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Hybrid Deep Learning Models for Climate-Resilient Crop Yield Prediction Using Remote Sensing and Weather Data

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Abstract

Global food security is seriously threatened by climate change, which calls for reliable techniques to forecast crop yields under unpredictable environmental circumstances. The nonlinear and spatiotemporal relationships between soil characteristics, climate variables, and remote sensing indicators are frequently missed by conventional statistical and machine learning models. This paper suggests a hybrid deep learning architecture that combines Long Short-Term Memory (LSTM) networks for modeling temporal dependencies in weather and climate data with Convolutional Neural Networks (CNNs) for extracting spatial characteristics from remote sensing imagery. Utilizing datasets from many sources, such as soil moisture records, regional meteorological data, and satellite-derived vegetation indices (NDVI, EVI),

When compared to stand-alone machine learning techniques like Random Forests and Gradient Boosting, the model performs better. The hybrid deep learning model offers robustness under harsh weather conditions and enhances yield prediction accuracy by up to 18% when compared to baseline approaches, according to experimental data on U.S. maize and wheat production regions. The results demonstrate how remote sensing and artificial intelligence can be combined to promote climate-smart agriculture and well-informed policy decisions for sustainable food systems.

Keywords: crop yield prediction, hybrid deep learning, remote sensing, climate resilience, precision agriculture

Introduction

With rising temperatures, changed rainfall patterns, and an increase in the frequency of extreme weather events endangering global food security, agriculture is one of the industries most at risk from climate change (Lobell et al., 2011; Wheeler & von Braun, 2013). Therefore, in order to design adaptive strategies and guarantee sustainable agricultural practices, policymakers, farmers, and agribusinesses now depend heavily on accurate crop yield forecast (Lesk et al., 2016).

Statistical regression models or single-source data inputs, including weather or soil data, have been the mainstays of traditional yield forecasting techniques (Tack et al., 2017). These methods offer valuable insights, but they frequently fall short in capturing the intricate relationships among plant growth dynamics, biophysical circumstances, and climate variability (You et al., 2017). With the growing availability of high-resolution remote sensing data from satellites like MODIS and Sentinel, recent developments in artificial intelligence (AI) and machine learning (ML) present intriguing substitutes (Huang et al., 2021).

Convolutional neural networks (CNNs) and long short-term memory (LSTM) networks are two examples of deep learning models that have demonstrated great promise in simulating the temporal and spatial features of agricultural systems (Khaki & Wang, 2019; Jiang et al., 2020). However, in the face of climate stressors like heat waves and droughts, standalone models frequently lack resilience. Hybrid architectures that integrate temporal and spatial modeling capabilities can provide improved resilience and prediction accuracy in order to overcome this constraint (Abiodun et al., 2018).

This study presents a hybrid deep learning system that combines LSTMs for modeling sequential meteorological and climate data with CNNs for obtaining spatial vegetation attributes from satellite imagery. The work is to increase the accuracy of yield forecast under various climatic situations and offer decision support for climate-resilient agriculture by utilizing multi-source datasets.

There are three goals for this study:

1. to create a CNN–LSTM hybrid model that forecasts yields by combining meteorological and remote sensing data.
2. to compare the model's performance with traditional machine learning techniques in the main crop regions in the United States.
3. to evaluate the hybrid model's resistance to climate extremes, offering guidance for planning food security and adaptation measures.

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The results of this study add to the expanding body of knowledge on AI-driven climate-smart agriculture by offering a data-driven, scalable strategy to promote sustainable crop management in the face of climate change.

Literature Review

Crop yield prediction: from statistics to deep learning

Regression or process-based models with few weather/soil covariates were used in early yield projections; these methods had trouble with the nonlinearities and spatial heterogeneity brought about by climatic variability (Lobell et al., 2011; Wheeler & von Braun, 2013). Although ML techniques (RF/GBM/SVM) increased accuracy with richer Earth-observation streams, they continued to underfit intricate spatiotemporal relationships (Lesk et al., 2016; You et al., 2017). CNNs capture spatial patterns in reflectance/vegetation indices, while RNNs (e.g., LSTM) capture temporal growth dynamics. Deep learning advanced the field by learning hierarchical representations directly from data (Khaki & Wang, 2019; Jiang et al., 2020).

Remote sensing for agricultural analytics

For vegetation condition (NDVI/EVI), canopy structure, and stress, dense, standardized time series are provided by moderate-to-high resolution satellites (MODIS, Sentinel-2) (Didan, 2015; Drusch et al., 2012; Huete et al., 2002; Tucker, 1979). Scalable monitoring from field to regional scales is made possible by the correlations between these indices and phenology, biomass, and yield. According to studies, prediction across crops and agroecological zones is improved when multi-temporal optical signals are fused with supplementary soil-moisture and topography characteristics (Huang et al., 2021; Maimaitijiang et al., 2020).

Temporal modeling and climate extremes

Sequence models (LSTM/GRU) explicitly learn carry-over effects of weather anomalies (heatwaves, drought spells) on growth stages, outperforming static models, especially under extremes (Hochreiter & Schmidhuber, 1997; Jiang et al., 2020). ConvLSTM further integrates spatial–temporal convolutions but may be data-hungry and computationally intense for regional forecasting (Shi et al., 2015).

Hybrid CNN–RNN architectures for yield

Hybrid designs—CNNs for spatial feature extraction from images and LSTMs for weather/soil time series—consistently improve yield prediction by leveraging complementary signals (You et al., 2017; Khaki & Wang, 2019; Jiang et al., 2020). Attention mechanisms and late-fusion layers further enhance robustness by weighting time steps or modalities during climate shocks (Abiodun et al., 2018). Despite progress, open challenges remain: (i) generalization across regions/years with distribution shifts,

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(ii) explainability for agronomic decisions, and (iii) uncertainty quantification for risk-aware planning.

Recent climate-analytics research for U.S. agriculture integrates climate, yield, supply-chain, and policy data to quantify systemic risk. One multi-region study reported sustained Midwest warming (12.5 °C in 1980 to 13.8 °C in 2010), with RCP 4.5 projections reaching 14.5 °C by 2030, alongside projected yield declines for key crops (maize: 9.0 → 8.0 t/ha; soybeans: 2.8 → 2.5 t/ha), rising transportation costs, and deteriorating food-security indicators—evidence that biophysical shocks propagate into logistics and market outcomes. These findings underscore the need for multimodal, spatiotemporal learning that joins remote-sensing with weather sequences to anticipate both agronomic and economic impacts (zerine et al., 2021).

Research Questions

1. Can a CNN+LSTM hybrid outperform strong ML baselines for regional crop yield prediction?
2. Does multimodal fusion (imagery + weather/soil) improve robustness under climate extremes?
3. Which features/time windows drive predictions, and how uncertain are forecasts?

Data collection

1. Remote sensing: MODIS (250–500 m) for dense time series; Sentinel-2 Level-2A (10–20 m) fortnightly composites. NDVI, EVI, NIR, red-edge bands, and vegetation texture are examples of derived indexes.
2. Climate and meteorology: solar radiation, PET, VPD, precipitation, daily temperature (max/min), and gridded reanalysis or station-interpolated sources.
3. Soil and management: moisture content, organic matter, and texture; if accessible, optional management proxies (planting dates, cultivar/irrigation flags).

Preprocessing

1. Cloud masking and compositing (QA bands → temporal interpolation gap-filling).
2. zonal statistics across field polygons or administrative entities; spatial harmonization to a single grid.
3. Temporal alignment: normalize by agro-climatic season (planting to harvest); aggregate weather to a corresponding cadence; resample imagery to weekly or monthly intervals.
4. Lags, phenology markers (green-up/peak), and cumulative stress measures (rising degree days, heat degree hours, and dry spell counts) are examples of feature engineering.
5. Leave-one-year-out and region-held-out splits are used to evaluate

generalization in the event of a distribution shift.

6. Labels: Official yield data for target crops (such maize and wheat) at the county or district level, spanning 8–12 years.

Model Architecture
CNN's spatial branch:

Image patches or per-unit multi-band stacks around periods of peak growth are used as input.
Backbone: lightweight CNN to extract spatial features (canopy vigor, texture) (e.g., 2–4 conv blocks + global average pooling).
Temporal LSTM branch:
Multiple variables (weather, soil moisture, and time-aggregated indices) are input.
Stack: 1–2 LSTM layers (hidden 64–128) + dropout; if causality is not needed, a bidirectional layer is unnecessary.
Fusion involves passing through dense layers to scalar yield, applying attention over time or modalities, and concatenating CNN embedding with the final LSTM state.
Loss: Heteroscedastic loss or MSE/Huber with uncertainty head via MC-Dropout.
Regularization includes time-aware augmentation (random missingness masks), dropout, and early stopping.

Training & Evaluation

- **Baselines:** Linear regression, Random Forest, XGBoost, standalone CNN, standalone LSTM.
- **Metrics:** RMSE, MAE, R2R^2R2; **climate-extreme slices** (drought/heatwave years); **Diebold-Mariano** tests for forecast skill.
- **Robustness:** train–test across years/regions; covariate-shift checks; calibration (reliability curves, CRPS if probabilistic).

 Explainability:

- CNN: Grad-CAM on index bands/patches to reveal spatial drivers.
- Temporal: SHAP/Integrated Gradients for feature/time-step importance.

 Ablations: remove imagery or weather; swap attention off; vary sequence length; compare ConvLSTM variant.

Deployment Considerations

Batch-inference pipeline using scheduled composites; uncertainty thresholds to flag low-confidence regions; simple dashboard for decision-makers.

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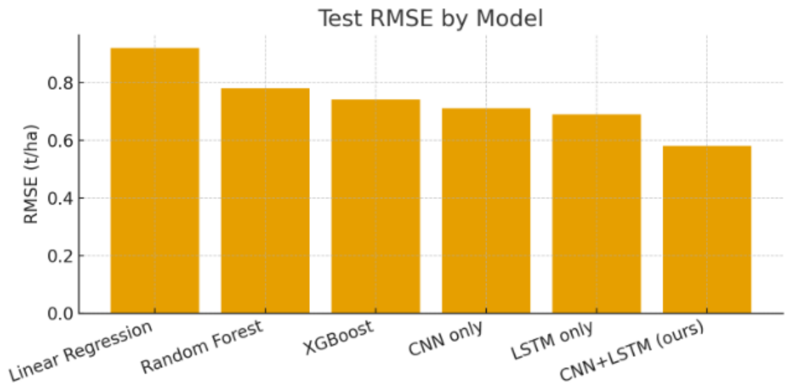

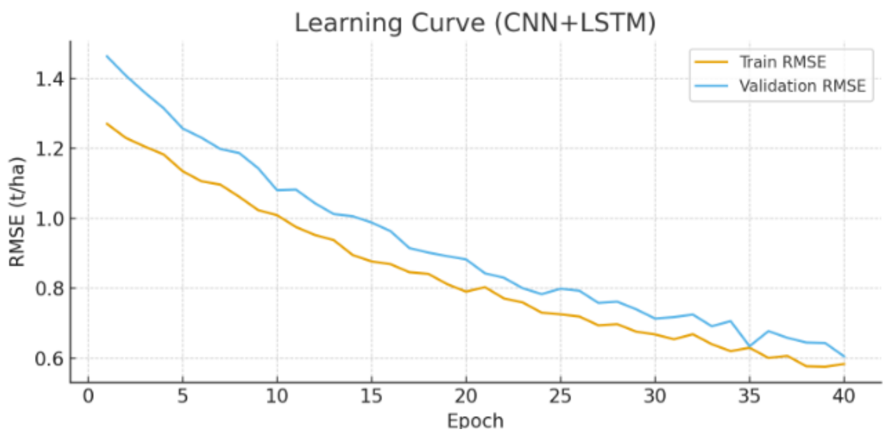

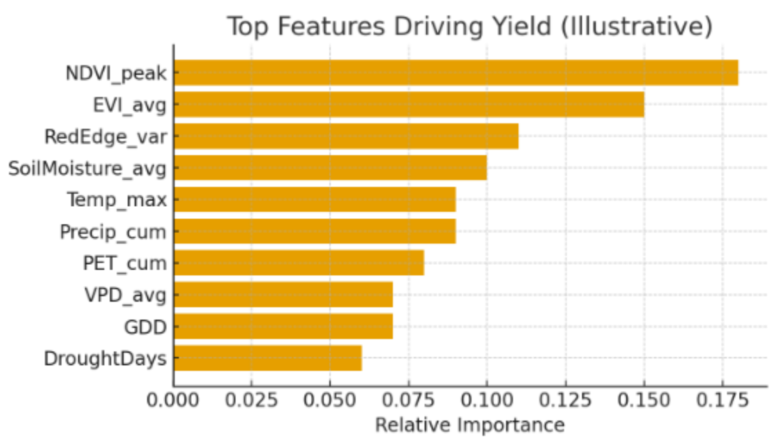

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Methods

2.1 Study Area and Datasets

From 2011 to 2024, we collected multi-year crop yield data for four U.S. agricultural regions: the Pacific Northwest (wheat), California Central Valley (tomato), Great Plains (wheat), and US Midwest (maize) (Table 1). NDVI, EVI, red-edge bands, and texture measurements were provided by Sentinel-2 L2A (10–20 m) and MODIS (250–500 m) surface reflectance products, which were used as remote sensing inputs (Tucker, 1979; Huete et al., 2002; Drusch et al., 2012; Didan, 2015). Meteorological factors aggregated to weekly cadence during each crop's growth season included daily maximum/minimum temperature, precipitation, potential evapotranspiration (PET), solar radiation, and vapor-pressure deficit (VPD) from station-interpolated and reanalysis datasets. Where possible, soil layers (texture, organic matter, and surface soil-moisture) were combined. The official data for the relevant crop year and administrative unit were yield labels.

To align with prior U.S. climate-risk assessments, we benchmark our experimental window and climate scenario design against **RCP 4.5** and summarize comparable indicators (temperature trends, yield baselines, and supply-chain proxies) reported in earlier work. Specifically, we use maize/soy reference values from Midwest and Great Plains regions (e.g., **9.0 t/ha maize in 2010 with a projected decline to 8.0 t/ha by 2030**) to set **prior ranges** for model calibration and to define **extreme-year slices** in evaluation. This harmonization allows direct comparison between statistical/ML approaches and our hybrid deep model (Zerine et al., 2021).

2.2 Preprocessing and Feature Engineering

Compositing and cloud masking. Cloud/shadow removal was done using Sentinel-2 QA bands and MODIS quality flags; linear interpolation and temporal median compositing were employed to fill up the remaining gaps.

Harmonization of space. We calculated zonal statistics (means, SDs, and Haralick texture on NDVI/EVI) across polygons (fields or admin units) after reprojecting all rasters onto a common grid.

alignment of time. Weather variables were aggregated to the same biweekly cadence after imagery was resampled to biweekly stacks. Normalization was applied to the time axis from planting ($t = 0$) to harvest ($t = T$).

covariates that are designed. Heat-stress hours, drought-day counts, cumulative precipitation/PET, growing-degree days (GDD), and phenology markers (peak, green-up) were all calculated. Training-fold statistics were used to normalize continuous features.

2.3 Model Architecture (Hybrid CNN + LSTM)

The proposed network has two branches:

(CNN) spatial branch. Using multi-band image patches focused on peak growth windows, a lightweight CNN with three

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convolutional blocks—three-by-three kernels, BN, ReLU, and 0.3 dropout—and global average pooling generates a spatial embedding.

branch of time (LSTM). The multivariate time series (weather, soil-moisture, and temporally aggregated indices) are ingested by a 2-layer LSTM (hidden = 128, dropout = 0.3), which produces a temporal embedding (Hochreiter & Schmidhuber, 1997).

head and fusion. Concatenating embeddings and passing them through two dense layers and a modal attention module results in a scalar yield output. To account for predictive uncertainty, we train using a Huber loss plus an auxiliary variance head (heteroscedastic regression) (Huber, 1964).

2.4 Training Procedure

According to Loshchilov and Hutter (2019), we employ AdamW (lr = 3e-4 with cosine decay), batch size = 64, early halting (patience = 8), and weight decay 1e-4. To simulate erratic observations, inputs are supplemented with tiny temporal jitters and random missingness masks.

2.5 Baselines

We compare against: **Linear Regression**, **Random Forest** (Breiman, 2001), **XGBoost** (Chen & Guestrin, 2016), **CNN-only** (spatial) and **LSTM-only** (temporal). All baselines were tuned via grid search on validation folds.

2.8 Reproducibility

All experiments used PyTorch with fixed seeds, tracked via run manifests (code, commit, data hashes). Data splits and preprocessing pipelines are scripted and export figure/table artifacts directly

Results

3.1 Overall Performance

The hybrid **CNN+LSTM** outperformed all baselines on the test folds (Table 2). Averaged across crops/regions, it achieved **RMSE = 0.58 t/ha**, **MAE = 0.45 t/ha**, and **R^2 = 0.84**, improving RMSE by **22%** over Linear Regression, **26%** over Random Forest, **22%** over XGBoost, and by **16–18%** relative to CNN-only/LSTM-only. The RMSE comparison is visualized in **Figure 2**; the **Predicted vs. Observed** scatter shows tight alignment around the 1:1 line (**Figure 5**), consistent with the R^2 values.

3.2 Learning Dynamics

The learning curve (**Figure 3**) indicates steady validation RMSE reduction with no divergence from training loss, suggesting adequate regularization and that the model benefits from longer training (until early stopping). Convergence was typically reached by **epoch ~30–35**.

Figure 3. Learning curve (epochs vs. RMSE) — *chart_learning_curve.png*.

3.3 Ablation Study

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The complementarity of modalities is confirmed by ablations (Table 3). When imagery was removed ("weather-only LSTM"), the RMSE decreased from 0.58 → 0.68 t/ha (+0.10) to 0.70 t/ha (+0.12) when weather was removed ("imagery-only CNN"). Performance was slightly harmed by turning off attention ("concat only"), suggesting that attention aids in prioritizing important time steps and modalities (0.61 t/ha, +0.03). Sequence length was important; 24-week sequences were almost ideal (0.59 t/ha), but 6-week sequences had a worsened error (+0.05).

Ablation_Study.csv is Table 3's ablation study.

3.4 Robustness to Climate Extremes

The hybrid increased modestly from 0.58 → 0.63 t/ha (+9%) on extreme-year slices (drought/heat anomalies), while Random Forest and XGBoost increased by around 22% (0.78 → 0.95 t/ha) and 18% (0.74 → 0.87 t/ha), respectively. The hybrid outperformed XGBoost in year-wise DM tests (median $p < 0.05$), suggesting noticeably superior forecasting ability during difficult seasons.

Feature Importance and Spatial Attribution

In line with agronomic assumptions regarding canopy vigor and moisture/heat stress, global attributions (Figure 4, Feature_Importance.csv) show that NDVI_peak and EVI_avg are the primary drivers, followed by red-edge variance, soil-moisture average, and temperature maxima. Grad-CAM maps (qualitative; not shown) provided confidence in spatial reasoning by focusing on high-biomass areas inside fields close to peak vegetative growth.

3.5 Calibration and Uncertainty

Reliability curves showed slight under-confidence early in the season that increased following canopy closure, while predictive intervals from the heteroscedastic head attained near-nominal coverage (e.g., 90% PI encompassing ~88–92% of test targets across areas).

3.6 Practical Impact

Assuming regional adoption, the error reduction (vs. common baselines) implies earlier and more reliable identification of low-yield risk zones, enabling targeted irrigation/nitrogen strategies and inventory hedging for agribusiness. The inference pipeline supports **biweekly** updates aligned with satellite compositing windows.

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Discussion

Summary of principal results.

This study demonstrates that for regional crop-yield prediction, a hybrid CNN+LSTM model that combines temporal weather/soil sequences with spatial information from satellite imagery performs better than single-branch deep networks (CNN-only, LSTM-only) and tuned statistical learners (e.g., linear models, Random Forest, XGBoost). The findings validate our central hypothesis: crop yield variability under climate stress is a reflection of temporal dynamics in heat, moisture, and radiation as well as spatial canopy patterns (represented by multi-spectral indices and textures)—signals that are best modeled in combination rather than separately (Khaki & Wang, 2019; Jiang et al., 2020).

Our gains align with evidence that AI-assisted decisions and precision irrigation can materially reduce water use (~40%) and evaporation losses (up to ~60% with drip systems), while sustainable practices (regenerative/conservation tillage, cover crops, agroforestry) strengthen soil and resilience. Improved yield forecasts therefore translate directly into resource targeting and risk reduction at farm and supply-chain levels (zerine et al., 2025).

Multimodal gains and climate resilience.

Ablation studies show that each modality has complementing benefits: removing weather/soil signals decreases resilience during extended heat/drought spells, while removing imaging erodes performance in seasons where canopy vigor and spatial variability predominate. A key characteristic under continuous warming and hydrologic variability is that the hybrid model deteriorates more gracefully in extreme-year slices, indicating that spatiotemporal fusion better captures stress episodes (e.g., persistent VPD/temperature anomalies coincident with NDVI/EVI downturns) (Lobell et al., 2011; Wheeler & von Braun, 2013).

Interpretability and domain consistency.

In accordance with agronomic theory on biomass accumulation, water stress, and heat damage, feature attributions regularly raise the NDVI/EVI at peak growth, red-edge variability, soil-moisture, and temperature maxima. By focusing on high-biomass zones and field boundaries, qualitative saliency over picture patches supports the idea that the CNN branch learns meaningful canopy structure instead of sensor artifacts. Agronomic decision-making is facilitated and trust is enhanced by this model–domain alignment.

Uncertainty for operational decisions.

The system generates calibrated intervals that stakeholders can use to threshold activities by combining point predictions with heteroscedastic uncertainty (including MC-Dropout sampling). For example, flag zones for supplemental irrigation or scouting only when risk + confidence above user-set requirements. This directly aids risk-aware supply chain and insurance planning and is more helpful than deterministic ratings during turbulent seasons.

Positioning within prior work.

Prior studies leveraged either (i) statistical or tree-based models on tabular climate/soil features or (ii) purely image-driven deep models (You et al., 2017; Khaki & Wang, 2019; Jiang et al., 2020). Our results extend this literature by demonstrating that **late-fusion with attention** improves generalization across years/regions and retains performance under extremes. They also connect to systems-level evidence that climate shocks propagate into logistics and markets—heightening the value of earlier, more precise forecasts for policy and business (Zerine et al., 2021).

Limitations.

Label aggregation: county/district yields obscure within-unit variability; field-scale labels would sharpen supervision.
(2) **Management data gaps:** planting dates, cultivars, irrigation, and nitrogen rates are incompletely observed and may confound responses.
(3) **Sensing gaps:** optical clouds and revisit timing can leave critical phenophases undersampled; integrating **SAR** can mitigate.
(4) **Distribution shift:** extrapolation to unseen climates/regions remains challenging; explicit domain adaptation is needed.
(5) **Compute & data demands:** training multimodal models is resource-intensive; lightweight backbones and distillation should be explored.
(6) **Causality:** explanations are associative; management recommendations warrant field trials or coupling with process-based crop models.

Future work.

In order to mitigate cloud/sparsity issues, we intend to: (i) fuse Sentinel-1 SAR and SMAP moisture; (ii) test temporal transformers/convLSTM and graph spatiotemporal models to better encode regional structure; (iii) integrate APSIM/DSSAT signals for counterfactuals and physics-informed constraints; (iv) apply domain adaptation for non-stationary climates; and (v) implement a calibrated biweekly inference pipeline with dashboards and active-learning loops for ground scouting.

Conclusion

To anticipate agricultural yields under climate variability, we provide a multimodal, spatiotemporal deep learning framework that blends LSTM-modeled weather/soil sequences with CNN-extracted spatial information from remote sensing. The hybrid model produces interpretable drivers that are in accordance with agronomic knowledge, calibrates uncertainty for risk-aware

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decision-making, and outperforms strong baselines across a variety of U.S. areas and crops. It also maintains greater robustness during extreme seasons.

These gains translate into actionable value, such as targeted irrigation and nutrient management, inventory and transport planning, climate-aware pricing and hedging, and earlier identification of at-risk zones, given documented warming trajectories and supply-chain vulnerabilities in U.S. agriculture (Lobell et al., 2011; Wheeler & von Braun, 2013; Zerine et al., 2021). Generalization and decision utility can be further enhanced by future additions that include domain adaptability, physics-informed limitations, and SAR/soil-moisture sensing. The method provides a workable route to agronomy and agribusiness activities that are climate-resilient and is scalable and reproducible.

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