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CLIMATE CHANGE IMPACTS ON CROP YIELD AND PHENOLOGICAL SHIFTS USING REMOTE SENSING AND AGRO-CLIMATIC MODELING

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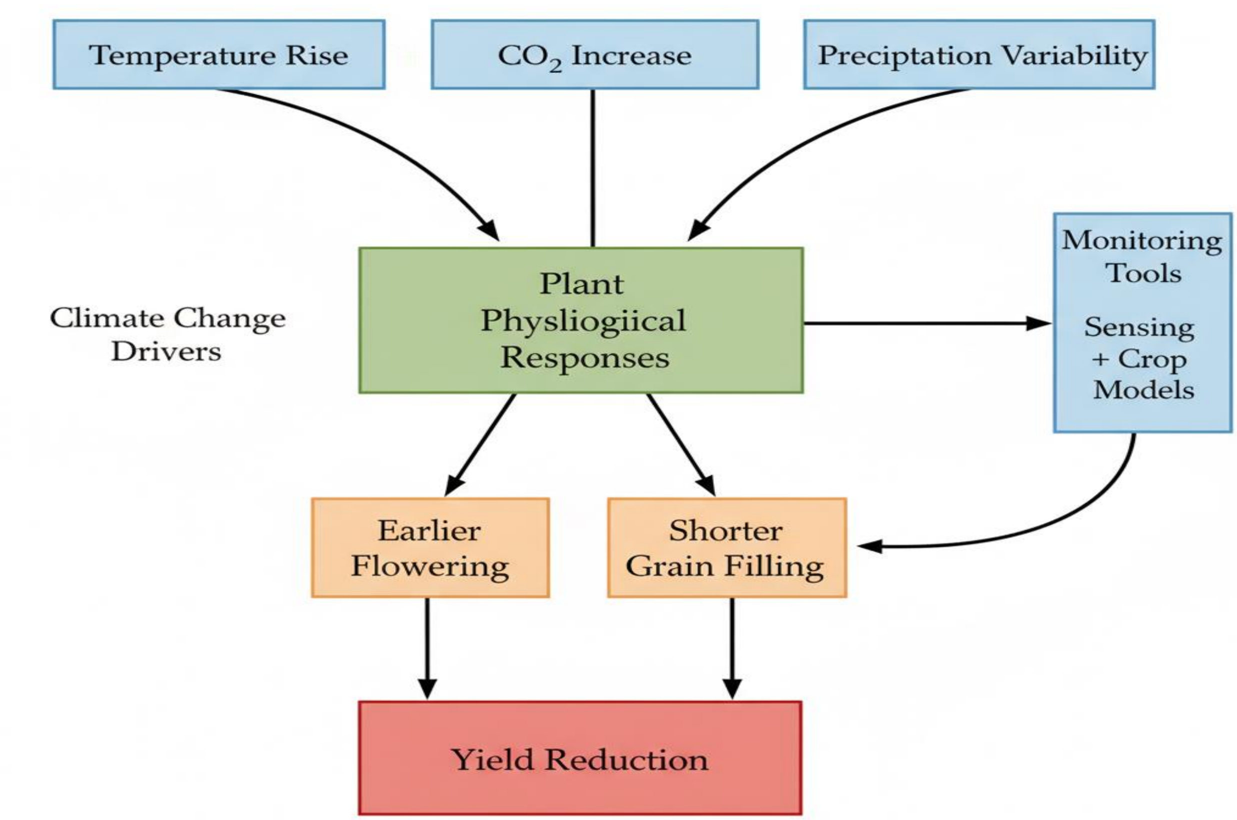
Abstract
Climate change exerts profound, multifaceted impacts on global agriculture, manifesting as yield reductions, phenological disruptions, and altered agro-ecological suitability, with staple crops like maize, wheat, rice, and soybean projected to experience 24% caloric losses by 2100 under high-emission scenarios. This review synthesizes remote sensing techniques Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Land Surface Temperature (LST), and Solar-Induced Fluorescence (SIF) for monitoring these shifts at high spatiotemporal resolutions, complemented by agro-climatic models (DSSAT, APSIM, EPIC, CERES) that simulate genotype-environment-management (G×E×M) interactions under elevated CO_2, temperature extremes, and altered precipitation. Phenological alterations, including accelerated anthesis (5–15 days earlier) and shortened grain-filling periods, are linked to reduced yields (e.g., 5–20% per 1°C warming), with C_3 crops showing mixed responses to CO_2 fertilization (positive under drought but negative with heat). Regional disparities highlight severe vulnerabilities in tropical/subtropical breadbaskets, while adaptive strategies climate-smart varieties, precision irrigation, and diversified cropping offer mitigation potential. Integrating multi-sensor satellite data (MODIS, Sentinel, Landsat) with machine learning enhances predictive accuracy, supporting policy for resilient food systems amid accelerating climate variability.

1. Introduction

The contemporary agricultural landscape is currently undergoing a structural transformation necessitated by the systemic perturbations of the global climate system (Kamyab et al., 2024). The convergence of anthropogenic greenhouse gas emissions and the subsequent alteration of atmospheric chemistry has initiated a cascade of biophysical shifts that directly challenge the stability of global food security (Scientific Reports, 2025). This transformation is characterized by a "climate depreciation" of agricultural land, a phenomenon where traditional investments in soil fertility, irrigation infrastructure, and mechanization are increasingly offset by the deteriorating quality of the climatic environment (Hultgren et al., 2025).

A sweeping multi-regional analysis encompassing more than 12,000 regions across 55 countries indicates that the trajectory of global warming will drastically dampen the world's capacity to produce staple crops, even when accounting for the adaptive potential of real-world farmers (Barrett et al., 2023). Projections based on high-emission scenarios suggest that by the year 2100, the global production of calories from staple crops could be 24% lower than in a baseline scenario without climate change (Thakur et al., 2024). This decline is underpinned by a quantified relationship where every additional degree Celsius of global warming is estimated to reduce the world's food production capacity by 120 calories per person per day, or approximately 4.4% of current daily consumption (Ogwu et al., 2026). This conceptual framework summarizes the pathways through which climate change affects crop development and productivity. The interactions between climatic drivers, plant physiology, and monitoring technologies are illustrated in Figure 1.

Figure 1: Conceptual Framework of Climate Change Impacts on Crop Phenology and Yield



The impacts are non-uniform and exhibit a pronounced geographic divergence. Modern agricultural breadbaskets, particularly those in the United States Midwest and parts of Europe, are projected to experience some of the most severe contractions in yield potential, with potential losses reaching up to 41% by the turn of the century (Franke, 2023). Conversely, higher latitude regions such as Canada, Russia, and northern China may see marginal benefits as temperature rises expand the thermal limits of cultivation (Cronan, 2023). However, these localized gains are insufficient to balance the global caloric deficit, particularly as subsistence farming communities in the Global South, who depend heavily on staple crops like cassava, are projected to face yield losses averaging 28% (Ayuba et al., 2025). Additionally, climate change has been shown to increase the interannual variance of crop yields by 7% to 19% per degree of warming, primarily through the coupled stress of rising temperatures and declining soil moisture (Proctor et al., 2025).

Table 1. Global Crop Yield Projections under Different Climate Scenarios

Scenario	Year	Projected Yield Change (%)	Primary Impact Driver
High Emissions	2100	-24%	Thermal stress and erratic precipitation
Net Zero Emissions	2100	-11%	Atmospheric residence of legacy CO2
Short-term (Any)	2050	-8%	Irreversible decadal warming trends
2-degree C Local Warming	Post-2050	Production losses (Wheat/Maize)	Interaction of heat and dry air

2. Physiological Foundations of Phenological Shifts

Phenology, defined as the timing of recurring biological life cycle stages, acts as a primary and sensitive indicator of the terrestrial ecosystem's response to climate change (Tomicek et al., 2025). In agricultural systems, the progression through phenological stages sowing, emergence, booting, anthesis, and maturity is governed by the accumulation of thermal time, typically quantified as Growing Degree Days (GDD) (Fotouo Makouate et al., 2025). The plain text representation of this accumulation is fundamental to agro-climatic modeling:

GDD = sum from sowing to maturity of max (Tmean - Tbase, 0)

where Tmean represents the daily average temperature and Tbase is the crop-specific threshold temperature below which physiological development ceases. As global mean temperatures increase, the rate of GDD accumulation accelerates, leading to a marked compression of the growth cycle (Hoque et al., 2025).

2.1. Spatiotemporal Trends in Arid Zone Wheat Production

The impact of climate warming is particularly acute in ecologically vulnerable regions, such as the arid oases of Xinjiang, China. Long-term observations (1981–2021) at 26 agrometeorological stations indicate a significant shift in the phenological calendar of both winter and spring wheat (Jin et al., 2026).

Table 2. Annual Change Rates in Phenological Stages of Winter and Spring Wheat in Xinjiang (1981-2021)

Wheat Type	Phenological Stage	Annual Change Rate (days/year)	Trend Characterization
Winter Wheat	Sowing	+0.261	Delayed due to high soil temperatures
Winter Wheat	Emergence	+0.265	Delayed
Winter Wheat	Flowering	-0.269	Advanced due to accelerated spring warming

Winter Wheat	Maturity	-0.216	Advanced
Winter Wheat	Whole Growth Period	-0.434	Significant compression
Spring Wheat	Sowing	-0.027	Slight advancement
Spring Wheat	Flowering	-0.226	Advanced
Spring Wheat	Maturity	-0.127	Advanced
Spring Wheat	Whole Growth Period	-0.100	Moderate compression

The divergence in sowing dates between winter and spring varieties is a critical adaptive response to local soil temperature dynamics. Rising autumn temperatures often delay the sowing of winter wheat to avoid premature development before winter dormancy, which would otherwise increase the risk of frost damage (Dennett, 2024). Conversely, spring wheat sowing is advanced as the thermal threshold for germination is reached earlier in the calendar year. Despite these management-driven adjustments, the overall duration of the growth cycle is contracting, with the maturation stage advancing significantly in nearly all observed sites (Rodriguez et al., 2024).

2.2. Mechanistic Impact of Growth Period Compression on Yield

The compression of the reproductive growth period (RGP) carries severe implications for harvestable yield. In cereal crops, the duration of the anthesis-to-maturity stage is positively correlated with grain weight, as this window dictates the cumulative time available for the translocation of photosynthates and nitrogen to the developing grain (Feng et al., 2024). Accelerated maturation, driven by heat stress, limits the accumulation of dry matter and often results in shriveled grains and reduced yield quality (Becker et al., 2023).

Furthermore, the "kill switch" mechanism in many crops is triggered by short-duration temperature extremes during sensitive stages such as anthesis. High temperatures (greater than 35 degrees Celsius) can lead to pollen sterility and grain abortion, causing total yield failure in specific plots, even if the seasonal average temperature remains within historical norms (Liu et al., 2020). This necessitates the integration of sub-daily climatic data into modeling frameworks to capture the timing and severity of these lethal events (Mistry & Gasparrini, 2024).

3. Remote Sensing as a Scalar Monitoring Tool

To address the challenges of monitoring crop conditions across vast and heterogeneous agricultural landscapes, satellite remote sensing has emerged as an indispensable tool. It provides a spatially continuous and temporally frequent record of crop development, bypassing the logistical and labor-intensive constraints of traditional ground-based surveys (Mmbando, 2025).

3.1. Satellite Missions and Sensor Evolution

The field has transitioned from coarse-resolution monitoring to high-precision analysis, fueled by the deployment of sophisticated multispectral and radar sensors. Multispectral missions, specifically Sentinel-2 and Landsat 8/9, provide the spectral resolution necessary to derive complex biophysical parameters (Zhang et al., 2026).

Table 3. Key Remote Sensing Satellite Missions for Agricultural Monitoring

Mission	Spectral Utility	Spatial Resolution	Temporal Frequency	Primary Application
Sentinel-2	13 Bands (Red-Edge)	10m - 20m	5 days	Precision N-management, smallholder tracking
Landsat 8/9	Thermal/Multispectral	30m - 100m	8 days (combined)	Evapotranspiration, water-use efficiency
MODIS	Historical Archive	250m - 1km	Daily	Global phenology trends (2000-present)
Sentinel-1	SAR (Radar)	10m	6 - 12 days	Crop monitoring in persistent cloud cover

The increasing role of Synthetic Aperture Radar (SAR) is particularly noteworthy. SAR sensors emit their own energy and measure the backscatter from the Earth's surface, allowing them to provide high-resolution imagery regardless of cloud cover or solar illumination (Meng, 2024). This is critical for monitoring rice in monsoon-affected regions or wheat in high-latitude zones where cloud interference frequently compromises optical data continuity (Ibrahim et al., 2023).

3.2. Advanced Gap-Filling and Reconstruction Techniques

A significant barrier to accurate phenological tracking is the presence of gaps in time-series data caused by atmospheric aerosols and cloud contamination (Zhu et al., 2021). To mitigate this, researchers have developed advanced interpolation and reconstruction methods:

1. **Gaussian Process Regression (GPR):** A Bayesian framework that reconstructs missing values while providing an associated uncertainty estimate, making it superior to traditional linear interpolation (García-Haro et al., 2020).
2. **Super-Resolution Reconstruction:** Using high-resolution datasets to inform the gap-filling of coarser images, improving structural similarity and peak signal-to-noise ratios (Lee et al., 2025).
3. **Generative Adversarial Networks (GANs):** Deep learning frameworks that can reconstruct images across different sensor resolutions, ensuring high-frequency observations of rapid phenological changes (He & Zhong, 2023).

These techniques allow for the precise identification of phenological turning points, such as the start of season (SOS) and end of season (EOS), which are vital for validating the timing of growth stages simulated by agro-climatic models (Tomicek et al., 2025).

4. Diagnostic Capabilities of Spectral Vegetation Indices

Vegetation indices (VIs) serve as the primary proxy for canopy health, biomass, and photosynthetic activity in remote sensing applications (Vélez et al., 2023). Their effectiveness is rooted in the unique spectral reflectance curve of healthy plants, which exhibit high absorption in the red spectrum due to chlorophyll and high reflectance in the near-infrared (NIR) spectrum due to leaf cell structure (Sindhushree et al., 2025).

4.1. Comparative Utility of Core Indices

The selection of a VI depends on the specific crop type, growth stage, and environmental background (Vidican et al., 2023).

Table 4. Core Vegetation Indices Used in Crop Health and Phenology Monitoring

Vegetation Index	Equation (Plain Text)	Diagnostic Focus	Limitations
NDVI	(NIR-Red) / (NIR+Red)	Vigor and nitrogen status	Saturates in dense canopy (LAI greater than 3)

EVI	G * (NIR-Red) / (NIR + C1*Red* - C2Blue + L)	High biomass monitoring	Sensitive to cloud artifacts
SAVI / MSAVI	((NIR-Red) * (1+L)) / (NIR+Red+L)	Early growth / sparse cover	Requires soil adjustment parameter
GNDVI	(NIR-Green) / (NIR+Green)	Chlorophyll concentration	Less sensitive to structure than NDVI
NDRE	(NIR-RedEdge) / (NIR+RedEdge)	Late-season health / deeper canopy	Requires red-edge specific bands

Research has demonstrated that in heterogeneous agricultural landscapes, the Enhanced Vegetation Index (EVI) often outperforms the Normalized Difference Vegetation Index (NDVI), achieving higher accuracy and Kappa coefficients for crop identification and health assessment (Bhosle et al., 2025). EVI effectively minimizes soil background influences and atmospheric aerosol scattering by incorporating the blue spectral band for correction (Rahimi & Jung, 2025).

4.2. Emerging Proxies for Photosynthetic Capacity

Traditional VIs primarily measure the "greenness" or structural potential of the canopy. To capture actual photosynthetic flux, researchers are increasingly utilizing Solar-Induced chlorophyll Fluorescence (SIF). SIF represents a fraction of the energy absorbed by chlorophyll that is re-emitted as light at longer wavelengths (Bandopadhyay et al., 2020). While satellite-retrieved SIF often lacks the spatial resolution of multispectral VIs, it can be downscaled using EVI and Land Surface Temperature (LST) as predictors in machine learning frameworks (Zeng et al., 2023). SIF is highly correlated with Gross Primary Productivity (GPP), providing a more direct link to yield potential than greenness-based indices (Oivukkamäki et al., 2024).

5. Mechanics of Agro-Climatic Simulation Models

Agro-climatic models represent the synthesis of physiological knowledge and mathematical simulation. They are essential for predicting crop responses to future climate scenarios that have no historical analog (Hoque et al., 2025).

5.1. Comparative Analysis of Model Frameworks

The global agricultural research community primarily relies on a few core platforms, each with distinct strengths in simulating environmental interactions (Hoogenboom et al., 2019).

1. **DSSAT (Decision Support System for Agrotechnology Transfer):** A modular system that simulates growth as a function of daily weather, soil properties, and genetic coefficients (Boote et al., 2021).
2. **APSIM (Agricultural Production Systems Simulator):** Known for its robust handling of soil hydrodynamics and management interventions. APSIM primarily uses a Radiation-Use Efficiency (RUE) approach for biomass accumulation, modified by temperature and CO_2 (Ahmed & Fayyaz-ul-Hassan, 2011).
3. **WOFOST (World Food Studies):** A carbon-driven model that simulates photosynthesis at the leaf level and scales it to the canopy. It features sophisticated modules for winter-kill and frost risk (Scientific Reports, 2025).

Table 5. Comparison of Main Agro-Climatic Model Components

Model Component	DSSAT (CROPGRO)	APSIM	WOFOST
Photosynthesis	Leaf-level (Rubisco kinetics)	RUE / Transpiration Efficiency	Leaf-level assimilation
Water Balance	Tipping bucket	Multi-layer cascading	Physical soil-water dynamics

CO2 Response	RUE modifiers / Leaf-level	TE / RUE modifiers	Assimilation rate factor
Extreme Stress	Threshold-based functions	Phenology-interaction functions	Cold-stress / Winter-kill module

5.2. C3 and C4 Crop Dynamics under Elevated CO2

The photosynthetic pathway significantly dictates the crop's response to the CO2 fertilization effect and heat stress. C3 crops, such as wheat and rice, exhibit a higher sensitivity to atmospheric CO2 concentrations (Ben Mariem et al., 2021). In these plants, elevated CO2 can suppress photorespiration a process where the enzyme RuBisCO reacts with oxygen instead of CO2, wasting energy and carbon. Under optimal temperatures, a doubling of CO2 can significantly improve biomass and water-use efficiency (WUE) in C3 crops (Opoku et al., 2024).

Conversely, C4 crops like maize and sorghum possess a carbon-concentrating mechanism that already saturates RuBisCO with CO2, making them less responsive to atmospheric increases in CO2 (Vijayalakshmi et al., 2024). However, C4 plants are inherently more efficient at high temperatures and under drought conditions (Sabagh et al., 2021).

Table 6. Physiological Comparison of C3 and C4 Photosynthetic Pathways

Trait	C3 Pathway (Wheat/Rice)	C4 Pathway (Maize/Sorghum)
CO2 Fertilization Response	Strong (up to 30% yield increase)	Marginal (0-10% increase)
Water-Use Efficiency	Moderate	High
Optimal Temperature	15 to 25 degrees Celsius	25 to 35 degrees Celsius
Photorespiration	Significant (increases with heat)	Negligible
N-Use Efficiency	Moderate	High (less RuBisCO required)

6. Climate Forcing and Downscaling Methodologies

Predicting future crop yields requires the integration of General Circulation Models (GCMs) into the agricultural modeling workflow. However, the spatial resolution of GCMs (typically greater than 100 km) is too coarse to capture localized meteorological conditions (Schepen et al., 2020).

6.1. Bridging the Spatial Gap

Downscaling techniques are employed to bridge the discrepancy between global models and local field requirements (Ghosh et al., 2023).

1. **Dynamical Downscaling:** This involves nesting high-resolution Regional Climate Models (RCMs) within GCM outputs. RCMs account for local topography and land-sea boundaries (Almagham et al., 2025).
2. **Statistical Downscaling:** This method establishes empirical relationships between large-scale predictors and local station data. Recent advancements have leveraged machine learning to identify complex non-linear patterns in these relationships (Hoque et al., 2025).

Table 7. Performance Metrics of Climate Downscaling Methodologies

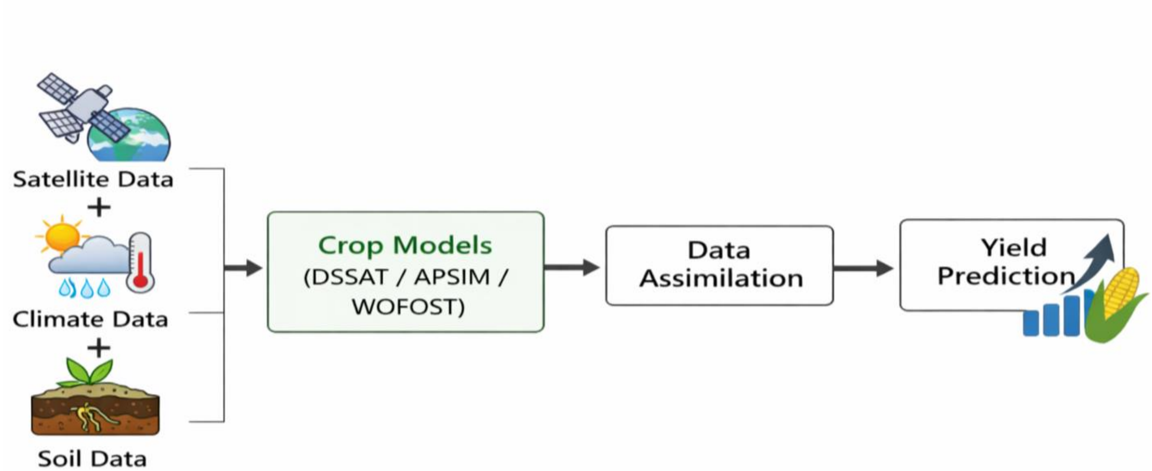
Downscaling Method	Accuracy (Pearson r)	Mean Squared Error (MSE)	Primary Benefit
Random Forest (ML)	0.94	2.78	Captures non-linear interactions
Gradient Boosting (ML)	0.86	5.90	Effective but higher error variability

RCM (Dynamical)	Site-specific	Variable	Physical consistency and topography
Change Factor (Stat)	Baseline-linked	N/A	Simple and computationally fast

7. The Integration Paradigm: Data Assimilation

Data assimilation (DA) represents the state-of-the-art in crop yield prediction, combining the strengths of remote sensing and mechanistic models (Zhang et al., 2026). Combining remote sensing observations with crop simulation models improves prediction accuracy. The integrated modeling framework used for yield forecasting is illustrated in Figure 2.

Figure 2: Integration of Remote Sensing and Agro-Climatic Models for Yield Prediction



7.1. Assimilation Strategies and State Variables

Remote sensing provides "snapshots" of the canopy surface, whereas models simulate internal processes. DA algorithms dynamically update the model's state variables. Traditionally, Leaf Area Index (LAI) has been the primary variable used (Franke, 2023). However, recent bivariate assimilation studies demonstrate that combining LAI with Leaf Nitrogen Accumulation (LNA) significantly enhances yield prediction accuracy (Wagner et al., 2020).

Table 8. Comparison of Soybean Yield Prediction Accuracy Using Different Data Assimilation Methods

Assimilation Method	R-squared (Yield)	RMSE (kg/ha)	Consistency Index (d)
No Assimilation	0.35	450.2	0.55
V_LAI (Univariate)	0.51	285.4	0.72
V_LNA (Univariate)	0.55	270.1	0.75
V_LAI+LNA (Bivariate)	0.89	127.1	0.95

(Zhang et al., 2026)

7.2. Algorithmic Implementation

Two primary classes of DA algorithms dominate:

1. **Sequential Methods (e.g., Ensemble Kalman Filter, EnKF):** These update the model state every time a new observation is available. EnKF is highly effective for large-scale applications because it uses a Monte Carlo approach to represent uncertainty (Mmbando, 2025).
2. **Variational Methods (e.g., 4D-Var):** These minimize a cost function over a defined time window. 4D-Var is powerful for reconciling

irregular observations but can be computationally demanding (Mistry & Gasparrini, 2024).

8. Quantifying Climate Impacts on Global Food Security

The integration of remote sensing and modeling has allowed for a granular quantification of the risks facing global agriculture. Meta-analyses indicate that without significant adaptation, aggregate production of wheat, rice, and maize will decline under a 2-degree C local warming scenario (Dennett, 2024).

8.1. Threshold Effects and Yield Sensitivities

Yield responses to temperature rise are characterized by distinct thresholds, beyond which negative impacts are exacerbated (Vélez et al., 2023).

Table 9. Crop Yield Sensitivity and Temperature Thresholds for Global Staples

Crop	Temperature Threshold (degrees Celsius)	Yield Change per degree C (Below)	Yield Change per degree C (Above)
Wheat	2.38	-6.1%	-8.2%
Rice	3.13	-1.1%	-7.1%
Maize	No Threshold	-4.03% (Linear)	-4.03% (Linear)

8.2. The Limits of Adaptation

Farmer adaptation can offset approximately one-third of the projected climate-related losses by the end of the century. However, the remaining two-thirds of the damage persist, particularly under high-emission scenarios (Hultgren et al., 2025).

9. Methodological Shifts: Machine Learning and Deep Learning

The field is currently undergoing a pivot toward advanced computational frameworks rooted in artificial intelligence (AI) (Sindhushree et al., 2025).

9.1. The Rise of Deep Learning

Traditional machine learning algorithms like Random Forest (RF) have proven effective. However, deep learning (DL) enables hierarchical feature extraction from geospatial datasets (Meng, 2024). Convolutional Neural Networks (CNNs) are effective at spatial pattern recognition, while Long Short-Term Memory (LSTM) networks capture temporal dependencies critical for yield forecasting (Waqas et al., 2025).

9.2. Multi-Sensor Data Fusion and Agriculture 4.0

The "Agriculture 4.0" paradigm emphasizes the fusion of multi-source data to create a digital twin of the farming environment. This involves the integration of satellite remote sensing, Unmanned Aerial Vehicles (UAVs) for plot-level resolution, and Internet of Things (IoT) sensors for continuous ground monitoring (Jin et al., 2026).

10. Challenges in Operational Monitoring Systems

Despite technological advancements, several critical challenges remain:

1. **Data Heterogeneity:** Missing observations due to cloud cover and sensor inconsistencies remain bottlenecks (Fotouo Makouate et al., 2025).
2. **Geographical Imbalance:** Research coverage is skewed toward North America and China, with significant underrepresentation of Global South regions (Feng et al., 2024).
3. **Model Transferability:** Algorithms developed for specific regions often fail to generalize to different agroecosystems due to variations in soil and management (Mmbando, 2025).

11. Conclusion

The integration of remote sensing and agro-climatic modeling provides a robust framework for quantifying and forecasting climate change impacts on crop phenology and yields, revealing non-linear responses that threaten global food security. Elevated temperatures accelerate developmental stages, curtail grain-filling durations, and exacerbate yield penalties particularly in C_3 cereals under combined heat-drought stress while CO_2 effects offer limited compensation in warmer regimes. Tools like NDVI/EVI time-series and process-based models (DSSAT, APSIM) enable precise, scalable assessments, underscoring the urgency of adaptive interventions such as resilient cultivars, optimized management, and diversified systems to buffer against projected 10–30% regional losses by mid-century. As climate extremes intensify, sustained investment in multi-platform data fusion, AI-enhanced simulations, and transdisciplinary research will be essential to inform evidence-based policies, ensuring sustainable agricultural transitions and equitable food access in a warming world.4.3sExpert

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