Anaerobic Parameterization Lowers Inferred Carbon Inputs but Yields Regionally Inconsistent RothC Performance Under Regional Input Scenarios for Chinese Paddy Soils

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Abstract. Anaerobic corrections to RothC remain insufficiently tested across paddy regions. Standard and modified RothC were compared using paired 1980s–2010s soil organic carbon (SOC) stocks at 104 Chinese sites. Published decomposition multipliers of 0.2 in assigned flooded months and 0.6 otherwise were applied without refitting. Simulated and observed stocks were standardized to 0–20 cm, and external precipitation and reference evapotranspiration were re-extracted from matched-period monthly climate products. Mean inferred carbon inputs were 4.67 and 1.75 t C ha^{-1} yr^{-1}. In a leakage-free benchmark of 1,469 external cropland profiles, modification reduced pooled root mean square error from 24.37 to 22.80 t C ha^{-1} (6.4%) and mean bias from +8.93 to +7.33 t C ha^{-1}. Both pooled R^2 values remained negative, and RMSE increased in Northeast China. Literature budgets contextualize inferred inputs without validating site-level additions. The correction strongly changes model-equivalent input requirements but provides only modest aggregate stock improvement; regional application requires independent carbon budgets, water-management records, and repeated SOC observations.

Keywords: soil organic carbon; RothC; paddy soil; carbon-input inversion; parameter equifinality; regional transferability

1 Introduction

RothC simulates long-term soil organic carbon (SOC) dynamics using five pools and modifiers for temperature, moisture, plant cover, and clay [1]. Developed mainly for aerobic uplands, its moisture function does not explicitly represent oxygen limitation or seasonal flooding–drainage transitions in paddy soils. Flooding restricts oxygen diffusion and alters microbial activity, potentially inflating the carbon (C) input required by an upland decomposition formulation. Anaerobic variants reduce decomposition through empirical rate multipliers tested against long-term experiments in Japan and southern China [2,3]. These corrections offer a practical structural alternative, but their

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transferability across Chinese rice regions remains uncertain. Multisite observations and national SOC datasets [4,5] permit broader comparisons, although heterogeneous climate and management complicate interpretation.

When residue-return records are incomplete, annual C input is inferred by inverting RothC against observed SOC change. This model-equivalent estimate combines unknown management supply with compensation for assumptions about turnover, initial pools, climate, and water management. Empirical initialization of inert organic matter (IOM) [6] adds uncertainty, while heterogeneous SOC responses to straw return [7] caution against treating regional input assumptions as measured additions. A six-model comparison at 16 European long-term experiments found substantial uncertainty in the C inputs required to meet a common SOC target, with water-related variables explaining divergence after calibration [8]. Alternative structures can therefore reproduce the same endpoint with different inputs; lower inferred input alone does not establish more realistic residue supply, greater C-use efficiency, or predictive skill. Pooled errors can also conceal opposing regional biases, requiring inferred inputs, regional transfer, and uncertainty to be assessed separately. A global review further identified restricted validation across land uses and pedoclimatic conditions, limiting the evidence for model transfer [9].

Here, standard and anaerobically modified RothC are compared using paired 1980s–2010s SOC stocks at 104 sites across five Chinese rice-growing regions. Three questions guide the analysis: how anaerobic parameterization changes inferred C requirements; whether improved pooled agreement accompanies consistent regional performance; and which uncertainties most strongly influence simulated stocks. Paired inversion quantifies structural effects on fitted inputs, while regional-input forward simulations examine specified supply scenarios. An external benchmark of 1,469 cropland profiles tests 0–20 cm stock transfer without using target SOC for initialization or input inference. Conditional uncertainty propagation examines sensitivity around fitted inputs. Absent repeated observations, verified paddy status, and harmonized management histories preclude treating the external benchmark as independent dynamic validation.

2 Materials and Methods

2.1 Data sources and Preprocessing

The paired dataset described by Yang et al. [4] yielded 104 valid 1980s–2010s paddy SOC records for 0–20 cm across five regions. For these sites, monthly temperature was reconstructed as $MAT + A_r \sin[2\pi(m-4)/12]$, where MAT is site mean annual temperature, m is month, and A_r is 14, 13, 11, 8, and 7 °C for Northeast, North China, Yangtze, Southwest, and South Double-rice, respectively. Regional monthly precipitation fractions summed to 1. Annual potential evapotranspiration was approximated by 600 + 0.6 × annual precipitation, bounded to 400–1500 mm, and distributed using these fractions; its open-pan proxy was 0.8 times this estimate. These reconstructed forcings were repeated for 30 years in both structures and are not monthly field observations.

The change in SOC stock was calculated as:

$$\Delta SOC_i = SOC_{i,2010s} - SOC_{i,1980s} \quad (1)$$

The national SOC-density dataset [5] supplied 1,469 external cropland profiles with directly measured stocks, complete 0–20 cm coverage, valid soil and climate data, and coordinates within the five regional province groups. Identical source–profile–coordinate–depth records were averaged; incomplete profiles, overlapping non-identical layers, indirectly estimated stocks, and the paired-data source were excluded. Layer stocks were summed over 0–20 cm, with proportional allocation where a layer crossed 20 cm and thickness-weighted clay. This assumes uniform within-layer stock density for 1,031 profiles; 438 required no boundary allocation and were evaluated separately. Missing repeated observations, verified paddy status, and management histories restrict the external analysis to a stock benchmark.

For external profiles, monthly precipitation was re-extracted at reported coordinates from WorldClim 2.1 [10] and monthly reference evapotranspiration (ET_0) from Global-ET_0 v3 [11], both at 30 arc-seconds for 1970–2000. Official annual precipitation divided by the supplied MAP field had a median ratio of 12.0 across the raw records; the ambiguous MAP field was replaced, not simply multiplied by 12. The supplied PET field was consistent with annual ET_0. Model annual precipitation and ET_0 were defined as the sums of the twelve extracted monthly totals and checked against the forcing; small differences from the separately published annual ET_0 raster were recorded without rescaling. External temperature retained the MAT-based reconstruction and the open-pan proxy remained $0.8 \times ET_0$. The RothC core applies its standard 0.75 open-pan factor. These proxies do not represent observed irrigation or flooding.

2.2 Model Structure and Initialization

Both Python implementations retained RothC-26.3 pool equations, clay response, forcing, and initialization. The moisture-response depth and all initial, observed, and predicted stocks were standardized to 0–20 cm; no depth multiplier was applied to Yang stocks. Yang clay below 8 μm was multiplied by 0.4 to approximate clay below 2 μm. Annual plant input was distributed equally among months, with a decomposable-to-resistant plant material ratio (DPM/RPM) of 0.3 and zero farmyard manure. Inert organic matter (IOM) followed Falloon et al. [6]:

$$IOM = 0.049 \times SOC^{1.139} \quad (2)$$

SOC and IOM are in t C ha^{-1}. Initially, DPM, RPM, and microbial biomass were zero; humified organic matter equalled SOC − IOM, and IOM remained fixed. Standard RothC used multiplier 1.0. The modified structure scaled decomposition in every active pool by 0.2 during June–September in Northeast, North China, and Yangtze, May–September in Southwest, and April–September in South Double-rice; otherwise, the multiplier was 0.6 [2,3]. These values retain 20% and 60% of unmodified rates. They were selected using RMSE and mean difference against 16–22 years of SOC observations from nine plots at five Japanese sites [2] and subsequently tested in southern China [3]. Neither multiplier was refitted here. Both are empirical rate scalars, not measured redox thresholds; flooded months were regional assumptions.

2.3 Carbon-input Inference and Scenario Evaluation

Annual input was inferred separately for each structure by 30-year simulation from observed 1980s SOC. Bisection searched 0.3–15.0 t C ha^{-1} yr^{-1} for up to 25 iterations, stopping below 0.05 t C ha^{-1} endpoint error. Targets outside the reachable endpoint range were flagged as bounded fits, with their residuals retained rather than interpreted as exact matches. Paired differences and ratios were:

$$D_i = C_{i,standard} - C_{i,paddy} \quad (3)$$

$$R_i = \frac{C_{i,standard}}{C_{i,paddy}} \quad (4)$$

Comparison scenarios used annual C inputs of 3.0 t C ha^{-1} yr^{-1} in four regions and 5.0 in South Double-rice. These specified magnitudes provide context for heterogeneous straw-return responses [7], not measured regional medians or complete input budgets. Their compatibility ratio, rather than C-conversion efficiency, was:

$$Q_i = \frac{C_{i,inferred}}{C_{region}} \quad (5)$$

Figure 3a instead used annual regional inputs of 3.0 t C ha^{-1} in Northeast and North China, 3.5 in Yangtze and Southwest, and 4.5 in South Double-rice. Simulations linked the same observed 1980s–2010s endpoints; performance was conditional on these scenarios, not independently validated.

2.4 External Stock-transfer Benchmark

Regional medians of 0–20 cm 1980s SOC and IOM initialized the external simulations; model-specific regional median inversions supplied input priors. External profiles supplied climate, clay, and endpoint SOC, but target SOC was excluded from initialization, input inference, and parameter selection. Monthly water deficits were cycled to a repeating annual sequence before the 30-year stock projection. Four diagnostic configurations separated depth and climate changes, with an additional comparison restricted to 1,273 common profiles. Only the corrected 20 cm configuration with re-extracted monthly precipitation and ET_0 is reported as the main benchmark. Absent initial observations and verified paddy status preclude dynamic validation.

2.5 Statistical and Uncertainty Analysis

A prespecified one-sided Wilcoxon signed-rank test assessed standard > modified input, as expected under reduced decomposition; zero differences were excluded. Bootstrap 95% confidence intervals (CIs) for the mean paired difference and site-level ratio used 10,000 resamples (seed 20260819); significance was $P < 0.05$. Mean bias error (MBE), root mean square error (RMSE), mean absolute error (MAE), and R^2 summarized performance, retaining negative R^2. Exploratory Spearman correlations related external residuals to temperature, precipitation, potential evapotranspiration, and clay,

pooled and within regions. Region-assigned flooding duration was not an independent covariate; cropping and management records were unavailable.

For each site and structure, 500 Monte Carlo draws sampled temperature (normal SD 1.5 °C), precipitation (normal relative SD 20%), clay (normal relative SD 10%), and IOM (normal relative SD 20%); the modified model also sampled flooded-month multipliers uniformly over 0.2–0.7. Temperature was untruncated; precipitation and clay had lower bounds of 50 mm yr^{-1} and 5%, and IOM/base-IOM was bounded to 0.1–2.0, with a minimum IOM of 0.1 t C ha^{-1}. HUM was adjusted when IOM changed to preserve the initial total SOC. Independent parameter draws were paired across structures using seed 42 + i (i = 0,…,103), with inferred inputs fixed. Coverage therefore measures conditional sensitivity. One-at-a-time tests varied input ±30%, temperature ±1.5 °C, precipitation ±20%, clay ±10%, IOM ±20%, and the flooded-month multiplier over 0.2–0.7.

3 Results and Discussion

3.1 Spatial Variation in SOC Change

Across 104 sites (12–25 per region), median SOC increased from 29.46 to 38.88 t C ha^{-1}; median change was 8.93 t C ha^{-1} (Fig. 1). Mean change was 10.95 ± 9.37 t C ha^{-1}, ranging from −4.63 to 57.87. Regional mean increases ranged from 5.32 in North China to 15.66 t C ha^{-1} in Southwest, demonstrating heterogeneous responses.

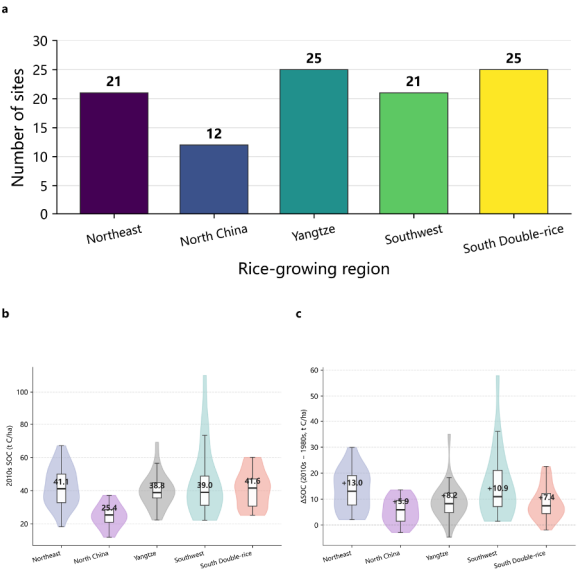


Fig. 1. Paddy sites and 0–20 cm SOC change: (a) regional site counts; (b) 2010s stocks; (c) 1980s–2010s changes.

3.2 Inferred Inputs, Mechanism, and Physical Plausibility

Standard and modified mean inputs were 4.67 ± 2.75 and 1.75 ± 1.12 t C ha^{-1} yr^{-1} (Fig. 2a). Their paired difference was 2.92 (95% CI 2.59–3.24), and mean site-level ratio was 2.69 (2.54–2.85; Fig. 2b). The one-sided Wilcoxon test supported standard > modified (104 pairs; W = 4950, P = 2.85 × 10^{-18}). Five standard and seven modified fits were constrained by the lower search bound and did not represent exact endpoint matches. Mean inferred-to-scenario ratios were 1.35 and 0.51 (Fig. 2c,d). Here, endpoint inversion absorbs structural differences into C inputs; lower inferred inputs therefore indicate compensation for slower turnover, not measured residue supply or improved C-use efficiency.

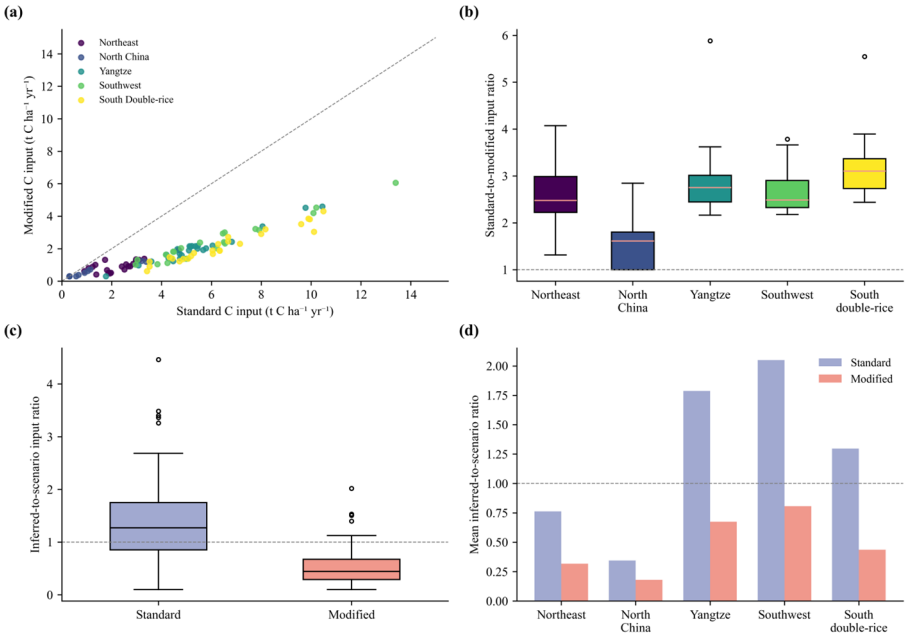


Fig. 2. Inferred C inputs: (a) paired estimates; (b) regional standard-to-modified ratios; (c) pooled and (d) regional inferred-to-scenario ratios. Boxes show medians and interquartile ranges, whiskers extend to 1.5 times that range, and points beyond are outliers; (d) shows means. Dashed lines indicate equality between models in (a,b) and with specified scenarios in (c,d), not validated input ranges.

The empirical correction has an oxygen-limitation rationale, while reduced non-submerged turnover was attributed to hypothesized microbial-community differences [2]. A comparative paddy–upland study linked SOC accumulation to mineral association mediated by iron cycling during wet–dry alternation [12]. This indicates that persistence involves mineral protection as well as oxygen-limited decomposition, processes not explicitly resolved by uniform rate scaling. Such evidence does not validate the exact 0.2/0.6 coefficients or identical responses of all pools.

Published belowground rice C input is 1.4–1.6 Mg C ha^{-1} per season, including 0.3–0.4 as rhizodeposition [13]. A nine-year rice–wheat trial in Jiangsu estimated annualized total C inputs of 4.30 and 4.51 Mg C ha^{-1} yr^{-1} without straw incorporation under conventional and adjusted fertilizer timing, respectively, and 11.74 with adjusted timing plus straw incorporation [14]. These averages divide the reported cumulative inputs by nine; they are biomass- and allocation-based estimates, not direct measurements of all carbon fluxes. Roots and associated belowground inputs are included and must not be added again. Such literature budgets contextualize the inferred means of 4.67 and 1.75 t C ha^{-1} yr^{-1} but differ in crop frequency, management, and component coverage. Neither numerical proximity nor seasonal-to-annual comparison validates physical accuracy; site-matched budgets and independent input-driven evaluation remain necessary [15].

3.3 Regional Performance and Residual Structure

At the 104 sites, standard MBE/RMSE were −1.22/17.97 t C ha^{-1}, versus +21.11/26.83 for the modified model (Fig. 3a). Standard pooled bias masked northern overestimation and southern underestimation. Modified regional biases were uniformly positive (+8.58 to +48.89), showing that input scenarios cannot be assumed compatible with both decomposition structures.

In the corrected external benchmark, MBE/RMSE/MAE were +8.93/24.37/18.50 t C ha^{-1} for standard and +7.33/22.80/17.72 for modified RothC (Fig. 3b). The pooled RMSE reduction was 6.4%, while R^2 remained negative (−0.448 and −0.268). Modified MBE was −3.33 in Northeast, −2.80 in North China, +12.37 in Yangtze, +20.60 in Southwest, and +4.19 in South Double-rice. Regional standard/modified RMSE values were 27.59/28.59, 18.00/17.60, 19.67/19.28, 33.99/29.04, and 18.62/18.12 t C ha^{-1}, respectively: improvement was not universal. Among the 438 profiles requiring no boundary allocation, pooled RMSE was 27.82 versus 24.92. These results indicate modest aggregate improvement, not established regional predictive reliability.

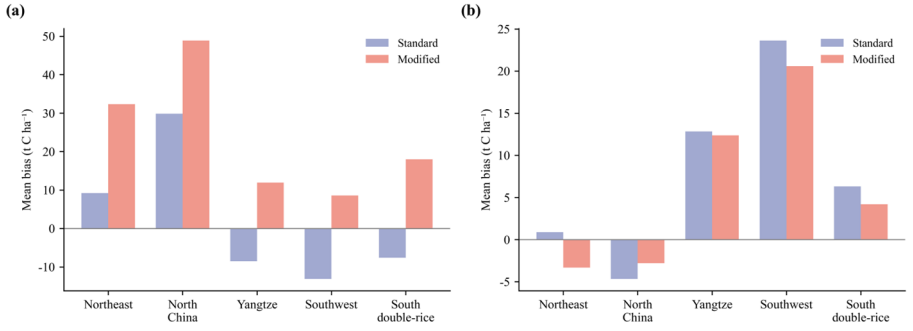


Fig. 3. Regional mean biases: (a) 104-site specified-input forward evaluation; (b) corrected 1,469-profile 0–20 cm cropland stock benchmark. Positive values indicate overestimation. The external comparison is not paddy-specific dynamic validation.

With corrected climate inputs, pooled residual correlations with temperature/precipitation were 0.08/0.02 for standard and 0.10/0.02 for modified RothC; annual ET_0 correlations were −0.06/−0.02, and clay correlations −0.10/−0.15. Within-region temperature correlations ranged from −0.45 to 0.60 and −0.43 to 0.65, respectively. Weak pooled relationships and changing regional directions do not support transferable climatic corrections or causal attribution.

A long-term double-rice trial in southern China found that SOC sequestration varied with the proportion of mineral fertilizer replaced by milk vetch and pig manure [16]. Here, region-assigned flooding was confounded with climate and SOC/input priors; missing crop sequences, residue, manure, tillage, and irrigation records prevented causal attribution. These factors remain hypotheses requiring independent time-series evaluation [15].

3.4 Conditional Uncertainty and Limitations

Conditional 95% intervals covered 100/104 endpoints (96.2%) under standard and 97/104 (93.3%) under modified RothC, but only 66.7% and 58.3% in North China. Endpoint-fitted inputs make this conditional spread, not predictive calibration. Modified-model mean absolute low-to-high SOC responses were largest for C input (9.81 t C ha^{-1}) and the flooded-month multiplier (8.58), followed by temperature (3.56), precipitation (2.25), clay (0.24), and IOM (0.18). These rankings depend on the stated perturbation ranges and are not a variance decomposition.

The 0.2/0.6 multipliers remain empirical, without independent decomposition-rate or redox validation at these sites, and uniform pool scaling simplifies flooding–drainage responses. Literature carbon budgets provide magnitude comparisons, not complete inputs matched to the 104 sites. Independent input-driven validation remains incomplete; lower inferred inputs establish neither physical accuracy nor improved C-use efficiency. SOC storage alone also cannot establish net climate mitigation: organic additions and continuous flooding can stimulate methane emissions [17], which were not simulated here.

Regional attribution remains constrained by assigned flooding schedules, incomplete management records, and external profiles without verified paddy status or repeated SOC. Depth was standardized to 0–20 cm, but proportional allocation of cross-boundary layers and fixed-depth rather than equivalent-soil-mass accounting remain approximations. The corrected stock benchmark therefore cannot establish dynamic or region-wide predictive validity.

Climate reconstruction at the paired sites, climatological rather than historical external forcing, the empirical ET_0-to-open-pan proxy, IOM initialization, and clay conversion retain uncertainty beyond the reported intervals. Preserving initial SOC during IOM perturbation corrects a computational inconsistency but does not resolve pool identifiability. Recent monitoring, reporting and verification frameworks emphasize consistent monitoring of SOC-stock changes [18]. For this application, repeated SOC, independently documented carbon inputs, and observed water regimes are required.

4 Conclusions

Anaerobic parameterization lowered mean inferred C input from 4.67 to 1.75 t C ha^{-1} yr^{-1}, demonstrating that SOC endpoints cannot uniquely separate carbon supply from decomposition. After standardizing stocks and model depth to 0–20 cm and replacing ambiguous external precipitation with matched-period monthly climate data, pooled external RMSE decreased by only 6.4%; performance worsened in Northeast China and both pooled R^2 values remained negative. The main contribution is therefore the distinction between strong structural effects on inferred inputs and limited evidence of predictive improvement. Literature budgets contextualize the estimates without independently validating them. Regional paddy evaluation requires joint constraints from SOC trajectories, complete carbon budgets, and observed water regimes, rather than selection by pooled stock agreement alone.

Data Availability

The data and analysis materials supporting this study are available from the corresponding author upon reasonable request.

Disclosure of Interests. The authors declare no competing interests.

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