

A Novel Machine Learning Approach for Cotton Yield Prediction

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Background

It is critical to forecast crop yields to address food security concerns amid global climate change. An array of stakeholders, including policymakers and producers, highlight the criticality of precise and timely yield estimation. However, it is challenging to develop a robust and accurate crop model



Different Modeling Techniques-

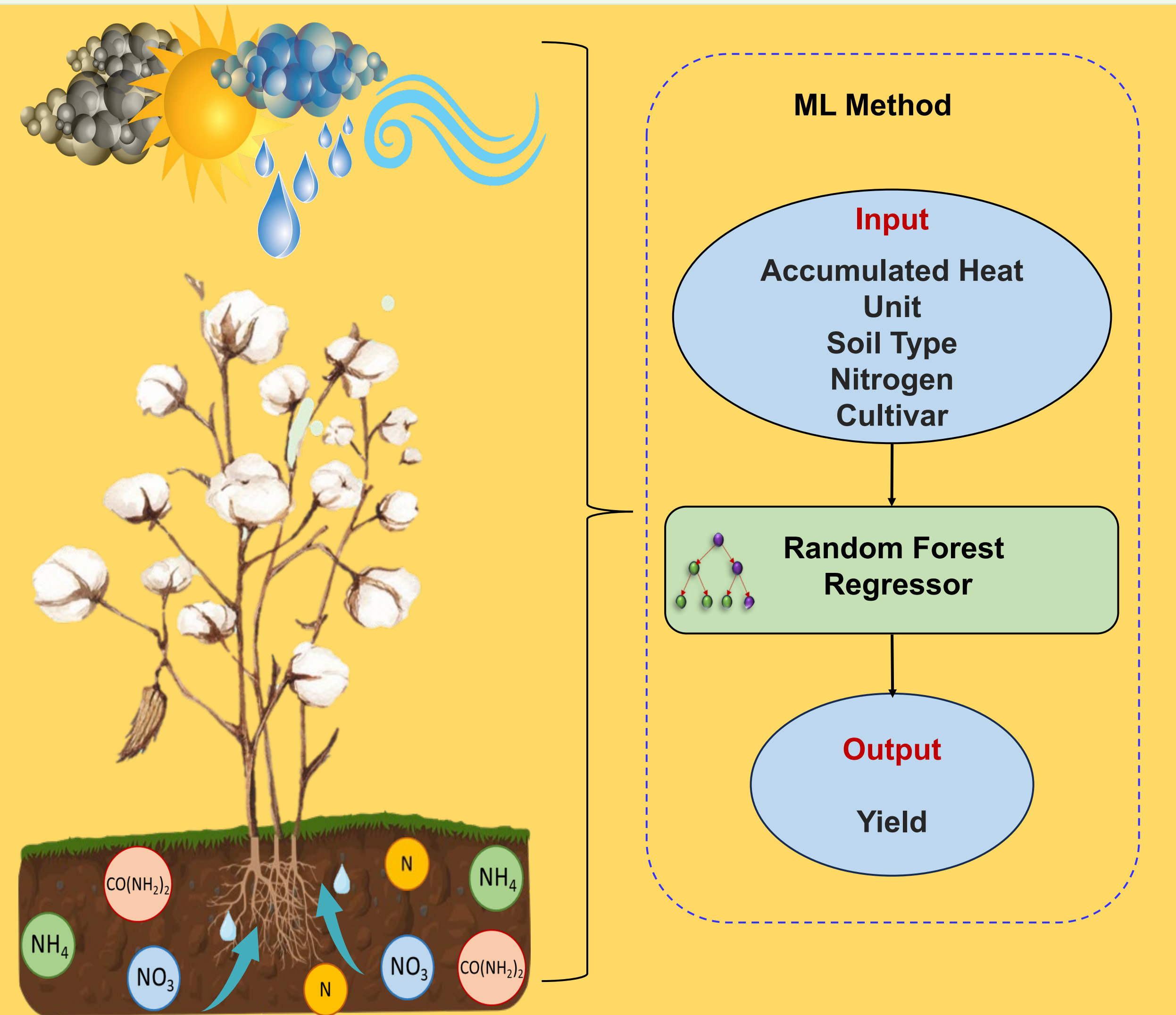
1. Process-based Models (effort and time-consuming and computation-heavy).
2. AI/ML Models (data-driven, learn patterns from the data, computationally light, work like black-box but need a lot of data).
3. Hybrid Models (the name suggests the model).

Research Problem

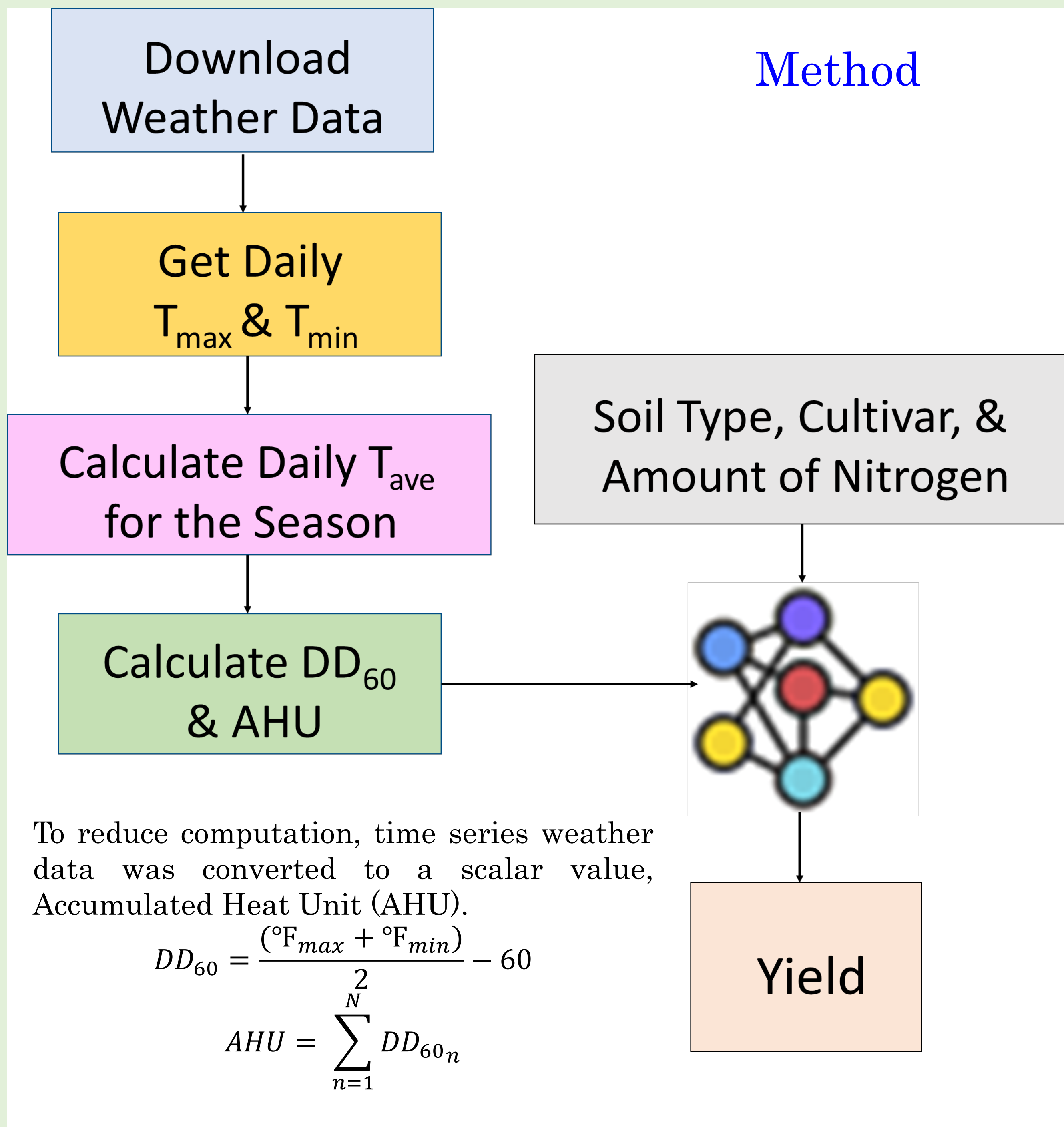
1. A robust and simple crop model that can predict yield accurately and is computationally light.
2. Training data scarcity inhibits the development of a high-performing model.

Solution

We aim to accurately **predict cotton yield** using a Random Forest Regressor (an ML method) incorporating the effects of climate change, soil varieties, cultivars, and the amount of nitrogen from the fertilizers.



Method



To reduce computation, time series weather data was converted to a scalar value, Accumulated Heat Unit (AHU).

$$DD_{60} = \frac{(^{\circ}F_{max} + ^{\circ}F_{min})}{2} - 60$$

$$AHU = \sum_{n=1}^N DD_{60n}$$

Implementation

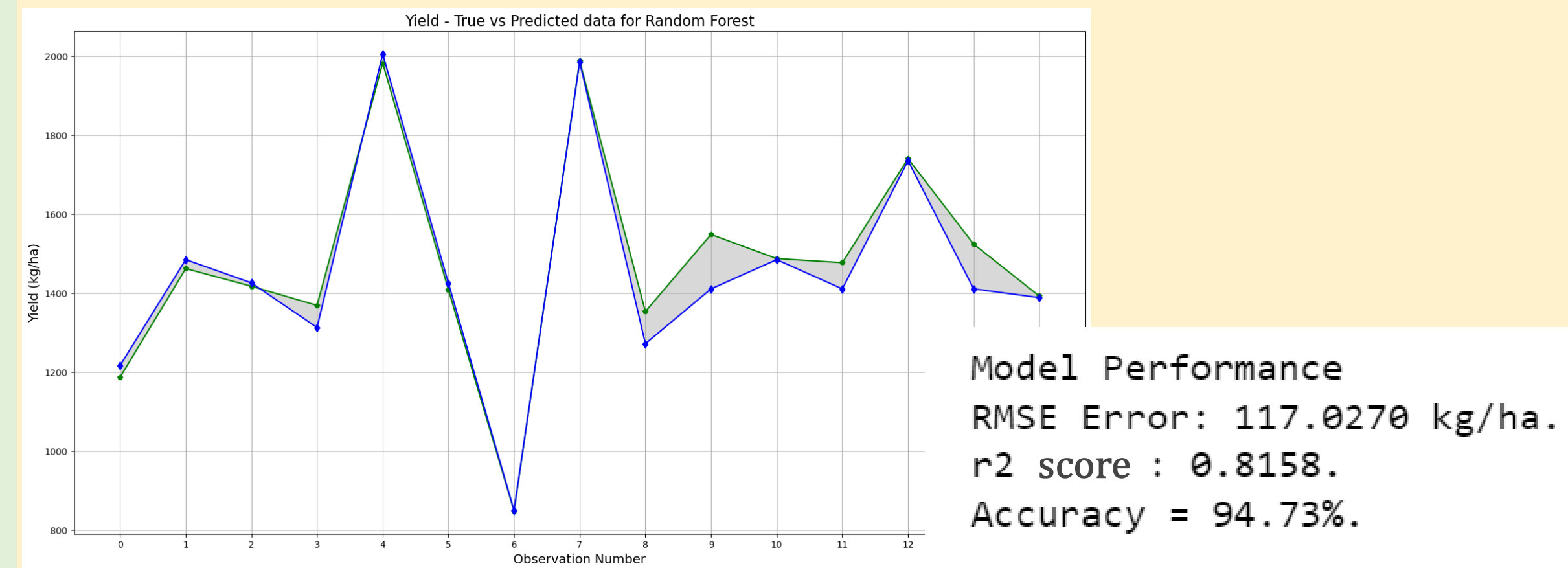
Machine Learning Algorithm

- We have used a Random Forest Regressor for predicting yield.
- We used 10 estimators.
- Bootstrap was kept False.
- 3-fold cross-validation used.

Training & Evaluation

- Keras [3] with the TensorFlow backend.
- Libraries used: pandas, numpy, matplotlib, sklearn etc.
- Trained on Intel Xeon Server with a 16-core CPU, 64 GB RAM, NVIDIA RTX A4000 GPU.
- Took few minutes to train.

Results



Yield Prediction (Results from Test Dataset)

True Yield	1186.74	1461.91	1417.19	1392.47	1523.86	1740.46
Predicted Yield	1216.47	1484.65	1425.82	1388.37	1410.54	1735.05

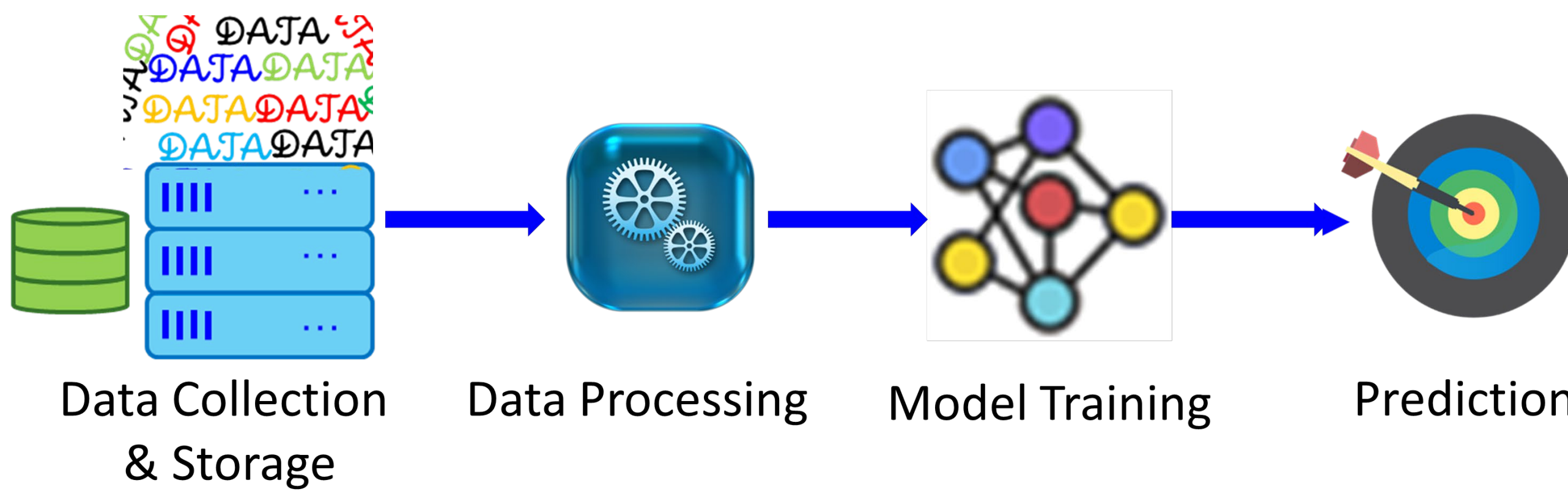
Conclusions

1. It reduces computation by converting time series weather data to a scalar value, Accumulated Heat Unit (AHU).
2. Application of ML makes the method simple but highly accurate [4].
3. No complex equation.
4. These are very initial results.
5. Final model has been trained with more variations on cultivars, soil types, and N amount.
6. High R² and much lower RMSE values have been obtained compared to the initial results.
7. Now, the final model can predict the cotton yield with high accuracy.
8. The detailed and final results are under review in a peer-reviewed journal.
9. As a future work, a detailed crop model with a simplistic approach will be explored.

References

1. NASA, "Power Data Access Viewer," [Online]. Available: <https://power.larc.nasa.gov/data-access-viewer/>. [Accessed 9 July 2023].
2. D. N. Baker, J. R. Lambert and J. M. McKinion, "GOSSYM: a simulator of cotton crop growth and yield," *SC Agricultural Experiment Station*, 1983.
3. F. Chollet and others, Keras, GitHub, 2015.
4. A. Mitra, S. P. Mohanty, and E. Kougianos, "Smart Agriculture - Demystified", in *Proceedings of the IFIP International Internet of Things Conference (IFIP-IoT)*, 2023, pp. 405—411.

Machine Learning Workflow



Dataset Details

Two types of cotton yield data—field data and synthetic data.

- Field data: Advanced Cropping Systems Laboratory, USDA-ARS Archive Data.
 - Collected in the 1980s and early 1990s.
 - Across the U.S. southern cotton belt.
- For Synthetic data:
 - Weather Data: POWER Data Access Viewer web interface [1].
 - Yield Data: Process-based cotton model GOSSYM [2].
 - Nine locations: Texas, Mississippi, and Georgia.
 - Two Soil Types, Two Cultivars, and Two Amounts of Nitrogen.
 - Last six years (2017-2022) of Weather data.

Dataset Processing

Two types of data processing:

1. Transforming categorical data → Numerical Data
2. Outliers Removal.