



High Sensitivity of Amazon Net Ecosystem Exchange Projections to Photosynthetic Optimal Temperature

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Abstract. The Amazon rainforest has historically functioned as a major carbon sink, but recent studies suggest this capacity is weakening under the combined pressures of deforestation and climate change. In the Vegetation Photosynthesis and Respiration Model (VPRM), the optimal temperature for photosynthesis (T_{opt}) controls the temperature dependence of carbon uptake. To investigate how T_{opt} influences long-term net ecosystem exchange (NEE) over the Amazon under the SSP5-8.5 scenario, we conducted multi-decadal sensitivity simulations (2030-2100) using fixed literature-derived and temperature-dependent T_{opt} formulations within VPRM. VPRM runs were conducted offline, driven by meteorological fields derived from Weather Research and Forecasting Greenhouse Gas (WRF-GHG) model simulations, and evaluated for April and September to contrast Amazon seasonal extremes. Under SSP5-8.5 warming, minimal land-use change leaves climate-driven thermal stress as the primary control on long-term NEE. During the dry-season peak (September), when thermal stress is most severe, the lower fixed- T_{opt} formulation causes the historical carbon sink to progressively weaken and transition to a net source by 2090–2100. In contrast, the temperature-dependent T_{opt} formulation mitigates high-temperature photosynthetic inhibition, preserving daytime uptake and delaying this sink-to-source transition. By 2100, T_{opt} formulation uncertainty introduces a regional NEE spread of $0.054 \text{ PgC month}^{-1}$ in April and $0.157 \text{ PgC month}^{-1}$ in September—sufficient during the dry season to reverse the sign of the regional carbon budget. These findings demonstrate that model representations of photosynthetic thermal acclimation can strongly influence the projected Amazonian carbon sink resilience under future warming.



1 Introduction

The Amazon rainforest is a complex and vital component of the Earth's climate system, playing a critical role in the global environment, biodiversity, and climate regulation. It stores an immense amount of carbon, estimated at 150–200 PgC across above- and below-ground biomass and soils, equivalent to 15–20 years of global CO₂ emissions (Flores et al., 2024). The region is also responsible for a significant portion of terrestrial ecosystem gross primary production (Science Panel for the Amazon, 2021). Furthermore, its influence extends to continental climate stability, as it contributes substantially to rainfall and moisture supply across South America through evapotranspiration (Staal et al., 2018).

Despite its historical role, the Amazon's capacity to absorb carbon is being profoundly altered and is increasingly threatened by compounding anthropogenic and climate pressures (Botía et al., 2026). Direct disturbances include large-scale deforestation, forest degradation, and wildfires, which are major drivers of carbon loss (Basso et al., 2023; Lapola et al., 2023; Rosan et al., 2024). Over recent decades, evidence indicates a long-term decline in the Amazon carbon sink associated with increasing tree mortality under changing environmental conditions (Brienen et al., 2015; Gomes et al., 2019). These impacts are further exacerbated by rising air temperatures, increasing water stress, and interactions among climatic and land-use disturbances, which increase the risk of critical ecological transitions across the basin (Artaxo, 2023; Flores et al., 2024). Specifically, deforestation accounted for approximately 74.5% of the observed decline in dry-season precipitation and 16.5% of the increase in maximum surface air temperature between 1985 and 2020 (Franco et al., 2025). Consistent with these trends, Gatti et al. (2021) reported that eastern Amazonia has experienced greater deforestation, warming, and dry-season moisture stress than western Amazonia over the past 40 years, with southeastern Amazonia acting as a net carbon source even after excluding fire emissions. However, recent atmospheric inversion estimates that account for water-vapor biases in aircraft CO₂ measurements indicate that the biogeographic Amazon remains a weak carbon sink (Botía et al., 2025). Source signals in the broader region are associated with fire emissions and carbon losses in the adjacent Cerrado and Caatinga rather than a pronounced east-west carbon gradient within Amazonia (Botía et al., 2025).

Given these contrasting observations, quantifying carbon exchange across the Amazon remains challenging because of complex regional processes and a lack of multi-decadal, observationally constrained surface flux records that capture both photosynthesis and respiration (Dayalu et al., 2025). This is compounded by discrepancies among methodologies: top-down atmospheric inversion approaches have estimated the Amazon as a small net land carbon source (e.g., 0.13 ± 0.17 PgC yr⁻¹ over 2010–2018), whereas bottom-up models often suggest a small net land carbon sink over the same period (Rosan et al., 2024). Crucially, these estimates often overlap within their large associated uncertainties, highlighting substantial remaining knowledge gaps. In addition, systematic observational biases, such as those caused by water vapor in non-dried airborne CO₂ samples, can significantly influence derived flux estimates and necessitate correction procedures (Botía et al., 2025). Consequently, resolving whether the entire Amazon region is currently a carbon source, sink, or neutral remains a key priority for future research.



These uncertainties in the present-day carbon balance are also reflected in projections of the Amazon carbon cycle. Future
 50 projections of the Amazon carbon sink under the Coupled Model Intercomparison Project Phase 6 (CMIP6) Shared Socioeco-
 nomic Pathways (SSPs) remain highly uncertain, with Earth system models (ESMs) showing divergent trajectories. Some mod-
 els project sustained biomass gains under lower-emission scenarios due to CO₂ fertilization, whereas high-emission scenarios
 can produce substantial wildfire-driven forest losses and variable post-fire recovery (Cano et al., 2022). However, observational
 evaluations show that current ESMs fail to reproduce the observed decline in the carbon sink of tropical forests associated with
 55 increasing tree mortality (Koch et al., 2021; Rammig et al., 2021). Under high-emission scenarios, CMIP6 ESMs project that
 up to 38% of the mid-20th-century Amazonian forest area could be lost by 2100 due to continued deforestation and global
 warming (Bultan et al., 2025).

These model-observation discrepancies highlight persistent uncertainties in the representation of carbon-cycle processes and
 motivate targeted sensitivity analyses of future net ecosystem exchange (NEE) projections. In particular, evaluating alternative
 60 formulations of the optimal temperature for photosynthesis (T_{opt}) provides an opportunity to assess how changes in temper-
 ature sensitivity may influence projected NEE under a high-emission scenario such as SSP5-8.5. This scenario combines a
 socioeconomic pathway characterized by high reliance on fossil fuels (SSP5; Kriegler et al., 2017) with a radiative forcing
 level of approximately 8.5 W m^{-2} by 2100. Under SSP5-8.5, the Amazon basin is projected to experience substantial changes
 in temperature and precipitation, potentially increasing the vulnerability of the region (Flores et al., 2024). Therefore, the main
 65 objective of this study is to evaluate long-term (2030–2100) changes in NEE across the Brazilian Amazon under SSP5-8.5,
 with particular emphasis on regional variability and sensitivity to alternative T_{opt} formulations. To achieve this, we analyze
 NEE dynamics during representative months of the late-wet (April) and dry (September) seasons and assess their sensitivity to
 horizontal resolution using an offline configuration of the Vegetation Photosynthesis and Respiration Model (VPRM), driven
 by Weather Research and Forecasting Greenhouse Gas (WRF-GHG) meteorology and Land-Use Harmonization version 2
 70 (LUH2) land-use projections.

2 Methods and Input Datasets

2.1 WRF-GHG model

The core component of the modeling system is the Weather Research and Forecasting (WRF) model, a fully compressible,
 non-hydrostatic atmospheric model (Skamarock et al., 2019). The WRF Greenhouse Gas model (Beck et al., 2011), hereafter
 75 referred to as WRF-GHG, is the greenhouse-gas tracer configuration of WRF-Chem, the chemistry extension of WRF (Grell
 et al., 2005). WRF-GHG supports online calculations of biospheric CO₂ fluxes through the Vegetation Photosynthesis and
 Respiration Model (VPRM) (Mahadevan et al., 2008), while specialized modules compute CH₄ emissions from wetlands,
 termites, and soil uptake. In addition, the model can ingest a variety of emission inventories and perform high-resolution
 weather-driven simulations of CO₂ transport and dispersion, with grid spacing as fine as 1 km. In WRF-GHG, CO₂ (along with
 80 CH₄ and CO) is simulated as a passive tracer within the WRF-Chem framework; that is, CO₂ contributions from anthropogenic,
 biospheric, and biomass burning sources as well as those from background concentrations are separately determined using



tagged tracers. Table 1 lists the main physics schemes used in the simulations, selected based on the sensitivity analysis of Benavente et al. (2026), which evaluated boundary layer and land-surface model configurations over the Amazon basin to identify the combinations that best reproduce regional meteorology and tracer transport.

Table 1. WRF-GHG physics schemes.

Atmospheric process	Parameterization schemes
Longwave radiation	RRTMG scheme (Iacono et al., 2008)
Shortwave radiation	RRTMG scheme
Boundary layer	YSU scheme (Hong et al., 2006)
Land surface	Unified Noah land-surface model (Chen and Dudhia, 2001)
Surface layer	Revised MM5 Monin-Obukhov scheme (Jimenez et al., 2012)
Cloud microphysics	WSM 6-class graupel scheme (Hong and Lim, 2006)
Cumulus clouds ¹	Grell-Devenyi ensemble scheme (Grell and Devenyi, 2002)

¹ Turned on for the outer domain only.

85 2.1.1 VPRM formulation

Although WRF-GHG supports online calculations of biospheric CO₂ fluxes through VPRM, in this study the CO₂ fluxes were simulated offline using the standalone VPRM module implemented in WRF-GHG. The VPRM framework estimates the net CO₂ exchange between terrestrial ecosystems and the atmosphere—referred to as net ecosystem exchange (NEE; Eq. (1))—as the balance between carbon uptake through gross primary productivity (GPP; Eq. (2)) and carbon release through ecosystem
 90 respiration (R_{eco}; Eq. (3)).

$$NEE = R_{eco} - GPP \quad (1)$$

$$GPP = \lambda \times T_{scale} \times P_{scale} \times W_{scale} \times EVI \times \frac{1}{1 + \frac{PAR}{PAR_0}} \times PAR \quad (2)$$

$$95 \quad R_{eco} = \alpha \times T_{2m} + \beta \quad (3)$$

$$T_{scale} = \frac{(T_{2m} - T_{min})(T_{2m} - T_{max})}{(T_{2m} - T_{min})(T_{2m} - T_{max}) - (T_{2m} - T_{opt})^2} \quad (4)$$

$$P_{scale} = \begin{cases} 1, & \text{for Forest and others with full canopy period,} \\ \frac{1+LSWI}{2}, & \text{for grassland, savanna, and others during bad-burst to full canopy period.} \end{cases} \quad (5)$$

$$100 \quad W_{scale} = \begin{cases} \frac{LSWI - LSWI_{min}}{LSWI_{max} - LSWI_{min}}, & \text{for grassland and savanna,} \\ \frac{1+LSWI}{1+LSWI_{max}}, & \text{for all other classes.} \end{cases} \quad (6)$$



where λ represents the ecosystem's maximum light-use efficiency, T_{scale} represents the temperature dependence of photosynthesis, P_{scale} accounts for the effect of leaf age, and W_{scale} represents canopy water content as a measure of water stress. T_{scale} is
105 calculated as a function of the 2 m air temperature (T_{2m}) alongside literature-derived values of minimum (T_{min}), optimal (T_{opt}),
and maximum (T_{max}) temperatures for photosynthesis. Both P_{scale} and W_{scale} are determined from the land surface water index
(LSWI), a satellite-derived metric tracking canopy moisture. The enhanced vegetation index (EVI), also a satellite-derived met-
ric, serves as a proxy for canopy greenness and structure. Photosynthetically active radiation (PAR) drives the light-dependent
assimilation, with PAR_0 representing the half-saturation parameter at which the photosynthetic rate reaches half its capacity.
110 Finally, α and β represent the temperature sensitivity and baseline rate of ecosystem respiration, respectively. VPRM reclassi-
fies the 20 land-use categories of the Modified IGBP MODIS NOAH scheme into eight biomes: Evergreen Forest, Deciduous
Forest, Mixed Forest, Shrubland, Savanna, Grassland, Cropland, and a residual "Others" category, including urban, water, bar-
ren land, and wetlands. The Modified IGBP MODIS NOAH scheme refers to a specific version of the land-use classification
used by the Unified Noah Land Surface Model (LSM). A detailed description of the VPRM model is provided by Mahadevan
115 et al. (2008).

The parameters λ , PAR_0 , α and β are empirical coefficients that are typically calibrated for each vegetation type. To evaluate
parameter sensitivity against eddy covariance observations at the ATTO site, we tested reference parameter sets reported by
Ravi et al. (2024) and Botía et al. (2025). While Ravi et al. (2024) adopted an existing VPRM parameterization previously
reported in the literature for tropical biomes, Botía et al. (2025) used an eddy-covariance-informed VPRM parameterization
120 based on Amazonian flux tower measurements and subsequently used the resulting VPRM flux estimates as a prior in their
regional atmospheric inversion.

For our primary simulations, parameter values for the four dominant land-use categories in the study region (Forest, Savanna,
Grassland, and Cropland) are listed in Table 2. These values were adopted primarily from Botía et al. (2025), with the sole
exception of the Forest respiration coefficients, which were adjusted so that the resulting NEE at 6 and 2 km resolutions
125 remained within ± 1 standard deviation of the ATTO observations during peak hours. This adjustment increased the magnitude
of carbon uptake relative to the original Forest parameterization and reduced the present-day bias that, if propagated into future
simulations, could substantially affect the magnitude and sign of projected NEE. Consequently, the comparison with ATTO
observations presented in Section 3.1 is intended primarily to assess the sensitivity of simulated NEE to spatial resolution and
 T_{opt} parameterization rather than to provide an independent validation of model performance.

130 The EVI and LSWI indices for each land-use category listed in Table 2 were derived by smoothing the 8-day composite
MODIS MOD09A1 data to produce daily values. For each of the months March, April, August, and September, the daily values
were averaged over the 2009–2011 period and subsequently applied unchanged to all simulation years. The WRF-compatible
input files containing EVI and LSWI fields were generated using the Python package pyVPRM (Glauch et al., 2025). This
package reads the land-use information from the WRF Preprocessing System (WPS) `geogrid` output file for each modeling
135 domain (`geo_em.d0*.nc`) and performs the MODIS-to-WRF spatial regridding using Earth System Modeling Framework
(ESMF) routines. In addition to these EVI and LSWI fields, the offline VPRM sensitivity experiments were driven by T_{2m}



Table 2. VPRM parameters used in this study. Parameter values are based primarily on Botía et al. (2025), with adjustments to the Forest respiration coefficients (α and β) to reduce the present-day NEE observational bias.

Land-use category	λ	PAR_0	α	β
Forest ¹	0.11	993.9	0.16	1.1
Savanna	0.02	6860.7	−0.25	7.11
Grassland	0.05	15475.5	−0.31	7.33
Cropland	0.04	2329	−0.08	3.67

¹ Referred to as "Evergreen Forest" in the VPRM classification.

and PAR derived from WRF-GHG output, with PAR approximated directly from SWDOWN using a 1:1 ratio, following the standard implementation of VPRM in WRF described by Beck et al. (2011).

For the Forest land-use category, an additional correction was applied to the LSWI fields. Due to saturation effects in dense
 140 canopies, MODIS-derived LSWI values yielded near-unity water stress scaling factors, causing W_{scale} to remain above 0.98 throughout the future simulations and thereby reducing the model sensitivity to moisture constraints. To mitigate artificial dry-season reflectance anomalies over the Amazon, we capped LSWI_{max} at 0.5 and applied a September climatological delta correction. These parameters were empirically derived from satellite-observed LSWI dynamics at the K67 flux tower in the Brazilian Amazon (Xiao et al., 2005). The corrected LSWI fields were subsequently used to drive the VPRM simulations.

145 More generally, because VPRM estimates biospheric CO_2 exchange using empirical relationships between vegetation indices and meteorological drivers, it does not explicitly represent physiological processes governing plant responses to environmental stress. Consequently, the model does not account for the effects of vapor pressure deficit or elevated atmospheric CO_2 concentrations on stomatal conductance and carbon uptake, which are represented in more process-based biosphere models (Cao et al., 2025).

150 2.2 Land Use

For the baseline year 2020, land-use data were derived from the MapBiomass Project (Souza et al., 2020), which provides annual high-resolution land-use and land-cover maps for Brazil. The maps encompass both natural and anthropogenic land-cover types and are produced using Google Earth Engine. They are designed to be compatible with the land-use classification systems of the Food and Agriculture Organization (FAO) and the Brazilian Institute of Geography and Statistics (IBGE). MapBiomass adopts
 155 a three-level land-use and land-cover hierarchy: Level 1 comprises six broad classes (forest, non-forest natural formations, farming, non-vegetated areas, water, and not observed); Level 2 subdivides these into more detailed classes (e.g., natural and planted forest, wetlands/grasslands, pasture/agriculture, and urban or mining areas); and Level 3 further distinguishes natural vegetation formations, including forest, savanna, and mangrove classes. For regions outside Brazil, land-use data were obtained from the MODIS MCD12Q1 land-cover product as distributed in the default WPS geographical dataset.



160 Land-use data for 2030–2100 were derived from the Land-Use Harmonization version 2 (LUH2) dataset (Hurtt et al., 2020)
 under the SSP5-8.5 scenario. LUH2 was developed for CMIP6 to provide harmonized historical and future land-use forcing for
 climate and Earth system models. For SSP5-8.5, the future land-use projections originate from the REMIND-MAGPIE frame-
 work, an integrated assessment modeling framework that combines the Regionalized Model of Investment and Development
 (REMIND) and the Model of Agricultural Production and its Impacts on the Environment (MAGPIE) (Kriegler et al., 2017;
 165 Hurtt et al., 2020). The LUH2 framework harmonizes projections from Integrated Assessment Models (IAMs) with the histori-
 cal land-use reconstruction and provides annual gridded land-use states and transitions from 850 to 2100 at a spatial resolution
 of $0.25^\circ \times 0.25^\circ$. The dataset represents 12 land-use states, including different forest and non-forest vegetation types, cropland,
 pasture, and urban land.

To bridge the spatial-resolution gap between the coarse LUH2 projections and the finer-resolution regional domains, we
 170 generated high-resolution future land-use maps by applying the LUH2-derived transitions to the 2020 MapBiomass baseline
 using a neighborhood-based spatial transition technique. Specifically, decadal changes in the LUH2 land-use fractions were
 translated to the higher-resolution grid using focal statistics, which adjust local pixel distributions within moving spatial win-
 dows according to the surrounding land-cover composition and prescribed transition magnitudes. This approach allows the
 coarse-scale land-use changes represented by LUH2 to be spatially distributed across the higher-resolution MapBiomass base-
 175 line while retaining its local spatial structure. The resulting land-use maps were subsequently mapped to the corresponding
 categories of the Modified IGBP MODIS Noah land-use classification required by WRF-GHG (Appendix A).

2.3 Initial and Boundary Conditions

Initial and boundary conditions (IC/BCs) for the meteorological fields were obtained from a globally gridded, bias-corrected
 dataset developed by Xu et al. (2021). Widely used in climate change studies (e.g., Rockström et al., 2023; Halpern et al.,
 180 2025; Zhao et al., 2025), this dataset combines CMIP6 Earth system model simulations (Eyring et al., 2016; O'Neill et al.,
 2016) with the ERA5 reanalysis (Hersbach et al., 2020). The dataset integrates the multi-model ensemble mean from 18 Earth
 system models to represent the long-term climate change signal with 6-hourly atmospheric fields from the high-resolution
 MPI-ESM1-2-HR model to preserve weather-scale and interannual variability. The meteorological forcing was generated us-
 ing the Multi-model Ensemble Variance and Nonlinear Trend (MVT) bias-correction method, which combines the ERA5 re-
 185 analysis (1979–2014), the nonlinear climate change signal from the 18-model CMIP6 ensemble, and 6-hourly anomalies from
 MPI-ESM1-2-HR. The dataset has a horizontal resolution of $1.25^\circ \times 1.25^\circ$ and a 6-hourly temporal resolution. Atmospheric
 variables, including air temperature, zonal and meridional wind, relative humidity, and geopotential height, are provided on
 14 pressure levels, while surface variables include sea surface temperature, skin temperature, mean sea-level pressure, surface
 pressure, soil moisture, and soil temperature.

190 In this study, the SSP2-4.5 scenario was used for the year 2020 to establish the baseline period, whereas the SSP5-8.5
 scenario provided the future climate forcing for 2030–2100. Appendix B describes the preprocessing procedures applied to
 prepare these bias-corrected fields for use as IC/BCs in the WRF-GHG simulations.

2.4 Experiment Design

WRF-GHG simulations were conducted using a two-way nesting configuration over three nested domains with horizontal resolutions of 18 km, 6 km, and 2 km for April and September at 10-year intervals from 2020 to 2100. The outer domain covered most of South America, while the inner domains focused on the Amazon region (Fig. 1). Rather than performing a single continuous simulation for each month, we adopted a 16-day spin-up period covering the end of the preceding month, followed by a sequence of 2-day rolling simulations for the target month. This approach was adopted because atmospheric CO₂ concentrations were also simulated, although their projections are not the primary focus of this study.

A baseline set of WRF-GHG simulations using the default T_{opt} configuration was conducted to generate the meteorological drivers for VPRM. Because physiological thermal acclimation can modify the temperature response of photosynthesis, including adjustments in the optimal temperature for photosynthesis in response to prevailing growth temperatures (Yamori et al., 2014; Tan et al., 2017; Kumarathunge et al., 2019; Liu et al., 2024), we evaluated the sensitivity of GPP and NEE to alternative representations of T_{opt} . Specifically, sensitivity experiments were performed by running the VPRM module in offline mode using the baseline meteorological fields (T_{2m} and SWDOWN), testing both fixed (literature-derived) and temperature-dependent T_{opt} formulations across the Forest, Savanna, Grassland, and Cropland land-use categories (see Table 3). The fixed- T_{opt} formulation represents the assumption that the photosynthetic temperature optimum remains unchanged over time, whereas the temperature-dependent formulation provides a simplified representation of thermal acclimation by allowing T_{opt} to adjust with changes in mean temperature.

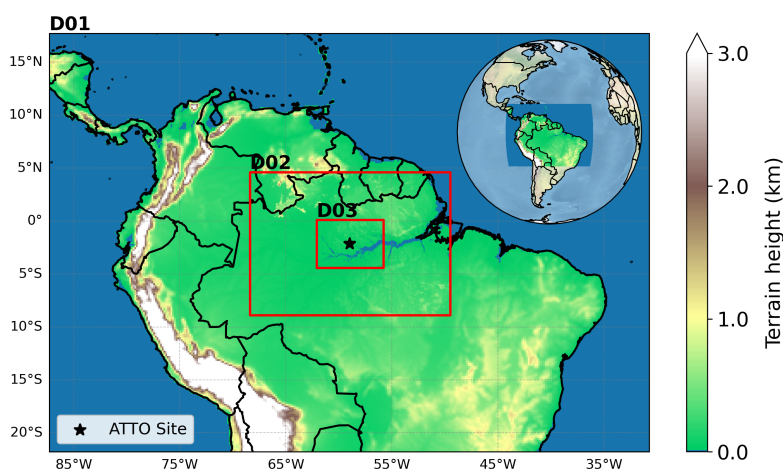


Figure 1. Nested model domains used in this study: D01 (18 km), D02 (6 km), and D03 (2 km), centered on the Amazon Tall Tower Observatory (ATTO) near Manaus, Brazil.

Systematic biases associated with sub-hourly time-step integration in the WRF-GHG simulations were partially mitigated by applying period-specific, component-wise baseline scalar corrections to the offline VPRM simulations. Table 4 summarizes the main modeling attributes, including grid configuration, input datasets, and simulation periods. Appendix C provides a detailed



Table 3. T_{opt} parameter configurations across land-use categories used in the sensitivity simulations.

Land-use category	Fixed T_{opt} ¹		Temperature-dependent T_{opt} ²
	FX-Low ³	FX-High ³	TD-Dyn ³
Forest	25.6 °C	28.9 °C	$T_{\text{opt},t} = T_{\text{opt},t-1} + \Delta(\overline{T_{2m}})_t$; $T_{\text{opt},0} = 28.9$ °C
Savanna	25.0 °C	29.5 °C	$T_{\text{opt},t} = T_{\text{opt},t-1} + \Delta(\overline{T_{2m}})_t$; $T_{\text{opt},0} = 29.5$ °C
Grassland	31.5 °C	31.5 °C	$T_{\text{opt},t} = T_{\text{opt},t-1} + \Delta(\overline{T_{2m}})_t$; $T_{\text{opt},0} = 31.5$ °C
Cropland	29.2 °C	29.2 °C	$T_{\text{opt},t} = T_{\text{opt},t-1} + \Delta(\overline{T_{2m}})_t$; $T_{\text{opt},0} = 29.2$ °C

¹ Minimum and maximum T_{opt} values for Forest were derived from Tan et al. (2017) and Huang et al. (2019), respectively, by averaging the reported T_{opt} values from the K34, K67, and K83 flux towers, all located in the Brazilian Amazon. T_{opt} values for Savanna and Grassland were similarly derived from reported values at flux towers within these ecosystems across the Amazon basin, whereas the T_{opt} for Cropland was assumed to be comparable to that reported for the US-Ne3 site in the U.S. Corn Belt (Huang et al., 2019).

² $T_{\text{opt},t}$ is the optimal temperature for the current decadal year, $T_{\text{opt},t-1}$ is the value for the previous decadal year, $\Delta(\overline{T_{2m}})_t$ represents the mean difference in T_{2m} between two consecutive decadal years, and the initial value $T_{\text{opt},0}$ is taken from the maximum Fixed T_{opt} value.

³ T_{opt} scenarios used in the offline simulations.

description of the spin-up and rolling simulation workflow, together with a schematic illustrating five consecutive 2-day rolling simulations.

Table 4. Model setup and input datasets.

Modeling attribute	Configuration
Domains ¹	D01: 251×351 grid points – 18 km – 51 σ -type levels D02: 253×352 grid points – 6 km – 51 σ -type levels D03: 253×352 grid points – 2 km – 51 σ -type levels
Initial and boundary conditions	Bias-corrected CMIP6 meteorological fields and CO ₂ concentrations (interpolated intra-daily using CAMS). Both datasets at $1.25^\circ \times 1.25^\circ$ resolution, 14 pressure levels, and 6-hourly temporal resolution under the SSP5-8.5 scenario.
Land-use	MapBiomas data at 250 m resolution for 2020 LUH2 SSP5-8.5-driven data at $0.25^\circ \times 0.25^\circ$ resolution for 2030–2100
VPRM satellite parameters	EVI, LSWI, and vegetation fraction derived from MODIS MOD09A1 data
Simulation periods ²	15 March–30 April and 15 August–30 September for the years 2020, 2030, 2040, 2050, 2060, 2070, 2080, 2090, and 2100

¹ All centered at ATTO (2°S, 59°W).

² Simulations included a 16-day continuous spin-up period followed by a 2-day rolling simulation strategy.



215 3 Results

The results focus on the effects of spatial resolution and T_{opt} parameterization on simulated NEE, with comparisons against ATTO observations used to assess the representation of the observed carbon exchange at the tower site. Resolution-related effects are assessed across all resolutions within the spatial extent of the innermost domain (D03) and at the ATTO site. To examine how global forcing and regional land-use change influence meteorology and the carbon balance, regional analyses are conducted for four regions of the Brazilian Amazon (A–D) using data from the 18 km domain (D01). The geographical subdivision follows the approach of Teixeira et al. (2025), who delineated the regions based on historical deforestation and land-use patterns.

3.1 Spatial Resolution Effects on Simulated NEE

The comparison with ATTO eddy covariance observations highlights a strong sensitivity of simulated NEE to spatial resolution, whereas the choice of T_{opt} parameterization has a comparatively smaller effect. The observations exhibit a pronounced daytime carbon sink, peaking near $-22 \mu\text{mol m}^{-2} \text{s}^{-1}$ at approximately 11:00 local time. The 6 km and 2 km model configurations reproduce this daytime sink reasonably well at the ATTO location, whereas the 18 km configuration systematically underestimates its magnitude, particularly in April (Figure 2). Because the Forest respiration parameters were constrained using observations at ATTO and subsequently applied throughout the modeling domains, the resulting simulations provide bottom-up, spatially distributed estimates of NEE, with the 18 km domain covering the Brazilian Amazon and the 6 km and 2 km domains providing higher-resolution estimates over their respective nested regions. These estimates are subject to the assumption that the ATTO-constrained parameterization is representative of the modeled Forest areas.

Simulated NEE under the TD-Dyn scenario (identical to FX-High for 2020; see Table 3) reproduces the observed daytime carbon uptake similarly to the FX-Low scenario. Mean bias (MB) and root mean square error (RMSE) differ by less than $0.5 \mu\text{mol m}^{-2} \text{s}^{-1}$ and $0.2 \mu\text{mol m}^{-2} \text{s}^{-1}$, respectively, between the two T_{opt} parameterizations at a given model resolution, indicating that the choice of T_{opt} parameterization has only a minor effect on simulated NEE. In contrast, increasing the model resolution from 18 km to 6 km produces a substantially larger reduction in RMSE, of up to $2 \mu\text{mol m}^{-2} \text{s}^{-1}$, whereas further refinement to 2 km results in a comparatively small reduction of less than $0.7 \mu\text{mol m}^{-2} \text{s}^{-1}$. Although both T_{opt} formulations reproduce the overall pattern of the observed NEE, all model configurations underestimate gross primary productivity (GPP) (Supplementary Material Figure S1) and ecosystem respiration (R_{eco}) (Supplementary Material Figure S2). The underestimation of GPP, particularly at 18 km resolution, is associated with underestimated surface downward shortwave radiation (SWDOWN) (Supplementary Material Figure S3). The underestimation of R_{eco} , in turn, may partly reflect physiological processes not explicitly represented in the VPRM formulation, which parameterizes R_{eco} using an empirical linear relationship driven solely by 2 m air temperature ($T_{2\text{m}}$).

The contrasting spatial distributions and diurnal magnitudes of NEE across the three nested domains highlight the strong influence of horizontal grid resolution on simulated carbon exchange over the central Amazon. Figure 3 illustrates the spatial distribution of monthly mean NEE simulated under the TD-Dyn scenario across all domains, with the 18 km and 6 km fields

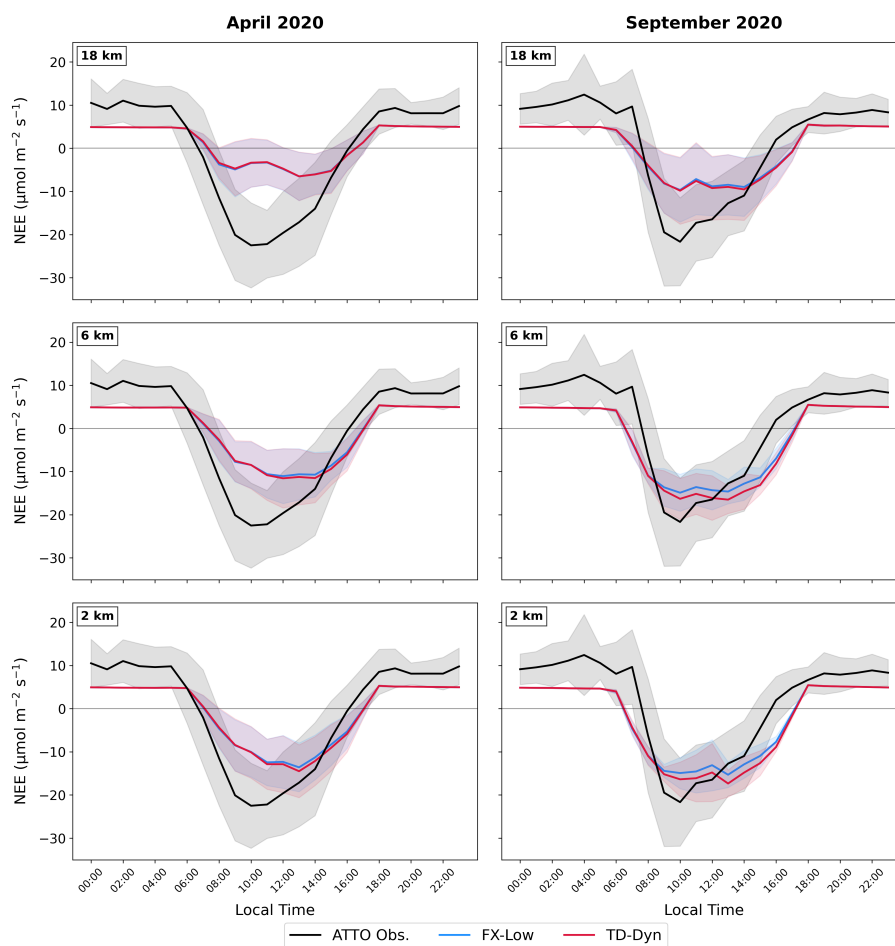


Figure 2. Evaluation of simulated and observed NEE diurnal cycles at the Amazon Tall Tower Observatory (ATTO) site for April and September 2020. The black solid lines represent eddy covariance observations, with the shaded light gray envelope indicating ± 1 standard deviation of the daily variability. Colored lines represent VPRM simulations from the 18 km (top panels), 6 km (middle panels) and 2 km (bottom panels) modeling domains for two T_{opt} parameterization scenarios: FX-Low (blue) and TD-Dyn (red). For 2020, the FX-High and TD-Dyn scenarios are identical (see Table 3). Colored shaded envelopes represent the corresponding ± 1 standard deviation for each model scenario. All fluxes are expressed in $\mu\text{mol m}^{-2} \text{s}^{-1}$ and are plotted in local time (UTC-4).

clipped to the spatial extent of the 2 km domain to facilitate direct comparison. Although coarser grid resolutions inherently mix continuous forest canopies with river networks and heterogeneous landscapes, this subgrid land-use mixing does not drive the observed flux discrepancies in our setup. Because the dense forest canopy remains highly continuous, the satellite-derived vegetation indices EVI and W_{scale} around the ATTO site are nearly invariant across the 18 km, 6 km, and 2 km resolutions (Supplementary Material Figures S4 and S5). Instead, the reduced net carbon uptake at 18 km resolution is primarily driven by a systematic underestimation of SWDOWN (Supplementary Material Figure S6), combined with slightly lower ecosystem

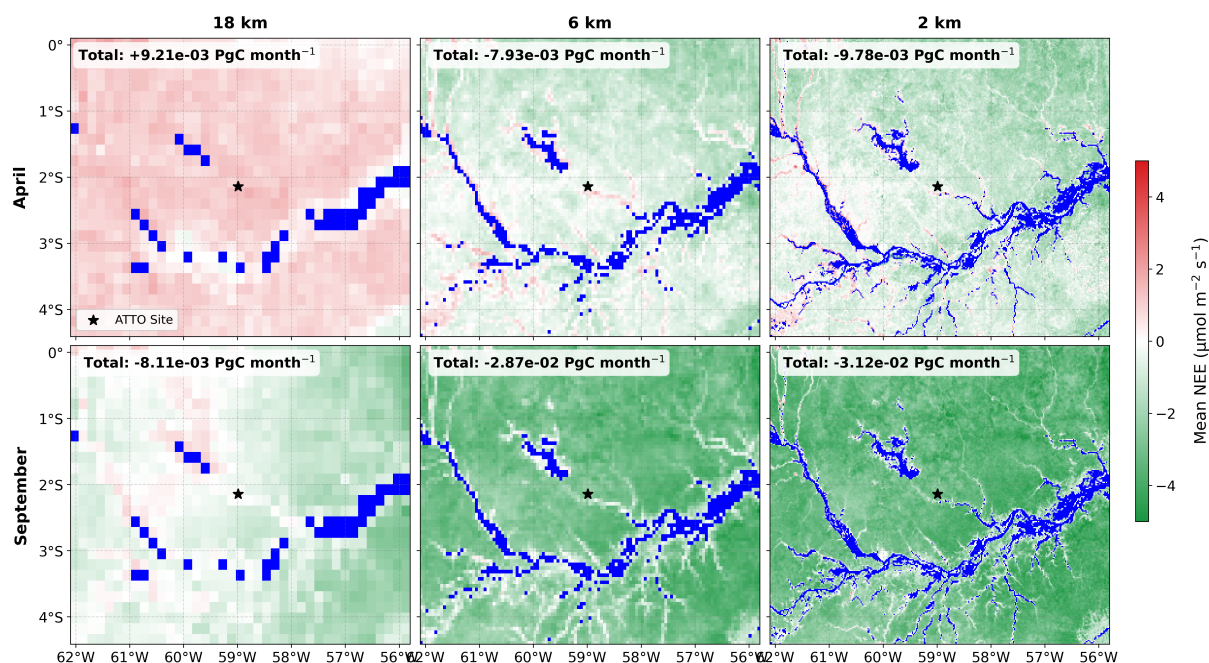


Figure 3. Spatial distribution of monthly mean NEE ($\mu\text{mol m}^{-2} \text{s}^{-1}$) over the innermost model domain for April and September 2020 under the TD-Dyn scenario. Panels compare the spatial patterns at the 18 km, 6 km, and 2 km model resolutions. The 18 km and 6 km domains were clipped to the spatial extent of the 2 km domain to facilitate direct comparison. The domain-integrated monthly NEE over the common spatial footprint is also shown. Grid cells classified as water bodies are masked and shown in solid blue.

respiration resulting from the spatial smoothing of T_{2m} gradients at this resolution (Supplementary Material Figure S7). While
 255 the domain-wide means calculated over the 2 km domain extent for EVI, W_{scale} , and T_{scale} (Supplementary Material Figure
 S8) are nearly identical across grid resolutions, with relative differences $\leq 1\%$, domain-wide mean values for SWDOWN
 differ substantially. For April, the relative differences in domain-wide mean SWDOWN between the coarse resolution (18 km)
 and the finer resolutions (6 km and 2 km) range from 58% to 64%, whereas for September they range from 46% to 53%.
 For T_{2m} , relative differences in domain-wide mean remain below 5%. The attenuation of SWDOWN and T_{2m} in the 18 km
 260 domain relative to the 6 km and 2 km domains—driven primarily by the attenuation of SWDOWN associated with the cumulus
 parameterization used only in the 18 km domain—is sufficient to reduce net carbon uptake by more than a factor of two and
 even produces a sign reversal in April.

It is worth noting that while structural biases in simulated biospheric fluxes over complex topography can be systematic and
 driven by the resolution dependence of satellite indices such as EVI and LSWI (e.g., Reif et al., 2026), our continuous-canopy
 265 application is unaffected by this spectral scaling issue. Beyond meteorological smoothing, the 18 km domain introduces larger
 spatial mismatches between the coarse model grid cells and the coordinate location of the ATTO tower. By preserving localized
 land-cover detail and improving spatial alignment, the higher-resolution domains better represent the specific canopy footprint

sampled by the eddy covariance observations. Consequently, when evaluated over an identical geographic footprint, the finer domains produce stronger simulated carbon uptake than the coarse domain, primarily because they better preserve the spatial and temporal variability of the meteorological drivers used by VPRM, particularly SWDOWN.

3.2 Regional Land-Use and Fractional Distribution

Geographically, the Regions A–D define a distinct northwest-to-southeast gradient across the Amazon basin. Region A is located within the core of the dense and continuous Amazon rainforest and represents the most pristine and climatically buffered region of the basin. This region contains the largest number of grid points and is composed almost entirely of Forest land cover. Regions B and C represent intermediate transition zones. Similar to Region A, Region B remains almost entirely forested in terms of grid-point distribution; however, its more southern location exposes it to stronger dry-season conditions. Region C captures a substantial baseline proportion of grassland in 2020, reflecting its proximity to the Arc of Deforestation, before transitioning toward a more homogenized forest profile under the future projections. In contrast, Region D differs substantially from the other regions. It encompasses the easternmost part of the study domain, exhibiting a highly heterogeneous baseline characterized by seasonal Savanna, widespread Grassland, and expanding agricultural footprints.

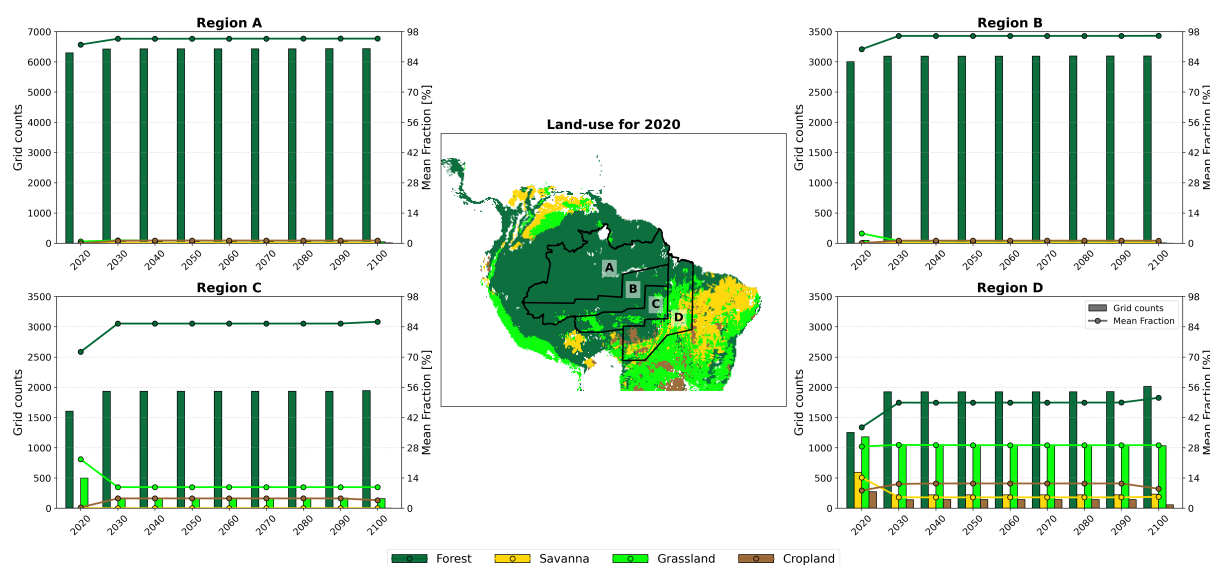


Figure 4. Decadal land-use distribution and sub-grid fractional area projections across four designated Amazonian regions (A–D) within the 18 km modeling domain (D01). The central panel illustrates the baseline spatial distribution of dominant land-use categories for the year 2020 derived from MapBiomass data, with region boundaries overlaid. The surrounding panels contrast the temporal evolution of land cover from the 2020 empirical baseline through the 2030–2100 future projections under the high-emission SSP5-8.5 scenario. Dual-axis plots quantify categorical grid-cell dominance via pixel counts (vertical bars, left axes) and continuous regional mean sub-grid area fractions (line charts with circular markers, right axes) for the four primary categories: Forest, Savanna, Grassland, and Cropland.



Figure 4 shows the decadal evolution of land use from 2020 to 2100, capturing the transition from the empirical 2020 baseline to the future SSP5-8.5 projections, as described in Section 2.2. The land-use trajectories are contrasted across two complementary structural metrics: dominant categorical grid-cell counts (left axes), which indicate the prevailing land-use class within each grid cell, and continuous sub-grid mean area fractions (right axes), which quantify the proportional contribution of each land-use class within the grid cells. Integrating the MapBiomass baseline with the LUH2 projections shows a distinct structural discontinuity between 2020 and 2030, followed by relatively limited changes in the aggregated land-use fractions within our four Amazonian regions through 2100. This behavior is most pronounced in the eastern and southern margins (Regions C and D). In Region C, the 2020 baseline captures a substantially lower forest dominance and a prominent Grassland presence, whereas the subsequent LUH2 projections produce a more forest-dominated distribution. Similarly, Region D exhibits a pronounced reduction in baseline Savanna dominance and a corresponding increase in forest representation between 2020 and 2030, after which the regional land-use fractions remain comparatively stable. In contrast, the pristine core of the basin (Regions A and B) displays high stability, with forest dominance remaining nearly unchanged throughout the 2020–2100 period. The abrupt changes between 2020 and 2030 therefore primarily reflect the transition from the empirical MapBiomass baseline to the scenario-based LUH2 projections, rather than a continuous land-use transition simulated within a single modeling framework. The relatively small subsequent changes within the study regions should likewise not be interpreted as an assumption of negligible land-use change under SSP5-8.5, but rather as a consequence of the spatial allocation and aggregation of the IAM-derived land-use projections in the LUH2 framework.

3.3 VPRM Meteorological Drivers and NEE Variability

The 2020 simulation served as the baseline year for evaluating the VPRM parameter configuration adopted in this study, incorporating MapBiomass land-use data alongside meteorological drivers from a moderate emission pathway (SSP2-4.5). Accordingly, 2020 is excluded from the future projections presented below, which span 2030–2100 and evaluate long-term trajectories under the SSP5-8.5 scenario. For each region (A–D), seasonal trends and diurnal cycles (April and September) of the two VPRM meteorological drivers—2 m air temperature (T_{2m}) and surface downward shortwave radiation (SWDOWN)—were analyzed across four key land-use categories: Forest, Savanna, Grassland, and Cropland, together with their effects on net ecosystem exchange (NEE) variability. Because land-use distributions within each region remain nearly static across the simulated years, the long-term trends in NEE primarily reflect the response to climate change, with minimal influence from direct land-use change, such as deforestation. Furthermore, fire emissions were not included in this modeling framework.

3.3.1 Forest Regions

Figure 5 shows the decadal evolution of T_{2m} and the maximum downward shortwave radiation flux (SWDOWN) for the Forest land-use category across Regions A–D. Across all regions and in both months, both the maximum (T_{2m} Max.; red curves) and minimum (T_{2m} Min.; blue curves) T_{2m} exhibit a clear upward trend from 2030 to 2100. In September, Regions A and B experience the strongest increases in T_{2m} Max., with daytime temperatures rising by approximately 3°C between 2030 and 2100, whereas Regions C and D exhibit the largest increases in T_{2m} Min., with nighttime temperatures increasing by approximately



4°C over the same period. Across all regions, September consistently exhibits higher T_{2m} Max. than April, exposing forest ecosystems to temperatures that increasingly exceed their photosynthetic optimum. In a comparable climate-only simulation experiment (RCP8.5 with the Amazon remaining completely forested), Bottino et al. (2024) found an area-averaged temperature increment of 3.3°C over the Amazon basin for the late-century period (2073–2100). Supplementary Material Figure S9 shows the decadal evolution of diurnal net ecosystem exchange amplitude ($\Delta NEE = NEE_{Max} - NEE_{Min}$) for the Forest land-use category across all T_{opt} scenarios and regions. As the climate warms, the three T_{opt} formulations exhibit increasingly divergent NEE responses. Under the FX-Low and FX-High formulations, warming progressively suppresses daytime photosynthesis, causing the daytime NEE minimum to move closer to the nighttime maximum. As a result, the diurnal NEE amplitude decreases over time. In contrast, the TD-Dyn formulation allows T_{opt} to adjust to the warming climate, maintaining substantially stronger daytime carbon uptake, particularly in Regions A and B. However, although the TD-Dyn scenario largely preserves the diurnal photosynthetic capacity of the ecosystem—as reflected by the sustained NEE amplitudes through 2100—this compensation is insufficient to offset the increase in ecosystem respiration associated with long-term warming. Consequently, the enhanced daytime carbon uptake does not prevent a gradual weakening of the net monthly carbon sink.

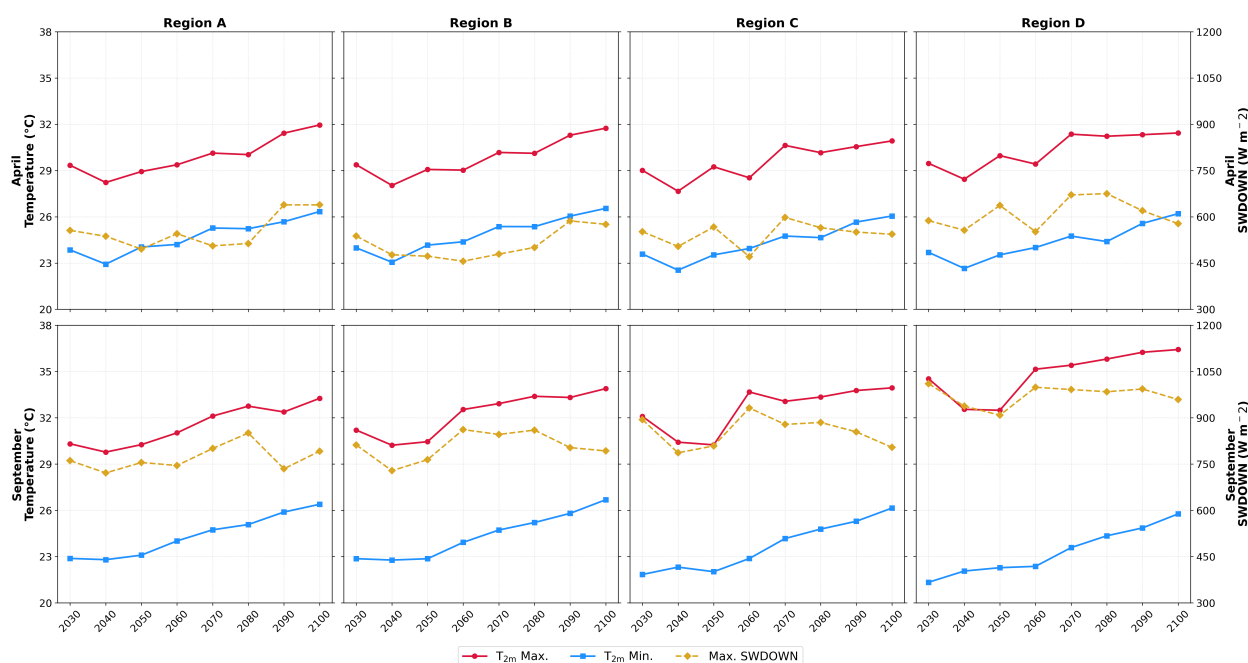


Figure 5. Decadal evolution (2030–2100) of maximum (T_{2m} Max.; red curves) and minimum (T_{2m} Min.; blue curves) 2 m air temperature (T_{2m}), together with maximum downward shortwave radiation flux (SWDOWN) for the Forest land-use category across Regions A–D during April (top row) and September (bottom row). Temperature (°C) is plotted on the left y-axis, and the absolute maximum diurnal SWDOWN ($W m^{-2}$) on the right y-axis.



The multi-decadal evolution of the diurnal T_{2m} cycle across all regions indicates a substantial warming trend, with important implications for CO_2 uptake (Supplementary Material Figure S10). The seasonal response is asymmetric. During April, day-time temperatures remain close to, or below, the upper fixed T_{opt} value ($28.9^\circ C$). In contrast, September exhibits substantially higher afternoon temperatures. From 2030 to 2100, daytime T_{2m} maxima increase to approximately $33^\circ C$ across most regions and reach up to $36^\circ C$ in Region D. Consequently, forest ecosystems are increasingly exposed to temperatures that exceed both fixed T_{opt} configurations, highlighting the potential importance of thermal acclimation under future climate conditions. As T_{2m} diverges from the fixed T_{opt} , it directly affects the VPRM temperature scaling factor (T_{scale}). Under the FX-Low scenario, afternoon temperatures of $33\text{--}36^\circ C$ lie well above the fixed T_{opt} of $25.6^\circ C$, substantially increasing the $(T_{2m} - T_{opt})^2$ term in the denominator of Eq. (4). As a result, T_{scale} decreases sharply during peak daylight hours, strongly reducing gross primary productivity (GPP) and, consequently, carbon uptake. In contrast, the TD-Dyn scenario allows T_{opt} to increase with warming, reaching approximately $30.7^\circ C$ by mid-century (2060) and about $33.0^\circ C$ by the end of the century (2100). This substantially reduces the $(T_{2m} - T_{opt})^2$ penalty term, enabling T_{scale} to remain high enough to sustain daytime photosynthetic carbon assimilation under future warming.

The multi-decadal evolution of SWDOWN at 18 km resolution serves as a critical diagnostic, confirming that long-term variations in daytime photosynthetic strength are predominantly governed by T_{2m} rather than changes in SWDOWN (Figure 5). Across all regions, both the maximum and daylight-mean (not shown) SWDOWN profiles exhibit structurally stable patterns over the 2030–2100 period, while retaining notable variability across the decadal projections, driven by domain-dependent cloud dynamics and the activation of the subgrid cumulus parameterization at 18 km resolution. Thus, the long-term decline in carbon uptake cannot be attributed to a systematic reduction in SWDOWN, although variations in radiation among the decadal projections contribute to variability in NEE amplitude. Crucially, the variability in NEE amplitude under the TD-Dyn scenario in Figure 5 closely tracks these SWDOWN fluctuations. Because the TD-Dyn configuration recursively recalculates T_{opt} following the T_{2m} trajectory, it minimizes the $(T_{2m} - T_{opt})^2$ thermal inhibition in Eq. (4), preventing the collapse of the temperature scaling factor (T_{scale}) during peak daylight hours. With T_{scale} stabilized, GPP becomes increasingly regulated by radiation availability rather than thermal stress. Conversely, the steady decoupling observed under the fixed FX-Low and FX-High configurations—where NEE amplitudes systematically drift downward even during high-radiation decades (such as late-century September in Region D)—highlights how increasing thermal stress can suppress photosynthetic capacity regardless of solar availability.

However, as discussed in Section 3.1, when comparing results across grid configurations over the same spatial footprint, horizontal resolution also alters these meteorological fields; the 18 km resolution severely attenuates SWDOWN while only slightly reducing T_{2m} (Supplementary Material Figure S11), which in turn dampens the simulated net carbon uptake over the central Amazon.

3.3.2 Non-Forest Land-Use Categories

The multi-decadal evolution of the diurnal T_{2m} cycle across the Savanna, Grassland, and Cropland categories reveals thermal environments that differ substantially from those of the Forest category. In Savanna areas, September afternoon temperatures



reach 35–37°C by the end of the century, particularly in Regions B and D, far exceeding the fixed T_{opt} value (29.5°C). Grassland exhibits the highest fixed T_{opt} value (31.5°C) among the four land-use categories, providing greater tolerance to warming but leaving less scope for thermal acclimation before temperatures approach the upper end of the projected range. Cropland, with a fixed T_{opt} of 29.2°C, also experiences a substantial divergence between $T_{2\text{m}}$ and T_{opt} as September daytime temperatures approach 35°C in Regions C and D. Unlike the Forest category, which maintains a relatively cooler microclimate through dense canopy cover, these more open land-use categories exhibit larger diurnal temperature ranges and stronger daytime warming.

The evolution of SWDOWN across the Savanna, Grassland, and Cropland categories further supports the conclusion that solar radiation is not the primary driver of the projected changes in carbon uptake, indicating that the projected changes are driven primarily by warming rather than by changes in solar radiation. Across these replacement land-use types, daylight-mean and maximum SWDOWN intensities exhibit distinct regional differences—such as exceptionally intense solar environments in Region D during the dry season, where September maxima consistently remain close to 1000 W m^{-2} . Radiative inputs remain generally stable throughout the century and even increase slightly in some regions (e.g., April in Region A). Therefore, the decline in NEE amplitude under the fixed T_{opt} scenarios (FX-Low and FX-High) cannot be attributed to reduced solar radiation or increased cloudiness. Instead, it reflects the increasing mismatch between $T_{2\text{m}}$ and the fixed T_{opt} , confirming that warming is the primary driver of the long-term reduction in carbon uptake.

Consistent with these thermal and radiative trends, the diurnal NEE amplitudes across non-forest categories remain relatively stable through 2100 under the TD-Dyn scenario. Unlike the Forest category, where warming drives enhanced ecosystem respiration, non-forest categories exhibit negative respiration temperature dependence ($\alpha < 0$). Consequently, in regions with significant open-canopy land cover (C and D), declining ecosystem respiration under future warming counterbalances GPP losses, stabilizing long-term NEE dynamics rather than amplifying carbon release.

3.4 Carbon Budget and Sink–Source Dynamics

Using the adjusted VPRM parameterization described in Section 2.1.1, the simulated NEE integrated across Regions A–D yields a weak net sink in April ($-0.015 \text{ PgC month}^{-1}$) and a pronounced net uptake in September ($-0.17 \text{ PgC month}^{-1}$). The stronger carbon uptake in September is consistent with the enhanced dry-season assimilation observed across the Amazon. For comparison, multi-year non-fire inversion estimates by Basso et al. (2023) report annualized rates of $+0.2 \text{ PgC yr}^{-1}$ ($+0.017 \text{ PgC month}^{-1}$) for April and -0.6 PgC yr^{-1} ($-0.05 \text{ PgC month}^{-1}$) for September. Direct quantitative comparison is nevertheless limited because our analysis covers the Brazilian Amazon, whereas Basso et al. (2023) considered the broader Amazonian region, and because our estimates represent a single year (2020) rather than their multi-year period (2010–2018).

3.4.1 Gross Primary Productivity (GPP)

The sensitivity experiments reveal a strong dependence of simulated GPP on the choice of empirical VPRM parameterization. The Ravi et al. (2024) parameter set produces substantially higher GPP than Botía et al. (2025), primarily due to its higher λ value (0.21 versus 0.11), which directly controls the maximum light-use efficiency in VPRM.



Figure 6 illustrates the decadal evolution (2030–2100) of monthly-integrated gross primary productivity (GPP) for April and September across Regions A–D, derived from the 18 km model simulations. Differences among the T_{opt} formulations highlight the sensitivity of canopy carbon assimilation to projected climate warming. In April, GPP evolves similarly across all T_{opt} formulations in the transitional Regions C and D, remaining close to $-0.07 \text{ PgC month}^{-1}$ and $-0.08 \text{ PgC month}^{-1}$, respectively. In contrast, Region A exhibits a clear divergence by 2100: under the FX-Low formulation, increasing thermal stress reduces GPP to $-0.258 \text{ PgC month}^{-1}$, whereas the temperature-dependent TD-Dyn formulation maintains greater carbon uptake, reaching $-0.287 \text{ PgC month}^{-1}$. This parametric divergence is vastly amplified during September, establishing GPP as the primary driver of T_{opt} -related uncertainty in the net carbon balance. Under the fixed FX-Low configuration, severe thermal overshoots trigger a severe downregulation of photosynthetic efficiency across all regions by 2100; most notably, September GPP in Region A decreases from $-0.402 \text{ PgC month}^{-1}$ in 2030 to $-0.354 \text{ PgC month}^{-1}$ by 2100, while Region B drops from -0.191 to $-0.165 \text{ PgC month}^{-1}$. Conversely, both the FX-High and TD-Dyn formulations successfully buffer this heat stress. In Region A, the TD-Dyn framework allows late-century canopy assimilation to expand to a peak uptake of $-0.425 \text{ PgC month}^{-1}$ by 2100. This absolute cross-scenario GPP spread ($\Delta \approx 0.071 \text{ PgC month}^{-1}$ in Region A) highlights how the mathematical assumptions underlying the canopy's photosynthetic thermal tolerance dictate future assimilation potential.

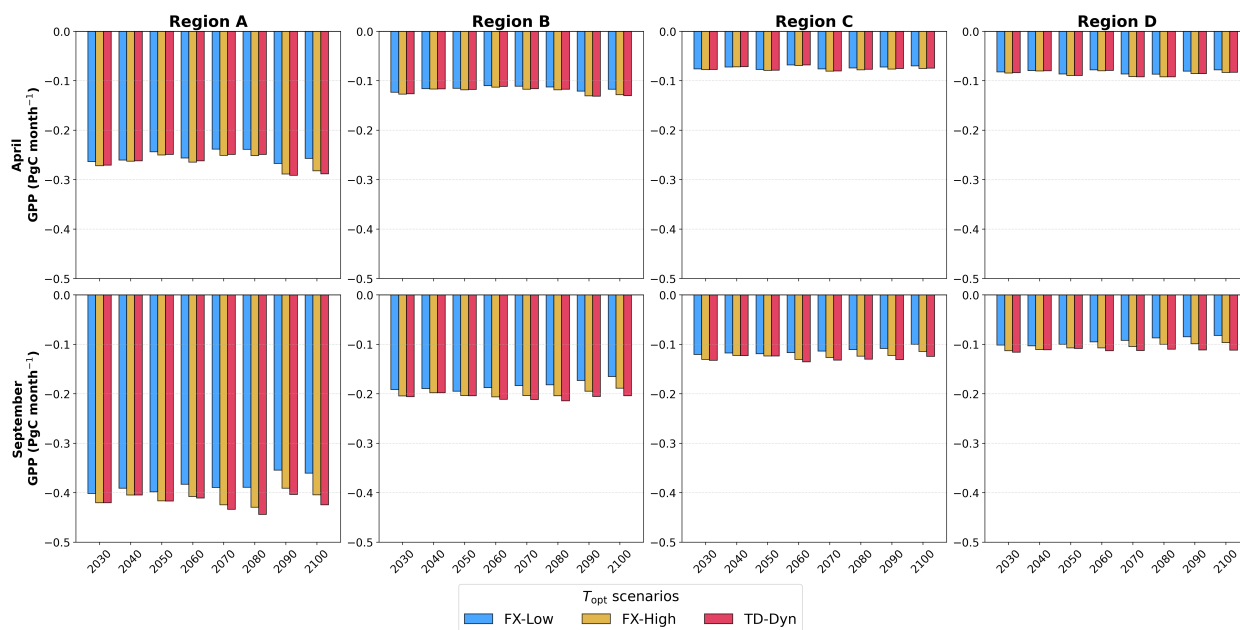


Figure 6. Decadal evolution (2030–2100) of monthly-integrated GPP (PgC month^{-1}) during April (top) and September (bottom) across Regions A–D, derived from the 18 km model simulations using the adjusted VPRM parameter set. Bar colors denote the three T_{opt} scenarios: FX-Low (blue), FX-High (gold), and TD-Dyn (red).



Although the magnitude of future GPP strongly depends on the chosen T_{opt} formulation, all parameterizations preserve the characteristic seasonal cycle of the central Amazon, with stronger carbon uptake during September than in April in Region A. This seasonal pattern is consistent with reported dry-season GPP enhancements in the central Amazon (Restrepo-Coupe et al., 2017), which VPRM captures primarily through its satellite-based vegetation index drivers and incoming solar radiation fields. Recent regional modeling by Prudente Jr. et al. (2026) further reproduced this seasonal behavior across the Brazilian Amazon, demonstrating that accurately representing seasonal increases in GPP is essential for capturing observed NEE dynamics over core equatorial forests.

To account for differences in domain size across Regions A–D, GPP fluxes were also evaluated per unit area (Supplementary Material Figure S12). While integrated totals in Figure 6 highlight Region A as the primary contributor to total regional carbon uptake due to its larger geographical extent, the area-normalized flux densities show that Regions B and C have per-unit-area assimilation rates comparable to those of Region A, reaching -1.8 to -2.1×10^{-7} PgC month $^{-1}$ km $^{-2}$ in September. Across Regions A–C, photosynthetic activity intensifies from April to September—reflecting the characteristic dry-season peak in carbon uptake associated with increased solar radiation—whereas Region D exhibits both lower overall flux densities ($< -1.0 \times 10^{-7}$ PgC month $^{-1}$ km $^{-2}$) and minimal seasonal variation.

3.4.2 Ecosystem Respiration (R_{eco})

The decadal evolution of monthly-integrated ecosystem respiration (R_{eco}) is shown in Figure 7. The three T_{opt} formulations (FX-Low, FX-High, and TD-Dyn) produce identical R_{eco} trajectories, with no differences among scenarios for any year or region. This reflects a fundamental characteristic of the VPRM formulation: whereas gross primary productivity is directly influenced by the prescribed T_{opt} , ecosystem respiration depends solely on $T_{2\text{m}}$ through empirically derived linear parameters (see Eq. (3)), thereby omitting key physiological processes (e.g., thermal acclimation). Consequently, the multi-decadal increase in $T_{2\text{m}}$ leads to a continuous rise in R_{eco} across forest-dominated pixels, progressively reducing the net carbon sink across the pristine core of the basin (Regions A and B). In contrast, across the transitional Regions C and D (particularly D), the negative respiration-temperature dependence ($\alpha < 0$) of non-forest land-use categories counterbalances the positive response of forests, resulting in a nearly stable regional R_{eco} .

In the core forest of Region A, monthly ecosystem respiration in April increases steadily from $+0.329$ PgC month $^{-1}$ in 2030 to $+0.361$ PgC month $^{-1}$ by 2100, representing an approximately 10% increase in respiratory carbon losses. A similar upward trend is observed in Region B, where R_{eco} rises from $+0.158$ PgC month $^{-1}$ to $+0.174$ PgC month $^{-1}$. During September, this increase remains pronounced, with Region A increasing from $+0.333$ PgC month $^{-1}$ to $+0.372$ PgC month $^{-1}$. Because R_{eco} is identical across all T_{opt} formulations, the regional evolution of ecosystem respiration is governed solely by the projected changes in $T_{2\text{m}}$. Consequently, for the forest-dominated regions of the Amazon, the persistence of the net carbon sink increasingly depends on the capacity of GPP to compensate for the resulting increase in ecosystem respiration.

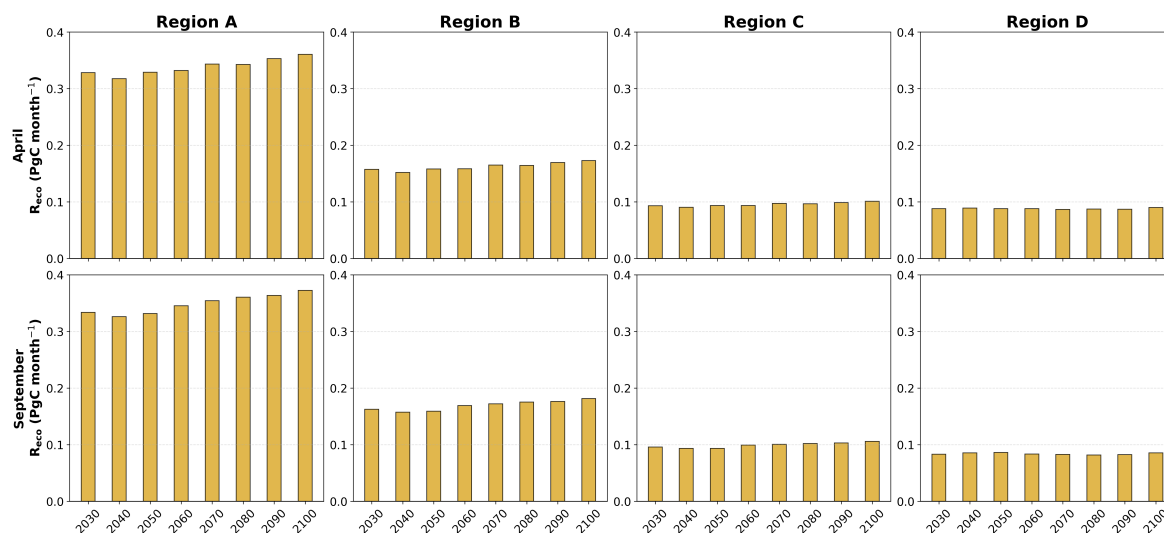


Figure 7. Decadal evolution (2030–2100) of monthly-integrated R_{eco} (PgC month^{-1}) during April (top) and September (bottom) across Regions A–D, derived from the 18 km simulations using the adjusted VPRM parameter set. The three T_{opt} formulations (FX-Low, FX-High, and TD-Dyn) produce identical R_{eco} values; therefore, only one scenario is shown.

3.4.3 Net Ecosystem Exchange (NEE)

Figure 8 shows the resulting decadal evolution of net monthly-integrated NEE for April and September across Regions A–D derived from the 18 km model simulations. A direct comparison of side-year projections (2030 and 2100) reveals a decadal upward trend in NEE across all regions, marking a widespread degradation of the basin’s historical carbon uptake capacity.

In April, the continuous forest in Region A increases its net CO_2 source under the FX-Low framework by approximately 60% from 2030 to 2100, rising from $+0.064 \text{ PgC month}^{-1}$ to $+0.103 \text{ PgC month}^{-1}$ as R_{eco} increases and outpaces stable or restricted GPP. This upward trajectory is mirrored in Regions B and C, which rise from $+0.033$ to $+0.056 \text{ PgC month}^{-1}$ and from $+0.016$ to $+0.030 \text{ PgC month}^{-1}$, respectively. In Region D, the upward trajectory rises from a nearly neutral $+0.005$ to $+0.012 \text{ PgC month}^{-1}$, although it is not as well sustained over time as it is for the other regions. Conversely, September trends showcase a steady erosion of dry-season sink capacities. Under the FX-Low scenario, where a low fixed T_{opt} downregulates late-century GPP while R_{eco} accelerates unhindered, the dry-season sink completely collapses by 2100. This results in a reversal into an active carbon source across Regions A ($+0.012$), B ($+0.016$), C ($+0.006$), and D ($+0.003 \text{ PgC month}^{-1}$). However, incorporating a higher fixed T_{opt} (FX-High) or a time-dependent dynamic adjustment (TD-Dyn) markedly buffers this low thermal tolerance by preserving daytime GPP against rising temperatures.

The temporal behavior of the TD-Dyn formulation, which buffers thermal stress during the mid-century but becomes progressively less effective by 2100, is broadly consistent with global-scale modeling studies. Using the JULES land-surface model under the RCP8.5 scenario, Oliver et al. (2025) likewise found that although thermal acclimation initially enhances GPP, this benefit gradually diminishes under continued warming. Together, these results suggest that the compensating effect

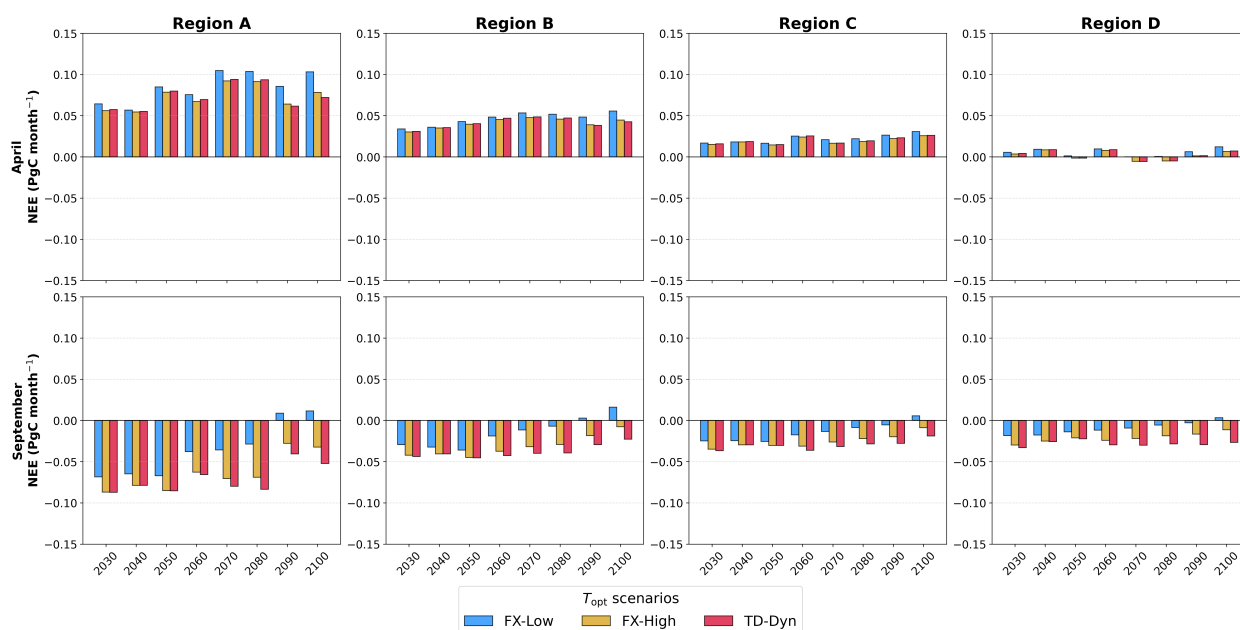


Figure 8. Decadal evolution (2030–2100) of monthly-integrated NEE (PgC month^{-1}) during April (top) and September (bottom) across Regions A–D, derived from the 18 km model simulations using the adjusted VPRM parameter set. Bar colors denote the three T_{opt} scenarios: FX-Low (blue), FX-High (gold), and TD-Dyn (red).

of thermal acclimation on warming-induced reductions in vegetation carbon uptake, as represented by the TD-Dyn parameterization, is limited under the SSP5-8.5 scenario, with late-century warming eventually overwhelming this imposed acclimation response at both global and Amazonian scales.

460 By 2100, the parametric spread (the absolute difference between FX-Low and TD-Dyn) reaches $0.031 \text{ PgC month}^{-1}$ for Region A in April, and expands to a critical difference of $0.064 \text{ PgC month}^{-1}$ in September—ranging from an active net source under FX-Low (0.012) to a well-preserved net sink under TD-Dyn ($-0.052 \text{ PgC month}^{-1}$). Spatial heterogeneity further establishes a clear gradient of this sensitivity; while the core forest of Region A exhibits the widest absolute scenario divergence ($\Delta \approx 0.064 \text{ PgC month}^{-1}$), the transitional fringes (Regions C and D) display highly constricted scenario spreads of less than $0.030 \text{ PgC month}^{-1}$ (Figure 9). Across all regions, uncertainty associated with T_{opt} corresponds to a 26.6% difference in net carbon flux in April 2100 ($0.054 \text{ PgC month}^{-1}$ between FX-Low and TD-Dyn), reflecting enhanced carbon uptake under TD-Dyn. In September 2100, this difference expands to over 430% ($0.157 \text{ PgC month}^{-1}$), driving a complete sign reversal from a net source under FX-Low to a sustained net sink under TD-Dyn. This substantial cross-scenario difference highlights that T_{opt} -based methodological uncertainty represents a dominant source of variability in diagnostic biosphere modeling, heavily influencing whether the future Amazon is projected as a resilient regional buffer or an accelerating climate feedback. A spatiotemporal heatmap detailing monthly-integrated NEE across all T_{opt} scenarios, regions, and decades is provided in Supplementary Material Figure S13.

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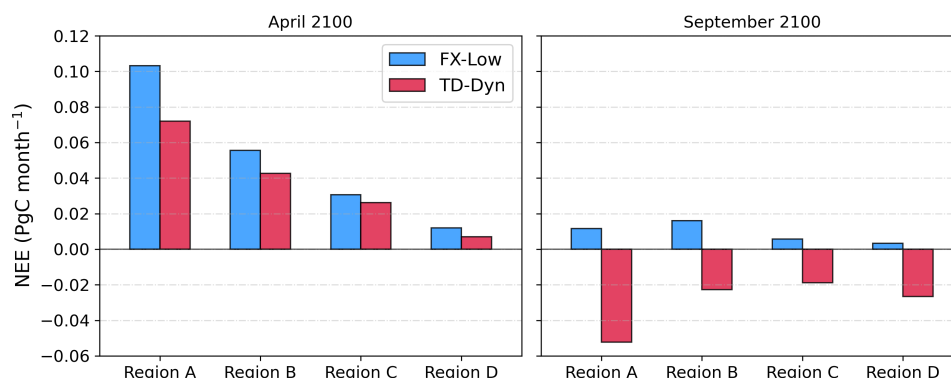


Figure 9. NEE-related (PgC month^{-1}) parameter spread and structural uncertainty between the lower fixed T_{opt} formulation (FX-Low) and the dynamic, temperature-dependent T_{opt} formulation (TD-Dyn) across Regions A–D for April and September 2100 under the SSP5-8.5 high-emission scenario.

Regardless of the horizontal grid resolution employed, a robust signal emerges across all T_{opt} scenarios indicating a decline in the carbon uptake capacity over the central Amazon by the end of the century. Figure 10 shows the decadal evolution of monthly-integrated NEE for April and September over the central Amazon across all T_{opt} scenarios from the 18 km and 6 km model simulations, with the 18 km domain clipped to the exact 6 km domain extent. Although the monthly-integrated NEE exhibits systematic magnitude differences between the clipped 18 km domain and the native 6 km domain over the same spatial footprint, both resolutions converge on the macro-climatic trajectory. In April, the region transitions from a near-neutral carbon balance in the 6 km simulations and a modest net carbon source in the 18 km simulations in 2030 to a more persistent net carbon source by 2100 across all T_{opt} configurations. Conversely, the pronounced September carbon sink in 2030 undergoes a progressive weakening from mid-century through 2100. Supplementary Material Figure S14 shows the decadal evolution of monthly-integrated NEE over the 2 km modeling domain, corroborating these trends while further illustrating the strong sensitivity to thermal parameterization across scales; the weakening of the late-century September sink is notably accelerated under the fixed T_{opt} scenarios (FX-Low and FX-High) compared to the dynamic T_{opt} scenario (TD-Dyn), which retains a more robust uptake capacity.

These concurrent trends demonstrate that while spatial downscaling heavily influences localized flux magnitudes and sub-grid ecosystem heterogeneity, the projected climate-driven degradation of the central Amazonian carbon buffer remains a resilient feature across spatial scales, though its ultimate velocity is governed by the chosen canopy thermal tolerance.

4 Conclusions

In this study, we conducted multi-decadal sensitivity simulations to evaluate how structural uncertainties in the optimal temperature for photosynthesis (T_{opt}) affect projected net ecosystem exchange (NEE) across the Brazilian Amazon. The simulations implemented fixed and temperature-dependent T_{opt} formulations within an offline configuration of the Vegetation Photosyn-

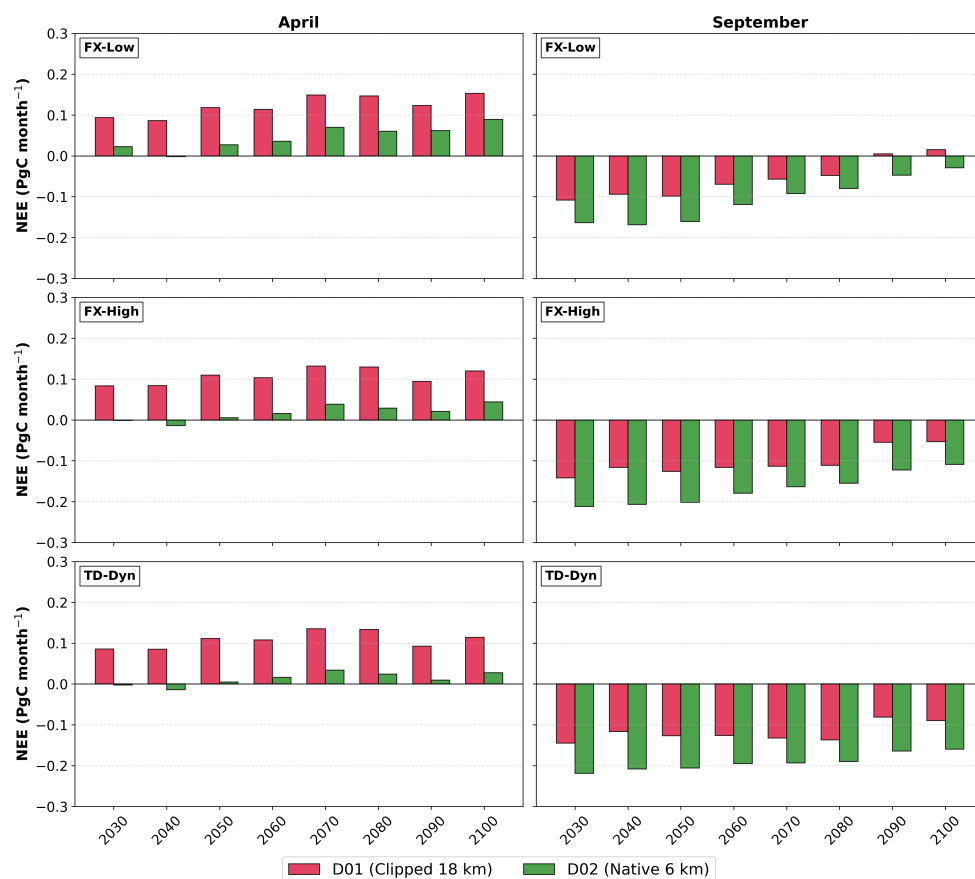


Figure 10. Decadal comparison (2030–2100) of monthly-integrated NEE (PgC month^{-1}) in the central Amazon across different grid resolutions and T_{opt} scenarios. Panels are organized by month (columns: April and September) and T_{opt} scenario (rows: FX-Low, FX-High, and TD-Dyn). Side-by-side bars contrast the clipped 18 km parent domain against the native 6 km nested domain evaluated over the same 6 km spatial footprint.

thesis and Respiration Model (VPRM) embedded in the Weather Research and Forecasting Greenhouse Gas (WRF-GHG) framework. The experiments were conducted using a three-domain nested configuration for April and September of selected years at decadal intervals from 2020 to 2100. Future meteorological and land-use conditions were prescribed using CMIP6 SSP5-8.5 projections, the highest-emission scenario among the core scenarios assessed in the IPCC Sixth Assessment Report. Because land-use distributions across the study region change marginally over the study period, the long-term evolution of NEE primarily reflects climate-driven warming rather than direct land-cover change.

The future simulations indicate a consistent transition toward a weaker carbon sink across the Brazilian Amazon by 2100. This decline results from an increasing imbalance between gross primary productivity (GPP) and ecosystem respiration (R_{eco}). While multi-decadal warming systematically enhances ecosystem respiration in the core region, downward shortwave radiation



(SWDOWN) remains comparatively stable, indicating that thermal stress, rather than changes in solar radiation, is the primary driver of the projected carbon budget evolution over the central Amazon. The magnitude of this response depends strongly on the representation of T_{opt} . Under the lower fixed- T_{opt} formulation (FX-Low), severe dry-season thermal overshoots suppress gross primary productivity, leading to a progressive decline in GPP and the transition of the historical September carbon sink to a net carbon source across all regions. Conversely, the temperature-dependent formulation (TD-Dyn) buffers this heat stress by continuously adjusting T_{opt} to increasing $T_{2\text{m}}$, thereby reducing the temperature limitation on photosynthesis and maintaining substantially higher daytime carbon uptake into the late century. Across the Brazilian Amazon, uncertainty associated with T_{opt} accounts for a 26.6% NEE reduction in April 2100 ($0.054 \text{ PgC month}^{-1}$), reflecting enhanced carbon uptake under TD-Dyn. In September 2100, this spread expands to over 430% ($0.157 \text{ PgC month}^{-1}$), driving a complete sign reversal from a net source under FX-Low to a sustained net sink under TD-Dyn.

Furthermore, our multi-scale evaluation reveals that although horizontal resolution alters key VPRM meteorological drivers—attenuating SWDOWN by 46–64% while affecting $T_{2\text{m}}$ by $< 5\%$ in the coarse resolution relative to the finer resolutions—the projected weakening of the Amazonian carbon buffer remains consistent across spatial scales. Over the central Amazon, the 6 km and 2 km simulations better resolve these meteorological drivers, thereby reducing the artificial smoothing inherent in the 18 km simulations. Consequently, the finer-resolution simulations produce stronger daytime carbon uptake and better agree with eddy covariance observations. Nevertheless, regardless of grid resolution, the systematic increase in R_{eco} offsets the enhanced daytime carbon uptake simulated by the dynamic TD-Dyn framework.

Despite the simplified carbon exchange formulation in VPRM, our finding that thermal acclimation of photosynthetic capacity reduces the vulnerability of carbon uptake to warming is consistent with other temperature-driven acclimation studies over tropical forests (e.g., Mercado et al., 2018; Oliver et al., 2025). Although our results demonstrate that the representation of T_{opt} substantially affects projected NEE, other sources of uncertainty, including VPRM parameters that were held fixed in this study (e.g., the photosynthetic scaling factor λ and the respiration coefficients α and β), as well as model horizontal resolution, can also substantially influence projected Amazonian carbon exchange. A comprehensive assessment of their relative contributions to projection uncertainty remains an important topic for future research. Reducing uncertainties in projected carbon exchange will further require incorporating additional physiological and ecological processes into the modeling framework, including stomatal responses to vapor pressure deficit and elevated atmospheric CO_2 concentrations (Li et al., 2023), CO_2 fertilization (Mastropierro et al., 2025), and the balance between tree growth and mortality (Yao et al., 2024). Together, these processes may either mitigate or amplify the effects of warming on the long-term evolution of the Amazon carbon sink under SSP5-8.5, thereby delaying or accelerating the transition from a net carbon sink to a net carbon source. Ultimately, our findings demonstrate that different representations of T_{opt} can strongly influence both the magnitude and the timing of the projected transition from carbon sink to carbon source under future climate warming.



Appendix A: Land-Use Classification Conversion Crosswalk

Table A1. Mapping between the MapBiomass 9, Modified IGBP MODIS Noah (excluding tundra categories), and CMIP6-LUH2 land-use classifications.

MapBiomass 9	Modified IGBP MODIS Noah	CMIP6-LUH2
–	(1) Evergreen Needleleaf Forest	–
1.1. Forest Formation	(2) Evergreen Broadleaf Forest	primf (forested primary land)
1.4. Floodable Forest		secdf (forested secondary land)
–	(3) Deciduous Needleleaf Forest	–
–	(4) Deciduous Broadleaf Forest	–
–	(5) Mixed Forests	–
1.5. Wooded Sandbank Vegetation	(6) Closed Shrublands	–
2.5. Herbaceous Sandbank Vegetation	(7) Open Shrublands	–
2.2. Grassland		
–	(8) Woody Savannas	–
1.2. Savanna Formation	(9) Savannas	primn (non-forested primary land) secdn (non-forested secondary land)
3.1. Pasture	(10) Grasslands	pastr (managed pasture) range (rangeland)
1.3. Mangrove	(11) Permanent Wetlands	–
2.1. Wetland		
2.3. Hypersaline Tidal Flat		
3.2. Agriculture	(12) Croplands	c3ann (C3 annual cropland) c3per (C3 perennial cropland) c4ann (C4 annual cropland) c4per (C4 perennial cropland) c3nfx (C3 nitrogen-fixing cropland)
4.2. Urban Area	(13) Urban and Built-Up	urban
3.3. Forest Plantation	(14) Cropland/Natural Veg. Mosaic	–
3.4. Mosaic of Uses		
–	(15) Snow and Ice	–
2.4. Rocky Outcrop	(16) Barren or Sparsely Vegetated	–
4.1. Beach, Dune and Sand Spot		
4.3. Mining		
4.4. Other non Vegetated Areas		
5. Water	(17) Water	gicew (glacier, ice, and water)



Appendix B: Preprocessing of CMIP6 Fields for WRF-GHG

535 The bias-corrected CMIP6 meteorological fields were processed to generate the initial and boundary conditions required by the WRF model. The WRF Preprocessing System (WPS) was used to convert the external meteorological datasets into the format required by WRF and to interpolate the fields onto the simulation domains. The WPS preprocessing chain includes the `geogrid`, `ungrib`, and `metgrid` components. The `geogrid` module defines the geographical characteristics of the simulation domains, including topography and land-surface properties. The `ungrib` module extracts the meteorological input
 540 fields and writes them into the WRF intermediate format. These intermediate fields were subsequently processed by `metgrid`, which interpolates the meteorological variables onto the horizontal and vertical grids defined for the WRF simulations. The resulting `met_em` files contain the fields required to generate the initial and boundary conditions.

The conversion of the bias-corrected CMIP6 fields into WRF intermediate files was performed following the standard procedures described in the WRF user guide. A Python implementation originally developed by Xu et al. (2021) for CMIP6-to-
 545 WRF dynamical downscaling experiments was adapted for the present study. The original code, available in the repository www.github.com/lzhenn/cmip6-to-wrfinterm, was modified to accommodate the specific requirements of our WRF configuration and to correct implementation issues identified during the preprocessing stage. The WRF intermediate binary files were generated at 6-hour intervals using the variables required for WRF initialization. The complete list of extracted fields, including their vertical levels, units, and dimensionality, is provided in Table B1.

Table B1. Bias-corrected CMIP6 variables used to generate the mandatory WRF intermediate binary files.

Variable	Vertical levels	Field	Units	Type
Sea surface temperature	1	SST	K	2D
Skin temperature	1	SKINTEMP	K	2D
Mean sea-level pressure	1	PMSL	Pa	2D
Surface pressure	1	PSFC	Pa	2D
Air temperature	14	TT	K	3D
Zonal wind component	14	UU	m s^{-1}	3D
Meridional wind component	14	VV	m s^{-1}	3D
Relative humidity	14	RH	%	3D
Geopotential height	14	GHT	m	3D
Soil moisture	4	SMmmm	$\text{m}^3 \text{m}^{-3}$	2D
Soil temperature	4	STmmm	K	2D



550 **Appendix C: Spin-up and Rolling Simulation Workflow**

The simulation strategy for each month is as follows. First, a 16-day spin-up simulation (covering the end of the preceding month) is performed to achieve stable CO₂ concentrations. This stage serves as a model initialization period, minimizing the influence of artificial initial conditions and allowing the model’s internal dynamics and physical processes to reach equilibrium. The final output from the spin-up phase is then used to initialize the first 2-day rolling simulation (1st run in Fig. C1). After
555 completion of this run, the first day is discarded as spin-up, and only the second day is retained for analysis. The second rolling simulation (2nd run in Fig. C1) does not start from the final output of the first run; instead, it begins one day earlier and uses CO₂ initial conditions derived from the first run. Similarly, the third rolling simulation (3rd run in Fig. C1) does not start from the end of the second run, but begins one day earlier using CO₂ initial conditions from the second run, and so on for subsequent simulations. In essence, the 2-day rolling simulations overlap by one day to ensure continuity, and only the second day of each
560 run is used for analysis.

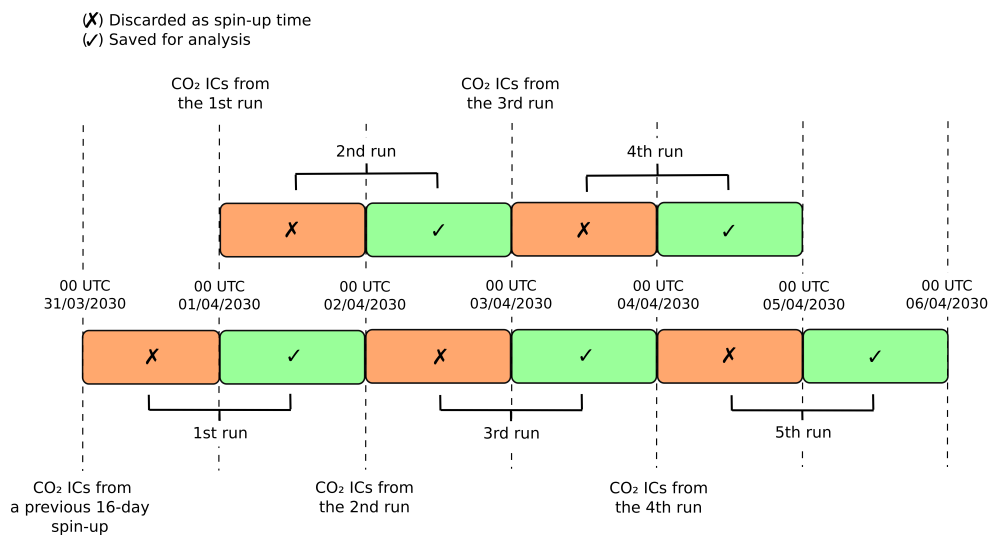


Figure C1. Schematic of the spin-up and 2-day rolling simulation workflow, showing overlapping runs, CO₂ initialization, and selection of output for analysis.



Code and data availability. The WRF-Chem model code version 4.2 is freely distributed by NCAR at https://www2.mmm.ucar.edu/wrf/users/download/get_source.html. Preprocessing and postprocessing scripts, together with the primary input and output datasets required to reproduce the modeling results presented in this study, are available from the corresponding author upon request.

565 *Author contributions.* Conceptualization: ALVV, LATM, NRB, LVR and SB; Data curation: ALVV, LATM, NRB, LVR, ACA, IMCT, SB and JS; Formal analysis: ALVV, LATM, LVR, NRB and SB; Funding acquisition: LATM, LVR and SB; Investigation: ALVV, LATM, NRB, LVR, MCV and SB; Methodology: ALVV, LATM, NRB, LVR and SB; Project administration: LATM, LVR, PA and UP; Resources: LATM, LVR, PA, UP and MAC; Software: ALVV, LATM, NRB, LVR, MG, DH and SB; Supervision: LATM, LVR and SB; Validation: ALVV, NRB and IMCT; Visualization: ALVV, NRB and IMCT; Writing – Original Draft: ALVV; Writing – Review & Editing: ALVV, LATM, LVR, NRB, PA, HA, MCV, ACA, MAC, IMCT, CQDJ, MG, DH, UP, JS, XX and SB.

570 *Competing interests.* The authors declare that they have no conflict of interest.

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