancements in precision agriculture sensor technologies along with IoT and Machine learning in the last two decades have enabled the optimization of water and nitrogen application to manage spatial and temporal variabilities within agricultural fields.

- High-resolution remote sensing data enables the monitoring of crop growth, assessment of stresses impacting yield, and accurate crop yield estimation.

Precision Agriculture

Reference: https://cropmetrics.com/



Leaf Nitrogen Status

- The acquisition of real-time nitrogen (N) nutritional status is of utmost importance for effective crop production.
- The current standard methods for reliable and accurate measurement are to collect leaf samples and transport samples from field sites to laboratory for assessment and experimentation.

WATERS AGRICULTURAL LABORATORIES, INC.

Soil Analysis

Waters Agricultural Laboratories, Inc

257 Newton Hwy | Camilla, GA 31730- | Phone (229) 336-7216

"Improving Growth... With Science"

Customer: 1725 | Sample ID: STEP-1-0-12

UNIVERSITY OF FLORIDA

Grower: VIVEK SHARMA | Received: 3/15/2022

Farm ID: POTATOE | Processed: 3/17/2022

7580 CTY RD 136
LIVE OAK, FL 32060
UNITED STATES

Test Method: Mehlich I

P Phosphorus	K Potassium	M Mag
116 H	90 M	44
Al Aluminum	Na Sodium	NO Nit
		0

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Soil Analysis

Waters Agricultural Laboratories, Inc

257 Newton Hwy | Camilla, GA 31730- | Phone (229) 336-7216

"Improving Growth... With Science"

Customer: 1725 | Sample ID: STEP-2-12-24

UNIVERSITY OF FLORIDA

7580 CTY RD 136
LIVE OAK, FL 32060
UNITED STATES

Grower: VIVEK SHARMA
Farm ID: POTATOE
Field ID:
Lab Number: 766197CC
Layer ID:

Received: 3/15/2022
Processed: 3/17/2022

Test Method: Mehlich I | Soil Laboratory Data (lbs/a) | Target pH 6

P Phosphorus	K Potassium	Mg Magnesium	Ca Calcium	Soil pH	Buffer pH Adams-Evans	S Sulfur	B Boron	Zn Zinc	Mn Manganese	Fe Iron	Cu Copper
45 M	53 L	27 L	267 L	5.9	7.80	11 L	0.3 L	0.4 L	2 L	37 VH	0.2 L

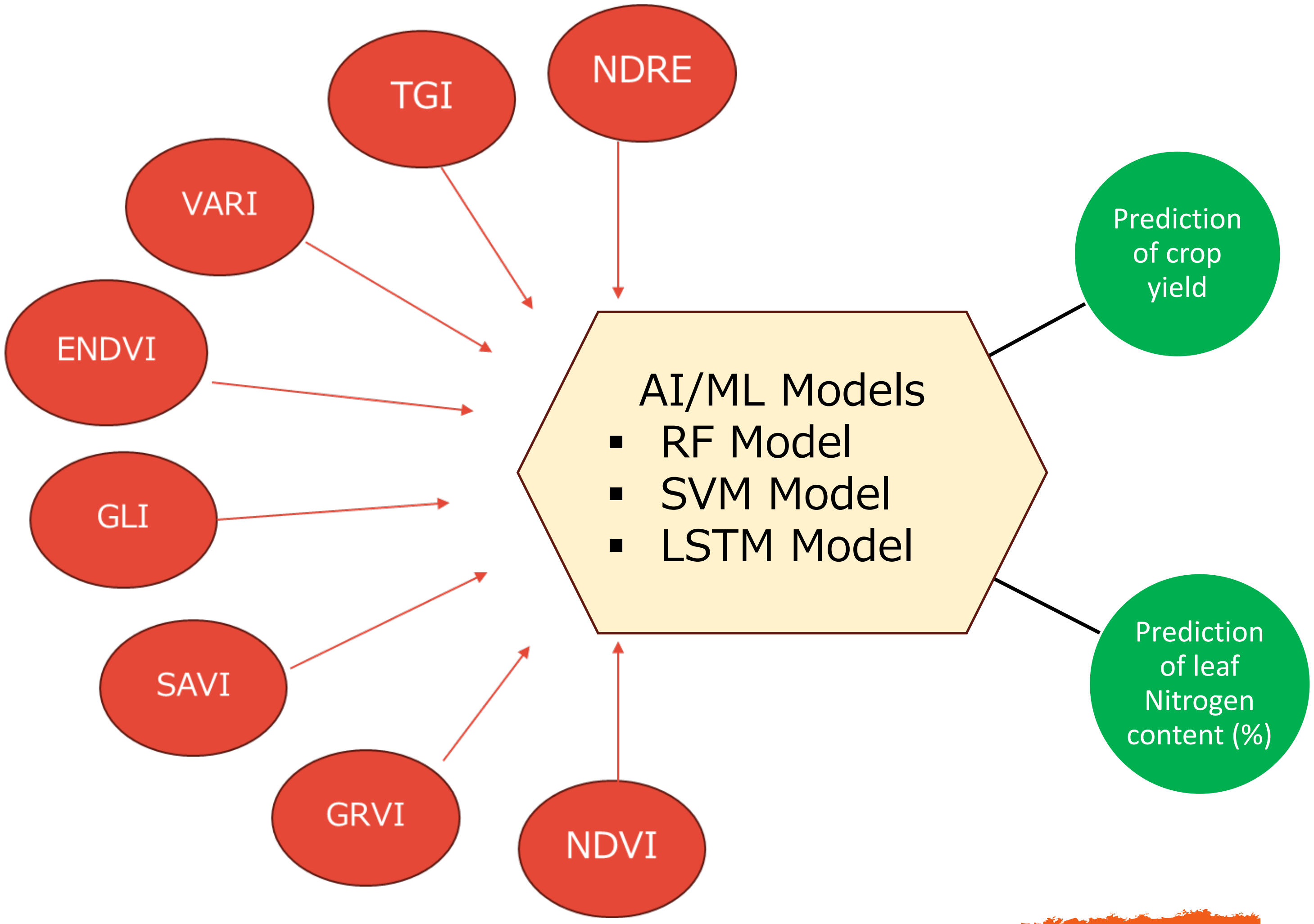
Al Aluminum	Na Sodium	NO3-N Nitrate-N	NH4 Ammonia	Soluble Salts	Organic Matter	ENR	Mo Molybdenum	Ni Nickel	BiCarbs	
		0.01 ppm	ppm	mmhos/cm	%		ppm	ppm	meq/L	

- Such an invasive approach does not allow timely measurements and prevents us from accurately characterizing and modeling processes occurring in plant.

Objective and Methodology

- **Objective:** The main objective of this study is to integrate the machine leaching approach with high resolution drone imageries to accurately predict the real-time in-situ nitrogen status and yield.
- **Methodology:**
  - Multiple high resolution drone imageries (18 RGB and multispectral dataset in 2023, and 10 images in 2022) was collected throughout the corn growing season at NFREC-SV.
  - All the images were uploaded to the SOLVI platform image processing and to generate the vegetative indices maps such as NDVI, NDRE etc.
  - Plant tissue samples were collected at the same time or near the drone image collection.

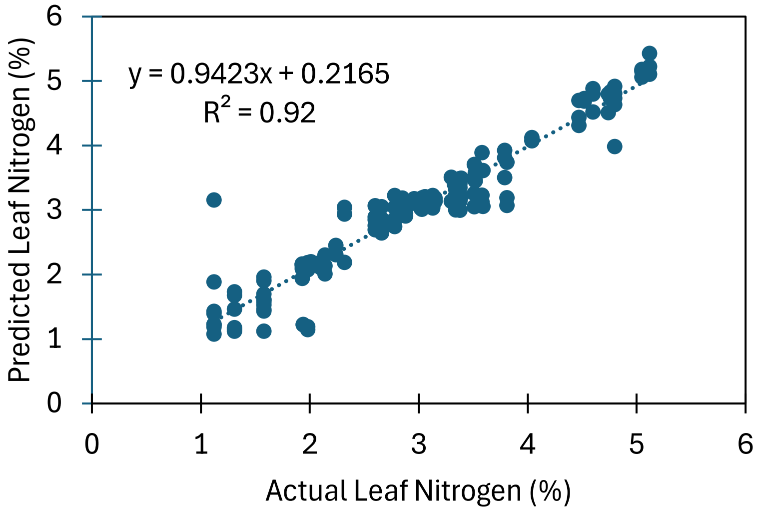
Methodology



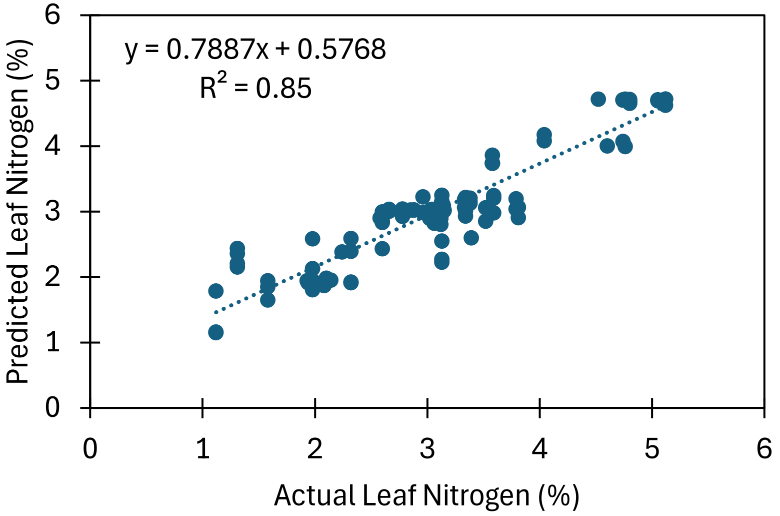
Models	Parameters	
M1	NDVI, ENDVI, GLI, SAVI, GRVI, VARI, TGI, NDRE	Leaf N %
M2	NDVI, ENDVI,GLI, SAVI, GRVI, VARI, TGI	Leaf N %
M3	NDVI, ENDVI,GLI, SAVI, GRVI, VARI	Leaf N %
M4	NDVI, ENDVI,GLI, SAVI, GRVI	Leaf N %
M5	NDVI, ENDVI,GLI, SAVI	Leaf N %
M6	NDVI, ENDVI,GLI	Leaf N %
M7	NDVI, ENDVI	Leaf N %
M8	NDVI	Leaf N %
M9	NDVI, GLI, SAVI, GRVI, VARI, TGI, NDRE	Leaf N %
M10	NDVI, SAVI, GRVI, VARI, TGI, NDRE	Leaf N %
M11	NDVI, GRVI, VARI, TGI, NDRE	Leaf N %
M12	NDVI, VARI, TGI, NDRE	Leaf N %
M13	NDVI, TGI, NDRE	Leaf N %
M14	NDVI, NDRE	Leaf N %
M15	NDVI, GLI	Leaf N %
M16	NDVI, VARI	Leaf N %

Model performance
- ☐ RMSE
- ☐ NSE
- ☐ MAE
- ☐ R2

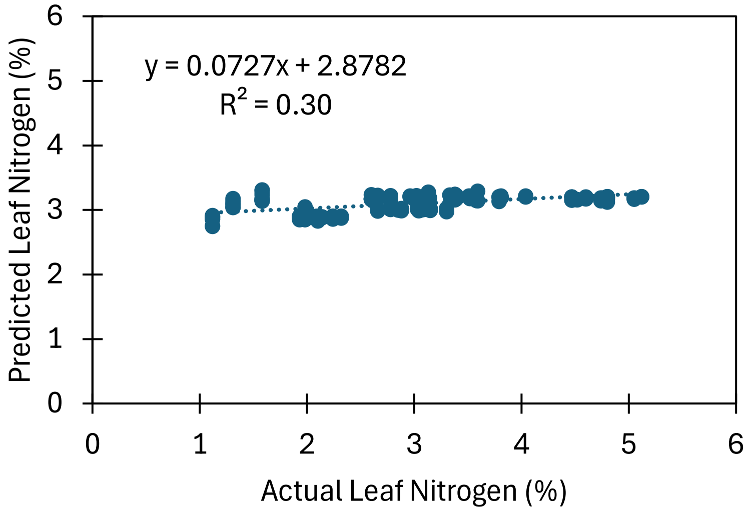
Validation Results



RF Model



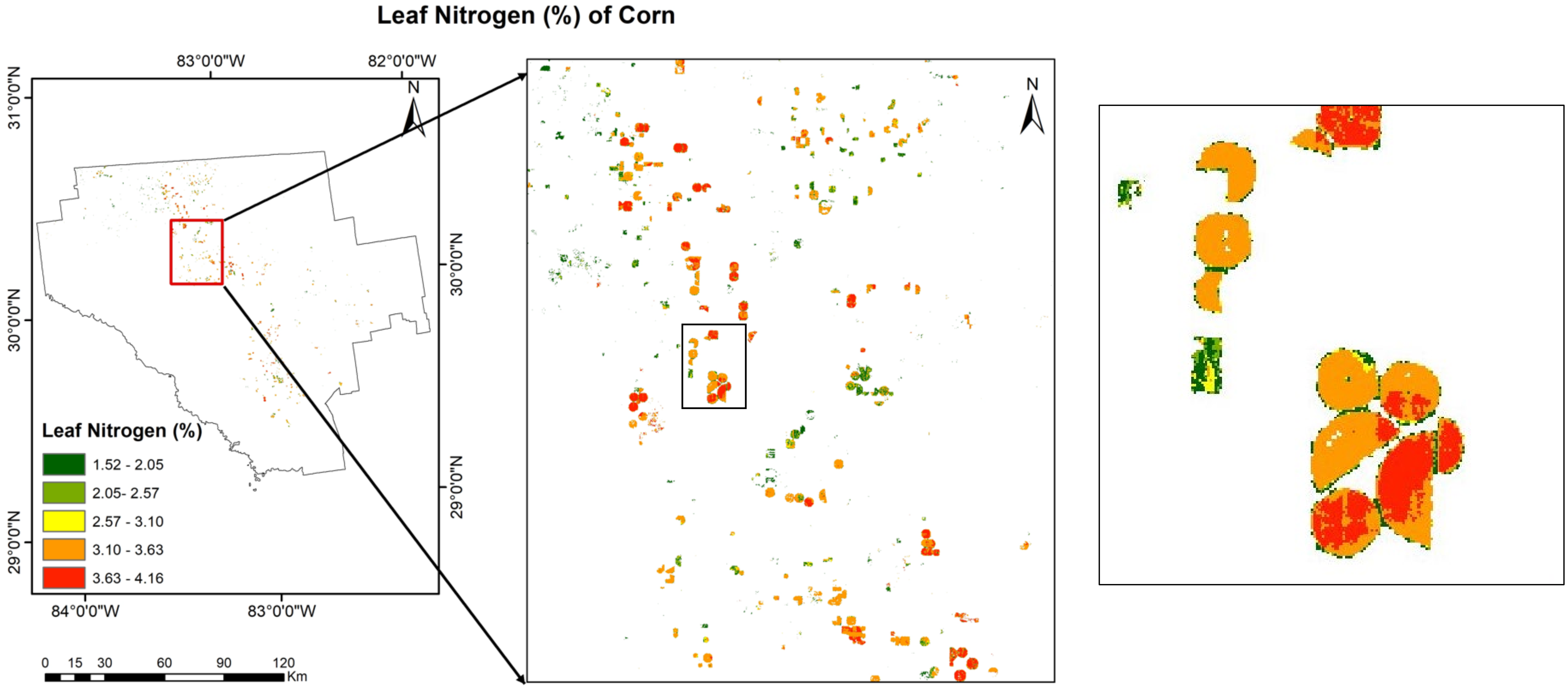
LSTM



SVM

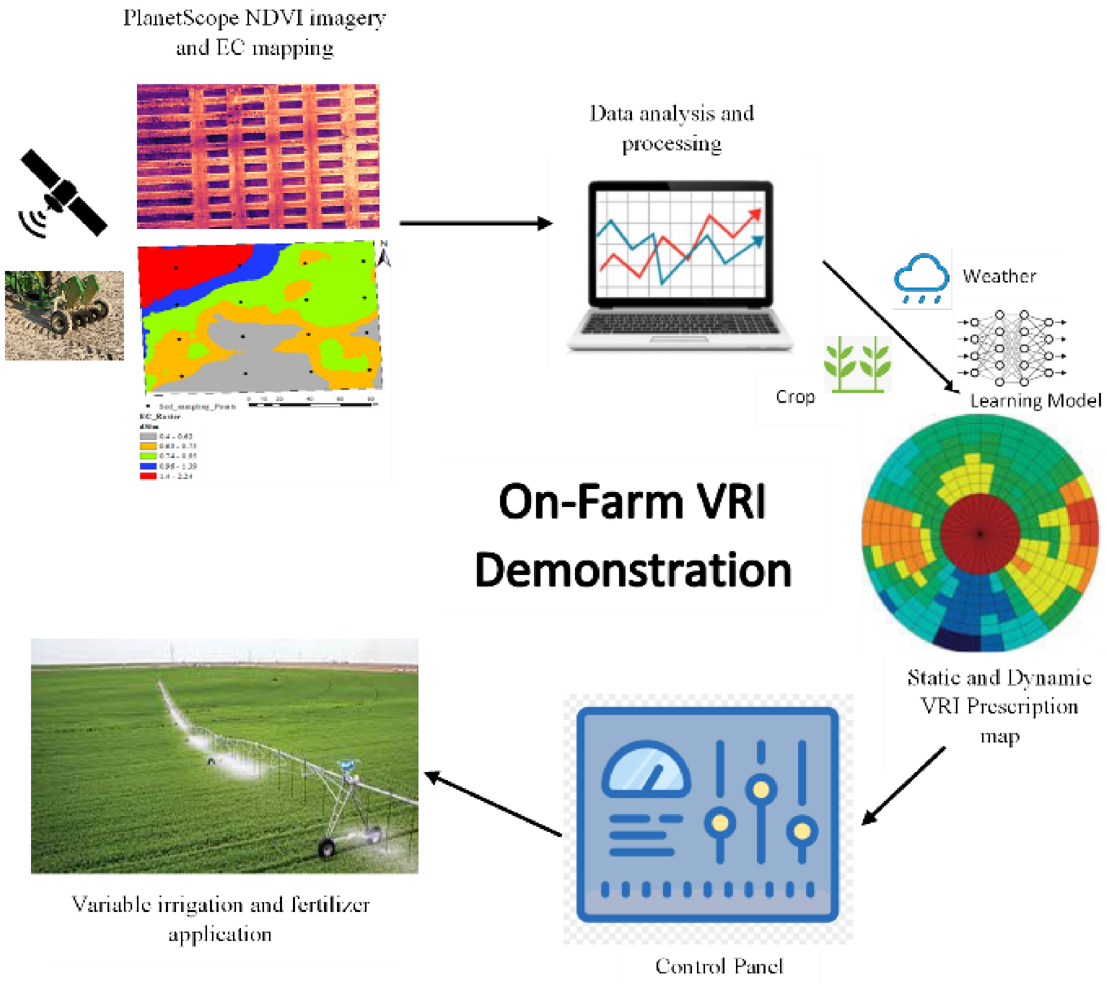
n = 120	RMSE	MAE	NSE
RF	0.4728	0.334	0.55
LSTM	0.95	0.79	0.43
SVM	1.03	0.8	0.12

Results


Leaf Nitrogen (%) of Corn
83°0'0"W
82°0'0"W
31°0'0"N
30°0'0"N
29°0'0"N
84°0'0"W
83°0'0"W
N
Leaf Nitrogen (%)
1.52 - 2.05
2.05- 2.57
2.57 - 3.10
3.10 - 3.63
3.63 - 4.16
0 15 30 60 90 120 Km
N

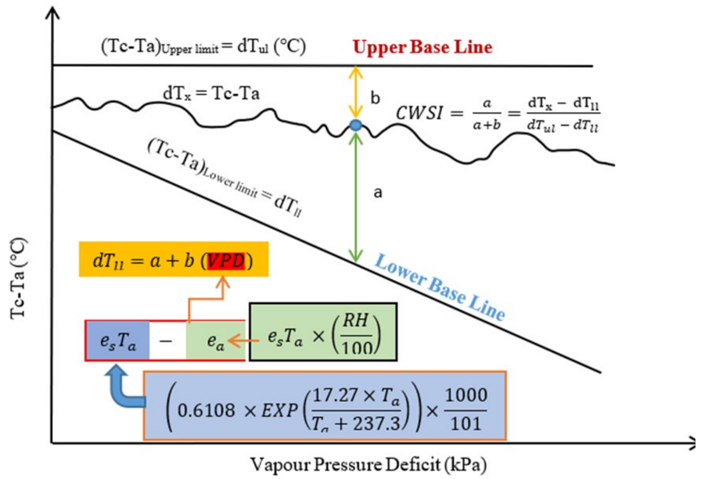
Variable Rate Irrigation

- **USDA-NRCS-CIG funded project** focusing on demonstrating a novel suite of existing technological solutions to stakeholders:
  - VRI,
  - soil electrical conductivity (soil EC),
  - remote sensing,
  - artificial intelligence/ Machine Learning (AI/MC)]
- The main goal is to build the capacity to provide science-based data on integrated precision irrigation management solutions and tools and technologies to optimize the water use efficiency and thereby increase the on-farm profitability and reduce the environmental impact of irrigated agriculture.



Thermal Image Generation using Generative Adversarial Networks

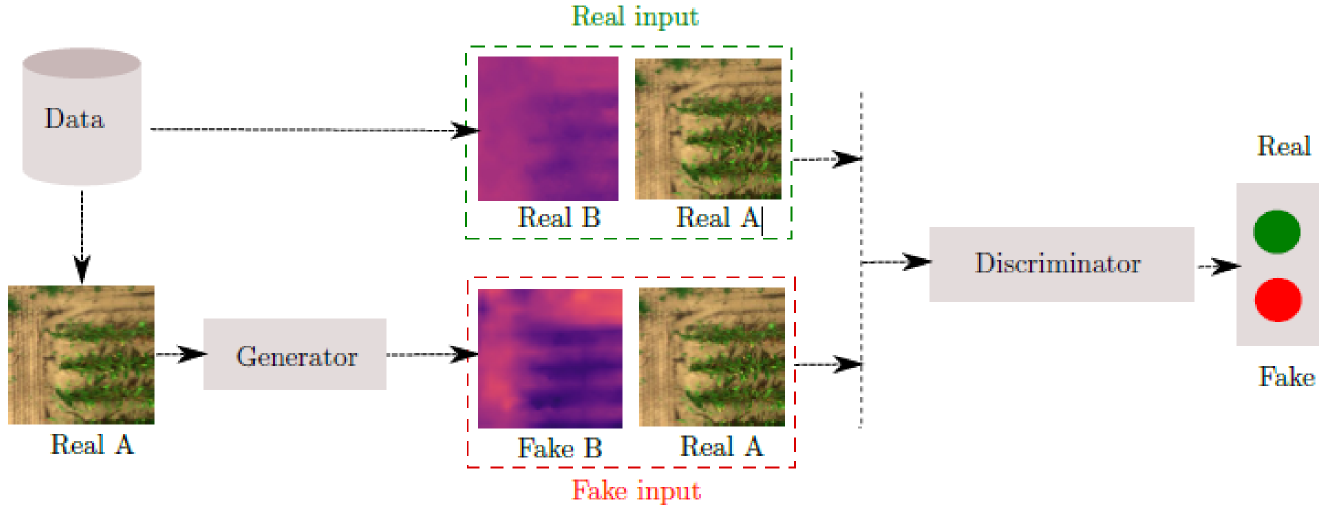
- Crop Water Stress Index (CWSI) approach is widely used water stress detection.
- This requires thermal imagery captured by thermal imaging equipment.
- However, most drone/satellite system are not equipped with the thermal imaging sensors and capture the RGB images.



- **Objective:** Our purpose is to design a model to learn a mapping between the RGB and thermal domains, i.e., converting visual information captured by an RGB camera into temperature values represented by thermal images so we can estimate soil irrigation levels.

Generative Adversarial Network

- The dataset comprises 10 paired images: the RGB images and their corresponding thermal images of a corn field collected at the NFREC-SV.
- We selected 5 images out of 10 for training. The selection was made in such a way that the dates were spaced out and so the conditions and state of the field were as varied as possible.
- Pix2Pix is a Generative Adversarial Network (GAN) that learns a conditional mapping from input to output images.
- The main two components of Pix2Pix:
  - generator
  - discriminator.



Medeiros et al. (2023)

Model Performance

- Three test images from the corn field (8 June, 22 June, 15 July) and one test image from potato field (25 May) have been used to evaluate the performance of the model.
    - **Peak signal-to-noise ratio (PSNR):** It measures the level of noise or distortion introduced during the modification process. A higher PSNR generally indicates that the reconstruction is of higher quality.
    - **Root mean square error (RMSE):** It measures the average magnitude of the pixel-wise differences between corresponding pixels in the two images.
    - **Spectral angle mapper (SAM):** It measures the spectral similarity between two spectra based on the angle between them in the hyperspectral feature space. Smaller angles indicate higher similarity.
    - **Signal to reconstruction error ratio (SRE):** It is used to assess the quality of a reconstructed signal. It measures the ratio between the strength of the original signal and the difference between the original signal and its reconstructed version. The higher the SRE value, the better the quality of the reconstruction compared to the original signal.
    - **Structural Similarity Index (SSIM):** It is used to evaluate the perceptual quality of images by taking into account their luminance, contrast, and structure. The SSIM ranges between -1 and 1. Higher values indicate higher structural similarity and thus better image quality.

Results: Testing Phase

- The test phase is run on patches of 256×256 pixels of the original images.
- To highlight the perceived quality of the generated image, we have selected four patches with different densities in terms of corn plants.
- Preliminary results indicated that whether the corn plants are dense, scattered, aligned, or even non-existent, the results show that the patch generated is similar to its real thermal version.

Patch	Field	PSNR	RMSE	SAM	SRE	SSIM
1	Corn	37.51	0.010	89.10	48.42	0.85
2	Corn	43.29	0.005	89.39	53.55	0.95
3	Corn	40.82	0.007	79.45	41.13	0.77
4	Corn	33.79	0.010	89.53	47.23	0.78

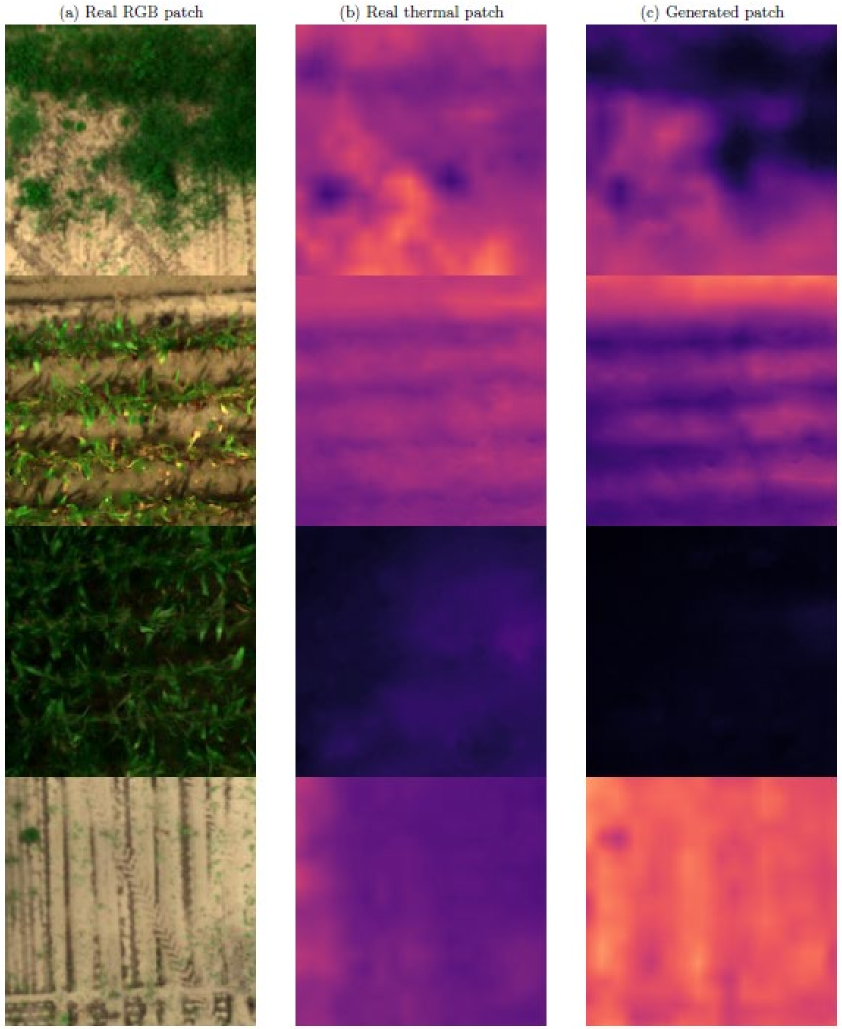
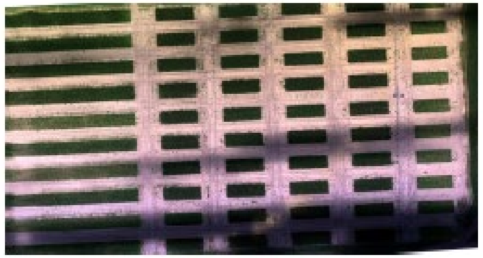


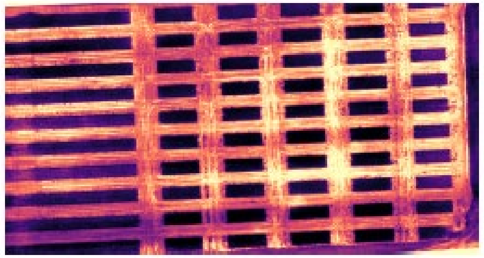
Figure 2: RGB patch vs. actual thermal patch vs. generated thermal patch.

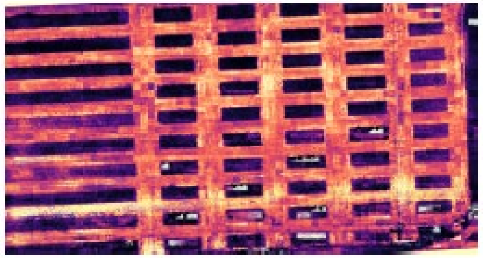
Results: Model Performance

- Three test images from the corn field (8 June, 22 June, 15 July) and one test image from potato field (25 May) have been used to evaluate the performance of the model.

Date	Field	PSNR	RMSE	SAM	SRE	SSIM
8 JUN 22	Corn	38.74	0.010	0.0	65.63	0.90
22 JUN 22	Corn	39.06	0.010	0.0	66.82	0.92
15 JUL 22	Corn	40.43	0.009	0.0	65.08	0.89
25 MAY 23	Potato	38.15	0.010	0.0	63.06	0.81

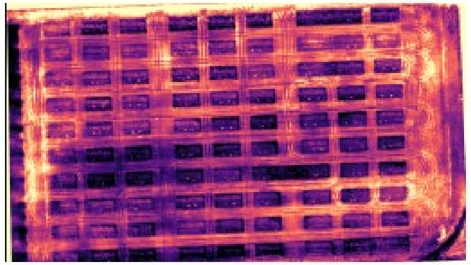

RGB real image

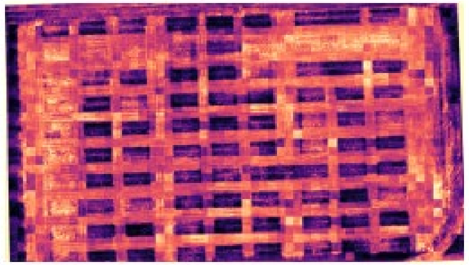

Real thermal image


Generated thermal image

June 8


RGB real image


Real thermal image


Generated thermal image

May 25

Preliminary Observations

- Model training was performed on corn data but tested on potato data too. An obvious area for improvement is to train the model on more images, including, of course, images from the different cropping systems.

- Patch-level learning results are promising but the reconstruction task produces relatively blurry images. Increasing the patch size may maintain a good learning level while reducing the effect of image pixelation.

- However, using a fairly large patch size causes the model to lose its predictive ability.

- One possible solution would be to use sliding window patches to overlap areas. We are exploring multi-scale training to effectively improve the generalization ability of the model at multiple scales.

- Bilinear filters could be another solution to smooth the images while preserving edges.

Strawberry Production

- Strawberries are one of the major fruits grown in Florida during the winter season with the production value of $511 million in 2022

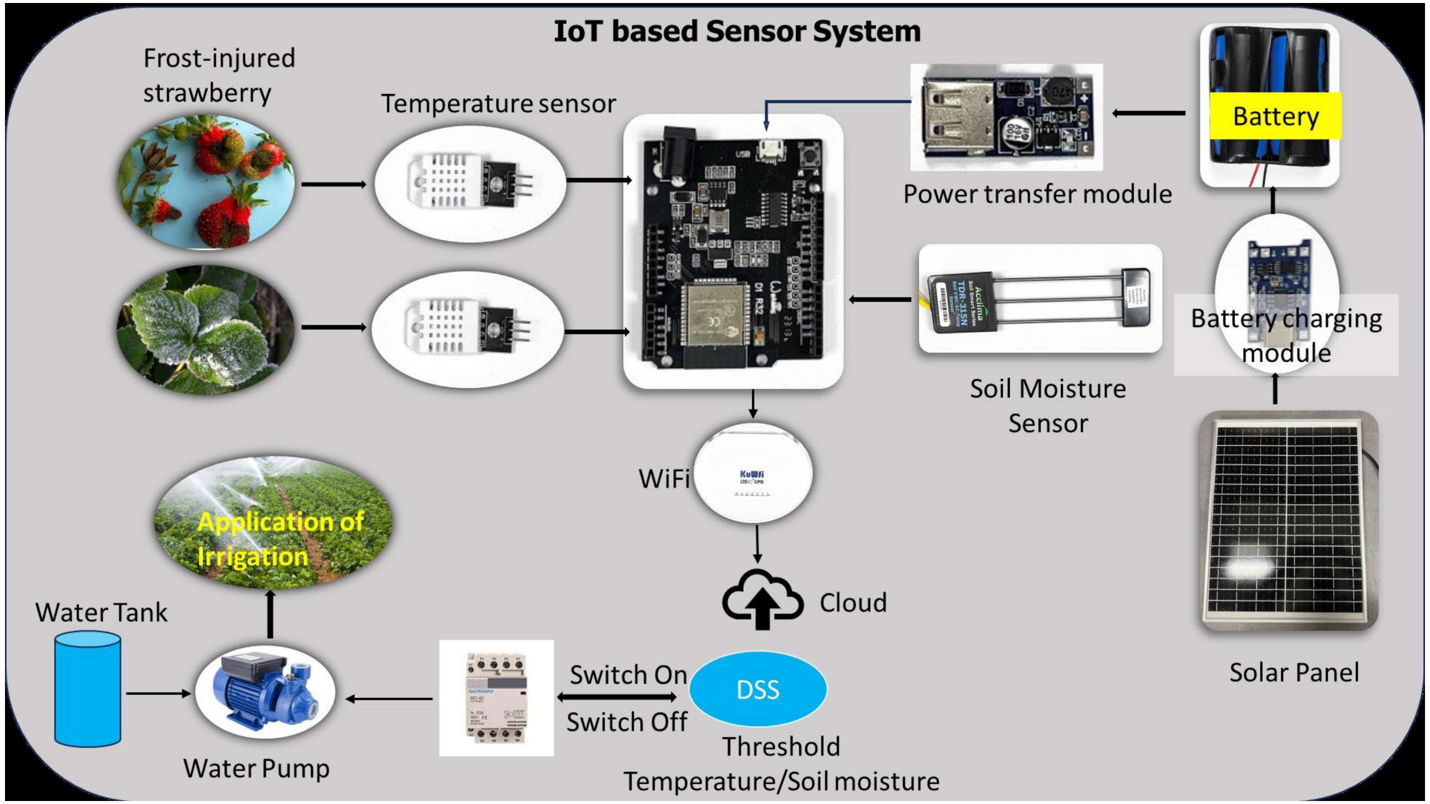
Bare-root Transplant Impaired Root System

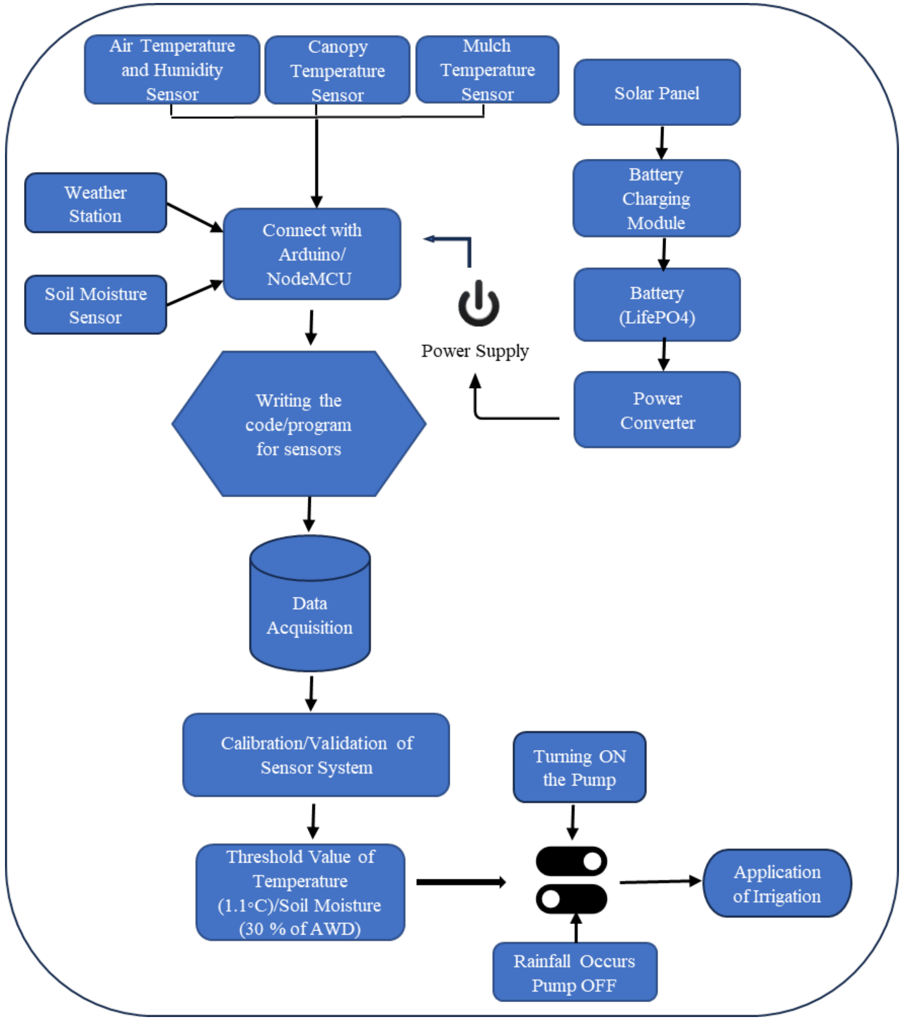
Black plastic film used as fumigation tarp and mulch for the crop

IoT-based Automated Irrigation System for Strawberry

- The precise amount of water and the exact timing of irrigation system operation are crucial for enhancing irrigation water use efficiency. This can be achieved by using IoT-based sensor systems integrated into precision irrigation.
- The IoT system can monitor real-time mulch and plant temperatures, microclimate conditions, and bed soil moisture to assess water stress and automate irrigation scheduling, ultimately optimizing water usage.
- Objectives:
  - Design and build an IoT-based automated irrigation system for strawberry irrigation scheduling.
  - Test the IoT-based irrigation system in different conditions such as establishment stage, growth stage, and freezing weather conditions.
  - Collect data on strawberry transplant establishment and growth, crop water use, and strawberry yield under conventional and IoT-based irrigation systems.

Components of Automated Strawberry Irrigation System





Thank you for your attention!
Questions

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