

Article

A CASA-Based, MODIS-Constrained Framework for Consistent Annual NPP Simulation in Alpine Complex Environments: A Case Study of the Gannan Plateau

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Highlights

What are the main findings?

- The MODIS-constrained CASA–GWR framework improved pooled pixel-level agreement between annual NPP estimates and the MODIS-constrained target during the 2014–2020 temporal transfer period, with R^2 increasing from 0.438 to 0.708 and RMSE decreasing from 91.4 to 68.7 g C m⁻² yr⁻¹.
- The GWR residual-alignment layer reduced residual spatial organization and produced a moderate, directionally consistent improvement in product-level agreement with GLASS, which was used as an independent product-level benchmark rather than ground truth.

What are the implications of the main findings?

- The framework provides a process-model-preserving approach for integrating CASA simulations with remote-sensing observational constraints without replacing CASA's mechanistic structure.
- The scenario application should be interpreted as a methodological scenario transfer experiment for exploring SSP pathway divergence, rather than as validation of future ecological processes.

Abstract

Net primary productivity (NPP) is a core diagnostic variable of terrestrial carbon cycling, yet consistent annual NPP simulation remains challenging in alpine heterogeneous regions where topography, hydrothermal gradients, vegetation structure, and nutrient constraints interact. Remote-sensing products such as MODIS provide valuable observational constraints, whereas light-use-efficiency models such as CASA retain process transparency and scenario transfer capability. This study develops a CASA-based, MODIS-constrained framework for annual NPP simulation over the Gannan Plateau. The framework preserves a locally parameterized CASA baseline and adds a geographically weighted regression (GWR) residual-alignment layer trained on CASA–MODIS residuals during 2005–2013. The fitted correction relationship was then applied to the 2014–2020 temporal transfer period and evaluated in a 2030s SSP scenario transfer experiment. MODIS was treated as the correction target rather than ground truth, and GLASS was adopted as an independent product-level benchmark. During 2014–2020, the GWR-corrected product showed improved pooled pixel-level agreement with the MODIS-constrained target relative to parameter-localized CASA, with R^2 increasing from 0.438 to 0.708 and RMSE

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decreasing from 91.4 to 68.7 g C m⁻² yr⁻¹. Residual Moran's I also decreased, indicating weaker residual spatial organization after correction. Product-level comparison with GLASS showed a moderate, directionally consistent improvement relative to uncorrected CASA, although this comparison was not interpreted as ground-truth validation. The 2030s scenario transfer experiment indicated that the correction layer changed the spatial expression of NPP divergence among SSP pathways. Overall, the proposed framework provides a process-model-preserving and observation-constrained approach for improving agreement between annual NPP estimates and the MODIS-constrained target in alpine heterogeneous regions, while its applicability remains subject to product uncertainty, spatial dependence, and future nonstationarity.

Keywords: net primary productivity; CASA model; MODIS constraint; residual alignment; product-level benchmark; geographically weighted regression; alpine ecosystems

1. Introduction

Net primary productivity (NPP) is a fundamental flux in the terrestrial carbon cycle and a key indicator of vegetation productivity, carbon sink capacity, and ecological function dynamics [1–3]. Under global change, NPP responses to climate variability, extreme events, and human activities have been widely used to assess ecosystem functional change and regional carbon balance [3–6]. Accurately characterizing the spatiotemporal patterns of NPP and the sources of its uncertainty is particularly important in complex regions with steep environmental gradients [3,5,7].

Regional-scale NPP estimation typically relies on two complementary sources of information. The first comprises remote-sensing NPP products such as MODIS and GLASS, which combine multi-source remote-sensing observations, meteorological reanalyses, and biophysical retrieval algorithms to deliver globally consistent, spatially continuous, and algorithmically coherent NPP references [8–11]. In particular, MODIS NPP, supported by the long-running MOD17 algorithm chain and extensive site-level evaluation, has become a widely adopted observational constraint and inter-model benchmark for regional productivity research [10–12]. However, MODIS NPP has two notable limitations as a driver-based simulation framework. First, its temporal coverage begins only around 2000, which is insufficient for long-term historical reconstruction since industrialization; second, the remote-sensing inputs and reanalysis-based forcing on which it depends cannot be naturally extended to future scenarios such as CMIP6/SSP. Consequently, obtaining both observation-constrained spatial consistency and extrapolability for historical and future applications requires retaining a process-based model as the mechanistic foundation, upon which a MODIS-based constraint can be imposed [8,9].

The second source is process-based light-use-efficiency (LUE) models, with CASA as a representative example. CASA has a relatively parsimonious structure, modest driving-data requirements, and straightforward coupling with remote-sensing data, and it can be naturally extrapolated to historical periods and future scenarios; it has therefore been widely used for regional and global NPP reconstruction [2,13–17]. Nevertheless, LUE models such as CASA typically rely on biome-level look-up tables and simplified environmental stress formulations, while key parameters within a single plant functional type may differ substantially across sites; as a result, products built on uniform parameterizations tend to exhibit directional systematic biases in strongly heterogeneous environments [12,14,18,19]. Alpine ecosystems such as those on the Qinghai–Tibet Plateau, subject to pronounced topographic relief, short growing seasons, and co-limitation by hydrothermal

and nutrient conditions, have NPP that is highly sensitive to environmental gradients, and CASA simulations and MODIS references typically exhibit spatially structured local deviations along these gradients rather than randomly distributed errors [20–24]. Such deviation is not uniformly distributed but clusters along environmental gradients, constraining the regional applicability of CASA in alpine complex environments.

To improve consistency between process-based NPP and observational references while preserving mechanistic representation, recent research has advanced along three main lines. (i) Parameter optimization and data assimilation, which uses MODIS, FLUXNET, and related observations to calibrate LUE parameters at site or regional scales, thereby improving simulation accuracy [14,25–28]. (ii) Hybrid modeling, which explicitly couples mechanistic and data-driven components to produce a mechanism–data integrated productivity estimation framework [16,29,30]. (iii) Posterior alignment and bias constraint, which, while preserving the process-model structure, uses remote-sensing references as the target and imposes a spatially explicit constraint on the residual between model and reference, aligning simulations with the reference benchmark [3,9,30,31]. More broadly, uncertainties in model structure and forcing data can propagate through terrestrial carbon-cycle simulations and amplify uncertainty in projected carbon responses [32,33]. Compared with parameter optimization and structural reconstruction, the posterior alignment line does not require rebuilding mechanistic modules and is well suited to situations where reference data are limited, scale mismatches are prominent, and the study domain is a spatially continuous surface.

Nevertheless, most existing remote-sensing-constrained NPP simulation studies have not fully reconciled three requirements critical for regional applications in alpine heterogeneous environments: preserving an intact process-based simulation backbone, improving consistency with a spatially continuous observational product, and retaining uncompromised transferability of the calibrated framework to unseen subsequent historical periods and independent scenario forcing. In this study, MODIS NPP is adopted as the correction target and observational constraint, rather than as ground truth, while GLASS NPP is used exclusively as an independent product-level benchmark. Motivated by these considerations, we selected the Gannan Plateau on the northeastern margin of the Qinghai–Tibet Plateau as a case study, and developed a CASA-based, MODIS-constrained framework for annual NPP simulation in alpine regions. The framework comprises three layers: (i) a CASA process-model layer that provides the core model logic and allows for scenario testing; (ii) a parameter-localization layer where key LUE settings are adjusted locally based on the area’s vegetation; and (iii) a spatially explicit GWR residual-alignment layer, which learns correction patterns from CASA–MODIS residuals over the 2005–2013 period and applies them to subsequent data. Therefore, the GWR layer is used as a posterior residual-alignment component rather than as a replacement for CASA or as direct proof of causal environmental sensitivity. This study aims to answer three questions: (1) whether the proposed framework improves the product-level agreement between CASA-simulated NPP and the MODIS-constrained target over 2014–2020; (2) whether the MODIS-constrained correction also leads to better agreement with GLASS, while recognizing that GLASS is not ground truth; and (3) whether the same correction framework can be applied in a 2030s SSP scenario experiment to explore changes in the spatial expression of NPP divergence among SSP pathways. The scenario-related application is interpreted as a methodological transferability experiment rather than as direct validation of future ecological processes.

2. Methods and Data

The overall modeling workflow and the study-area context are presented in Figures 1 and 2, respectively.

2.1. Study Area

The Gannan Plateau is located on the northeastern margin of the Qinghai–Tibet Plateau, representing a critical transitional zone from alpine ecosystems to monsoon-influenced regions and an important component of the upper Yellow River ecological function zone [34,35]. The region features pronounced topographic relief, steep elevation gradients, and marked spatial heterogeneity in hydrothermal conditions, vegetation composition, and ecosystem productivity along topographic and climatic gradients [36]. For such alpine heterogeneous landscapes, uniformly parameterized LUE process models can characterize vegetation radiation absorption and light-use efficiency but often inadequately capture local environmental constraints, scale mismatches, and spatial relationship variability, rendering them more susceptible to producing spatially structured systematic biases [18,19].

2.2. Overall Research Design

We built a CASA-based, MODIS-constrained framework for annual NPP simulation in complex alpine environments. The design logic is as follows: CASA provides the process-based simulation backbone, MODIS NPP serves as the observational constraint, and the GWR layer acts as a spatially explicit residual-alignment component. In this framework, MODIS is not treated as ground truth. Therefore, any improvements relative to MODIS are interpreted as improvements in product-level agreement with the MODIS-constrained target.

The framework comprises three layers. First, the CASA process layer produces annual NPP estimates for the Gannan Plateau while maintaining model applicability to historical conditions and scenario forcings. Second, the parameter-localization layer adjusts key LUE parameters by vegetation types to refine the mechanistic baseline. Third, the GWR residual-alignment layer estimates spatially varying residual relationships using multi-year CASA–MODIS residual samples over the 2005–2013 period, and applies the fitted correction to 2014–2020 under the same predictor specification. The estimated GWR coefficients are interpreted as spatially varying residual-alignment parameters rather than as causal ecological sensitivity coefficients.

Framework performance was evaluated along three dimensions: (i) agreement with the MODIS-constrained target during the 2014–2020 temporal transfer period; (ii) product-level agreement with GLASS over the same period, recognizing that GLASS serves as an independent NPP product rather than ground truth; and (iii) methodological scenario transfer experiment under 2030s SSP forcing. Residual Moran's I and clustering patterns are used as diagnostics of residual spatial organization, but reduced spatial autocorrelation alone is not interpreted as evidence of improved realism in true NPP.

2.3. Methods

2.3.1. Definition of Consistency

In this study, “consistency” refers to agreement between simulated or corrected NPP and a reference product used as either an observational constraint target or a product-level benchmark. It does not denote ground-truth accuracy. For MODIS-based evaluation, consistency refers to agreement with the MODIS-constrained target. For GLASS-based evaluation, consistency refers to product-level agreement with an independent NPP product.

Consistency is evaluated along three complementary axes. First, spatial pattern association is quantified using Pearson's correlation coefficient and R^2 . Second, magnitude agreement is assessed via RMSE, MAE, bias, unbiased RMSE, and the concordance correlation coefficient (CCC). Third, residual spatial organization is diagnosed using Moran's I of the residual field. Moran's I serves solely as an indicator of spatially structured residuals; a lower value suggests weaker residual spatial organization but does not in itself indicate improved realism of true NPP.

2.3.2. CASA Model and Residual Definition

This study employed the CASA model at the pixel scale to estimate annual net primary productivity [2,17]. To improve model applicability in the alpine environment of the Gannan Plateau, regional parameter adjustments were implemented based on existing schemes [37,38]. All NPP products and environmental predictors were resampled to a consistent 1 km grid and aggregated to the annual resolution prior to model fitting. Following the harmonization of spatial grid, temporal scale, and valid pixel extent, the CASA–MODIS residual was defined using MODIS annual NPP as the observational constraint [10–12]:

$$y_{i,t} = NPP_{i,t}^{obs} - NPP_{i,t}^{CASA} \quad (1)$$

where $y_{i,t}$ represents the CASA–MODIS residual of pixel i in year t , calculated as MODIS annual NPP minus CASA-simulated NPP. Positive values indicate that CASA underestimated the MODIS-constrained target, whereas negative values indicate CASA overestimation. This residual field served as the response variable in subsequent spatial diagnostics, predictor screening, and GWR residual-alignment modeling.

The residual $y_{i,t}$ is a MODIS-constrained CASA residual. In this study, it was used to characterize the spatial organization of CASA–MODIS disagreement. Global Moran's I, local Moran indices [39–41], and cluster overlap analysis were applied as auxiliary diagnostics to assess whether this disagreement exhibited spatial structure suitable for spatially explicit residual alignment.

2.3.3. MODIS Constraint GWR Layer Based on Multi-Year Pooling

The GWR residual-alignment layer was constructed using the CASA–MODIS residual $y_{i,t}$ as the response variable. Candidate predictors included climatic, atmospheric, vegetation, topographic, and soil-related variables. SHAP values derived from an XGBoost residual model were used to rank preliminary variable importance, followed by global VIF screening to reduce redundancy among candidate predictors. With consideration of statistical importance, collinearity control, and ecological interpretability, the final predictor set included CO_2 , temperature, precipitation, ForestAge, NDVI, VPD, Ndep, and elevation.

Predictor standardization was fitted using the 2005–2013 calibration samples. The resulting means and standard deviations were subsequently applied to the 2014–2020 temporal transfer samples and the 2030s SSP scenario transfer inputs. This design maintained a consistent scaling basis across the calibration, temporal transfer, and scenario transfer stages.

A GWR model was then applied to estimate spatially varying relationships between the CASA–MODIS residual and the selected predictors [42,43]. The local GWR model was written as

$$y_{i,t} = \beta_0(u_i, v_i) + \sum_{k=1}^p \beta_k(u_i, v_i) x_{k,i,t} + \varepsilon_{i,t} \quad (2)$$

where (u_i, v_i) denotes the spatial coordinates of pixel i , $x_{k,i,t}$ is the standardized value of predictor k , $\beta_k(u_i, v_i)$ is the local coefficient for predictor k , and $\varepsilon_{i,t}$ is the local error term.

Local weights were defined using an adaptive k-nearest-neighbor Gaussian kernel. Candidate adaptive bandwidths included 48, 50, 70, 100, 150, 200, 250, 300, 500, 750, and 1000 nearest neighbors. The main analysis adopted a bandwidth of 500, which provided the highest mean annual R^2 and the lowest mean annual RMSE over the 2014–2020 temporal transfer period sensitivity analysis, while also achieving continued reduction in residual Moran's I.

A ridge-stabilized local normal equation was employed to enhance numerical stability in local estimation. The ridge parameter was set to $\lambda = 1 \times 10^{-5}$. Sensitivity tests indicated that local solutions became unstable without ridge stabilization, while non-zero λ values ranging from 1×10^{-8} to 1×10^{-3} produced nearly identical temporal transfer period performance. This supported the use of $\lambda = 1 \times 10^{-5}$ as a numerical stable setting.

The fitted GWR relationship from 2005 to 2013 was applied to the 2014–2020 temporal transfer period and to the 2030s SSP scenario transfer inputs under the same predictor specifications and standardization parameters. The corrected NPP was calculated as

$$NPP_{i,t}^{corr} = NPP_{i,t}^{CASA} + \hat{y}_{i,t} \quad (3)$$

where $\hat{y}_{i,t}$ represents the GWR-predicted CASA–MODIS residual. Detailed GWR settings, bandwidth sensitivity, ridge sensitivity, and local collinearity diagnostics are reported in Supplementary Tables S1 and S3–S5.

2.3.4. Consistency Evaluation and Robustness Diagnostics

Framework performance during the 2014–2020 temporal transfer period was evaluated using three groups of metrics. Pattern association was quantified through Pearson's correlation coefficient and R^2 . Magnitude agreement was assessed using RMSE, MAE, bias, unbiased RMSE, and the CCC. Residual spatial organization was characterized by Moran's I of the residual field. These metrics were calculated for CASA and GWR-corrected NPP relative to the MODIS-constrained target. GLASS annual NPP was used as an independent product-level benchmark to examine cross-product agreement over the same period.

Robustness was evaluated through supplementary diagnostics encompassing annual transfer variability, bandwidth sensitivity, ridge sensitivity, local collinearity, predictor-set robustness, model-type comparison, and spatial-dependence-aware temporal transfer. The model-type benchmark compared CASA baseline, OLS residual correction, spatial trend-surface correction, random forest, XGBoost, and GWR under an identical calibration–transfer protocol. The spatial-dependence-aware diagnostics included same-grid support auditing, spatially stratified transfer evaluation, and spatial block-bootstrap confidence intervals. These analyses are summarized in Supplementary Tables S1–S9 and Supplementary Figures S1–S4.

Correction gain was defined as the pixel-level reduction in absolute disagreement following GWR correction. Raw gain was calculated as the pre-correction absolute disagreement between MODIS and CASA minus the post-correction absolute disagreement between MODIS and GWR-corrected NPP. Positive values indicate a reduction in absolute disagreement after correction. To account for the influence of initial error magnitude,

the baseline relationship between raw gain and pre-correction absolute error was removed using linear regression. The residualized gain was defined as

$$Gain_{i,t}^{res} = Gain_{i,t} - (\hat{\alpha} + \hat{\beta} \cdot |NPP_{i,t}^{obs} - NPP_{i,t}^{CASA}|) \quad (4)$$

where $Gain_{i,t}^{res}$ represents the relative net benefit obtained after controlling for initial error magnitude. An XGBoost model was then fitted with residualized gain as the response variable and environmental variables as predictors. SHAP values were used to summarize the relative contribution and nonlinear response patterns of gain-related variables. Python-based data processing, model implementation, spatial analysis, statistical evaluation, and visualization were conducted in Python 3.12.5 using NumPy 1.26.4, pandas 2.2.3, SciPy 1.15.3, scikit-learn 1.5.2, XGBoost 2.1.2, SHAP 0.47.2, statsmodels 0.14.4, libpysal 4.13.0, esda 2.7.0, GeoPandas 1.0.1, rasterio 1.4.2, pyproj 3.6.1, and Matplotlib 3.8.4. Spatial data preprocessing and cartographic production were additionally performed using ArcGIS Pro 3.1.6 (Esri, Redlands, CA, USA). The adaptive GWR residual-alignment layer was implemented using custom Python code.

2.4. Data Sources and Variable Construction

A pixel-year database was constructed for the Gannan Plateau (2005 to 2020) to support CASA simulation, residual modeling, and transfer period evaluation. MODIS annual NPP was used for residual construction and MODIS-constrained target consistency assessment, while GLASS annual NPP [44,45] served as an independent product-level benchmark over the 2014–2020 temporal transfer period. All NPP products [11,44–46] were converted to annual units and matched pixel by pixel after harmonization of spatial grid, temporal scale, and valid pixel extent.

Environmental predictors encompassed climatic [47–49], atmospheric composition [50,51], vegetation [52–54], topographic, and soil [55,56] variables. Climatic variables comprised temperature, precipitation, solar radiation, and vapor pressure deficit. Atmospheric composition variables included annual CO₂ concentration and nitrogen deposition. Vegetation variables included NDVI, forest age, and plant functional traits. Topographic variables included elevation and slope, and soil variables included texture, bulk density, pH, total nitrogen, and related physicochemical properties.

Historical nitrogen deposition was derived from the gridded dataset of Zhou et al. [50], which provides spatially complete deposition estimates across China over the 2005–2020 period at approximately 0.25° resolution. This product integrates ground observations, chemical transport simulations, satellite-derived column information, and meteorological and geographic predictors. In this study, total N deposition (kg N ha⁻¹ yr⁻¹) was used as the historical Ndep variable. Available anchor-year layers for 2005, 2010, 2015, and 2020 were resampled to the 1 km Gannan Plateau CASA–GWR modeling grid, with annual Ndep values for intermediate years generated by pixel-wise linear interpolation. This procedure produced a continuous annual Ndep predictor series for the historical pixel-year modeling table over 2005–2020.

All dynamic variables were aggregated to annual resolution before being entered into the sample table. Static variables were resampled to the 1 km grid and held constant across years. The final historical modeling table followed a unified pixel-year structure, with each valid record containing annual NPP, CASA residuals, and the corresponding environmental predictors.

For the 2030s scenario transfer experiment, forcing inputs were prepared under SSP1-2.6, SSP2-4.5, and SSP5-8.5. The 2030s forcing represents aggregated data from 2026 to 2035, which served as representative scenario forcing inputs in the CASA workflow. Future temperature, precipitation, and solar radiation were derived from a bias-corrected and downscaled CMIP6 multi-model ensemble, including ACCESS-CM2, BCC-CSM2-

MR, CanESM5, CESM2-WACCM, CNRM-CM6-1, GFDL-ESM4, IPSL-CM6A-LR, MIROC6, MRI-ESM2-0, and NorESM2-MM. Future CO₂ was derived from the SSP atmospheric CO₂ dataset of Cheng et al. [51]. Future Ndep data originated from pre-processed CMIP6 fNdep-Emon monthly outputs, which were aggregated to the scenario forcing period and resampled to a 1 km resolution grid; no additional observational bias correction was applied to future Ndep. Projections for LUCC were sourced from FLUS-simulated scenarios. NDVI and elevation were treated as invariant, with NDVI held constant at recent baseline levels. All scenario transfer inputs employed the same final predictor specification and historical standardization parameters as in the 2014–2020 temporal transfer evaluation. Detailed scenario forcing metadata and nitrogen deposition treatment are available in Supplementary Tables S10 and S11. Data sources, resolutions, temporal coverage, and their roles in this study are summarized in Table 1.

Table 1. Data sources, variables, spatial resolutions, temporal coverage, and roles in the modeling framework.

Data/Variable	Source	Resolution and Temporal Coverage	Role in This Study
MODIS NPP	[11]	Annual; 2005–2020	Residual construction and assessment against the MODIS-constrained target
GLASS NPP	[44,45]	Annual; 2005–2020	Independent product-level benchmark during the 2014–2020 temporal transfer period
Climate variables (Temp, Prec, SolarRad, VPD)	[47–49]	Unified to 1 km annual; 2005–2020	CASA driver and candidate variables for residual diagnostics
Atmospheric composition variables (CO ₂ , Ndep)	[50,51]	Annual; 2005–2020	Residual explanation, environmental predictors for residual diagnostics, GWR residual alignment, and scenario transfer forcing
Vegetation state/structure variables (NDVI, ForestAge, plant functional traits)	Landsat-derived NDVI; [52–54]	Various original resolutions; unified to 1 km annual or static raster	Characterize vegetation growth status and developmental stage
Topographic variables (elevation, slope)	ASTER GDEM V1 [56]	30 m, unified to 1 km static raster	Characterize topographic background and spatial correction candidates
Soil properties	[55]	High-resolution soil grid, unified to 1 km static raster	Characterize soil physicochemical background
Land use/land cover (LUCC)	[57]	Unified to 1 km	Auxiliary residual diagnostics, variable screening, and result interpretation

3. Results

3.1. Local CASA–MODIS Inconsistency and Residual Spatial Organization

3.1.1. Residual Spatial Differentiation Under Regional Pattern Agreement

CASA and MODIS annual NPP exhibited broad regional pattern agreement, though residuals displayed clear spatial differentiation (Figure 3). Based on 493,558 valid pixel-year samples, CASA and MODIS yielded $R^2 = 0.52$ and $RMSE = 82.6 \text{ g C m}^{-2} \text{ yr}^{-1}$. The residual mean was slightly negative ($\mu = -3.9 \text{ g C m}^{-2} \text{ yr}^{-1}$, $\sigma = 82.5 \text{ g C m}^{-2} \text{ yr}^{-1}$), indicating limited regional bias but substantial local disagreement. The multi-year mean residual map showed contiguous zones of positive and negative residuals, suggesting persistent spatial structure in CASA–MODIS disagreement across the study area.

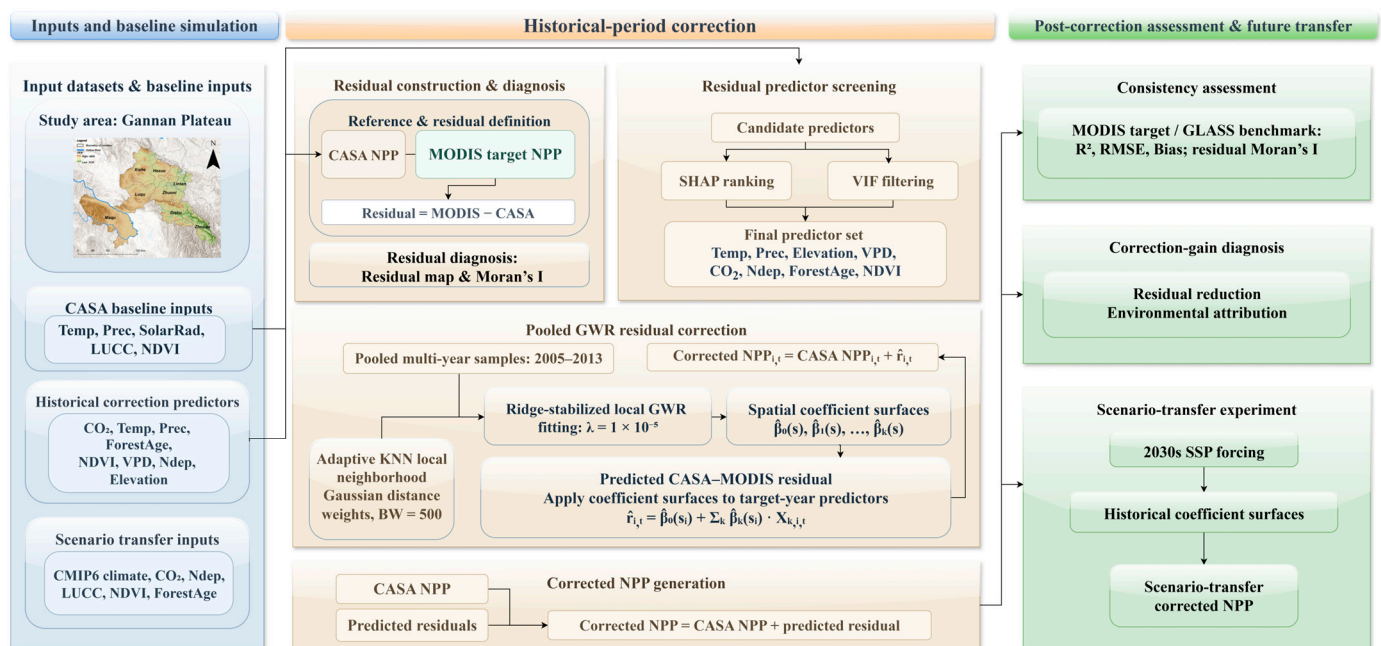


Figure 1. CASA-based, MODIS-constrained residual-alignment framework for annual NPP simulation in the Gannan Plateau. The workflow links baseline CASA inputs, historical CASA–MODIS residual construction, predictor screening, pooled ridge-stabilized GWR residual alignment, corrected NPP generation, product-level assessment with the MODIS target and GLASS benchmark, correction-gain diagnosis, and 2030s SSP scenario transfer. Blue, orange, and green blocks represent inputs and baseline simulation, historical-period correction, and post-correction assessment and future transfer, respectively; arrows indicate the direction of data and model flow.

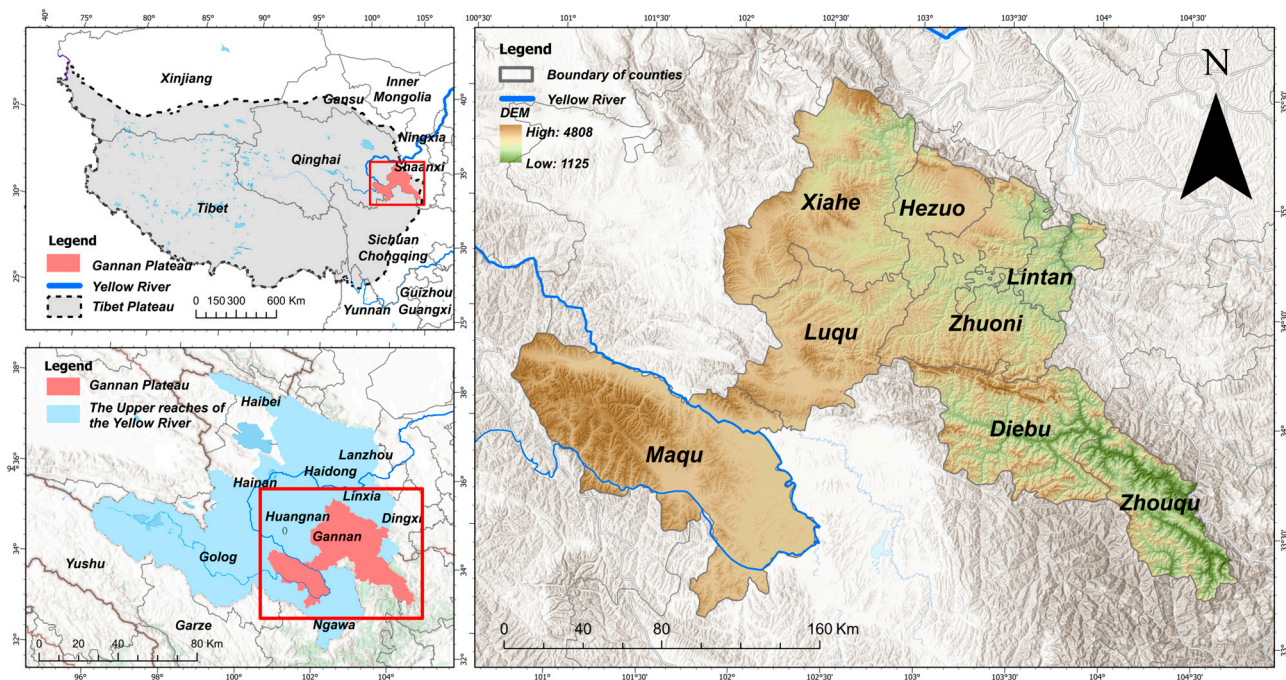


Figure 2. Overview of the Gannan Plateau study area. The red boxes in the national- and regional-scale inset maps indicate the location of the Gannan Plateau within China and the upper Yellow River region, respectively.

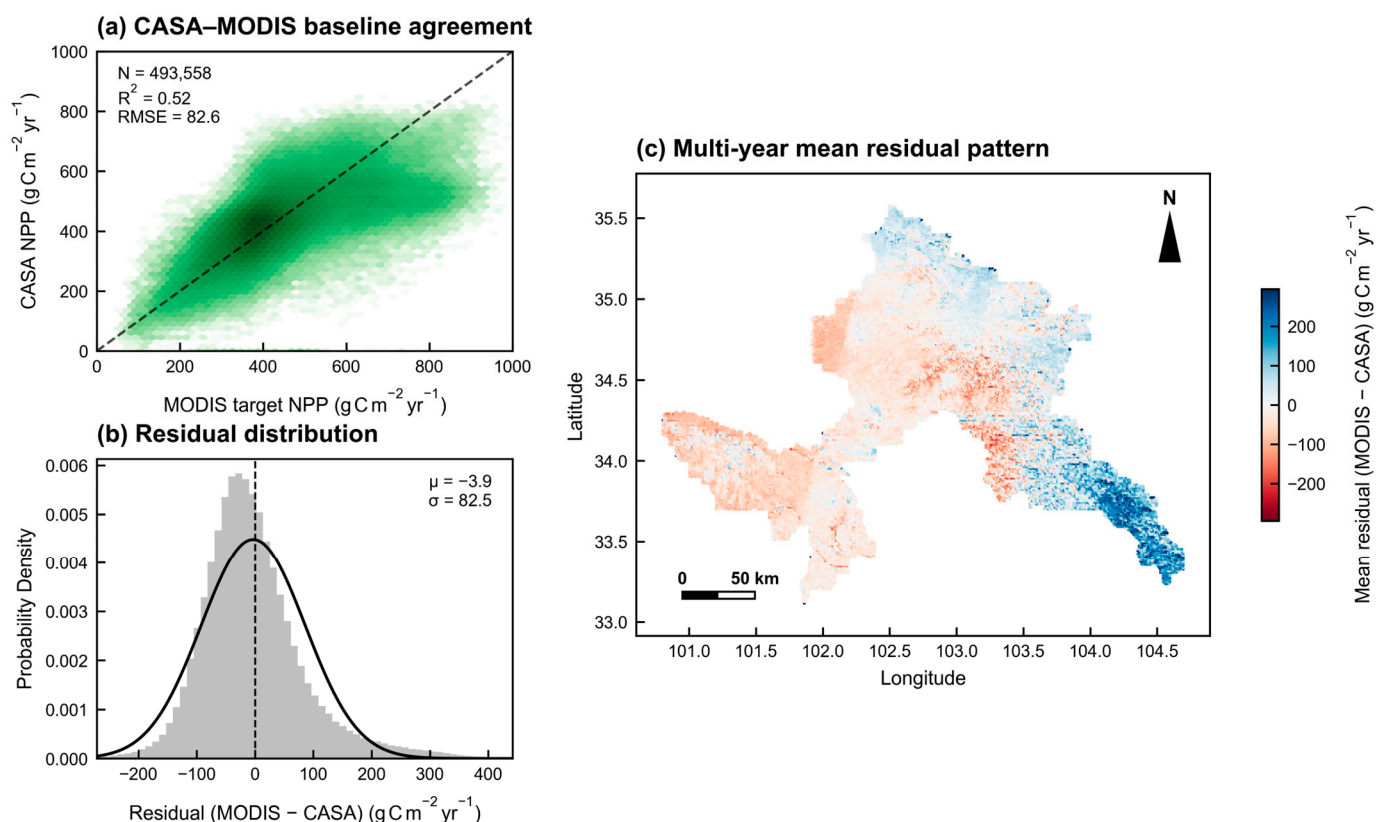


Figure 3. CASA–MODIS baseline agreement and residual spatial pattern during 2005–2020. (a) Scatter-density distribution of CASA-simulated NPP versus MODIS target NPP for all valid pixel-year samples; the dashed line indicates the 1:1 reference line, and N , R^2 , and RMSE summarize product-level agreement. (b) Probability-density distribution of CASA–MODIS residuals, defined as MODIS–CASA; gray bars show the empirical distribution, the black curve shows the fitted normal distribution, and the dashed vertical line marks zero residual. μ and σ denote the residual mean and

standard deviation. (c) Spatial distribution of the 2005–2020 multi-year mean residual, with positive values indicating higher MODIS target NPP than CASA-simulated NPP and negative values indicating lower MODIS target NPP than CASA-simulated NPP.

3.1.2. Spatial Clustering of Residuals and Environmental Context

The residual field exhibited significant spatial autocorrelation (Figure 4). Global Moran's I was 0.749 under permutation testing ($p = 0.001$), indicating strong spatial clustering of CASA–MODIS residuals. Local LISA results revealed that significantly clustered pixels accounted for approximately 34.0% of the study area. Among these, HH-type clusters (CASA underestimation relative to MODIS) constituted 14.9%, LL-type clusters (CASA overestimation) constituted 17.9%, and transition-type clusters (HL and LH) each accounted for less than 1%. Because the residual was calculated as MODIS minus CASA, HH clusters represent localized underestimation by CASA, whereas LL clusters correspond to local overestimation.

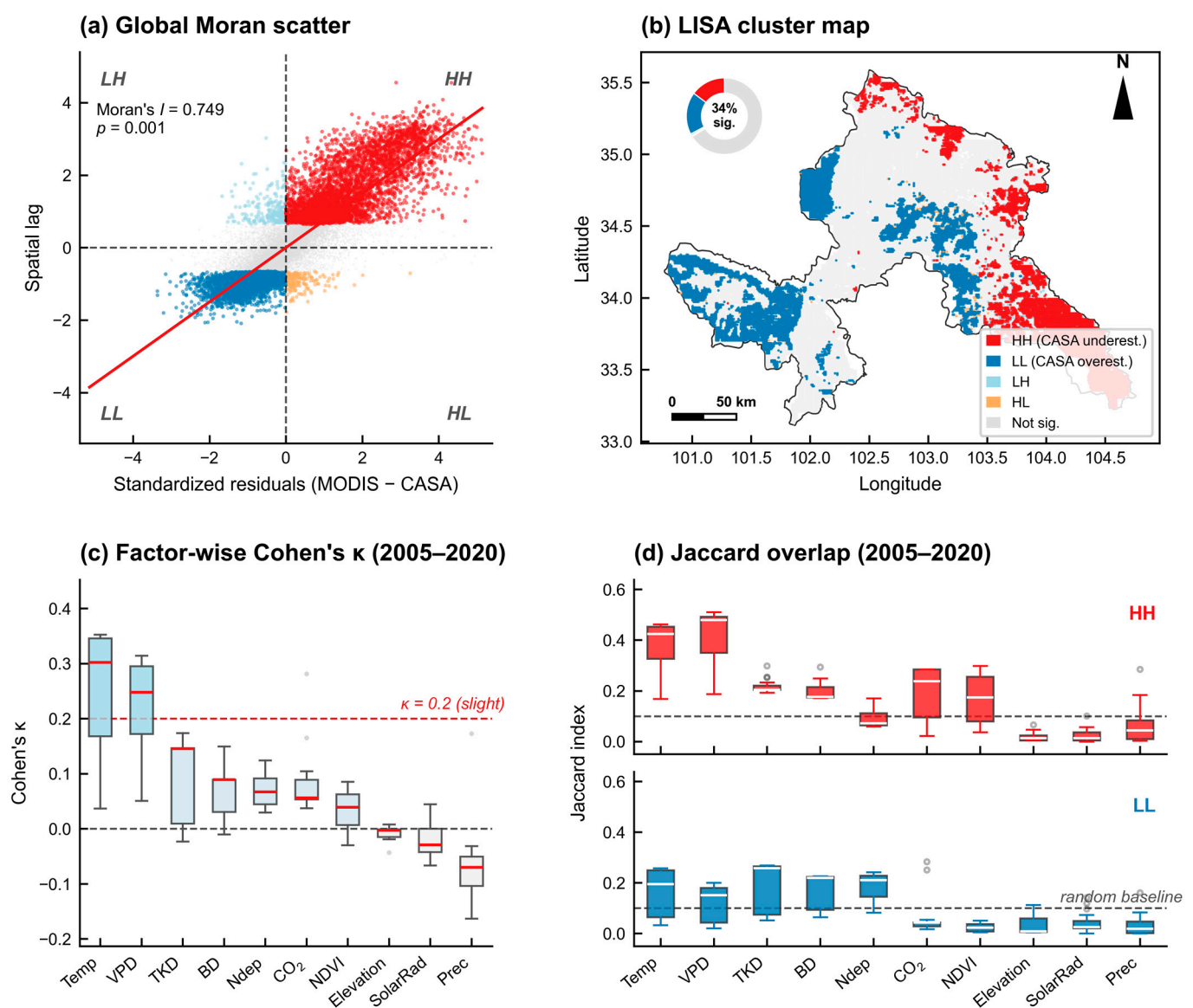


Figure 4. Spatial autocorrelation of CASA–MODIS residuals and their association with environmental-factor clusters. (a) Global Moran scatter plot of the 2005–2020 multi-year mean residual, with the red line showing Moran's I regression slope. (b) LISA cluster map of the multi-year mean residual. HH clusters indicate local CASA underestimation relative to the MODIS target, LL clusters indicate

local CASA overestimation, and LH and HL indicate spatial outlier zones. The inset pie chart shows the proportion of significantly clustered pixels. (c) Annual Cohen's κ distributions between environmental-factor clustering patterns and residual clustering patterns. In panel (c), the light-blue box-plots summarize the annual distributions, the red horizontal lines within the boxes indicate medians, gray circles denote outliers, the red dashed line indicates $\kappa = 0.2$, and the gray dashed line indicates $\kappa = 0$. (d) Jaccard overlap distributions between environmental-factor clusters and residual HH and LL clusters; the dashed line indicates the random-overlap baseline.

The correspondence between residual clusters and individual environmental-factor clusters was limited and inconsistent across factors (Figure 4). While temperature exhibited a modestly higher spatial correspondence, precipitation exhibited no stable correspondence pattern. No single factor adequately captured the residual clustering structure. This pattern indicates that the spatial organization of the CASA–MODIS residuals reflects the combined influence of multiple environmental gradients.

3.1.3. Residual-Related Predictors Differ from Productivity-Dominant Gradients

The predictor-contribution structure of CASA–MODIS residuals differed from those of both the MODIS-constrained target and CASA-simulated NPP (Figure 5). In the residual diagnostic model, CO₂, VPD, NDVI, and Ndep ranked among the leading predictors, whereas the MODIS-constrained target was more closely associated with productivity-gradient variables such as ForestAge, elevation, clay, and NDVI. Compared with both CASA NPP and the MODIS-constrained target, residual-related importance shifted toward CO₂, VPD, and Ndep. In particular, Ndep ranked lower for the MODIS-constrained target but higher for the residual model, suggesting that nutrient-background information helped explain part of the CASA–MODIS disagreement.

After collinearity screening, the variables retained for GWR residual-alignment modeling were CO₂, temperature, precipitation, ForestAge, NDVI, VPD, Ndep, and elevation. The corresponding local collinearity and feature-exclusion diagnostics are reported in Supplementary Table S5. Together, the distinct residual-related predictor ranking and the spatial organization of CASA–MODIS residuals supported the use of a spatially explicit residual-alignment layer.

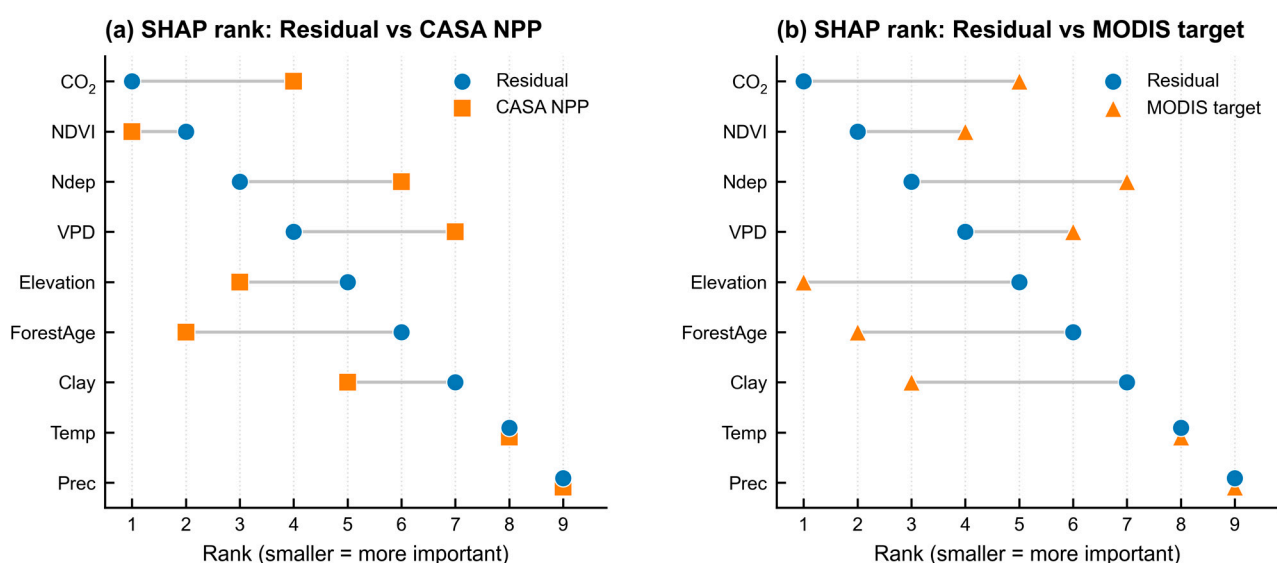


Figure 5. SHAP-based predictor-rank comparison among CASA–MODIS residuals, CASA-simulated NPP, and the MODIS-constrained target. (a) Rank comparison between CASA–MODIS residuals and CASA-simulated NPP. (b) Rank comparison between CASA–MODIS residuals and the

MODIS-constrained target. Gray connecting lines link the rank positions of the same predictor across the two compared targets. Smaller rank values indicate higher SHAP-based predictor contribution. The comparison focuses on the final residual-alignment predictor set, with clay included as an additional productivity-gradient reference variable for the MODIS-constrained target. Clay was not retained in the final GWR residual-alignment predictor set; the corresponding local collinearity and feature-exclusion diagnostics are reported in Supplementary Table S5.

3.2. Hierarchical Improvement in MODIS-Constrained Agreement

3.2.1. Stepwise Changes After Parameter Localization and GWR Residual Alignment

During the 2014–2020 temporal transfer period, untuned CASA, parameter-localized CASA, and GWR-corrected CASA-NPP showed a stepwise increase in agreement with the MODIS-constrained target. Untuned CASA showed weak agreement, with $R^2 = 0.047$, $RMSE = 235.3 \text{ g C m}^{-2} \text{ yr}^{-1}$, and $\text{bias} = 186.4 \text{ g C m}^{-2} \text{ yr}^{-1}$. After parameter localization, R^2 increased to 0.438, $RMSE$ decreased to $91.4 \text{ g C m}^{-2} \text{ yr}^{-1}$, and bias decreased to $5.8 \text{ g C m}^{-2} \text{ yr}^{-1}$. After GWR residual alignment, R^2 further increased to 0.708 and $RMSE$ decreased to $68.7 \text{ g C m}^{-2} \text{ yr}^{-1}$. These results indicate that parameter localization primarily reduced regional magnitude bias, while GWR residual alignment enhanced spatially explicit agreement with the MODIS-constrained target.

The metrics reported in Figure 6 are pooled pixel-level evaluation results for the 2014–2020 temporal transfer samples, whereas Table 2 reports mean $\pm$ standard deviation of annual product-level benchmark metrics. The pooled residual Moran's I increased from 0.750 for untuned CASA to 0.783 after parameter localization, then declined to 0.481 after GWR residual alignment. This reduction indicates weaker residual spatial organization after GWR correction. Annual diagnostics for the transfer period (2014–2020) confirmed that GWR residual alignment consistently improved MODIS-constrained agreement and reduced residual Moran's I in each year, albeit with interannual variation in magnitude (Supplementary Table S2; Figure S1). The final model-type benchmark is reported in Table 2.

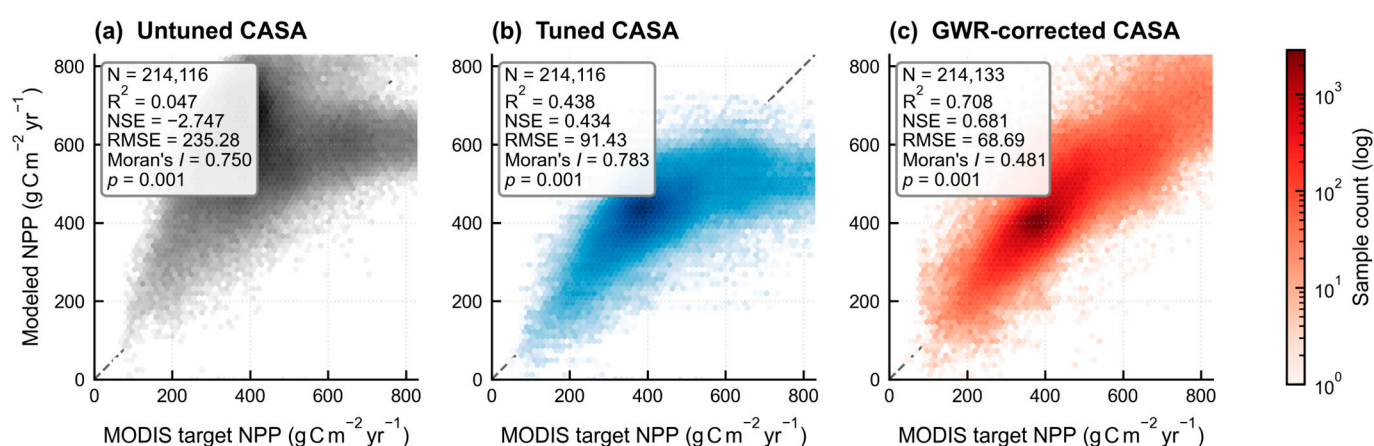


Figure 6. Three-stage comparison of untuned CASA, tuned CASA, and GWR-corrected CASA during the 2014–2020 temporal transfer period. (a–c) Two-dimensional density distributions of model NPP versus the MODIS-constrained target for pooled pixel-level evaluation samples, corresponding to untuned CASA, tuned CASA, and GWR-corrected CASA, respectively. Gray, blue, and red density distributions represent untuned CASA, tuned CASA, and GWR-corrected CASA, respectively. The dashed line indicates the 1:1 reference line. N, R^2 , NSE, RMSE, and residual Moran's I are shown in each panel. The color bar indicates the logarithmic sample count.

Table 2. Product-level benchmark of residual-correction models during the calibration and temporal transfer periods. Values are mean $\pm$ standard deviation of annual metrics. The CASA baseline and all residual-correction models were evaluated under the final product-level protocol, in which the predicted residual was added back to CASA NPP and the resulting NPP product was compared against the MODIS-constrained target. The calibration period covers 2005–2013, and the temporal transfer period covers 2014–2020. R^2 and CCC quantify product-level agreement, RMSE and bias quantify magnitude discrepancy, and residual Moran's I quantifies the spatial organization of the MODIS-referenced NPP residual field. Bias was calculated as the mean ($NPP_{\text{model}} - NPP_{\text{obs}}$). STS denotes the spatial trend-surface residual model, which includes longitude, latitude, their quadratic terms, and interaction terms. Boldface identifies the final selected GWR residual-alignment model and does not indicate the best value for every metric.

Calibration period (2005–2013).					
Model	R^2	RMSE	Bias	CCC	Residual Moran's I
CASA baseline	0.426 $\pm$ 0.085	86.71 $\pm$ 8.85	1.07 $\pm$ 13.61	0.693 $\pm$ 0.089	0.520 $\pm$ 0.129
OLS residual	0.520 $\pm$ 0.068	79.22 $\pm$ 6.79	0.29 $\pm$ 15.96	0.767 $\pm$ 0.037	0.408 $\pm$ 0.097
STS residual	0.584 $\pm$ 0.086	73.48 $\pm$ 7.63	0.27 $\pm$ 14.35	0.805 $\pm$ 0.028	0.348 $\pm$ 0.082
Random forest residual	0.680 $\pm$ 0.062	64.32 $\pm$ 4.86	−0.17 $\pm$ 4.14	0.846 $\pm$ 0.024	0.213 $\pm$ 0.076
XGBoost residual	0.675 $\pm$ 0.064	64.85 $\pm$ 5.27	0.09 $\pm$ 2.54	0.844 $\pm$ 0.025	0.226 $\pm$ 0.048
GWR residual	0.630 $\pm$ 0.071	69.20 $\pm$ 5.47	1.10 $\pm$ 14.71	0.828 $\pm$ 0.026	0.283 $\pm$ 0.111
Temporal transfer period (2014–2020).					
Model	R^2	RMSE	Bias	CCC	Residual Moran's I
CASA baseline	0.424 $\pm$ 0.023	91.44 $\pm$ 4.86	5.77 $\pm$ 16.15	0.595 $\pm$ 0.019	0.683 $\pm$ 0.042
OLS residual	0.553 $\pm$ 0.014	80.57 $\pm$ 4.34	3.61 $\pm$ 16.01	0.712 $\pm$ 0.014	0.523 $\pm$ 0.046
STS residual	0.638 $\pm$ 0.018	72.48 $\pm$ 3.16	12.96 $\pm$ 13.70	0.771 $\pm$ 0.011	0.415 $\pm$ 0.039
Random forest residual	0.580 $\pm$ 0.084	77.63 $\pm$ 6.92	31.74 $\pm$ 19.13	0.778 $\pm$ 0.031	0.415 $\pm$ 0.067
XGBoost residual	0.613 $\pm$ 0.034	74.88 $\pm$ 4.06	23.20 $\pm$ 15.97	0.793 $\pm$ 0.024	0.383 $\pm$ 0.079
GWR residual	0.673 $\pm$ 0.053	68.60 $\pm$ 3.87	18.42 $\pm$ 14.31	0.826 $\pm$ 0.014	0.333 $\pm$ 0.031

3.2.2. Final Product-Level Benchmark Under the Calibration–Transfer Protocol

The model-type benchmark was evaluated under the final product-level protocol (Table 2). For each residual-correction model, the predicted residual was added back to CASA NPP, and the resulting product was compared against the MODIS-constrained target. This design provides an end-to-end benchmark of corrected NPP products across the calibration period (2005–2013) and the temporal transfer period (2014–2020).

During calibration, random forest and XGBoost exhibited the strongest residual-fitting capacity, with R^2 values of 0.680 and 0.675, respectively. GWR showed lower fitting performance ($R^2 = 0.630$, RMSE = 69.20 g C m^{−2} yr^{−1}) than these two machine learning models during this period. However, in the temporal transfer period, GWR achieved the strongest combination of product-level agreement and residual spatial-organization reduction among all tested models, with $R^2 = 0.673$, RMSE = 68.60 g C m^{−2} yr^{−1}, CCC = 0.826, and residual Moran's I = 0.333.

The transfer period comparison indicates that the GWR layer achieved the best balance among product-level agreement, magnitude error, concordance, and residual spatial-organization reduction under the final product-level evaluation. OLS and STS improved over the CASA baseline, suggesting that global environmental relationships and coarse spatial trend terms captured part of the organized residual structure. Random forest and XGBoost also improved product-level agreement relative to CASA, though their transfer period performance remained below that of GWR. Local coefficient summaries further revealed spatial variation in residual–predictor relationships, supporting the use of a local residual-alignment layer for the Gannan Plateau.

3.3. Spatial Variability of Consistency Gain and Its Environmental Context

After accounting for initial error magnitude, GWR correction gains remained spatially heterogeneous (Figure 7). Raw gain was positive for 73.2% of pixels, with a median of $22.65 \text{ g C m}^{-2} \text{ yr}^{-1}$, indicating that most pixels exhibited reduced absolute disagreement after correction. After removing the baseline relationship between raw gain and initial absolute error, the median residualized gain decreased to $7.18 \text{ g C m}^{-2} \text{ yr}^{-1}$. The residualized gain distribution still showed considerable variation around zero, indicating that correction benefit was not solely determined by initial error magnitude.

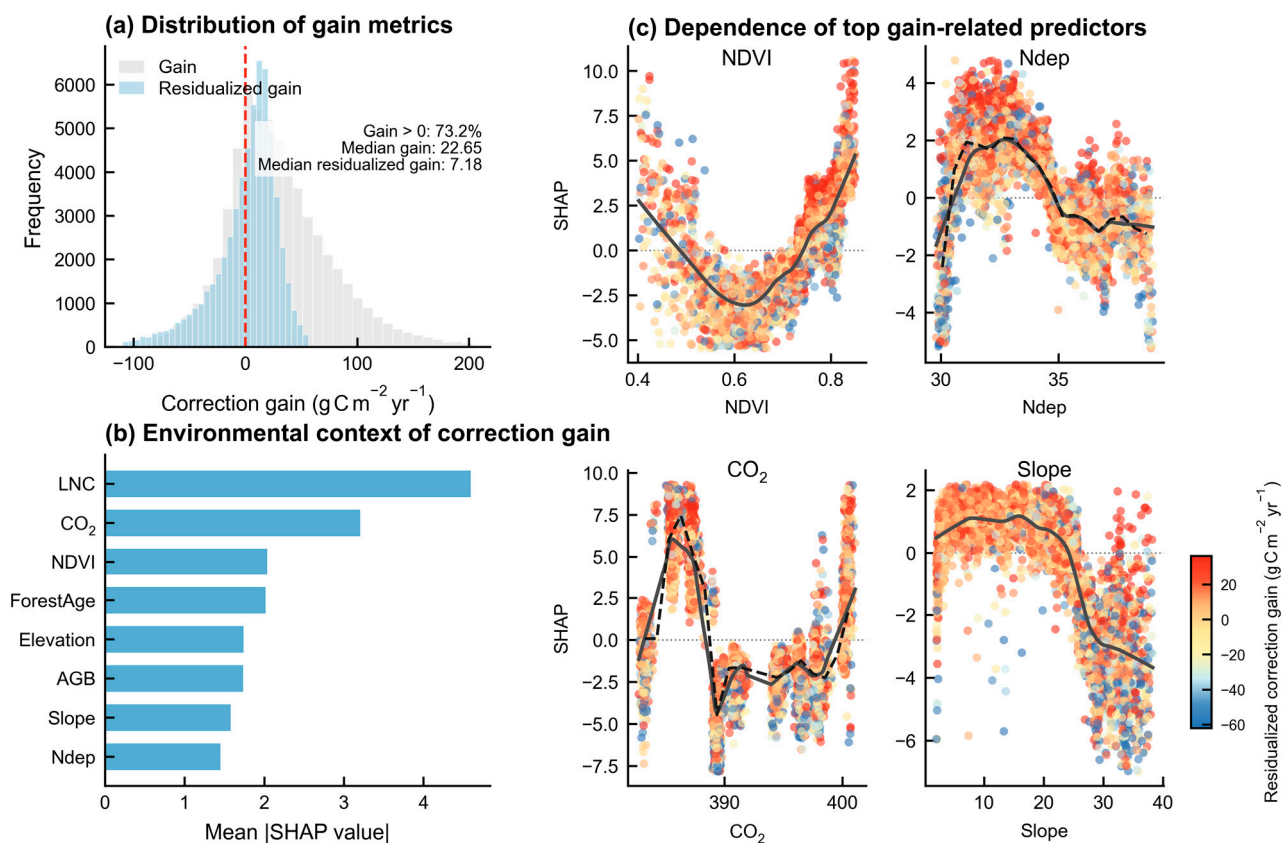


Figure 7. Correction-gain distribution and environmental context of residualized gain. (a) Distributions of raw correction gain and residualized correction gain. Raw gain was defined as the reduction in absolute MODIS-referenced disagreement after GWR correction, and residualized gain was calculated after removing its linear dependence on initial absolute disagreement. The red dashed line marks zero gain. (b) SHAP ranking of gain-related predictors using residualized gain as the response variable. (c) SHAP dependence patterns for the main gain-related predictors, with point color indicating residualized correction gain and the black curve showing the smoothed trend. The analysis characterizes the environmental context of correction benefit.

The gain-diagnostic XGBoost–SHAP analysis identified LNC, CO_2 , NDVI, ForestAge, elevation, AGB, slope, and Ndep as the leading gain-related variables (Figure 7). SHAP dependence plots revealed nonlinear associations between residualized gain and NDVI, Ndep, CO_2 , and slope. These patterns indicate that pixels with similar initial error magnitude can exhibit differing correction gains depending on vegetation, nutrient-background, atmospheric, and topographic contexts.

3.4. Cross-Product Benchmark with GLASS and Scenario Transfer Response

The GLASS comparison provided an independent product-level benchmark for the corrected CASA–NPP product (Figure 8). During the 2014–2020 temporal transfer period,

GWR-corrected NPP showed a Pearson correlation of $r = 0.841$ with the MODIS-constrained target and $r = 0.758$ with GLASS. The improvement observed against GLASS was smaller than that against MODIS, consistent with the magnitude difference between the MODIS and GLASS products. Nevertheless, both product comparisons indicated the same directional effect: GWR residual alignment improved product-level agreement and reduced spatial organization of the corresponding difference fields.

Product-level benchmark of GWR-corrected CASA-NPP with MODIS and GLASS

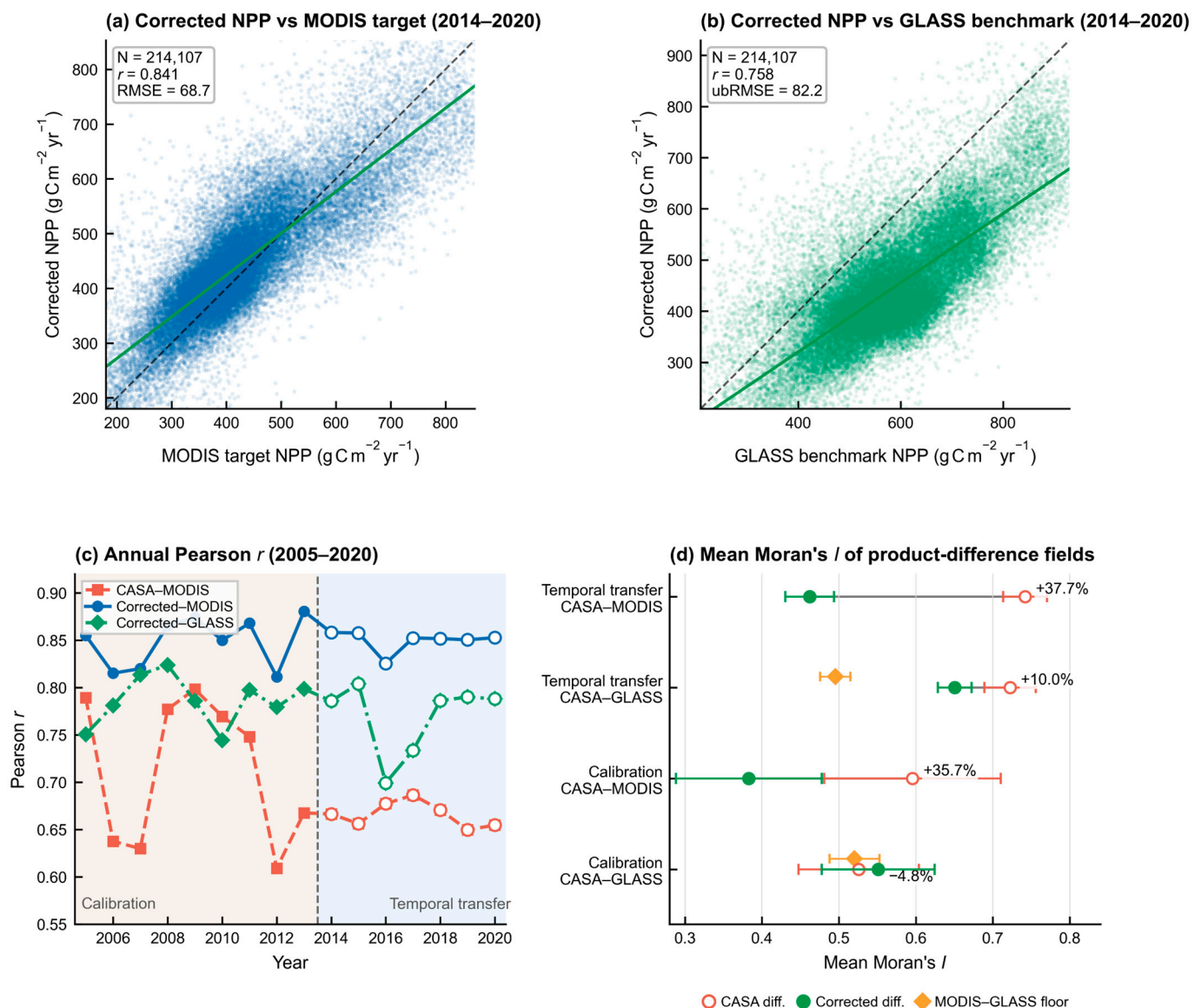


Figure 8. Product-level benchmark of GWR-corrected CASA-NPP against MODIS and GLASS. **(a)** Scatter distribution of corrected NPP versus the MODIS target during the 2014–2020 temporal transfer period; the dashed line is the 1:1 reference line, and the solid line is the fitted relationship. Sample size (n), Pearson correlation coefficient (r), and RMSE are shown. **(b)** Scatter distribution of corrected NPP versus the GLASS benchmark during the same period; the dashed line is the 1:1 reference line, and the solid line is the fitted relationship. Sample size (n), Pearson correlation coefficient (r), and unbiased RMSE (ubRMSE) are shown. **(c)** Annual Pearson r trends from 2005 to 2020, comparing CASA versus MODIS, corrected NPP versus MODIS, and corrected NPP versus GLASS; background shading delineates the calibration and temporal transfer periods. The red, blue, and green lines denote CASA–MODIS, corrected–MODIS, and corrected–GLASS correlations, respectively. **(d)** Mean Moran's I of product-difference fields before and after correction. Pre-GWR and Post-GWR

represent the spatial organization of MODIS- or GLASS-referenced difference fields before and after correction, respectively. The MODIS–GLASS floor represents the inter-product difference field between MODIS and GLASS. Error bars indicate interannual dispersion, and percentages indicate the relative decrease in Moran's I after correction.

The 2030s scenario transfer experiment showed that applying the fitted GWR residual-alignment layer altered the spatial expression of NPP differences among SSP pathways (Figure 9). Using the final predictor specification, historical standardization parameters, and scenario forcing inputs, GWR-corrected NPP changed the regional mean differences between scenario pairs relative to uncorrected CASA, with positive changes for the three pathway contrasts examined. The largest regional change occurred for SSP5-8.5 minus SSP1-2.6. Spatially, positive pathway-divergence changes were concentrated mainly in the eastern and central parts of the study area. These results suggest that the residual-alignment layer modulates the spatial expression of scenario contrasts under future forcing inputs.

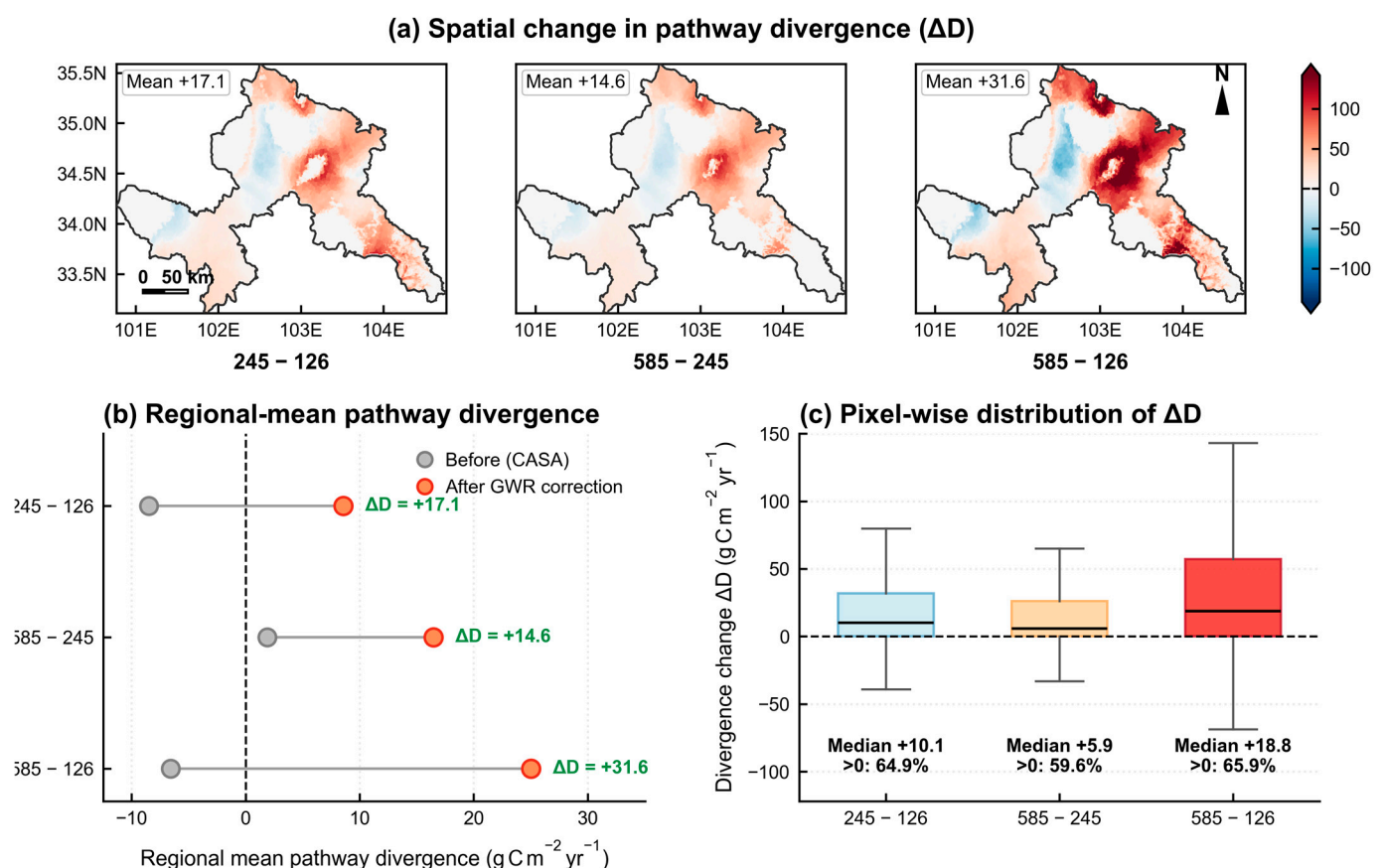


Figure 9. Changes in NPP pathway divergence among SSP scenarios in the 2030s scenario transfer experiment after GWR correction. **(a)** Spatial distribution of NPP pathway-divergence change (ΔD) under three SSP scenario pairs: SSP2-4.5 minus SSP1-2.6, SSP5-8.5 minus SSP2-4.5, and SSP5-8.5 minus SSP1-2.6. ΔD is defined as the corrected scenario difference minus the original CASA scenario difference. Positive values indicate increased inter-scenario divergence after correction, whereas negative values indicate reduced divergence. **(b)** Dumbbell plot comparing regional mean scenario differences before correction (CASA, gray dots) and after correction (GWR-corrected, orange dots); connecting lines and annotations quantify the regional-scale change. The dashed reference lines in panels (b) and (c) indicate zero regional-mean pathway divergence and zero pixel-level divergence change, respectively. **(c)** Box plot of the pixel-level distribution of ΔD across the study area. The

interquartile range is shown, with outliers omitted for clarity. Annotations show the spatial median and the percentage of pixels with positive values. All NPP differences and divergence-change values are in $\text{g C m}^{-2} \text{ yr}^{-1}$.

4. Discussion

4.1. Positioning and Significance of the CASA-Based, MODIS-Constrained Framework

The results indicate that CASA–MODIS residuals on the Gannan Plateau exhibit clear spatial organization and multi-factor environmental associations [41,58,59]. Residual clusters did not correspond consistently to any single environmental factor, and the predictor structure of the residuals differed from the dominant gradients of MODIS-constrained target and CASA-simulated NPP. This pattern suggests that local CASA–MODIS disagreement is shaped by combined environmental settings, including vegetation condition, hydrothermal gradients, atmospheric forcing, nutrient background, and terrain context [60–62]. In alpine complex environments, these factors jointly affect the local agreement between process-model simulations and remote-sensing products.

The SHAP comparison among MODIS-constrained target, CASA-simulated NPP, and CASA–MODIS residuals further clarifies the role of residual diagnostics (Figure 5). Productivity-related variables such as ForestAge, elevation, clay content, and NDVI were important for MODIS-constrained target, whereas residual-related importance shifted toward CO_2 , VPD, Ndep, and NDVI [12,13,19,63]. The elevated contribution of Ndep in the residual diagnostic model suggests that nutrient-background information helped explain part of the CASA–MODIS disagreement. Residual analysis thus offers a practical means of identifying where the CASA baseline requires spatially differentiated alignment with the MODIS-constrained target.

4.2. Spatially Explicit Residual Alignment and Temporal Transfer

Within this framework, GWR serves as a spatially explicit residual-alignment layer added to the CASA baseline. A global correction can reduce regional mean discrepancy, yet it has limited capacity to represent coexisting underestimation and overestimation across heterogeneous alpine landscapes. By allowing residual–predictor relationships to vary spatially, GWR is well suited to residual fields that exhibit significant local clustering and spatially varying environmental associations [42,43,64].

The comparison with OLS and STS supports this interpretation. STS improved over OLS, indicating that large-scale spatial trend terms captured part of the organized residual structure [19,65,66]. However, its transfer period RMSE and residual Moran's I remained higher than those of GWR, suggesting that coarse spatial trend terms did not fully describe the local residual pattern. The final product-level benchmark showed a calibration–transfer trade-off: random forest and XGBoost achieved stronger calibration-period fitting capacity, whereas GWR provided the strongest temporal transfer balance across R^2 , RMSE, CCC, and residual Moran's I among the models tested in this study (Table 2; Figure S4). This result provides empirical support for using GWR within the present workflow, but it does not establish that GWR is universally superior to other spatially informed approaches. Although these methods were not evaluated in the present study, spatial random forest approaches such as RFsp, geographically weighted random forest, and CatBoost or LightGBM models incorporating coordinates or other spatial predictors may also be suitable alternatives for residual correction. GWR was selected here because its local coefficient surfaces provide an interpretable and transparent residual-alignment layer that can be directly linked to the CASA baseline and transferred under a consistent coefficient-surface framework [31,64]. A systematic comparison with a broader family of spatial machine learning methods remains an important direction for future work.

The multi-year pooled GWR design estimates recurrent residual–environment relationships within the historical period. In alpine complex environments, slowly changing variables such as topographic position, soil and nutrient background, and vegetation developmental state define persistent local environmental settings. In contrast, annual climate and vegetation variables modulate year-specific residual expression [60,67]. Studies of alpine plant communities and cold-region vegetation have also reported lagged or disequilibrium responses to climate change. This supports using a multi-year window to stabilize residual-alignment estimates across adjacent years [60,68]. Pooling samples from 2005 to 2013 helps reduce anomalous-year noise and extract local relationships applicable to 2014–2020 temporal transfer. Supplementary robustness analyses further indicate that the improvement is associated with local relationship characterization under predictor redundancy and collinearity control [31,64].

4.3. Cross-Product Benchmark, Scenario Transfer, Applicability, and Limitations

The residualized gain analysis provides a more stable basis for examining spatial variation in correction benefit than raw gain alone. Raw gain is directly affected by pre-correction error magnitude. Residualized gain removes the baseline relationship between gain and initial absolute error [69]. After this adjustment, correction benefit still varied across environmental contexts (Figure 7). The gain-diagnostic SHAP results associated higher or lower residualized gain with vegetation condition, nutrient background, atmospheric forcing, biomass structure, and terrain variables. These results suggest that GWR residual alignment is most informative where CASA–MODIS disagreement has an identifiable local residual–environment association [16,30,70].

The GLASS comparison provides a product-level benchmark for the corrected CASA–NPP product. Corrected NPP showed stronger association with MODIS than with GLASS. This reflects the role of MODIS as the correction target and the magnitude differences between remote-sensing products [11,71]. The GLASS-based comparison still showed a directionally consistent improvement relative to the CASA baseline, with reduced spatial organization in the GLASS-referenced difference field. These results support the cross-product relevance of the correction and also indicate that product uncertainty remains an important boundary for interpretation.

These product-level comparisons should not be interpreted as evidence that the corrected product is closer to actual ecosystem NPP. Because the residual-alignment layer was calibrated against MODIS and evaluated primarily against the same product, the reported gains quantify improved consistency with the MODIS-constrained target. GLASS provides an independent product-level comparison, but it is also a remote-sensing NPP product rather than ground truth and therefore does not substitute for field or flux observations. In the absence of independent field-measured NPP or flux-based ecosystem-productivity constraints, this study cannot determine whether actual NPP estimation has improved.

The 2030s scenario transfer experiment shows that the residual-alignment layer alters the spatial expression of NPP differences among SSP pathways. Using the final predictor specification, historical standardization parameters, and scenario forcing inputs, GWR correction changed regional mean differences among several scenario pairs. Positive pathway-divergence changes were concentrated in the eastern and central parts of the study area. This result represents a methodological scenario transfer outcome [72]. It illustrates how a historically fitted residual-alignment layer can modulate scenario contrasts under future forcing assumptions. Future process validation would require independent future observations or additional process constraints. Scenario interpretation also remains subject to future forcing uncertainty and potential nonstationarity in residual–environment relationships [73,74].

The framework has three main applicability conditions. First, the correction target determines the meaning of consistency. In this study, MODIS defines the primary observational constraint, and GLASS provides a product-level benchmark [11,71]. Second, transfer application of GWR relies on persistence in residual–environment relationships over the evaluated period [16,30,70]. Third, future scenario application is affected by forcing uncertainty, including future climate, Ndep, LUCC, and the fixed-NDVI assumption [72–74]. These conditions define the scope of the proposed CASA-based, MODIS-constrained framework.

5. Conclusions

Using the Gannan Plateau on the northeastern margin of the Qinghai–Tibet Plateau as a case study, this study developed a CASA-based, MODIS-constrained framework for annual NPP simulation in alpine complex environments. The framework combines a locally parameterized CASA baseline with a spatially explicit GWR residual-alignment layer. This layer was trained on CASA–MODIS residuals. During the 2014–2020 temporal transfer period, GWR-corrected CASA–NPP showed stronger agreement with the MODIS-constrained target than parameter-localized CASA. R^2 increased from 0.438 to 0.708, and RMSE decreased from 91.4 to 68.7 g C m⁻² yr⁻¹. Residual Moran’s I also decreased after GWR residual alignment, indicating weaker residual spatial organization. These changes quantify improved consistency with the MODIS-constrained target and should not be interpreted as evidence that the corrected product is closer to actual NPP.

The final product-level benchmark showed that random forest and XGBoost had stronger calibration-period fitting capacity, whereas GWR achieved the strongest transfer period balance across R^2 , RMSE, CCC, and residual Moran’s I among the models tested in this study. This result supports GWR as an interpretable and practical choice for the present residual-alignment workflow, but it does not imply universal superiority over other spatially informed methods. The GLASS product-level benchmark showed a smaller but directionally consistent improvement; however, GLASS is also a remote-sensing NPP product rather than ground truth. Accordingly, this cross-product comparison does not validate improvement in actual NPP accuracy. The residualized gain analysis further showed that correction benefit varied with vegetation, nutrient-background, atmospheric, biomass, and topographic contexts. This variation remained after accounting for initial error magnitude.

The 2030s SSP scenario transfer experiment showed that the residual-alignment layer altered the spatial expression of NPP pathway divergence under future forcing inputs. This application demonstrates the methodological value of applying a historically fitted residual-alignment layer to scenario comparison. However, its interpretation remains bounded by forcing uncertainty and future nonstationarity.

Overall, the proposed framework provides a process-model-preserving and observation-constrained approach for improving consistency between CASA-based annual NPP estimates and the MODIS product in alpine heterogeneous regions. The present study does not provide evidence that actual NPP estimation has improved because independent field-based NPP measurements or flux-based productivity observations were unavailable. Future work should combine such independent observations with systematic comparisons of additional spatially informed correction methods that were not evaluated in the present study, and should further examine dynamic vegetation assumptions. These extensions would allow actual NPP performance, methodological generality, and scenario-transferability to be evaluated more rigorously.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/rs18152456/s1>, Figure S1: Annual transfer-period

performance under the final GWR residual-alignment layer; Figure S2: Bandwidth sensitivity of the GWR residual-alignment layer; Figure S3: Product-level MODIS–GLASS benchmark and cross-product agreement diagnostics; Figure S4: Final product-level benchmark of residual-correction models during the calibration and temporal-transfer periods; Table S1: Reproducibility settings of the final GWR residual-alignment layer; Table S2: Annual transfer-period performance and residual Moran’s I of GWR-corrected CASA–NPP during 2014–2020; Table S3: Bandwidth sensitivity of the GWR residual-alignment layer; Table S4: Ridge λ sensitivity of the GWR residual-alignment layer; Table S5: Local collinearity and feature-exclusion rank diagnostics; Table S6: MODIS–GLASS product-level benchmark; Table S7: Predictor-set robustness analysis; Table S8: Annual product-level benchmark of residual-correction models during the temporal-transfer period; Table S9: Spatial-dependence-aware temporal-transfer robustness diagnostics; Table S10: SSP forcing metadata and scenario-transfer assumptions; Table S11: Nitrogen deposition metadata and scenario-transfer treatment.

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