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).

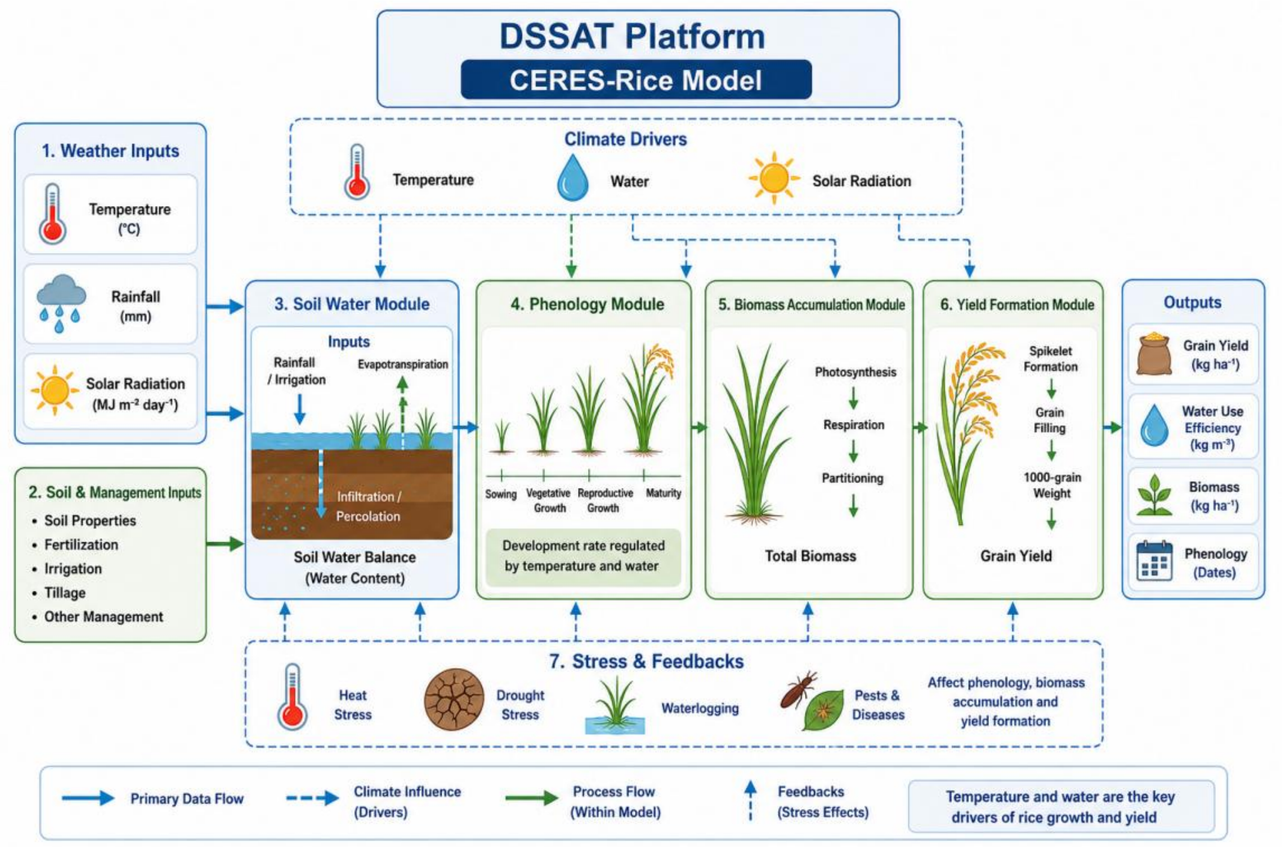

Figure 1 Conceptual framework of the CERES-Rice model embedded in DSSAT, illustrating interactions among weather inputs, soil-water balance, crop phenology, biomass accumulation, and grain yield formation

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