Optimizing Parameterization for Agricultural Productivity Using Deep Learning
ディープラーニングを用いた農業生産性のためのパラメータ最適化

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1. Introduction

Environmental changes, particularly climate warming and accelerated urbanization, underscore the importance of understanding land dynamics, especially for agricultural production. Land Surface Models (LSMs) simulate the interactions between the Earth's land surface and atmosphere, providing detailed insights into multiple ecosystem dynamics. A central challenge with LSMs is the strong influence of unobservable or underdetermined parameters on their behavior and skill.

In the agricultural domain, the accuracy of crop growth and yield simulations relies heavily on the setting of vegetation type parameters, such as the maximum water storage. Parameter calibration has been a fundamental practice in various geoscientific domains for decades. Although some parameter transformation methods exist, their structures are based on human cognition, which can rigidly constrain the effectiveness of parameter information. This research proposes a novel approach leveraging deep learning techniques to identify optimal parameters and enhance parameterization efficiency for agricultural productivity. By creating a unified parameter set, we aim to improve the accuracy of LSMs, leading to better decision-making and resource management.

2. Materials and Methods

The framework of our method MdPL is illustrated in Figure 1. The calibration of LSM parameters involves two main steps. The first step is training Multiple Task Surrogate Model for the LSM, as shown in Figure 1(a). This step aims to ensure that the surrogate model replicates the outputs of the LSM as closely as possible.

The second step involves learning the optimal parameters of the LSM through a parameter generation model g_z, as shown in Figure 1(b). g_z is a deep learning framework that takes meteorological forcing data X and auxiliary information A (archived site-level data and land surface properties) as inputs, and outputs the calibration parameters.

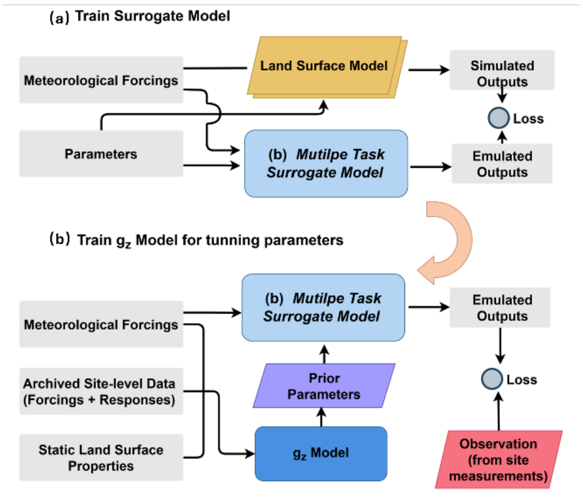

Figure 1. Overview of the Differentiable Parameter Learning framework for Land Surface Models.

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This study's data was sourced from the PLUMBER2 (PALS Land sUrface Model Benchmarking Evaluation Project), which is a public dataset and framework designed to evaluate and compare the performance of LSMs and data-driven models. It includes meteorological forcing data, site attributes for driving the models, observational data for model evaluation.

To verify the effectiveness of the MdPL in parameter calibration, we selected 5 datasets from cultivation sites. For each site, the Plant Function Type parameters were calibrated for sensible and latent heat simulation.

3. Results and Discussion

The calibrated parameters were fed into the LSM to simulate sensible heat and latent heat, and the simulated results before and after calibration were compared with the observations. Figure 2 shows Taylor diagrams illustrating the normalized RMSE, R, and STD for all sites against observations.

Figure 2(a) shows that the MdPL calibration significantly improves the model performance compared to the default parameter set across cultivation sites. The RMSE decreases 10.32%. For R, the cultivation sites exhibit good correlation improvement (3.0%).

Figure 2(b) presents the latent heat simulation results. The RMSE decreases 20.01%. However, for the R, the cultivation sites exhibit a negative correlation change (-4.77%). We attribute this phenomenon to the following two main reasons:

1. The R was not explicitly included in the loss function during calibration, so the model parameters were not optimized for this metric.
2. Human activities and seasonal changes highly influence the Plant Function Type parameters for cultivation sites. Since the LSM uses fixed Plant Function Type parameters rather than dynamic ones over time, it fails to capture the temporal variability of latent heat fluxes accurately.

The overall trend demonstrates that the MdPL consistently improves performance across most sites and output variables, proving its effectiveness in parameter calibration for land surface models.

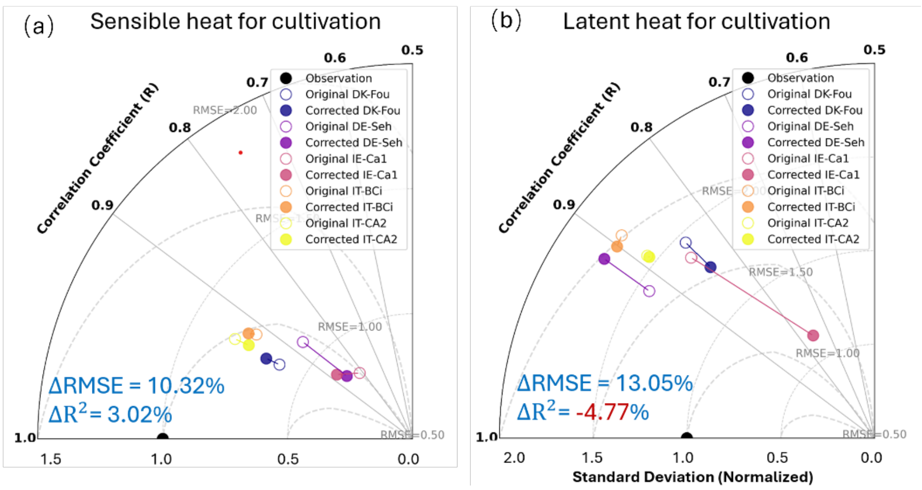

Figure 2. Taylor diagrams comparing the normalized RMSE, R, and STD for sensible heat and latent heat output. (a) Results for sensible heat simulations. (b) Results for latent heat simulation. Δ donates change percentage.