



A Coupled WRF-CLM5 Framework for Simulating Carbon-Nitrogen Dynamics and Biogeochemical Feedbacks

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Abstract. Neglecting biogeochemical cycles in regional climate simulation compromises the representation of land-atmosphere interaction and the exchanges of materials and energy. The WRF (Weather Research and Forecasting) model coupled with CLM4 (Community Land Model, version 4) (WRF-CLM4) was widely used to simulate regional climate and environment. However, this open-source model lacks advanced biogeochemical cycle module. To address this, we develop an online coupling framework that embeds the advanced biogeochemical processes of CLM5 (Community Land Model, version 5) into WRF model (WRF-CLM5), integrating the fixation and uptake of nitrogen (FUN), leaf utilization of nitrogen for assimilation (LUNA), and Medlyn stomatal models. By introducing the pre-stabilized initial fields, this system achieves full biogeochemical simulations across all subgrid patches. Three sensitivity experiments: WRF-CLM4 (Exp_CTL), WRF-CLM5 with LUNA and Medlyn (Exp_LUNA); and WRF-CLM5 with LUNA, Medlyn, and FUN (Exp_FUN), are designed to evaluate model's capacity in representing carbon-nitrogen (C-N) processes. Compared with Exp_CTL, both Exp_LUNA and Exp_FUN markedly reduce gross primary production (GPP) overestimation. The Exp_FUN, which incorporates flexible C:N ratios and novel nitrogen uptake strategies, yields the best performance. The three experiments yield magnitudes and spatio-temporal patterns of net primary production (NPP) and net ecosystem exchange (NEE) align with the reference data. However, their predicted leaf area index (LAI) values are considerably higher than observation, a discrepancy primarily arising that the model represents total LAI while the observations represent effective LAI. The Exp_FUN reveals that nitrogen acquisition is dominated by active uptake and symbiotic pathways, with carbon costs generally ranging 5–20 gC/gN, and shows pronounced spatial and temporal variations. Compared with flux site observations, Exp_FUN improves GPP simulations, lowering the averaged RMSE by 3.74 gC/m²/d. The improved representation of C-N processes enhances latent heat simulation at the expense of sensible heat simulation, since it alters surface energy partitioning without changing the total surface energy budget. Overall, the coupled model advances regional climate modeling by capturing critical C-N interactions, yet further refinements in initial fields and parameter calibration are essential to reduce residual biases.



1. Introduction

Land surface processes play a pivotal role in modulating exchanges of energy, moisture, momentum, and carbon fluxes between the terrestrial and the atmosphere (Fisher and Koven, 2020; Koster et al., 2004; Seneviratne et al., 2006), affecting the underlying surface and boundary layer conditions, and thereby the weather and climate processes (Gentine et al., 2019; Li et al., 2023; Wang et al., 2026; Wang et al., 2022). As a key conduit of these exchanges, terrestrial vegetation directly influences surface energy partitioning, evapotranspiration, and carbon turnover through physiological activities like photosynthesis, respiration, and transpiration (Li et al., 2022; Lin et al., 2015; Miralles et al., 2025). Moreover, the structural properties of surface vegetation, such as leaf area index, canopy height, and rooting depth/density, regulating surface roughness, albedo, and hydrological cycles (Bieri et al., 2025; Li et al., 2024b; Maertens et al., 2021). Collectively, these biogeochemical and biogeophysical processes determine land-atmosphere interactions and climate feedbacks at varying spatio-temporal scales (Bonan et al., 2011; Cai et al., 2024; Foley et al., 2000), particularly under background of global and climate changes.

Adequate representation of the vegetation dynamics and their feedbacks to weather/climate system in weather/climate simulation is crucial for capturing complex land-atmosphere interactions (Lawrence et al., 2019). Land surface model (LSM) is initially developed to provide essential lower boundary layer conditions and serves as land components of Earth system models or global climate models (Huang et al., 2025). However, those global/climate models are inadequate for handling land-atmosphere feedbacks when fine spatial resolution or short-term weather processes are involved (Cai et al., 2024; Huang et al., 2025), such as the micro-scale turbulence processes (Bonan et al., 2018). In contrast, the Weather Research and Forecasting (WRF) model coupled with LSM exhibits advantages in capturing regional and short-term land-atmosphere interactions. The current WRF has integrated multiple LSMs such as Simplified Simple Biosphere (SSiB), Noah, Noah-MP, Community Land Model (CLM), and others (Li et al., 2015). Among them, CLM stands out the most sophisticated and advanced, owing to its comprehensive representation of both biogeophysical and biogeochemical processes (Jin et al., 2010; Lu and Kueppers, 2012), particularly because the introduction of nitrogen dynamic is absent in other LSM schemes. The earlier CLM version 4.0 has been incorporated into WRFv3.5 in 2013 and has since been validated within WRF (Jin and Wen, 2012; Lu and Kueppers, 2012; Subin et al., 2011). In most conventional WRF-CLM runs, however, its biogeochemical function is often turned off, and only static vegetation parameters based on look-up table were used to describe biogeophysical processes (Yin et al., 2020). This limits the model's capacity in representing the two-way feedbacks between dynamical terrestrial vegetation and weather/climate system.

As core component of biogeochemical processes, carbon-nitrogen (C-N) cycles determine vegetation growth, phenology, and production, which in turn indirectly alter energy and water allocation, as well as radiation and dynamic effects (Gotangco Castillo et al., 2012; Xiang et al., 2024). Building upon progresses regarding the C-N interactions in CLM4 and the modified biogeochemical cycles in CLM4.5 (Lawrence et al., 2011; Oleson et al., 2013), the latest version, CLM5, introduces substantial changes to the C-N cycles, further strengthening the C-N coupling of vegetation (Fisher et al., 2019).



For instance, the photosynthetic capacity is determined by foliar C-N contents, but previous versions of CLM did not describe its response to environmental changes (e.g., temperature, humidity, radiation, CO₂ fertilization). In contrast, CLM5 introduces a leaf utilization of nitrogen for assimilation (LUNA) model (Ali et al., 2016), which optimizes photosynthetic parameters and thereby adjusts foliar nitrogen allocation under given ambient factors. CLM5 replaced the previous semi-empirical model, namely the Ball-Berry model (Collatz et al., 1992) with the Medlyn stomatal conductance model (Medlyn et al., 2011), enabling the model to adjust the stomatal resistance according to growth temperature and water use efficiency, thus maintaining a balance between carbon gain and water loss. For nitrogen cycles, CLM5 integrates the state-of-the-art vegetation fixation and uptake of nitrogen (FUN) model (Brzostek et al., 2014; Fisher et al., 2010; Shi et al., 2013). Drawing upon soil and tissue nitrogen content, FUN accounts for carbon consumption during nitrogen acquisition, selects the optimal pathway from different ambient nitrogen sources, and prioritizes the utilization of excess carbon. Therefore, the FUN model allows CLM5 no longer dependent on immediately down-regulating the potential photosynthetic rate in response to soil nitrogen availability to enforce plant nutrient limitation. Based on the FUN model, CLM5 allow the tissue C:N ratios to be prognostic through varying nitrogen acquisition and carbon consumption (Zachle and Friend, 2010).

The above advances allow CLM5 to feature more tightly coupling of C-N cycles (Cai et al., 2024) and incorporate external environmental forcing compared with previous versions, thereby demonstrating improved performances in representing C-N processes (Fisher et al., 2019; Wieder et al., 2019). Although CLM4 has been previously incorporated into WRF, its representation of the C-N dynamics remain simplified. An explicit description of carbon expenditure associated with nitrogen acquisition, as well as the full integration of nitrogen constraints on photosynthesis capacity and stomatal conductance, are still lacking. Meanwhile, its biogeochemical functions have seldom been activated in a regional climate simulation. Realistic simulation of land surface feedbacks requires accurate representations of how vegetation allocates tissue C-N concentrations based on photosynthetic limits and nitrogen availability, and how this allocation responds to diurnal and synoptic variations (Lawrence et al., 2019; Zachle and Friend, 2010). To date, few LSMs with complete C-N dynamics have been incorporated into the regional climate model WRF, nor have they were systematically evaluated how the C-N cycles and interactions propagate through the coupled system to affect plant growth and weather/climate processes.

Consequently, this study extends the CLM5's advances regarding biogeochemical processes into the WRFv4.2 model, enabling both a more realistic representation of C-N dynamics under online land-atmosphere interactions and high-resolution regional climate simulations with fully coupled biogeochemical functions. We aim to: (1) assess how the nitrogen constraints alter vegetation photosynthetic capacity and structures; (2) quantify the explicit carbon expenditure required for nitrogen acquisition; and (3) further examine the land surface feedbacks within the coupled framework.

2. Materials and Methods

2.1 C-N feedbacks in CLM5

Serving as a key nutrient that determines vegetation growth, nitrogen availability directly regulates the carbon assimilation,



allocation, storage, decomposition, and respiration. In the previous CLM4, the coupling of C-N cycles can be summarized as follows: (1) the instantaneous downregulation of photosynthetic carbon production depends on nitrogen availability and nitrogen demand; (2) the nitrogen allocation is based on effective carbon acquisition and stoichiometric C:N ratios, and the nitrogen decomposition rate is limited by soil and litter carbon loss; and (3) biological nitrogen fixation is modeled as an empirical function driven by the total net primary production (NPP) of the previous year. Beyond these mechanisms, CLM5 integrates the LUNA and FUN models, wherein photosynthetic capacity is co-limited by environmental conditions and foliar nitrogen allocation, and tissue nitrogen acquisition requires the consumption of a certain amount of NPP.

In CLM5, the LUNA model predicts two key photosynthetic parameters: the maximum rate of carboxylation at 25 °C (V_{cmax25}) and the maximum rate of electron transport at 25 °C (J_{max25}). As a result, photosynthetic capacity becomes constrained by environmental conditions such as temperature, humidity, radiation, day length, and CO₂ concentration. Additionally, the LUNA model allocates foliar nitrogen by optimizing the fraction of nitrogen distributed among light capture, carboxylation, electron transport, respiration, and storage, under an assumption that this allocation maximizes daily photosynthetic carbon gain. It also takes into account the enzyme turnover rate and the decay under stress conditions. Compared with traditional photosynthesis models, the LUNA model incorporates a dynamic regulation and adaptation mechanism for photosynthetic capacity, thereby avoiding erroneous estimates of photosynthetic gross primary production (GPP) under nitrogen limited conditions.

The FUN model strengthens the C-N feedbacks and approaches more real-world nitrogen acquisition. If the passive nitrogen uptake (i.e., plant transpiration transport) does not cover the nitrogen demand, there are three pathways (i.e., active uptake, symbiotic fixation, and retranslocation) to acquire nitrogen by paying some carbon costs. A large amount of ambient nitrogen is a potential source for plant nitrogen acquisition. Specifically, symbiotic nitrogen fixation refers to the symbiotic relationship between root nodules and plants (e.g., soybean); the fixation products can be directly utilized by the plants. The nitrogen uptake from soil is controlled by two parameters that respectively correspond to the relationship between nitrogen content and the rate of uptake. Non-mycorrhizal uptake independently absorbs nitrogen from the soil, rather than relying on symbiotic fungi. Mycorrhizal uptake encompasses two types of mycorrhiza based on plant functional type (PFT), namely arbuscular mycorrhiza (AM) and ectomycorrhiza (ECM). AM can rapidly absorb nitrogen through arbuscular fungi, and ECM is commonly found in temperate forests. When nitrogen is insufficient in the ambient environment, ECM fungi can absorb nitrogen from organic matter with a larger carbon cost. Nitrogen retranslocation commonly removes nitrogen from litter pools; free translocation removes nitrogen from the labile pool, while paid-for translocation removes nitrogen from more recalcitrant litter pools with increased carbon consumption.

On this basis, the FUN model can adjust the stoichiometric C:N ratios in response to the varying nitrogen acquisition cost. It follows a cheaper carbon cost pathway by prioritizing the consumption of excess carbon and the use of symbiotic nitrogen fixation. For a given PFT, the fraction of total carbon acquisition used for nitrogen fixation is prescribed; therefore, the fixation cost is calculated twice, once for the scenario where fixation is possible and once for where it is not. For active nitrogen uptake, the earlier FUN model utilized the cheapest pathway to take up nitrogen from the soil. Brzostek et al. (2014)



proposed a method for simultaneously extracting nitrogen from different uptake pathways. Similar to parallel circuits, each uptake pathway is treated as a resistor, and a "conductance" or "cost" of nitrogen uptake is derived. The more expensive the uptake pathways, the less carbon is paid. Retranslocation employs an iterative algorithm to extract nitrogen from falling leaf litter. Part of the foliar nitrogen pool is extracted without carbon expenditure, while the remaining calculation needs to take into account the nitrogen extraction cost that aligns with the current leaf C:N ratio. As more nitrogen is extracted, the C:N ratio increases, and the expenditure per unit of nitrogen will increase exponentially.

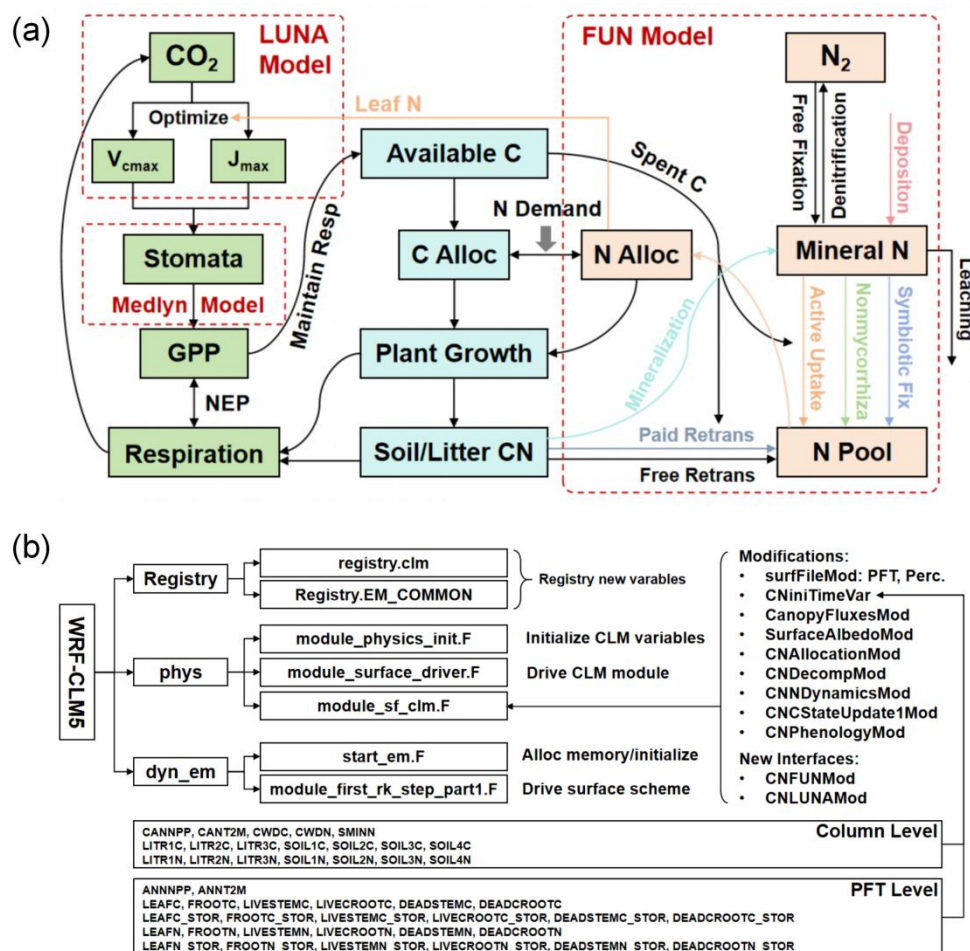
2.2 Implementation of WRF-CLM5 coupling

Given the advantages of CLM5 in representing more advanced C-N dynamics, this study introduces several compatible modules associated with CLM5's biogeochemistry into the original WRF-CLM4. Fig. 1a shows the overall coupling architecture, where we incorporate the FUN model for nitrogen cycles, together with the LUNA model and the Medlyn stomatal model for carbon cycles. The three models collectively enable a more tightly coupled simulation of C-N interactions across terrestrial ecosystem.

Accordingly, we added a new interface (named "CNFUNMod") here, which is now called by the "CNAllocationMod" module (Fig. 1b). The nitrogen acquisition methods in FUN encompass four pathways: active uptake (AM, ECM) from the soil, non-mycorrhiza uptake, retranslocation from senescent tissues, and symbiotic nitrogen fixation. Nitrogen acquisition requires the consumption of carbon energy, accounting for some fraction of NPP. Moreover, multiple potential nitrogen sources in the environment (e.g., symbiotic fixation) can be used for carbon exchange. Therefore, the FUN scheme prioritizes the consumption of excess carbon or the use of symbiotic nitrogen fixation first. In contrast, the nitrogen fixation to the soil mineral pool (inorganic nitrogen) predicted by WRF-CLM4 is only a linear function of NPP, plant nitrogen acquisition depends on ambient nitrogen content, available carbon and tissue C:N ratio. Further details of the FUN model are presented in Appendix A.

To adapt the FUN interface, several additional modules were accordingly updated. (1) CNAllocationMod: The vertical profiles of external nitrogen sources has also been added, the nitrogen fixation profiles use the vertical distribution of root profiles, and the nitrogen deposition profiles are based on an exponential decay function of soil depth. The exponential decay is scaled as $\exp(-z/d)$, where z is soil depth and the e-folding depth d is set to 0.1 m, implying that over 80% of nitrogen deposition maintains within the top 20 cm of the soil. Subsequently, the vertical distribution of the soil mineral nitrogen pool can be generated. The soil mineral nitrogen at each layer is then used to calculate the overall nitrogen uptake profiles, which serve to resolve the competition between plant and heterotroph for mineral nitrogen, to derive the vertical profiles of actual nitrogen immobilization and mineralization, and also to compute the plant nitrogen uptake from the soil mineral nitrogen pool. For the C-N allocations in CLM5, the growth respiration is not considered when calculating the carbon allometry, and the plant nitrogen demand is just as a maximum draw on soil nitrogen pools. (2) CNphenologyMod: Foliar nitrogen retranslocation is now partitioned into paid-for and free components when calculating the background litter and offset litter phenology. As a result, the leaf C:N ratio during the offset phenology period is recalculated from foliar carbon and nitrogen

170 CNCStateUpdate1Mod: The carbon expenditure on absorbing nitrogen has been subtracted from the temporary
photosynthesis carbon pool.



175 module and CLM scheme, initial files for WRF variables, and adjustments to physical schemes. In addition, modifications to the CLM scheme involve several associated modules and two new interfaces.

For the carbon cycle processes, we incorporated the LUNA model through a new interface named "CNLUNAMod". This model is now used to update the photosynthetic capacity (i.e., V_{cmax25} and J_{max25}) of C3 and non-crop PFTs prior to photosynthesis calculation. Based on foliar nitrogen content and 10-day averages of radiation, temperature, humidity, leaf



180 temperature, O_2 , CO_2 , and leaf boundary layer resistance, the LUNA model calculates the optimal V_{cmax25} and J_{max25} by optimizing the nitrogen allocation among the Rubisco, chlorophyll, respiration, and storage pools. The model updates these photosynthesis parameters once per day, and the optimized V_{cmax25} and J_{max25} are directly passed to the "CanopyFluxesMod" module for photosynthesis calculation. Meanwhile, the LUNA model scales the V_{cmax25} and J_{max25} for shaded leaves from those of sunlit leaves; the scaling coefficients are now calculated in the two-stream radiation module ("SurfaceAlbedoMod").

185 For C4 and crop PFTs, V_{cmax25} and J_{max25} still follow the traditional methods. The LUNA model is typically activated together with the FUN model to improve the representation of C-N dynamics (Fisher et al., 2019). Appendix B provides details for the LUNA model.

In CLM5, the previous Medlyn model for stomatal resistance and photosynthesis has been replaced with the Ball-Berry model. The calculation of leaf photosynthesis rate (A), which was originally based on Farquhar et al. (1980) and Collatz et al. (1992), now employs the modified version by Bonan et al. (2011). The current solving for A based on a quadratic equation is closer to physiological process. The maximum rate of electron transfer (J_{max}) is derived via combining V_{cmax25} , rather than using a PFT-based constant in WRF-CLM4. The CO_2 partial pressure at leaf surface (c_s) and inter-cellular leaf (c_i), leaf stomatal resistance (r_s), and net photosynthesis rate (A_n) are solved iteratively until c_i converges. Only three times of iteration are implemented in WRF-CLM4, which does not always ensure convergence (Sun et al., 2012). Herein, we adopt a hybrid

195 algorithm combining the secant method and Brent method to solve them. Appendix C gives detailed comparison of photosynthesis calculation and stomata conductance between CLM4 and CLM5.

Besides the above added interfaces and updated modules, several unitless parameters required for employing the LUNA, FUN, and Medlyn models are involved into the coupling framework. These parameters vary across 16 PFTs and refer to the nitrogen fixation (a_{fix} , b_{fix} , c_{fix} , s_{fix} , $FUN_fracfixers$), active nitrogen uptake (akc_active , akn_active , ekc_active , ekn_active , kc_nonmyc , kn_nonmyc), nitrogen retranslocation ($grperc$), and flexible C:N ratio ($fun_cn_flex_a$, $fun_cn_flex_b$, $fun_cn_flex_c$), as well as the Medlyn stomatal conductance ($medlynslope$, $medlyninter$). All the parameters were collected from the officially released CLM5, see Table S1 and Appendix A for details. Since the parameters " kc_nonmyc " and " kn_nonmyc " were switched in the released version of CLM5, this study adopts their corrected values at

200 <https://github.com/ESCOMP/CTSM/issues/2120>.

205 2.3 Preparation for running WRF-CLM5

CLM employs a nested subgrid structures to represent surface heterogeneity. A grid cell is composed of multiple land units, each of them has multiple columns, and each column encompasses multiple PFTs. The PFT configurations in WRF-CLM4 are not read directly. When the CLM scheme is set, it automatically maps land use/covers, based on USGS or IGBP classification, to the PFTs required by CLM. Therefore, the static geographic inputs from "geogrid.exe" provide the

210 necessary information for mapping PFTs in the WRF-CLM4. However, the types and percentages of mapped PFTs depend solely on land use/covers, meaning that the PFT and percentage corresponding to each land use/cover is fixed, which largely ignores the spatial heterogeneity of PFT. Consequently, based on the surface input data of CLM, we created grid-based



global datasets of PFT and its percentages at a spatial interval of ~ 100 km. When running WRF-CLM5, the specified PFT and percentage datasets are directly read by the "surfFileMod" module and then mapped to the simulation domain using nearest neighbor interpolation method. Fig. S1 compares the percentages of 16 PFTs between WRF-CLM4 and WRF-CLM5, showing that the PFTs in WRF-CLM5 exhibit considerable spatial changes, especially in the discrimination of temperate trees, alpine grassland, and crop fields. The first four PFTs at each grid cell shown in Figs. 2b-e, which differ significantly from the prescribed PFTs in WRF-CLM4.

The biogeochemical functions in WRF-CLM4 are not activated in the default configuration and are rarely utilized. Prior studies developed the WRF-CLM coupling and utilized its biogeochemistry functions (via activating "CN" option) to detect surface energy partitioning, hydrology, and plant physiology (Lu et al., 2017; Lu et al., 2015; Lu and Kueppers, 2012); however, their simulations focused only on crop PFTs. Likewise, Cai et al. (2024) also investigated C-N fluxes in crops using a nitrogen-augmented Noah-MP scheme coupled with WRF. This is because crop growth in CLM is highly determined by temperature driven phenology periods and photosynthesis allocation; thus, the initial trigger carbon is not a main carbon source, and crop growth relies less on the long-term turnover from ecological C-N pools. Although these LSM schemes have the capacity to capture reasonable C-N fluxes, its application remains severely limited. A crucial limitation for C-N simulation is the initial conditions, since the biogeochemistry component of CLM usually require very long spin-up for C-N, up to hundreds even thousands of years (Lu et al., 2017; Shi et al., 2013). Such long-term spin-up enable the model to reach equilibrium states aligning with the real world, thereby providing a reliable start point for the subsequent simulation. This requires numerous time and computation resources, and is difficult to directly implementation in regional climate models.

In WRF-CLM4, almost all initial C-N fluxes (tissue, soil, and litter) were set to zero, providing only 1.0 gC/m^2 for the implicit (non-evergreen) or displayed (evergreen) leaf C pool of vegetation (excluding crops). To accelerate WRF-CLM5 to reach equilibrium, we thereby incorporated the steady states generated by the National Center for Atmospheric Research (NCAR; <https://svn-ccsm-inputdata.cgd.ucar.edu/trunk/inputdata/lnd/clm2/initdata/>) at year 2000 into the WRF model, a similar way as off-line CLM running Shi et al. (2016) and Li et al. (2024b). This provides the model with already equilibrated C-N states and can significantly shorten the spin-up time. Accordingly, we generated global datasets of initial C-N states that consist of three litter C-N pools and four soil C-N pools at the column levels, as well as displayed and implicit tissue C-N pools (leaf, fine root, live stem, dead stem, live coarse root, dead coarse root) at the PFT levels. We also incorporated initial fields of annually averaged 2m temperature and annual total NPP to drive those accumulate fields based computation in CLM. The above initial fields are read in the first time step by the "CNiniTimeVar" subroutine and then interpolated to the model domain (Fig. 1b).

2.4 Experimental design

This study designs three long-term biogeochemical simulation experiments: the control experiment (Exp_CTL) using the original WRF-CLM4 configuration; the photosynthesis capacity experiment (Exp_LUNA) using the new LUNA model and Medlyn stomata model of CLM5; and the combined experiment (Exp_FUN) adding the FUN model



on the basis of Exp_LUNA. Based on the three experiments, we diagnosed C-N fluxes, plant physiology, and near-surface fluxes, and performed a quantitative assessment after introducing LUNA, FUN, and Medlyn models of CLM5 into a regional model. We conducted a 11-years of WRF simulation (2000–2010) over China, as shown in Fig. 2a. The simulation was configured as a single domain with a horizontal grid spacing of 50 km (90×120 grid cells), centered at 32.0°N, 112.0°E, with the same spatial resolution as previous WRF-CLM running by Lu et al. (2015; 2016). The model top is 100 hPa and 30 vertical levels were set below it. Initial fields and lateral boundary conditions were acquired from National Center for Environmental Prediction (NCEP) Final Analysis, which has a spatial resolution of 1° and a temporal resolution of 6-hours. The outermost five grid points of the model are treated as a buffer zone and were excluded from our analysis. The first ten simulation years are regarded as the spin-up period, and our analyses focused only on model outputs at the year 2010.

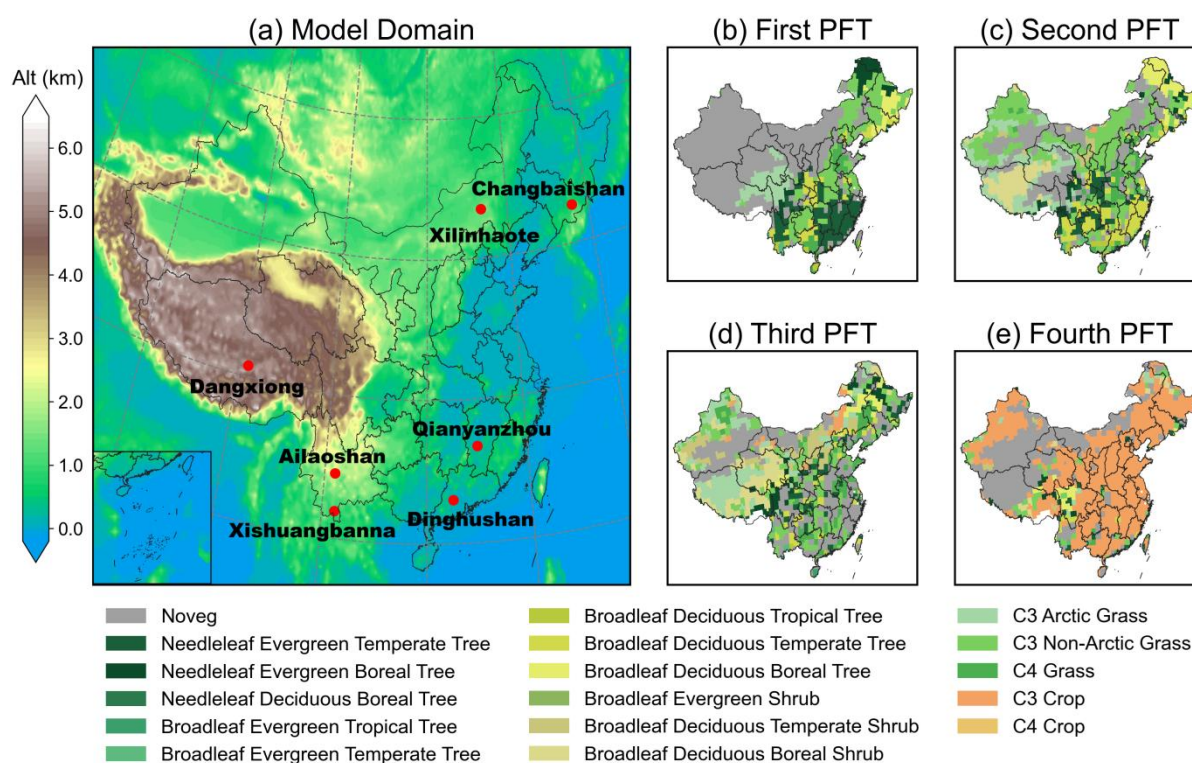


Figure 2: (a) Configuration of the model domain, showing the locations of seven surface flux observation sites. (b-e) Plant functional types assigned to the first four sub-grid patches.

The remaining physical schemes are configured as follows: the WSM6 micro-physics scheme (Hong and Lim, 2006); the Revised MM5 surface layer scheme (Jiménez et al., 2013); the YSU boundary layer scheme (Hong, 2010); the RRTM longwave and RRTMG shortwave radiation schemes (Iacono et al., 2008; Mlawer et al., 1997); and the Grell-Freitas cumulus scheme (Grell and Freitas, 2014), which features improved scale-aware and is suited for our long-term simulation.



The urban canopy scheme was disabled during the simulation. Long-term WRF simulation poses a challenge due to inevitable model drift, which leads to the continuous accumulation of systematic errors arising from physical parameterization, the model's own dynamic framework, and lateral boundary forcing. To address this problem, we configured spectral nudging during the simulation experiment. This gradually adjusts the large-scale circulation fields toward the driven fields throughout the integration, allowing the model to develop middle- and small-scale features while effectively suppressing systematic drift in the large-scale circulation. Actually, the spectral nudging yields better performance compared to relying solely on conventional restart method (Ma et al., 2021).

2.5 Datasets for simulation validation

To evaluate the performances of WRF-CLM5 in simulating C-N dynamics and associated surface feedbacks, we obtained ground flux observations from seven available sites of the National Ecosystem Science Data Center of China (<https://www.nesdc.org.cn/>). As shown in Fig. 2a, these flux sites represent different PFTs: broadleaf_evergreen_temperate_tree (Xishuangbanna), needleleaf_evergreen_temperate_tree (Qianyanzhou, Ailaoshan, and Dinghushan), broadleaf_deciduous_boreal_tree (Changbaisha), C3_no-arctic_grass (Xilinhaote), and C3_arctic_grass (Dangxiong). Using the eddy covariance technique, these sites provide measurements of GPP, sensible heat (SH), and latent heat (LH) at 30-minute intervals. In this study, we utilize their daily aggregated values to validate the model's performances.

For spatial or large-scale performance analysis, we obtained two spatially contiguous GPP and leaf area index (LAI) datasets: the remote sensing-based MODIS products and the eddy covariance-light use efficiency (EC-LUE) model-based Global Land Surface Satellite (GLASS) products. The MODIS GPP product (MOD17A2HGF) used in this study is generated from vegetation physiological parameters and meteorological data (Yan et al., 2016). The GLASS GPP product is based on the EC-LUE model (Yuan et al., 2007) and accounts for variations in CO₂ concentration, radiation, and vapor pressure deficit (VPD). The MODIS LAI product (MOD15A2H) is derived from a 3-D radiation transfer model within the vegetation canopy and a look-up table, whereas the GLASS LAI product is derived from the bidirectional long short-term memory model, which effectively integrates current global LAI products along with the temporal and spectral information of MODIS surface reflectance. Both GPP and LAI products have a spatial resolution of 500 m and an 8-day temporal resolution. Since MODIS and GLASS do not provide NPP and net ecosystem exchange (NEE) products at fine temporal scales, we collected daily NEE and NPP products on $0.1^\circ \times 0.1^\circ$ grids from the MiCASA (Más Informada Carnegie-Ames-Stanford Approach) dataset. MiCASA is a land carbon flux model based on light use efficiency and represents an upgraded version of the classical CASA model (Potter et al., 1993). It is primarily utilized to estimate carbon exchanges between terrestrial ecosystems and the atmosphere. Although the above three datasets significantly fill the observation gaps, their uncertainty should not be ignored (Jung et al., 2020; Zhang et al., 2023). Therefore, instead of exploring how precisely the WRF-CLM5 captures the three outputs, this



295 study focus on weather their spatial patterns and temporal variations are reasonably aligned.

3. Results and Discussions

3.1 Comparison of photosynthetic capacity

The WRF-CLM4 model calculates the potential photosynthetic rate largely based on prescribed parameters, with predicted response of photosynthetic capacity to environmental conditions is static (Wieder et al., 2019). Despite the nitrogen limitation persists, it only computes an instantaneous down-regulation factor to remove excess carbon after tissue C-N is allocated. In contrast, WRF-CLM5 removes this down-regulation mechanism and employs the LUNA model to optimize key photosynthetic parameters (V_{cmax} and J_{max}) based on foliar nitrogen contents and environmental factors. This allows photosynthetic capacity to respond dynamically to changes in plant growth and nutrient status. Fig. 3 compares the simulated GPP and LAI from Exp_CTL, Exp_LUNA, and Exp_FUN against the outputs from MODIS and GLASS. Herein, the spatial distributions of daily average values are present, all the three experiments effectively capture the spatial patterns of GPP and LAI. The overall pattern features high values in the southeast and low values in the northwest, consistent with previous studies (Cheng et al., 2026; Zhao et al., 2025). Compared with MODIS and GLASS, the three simulations generally overestimate GPP and LAI magnitudes. However, Exp_LUNA and Exp_FUN significantly mitigate this overestimation, which aligns with a recent report on Noah-MP simulations over China that incorporated nitrogen dynamics (Liang et al., 2020). Notably, among the three simulations, Exp_FUN shows the closest agreement with MODIS and GLASS in terms of GPP and LAI magnitudes, as illustrated in Fig. S2. It can be concluded that the WRF-CLM5 introducing the LUNA and Medlyn stomatal models effectively corrects the GPP overestimation in WRF-CLM4. Furthermore, the FUN model, which optimizes nitrogen allocation and absorption while making certain carbon expenditure, can further reduce such overestimation. Additionally, WRF-CLM5 increases the GPP and LAI magnitudes in northwest China (Fig. S2).

Likewise, the WRF-CLM5 simulation also mitigates the overestimation of LAI, although the current LAI magnitudes (Exp_LUNA, Exp_FUN) are much higher than those of MODIS and GLASS; many previous CLM simulation also support this finding (Huo et al., 2024; Zhao et al., 2025; Zheng et al., 2023). This is partly because when vegetation coverage reaches a certain level, spectral signals from satellite remote sensing tend to become saturated (Claverie et al., 2016), thereby reducing sensitivity to LAI, which may explain the lower LAI values observed in MODIS and GLASS (GLASS LAI is also based on MODIS surface reflectance information). On the other hand, the LAI simulated by the model is based on several prescribed parameters and foliar carbon content, and uncertainties in these factors can introduce biases into the simulations. Overall, there is insufficient evidence to determine whether the simulations or the observations are more accurate. The LAI derived from MODIS and GLASS better represents the effective LAI available for photosynthesis, whereas the model-calculated LAI based on total foliar biomass represents the potential maximum LAI, which can also explain why the model-simulated GPP tends to be overestimated. Although the WRF-CLM5 serves as a two-leaf model, it still treats the entire

canopy as a whole without considering the extinction effect of the top canopy. If a multi-layer canopy structure are included in WRF-CLM5, the overestimation of GPP could be further mitigated.

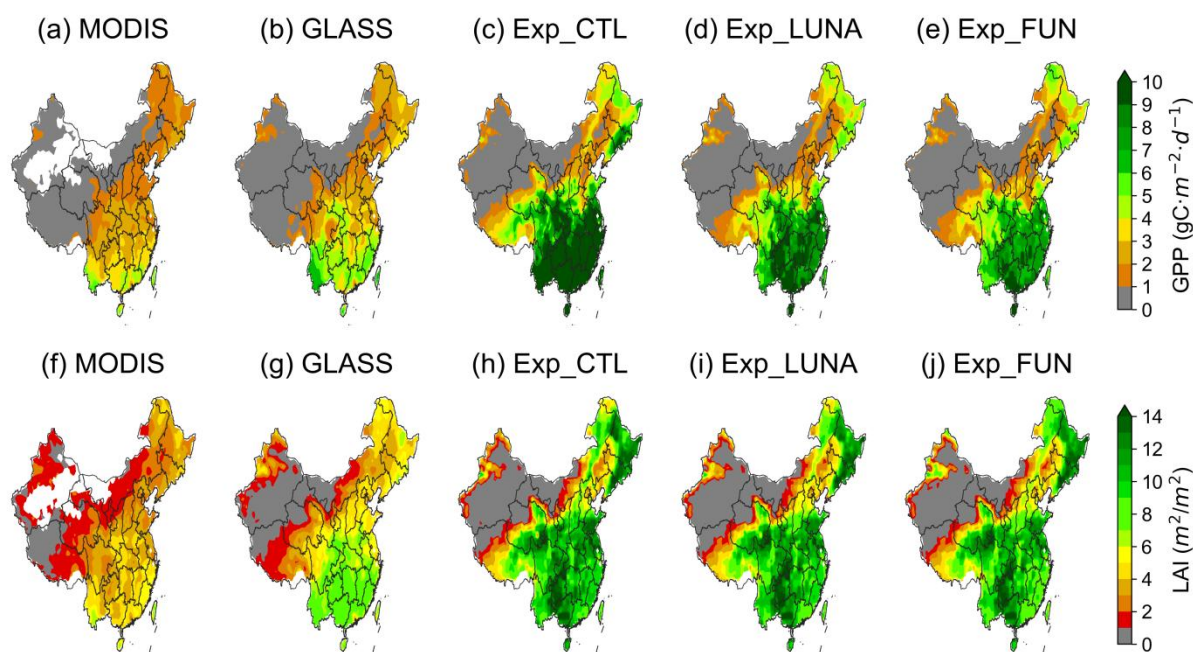


Figure 3: (a-e) GPP derived from MODIS, GLASS, Exp_CTL, Exp_LUNA, and Exp_FUN. (f-j) LAI derived from these observations and simulations.

Figure 4 depicts the temporal correlations between the simulated GPP and LAI (on an 8-day average scale) and the MODIS and GLASS products. The simulated GPP aligns closely with both reference datasets, indicating that the three models adequately capture the evolution of GPP. In comparison, Exp_LUNA and Exp_FUN yield better temporal agreement in GPP over the Tibetan Plateau and semi-arid regions of China than Exp_CTL, suggesting that the LUNA model performs better for arctic grass and boreal shrub. Compared with GPP, the temporal correlations for LAI are considerably lower, even becoming insignificant over most of the simulation domain. Such relatively lower temporal consistency in LAI may partly attributes to observations and models reveal different aspects of LAI (i.e., effective and total LAI). In terms of simulation assessment, this indicates that the WRF-CLM simulation cannot adequately represent the temporal evolution of vegetation structures or phenological features. Specifically, Exp_LUNA and Exp_FUN exhibit lower simulation biases in LAI magnitudes, but they exhibit slightly lower temporal correlations, implying that WRF-CLM5 predicts more reasonable LAI magnitudes but poorer leaf phenology, a finding similar to reports by Li et al. (2022; 2024).

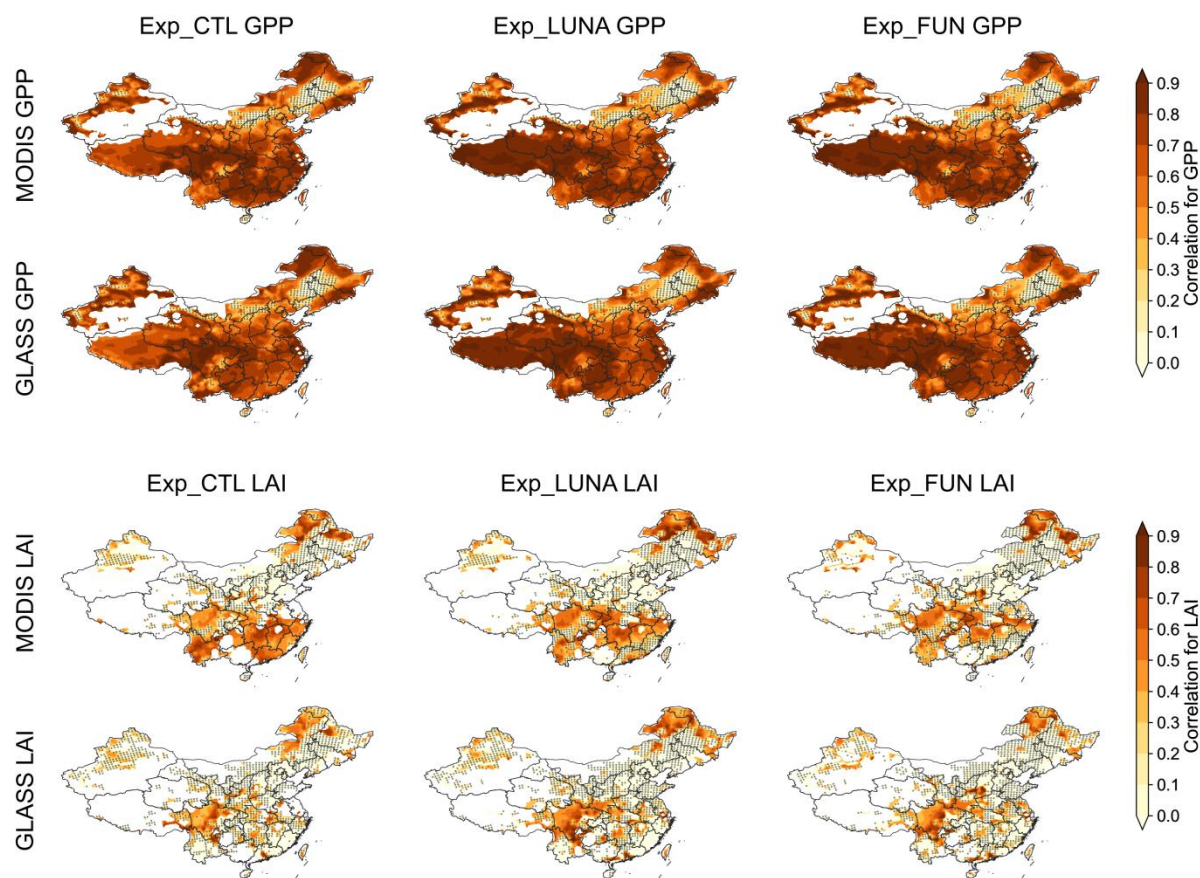


Figure 4: Temporal correlations of GPP and LAI between the three simulation experiments and the two reference datasets. The dotted area indicates that the significance test ($p < 0.5$) was not passed, the blank areas indicate too little valid data to calculate the correlation.

The quantitative assessment of spatial patterns are revealed using Taylor diagrams in Fig. 5. Overall, the three models capture the spatial patterns of GPP and LAI well, with spatial correlations exceeding 0.8, except for the comparison with MODIS LAI where the correlation is around 0.7. This indicates that although the three simulations overestimate the magnitudes of GPP and LAI to varying degrees and fail to capture aligned phenological phases, their spatial distributions are well predicted. In fact, these spatial patterns are closely related to land cover or PFTs, suggesting that the officially released PFT cover and percentage data (Fig. S1) provide accurate terrestrial vegetation distribution, thereby ensuring robust spatial variations in GPP and LAI. The STD and RMSD values in Fig. 5 reflect the relative spatial differences and simulation biases with respect to the reference data. Exp_LUNA and Exp_FUN significantly reduce the STD and RMSD of GPP, indicating that our WRF-CLM5 simulation predicts the spatial pattern of GPP better than the WRF-CLM4 simulation, with lower biases. However, the LAI simulation from WRF-CLM5 shows less improvement in spatial patterns.

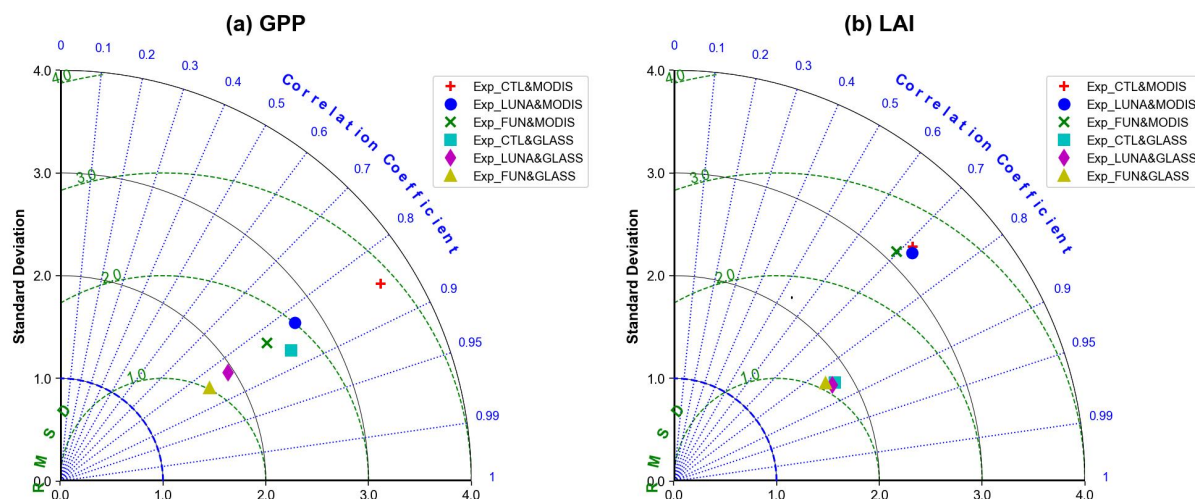


Figure 5: Taylor diagrams comparing spatial patterns (correlation, standard deviation, and RMSD) of the three simulation experiments against the two reference datasets for (a) GPP and (b) LAI.

GPP represents the total amount of photosynthetic carbon production, whereas NPP and NEE further characterize the carbon remaining after subtracting autotrophic respiration and ecosystem respiration, respectively, based on GPP. Fig. 6 validates the model outputted NPP and NEE against MiCASA data at a daily scale. The overall spatial patterns of NPP from the three experiments are generally consistent with the reference data, but their magnitudes are significantly different in southern China. Exp_CTL significantly overestimate the NPP, as reported by (Wang et al., 2015). Exp_LUNA yields a slight overestimation, while Exp_FUN shows a minor underestimation, especially in the southern region. The NPP across the three experiments follows the similar magnitude ranking as their respective GPP outputs (Fig. 3). Since the three experiments share the same initial carbon pools (those in leaf, stem, root, litter, and soil), their respiratory consumption remains nearly the same levels, aside from minor adjustments during the spin-up period. Such that the NPP across the three experiments can be ranked as: Exp_CTL > Exp_LUNA > Exp_FUN. In most regions, the simulated temporal variations of NPP from all three experiments agree well with the MiCASA reference. The major vegetation covered areas (the southeastern part of the domain) exhibit relatively lower correlations, though still statistically significant, which may be partly attributed to the models' limited ability to capture phenological growth cycles. Furthermore, Exp_LUNA and Exp_FUN perform better than Exp_CTL in southwest China and arid regions.

Conceptually, NEE encompasses autotrophic respiration, heterotrophic respiration (from litter and soil pools), and other carbon losses (e.g., fires, harvesting, mortality), whereas NPP reflects only the plant autotrophic respiration. In terms of NEE simulation, all three experiments roughly capture its sign across China, positive in the northwest and negative in the southeast. This suggests that the carbon source/sink patterns predicted by the coupled WRF-CLM are generally plausible, though the carbon source regions in the northwest appear broader than those in the reference data. Compared with the MiCASA NEE, the three experiments yield larger NEE magnitudes for both carbon sources and sinks, which may be attributable to their higher simulated GPP values. When ecosystem respiration is held constant, overestimated GPP would

lead to lower (more negative) NEE. However, the pronounced positive NEE over northwestern China may indicate a tendency toward GPP underestimation in these areas (Fig. S2).

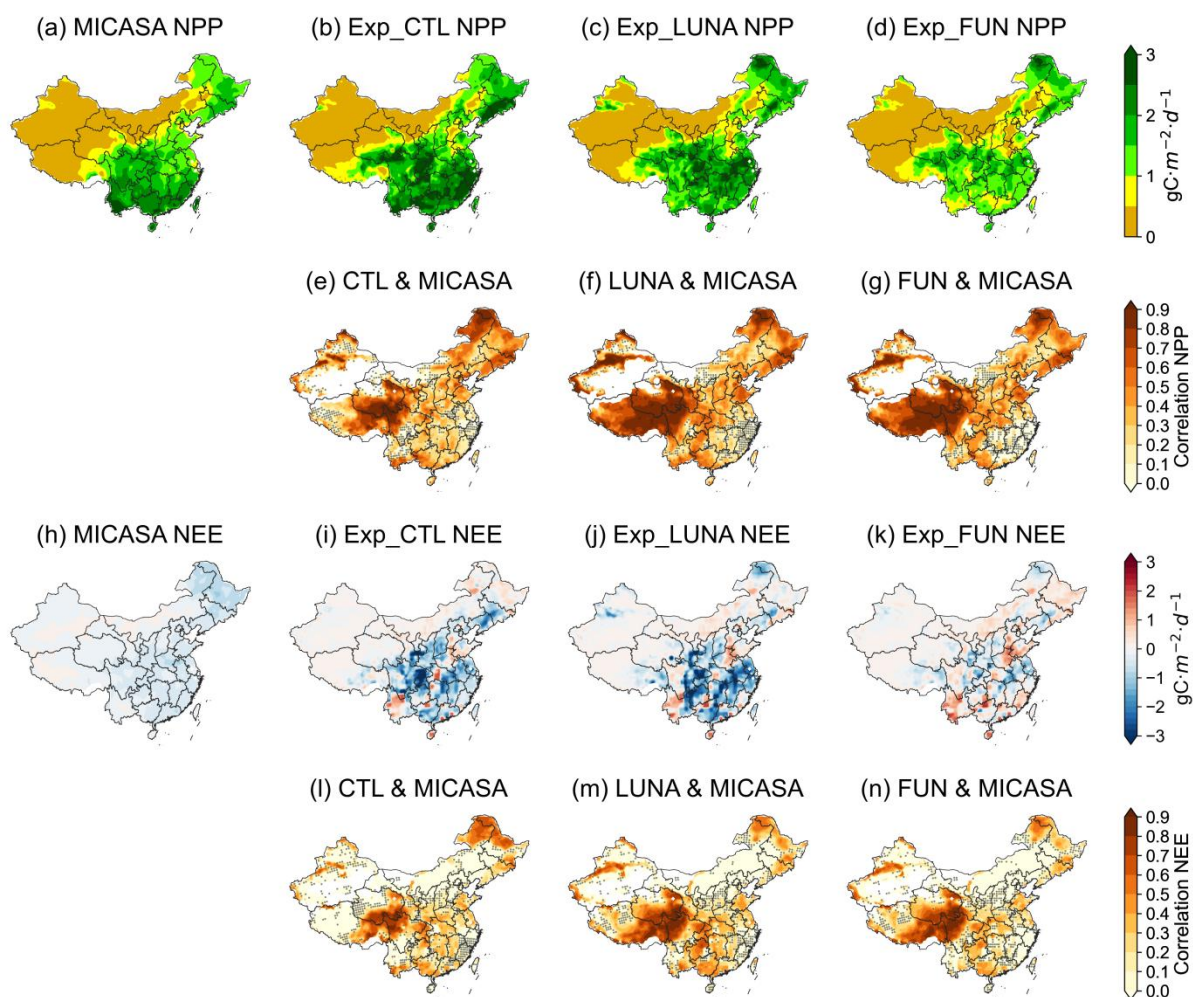


Figure 6: Spatial patterns of NPP (a-d) and NEE (h-k) derived from MiCASA and the three simulation experiments. (e-g) and (l-n) denote their temporal correlations, respectively.

Notably, the Exp_FUN simulated NEE deviates markedly from the two others, with the sign of NEE shifting over much of southern China. This divergence arises, on the one hand, from Exp_FUN producing the lowest GPP; on the other hand, the FUN model modifies the logic of soil nitrogen uptake and relies on stratified nitrogen profiles, which fundamentally alters the decomposition and allocation of soil C-N pools. Consequently, ecosystem respiration in Exp_FUN may differ substantially from that in Exp_CTL and Exp_LUNA. Moreover, since the three experiments share identical initial C-N pools for litter and soil organic matter, and because a spin-up of only 10 years may be insufficient for the extensively code-adjusted Exp_FUN to reach a fully equilibrium state for its soil C-N pools. Employing the CLM5 derived initial fields or a longer spin-up period might be necessary to mitigate this bias, though a lengthened spin-up is challenging for the regional

WRF model. Nevertheless, our primary focus here is on the photosynthetic capacity and nitrogen constraints of the newly
 coupled WRF-CLM5; whole-ecosystem carbon exchange falls beyond our current scope. Regarding temporal variations, the
 spatial correlation patterns for NEE are consistent with those for NPP, albeit with lower correlation coefficients. Correlations
 over major vegetation areas remain relatively low, particularly for Exp_FUN.

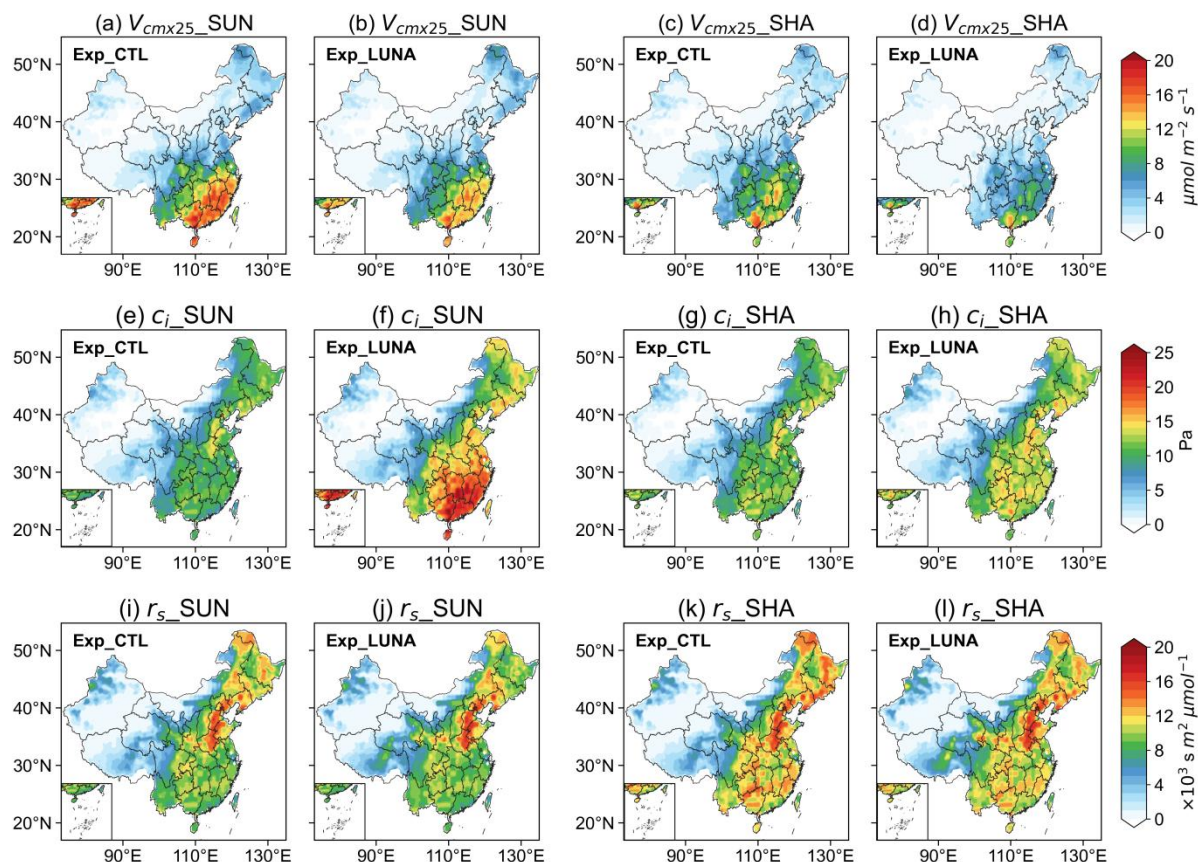


Figure 7: Comparison of photosynthetic parameters regulating photosynthetic capacity in sunlit and shaded leaves. They are (a-d) maximum carboxylation rates at 25°C, (e-h) internal leaf CO₂ partial pressure, and (i-l) stomatal resistance.

The above results demonstrate that WRF-CLM5 can improve GPP simulation, suggesting that the LUNA model, combining with the Medlyn stomatal conductance model, represents the photosynthesis processes more accurately. Figs. 7a-d compares the V_{cmx25} of sunlit and shaded leaves between Exp_CTL and Exp_LUNA. The V_{cmx25} values are significantly
 lower when adopting the LUNA model, which reduces photosynthetic carbon production and thereby mitigates the
 overestimation of GPP by WRF-CLM4. In WRF-CLM4, V_{cmx25} varies with specific leaf area, leaf temperature, and soil
 transpiration. In contrast, WRF-CLM5 predicts the photosynthetic capacity through the LUNA model, where the V_{cmx25}
 is constrained by foliar nitrogen content. The LUNA model achieves optimal nitrogen allocation for maximum photosynthetic
 carbon gain by incrementally increasing the nitrogen proportion allocated to light capture. In other words, the LUNA model



410 enables the model to dynamically adjust according to environmental conditions and foliar nitrogen allocation. Moreover, the V_{cmax25} of shaded leaves decreases notably in WRF-CLM5 because the LUNA model computes scaling coefficients specifically for shaded leaves, whereas the shaded V_{cmax25} in WRF-CLM4 is only dependent on the specific leaf area of shaded leaves.

Beyond the LUNA model, Medlyn stomatal conductance also affect the photosynthetic capacity. In WRF-CLM5, r_s is
 415 determined by A_n , c_s , and VPD, while A_n is further a function of c_s , c_i , and r_s . Therefore, their numerical solutions are iteratively solved until c_i converges. Since WRF-CLM5 adopts a hybrid solver (Appendix C) instead of the three-steps iteration scheme used in WRF-CLM4, we further compare c_i and r_s values in Figs. 7e-l. Here, r_s represents the resistance that CO_2 encounters when passing through stomata. Compared with the Ball-Berry model, the Medlyn model derived r_s is marginally smaller over northeast China but slightly higher over northwest China, exhibiting negligible differences. This
 420 indicates that the selection of stomatal conductance parameterization exerts little influence on stomatal resistance. However, adopting the Medlyn model and hybrid solver cause obvious differences in c_i . WRF-CLM4 calculates c_i based on gross photosynthesis rather than A_n , meaning that its derived c_i values are always below c_s . While in WRF-CLM5, when A_n is less than zero, a c_i value exceeding c_s value occurs, suggesting that plant respiration exceeds photosynthesis, a situation that more closely reflects real plant physiology. Therefore, the c_i values for both sunlit and shaded leaves in WRF-CLM5 are higher
 425 than those in WRF-CLM4. This can weaken the photosynthetic rates in WRF-CLM5 relative to WRF-CLM4.

3.2 Validating the nitrogen acquisition and carbon expenditure

The FUN model implements nitrogen acquisition through distinct pathways based on the dynamical optimization of trade-offs between plant carbon costs and nitrogen demands from the external environment. Figs. 8a-e present the annual magnitude of nitrogen acquisition from five pathways, and obvious differences among them can be found. In China, the
 430 major nitrogen acquisitions are from active uptake, symbiotic fixation, and free retranslocation. The spatial patterns of the two uptake pathways and the two retranslocation pathways are similar; however, the amount of non-mycorrhizal uptake and paid retranslocation are substantially lower than those of active uptake and free retranslocation. These results align well with a prior simulation by Shi et al. (2016) using a coupled CLM4-FUN model. Although the total nitrogen acquisition in this work is lower than those reported by Shi et al. (2016), the spatial patterns are roughly agreed. Herein, the main nitrogen
 435 acquisitions are observed in the southwest, southeast, and northeast of China, corresponding to large areas of evergreen forests shown in Fig. S1, such as temperate and boreal needleleaf forests. These evergreen trees do not need to undergo processes such as litterfall and dormancy; instead, their physiological activities occur throughout the year. Consequently, they can yield more GPP and have a higher nitrogen demand than other PFTs. Overall, nitrogen acquisitions in southern China are significantly higher than those in northern China, especially than those in the northwestern domain. However,
 440 there remain lower nitrogen acquisitions in some parts of southern China, which just align with pronounced areas of crop or grass distributions (Fig. S1); they have lower nitrogen demands compared to forest PFTs.

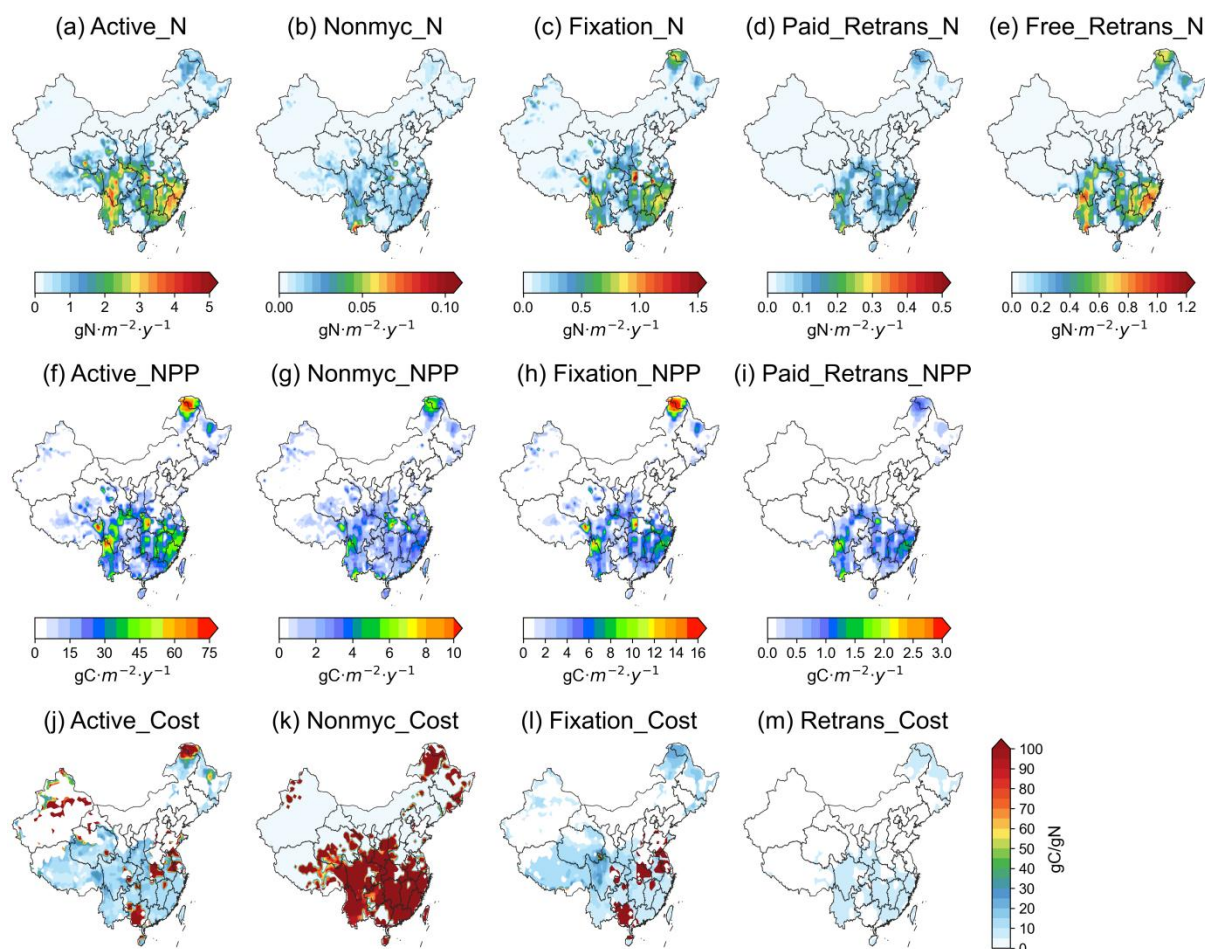
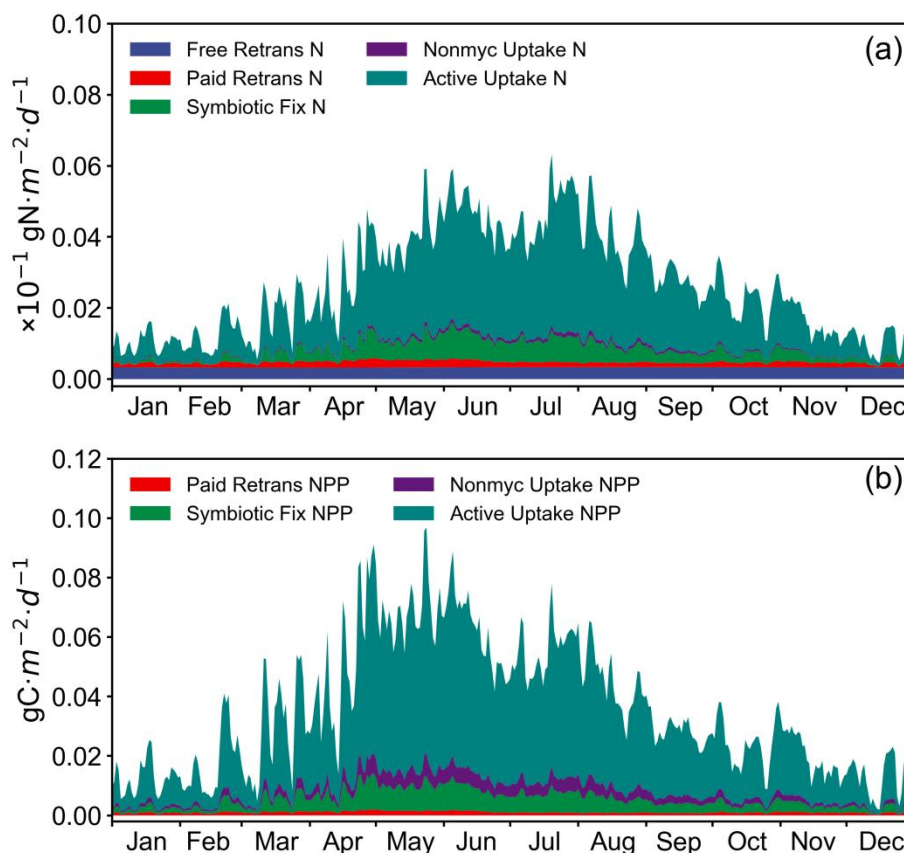


Figure 8: (a-e) Amounts of nitrogen acquired from five pathways, (f-i) carbon consumed for nitrogen extraction through different pathways, and (j-m) carbon cost per unit of nitrogen uptake.

Nitrogen absorption via the above pathways requires carbon expenditures, and Figs. 8f-i present the corresponding NPP consumption. Since active uptake serves as the primary nitrogen source, its associated carbon cost also plays a dominant role, being approximately an order of magnitude larger than that of the other pathways. The carbon costs for nitrogen acquisition are shown in Figs. 8j-m, and the carbon expenditure per unit of nitrogen acquisition varies across different pathways. Generally, the acquisition costs for active uptake, fixation, and retranslocation are about 5–20 gC/gN, whereas those for non-mycorrhizal uptake are significantly higher than those of other pathways. Because the FUN model follows the optimal cost path, the amount of nitrogen acquired via non-mycorrhizal uptake is far less than that from other pathways. In areas where non-mycorrhizal uptake is infeasible, the model acquires nitrogen through active uptake and symbiotic fixation, albeit at a high cost, as reflected by the sporadic extremely high-value regions in Figs. 8j and 8l, which complement the low-value areas in Fig. 8k. Additionally, carbon costs vary by region, with substantially higher carbon expenditure observed in northeastern China. This regional variation further demonstrates the sensitivity C-N processes to environmental stress in

WRF-CLM5. Colder and drier areas require more carbon to absorb nitrogen than warmer and wetter areas. Accordingly, northern China exhibits higher carbon costs than southern China.



460 **Figure 9: Daily time series of (a) nitrogen acquisition and (b) carbon expenditure across different pathways.**

The day-to-day variations in regionally averaged nitrogen acquisitions and carbon expenditures across different pathways are presented in Fig. 9, the intense fluctuations indicate that the C-N dynamics respond sensitively to short-term weather conditions. This also highlights the important significance of representing biogeochemical simulation in a regional climate model. Since vegetation phenology changes throughout the year, both nitrogen acquisition and carbon expenditure exhibit distinct seasonal cycles. They peak in summer, with the maximum total nitrogen acquisition about $0.006 \text{ gN} \cdot \text{m}^{-2} \cdot \text{d}^{-2}$. In this model setup, free retranslocation remains constant throughout the year because the litterfall rate is fixed at each time step of WRF-CLM5. The magnitude of paid nitrogen retranslocation is much lower; however, its maximum occurs in spring, which is somewhat inconsistent with the other pathways. This may be because during the period when seasonal phenology starts in spring, new leaves are not yet fully developed and overall photosynthesis remains limited. Accordingly, the nitrogen stored throughout the dormant period becomes an effective supply way. Furthermore, symbiotic nitrogen fixation is the second most dominant nitrogen supply. It is particularly prominent during the vegetation growing season and becomes negligible in



the non-growing season. The magnitudes of active uptake and non-mycorrhizal uptake differ greatly. Although the FUN model allocates some carbon costs to non-mycorrhizal uptake (even exceeds those to paid retranslocation), the amount of nitrogen acquisition through this pathway is rather small. This further demonstrates the advantage of the FUN model that evaluating different nitrogen acquisition pathways based on "carbon-cost economics" and selecting the optimal pathways.

3.3 Diagnosing the surface fluxes at in-situ sites

The above assessments are based on remote sensing or model-derived measurements. Although widely used, these values do not represent true ground fluxes. Therefore, in this section, we further evaluate GPP and heat fluxes (SH, LH) at the seven flux observation sites. Our goal is to determine whether the coupled model can capture the temporal variations of surface fluxes well, and how the simulation biases change after introducing the FUN, LUNA, and Medlyn models. The assessments focus on daily aggregated values of these fluxes.

Fig. 10 presents the daily GPP series from observations and three experiments for the year 2010, along with the corresponding statistical metrics (R and $RMSE$) evaluated against the observed values. For most sites, the temporal correlations of Exp_LUNA and Exp_FUN are higher than those of Exp_CTL (except for Dinghushan and Xilinhaote), indicating that WRF-CLM5 captures the temporal evolution of GPP better than WRF-CLM4. Although these higher temporal correlations suggest that the response of GPP to environmental factors is consistent between the observations and models, they do not necessarily imply that WRF-CLM provides accurate predictions of plant growing seasons or physiological cycles. For instance, at sites with deciduous phenology types (Changbaishan, Dangxiong, and Xilinhaote), the simulated phenology periods are extended: the onset day is advanced, and the offset day is postponed. Notably, the onset is advanced by approximately one month, indicating that the parameters and thresholds of the phenology module in WRF-CLM5 require further calibration. At least, these results prove a significant degree of uncertainty in the model's ability to represent phenology periods across China. This predicted phenological expansion is also part of the reason for the overestimation of GPP in Fig. 3.

Regarding simulation biases, Exp_LUNA and Exp_FUN significantly mitigate the evident overestimation observed in Exp_CTL, reducing the averaged RMSE by $3.27 \text{ gC/m}^2/\text{d}$ (Exp_LUNA) and $3.74 \text{ gC/m}^2/\text{d}$ (Exp_FUN). The improvements are particularly notable at forest sites (Ailaoshan, Changbaishan, Dinghushan, and Xishuangbanna). Compared with these four sites, Qianyanzhou is an evergreen needleleaf forest, exhibits a pronounced overestimation in all three experiments, although its temporal variations are well captured. This discrepancy may arise because Qianyanzhou is a plantation site, and the WRF-CLM model does not incorporate management practices such as rotation cutting, replanting, and cultivation, leading to reduced performances in representing the structure features and dynamics of this same-aged plantation. Obvious biases also exist in spring GPP at the Ailaoshan site. Despite the site being generally evergreen, the observed GPP seems to exhibit distinct seasonal features, and our models fail to capture these spring variations. Moreover, Exp_FUN further reduces the overestimation of GPP at forest sites such as Dinghushan, Qianyanzhou, and Xishuangbanna, causing their simulations more closely match the observations. This improvement indicates that the FUN model, which absorbs nitrogen by first



505 consuming excess carbon and employing a flexible leaf C:N ratio, can enhance the simulation of photosynthesis. It also demonstrates the advantages of combining the LUNA and FUN models within CLM5.

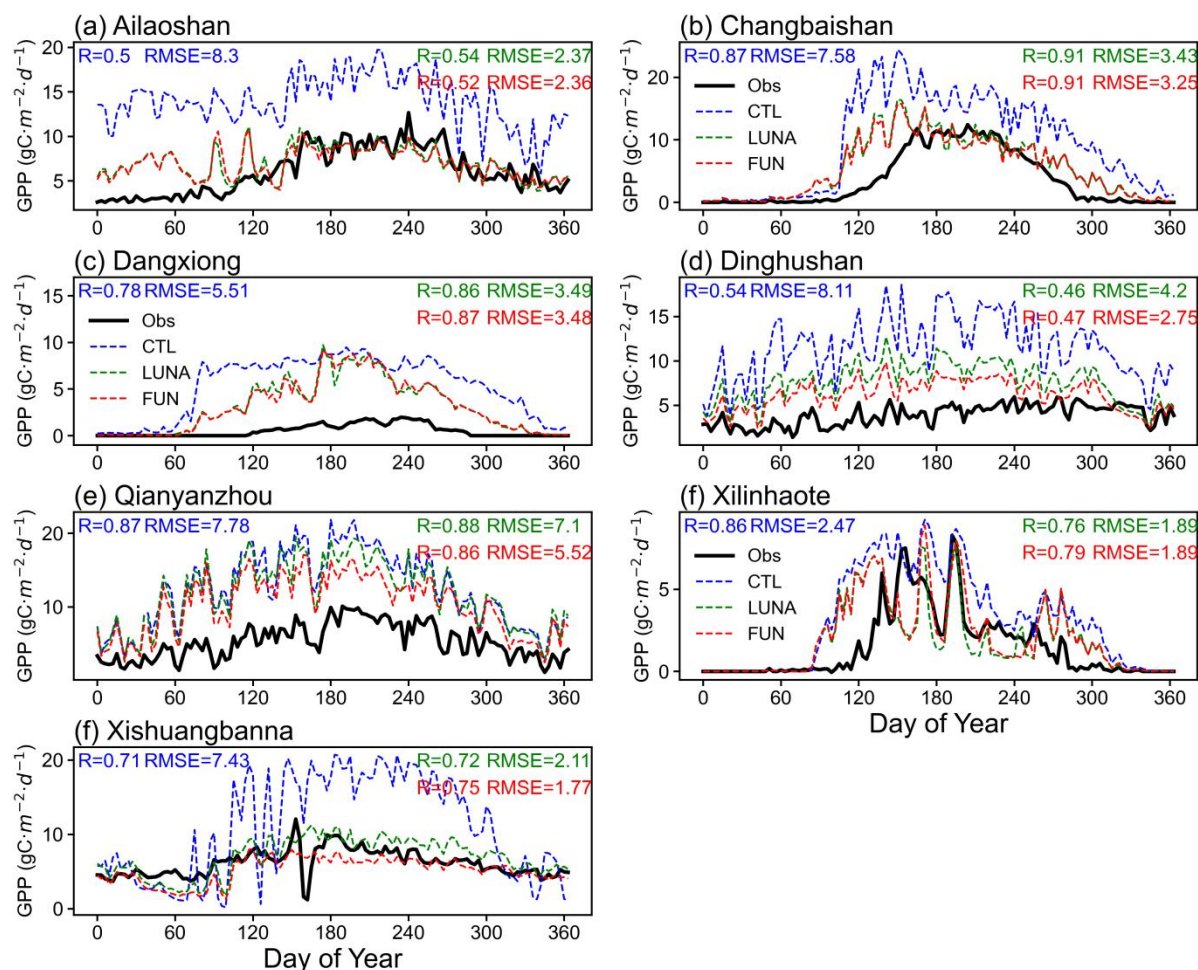


Figure 10: The GPP series at seven in-situ observation sites, with values derived from eddy-covariance observation (black solid line), Exp_CTL (blue dashed line), Exp_LUNA (green dashed line), and Exp_FUN (red dashed line).

510 Compared to forest sites, the improvements brought by Exp_LUNA and Exp_FUN for grass sites (Dangxiong and Xilinhaote) are relatively slight, as Exp_CTL already simulates their GPP reasonably well. Specifically at Xilinhaote, all three experiments capture the peaks, fluctuations, and variations quite well, despite poorly predicting the phenology periods. In contrast, at the Dangxiong site, which features alpine grass, differing from the non-alpine grassland at Xilinhaote, the three experiments exhibit consistent temporal variations but significant overestimation of the GPP magnitude during the

515 growing season. Despite WRF-CLM5 is able to mitigate this overestimation, substantial biases remain. This may be because the initial field values employed in this study (based on the older CLM version) overestimate the carbon pools (e.g., storage and displayed pools) of the alpine grass PFT to some extent. Additionally, the physiological and photosynthetic parameters specific to the alpine grass PFT may require further calibration.

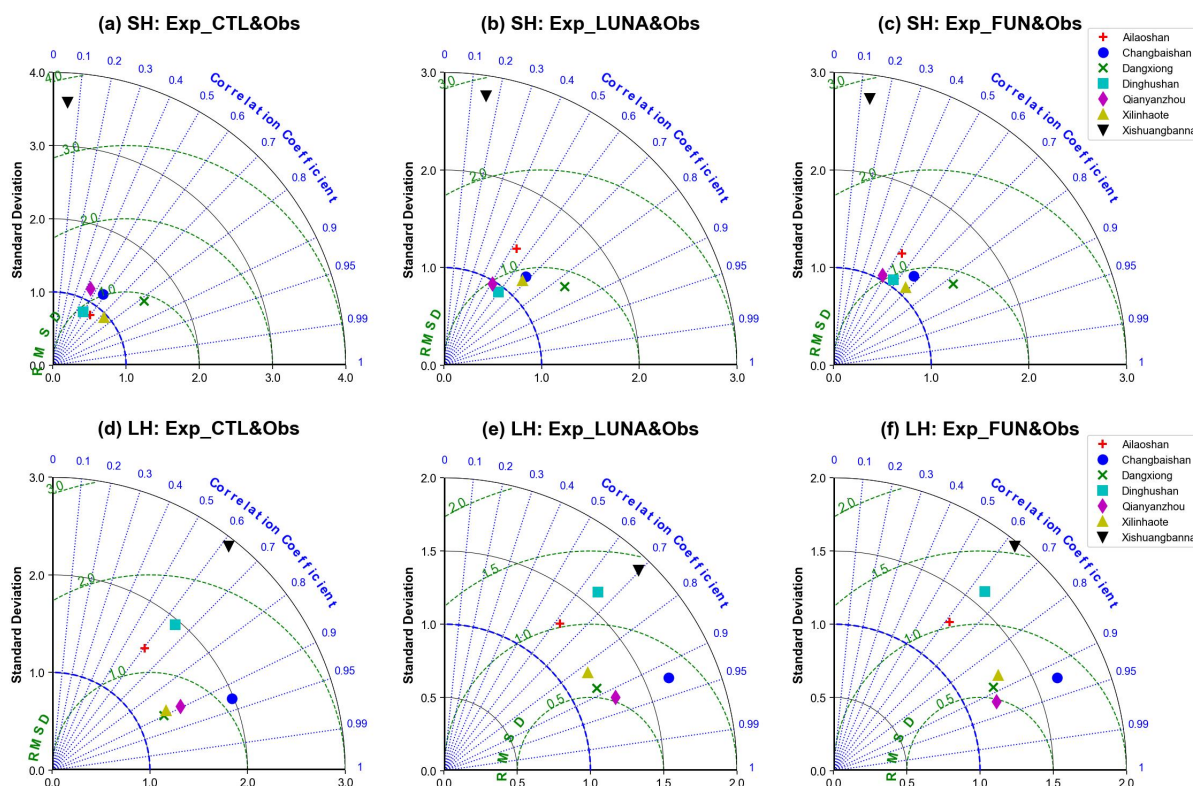


Figure 11: Taylor diagrams comparing SH (a-c) and LH (d-f) from the three simulation experiments with the corresponding observations at seven flux sites.

Through physiological and structural regulation, terrestrial biogeochemical processes can indirectly alter surface energy partitioning (Li et al., 2024a), thereby affect land-atmosphere interactions and feedbacks. The WRF-CLM scheme can directly compute surface energy fluxes (SH and LH), which are modulated by biogeochemical processes resulted changes in surface temperature, humidity, albedo, and roughness. Accordingly, Figs. S3 and S4 present the time series of simulated and observed SH and LH at seven in-situ flux sites. It can be seen that WRF-CLM4 and WRF-CLM5 exhibit a complementary performances in simulating SH and LH. Specifically, WRF-CLM4 performs better in simulating SH but is less effective for LH, whereas WRF-CLM5 simulates LH more accurately but deteriorates the performance for SH, as reported by (Ma et al., 2023).

The statistical metrics are displayed as Taylor diagrams in Fig. 11. In Exp_LUNA and Exp_FUN, the temporal correlations for both SH and LH show slight improvements, indicating that adopting the WRF-CLM5 simulation can better capture the temporal evolution of surface energy flux. However, simulation biases for SH are somewhat increased at most sites. While Exp_CTL results coincide well with the observations (Fig. S3), Exp_LUNA and Exp_FUN show a significant overestimation of SH. However, the pronounced overestimation of LH by Exp_CTL is substantially mitigated in Exp_LUNA and Exp_FUN (Fig. S4). This can be explained by the improvements in WRF-CLM5's representation of plant



540 growth. Its more accurate representation of the photosynthetic carbon cycle leads to more precise estimates of vegetation evapotranspiration and soil moisture. That is, the reduction in GPP magnitude and the increase in stomatal resistance (Fig. 7) result in lower evapotranspiration, corresponding to a smaller LH. However, when all other conditions remain unchanged, the reduction in LH partitioning leads to an increase in SH partitioning, causing the SH values simulated by WRF-CLM5 to be higher than those simulated by WRF-CLM4.

4. Conclusions

545 This study develops an online coupling framework to incorporate the biogeochemical progresses of CLM5 into the regional climate model WRF. It integrates three advanced modules, including the FUN model, the LUNA model, and the Meldyn stomatal conductance model, which optimize the nitrogen acquisition and associated carbon costs, as well as photosynthetic capacity and nitrogen limitations. These integrations promote tighter coupling between carbon and nitrogen cycles and enhance their responsiveness to environmental drivers. Beyond the standard biogeophysical simulations of WRF-CLM, this work represents for the first time to conduct full biogeochemical simulations across all PFT patches, achieved by initializing the model with pre-stabilized soil and tissue C-N pools.

550 We design three sensitivity experiments to evaluate the model performance in representing carbon fluxes (GPP, NPP, NEE) and LAI. Compared with the Exp_CTL, both Exp_LUNA and Exp_FUN significantly improved the simulation of GPP. By introducing nitrogen limited photosynthetic capacity and more robust calculation of photosynthetic parameters, Exp_LUNA mitigates the pronounced overestimation of GPP seen in Exp_CTL. On this basis, the FUN model adopts a new nitrogen uptake strategy and flexible C:N ratios, which further reduce the overestimation present in both Exp_LUNA and Exp_CTL. The spatial and temporal patterns of GPP simulated by WRF-CLM5 align well with MODIS and GLASS products. The improved GPP performances of WRF-CLM5 also yield better simulations of NPP and NEE, which are closer to reference data. However, the Exp_FUN performs relatively poorly for NEE due to an insufficient representation of heterotrophic respiration. As for LAI, all three experiments produce values significantly higher than the reference data, mainly because the simulation and observation the total LAI and effective LAI, respectively. Nonetheless, WRF-CLM5 alleviates this overestimation to some extent.

560 The FUN model's representation of nitrogen cycling processes is more closely aligned with actual vegetation physiology. Based on the optimal carbon cost economics, there are significant differences in nitrogen uptake and carbon expenditure across different pathways. In major vegetation-covered areas, nitrogen primarily comes from active uptake, symbiotic nitrogen fixation, and free retranslocation. The cost of active uptake and symbiotic nitrogen fixation ranges from approximately 5–20 gC/gN. However, when these cheaper pathways cannot meet nitrogen demands, the cost of nitrogen uptake via non-mycorrhizal pathways is much higher. Additionally, nitrogen acquisition costs in cold, dry northern regions are larger than those in warm, wet southern regions. Furthermore, there are substantial fluctuations in nitrogen uptake and carbon costs over short-term (daily) scales, indicating the practical significance of representing biogeochemical processes in



fine-scale regional climate model.

At in-situ flux sites, Exp_FUN (Exp_LUNA) captures more temporally consistent and lower biased GPP, with the *RMSE*
 570 reduced by 3.74 (3.27) gC/m²/d compared to Exp_CTL. At most sites, WRF-CLM5 is able to reproduce the observed
 magnitude of GPP, despite an overall tendency towards overestimation. However, at plantation and alpine grassland sites,
 WRF-CLM5 still shows significant overestimation. Changes in surface vegetation physiology and structure can indirectly
 affect surface energy partitioning. It is found that WRF-CLM5 significantly improves the simulation of LH, indicating that
 vegetation growth and physiological processes are closely related to changes in surface water cycles. However, from the
 575 perspective of energy partitioning, the improvement in WRF-CLM5's simulation performance for LH leads to a deterioration
 in the simulation of SH.

There are still limitations in the current WRF-CLM5 that need to be addressed in future work. First, accurate initial inputs
 are essential for adequately representing the complete C-N cycles and for reducing spin-up time. The initial fields derived
 from previous versions of CLM make our model fails to enable slower-turnover C-N pools to reach a complete equilibrium
 580 within a short simulation period. Future efforts could focus on constructing fine-resolution initial fields via CLM5 to better
 drive the WRF-CLM5 coupling system. Second, the current WRF-CLM5 tends to overestimate carbon fluxes and LAI, and
 produce biased estimates of phenological phases. Therefore, further parameter calibration may be necessary to develop
 adaptive parameter datasets, which would allow for a more reasonable representation of vegetation physiology and
 phenology. Third, in the current model, global nitrogen deposition is held constant, which may constrain nitrogen uptake and
 585 utilization efficiency across different regions. In future work, by leveraging WRF's capability in simulating atmospheric
 chemistry (e.g., WRF-Chem), real-time nitrogen deposition could be integrated into biogeochemical processes, thereby
 further re-fine the C-N simulation.

Appendix A

The following description of the FUN model closely follows the "Fixation and Uptake of Nitrogen (FUN)" section of the
 590 CLM5 Technical Note (https://escomp.github.io/CTSM/release-clm5.0/tech_note/FUN/CLM50_Tech_Note_FUN.html).

The FUN model (Fisher et al., 2010; Brzostek et al., 2014) indicates that nitrogen acquisition requires a certain amount of
 carbon consumption. The pathways of nitrogen extraction include: fixation by symbiotic bacteria, retranslocation from litters,
 active uptake (by AM and ECM), and non-mycorrhizal uptake. For each PFT, a fraction of carbon that can be used for
 nitrogen fixation is fixed. The cost of all forms of active nitrogen uptake depends on the varying nitrogen concentrations
 595 along the soil profile.

1. Cost of nitrogen fixation

The nitrogen fixation cost is calculated as:



$$N_{cost,fix} = -s_{fix} / \left(1.25 e^{a_{fix} + b_{fix} t_{soil} (1 - 0.5 t_{soil} / c_{fix})} \right),$$

where a_{fix} , b_{fix} , c_{fix} are parameters of the empirical function response to temperature (Houlton et al., 2008), t_{soil} is the soil temperature. The term is inverted to produce a resistance/cost analogue, and then multiply the temperature term by the minimum cost at optimal temperature (s_{fix}) to give a temperature limited costs in terms of C:N ratios.

2. Cost of active nitrogen uptake

The cost of nitrogen uptake from each soil layer j is controlled by two uptake parameters: the relationship between nitrogen content and nitrogen uptake, and root carbon density and nitrogen uptake. For non-mycorrhizal uptake:

$$N_{cost,nonmyc,j} = \frac{k_{n,nonmyc}}{N_{simn,j}} + \frac{k_{c,nonmyc}}{C_{root,j}},$$

and for active uptake:

$$N_{cost,active,j} = \frac{k_{n,active}}{N_{simn,j}} + \frac{k_{c,active}}{C_{root,j}},$$

where $k_{n,active}$ varies based on whether it is ecto or arbuscular mycorrhizal uptake:

$$k_{n,active} = \begin{cases} k_{n,Eactive} & e = 1 \\ k_{n,Aactive} & e = 0 \end{cases},$$

here $e = 1$ indicates the PFT is ectomycorrhizal, which is opposed to arbuscular mycorrhizal.

3. Carbon expenditure on fixation and active uptake

At each time step, the total cost of nitrogen acquisition is calculated based on the C:N ratio. The available carbon is allocated into two parts, namely payments for nitrogen acquisition and for plant growth. For the plant growth, the corresponding nitrogen must be made available. When the plant target C:N ratio is fixed, the partition for growth and nitrogen acquisition is calculated by solving a simultaneous equations.

$$\begin{cases} C_{growth} + C_{nuptake} = C_{avail} \\ C_{nuptake} / N_{cost} = C_{growth} / CN_{target} \end{cases},$$

its solutions can be used to estimate the ideal carbon cost on nitrogen acquisition as:

$$C_{nuptake} = C_{tospend} / \left((1 + f_{gr} * (CN_{target} / N_{cost})) + 1 \right).$$

Also, the other C-N fluxes can be determined following the same logic.

4. Cost of nitrogen retranslocation



In CLM5, part of leaf nitrogen pool is removed without the need of carbon expenditure. This free nitrogen retranslocation is calculated as:

$$N_{\text{retrans, free}} = \max \left(N_{\text{fallingleaf}} - \left(C_{\text{fallingleaf}} / CN_{\text{litter, min}} \right), 0 \right),$$

where $CN_{\text{litter, min}}$ is the minimum C:N ratio of the falling litter.

625 The remaining nitrogen retranslocation is calculated iteratively, nitrogen retranslocation from leaf is paid for as C:N ratios and thus its cost increases as nitrogen is extracted. The iteration continues until any below condition is meet: 1) the retranslocation cost increases beyond the cost from alternative pathways; 2) $CN_{\text{fallingleaf}}$ reaches a peak, after which no more nitrogen is possible or; 3) there is no more carbon for nitrogen extraction.

The extraction cost for the current leaf C:N ratio is calculated as:

630
$$\text{cost}_{\text{retrans}} = k_{\text{retrans}} / \left(1 / CN_{\text{fallingleaf}} \right)^{1.3},$$

where k_{retrans} is a parameter regulating the total translocation cost, which increases exponentially as C:N ratio. The carbon paid for increased C:N ratio by 1 in next iteration is:

$$C_{\text{retrans, spent, i}} = \text{cost}_{\text{retrans}} \left(N_{\text{fallingleaf}} - N_{\text{fallingleaf}} / (CN_{\text{fallingleaf}} + 1) \right),$$

and then it is needed to check whether this is larger than available carbon.

635 The amount of nitrogen retranslocated in this iteration is calculated as:

$$\text{cost}_{\text{retrans}} = k_{\text{retrans}} / \left(1 / CN_{\text{fallingleaf}} \right)^{1.3}.$$

The carbon allocated to plant growth is accounted by nitrogen extraction in this iteration. This is calculated using the current C:N ratios, and also for the additional carbon which will need to spent on growth respiration to construct new tissue:

$$C_{\text{retrans, accounted, i}} = N_{\text{retrans, paid, i}} CN_{\text{plant}} (1 + gr_{\text{frac}}).$$

640 Appendix B

The following description of the LUNA model closely follows the "PHOTOSYNTHETIC CAPACITY" section of the CLM5 Technical Note (https://escomp.github.io/CTSM/release-clm5.0/tech_note/Photosynthetic_Capacity/CLM50_Tech_Note_Photosynthetic_Capacity.html).

645 In CLM5, photosynthetic capacity is predicted by the Leaf Utilization of Nitrogen for Assimilation (LUNA) model (Ali et al., 2016) based on the optimal hypothesis for nitrogen allocation among light capture, electron transport, carboxylation, respiration, and storage. The LUNA model allocates nitrogen by incrementally increasing the nitrogen fraction into light capture, such that daily net photosynthetic carbon gain is maximized. Nitrogen allocation is optimized only during plant growth periods, whereas certain enzymes decay at a rate of 0.1 per day when daily GPP falls below zero.



1. Plant Nitrogen

650 The LUNA model is adapted from (Xu et al., 2012), where the plant nitrogen at the leaf (LNC) is composed of four pools: structural nitrogen (N_{str}), photosynthetic nitrogen (N_{psn}), storage nitrogen (N_{store}), and respiration nitrogen (N_{resp}). That is, $LNC = N_{str} + N_{psn} + N_{store} + N_{resp}$. The N_{psn} includes nitrogen for light capture (N_{lc}), nitrogen for electron transport (N_{et}), and nitrogen for carboxylation (N_{cb}): $N_{psn} = N_{et} + N_{cb} + N_{lc}$. The N_{str} is calculated from leaf mass per unit area (LMA) and the structure nitrogen content (SNC). Namely, $N_{str} = SNC \cdot LMA$, SNC is fixed at 0.002 gN/g biomass, LMA is the inverse of
 655 specific leaf area at the top of canopy.

CLM5 assumes that plants optimize nitrogen allocation to maximize carbon gain from photosynthesis, defined under given environmental conditions and leaf nitrogen use as the difference between photosynthesis (A) and the maintenance respiration for photosynthetic enzymes (R_{psn}). The solution for nitrogen allocation is:

$$\left\{ \hat{N}_{store}, \hat{N}_{resp}, \hat{N}_{lc}, \hat{N}_{et}, \hat{N}_{cb} \right\} = \arg \max_{N_{store} + N_{resp} + N_{lc} + N_{et} + N_{cb} < FNC_a} (A - R_{psn}),$$

660 where FNC_a is the functional nitrogen content, namely the LNC minus the N_{str} .

2. Maximum rate of electron transport

The maximum rate of electron transport (J_{max}) is estimated to consist of a baseline nitrogen allocation and an additional amount of nitrogen that can be adjusted, depending on daily photosynthetic active radiation (PAR), day length and relative humidity. Specifically, $J_{max} = J_{max0} + J_{maxb1} \cdot f(\text{day length}) \cdot f(\text{humidity}) \cdot \alpha \text{PAR}$. The J_{max0} is baseline electron transport rate:

665 $J_{max0} = J_{maxb0} \cdot FNC_a \cdot \text{NUE}_{J_{max}}$, where J_{maxb0} is proportion of nitrogen allocated for electron transport rate, $\text{NUE}_{J_{max}}$ is nitrogen use efficiency, J_{maxb1} is a coefficient representing the response of the electron transport rate to αPAR .

$f(\text{day length})$ is a function specifies the impact of day length on J_{max} , given that previous studies have demonstrated that longer day length alters V_{cmax25} and J_{max25} through photoperiod sensing and regulation (Bauerle et al., 2012). The $f(\text{day length})$ is calculated as:

670
$$f(\text{day length}) = \left(\frac{\text{day length}}{12} \right)^2.$$

$f(\text{humidity})$ represents the effect of relative humidity on J_{max} . Higher humidity is assumed to promote J_{max} by reducing stomatal water limitation, whereas lower humidity imposes greater water limitation, thereby influencing nitrogen allocation. When humidity drops below a critical threshold (relative humidity $RH_0 = 0.25$), plants are assumed to be physiologically incapable of reallocating nitrogen, resulting in no optimal nitrogen allocation. Consequently, $f(\text{humidity})$ is derived as:

675
$$f(\text{humidity}) = \left(1 - \exp\left(-H \frac{\max(RH - RH_0, 0)}{1 - RH_0}\right) \right),$$



where H indicates the impact of relative humidity on electron transport rate.

The light absorption efficiency α is defined from nitrogen allocation for light capture (Niinemets et al., 1998):

$$\alpha = \frac{0.292}{1 + 0.076/N_{lc}C_b},$$

where N_{lc} is amount of nitrogen for light capture, $C_b = 1.78$ is a conversion factor from nitrogen to chlorophyll.

680 3. Maximum rate of carboxylation

The maximum rate of carboxylation at 25 °C (V_{cmax25}) depends on leaf nitrogen and specific leaf area, and here is calculated following (Thornton and Zimmermann, 2007): $V_{cmax25} = N_{cb} \cdot NUE_{V_{cmax25}}$, where N_{cb} is nitrogen for carboxylation, and $NUE_{V_{cmax25}}$ is the nitrogen use efficiency for V_{cmax25} . The V_{cmax25} also varies with seasonal variation by introducing the day length function:

$$685 \quad f(DYL) = \frac{(DYL)^2}{(DYL_{max})^2},$$

from latitude and declination angle, the DYL is derived by:

$$DYL = 2 \times 13750.9871 \cos^{-1} \left[\frac{-\sin(lat) \sin(decl)}{\cos(lat) \cos(decl)} \right],$$

the DYL_{max} is calculated using maximum declination angle for current day orbital geometry.

Appendix C

690 The following description is reproduced from "Stomatal Resistance and Photosynthesis" section of the CLM5 Technical Note (https://escomp.github.io/CTSM/release-clm5.0/tech_note/Photosynthesis/CLM50_Tech_Note_Photosynthesis.html) and CLM4 Technical Note (<https://opensky.ucar.edu/islandora/object/technotes:493>).

1. Stomata model

695 CLM5 replaces the Ball-Berry stomatal conductance model with the Medlyn stomatal conductance model. The Ball-Berry model drives stomatal conductance based on the relative humidity of the leaf surface, CO₂ concentration, and total photosynthetic rate, and is expressed by:

$$\frac{1}{r_s} = m \frac{A}{c_s} \frac{e_s}{e_i} P_{atm} + b,$$



where m represents the PFT dependent constant ($C3 = 9$, $C4 = 4$). b equals 2000 and denotes the minimum stomatal conductance. c_s and e_s are the CO_2 and vapor partial pressure on the leaf surface, respectively; e_i is the saturated vapor pressure inside the leaf, and P_{atm} is the atmospheric pressure, A is the total photosynthesis rate. While the Medlyn model, by incorporating vapor pressure deficit (VPD) as a key driver of the model, makes it more in line with the actual responses of plant stomata to water stress. The formula is:

$$\frac{1}{r_s} = g_0 + 1.6 \left(1 + \frac{g_1}{\sqrt{D}} \right) \frac{A}{c_s / P_{atm}},$$

where g_0 equals 100 and represents the minimum stomatal conductance, and g_1 is a PFT dependent constant ($C3 = 5.25$, $C4 = 1.62$), D indicates the VPD, A_n is net leaf photosynthesis.

2. Calculation of photosynthesis rate

Both the above stomata models are highly dependent on A , but its calculation differs in the two versions of CLM. In CLM4, A is derived from the minimum values of three factors, RuBP limited (w_c), light limited (w_j), and product limited (w_e) rates of carboxylation. Their formulas are presented in Table C1, and with $A = \min(w_c, w_j, w_e)$. However, the CLM5 incorporates the collaboratively limited logic of three factors to calculate A . Solving the actual photosynthetic rate through quadratic equations. First, an intermediate co-limited factor A_i is calculated using the quadratic equation: $\Theta_{ej} A_i^2 - (A_c + A_j) A_i + A_c A_j = 0$ for A_c and A_j , with A_i being the smaller root. And then A is given by the smaller root of equation for A_i and A_p : $\Theta_{ip} A^2 - (A_i + A_p) A + A_i A_p = 0$. Here, $\Theta_{ej} = 0.98$ and $\Theta_{ip} = 0.95$ for $C3$ plants; and $\Theta_{ej} = 0.80$ and $\Theta_{ip} = 0.95$ for $C4$ plants. A_c , A_j , and A_p represent the RuBP limited, light-limited, and product limited carboxylation rates. The net photosynthesis rate A_n is derived as: $A_n = A - R_d$, R_d is the leaf respiration flux.

Table C1. Comparison of the three photosynthetic limited factors between CLM4 and CLM5.

Carboxylation rate	CLM4	CLM5
RuBP limited	$w_c = \begin{cases} \frac{V_{c \max} (c_i - \Gamma)}{c_i + K_c (1 + o_i / K_o)} & \text{for } C_3 \\ V_{c \max} & \text{for } C_4 \end{cases}$	$A_c = \begin{cases} \frac{V_{c \max} (c_i - \Gamma)}{c_i + K_c (1 + o_i / K_o)} & \text{for } C_3 \\ V_{c \max} & \text{for } C_4 \end{cases}$
Light limited	$w_j = \begin{cases} \frac{(c_i - \Gamma) 4.6 \phi \alpha}{c_i + 2\Gamma} & \text{for } C_3 \\ 4.6 \phi \alpha & \text{for } C_4 \end{cases}$	$A_j = \begin{cases} \frac{(c_i - \Gamma) J_x}{4(c_i + 2\Gamma)} & \text{for } C_3 \\ 4.6 \phi \alpha & \text{for } C_4 \end{cases}$



$$\text{Product limited} \quad w_e = \begin{cases} 0.5V_{c \max} & \text{for } C_3 \\ 4000V_{c \max} \frac{c_i}{P_{atm}} & \text{for } C_4 \end{cases} \quad A_p = \begin{cases} 0.5V_{c \max} & \text{for } C_3 \\ k_p \frac{c_i}{P_{atm}} & \text{for } C_4 \end{cases}$$

3. Key photosynthetic parameters

Although the photosynthesis parameters in CLM4 and CLM5 follow the Farquhar et al. (1980) model for C3 plants and the Collatz et al. (1992) model for C4 plants, the key parameters differ from each other. The maximum rate of carboxylation at 25°C ($V_{c \max 25}$) is based on leaf nitrogen concentration, fraction of leaf nitrogen in Rubisco. CLM4 commonly calculates the parameters based on prescribed values (such as specific leaf area, leaf C:N ratio, etc.), while in CLM5, it uses dynamic leaf nitrogen concentration derived via the optimal resource allocation strategy of plants. Also, the $V_{c \max}$ in CLM4 is scaled through $V_{c \max 25}$ and varies with leaf temperature T_v , soil water β_i , Q_{10} function $f(T_v)$, and day length factor $f(DYL)$:

$$V_{c \max} = V_{c \max 25} (2.4)^{(T_v - 25)/10} f(T_v) \beta_i f(DYL).$$

While in CLM5, $V_{c \max}$ adjusts with leaf temperature by integrating the thermal stability function: $V_{c \max} = V_{c \max 25} \cdot f(T_v) \cdot f_H(T_v)$, which is more complex than in CLM4.

CLM5 has added the maximum rate of electron transfer (J_{max}) to regulate the light-limited carboxylation, instead of using a constant value dependent on PFT (in CLM4). $J_{max} = J_{max 25} \cdot f(T_v) \cdot f_H(T_v)$. Among them, $J_{max 25}$ and $V_{c \max 25}$ are calculated in combination. For C4 plants, the product limited carboxylation is also dependent on the varying $V_{c \max 25}$, $k_p = k_{p 25} Q_{10}^{(T_v - 298.15)/10}$, in which $k_{p 25} = 20000 V_{c \max 25}$.

4. Numerical implementation and convergence

In CLM5, the equations for e_i , c_i , and A_n are solved iteratively until c_i converges. CLM4 provides an initial estimated value of the c_i ($C_3 = 0.7$, $C_4 = 0.3$), and solves it through only three iterations. There is a risk of numerical non-convergence in CLM4 (Sun et al., 2012). While CLM5 adopts a hybrid iterative algorithm combining the secant method and Brent method, until c_i converges, it addresses the convergence problem posed by the CLM4. In the calculation process, the ratio of CO₂/H₂O diffusion coefficient (the boundary resistance ratio changes from 1.37 to 1.4) is adjusted to optimize the calculation accuracy of gas mass transfer.



Code and data availability

740 The coupling WRF-CLM5 code incorporating the FUN, LUNA, and Medlyn stomatal model was archived in the Zenodo repository, accessible under the DOI: <https://doi.org/10.5281/zenodo.21671875> (Li, 2026).

Author contributions

YL: Methodology, Formal analysis, Investigation, Writing-original draft, Software, Validation. JH: Conceptualization, Formal analysis, Methodology, Supervision, Writing-review and editing.

Competing interests

745 The contact author has declared that none of the authors has any competing interests.

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