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Modeling Grain Yield Formation in Rice Based on Temperature and Water Management

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Abstract Rice yield formation is jointly influenced by temperature and water conditions; these two factors not only determine the progression of rice growth and development but also directly impact photosynthesis, dry matter accumulation, and grain-filling efficiency. With the intensification of global climate change and the increasingly prominent issue of agricultural water scarcity, the development of rice yield formation models-based on the management of temperature and water-holds significant importance for enhancing rice production efficiency and ensuring food security. This paper systematically reviews the physiological and ecological foundations of rice yield formation, with a particular focus on analyzing the mechanisms by which temperature, water, and their interactions influence rice growth and yield components. Furthermore, it compares and summarizes empirical statistical models, process-based mechanistic models, and AI-driven predictive models, while exploring the application of model parameterization, calibration, and validation methods in yield forecasting. Additionally, by incorporating typical management strategies-such as alternate wetting and drying (AWD) irrigation-the paper analyzes rice yield simulation results under various hydrothermal conditions and evaluates their practical value in agricultural applications. The findings indicate that rational temperature regulation and water management can significantly enhance water-use efficiency and yield stability, and that the fusion of multi-source data coupled with intelligent modeling will constitute a key direction for future research on rice yield modeling. This paper serves as a theoretical reference and provides technical support for precision agriculture, the optimal allocation of water resources, and the management of stable rice production within the context of climate change.
Keywords Rice yield model; Temperature regulation; Water management; Crop simulation; Precision agriculture

1 Introduction

Rice is a cornerstone of global food security, feeding more than half of the world's population and supplying a large share of calories in Asia and many low-income regions (Rezvi et al., 2022). However, climate change is already exerting measurable impacts on rice production through shifts in temperature regimes and altered water availability, contributing to observed yield declines in major producing and food-insecure areas (Algarni et al., 2025). Maintaining and increasing rice yields under these pressures requires a quantitative understanding of how grain yield is formed as a function of temperature and water dynamics across critical growth stages (Shrestha et al., 2022). Process-based modeling that links environmental drivers with physiological processes offers a way to anticipate risks, design adaptive management, and support policy decisions for sustainable rice systems (Farooq et al., 2023).

Rising temperatures threaten rice grain yield through both chronic warming and short, extreme events, especially around reproductive stages. High-temperature stress during booting and flowering increases spikelet sterility and alters yield components, with yield per plant declining sharply as heat degree days accumulate at these stages. Recent work also emphasizes that microclimate and organ temperature, rather than air temperature alone, determine sterility risk, indicating that accurate prediction requires modeling canopy and panicle temperature within the crop-water-atmosphere continuum. At the same time, irrigation water is becoming increasingly scarce, and meta-analyses show that water-saving irrigation strategies such as alternate wetting and drying can substantially reduce irrigation inputs and increase water productivity, although yield responses vary with climate and soil conditions. Integrating these temperature and water processes in yield formation models is therefore crucial for realistic projections under future climates.

Process-based rice models such as ORYZA and APSIM-Oryza have been widely used to simulate phenology, biomass accumulation, and grain yield across diverse environments and management scenarios. These ecophysiological models dynamically represent photosynthesis, development, and soil water balance, and have been extended to include responses to drought and salinity, achieving yield root mean square errors generally within experimental uncertainty across stress gradients (Chang et al., 2023). More recently, mechanistic models of grain filling have been developed that explicitly link leaf-level photosynthesis, whole-plant carbon-nitrogen interactions, and panicle sink dynamics, reproducing observed yield formation under varied environmental and genetic perturbations and identifying stability of grain filling rate as a key determinant of maximum yield. Nonetheless, model evaluations indicate that conventional formulations often underperform when simulating yield responses to low-temperature stress or high-temperature-induced sterility at multiple stages, highlighting the need for improved temperature response functions that are stage-specific and variety-dependent (Shrestha et al., 2022; Shi et al., 2024).

The objective of this study is to develop and evaluate a modeling framework for grain yield formation in rice that explicitly couples temperature stress responses with water management effects across key developmental stages. Building on established process-based models, the approach refines algorithms for spikelet fertility, grain number per panicle, and grain filling under low and high temperatures, while incorporating contrasting irrigation regimes representative of traditional flooding and water-saving practices. The scope of the study includes calibration and validation using multi-environment experimental datasets, sensitivity analysis to identify dominant climatic and management drivers, and scenario simulations to quantify yield risks and opportunities under projected warming and alternative water regimes. By integrating temperature and water processes at the level of yield components, the work aims to provide a more reliable tool for assessing adaptation strategies-such as adjusted planting dates, stress-tolerant varieties, and optimized irrigation-for sustaining rice production and water productivity in a changing climate.

2 Physiological Basis of Rice Yield Formation

2.1 Growth stages and yield components of rice

The rice growth cycle is commonly divided into vegetative, reproductive, and grain-filling (ripening) stages, each with characteristic organs and yield-related processes. During vegetative growth, plant height, root development, leaf area, and especially tillering determine the potential panicle number per unit area and thus set the primary framework for yield. In the reproductive stage, panicle development, booting, and flowering occur; here the number of spikelets per panicle is defined, and this stage is the most sensitive to biotic and abiotic stresses, including temperature extremes.

Grain filling and ripening determine spikelet weight through endosperm development and carbohydrate deposition, with asynchronous filling between superior and inferior spikelets often limiting full yield potential (Liu et al., 2025). Yield analyses across diverse varieties show that total spikelet number (a function of panicle number and spikelets per panicle) correlates strongly and positively with grain yield, while higher spikelet numbers can trade off with filled grain percentage and grain weight if sink capacity exceeds source supply (Liu et al., 2024). Thus, yield modeling must capture how growth stages sequentially define panicle number, spikelet number, spikelet fertility, and grain weight.

2.2 Effects of temperature on rice physiology

Rice is highly sensitive to temperature, particularly during reproductive and grain-filling stages, where both high day temperatures and high night temperatures reduce yield through impaired reproductive development and altered carbon balance (El-Mageed et al., 2022; Shrestha et al., 2022). Heat stress at panicle initiation diminishes spikelet number by attenuating secondary branch and floret differentiation and enhancing degradation, while later heat episodes mainly affect spikelet fertility and grain weight, emphasizing the need for stage-resolved temperature response functions in models.

At flowering and grain filling, high temperatures increase spikelet sterility and reduce grain weight via multiple morpho-physiological pathways, including distortion of floral organs, reduced pollen viability, impaired anther dehiscence, and shortened grain-filling duration (Shrestha et al., 2022). Night-time warming further elevates respiration, accelerates senescence, and contributes to yield penalties estimated at several percent per °C increase above critical thresholds, with reported yield declines of about 4-5% per 1 °C rise beyond 27 °C and up to 41% reduction by 2100 under projected high night temperatures (El-Mageed et al., 2022).

2.3 Effects of water management on rice growth

Water availability and irrigation strategies strongly influence both biomass production and yield components in rice. Under drip irrigation and mulching, progressive water stress at tillering reduces chlorophyll content, leaf photosynthesis, and final tiller number, leading to fewer effective panicles, lower seed-setting rate, and reduced thousand-grain weight, although moderate stress can substantially increase water-use efficiency relative to flooding (Xu et al., 2020). Field experiments with aerobic varieties show that mild water-saving irrigation (~20% less water than conventional) can enhance antioxidant activity, maintain photosynthesis, increase harvest index, and significantly improve grain yield and quality, indicating a non-linear response of growth and yield to water deficit intensity (Gao et al., 2024).

Across broader environments, meta-analysis of water-saving irrigation practices (controlled, intermittent, shallow-wet, AWD) reveals consistent increases in water productivity (4.7%-14.3%) relative to traditional flooding, with variable effects on yield depending on system, soil, and climate. Alternate wetting and drying regimes typically save 17%-34% of irrigation water and can increase or only slightly reduce yield, yielding higher water productivity, while continuous flooding maximizes yield but at the cost of much greater water consumption (Mboyerwa et al., 2021; Roushan et al., 2023). These quantitative relationships between water regime, evapotranspiration, yield components, and water productivity form a critical foundation for modeling grain yield under diverse water management scenarios.

3 Temperature and Water Interactions in Rice Production

3.1 Synergistic effects of temperature and soil moisture

Temperature and soil moisture interact strongly to determine rice yield, with compound extremes often causing larger losses than either stress alone. A panel analysis of rainfed and irrigated rice in India (2000-2018) showed that excessive heat markedly reduced yield, and that losses were greatest when high temperatures coincided with low soil moisture; in contrast, high soil moisture partly offset heat damage, underscoring the importance of managing root-zone water to buffer thermal stress (Mishra et al., 2024). A global empirical assessment similarly found that models using root-zone soil moisture, rather than precipitation, explained much more interannual yield variation and revealed that soil moisture and temperature contribute roughly equally to historical yield fluctuations, highlighting the need to explicitly represent both drivers in yield formation models (Proctor et al., 2022).

These synergistic effects arise because water status controls canopy cooling, stomatal conductance, and thus plant temperature under heat stress. Field experiments with super hybrid rice showed that as water supply was reduced from shallow flooding to mild and severe water stress, canopy relative humidity and plant-atmosphere and soil-atmosphere temperature differences declined, and grain yield fell by up to ~35%, with positive correlations between temperature differentials and yield (Meng et al., 2020). Long-term field data from Taiwan indicated that climate-change-induced increases in water-deficit stress, quantified via crop water status across growth stages, have increasingly constrained rice growth in recent decades, particularly during developmental stages, confirming that water deficits and warming jointly shape yield trajectories over time (Chen et al., 2023).

3.2 Stress responses under extreme climate conditions

Extreme hot-dry or cold-wet events are projected to become more frequent and can sharply disrupt grain yield formation. A global analysis for 1980-2009 showed that co-occurring extremely hot and dry events consistently reduced yields of major crops, including rice, worldwide, with probabilities of such compound extremes increasing over time (Heino et al., 2023). A review of compound heat and moisture extremes reported that hot droughts since about 2000 have been linked to yield losses up to 30% in key breadbasket regions, and that interactions among plant physiology, soil-plant-atmosphere water fluxes, and climate dynamics complicate prediction of net yield impacts under future compound extremes (Lesk et al., 2022).

Rice is particularly vulnerable when drought and temperature stress coincide at sensitive stages such as booting, flowering, and grain filling. Field experiments imposing combined drought and heat during flowering and early grain filling in contrasting cultivars recorded 20%-80% yield reductions, with cultivar-specific differences in which stage was most vulnerable and strong increases in panicle tissue temperature due to reduced panicle conductance under stress. Controlled-environment studies further demonstrated that simultaneous drought and high temperature at early stages (seedling, tillering) can completely prevent panicle formation and thus eliminate yield in susceptible cultivars, while tolerant genotypes maintain some productivity and show distinct patterns in grain quality and health-promoting compounds under combined stress.

3.3 Regional differences in rice production systems

Temperature-water interactions, and thus yield responses, vary widely among regions and production systems. A modeling study for Africa, covering irrigated and rainfed upland and lowland systems under multiple RCP scenarios, projected that without adaptation, higher temperatures shorten crop duration and reduce yields by about 24% under RCP8.5 by 2070; with higher-temperature-sum varieties, some rainfed systems gained modestly, but yields remained constrained by water availability, and irrigated dry-season rice in West Africa still faced large losses driven by photosynthesis reductions at extreme heat. In China, a comprehensive review found that climate change has shifted single and double rice belts northward, altered precipitation patterns, and increased the frequency of droughts and floods, leading to regionally divergent impacts where warming can either increase yields in cooler areas or reduce them in already warm zones through heat damage around flowering (Saud et al., 2022).

Finer-scale analyses highlight that regional differences in climate, water resources, and management produce contrasting yield trajectories and adaptation needs. Regional inequality assessments using ORYZA(v3) combined with climate projections for China showed average yield declines of 3.7-16.4% across regions, with central, eastern, and northwestern China most at risk under both rainfed and irrigated conditions, while northeastern and some southern areas may benefit under low-emission scenarios due to more favorable temperatures and water regimes (Zhan et al., 2023). At the farm scale in Indonesia, qualitative work revealed that upstream irrigated farmers mainly perceive climate impacts through pest outbreaks and heat, whereas downstream farmers, despite nominal irrigation access, experience climate change primarily as water shortages and rising temperatures, leading them to adopt distinct, locally tailored adaptation strategies for managing water scarcity and heat risk (Arifah et al., 2022).

4 Modeling Approaches for Rice Yield Formation

4.1 Empirical and statistical models

Empirical and statistical models relate rice yield directly to weather and agrometeorological indices, providing relatively simple tools for forecasting at regional scales. Panel regression and time-series analysis across 15 major rice-producing countries showed that increases in temperature tend to reduce production, while rainfall volume strongly affects output, highlighting rice's sensitivity to both warming and hydrological variability (Joseph et al., 2023). At subnational scales, climate-index-based regression models using modified Hendrik and Scholl methods successfully linked yields to maximum and minimum temperature, rainfall, humidity and other indices, with good coefficients of determination and accurate forecasts for Maharashtra districts (Sasane, 2023).

Comparisons of alternative statistical formulations emphasize the importance of choosing appropriate regression structures for non-linear climate-yield relationships. In Sri Lanka, multiple linear, power, robust and Gaussian process regressions, together with several machine learning methods, were applied to three decades of climate and yield data; Gaussian process regression achieved the lowest errors and highest correlation between observed and simulated yields (Wickramasinghe et al., 2021). Similar work in Uttarakhand used stepwise linear regression, LASSO, ridge and elastic net on seasonal weather variables, finding that penalized regressions such as LASSO and elastic net generally outperformed ordinary multiple regression, especially when multicollinearity among climate predictors was substantial (Setiya et al., 2023).

4.2 Process-based crop simulation models

Process-based crop models simulate rice growth and yield by representing phenology, biomass accumulation, and soil-water balance, offering mechanistic insight into temperature and water effects. The CERES-Rice model embedded in DSSAT has been extensively evaluated across Asia, typically predicting phenology with normalized RMSE of 1%-5% and grain yield with errors of 2%-5%, though performance often declines under severe water stress (Goswami and Dutta, 2020). Simulations with ORYZA2000 and an empirical energy-equivalent (EEQ) model showed yield declines of about 3.5%-7.6% per °C over a 4 °C range, but also demonstrated that simple regressions on minimum temperature can misattribute yield losses when solar radiation and rainfall covary with temperature (Sheehy et al., 2006).

Recent applications integrate detailed water management and greenhouse gas processes into process-based frameworks. Coupling CSM-CERES-Rice with the DSSAT-GHG module in subtropical Brazil allowed simultaneous evaluation of grain yield and methane emissions under continuous flooding, alternate wetting and drying, and sprinkler irrigation, with grain yield biases below 600 kg/ha and good agreement for daily CH_4 fluxes after calibration of key soil parameters (Figure 1) (Da Silva et al., 2025). In China, a calibrated CERES-Rice model was used with 60-year weather series to compare alternate wetting and drying, controlled drainage, and combined irrigation-drainage schemes; alternate wetting and drying produced the highest yields, while controlled irrigation-drainage treatments maximized irrigation and rainwater use efficiency, guiding optimization of water-saving strategies (Gao et al., 2023).

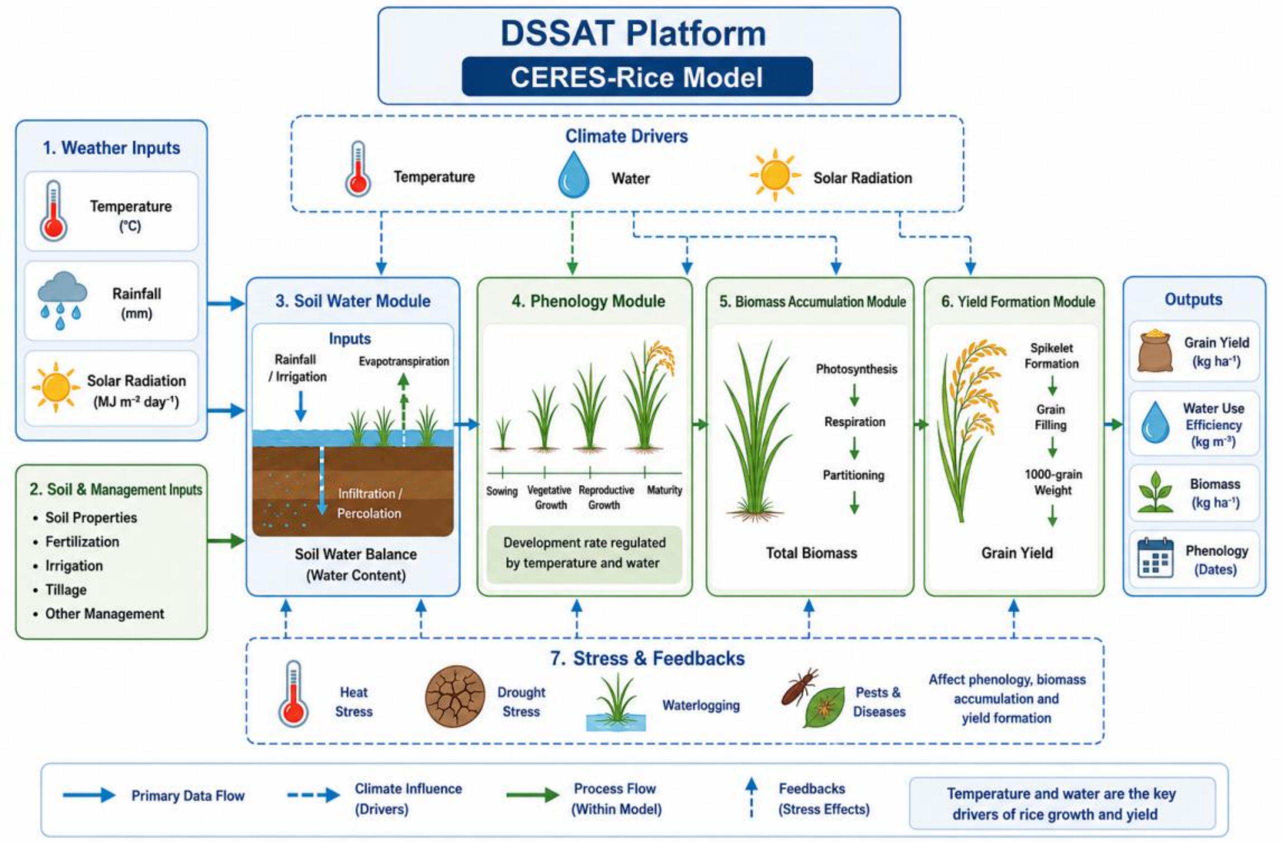

Figure 1 Conceptual framework of the CERES-Rice model embedded in DSSAT, illustrating interactions among weather inputs, soil-water balance, crop phenology, biomass accumulation, and grain yield formation

4.3 Machine learning and artificial intelligence approaches

Machine learning and deep learning methods provide flexible, data-driven alternatives for rice yield prediction that can ingest large climate, soil, and remote-sensing datasets. A comparative study in Chhattisgarh tested stepwise linear regression, penalized regressions, and artificial neural networks with 21 years of district-level yield and weather data; neural networks achieved R^2 values up to 1.0 in calibration and validation for some districts, and ensemble methods such as random forest further improved performance over single models. Likewise, integrating phenology, growing-season climate, and geographic information in China showed that support vector machines, random forests, and backpropagation neural networks all outperformed multiple linear regression, with phenological variables contributing importance comparable to climatic predictors (Guo et al., 2020).

Deep learning and hybrid architectures have pushed yield prediction towards finer spatial and temporal scales. At the county scale across China, models based on LASSO, random forest, and long short-term memory (LSTM) networks were trained on satellite vegetation indices, meteorological indices, and soil properties; LSTM achieved R^2 values of 0.77-0.87 and lower RMSEs than both random forest and LASSO, and combining solar-induced chlorophyll fluorescence with EVI slightly enhanced performance by capturing drought and heat stress signals (Cao et al., 2021). At pixel scale in South and North Korea, satellite-integrated crop model outputs were used as training labels for a hybrid LSTM-1D-CNN network, which reached $R = 0.859$ and identified water-related indices and maximum temperature (North Korea) and vegetation and geographic variables (South Korea) as key predictors, illustrating the potential of crop model-AI fusion for spatially explicit yield formation under temperature and water variability (Jeong et al., 2021).

5 Key Variables and Parameterization in Yield Models

5.1 Temperature-related parameters

Temperature-related parameters in rice yield models describe how development rate and yield components respond to thermal conditions across growth stages. A foundational approach uses cardinal temperatures-base, optimum, and ceiling-to define a nonlinear response of development rate to temperature; the Beta-function framework derives optimum temperature and maximum development rate from these three temperatures and curvature coefficients, and has been shown to outperform simple thermal-time formulations in predicting flowering time in rice. Empirical and mechanistic simulations further demonstrate that yield declines with warming are moderate when temperature acts alone, but regression-based estimates may be biased if correlated factors such as solar radiation and rainfall are not properly separated, underscoring the importance of mechanistically grounded temperature functions in models.

Recent modeling work has refined temperature sensitivity at the level of yield components. Using a calibrated CERES-Rice model over six climate regions in China, yield sensitivity to temperature was decomposed into panicle number, filled grain number per panicle, and grain weight, revealing that negative yield responses were mainly driven by reductions in filled grains per panicle and were more strongly linked to high-temperature degree days than to growing degree days (Zhou et al., 2025). Other analyses show that conventional rice models often under-represent damage from extreme high or low temperatures, motivating adjustment of base and optimal temperatures or explicit heat-stress modules to improve simulation of growth duration and yield under warm or cold conditions (Figure 2) (Li et al., 2020).

5.2 Water management parameters

Water management parameters in rice models control soil water balance, root-zone moisture, and associated effects on evapotranspiration, biomass, and yield. In water-driven models such as AquaCrop, key parameters include the normalized crop water productivity (WP), stage-specific basal and single crop coefficients (Kc), and water-stress coefficients that reduce transpiration, canopy growth, and harvest index when soil water falls below critical thresholds; for rice, calibrated WP around 19 $g \cdot m^{-2}$ and harvest index near 0.47 have provided good simulations of canopy cover, biomass, yield, and water balance under multiple irrigation regimes in arid and sub-humid environments (Elsadek et al., 2023; Mostafa et al., 2023). A broader review of soil water balance modeling highlights the need for careful parameterization of dual Kc (separating soil evaporation and crop transpiration), soil water holding characteristics, and root-zone depth to derive realistic irrigation requirements and to link water use to yield and water productivity indicators (Pereira et al., 2020).

Process-based rice models with explicit soil modules use management parameters to represent alternative irrigation strategies such as continuous flooding, alternate wetting and drying (AWD), controlled irrigation, and different ponding depths. For example, a calibrated CERES-Rice model successfully reproduced grain yield, evapotranspiration, irrigation volume, and leaf area index across AWD and controlled irrigation-drainage schemes, then used long-term meteorological scenarios to compare water-saving and yield responses among treatments (Gao et al., 2023). Similarly, AquaCrop-based simulations under drying-wetting cycles in paddy soils and fixed-interval irrigation in direct-seeded rice quantified how changes in irrigation frequency alter evapotranspiration, percolation, and soil moisture dynamics, revealing that current stress coefficients may overestimate water deficit under certain conditions and should be revised for rice-specific hydrology (Elsadek et al., 2023).

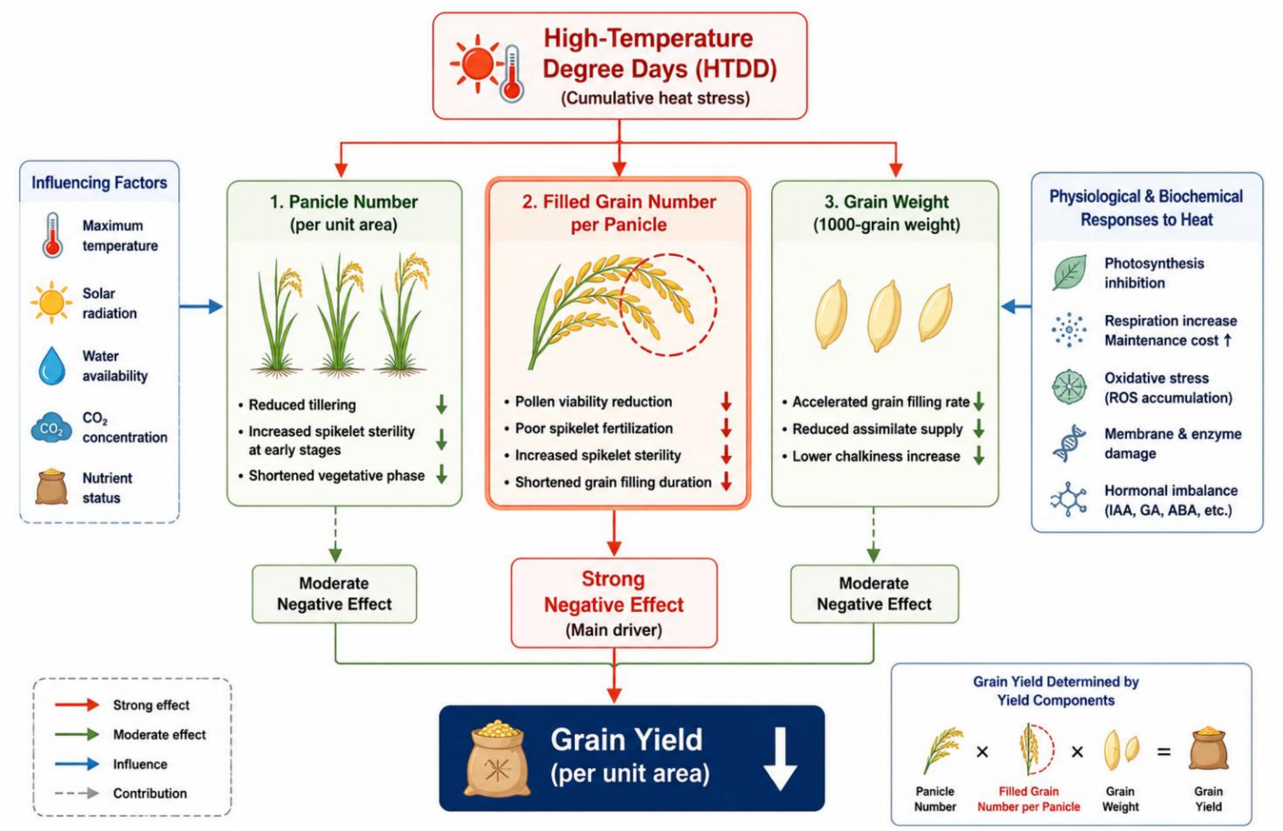

Figure 2 presents the pathways through which high-temperature stress affects rice yield formation. Among the yield components, reductions in filled grain number per panicle contribute most strongly to negative yield responses under warming conditions

5.3 Calibration and validation of models

Accurate representation of temperature and water effects in yield models depends on rigorous calibration and validation of both genetic and environmental/management parameters. In DSSAT-CERES-Rice applications, cultivar-specific coefficients (e.g., phenology, tillering, grain filling, spikelet number, temperature tolerance) are estimated using multi-year field experiments with contrasting genotypes, establishment methods, and nitrogen levels; evaluation against observed yields and phenology has shown low normalized RMSE and realistic sensitivity to ±1 °C temperature changes, confirming that calibrated models can capture both baseline performance and climate sensitivity (Islam and Hasan, 2021). For upland rice, detailed documentation of coefficients such as P2R (photoperiod sensitivity), P5 (grain-filling duration), G1 (spikelet number), G3 (tillering), and G4 (temperature tolerance) illustrates how parameter sets encode cultivar adaptation to different temperature regimes and allow tested models to simulate flowering and maturity across controlled temperature treatments.

Validation must also address parameter uncertainty and model robustness across sites and years. A cross-validation study with ORYZA (v3) generated multiple feasible parameter sets for a high-yielding variety under limited data and showed that several sets produced satisfactory simulations of biomass components and total aboveground biomass when tested with independent datasets, implying that non-uniqueness of calibrated parameters should be explicitly recognized (Nurulhuda et al., 2022). At larger scales, DSSAT-based studies have calibrated models using gridded weather, management information, and representative genetic coefficients, achieving district-level correlations above 0.7 and relative RMSE below 25% for most major rice-growing districts, and demonstrating reasonable skill in reproducing yield anomalies in out-of-sample years-supporting their use for near-real-time yield estimation and risk assessment (Arumugam et al., 2020).

6 Applications of Rice Yield Formation Models

6.1 Decision support for irrigation and fertilization

Rice yield formation models are increasingly used to optimize coupled water-nitrogen management, balancing grain yield with resource efficiency and environmental impacts. Field experiments combined with regression modeling show that irrigation regime and nitrogen rate jointly determine grain yield, total water productivity, and nitrogen recovery efficiency, but that these objectives cannot be maximized simultaneously, motivating multi-objective decision tools based on water-nitrogen-yield response surfaces (Cao et al., 2020). Multi-objective quadratic models integrating water-nitrogen-yield and water-nitrogen-quality relationships further demonstrate that optimal irrigation and nitrogen combinations differ among management scenarios, and that excessive inputs can become counterproductive for both yield and grain quality.

Model-based seasonal and long-term scenario analyses allow irrigation and fertilization decisions to be tailored to local climate risk. Using CSM-CERES-Rice within DSSAT, one study quantified how early direct seeding, no-tillage, and moderate nitrogen rates simultaneously improved yield, irrigation efficiency, and reduced methane emissions over 35 years, providing concrete guidance on planting date, tillage, and N rate selection (Figure 3) (Darikandeh et al., 2025). Machine-learning decision models that couple ensemble yield prediction (e.g., extremely randomized trees) with swarm-intelligence optimization have also been proposed, enabling site-specific recommendations of N-P-K base fertilizer that increase average rice yields by more than 13% while reducing the need for extensive field experimentation (Gao et al., 2023).

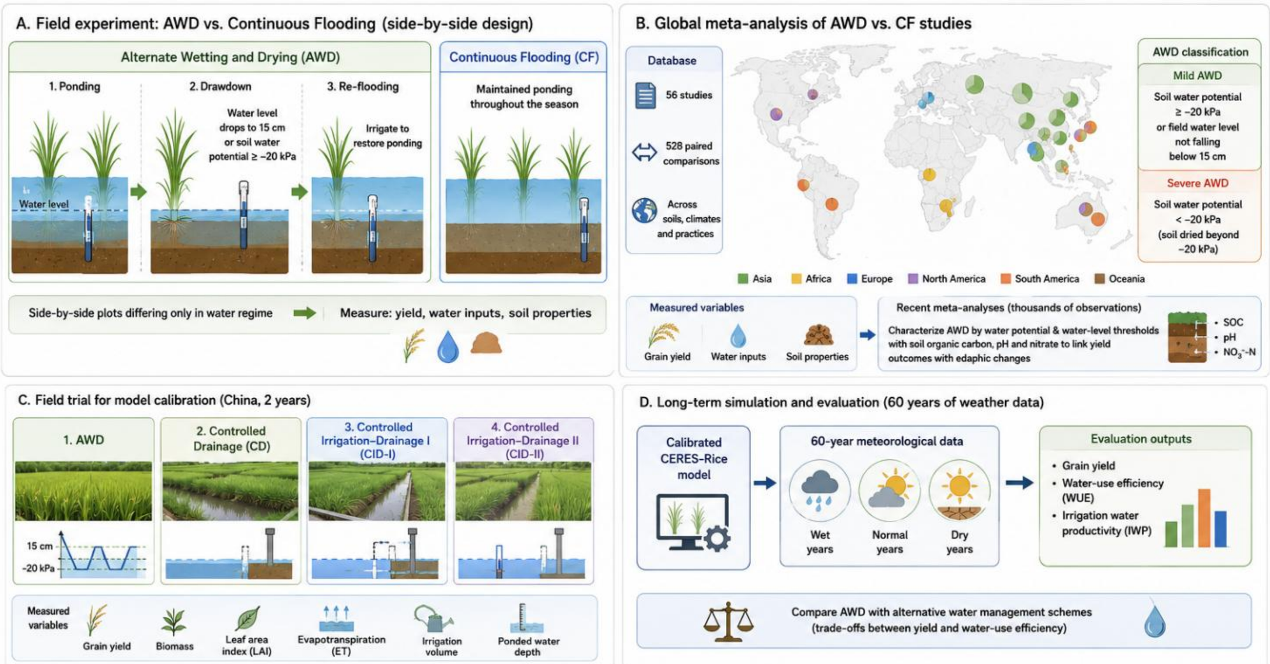

Figure 3 Experimental designs and analytical frameworks used to compare alternate wetting and drying (AWD) with continuous flooding (CF) in rice production systems

6.2 Climate change adaptation and risk assessment

Process-based crop models calibrated for local cultivars are widely applied to assess climate change impacts and identify adaptation levers. In Mediterranean Türkiye, DSSAT-CERES-Rice simulations under multiple GCMs and RCPs showed that irrigated yields could increase slightly in late-century, whereas rainfed yields declined by 15%-25% due to higher temperatures, shorter growth duration, and soil-moisture stress, illustrating how yield-formation models support evaluation of irrigation as an adaptation option (Baydar, 2026). In Central Java, coupling MarkSim-generated weather with CERES-Rice projected yield decreases in all seasons under RCP2.6-8.5, with up to 11.8% reduction in the second dry season, and pointed to dynamic cropping calendars, irrigation modernization, and integrated nutrient management as priority adaptations (Ansari et al., 2021).

Meta-analytic and multi-model frameworks extend these assessments to global and regional risk profiles. A global meta-model derived from 8,703 process-model simulations showed that, under RCP4.5 without adaptation, major crops including rice face mean yield losses of 6%-21%, but that cultivar choice for rice and irrigation method for maize are among the most influential adaptive strategies, partially offsetting losses as warming intensifies (Abramoff et al., 2023). A separate meta-analysis of 111 climate-rice modeling studies quantified that each 1 °C increase in mean temperature reduces rice yield by 3.85% on average, while elevated CO_2 and adaptive management can compensate some losses, underscoring the role of yield models in probabilistic risk assessment and in designing adaptation portfolios (Li et al., 2024).

6.3 Precision Agriculture and Digital Farming

Yield formation models are increasingly embedded in precision agriculture systems that combine remote sensing, IoT, and AI to support within-field management. An integrated IoT-based framework uses multispectral satellite indices, machine-learning yield prediction (random forest $R^2 \approx 0.96$), and fuzzy-logic irrigation control to recommend suitable crops and fertilizer, while a solar-powered irrigation system achieves about 61% water savings compared with average logic, demonstrating how digital decision layers can operationalize model insights on crop water and nutrient requirements (Saha et al., 2025). At a broader scale, reviews of remote-sensing applications in precision agriculture highlight how satellite and UAV data, linked to crop growth and yield models, are now used operationally for crop monitoring, irrigation scheduling, variable-rate nutrient application, and yield prediction, supported by cloud computing and machine learning workflows (Sishodia et al., 2020).

Recent syntheses of IoT- and AI-enabled sensing technologies emphasize that dense soil-moisture, nutrient, and plant-stress sensor networks, combined with models and ML (e.g., SVMs, CNNs, random forests), underpin real-time optimization of irrigation, fertilization, and pest management across arable systems (Miller et al., 2025). Complementary reviews of precision agriculture for yield prediction stress that hybrid systems merging deep learning (e.g., Bi-LSTM) with multisource remote-sensing inputs can capture the combined effects of temperature, water status, and other stresses on yield, pointing toward digital twins of rice cropping systems where grain yield formation under variable temperature and water regimes is continuously simulated and updated from field data (Saha et al., 2025).

7 Case Study: Modeling Rice Yield Under Alternate Wetting and Drying Irrigation

7.1 Experimental design and data collection

Field experiments comparing alternate wetting and drying (AWD) with continuous flooding (CF) typically use side-by-side plots differing only in water regime, enabling quantification of yield and water responses across soils, climates, and management practices. A global meta-analysis synthesized 56 such studies (528 paired comparisons) and defined mild AWD using thresholds of soil water potential ≥ -20 kPa or field water level not dropping below 15 cm, and severe AWD when soils dried beyond -20 kPa, with associated measurements of yield, water inputs, and basic soil properties. More recent meta-analyses have expanded this database, assembling thousands of observations worldwide and characterizing AWD treatments by water potential and water-level thresholds together with soil organic carbon, pH, and nitrate to link yield outcomes with edaphic changes (Zhou et al., 2025).

Experimental designs used for model calibration and testing often include multiple irrigation schemes and long weather records. In China, a two-year field trial with four irrigation and drainage treatments-AWD, controlled drainage, and two controlled irrigation-drainage regimes-was established to calibrate CERES-Rice using detailed measurements of grain yield, biomass, leaf area index, evapotranspiration, irrigation volume, and ponded water depth. Long-term simulations then combined these calibrated parameters with 60 years of meteorological data classified into wet, normal, and dry years to evaluate yield and water-use efficiency trade-offs among AWD and alternative schemes (Gao et al., 2023).

7.2 Model construction and simulation results

Case-study modeling of AWD typically couples a calibrated crop growth module with an explicit water-balance representation of ponded depth, soil water status, and irrigation triggers. In a DSSAT-CERES-Rice application for central China, cultivar coefficients were first calibrated under observed AWD and non-AWD regimes, achieving normalized RMSE of 3%-10% for yield, biomass, evapotranspiration, irrigation, and leaf area index, indicating reliable capture of growth and water use across treatments. The calibrated model was then driven with historical climate sequences and AWD rules defined by reflooding thresholds, allowing simulation of grain yield and water productivity under contrasting hydrological years and irrigation strategies (Gao et al., 2023).

To better represent AWD hydrology, an improved ORYZA2000 framework integrated a new water-balance simulation tailored to intermittent flooding and drying, along with dynamic root-length growth and revised water-stress algorithms. Applied to paddy fields under CF and AWD in two Chinese regions, the enhanced model substantially improved the simulation of ponded water depth, irrigation and drainage volumes, evapotranspiration, and percolation, with Nash-Sutcliffe efficiencies for ponded depth of 0.82-0.94 and relative errors for total irrigation and drainage mostly within ±10%. Yield prediction remained comparable to or slightly better than the original version, demonstrating that explicit AWD parameterization can capture both water balance and yield formation with good accuracy.

7.3 Implications for sustainable rice production

Model-supported analyses clarify under which conditions AWD can save water without compromising yield, informing sustainable irrigation guidelines. Meta-analysis of 528 AWD-CF comparisons showed that, overall, AWD reduced yields by 5.4%, but mild AWD regimes did not significantly decrease yield, whereas severe AWD caused average losses of 22.6%, particularly in higher-pH and low-carbon soils. A broader synthesis of 3194 observations from 200 studies confirmed that AWD increased water-use efficiency by about 31% but imposed an average 6% yield penalty, and identified optimal thresholds (soil water potential > -15 kPa, water depth < 18.5 cm) and favorable soil conditions under which AWD can actually raise yields by up to 4-7% when combined with appropriate nitrogen, straw, or biochar management.

Process-based simulations extend these insights to long-term climate variability and regional planning. CERES-Rice modeling over 60 historical weather years showed that AWD often produced the highest yields among several water-saving schemes across wet, normal, and dry years, though other controlled irrigation-drainage strategies sometimes achieved greater irrigation and rainwater-use efficiency, suggesting context-specific trade-offs between yield maximization and water conservation (Gao et al., 2023). Global analyses indicate that implementing soil-water-potential-based AWD on suitable irrigated rice areas can increase water productivity over large fractions of Asia, particularly in India, Bangladesh, and central China, demonstrating that AWD-informed models can underpin strategies for sustainable intensification that jointly address food security and freshwater scarcity (Bo et al., 2024).

8 Challenges, Future Perspectives, and Conclusions

Despite substantial advances, rice yield projections under future climate remain highly uncertain. A meta-analysis of 111 studies showed large variability in simulated yield responses to changes in temperature, precipitation, radiation, and CO_2, reflecting differences in climate models, emission scenarios, and, critically, crop model structure and parameterization. Similarly, a multi-model intercomparison of 13 rice models found that spread among crop models exceeded that from 16 global climate models, and that individual models did not consistently reproduce yields across very cool and very warm sites, indicating structural weaknesses in representing temperature and CO_2 responses. Key physiological processes are still imperfectly captured. Sensitivity analysis of the 13-model ensemble identified biomass formation and harvest index responses to warming and elevated CO_2 as major sources of error, while most simulations assumed ideal water and nutrient management and ignored pests, diseases, and sub-optimal farmer practices. Meta-regression work further demonstrated that yield responses aggregate multiple interacting drivers (temperature, precipitation, CO_2, management), and that the choice of study sites, climate scenarios, and adaptation assumptions introduces additional unexplained variation into projected yield changes.

Future modeling must better integrate climate, hydrology, and crop growth, particularly in data-scarce, climate-vulnerable regions. A review of climate-hydrological-crop modeling for Indonesian rice production highlighted critical gaps in long-term observations, local cultivar data, and systematic calibration/validation, as well as limited use of fully coupled multi-model frameworks. Bayesian multi-model ensemble methods applied to Chinese rice regions showed that statistically combining multiple climate models can reduce bias in temperature, radiation, and wind projections and provide more robust estimates of future yield, evapotranspiration, and irrigation requirements. There is also strong scope for hybrid approaches linking process-based models with machine learning and explainable AI. A recent study in China coupled DSSAT with random forests and SHAP analysis to project rice yields under multiple SSP scenarios and to rank the relative influence of variables such as growing degree days, shallow versus deep soil moisture, and precipitation regimes on yield. Global meta-modeling across 8,703 process-model simulations similarly used machine learning to map yield change as a function of climate and adaptation, revealing that for rice, cultivar choice is a dominant lever for avoiding large losses, and demonstrating how statistical emulators can synthesize complex multi-model ensembles for risk analysis.

Rice yield formation under changing temperature and water regimes is governed by interacting physiological processes and management decisions that are only partially resolved in current models. Meta-analyses show that rising temperature and altered precipitation generally reduce rice yields, but that elevated CO_2 and adaptive practices, including improved management, can offset part of these losses; however, the magnitude and direction of impacts vary widely across models and regions. Probabilistic assessments and global meta-models further indicate that without adaptation, most rice-growing areas face significant yield declines as global mean temperature rises, while adaptation-particularly through cultivar choice and irrigation strategies-substantially narrows projected losses. Going forward, credible prediction and decision support will require to reduce structural and parametric uncertainty in ecophysiological models; embedding them in integrated climate-hydrological-crop frameworks; and exploiting machine learning and ensemble techniques to quantify risk and design robust adaptation portfolios. By explicitly representing temperature and water interactions, and by using improved data and hybrid modeling strategies, next-generation rice yield models can more reliably guide climate-smart water management, cultivar deployment, and policy for sustainable rice production under a warming and water-constrained climate.

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Conflict of Interest Disclosure

The author affirms that this research was conducted without any commercial or financial relationships that could be construed as a potential conflict of interest.

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