



AgriSense

Where precision meets sustainability.

Pascual Eley | Josh Fram | Maria Manna
Diego McDonald | Cameron Yenche

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Minimum Viable Product (MVP)



Yield Prediction

Helps farmers plan their harvest and market strategy



Crop Health Monitoring

Assess health more effectively, ID issues early & take corrective action to maximize yield



Intuitive Dashboard

Track farm performance metrics and understand the impact of resource allocation decisions

Stakeholder feedback to product



Yield Predictions

What will the expected yield for my strawberries be this season? How does that compare to previous seasons?



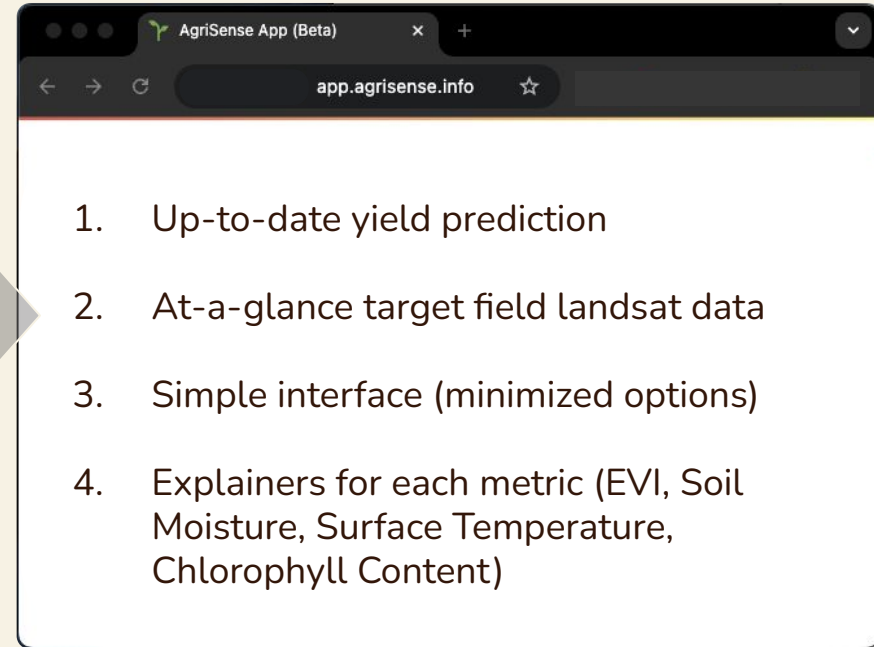
Crop Health

What areas of my farm are over or under-irrigated? Signs of stress or disease in certain areas?

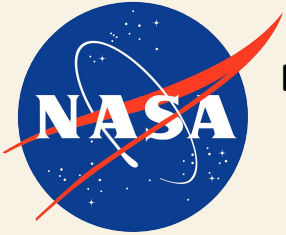


Hesitant About New Tech

Some farmers might be skeptical about adopting new technology and changing traditional practices.



Public Datasets



Landsat (NASA) Satellite Imagery

- High-resolution multi-spectral imagery for monitoring vegetation, land use, and environmental changes.



CropScape (GMU CSISS)

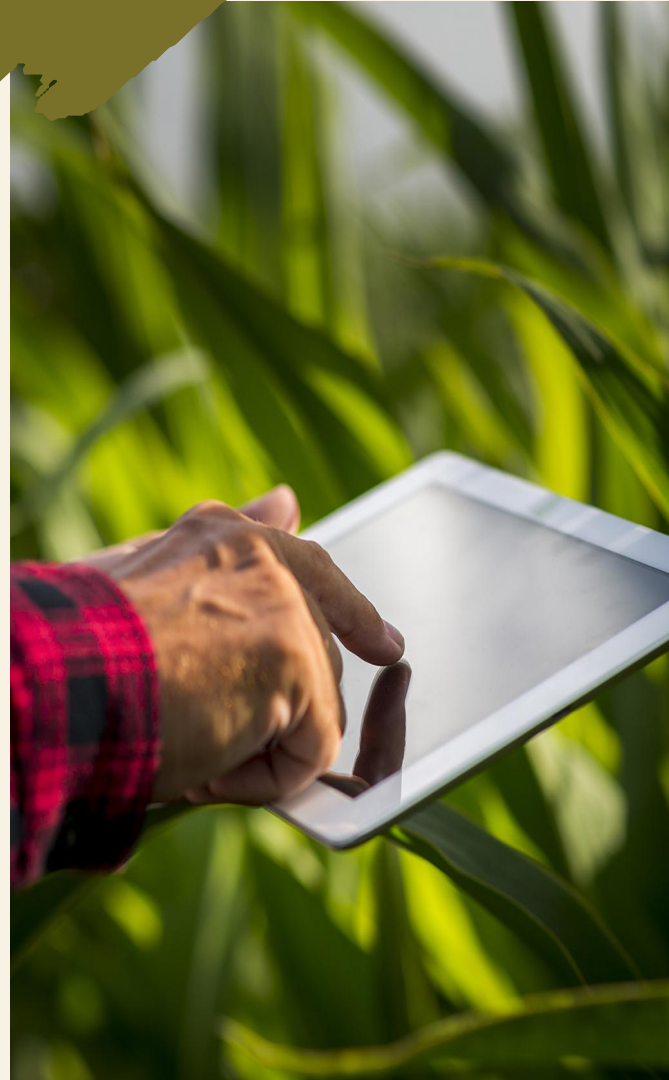
- Online tool for visualizing farmland by crop.



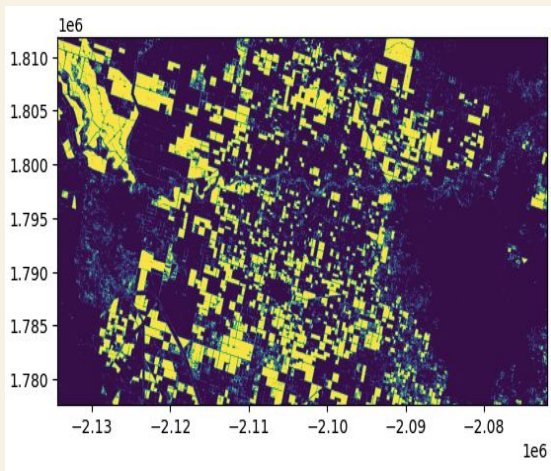
California Strawberry Commission (Daily Yield)

- Data on strawberry crop acreage, yields, and production estimates.

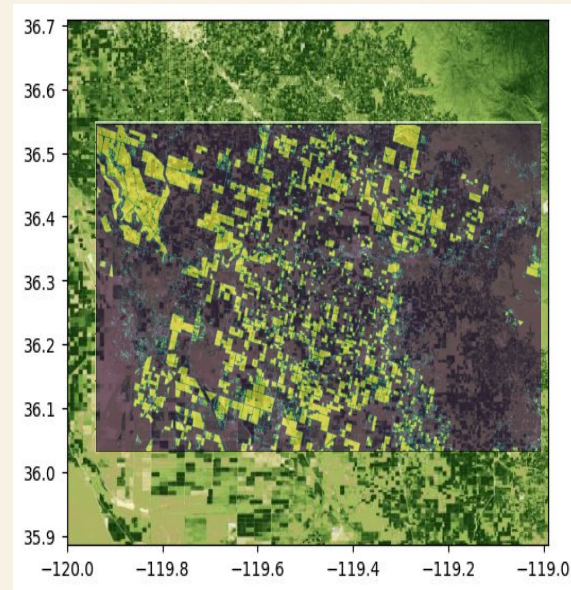
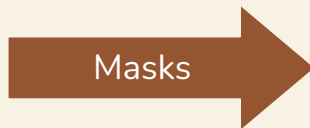
**CALIFORNIA
STRAWBERRIES**



Data Analysis



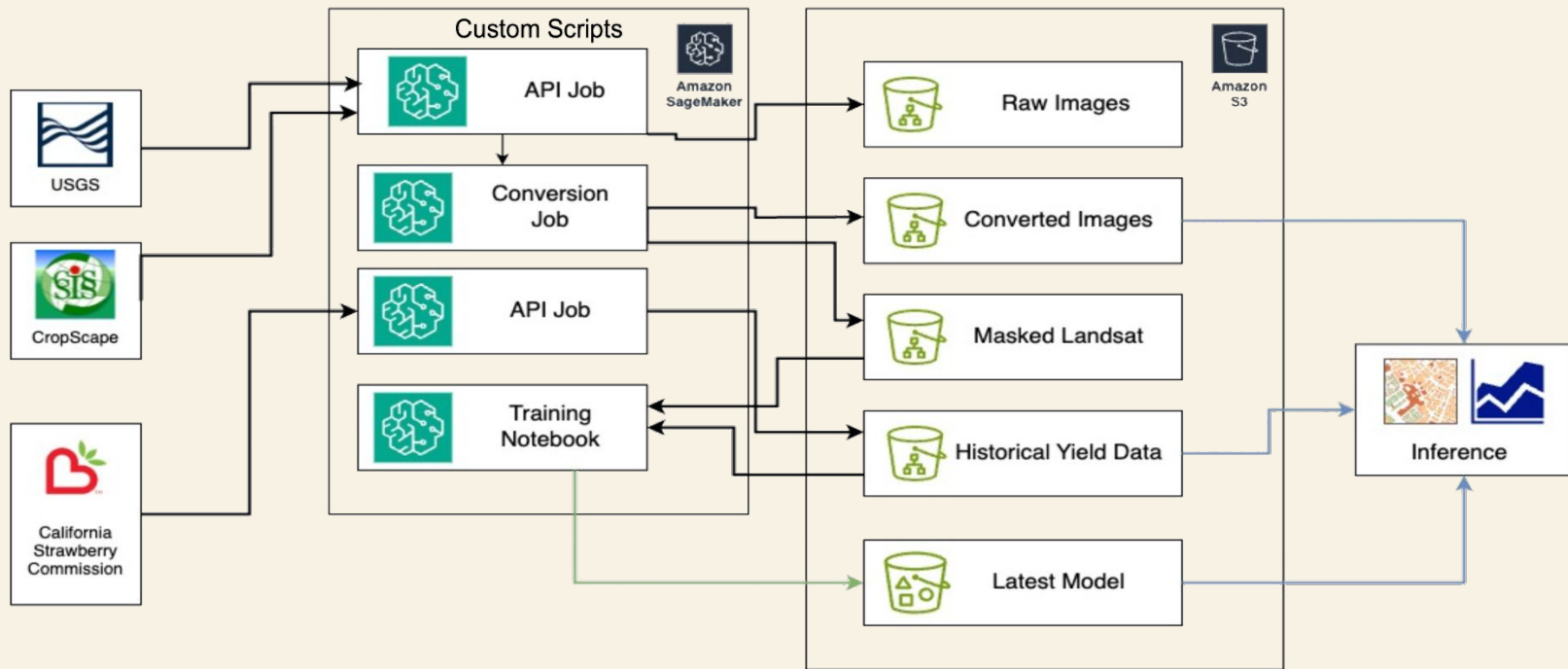
Identify strawberry farms
using CropScape



Mask satellite data for model input

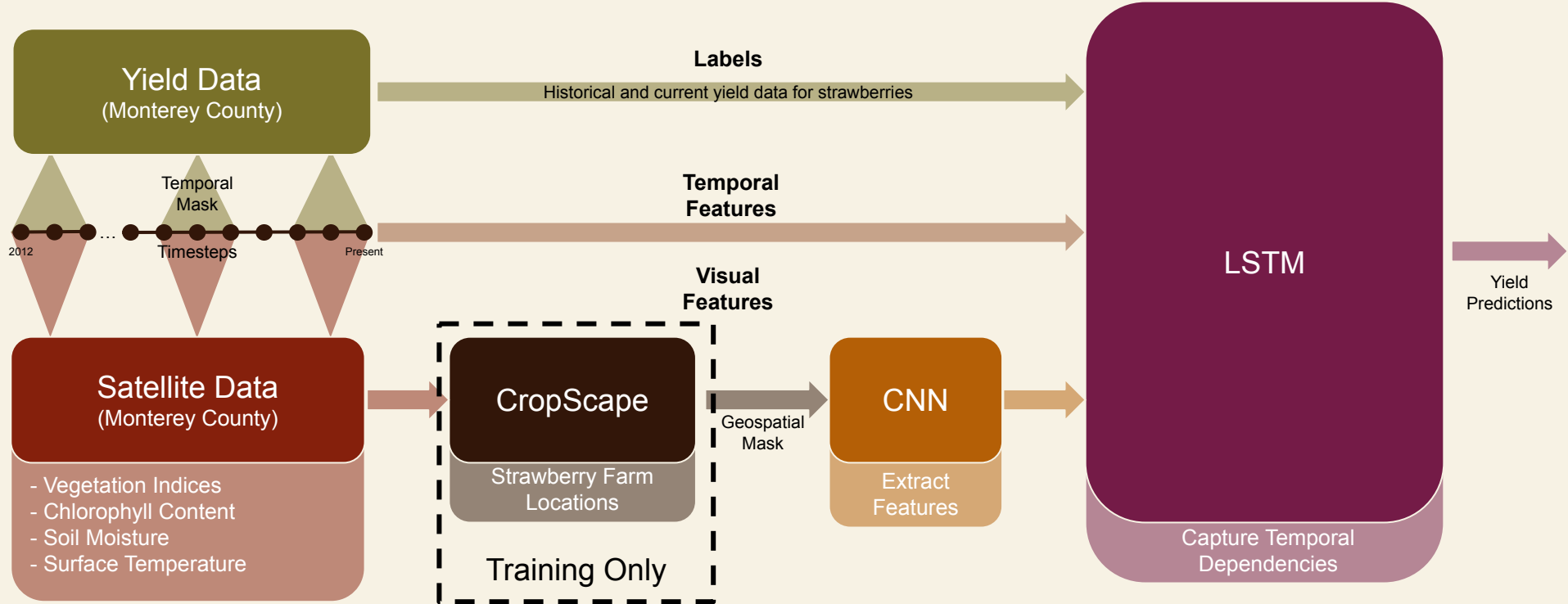


Data Pipeline



- Custom scripts resample and **apply uniform spatial resolution** and coordinate system
- Amazon S3 for secure storage and easy access

Model Design - Training





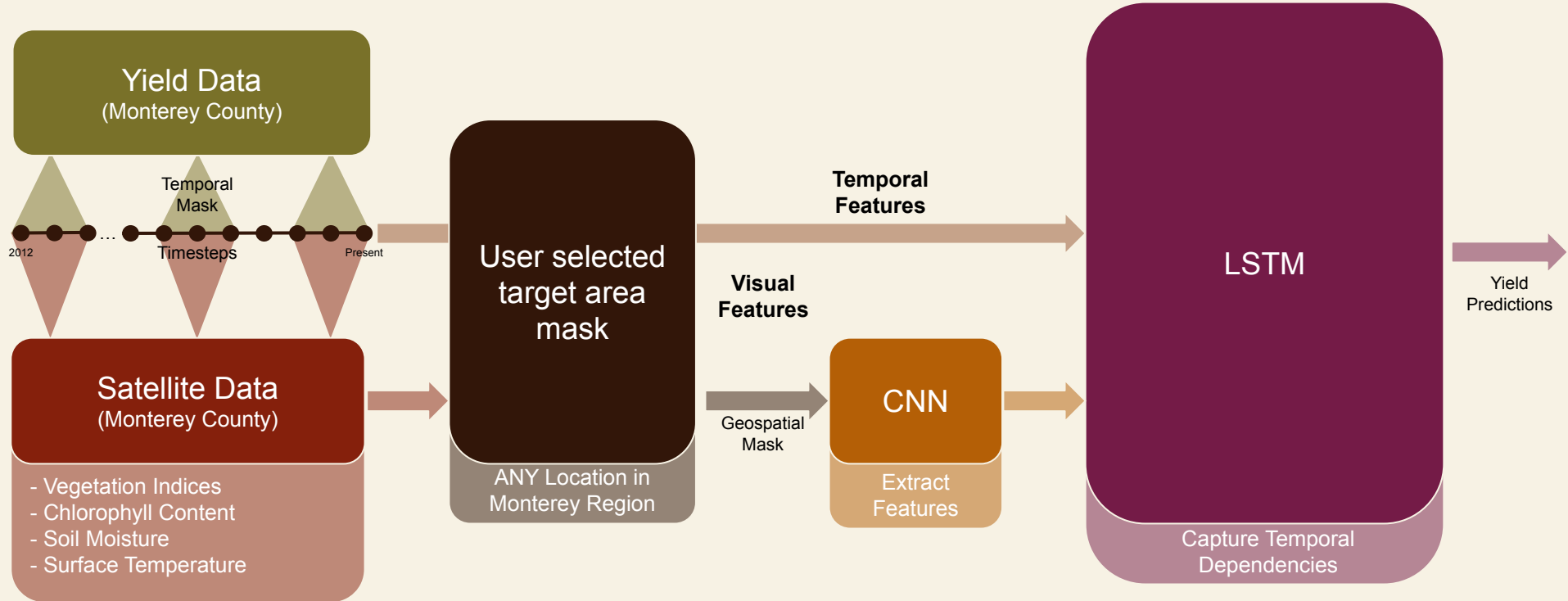
AgriSense

Make a selection below to view desired content:

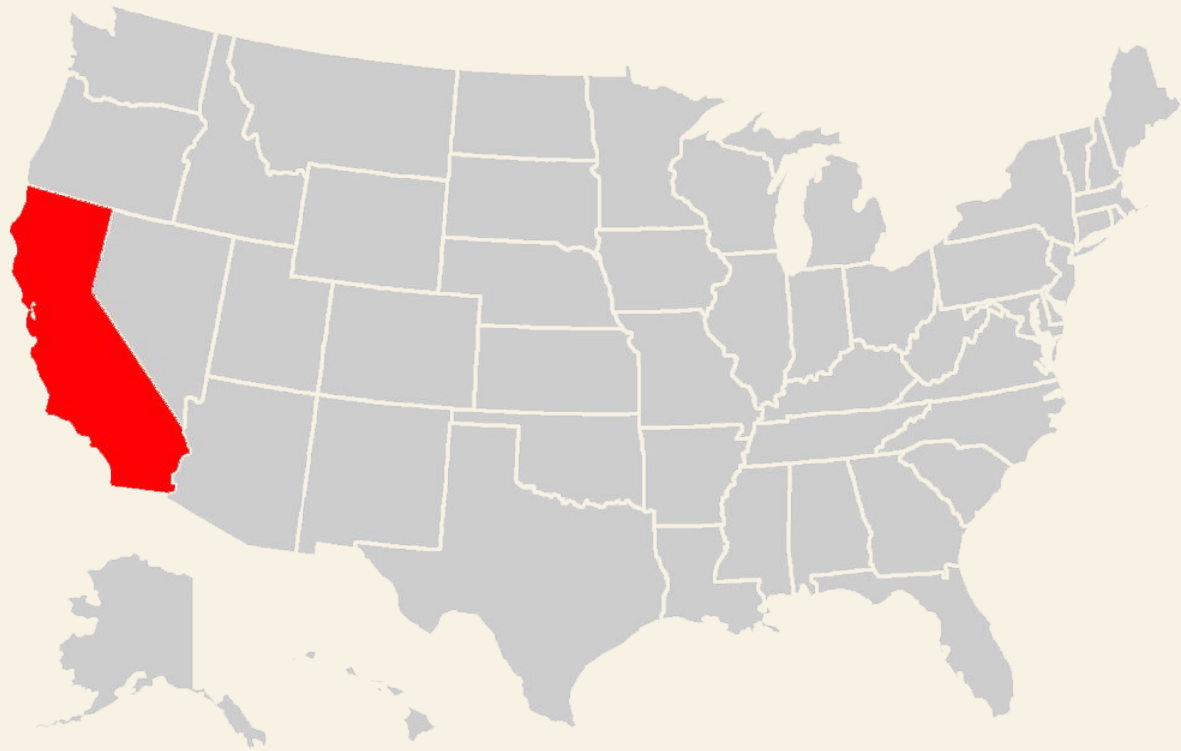
Crop Health



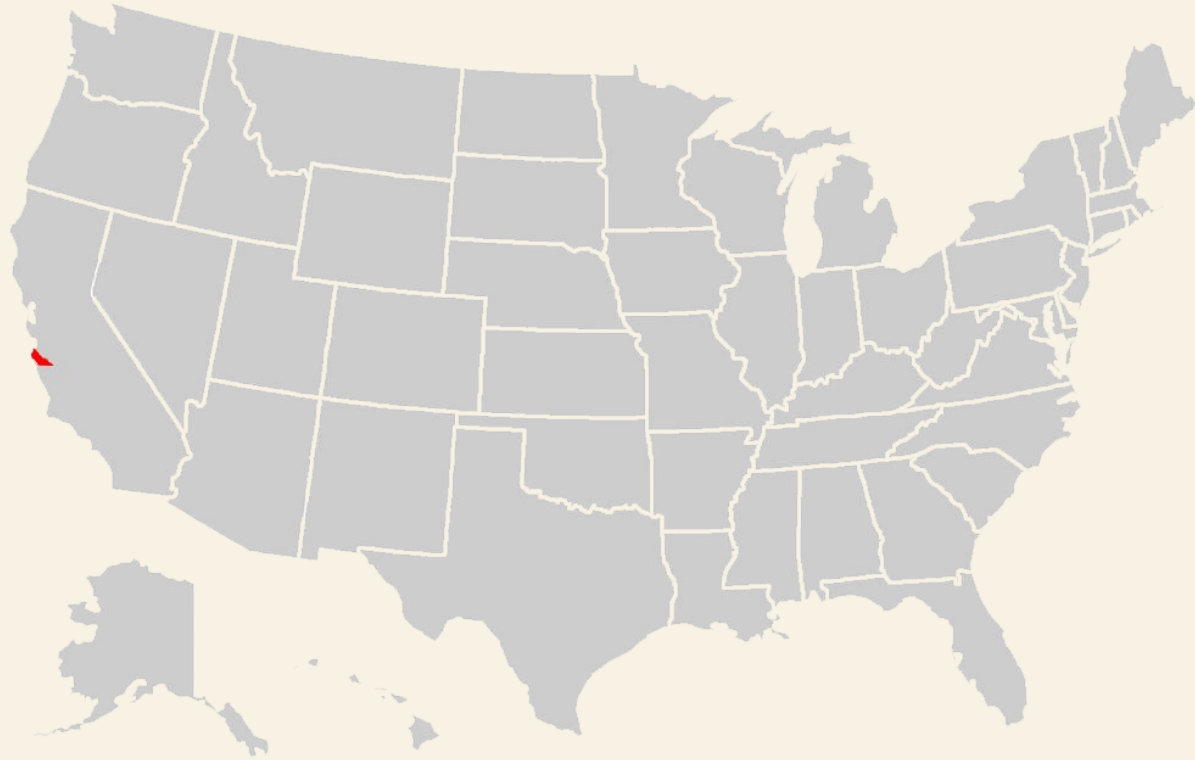
Model Design - Inference



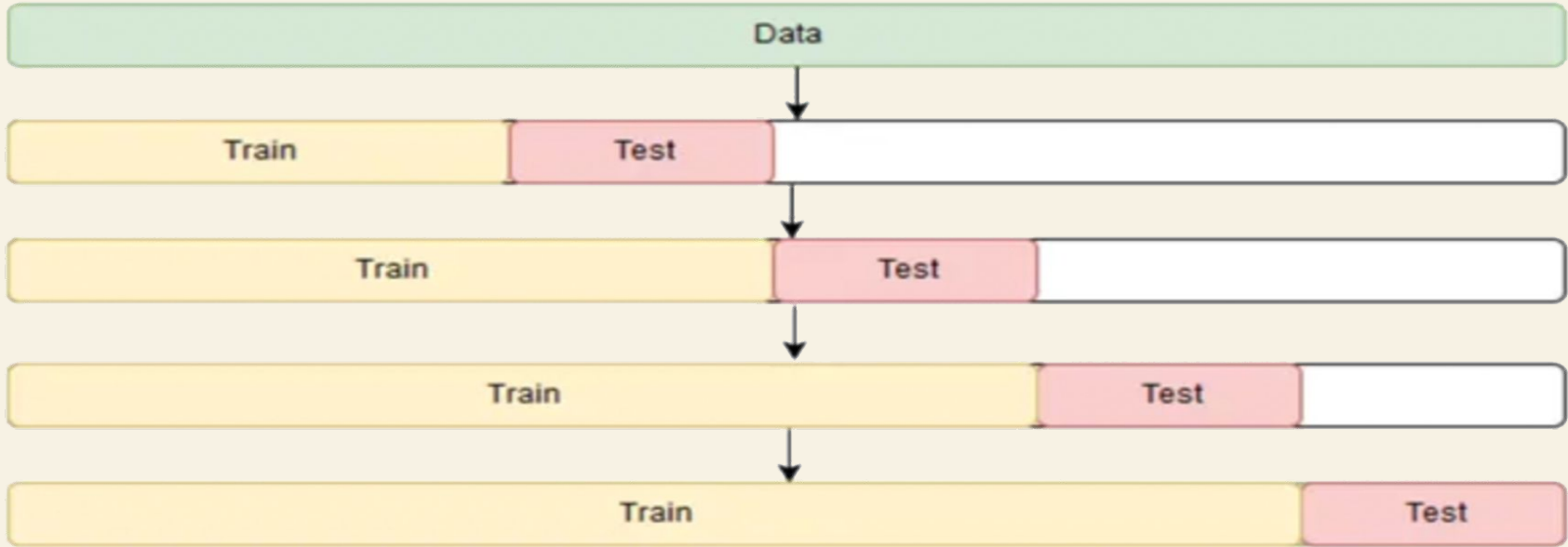
Current Limitations



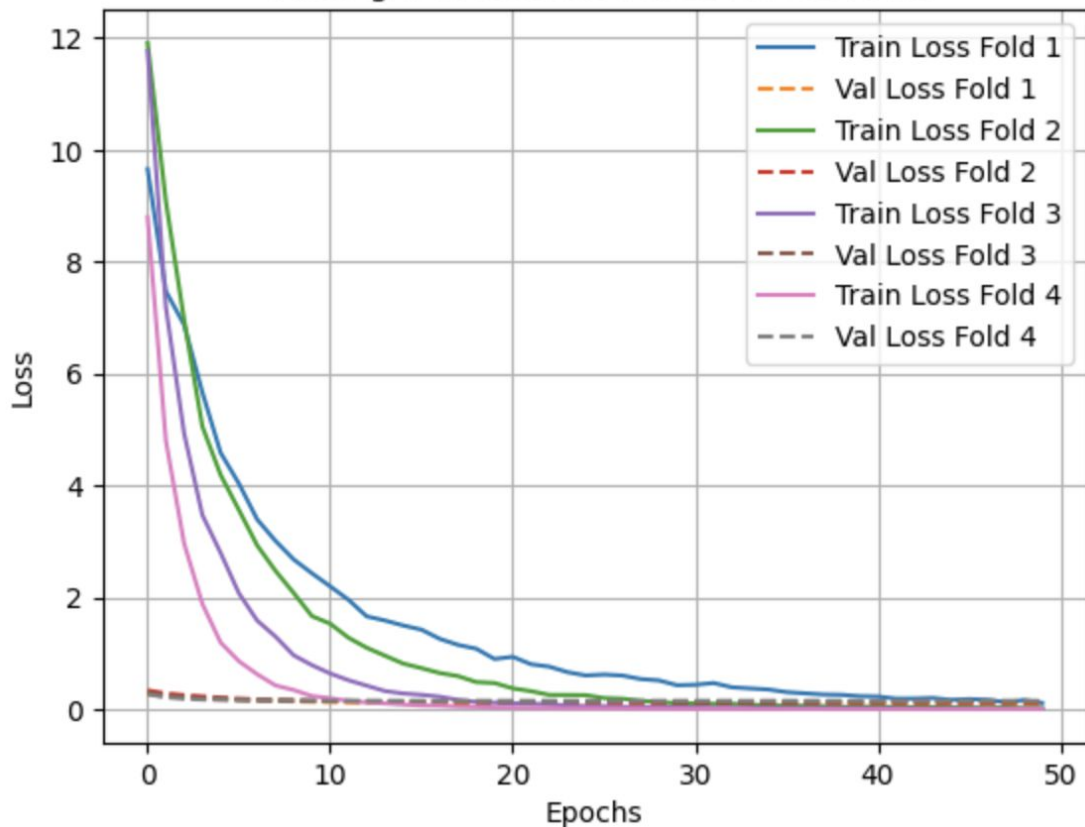
Current Limitations



Time Series Cross Validation

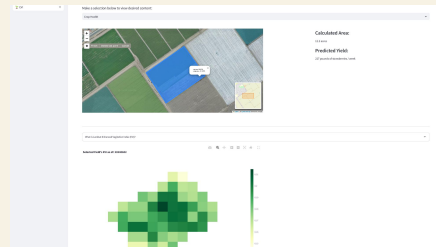
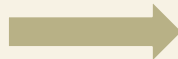
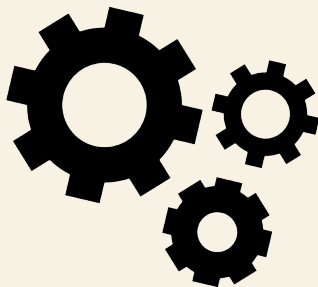
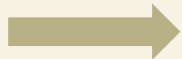
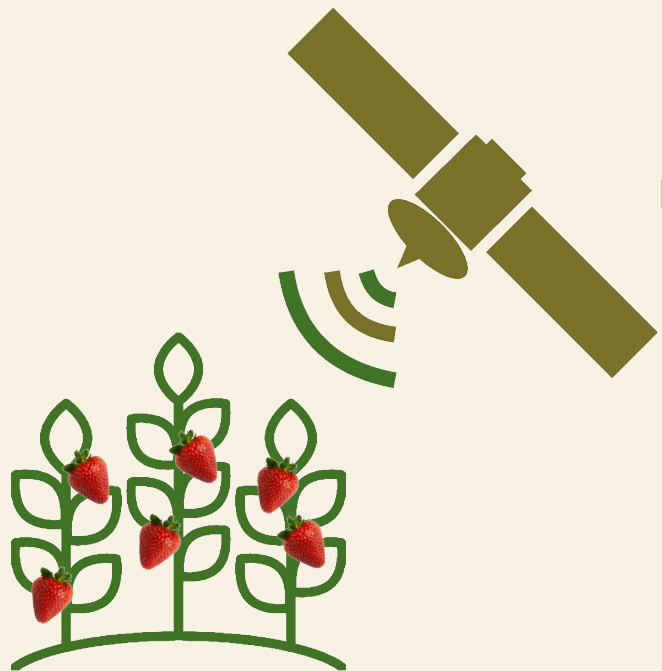


Training and Validation Loss Across Folds



# of Epochs	50
Avg MSE	0.12172
Avg RSME	0.34728
Avg MAE	0.25232
MedAE	0.25512

Insights





Technical Challenges

1. Pixel level precision
2. Data age
3. Growing Storage



Future Work



01

Model Improvement

Train on additional data:

- More satellite bands
- Inputs from farmers (self-reported crop yields, sensor data)



02

Frontend Performance

Better results in less time:

- User profiles
- Saved farm areas (pre-mask landsat data)



03

Generalization

More crops and more locations!

- Almonds, grapes, tomatoes, lettuce
- Washington, Oregon



AgriSense

Where precision meets sustainability.

We empower farmers with tech-driven solutions.

**We contribute to the economic viability &
sustainability of farming.**

**We support the long-term health of the
environment.**





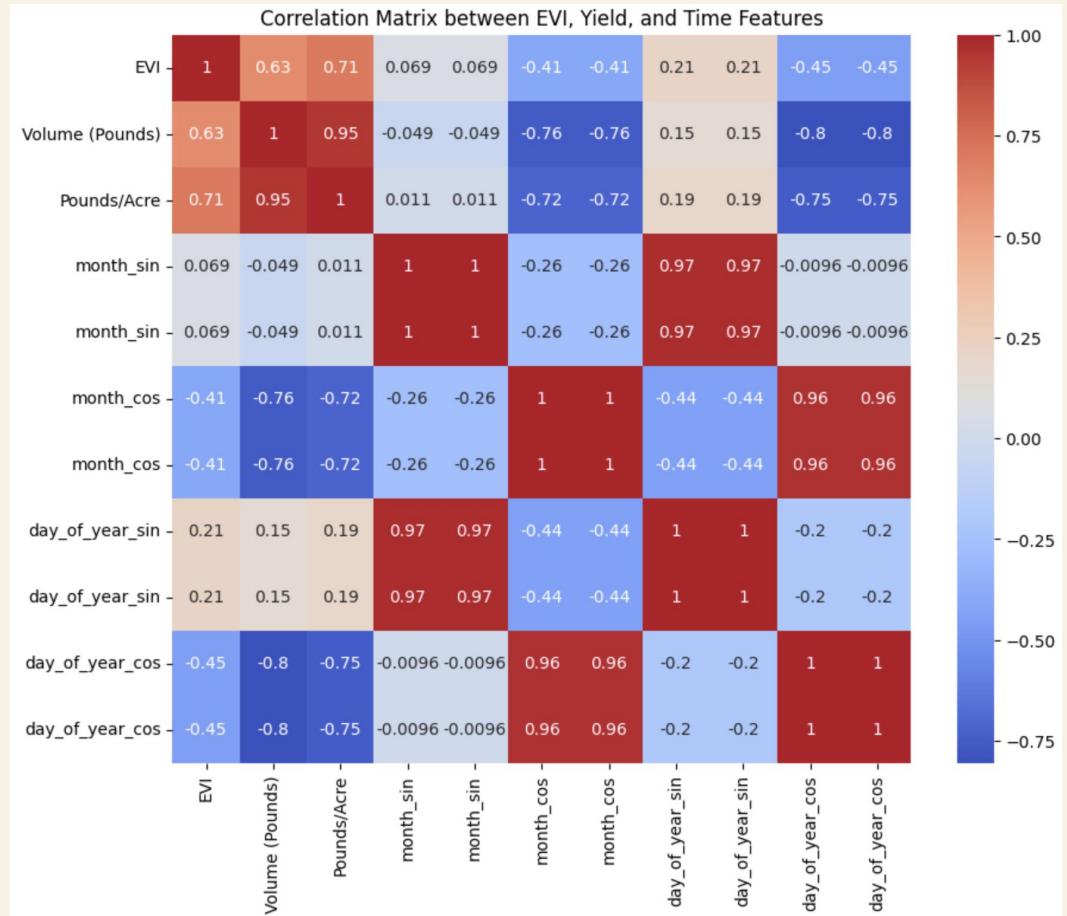
AgriSense

Appendix

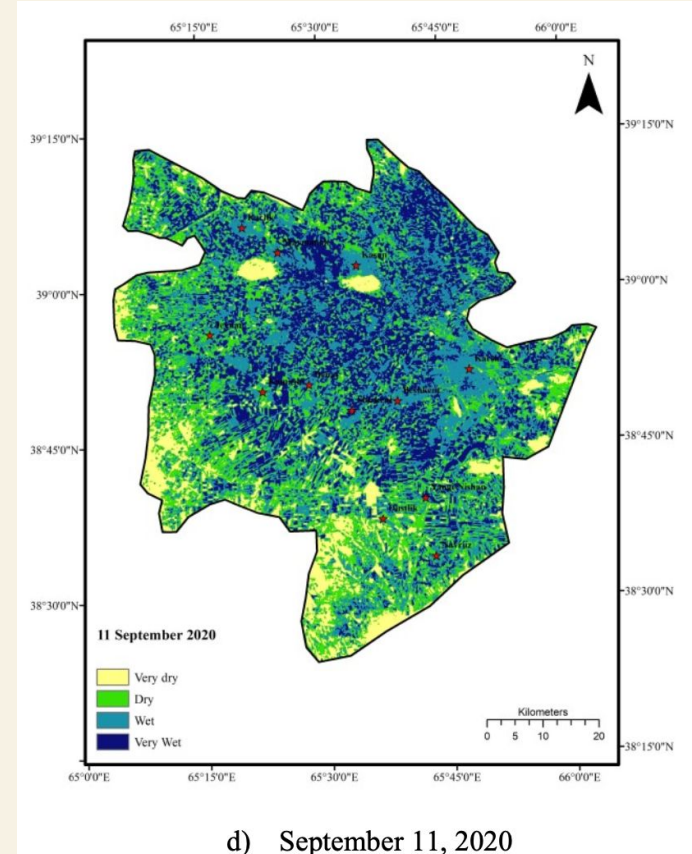
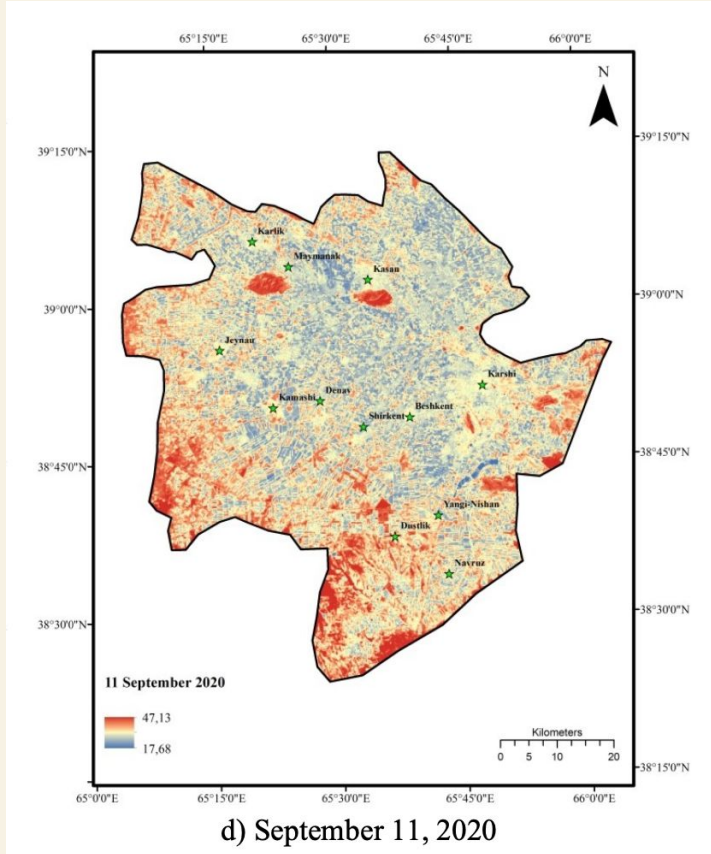
1. Correlation Matrix between EVI, Yield, and Time Features
2. Surface Temperature & Soil Moisture Plots
3. Limitations of Aggregated Yield Data
4. Ethical and Data Privacy Considerations
5. Market Research
6. Sources

EDA Correlation Matrix

- Pounds/Acre & EVI: 0.71
- Volume & EVI: 0.63
- Pounds/Acre & Month_cos: -0.76
- Volume & Month_cos: -0.72



Surface Temperature & Soil Moisture



Limited by Aggregated Yield Data

What

- R^2 Value differs from metrics.
 - Cannot account for detailed variance and outliers

Why

- Yield data was aggregated on a county-level
 - No farm-level data for model training
- Smooths out the variance expected at the farm level

The Fix

- Higher granularity, farm-level, yield data is a vital future improvement and next step for the project

# of Epochs	50
Avg MSE	0.12172
Avg RSME	0.34728
Avg MAE	0.25232
MedAE	0.25512
R^2 Value	-1.0912

Ethical and Data Privacy Considerations



Environmental Impact

There is a risk that data-driven farming practices could lead to unintended ecological consequences.



Data Ownership & Confidentiality

Farmers should retain ownership of their data and have control over how it is shared and used, especially due to market competition



Impact on Employment

Automation and optimization may reduce the need for manual labor, impacting farm workers.



Biases in ML Models

ML models may inherit biases from training data, leading to skewed recommendations that might not be universally applicable.



Fair Access

While our product will cater towards medium and large farms, we want to make sure our technology is accessible to farmers who don't have substantial financial resources

Market Research

OneSoil

Satellite Monitoring

NDVI Index

Specify Individual Fields

Weather Data

Farmers,
agri-food/retail

Planet Labs

Satellite Monitoring &
Imagery

Planetary Variables

Historical Image Library

Agriculture,
government &
defense, forestry




Farmers Edge

Satellite Monitoring

Data Portal
(Farm-Specific)

Soil Sampling

Farmers, insurance,
agri-food/fuel/retail

Company	 FarmersEdge™	 OneSoil	 AgriSense
Satellite Imagery Data	✓	✓	✓
Weather Data	✓*	✓	✓
AI-Driven Modeling	✗	✗	✓
Optimization Insights	✗	✗	✓
Seeding & Fertilization Data	✗	✓	✗

* Only Available in Premium Tier

Sources

- [1] "Water Scarcity". *World Wildlife Fund*, 11 Nov. 2014, [Link](#).
- [2] Khokhar, T. "Globally, 70% of Freshwater is Used for Agriculture". *World Bank*, 22 Mar. 2017, [Link](#).
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- [7] Sichugova, L., Fazilova D. "Soil Moisture Estimation Using Landsat-8 Satellite Data: A Case Study the Karshi Steppe, Uzbekistan". *International Journal of Geoinformatics* 18 (1):63-69, 7 Feb. 2022, [Link](#).
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