Beyond peach, crop modeling research highlights the need to balance accuracy and interpretability when selecting prediction models. An interaction regression framework for corn and soybean yielded lower relative RMSE than state-of-the-art machine learning methods while explicitly decomposing yield into contributions from weather, soil, and management, demonstrating that carefully regularized regression with interaction selection can outperform black-box models and provide mechanistic insight on temperature effects (Ansarifar et al., 2021). Phenology-guided deep learning for soybean showed that incorporating heat-related predictors and phenological-stage windows in a Bayesian CNN architecture substantially improved yield prediction relative to benchmark models, underscoring that model choice should reflect both temperature process representation and the temporal structure of response variables (Zhang and Diao, 2023).

6.2 Error decomposition and robustness testing

For temperature-driven crop models, decomposing prediction errors helps clarify limitations in both structure and parameterization. In a grapevine phenology-yield model calibrated with a frequentist framework, the joint objective function based on normalized RMSE revealed that no single parameter vector minimized errors for both phenology and yield simultaneously, and yield RMSE exhibited much larger spread than phenology RMSE, indicating structural or parameter constraints in capturing yield responses to weather variability (Yang et al., 2024). Follow-up uncertainty analysis showed that fruit-setting parameters were the dominant contributors to yield prediction variability, illustrating how error decomposition can pinpoint biologically meaningful leverage points for improving reproductive and yield submodels.

Robustness of phenology and yield simulations to temperature extremes and calibration data coverage has been explicitly tested in multi-model rice phenology assessments. Using six model structures and leave-one-out cross-validation, regional simulations of maturity dates achieved RMSE of 2-4 days, but evaluation errors were larger than calibration errors, especially in areas with frequent high-temperature episodes, where divergent model responses increased structural uncertainty. Decomposition of total uncertainty into parameter and structural components showed that parameter variability dominated overall uncertainty in most regions, except in high-temperature zones where structural differences in temperature response functions were more important, emphasizing that robustness testing must consider both parameter and model-form uncertainties across temperature regimes.

6.3 Sensitivity and uncertainty analysis of temperature variables

Sensitivity and uncertainty analyses provide a quantitative basis for prioritizing temperature-related variables and parameters in peach yield and quality models. Global sensitivity analysis of a fertigation crop model (HORTSYST) using Sobol indices identified nine key parameters-including minimum and maximum optimal temperatures and radiation-use efficiency-as most influential on photo-thermal time, dry matter production, and transpiration, guiding calibration toward the subset of parameters that control temperature and radiation responses. In the same framework, parameters showed stage-dependent importance, with more parameters affecting outputs early in fruiting than late in the season, suggesting that temperature sensitivities should be evaluated for specific phenological windows when modeling fruit crops.

Other dynamic crop models combine variance-based sensitivity analysis with uncertainty propagation to understand climate effects on yield. For Lycium barbarum in WOFOST, Morris and extended FAST methods demonstrated that parameters related to CO_2 assimilation, leaf area expansion, and thermal time during specific periods had the largest impact on simulated yield, and sensitivity rankings were consistent across climate sites, supporting the transferability of temperature- and development-related parameter priors across regions. A similar strategy in a grapevine soil-plant-atmosphere model quantified prediction uncertainty as the spread of nRMSE across hundreds of thousands of parameter vectors, then used parameter-wise reductions in uncertainty to identify those most responsible for yield and phenology variance, providing a template for implementing global sensitivity and uncertainty analysis in peach temperature-yield-quality models.