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Bridging process knowledge and deep learning for daily-scale maize phenology modeling under climate variability

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Abstract: Accurate simulation of crop phenology under increasing climate variability is critical for anticipating yield fluctuations and informing adaptation strategies, yet existing process-based models face limitations in capturing complex agroecosystem dynamics while maintaining operational practicality. Here, we present the Physiology-coupled Daily Evolving AI Phenology Model (PHEA-Phe), a knowledge-guided deep learning framework that integrates thermal time theory and mechanistic priors from a process-based model into a modular neural architecture for daily-scale maize phenology simulation. The architecture is organized according to the causal logic of thermal time (TT) accumulation: when cumulative TT exceeds a phase-specific threshold, the system transitions from one growth-phase module to the next. This design enhances interpretability and provides a natural lever for continual learning.

PHEA-Phe comprises three coordinated components. First, a Daily TT Emulation Module uses a multilayer perceptron to reproduce APSIM's piecewise-linear TT calculation from daily maximum and minimum temperatures, thereby inheriting core thermal physiology. Second, a Daily TT Adjustment Module based on gated recurrent units extracts nonlinear and sequential patterns that are difficult to encode explicitly, with two structurally identical but independently trained parameter sets for the vegetative growth phase (VGP) and the reproductive growth phase (RGP). Third, a dynamic Knowledge Base stores cultivar-specific cumulative TT thresholds for VGP and RGP, enabling explicit representation of genotype effects; heading and maturity timing can be derived from phase transitions.

We implement a "mechanism inheritance and refinement" training strategy. The Emulation Module is trained on large-scale APSIM-simulated daily TT to capture canonical thermal responses. The Adjustment Module is then trained using outputs from the Emulation Module together with a remote sensing–based phenology dataset from the Chinese Maize Belt, while the Knowledge Base is initialized and updated to estimate cultivar-specific thresholds. A process-based loss (PB-loss) imposes physiological constraints during training, which improves stability and reduces overfitting.

Through initial training and subsequent continual learning on additional phenology datasets, PHEA-Phe adapts to broader cultivars and regions while mitigating catastrophic forgetting via its knowledge-guided internal structure, PB-loss constraints, and threshold anchoring in the Knowledge Base. The model achieves high predictive accuracy across diverse agroecological conditions (RMSE: 3.7 days for VGP and 7.5 days for the full growth cycle) against remote sensing datasets. Compared with a well-calibrated APSIM, these errors are reduced by approximately fivefold and fourfold, respectively. TimeSHAP analyses confirm that the system adaptively compensates for thermal time estimation biases during heat stress, which leads to physiologically consistent response patterns. By unifying mechanistic priors with data-driven learning, PHEA-Phe offers a transparent and evolvable tool for climate-resilient agriculture that reduces reliance on parameter calibration.

Keywords: *Maize phenology; KGML; Thermal time theory; Continual learning; TimeSHAP*