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Physics-Guided Deep Learning for Crop Phenology Simulation

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Abstract: Accurate simulation of maize phenology under increasing climate variability is essential for anticipating yield fluctuations and guiding adaptive agricultural strategies, yet existing models face inherent limitations. Process-based models (PBMs) such as APSIM, while mechanistically interpretable, suffer from complex parameter calibration, limited flexibility in capturing nonlinear agroecosystem dynamics (e.g., extreme heat impacts), and high operational barriers for real-world use. In contrast, pure data-driven AI models exhibit structural flexibility but operate as "black boxes," lacking physiological interpretability and relying heavily on large, high-quality datasets. To address these gaps, this study develops PhysioGuide-PhenoDL, a physics-guided deep learning framework that integrates APSIM-derived mechanistic knowledge (e.g., thermal time theory) with advanced deep learning architectures for daily-scale maize phenology modeling across China's Maize Belt (CMB).

The framework consists of three interconnected components: 1) A Daily Thermal Time Emulation Module (multilayer perceptron, MLP) designed to replicate APSIM's thermal accumulation logic, achieving an RMSE of 0.8 °C and R^2 of 0.99 when validated against APSIM-simulated data; 2) A Temporal Adjustment Module (gated recurrent unit, GRU, or attention-LSTM) that captures nonlinear phenological dynamics—such as growth responses to extreme heat or variable precipitation—unrepresented by APSIM's deterministic formulas; 3) A dynamic Knowledge Base storing cultivar-specific cumulative thermal thresholds, initialized using APSIM outputs and refined via real-world data to adapt to diverse maize varieties. The training process follows a "mechanism inheritance-refinement" strategy: initial training with APSIM-simulated datasets (1955–2016, 4026 cropland grids) ensures physiological consistency, while continual learning with real phenology data (e.g., ChinaCropPhen1km, 2000–2019) enables incremental error reduction without catastrophic forgetting.

Validation across the CMB shows PhysioGuide-PhenoDL outperforms a well-calibrated APSIM model: for the vegetative growth phase (VGP), its RMSE is 3.7 days (vs. 16.8 days for APSIM), and for the full growth cycle (FGC), the RMSE is 7.5 days (vs. 24.2 days for APSIM)—representing ~4–5-fold error reductions. Under extreme heat conditions (max temperature >37 °C), TimeSHAP interpretability analysis confirms the framework adaptively corrects thermal overestimation from the Emulation Module, maintaining physiologically consistent responses. With incremental addition of real phenology data (0–12 years), continual learning further reduces FGC RMSE from 27.8 days to 5.5 days, outperforming "from-scratch" training in all phenological phases.

PhysioGuide-PhenoDL balances high predictive precision, mechanistic interpretability, and operational scalability, leveraging PBM insights to mitigate AI "black-box" limitations while using deep learning to overcome PBM parameter complexity. This framework provides a transparent, evolvable tool for simulating maize phenology under climate stress, supporting climate-resilient agricultural management and food security efforts.

Keywords: *Physics-guided deep learning, Crop phenology simulation, Thermal time theory, Continual learning, Climate resilience*

