

Radar-optical fusion of Sentinel-1/2 for high-resolution NDVI reconstruction and landscape-driven carbon flux assessment in Kuala Selangor, Malaysia (2020–2024)

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ABSTRACT

Reliable quantification of carbon fluxes in humid tropical regions is constrained by persistent cloud cover, heterogeneous land mosaics, and the limited resolution of existing products. To address these challenges, this study developed a Cloud-Resilient Fusion Network (CRFNet) that integrates Sentinel-1 SAR backscatter with cloud-screened Sentinel-2 NDVI using a CNN–BiLSTM–multi-head attention architecture. The framework reconstructed 10 m NDVI time series in Kuala Selangor, Malaysia (2020–2024), achieving annual R^2 above 0.82 and RMSE below 0.12, thereby improving temporal continuity under heavy cloud–rainfall interference. The reconstructed NDVI was used to drive a light-use-efficiency model for net ecosystem productivity (NEP) estimation, supported by temperature-based heterotrophic respiration. Results showed a 7.4 % decline in mean annual NEP across five years, with degraded mangroves and sloping croplands emerging as hotspots of sink-to-source transitions. Landscape analysis revealed strong structure–function coupling: stable forests and mangroves were characterized by large cohesive patches with largest patch index values above 40 % and edge density below 20 m ha^{−1}, while croplands and degraded slopes exhibited higher patch numbers, reduced patch dominance, and greater edge complexity, which increased carbon source risk. By linking fine-scale NDVI reconstruction with process-based carbon modeling and landscape metrics, this study provides a transferable workflow for high-resolution carbon flux monitoring and a robust scientific basis for carbon budget assessment, ecosystem management, and carbon-neutrality planning in tropical monsoon regions.

1. Introduction

Against the backdrop of global climate change, the carbon cycle of terrestrial ecosystems plays a vital role in maintaining climate regulation and ecosystem stability (Beer et al., 2010). The tropical region has extremely high primary productivity and carbon sink potential due to its abundant solar radiation, sufficient precipitation and high biodiversity (Sayer et al., 2024). Tropical regions cover only about 12 % of the global land area. Yet, they contribute more than 40 % of terrestrial net primary productivity (NPP) and account for over one-third of the global carbon sink capacity (Sha et al., 2022). However, tropical carbon sinks are weakening. Intensified land use change, anthropogenic disturbance, and

more frequent extreme climate events have substantially reduced the sink function. Several regions have even shifted from carbon sinks to carbon sources (Gatti et al., 2021). In addition, the ecological mosaic of tropical regions-comprising forests, wetlands, mangroves, and agricultural lands-presents a highly fragmented and heterogeneous spatial pattern (Friess et al., 2019), which significantly complicates the fine-scale modeling and monitoring of carbon flux. This complexity is further exacerbated by the pronounced spatiotemporal variability in ecosystem processes, rendering conventional approaches based on medium- to low-resolution remote sensing products insufficient for capturing fine-scale carbon dynamics in these regions (Hu et al., 2023).

The Normalized Difference Vegetation Index (NDVI) remains one of

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the most widely used indicators for assessing vegetation photosynthetic activity, canopy structure, and growth status, and it plays a central role in linking remote sensing observations to ecological modeling (Capelle et al., 2022; Dong et al., 2025). NDVI is extensively applied in the estimation of carbon flux components such as NPP, heterotrophic respiration (Rh), and net ecosystem productivity (NEP), yet its effectiveness in tropical environments is constrained by persistent cloud cover, frequent rainfall, and extensive cloud shadow contamination, which result in severe data gaps in optical remote sensing products (Li et al., 2022). Even with Sentinel-2's five-day revisit cycle, annual effective observations in Southeast Asia typically remain below 30, far fewer than in mid-latitude regions, leading to fragmented time series and compromised reliability (Wang et al., 2023). Such discontinuities reduce the temporal coherence of NDVI data. They also limit its accuracy in carbon flux modeling (Frankenberg et al., 2024). Thus, improving the temporal continuity of NDVI while maintaining high spatial resolution and ecological relevance remains a pressing challenge for carbon flux monitoring in tropical cloudy regions (He et al., 2023).

To address the persistent gaps in optical remote sensing NDVI, multi-source data fusion and time series reconstruction techniques have emerged as promising approaches (Zhu et al., 2022). Synthetic Aperture Radar (SAR), with its all-weather, day-and-night imaging capability, provides complementary structural and moisture information for tropical landscapes (Y. Chen et al., 2024). Specifically, Sentinel-1's VV/VH backscatter characteristics are strongly correlated with vegetation structure and soil moisture, making them effective auxiliary variables for reconstructing optical NDVI (G. Chen et al., 2024). Meanwhile, deep learning methods, with their superior ability to model nonlinear relationships and extract spatiotemporal features, have demonstrated strong potential in time series reconstruction, phenological analysis, and multi-source data fusion (Li et al., 2024). Architectures combining convolutional neural networks (CNNs), recurrent neural networks (RNNs), and attention mechanisms have shown particular promise in capturing complex spatiotemporal dependencies for high-precision NDVI prediction (Ojwang et al., 2024). Nevertheless, challenges remain. Multi-source time series consistency is often overlooked. The ecological interpretability of model outputs is limited. Validation in highly cloudy tropical environments is also scarce (X. Chen et al., 2024). These limitations highlight the need for a robust deep learning framework that integrates multi-source data and addresses the unique complexities of tropical ecosystems.

In this study, we propose the **Cloud-Resilient Fusion Network (CRFNet)**, a deep learning model designed to integrate Sentinel-1 SAR backscatter (VV/VH) and Sentinel-2 optical NDVI with cloud mask information to achieve high-resolution, temporally continuous NDVI reconstruction in tropical cloudy regions. We selected Kuala Selangor, Malaysia, as the study area. This tropical monsoon region has diverse land cover types, including mangroves, paddy fields, wetlands, and tropical forests. It also shows pronounced landscape heterogeneity (Pacheco-Cancino et al., 2024). The reconstructed NDVI time series were then used to drive a light use efficiency (LUE) model for estimating NEP from 2020 to 2024. Furthermore, land use/cover (LULC) data and landscape metrics such as patch number, maximum patch index, and edge density were incorporated to analyze the spatial heterogeneity of NEP and its driving mechanisms. The objectives of this study are: (1) to construct and evaluate the CRFNet model for robust NDVI reconstruction under persistent cloud cover; (2) to achieve fine-scale NEP estimation based on the reconstructed NDVI; and (3) to explore the spatial heterogeneity and structural drivers of carbon flux through landscape pattern analysis. This study provides methodological innovation for NDVI reconstruction and carbon flux estimation in tropical regions, offering a high-resolution scientific basis for regional carbon neutrality strategies and ecosystem management (Poulter et al., 2022).

2. Research methodology

2.1. Study area

This study selected Kuala Selangor (3°15'–3°45' N, 101°10'–101°35' E) on the west coast of Peninsular Malaysia as the study area. The region has a typical tropical monsoon climate (Fig. 1). The mean annual rainfall is about 2500 mm. The temperature remains between 26 and 32 °C throughout the year, and the air humidity stays high for extended periods (De La Barreda-Bautista et al., 2024). In this region, the wet season generally spans from October to March, while the dry season extends from April to September. Precipitation and radiation are controlled by the alternation of northeast and southwest monsoons (Vijayanathan et al., 2021). Interannual variability is strongly modulated by El Niño–Southern Oscillation (ENSO) events. The years 2020 and 2022 were La Niña years, characterized by earlier and prolonged rainy seasons, higher total rainfall, and reduced solar radiation. The year 2023 corresponded to an El Niño phase, marked by reduced rainfall, higher radiation, and frequent dry spells. The years 2021 and 2024 were neutral years, with hydroclimatic conditions falling between these extremes (Tangang et al., 2017). The terrain consists mainly of coastal alluvial plains and low hills, with elevations below 100 m. Local estuarine deltas have formed under tidal and sediment deposition, creating extensive mangrove wetlands (Pacheco-Cancino et al., 2024). The regional land use/cover types are highly heterogeneous, including mangroves, river wetlands, lowland rainforests, oil palm plantations, farmlands and rapidly expanding built-up areas (Ehsan et al., 2022). This complex pattern of natural and artificial landscapes leads to significant spatial mosaic of carbon source-sink states and significant differences in responses to climate anomalies, making this region an ideal sample area for testing remote sensing methods of carbon dynamics in tropical cloudy areas.

2.2. Data and preprocessing

2.2.1. Data sources and acquisition

This study integrates multi-source remote sensing and environmental datasets to support high-resolution NDVI reconstruction and carbon flux estimation for the period 2020–2024. The core remote sensing data include Sentinel-1 synthetic aperture radar (SAR) imagery, which provides C-band backscatter coefficients in VV and VH polarization modes with a 6–12-day revisit cycle and all-weather observation capability (Vreugdenhil et al., 2018), and Sentinel-2 multispectral imagery, which offers surface reflectance products across 13 spectral bands (400–2400 nm), of which the red (Band 4) and near-infrared (Band 8) bands are used for NDVI computation (Li et al., 2022). In addition to the remote sensing data, climate and ecological driving variables were incorporated for carbon flux modeling. These include monthly cumulative precipitation from CHIRPS (~5 km resolution), monthly mean temperature and photosynthetically active radiation (PAR) from ERA5-Land (~10 km resolution) (Muñoz-Sabater et al., 2021), and terrain attributes derived from the 30 m Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM). Soil properties were represented by soil organic carbon (SOC) data from OpenLandMap (~250 m resolution) (Cai, 2025), which served as auxiliary variables for carbon cycle modeling. Land cover information was extracted from the ESA WorldCover 2020 product at 10 m resolution, covering major land types such as forests, wetlands, croplands, and mangroves (Xu et al., 2024; Zanaga et al., 2021).

Table 1 provides a summary of the main datasets used in this study, including their sources, spatial resolutions, temporal coverage, and roles in NDVI reconstruction and carbon flux estimation.

2.2.2. Preprocessing and sample construction

Acquire 2020–2024 Sentinel-1C-band synthetic aperture radar (SAR) Ground Range Detected (GRD) images (VV, VH polarization, 10 m

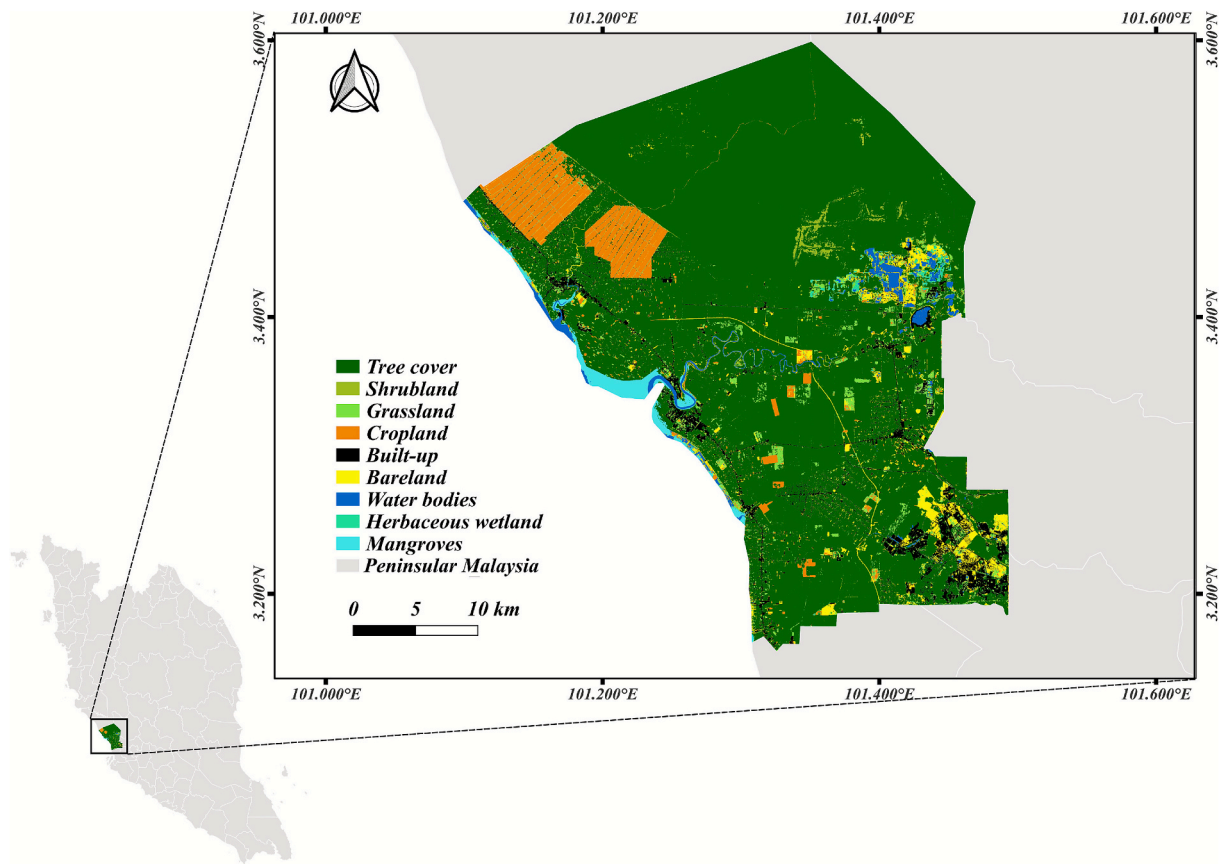


Fig. 1. Study area in Kuala Selangor, Peninsular Malaysia, and dominant land-cover classes (ESA WorldCover 2020, 10 m).

Table 1

Overview of major remote sensing and environmental datasets used in research.

Data Type	Time Range	Spatial Resolution	Source Platform
Sentinel-1 GRD SAR Data	2020–2024	10 m	Google Earth Engine
Sentinel-2 L2A Optical Imagery	2020–2024	10 m	Copernicus Open Access Hub (ESA)
CHIRPS Monthly Precipitation	2020–2024	~5 km	Google Earth Engine
ERA5-Land Monthly Climate Variables	2020–2024	~10 km	Google Earth Engine
FLDAS Soil Moisture	2020–2024	~10 km	Google Earth Engine
SRTM Terrain Indices (DEM, Slope, etc.)	Static	30 m	Google Earth Engine
OpenLandMap Soil Organic Carbon (SOC)	Static	~250 m	Google Earth Engine
ESA WorldCover Land Use Map	2020	10 m	Google Earth Engine

resolution) and Sentinel-2 Level-2A multispectral images (13 bands, 10 m resolution) (ESA Copernicus Open Access Hub, 2022). In view of the problem that optical observations in tropical regions are easily disturbed by clouds and rain, a multi-step quality control strategy is adopted: first, a pixel-level cloud mask is generated based on the Sentinel-2 Scene Classification Layer (SCL), and images with cloud coverage exceeding 80 % or full-frame NDVI missing are removed (Sanchez et al., 2020); second, CHIRPS daily rainfall data is introduced to remove images with rainfall exceeding 10 mm on the day of acquisition to reduce spectral anomalies caused by surface water accumulation (Mu et al., 2024); finally, based on the Sentinel-1 image as the benchmark, a ± 7 -day time tolerance window is used to match the Sentinel-2 image with the closest phase to form a radar-optical paired dataset for NDVI reconstruction model training (Roßberg and Schmitt, 2023).

Fig. 2 shows the monthly mean cloud fraction (%) of usable and matched Sentinel-2 scenes from 2020 to 2024. White cells indicate months with no valid scenes after quality control, reflecting complete optical data loss caused by extensive cloud obstruction. In such months, NDVI reconstruction is not possible; CRFNet fills cloud-induced gaps by combining Sentinel-1 with available Sentinel-2 inputs, but cannot operate when no usable optical data exist.

Fig. 3 shows the month-by-month pairing between Sentinel-1 and Sentinel-2 from 2020 to 2024. The timeline provides a fine-scale view of sample construction. Sentinel-1 acquisitions are regular, while Sentinel-2 availability varies by month. Matched pairs are frequent from January to May in 2020 and 2021, in May and June of 2022, and from March to June of 2023. Months with few or no pairs include June to December 2020, August to October 2022, July to December 2023, and many months in 2024. Within each matched scene, the validation subset uses only cloud-free pixels from the Sentinel-2 image; reconstructed NDVI from Sentinel-1 is compared against those pixels.

Table 2 reports annual totals for scene availability and pairing outcomes, including Sentinel-1 effective acquisitions, Sentinel-2 raw and eligible scenes, paired Sentinel-2 counts, pairing rate, and unmatched categories. These totals make the pool of usable samples explicit for training and validation.

To support carbon flux modeling and spatial heterogeneity analysis, multiple ecological and environmental variables were integrated: climate data included monthly cumulative rainfall from CHIRPS (approximately 5 km resolution) and monthly mean temperature and PAR from ERA5-Land (approximately 10 km resolution) (Hersbach et al., 2020); soil data used soil organic carbon (SOC) from OpenLandMap (approximately 250 m resolution) (Hengl et al., 2014); terrain data from the Shuttle Radar Topography Mission (SRTM) digital elevation model (30 m resolution) was used to calculate terrain correction factors such as slope; and land use data from the ESA WorldCover 2020

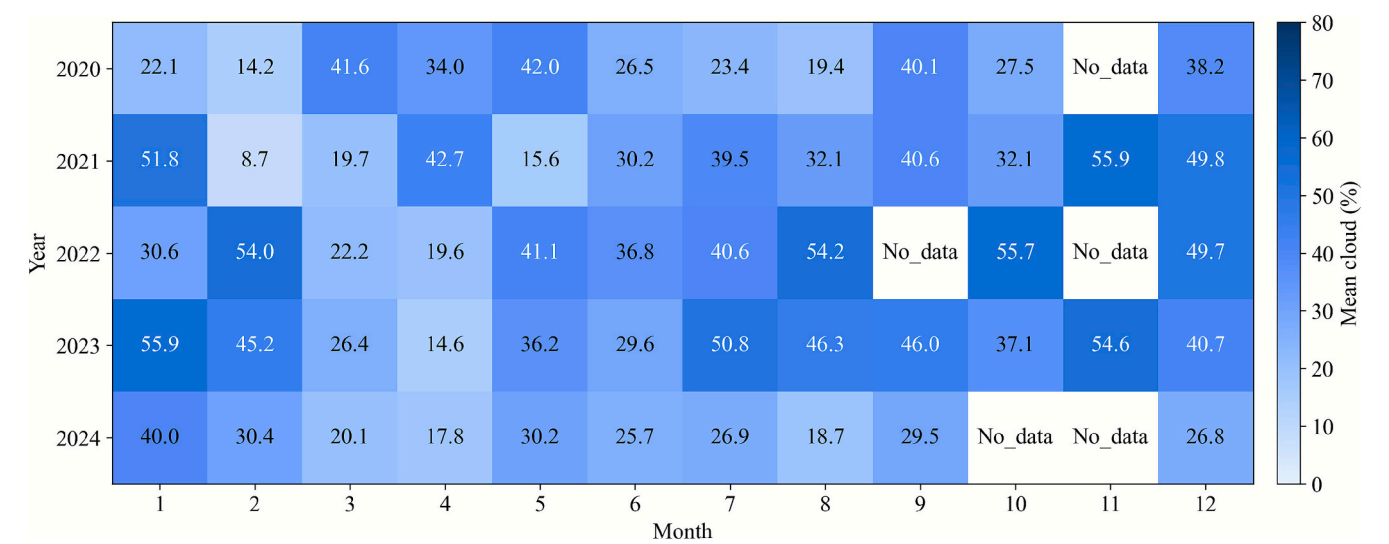


Fig. 2. Monthly mean cloud fraction (%) of usable Sentinel-2 scenes from 2020 to 2024. White cells indicate months with no valid scenes after quality control.



Fig. 3. Monthly Sentinel-1 and Sentinel-2 pairing outcomes from 2020 to 2024.

Table 2
Annual Sentinel-1 and Sentinel-2 pairing outcomes (2020–2024).

Indicators	2020	2021	2022	2023	2024
Sentinel-1 effective acquisitions	31	31	31	31	30
Sentinel-2 raw scenes	58	66	56	71	69
Sentinel-2 eligible after screening	23	44	37	54	31
Paired Sentinel-2 NDVI scenes	21	27	24	31	24
Pairing rate (%; paired Sentinel-2)	91.3	61.4	64.9	57.4	77.4
Sentinel-1 unmatched acquisitions	10	4	7	0	6
Sentinel-2 usable but unmatched scenes	5	20	14	23	8
Sentinel-2 not-usable scenes after QC	35	22	19	17	38

product (10 m resolution) covering major land types such as forests, wetlands, farmland, and mangroves (Burton et al., 2024).

All datasets were projected to WGS84 and resampled to a common 10 m NDVI grid. Continuous variables (e.g., precipitation, temperature, PAR, elevation, SOC) were resampled using bilinear interpolation, while categorical variables (land cover) were resampled with nearest-neighbor to preserve class labels. For coarse-resolution inputs, each parent pixel was disaggregated into 10 m sub-pixels with constant values, assuming homogeneity within the coarse pixel. This ensured exact pixel-level alignment with the NDVI reference grid, while acknowledging potential smoothing and aliasing effects. All outputs were compressed GeoTIFFs with unified nodata handling, clipped to the study area. These

resampling steps inevitably reduce fine-scale variability from coarser inputs and may introduce block effects, but they ensure spatial consistency across variables. The resulting dataset provides a harmonized framework suitable for model training, while residual scale-related uncertainties are further considered in the interpretation of results.

2.3. Methods

2.3.1. Method Overview

To address the dual challenges of severe lack of optical remote sensing data in tropical cloudy areas and insufficient accuracy of carbon flux estimation, this study proposes a comprehensive framework for NDVI reconstruction and NEP estimation driven by multi-source remote sensing (Fig. 4). This framework combines deep learning-based spatio-temporal feature modeling with ecological process-driven carbon cycle modeling. The goal is to achieve time-series continuous reconstruction of high-resolution NDVI and provide refined estimation of NEP.

The overall method includes four core links: (1) Multi-source data preprocessing and sample construction: integrating SAR and optical images, removing high cloud cover and rainfall interference images, and constructing a high-quality paired sample set; (2) Development and training of NDVI time series reconstruction model (CRFNet): designing a deep learning model that integrates convolutional neural network (CNN), bidirectional long short-term memory network (Bi-LSTM) and multi-head self-attention mechanism (MHA) to achieve joint modeling

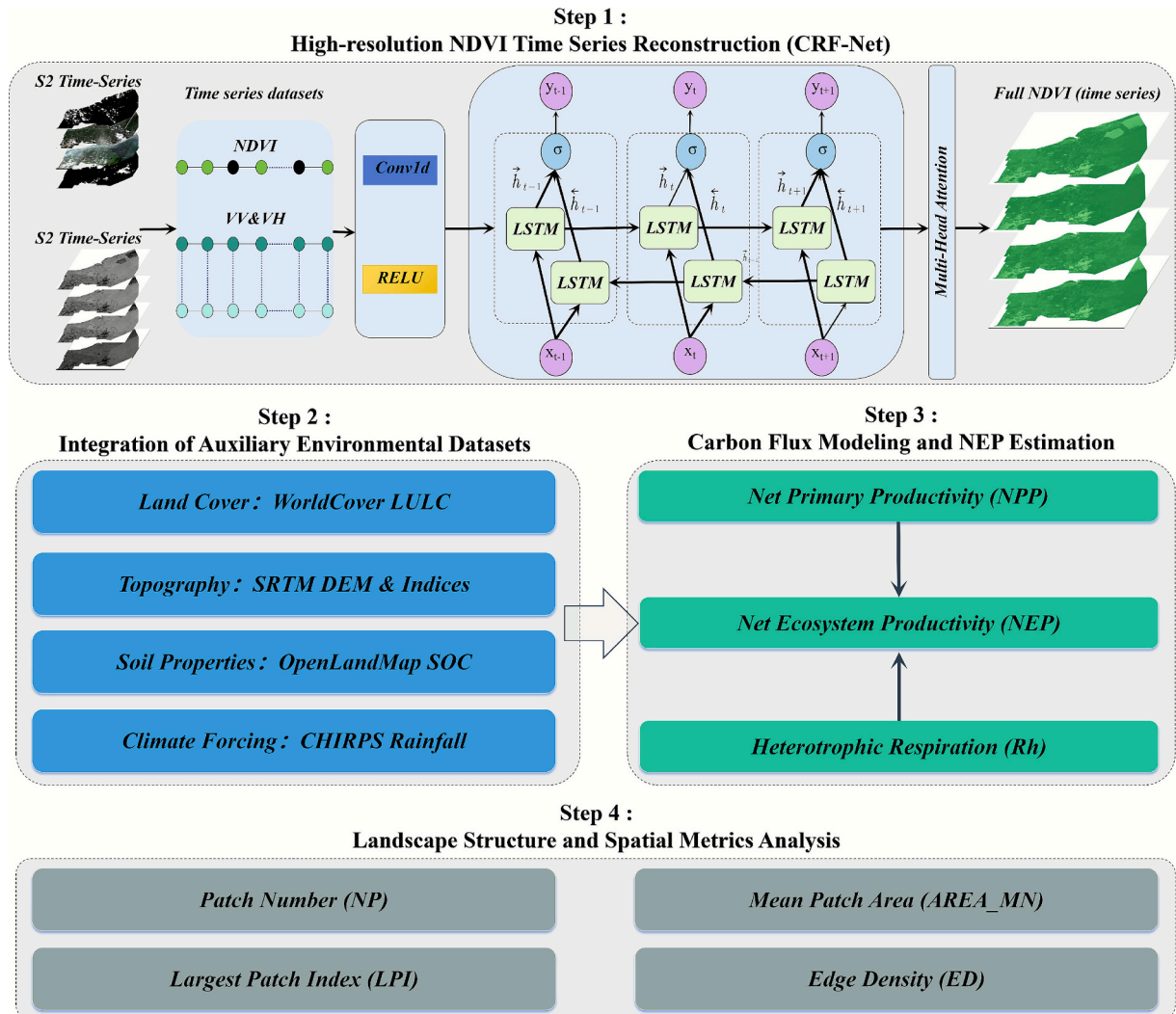


Fig. 4. Research methods and workflow for CRFNet radar-optical fusion, NDVI reconstruction, and NEP mapping (2020–2024).

of multi-source data and high-precision reconstruction of NDVI pixel by pixel; (3) NEP estimation: using the reconstructed NDVI sequence to drive the LUE model to estimate the NEP at the regional scale and reveal the dynamics of carbon budget; (4) Landscape pattern and land use coupling analysis: combining landscape pattern index with land use/cover (LULC) data to explore the spatial heterogeneity of NEP and its land type driving mechanism. Through this method, this study not only improved the temporal continuity of NDVI, but also enhanced the applicability of carbon flux modeling in the heterogeneous subsurface of cloudy tropical regions, providing technical support for regional carbon budget assessment and ecological management.

2.3.2. Crfnet architecture and implementation details

To address the long-term data gaps of Sentinel-2 NDVI in tropical cloudy regions, we developed a CRFNet that integrates multi-source radar and optical data for pixel-wise high-precision NDVI reconstruction. The model takes Sentinel-1 VV/VH backscatter coefficients, Sentinel-2 NDVI, and the corresponding cloud masks as inputs. A convolutional neural network (CNN) is first applied to extract local spatiotemporal features, followed by a bidirectional long short-term memory (Bi-LSTM) network to capture long-term dependencies (Y. Chen et al., 2024; Lasko, 2022). A multi-head self-attention (MHA) mechanism is then incorporated to assign higher weights to key time steps, thereby enhancing the model's sensitivity to abnormal vegetation dynamics. The final reconstructed NDVI values are produced through fully connected layers.

To improve gap filling performance in heavily cloud-masked areas, a mask-weighted mean squared error (mask-weighted MSE) loss function is introduced; higher weights are assigned to persistently cloud-affected pixels to optimize reconstruction under incomplete NDVI time series. This builds on similar cloud resilience strategies used in deep learning gap-filling frameworks (Lasko, 2022). Training employed the Adam optimizer with automatic mixed precision (AMP) to accelerate convergence, and early stopping to prevent overfitting. Model evaluation was conducted on independent validation samples using the coefficient of determination (R^2) and root mean square error (RMSE) as performance metrics (Zhao et al., 2020).

The mathematical formulations of CRFNet are expressed as follows:

$$z_t = \text{ReLU}(W_{\text{conv}} * x_t + b_{\text{conv}}) \quad (1)$$

$$h_t, c_t = \text{Bi-LSTM}(z_t, h_{t-1}, c_{t-1}) \quad (2)$$

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d}}\right)V \quad (3)$$

$$\hat{y}_t = W_{\text{out}}h_t + b_{\text{out}} \quad (4)$$

$$\text{Loss} = \frac{1}{N} \sum_{i=1}^N \{\text{Mask}(y_i - \hat{y}_i)^2\} \quad (5)$$

Among them, formula (1) is CNN local feature extraction, formula (2) is Bi-LSTM long-term dependency modeling, formula (3) is multi-head self-attention weighting, formula (4) is the linear output layer to generate reconstructed NDVI, and formula (5) is the mask weighted mean square error loss function.

The CRFNet architecture was implemented in PyTorch 2.2 with CUDA acceleration. The input sequence consisted of Sentinel-1 VV/VH backscatter and cloud-masked Sentinel-2 NDVI. A one-dimensional convolutional layer (kernel size = 3, 32 filters, ReLU activation) was first applied to extract local temporal features, followed by a single-layer bidirectional LSTM with 64 hidden units to capture sequential dependencies. The encoded features were then passed to a Transformer encoder composed of two stacked encoder layers, each with a hidden size of 64 and four attention heads, which enabled the model to attend to informative time steps under irregular cloud contamination. A fully connected layer with linear activation produced pixel-wise NDVI

predictions.

Model training used a mask-weighted mean squared error (MSE) loss, where cloud-free pixels were weighted higher to prioritize valid supervision and stabilize optimization under incomplete time series. Optimization was performed with Adam (learning rate = 0.001, weight decay = 1×10^{-5}) using automatic mixed precision (AMP) to accelerate training. A batch size of 64 and a maximum of 25 epochs were used, with early stopping (patience = 5 epochs) based on validation RMSE. To reduce overfitting, dropout (rate = 0.2) was applied in the fully connected layers.

During training, predictions were masked by valid pixels and evaluated against cloud-free Sentinel-2 NDVI observations. Performance was tracked using the coefficient of determination (R^2) and root mean square error (RMSE), recorded at each epoch. The best model checkpoint was saved when R^2 improved, and the training history was exported to CSV for reproducibility. The key input features, intermediate variables, and model parameters are summarized in Table 3 to provide a clear reference for implementation and replication. Formal definitions of evaluation metrics are given in Section 2.3.5.

2.3.3. Net ecosystem productivity (NEP) estimation method

To quantify the carbon balance of the study area, a LUE model was employed to estimate vegetation NPP, and an empirical temperature- and vegetation-driven model was applied to estimate Rh. NEP was calculated as the difference between NPP and Rh.

The LUE model assumes that vegetation productivity is proportional to the absorbed PAR and LUE, where NDVI serves as an approximate proxy for the fraction of absorbed PAR (fAPAR) (Xiao et al., 2019). This is combined with the maximum LUE (ϵ_{max}) and a slope correction factor to account for topographic and land-cover constraints on productivity (Zhang-Zheng et al., 2024).

Rh was estimated using an exponential model to simulate the nonlinear enhancement of soil microbial respiration with increasing vegetation activity and temperature (Beer et al., 2010). Finally, NEP was calculated as the difference between NPP and Rh, where positive values indicate a carbon sink and negative values indicate a carbon source.

All calculations were performed at the pixel level. Outputs were exported as single-band GeoTIFF files at 10 m resolution to remain consistent with the NDVI data and compatible with landscape analysis.

The NEP estimation formulas are as follows:

$$\text{NPP} = \text{PAR} \times f_{\text{APAR}} \times \epsilon_{\text{max}} \times e^{-k \times \text{slope}} \quad (6)$$

$$\text{Rh} = a \times e^{b \times \text{NDVI}} \times e^{c \times T} \quad (7)$$

$$\text{NEP} = \text{NPP} - \text{Rh} \quad (8)$$

The variables and parameters used in the NEP estimation are summarized in Table 4.

Table 3

Description of variables and parameters in the CRFNet model.

Symbol	Description	Source/Setting
x_t	Input features at time t	Sentinel-1 VV/VH backscatter, NDVI, and cloud mask
z_t	CNN-encoded features	Extracted via convolutional layers
h_t, c_t	Bi-LSTM hidden and cell states	Outputs from bidirectional LSTM
Q, K, V	Attention mechanism matrices	Query, Key, and Value vectors
$y_t, \hat{y}_t$	Ground-truth and predicted values	Observed NDVI samples and reconstructed NDVI
Mask_i	Pixel-wise mask weights	Higher weights for cloud-affected pixels
$W_{\text{conv}}, W_{\text{out}}$	Convolution/output layer weights	Learnable parameters optimized during training

Table 4

Variables and parameters used in the NEP estimation model.

Symbol	Description	Source/Setting
PAR	Photosynthetically Active Radiation ($J \cdot m^{-2} \cdot day^{-1}$)	Monthly mean from ERA5–Land (Hersbach et al., 2020)
f_{APAR}	Fraction of absorbed PAR	Approximated by NDVI (Huete et al., 2002)
ϵ_{max}	Maximum LUE ($gC \cdot MJ^{-1}$)	Set by land–cover type (Bond-Lamberty and Thomson, 2010)
k	Slope correction coefficient	Empirical value 0.15
$slope$	Terrain slope ($^{\circ}$)	Derived from SRTM DEM
a, b, c	Parameters for heterotrophic respiration model	Empirical parameters
T	Monthly mean temperature ($^{\circ}C$)	ERA5–Land data
NEP	Net Ecosystem Productivity ($gC \cdot m^{-2} \cdot month^{-1}$)	Calculated result

2.3.4. Landscape pattern analysis and land use coupling

To analyze the spatial distribution and heterogeneity of carbon flux, we applied landscape pattern indices to reconstructed NDVI and estimated NEP. These indices quantify spatial structure and fragmentation. Landscape metrics reflect ecosystem fragmentation, patch dominance, and spatial heterogeneity. They also help reveal how different land types relate to carbon sink and source patterns (McGarigal, 2001).

First, the NDVI and NEP grids were reclassified using defined thresholds. NDVI was divided into five vegetation cover levels (from low to high) using four fixed thresholds: 0.1, 0.2, 0.4, and 0.6. NEP was classified into carbon sink and carbon source categories based on internationally recommended ecological thresholds, where positive values indicate sinks and negative values indicate sources (Dong et al., 2024). After reclassification, patches were delineated using the eight-neighborhood connectivity rule. For each patch, we calculated its area and boundary characteristics. These steps enabled the landscape metrics to capture both compositional and configurational properties of the NDVI and NEP landscapes.

The calculation formulas for the observation indicators are as follows (McGarigal and Marks, 1995):

$$AREA_MN = \frac{1}{n} \sum_{i=1}^n a_i \quad (9)$$

$$ED = \frac{E}{A} \quad (10)$$

$$LPI = \frac{a_{max}}{A} \times 100 \quad (11)$$

$$NP = n \quad (12)$$

where a^i represents the area of the i^{th} patch, a_{max} denotes the area of the largest patch, E is the total length of all patch edges, A represents the total area of the study region, and n is the total number of patches. The selected metrics and their ecological interpretations are listed in Table 5.

To further explore the structural differences of carbon fluxes across ecosystems, these landscape metrics were calculated separately for major land cover types-forests, wetlands, mangroves, and croplands-

Table 5

Landscape metrics (NP, LPI, AREA_MN, ED) and their ecological interpretations.

Metric	Description	Ecological significance
NP	Number of patches	Indicates landscape fragmentation; higher values reflect greater fragmentation
LPI	Largest Patch Index	Measures the dominance of the largest patch in controlling landscape structure
AREA_MN	Mean patch area	Reflects the average size and connectivity of patches
ED	Edge density	Describes edge complexity and fragmentation of the landscape

based on the ESA WorldCover 2020 dataset. Metrics were aggregated monthly and averaged annually to generate a time series of landscape pattern changes from 2020 to 2024.

Through multitemporal analysis of landscape metrics across different land-cover types, we revealed the spatial response patterns of ecosystems under the carbon source and carbon sink status, helping identify vulnerable ecological types and priority areas for conservation, thereby providing references for regional ecological restoration and carbon management (Du et al., 2025).

2.3.5. Statistical analysis

To evaluate CRFNet performance, we used three metrics: coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE). R^2 measures the fraction of variance explained. Higher values indicate closer agreement with observations. RMSE and MAE quantify absolute deviations. Lower values indicate smaller residual errors. All metrics were calculated by comparing reconstructed NDVI against cloud free Sentinel 2 pixels from matched Sentinel 1 and Sentinel 2 pairs after quality control.

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2} \quad (13)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (14)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (15)$$

here y_i and $\hat{y}_i$ are the observed and predicted NDVI for pixel (or sample) i , $\bar{y}$ is the mean observed NDVI over the evaluation set, and N is the number of valid samples after cloud masking.

3. Results

3.1. NDVI reconstruction results

CRFNet was used to reconstruct a 10 m-resolution pixel-level time series of NDVI for the Kuala Selangor region from 2020 to 2024, achieving high accuracy and consistency in a cloudy tropical environment (Fig. 5). Overall, the pixel-by-pixel R^2 for the five years ranged from 0.824 to 0.883, RMSE was 0.103 to 0.125, and MAE remained between 0.080 and 0.091. The year 2024 achieved the best performance ($R^2 = 0.883$, RMSE = 0.110), while 2022 performed slightly worse ($R^2 = 0.835$) due to continuous heavy rainfall and overcast conditions. The slope remained stable between 0.77 and 0.82, and the intercept was consistently less than 0.10, indicating no systematic drift across the years. These results highlight the advantages of radar–optical fusion in compensating for optical data gaps. In particular, when Sentinel 2 was obscured by long-term cloud cover or rainfall, the backscatter signatures from Sentinel 1 provided temporal continuity and maintained NDVI accuracy.

To complement spatial validation, we performed temporal validation by grouping matched samples into dry (April to September) and wet (October to March) seasons for each year from 2020 to 2024. We compared reconstructed NDVI from Sentinel-1 against cloud-free Sentinel-2 pixels from the matched pairs.

Fig. 6 shows that CRFNet maintained stable performance across both seasons. Dry-season reconstructions achieved R^2 values between 0.828 and 0.886 with RMSE from 0.110 to 0.125, while wet-season reconstructions yielded R^2 between 0.794 and 0.869 with RMSE from 0.104 to 0.128. Although accuracy was slightly lower in the wet season due to frequent cloud cover and rainfall, the differences remained modest, confirming that the model provides robust temporal consistency under variable climatic conditions.

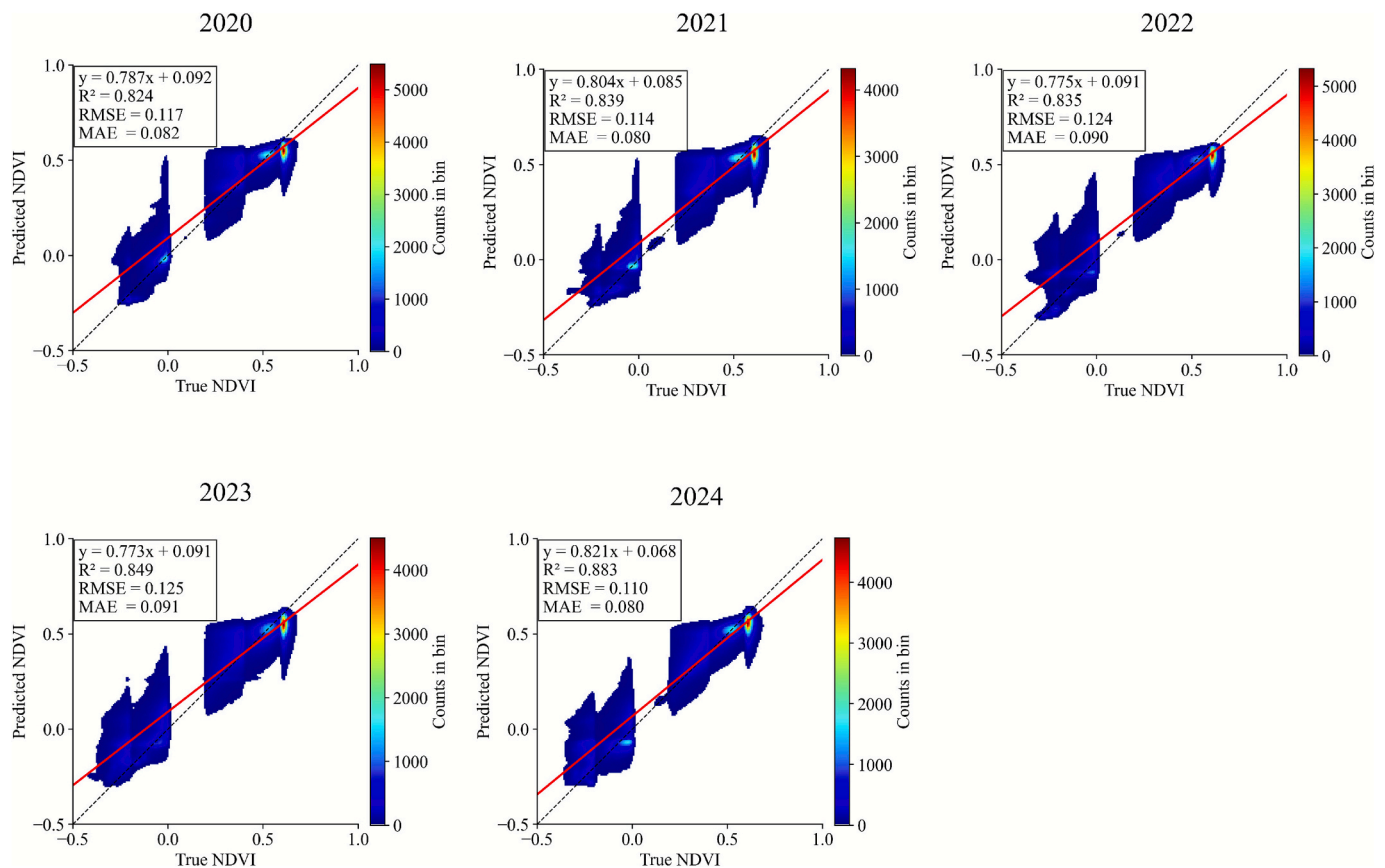


Fig. 5. Spatial validation of reconstructed NDVI against cloud-free Sentinel-2 pixels from matched pairs across 2020 to 2024 (annual pixel-wise R^2 , RMSE, MAE).

On a daily scale, the model demonstrates good robustness even under high-missing conditions (Table 6). For the 23 valid dates in 2024, the average R^2 for the 11 days with cloud cover below 50 % was 0.87, with an RMSE of approximately 0.105. Even under extreme conditions with cloud cover exceeding 70 % and daily rainfall above 7 mm (such as July 9 and September 19), the R^2 remained between 0.748 and 0.846, with slopes ranging from 0.656 to 0.89, showing no systematic bias. This demonstrates that CRFNet maintains high stability under persistent cloud cover and extreme rainfall.

Monthly-scale reconstructions further validate the model's consistency under cloudy conditions (Fig. 7). Of the 60 months from 2020 to 2024, only five were missing due to exceeding the thresholds of “cloud cover > 80 % and daily rainfall > 10 mm,” resulting in a 91.7 % completeness rate, which is significantly higher than the standard Sentinel 2 product (typically fewer than 30 valid observations per year in Southeast Asia). The monthly mean NDVI exhibits a typical seasonal pattern for tropical monsoon vegetation: lows (0.35–0.40) in March–April and October–November, and peaks (~0.55) in July–September. In the La Niña years (2020 and 2022), a short-term rebound in NDVI was observed at the end of the year. In contrast, during the El Niño year (2023), NDVI remained suppressed in the second half of the year, reflecting reduced rainfall and higher radiation. These results indicate that ENSO anomalies modulated vegetation photosynthetic activity through hydrothermal interactions (Fan and Fan, 2017).

Aggregating NDVI to the annual scale (Figs. 8–9) reveals that the annual average NDVI decreased gradually from 0.44 to 0.41 from 2020 to 2024 (linear slope -0.007 a^{-1} , $p < 0.05$). The decline was concentrated in the oil palm–sugarcane multi-cropping area and the northern edge of the mangrove forest, reflecting the suppressive effects of consecutive cold–wet years and ENSO anomalies on leaf area index and canopy cover in this sensitive ecosystem. The monthly amplitude remained between 0.35 and 0.46, with stable peak and trough timing, indicating that

regional vegetation exhibited a strong synchronous response to monsoon rainfall and ENSO events.

Overall, CRFNet achieved continuous reconstruction of 10 m-resolution NDVI, with inter-annual R^2 above 0.82 and RMSE around 0.11, effectively compensating for Sentinel 2 gaps in cloudy monsoon regions. The reconstructed series provides reliable inputs for NDVI-based carbon flux estimation and landscape analysis. The absence of data in a few months with extreme rainfall and persistent dense clouds highlights the need for future use of higher-temporal-resolution radar or improved time-series interpolation methods to further enhance completeness under extreme climate conditions.

3.2. Spatiotemporal variation of carbon flux

To clarify the drivers of NEP, the spatiotemporal dynamics of its two main components, NPP and Rh, were first examined. NPP reflects vegetation photosynthetic production, while Rh represents soil heterotrophic respiration under varying temperature and moisture conditions. Their seasonal and spatial patterns provide essential context for interpreting NEP variability.

Fig. 10 shows the monthly distribution of NPP from 2020 to 2024 at 10 m resolution. NPP followed a clear monsoon rhythm. Values increased steadily from April to September and peaked in July–September, before declining from October to March under reduced solar radiation. High NPP values were concentrated in northern hill forests and estuarine mangroves. Oil palm and sugarcane multi-cropping areas displayed stronger fluctuations linked to cultivation cycles.

Fig. 11 presents the corresponding monthly Rh maps. Rh varied with temperature and soil moisture. Short-term increases occurred during months of heavy rainfall, when waterlogged conditions enhanced microbial respiration. Spatial variation was less pronounced than for NPP, although wetlands and mangroves consistently showed higher values.

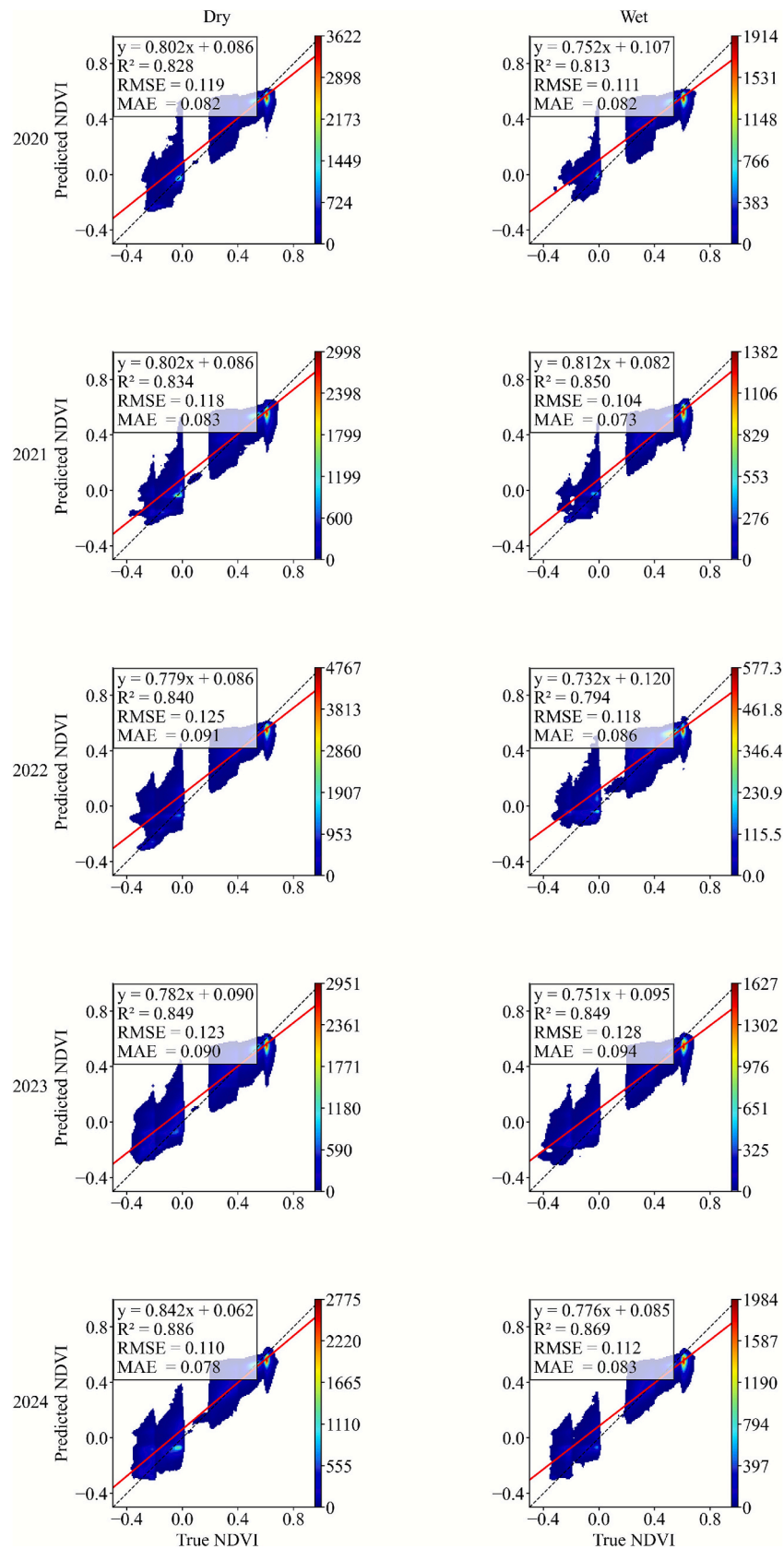


Fig. 6. Seasonal validation of reconstructed NDVI against cloud-free Sentinel-2 observations (2020–2024). Scatter-density plots show regression lines and accuracy metrics (R^2 and RMSE) for dry (April–September) and wet (October–March) seasons.

Table 6
Daily NDVI Reconstruction Error and Meteorological Conditions in 2024.

Date	Cloud_percent (%)	Rainfall (mm)	R ²	RMSE	MAE	slope
20240113	64.041	0.238	0.854	0.113	0.083	0.809
20240123	79.183	4.788	0.859	0.103	0.083	0.739
20240212	77.784	0.000	0.729	0.082	0.061	0.669
20240217	39.974	0.006	0.848	0.117	0.082	0.814
20240227	45.630	0.000	0.880	0.116	0.082	0.827
20240313	50.522	0.000	0.879	0.112	0.085	0.807
20240323	21.583	0.490	0.874	0.111	0.081	0.840
20240407	48.822	0.291	0.862	0.099	0.073	0.892
20240412	14.921	1.446	0.858	0.123	0.090	0.816
20240517	24.292	4.304	0.871	0.122	0.087	0.838
20240527	79.710	0.522	0.829	0.088	0.070	0.893
20240611	46.023	3.605	0.876	0.105	0.077	0.863
20240701	43.202	0.316	0.789	0.063	0.046	0.789
20240711	44.091	4.677	0.904	0.116	0.079	0.813
20240721	57.163	1.007	0.847	0.107	0.081	0.837
20240805	32.062	4.780	0.918	0.093	0.067	0.898
20240815	34.903	2.791	0.868	0.118	0.085	0.864
20240904	10.012	2.144	0.807	0.115	0.088	0.672
20240909	79.850	7.177	0.846	0.070	0.051	0.813
20240919	59.972	1.509	0.748	0.089	0.070	0.656
20240929	56.191	3.408	0.887	0.119	0.089	0.835
20241208	28.050	5.396	0.871	0.115	0.083	0.796
20241228	67.683	4.003	0.805	0.104	0.079	0.762

Compared with NPP, Rh exhibited smoother temporal dynamics, reflecting a closer coupling with soil hydrothermal conditions than with vegetation growth cycles.

The monthly NEP grids for 2024 revealed pronounced ecological differentiation (Fig. 12). Northern hill forests and estuarine mangroves maintained long-term high carbon sinks (NEP > 100 g C m⁻² month⁻¹), acting as stable regional “carbon storehouses.” Oil palm and sugarcane areas in central and southern Kuala Selangor ranged between 60–90 g C m⁻² month⁻¹, with fluctuations consistent with cropping cycles. In southeastern slopes and degraded farmland, patches of carbon source (NEP < 0 g C m⁻² month⁻¹) appeared during La Niña years, expanding to 10–15 % of the area. These findings highlight the risk of sinks shifting to sources under cold and wet conditions.

The temporal evolution of NEP was assessed at the interannual scale (Fig. 13). Mean annual NEP declined from 68.9 g C m⁻² in 2020 to 63.8 g C m⁻² in 2024, representing a five-year reduction of 7.4 % (p < 0.05) with a linear slope of −1.26 g C m⁻² yr⁻¹. The monthly series showed a typical “double peak–trough” monsoon pattern: peaks above 80 g C m⁻² in February and July, troughs near 50 g C m⁻² in November–December, and marked fluctuations during La Niña years.

Annual NEP distributions further highlighted areas of decline (Fig. 14). Reductions were concentrated along the northern edge of mangroves and on sloping farmland, with local decreases exceeding −20 g C m⁻² yr⁻¹. These reductions preceded significant declines in NPP, suggesting that water and salinity stress preferentially weakened soil redox processes and reduced net carbon uptake. The asymmetric response was most pronounced in degraded mangroves and on farmland

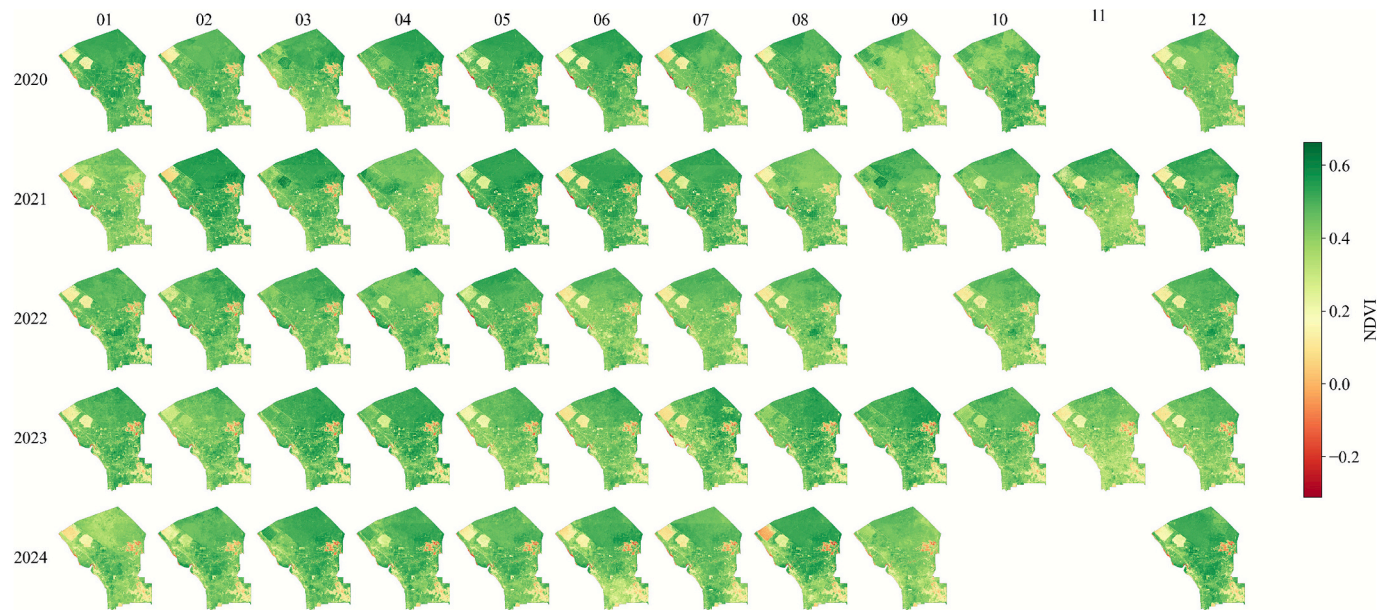


Fig. 7. Monthly NDVI maps at 10 m resolution for 2020 to 2024 (months with no data shown in white).

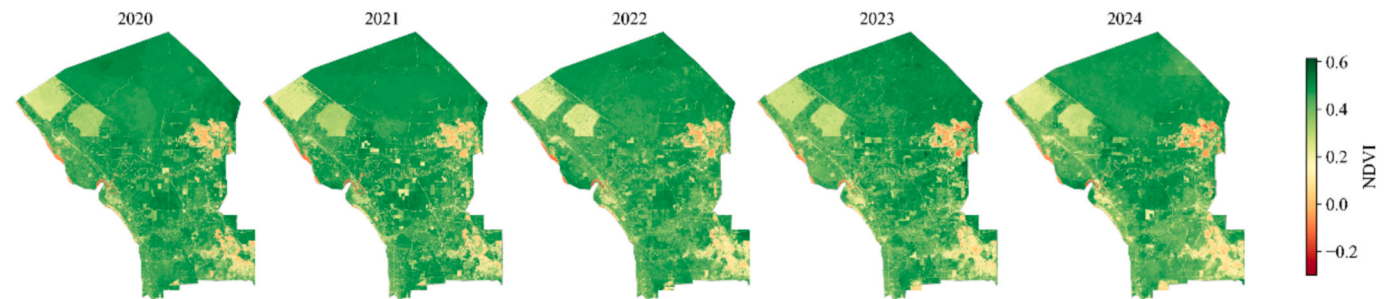


Fig. 8. Annual mean NDVI (10 m) for 2020 to 2024.

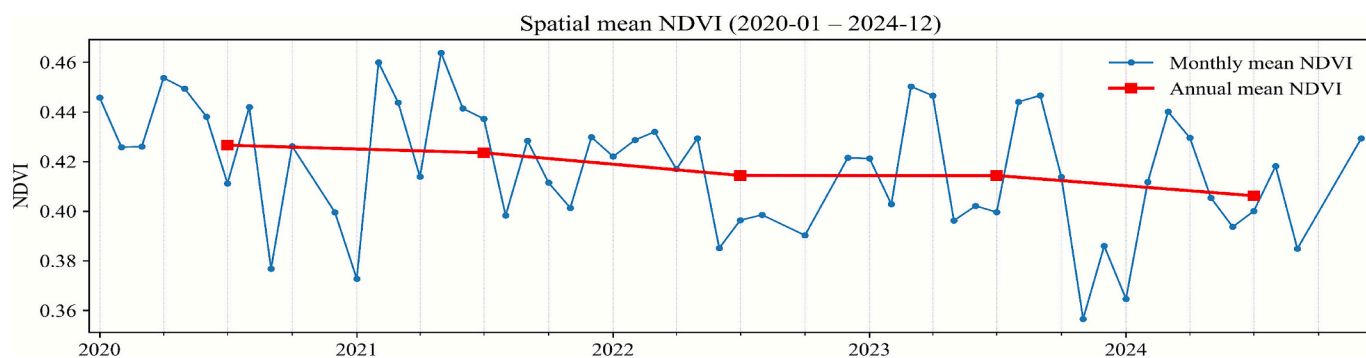


Fig. 9. Monthly and annual mean NDVI time series (2020–2024) with linear trend.

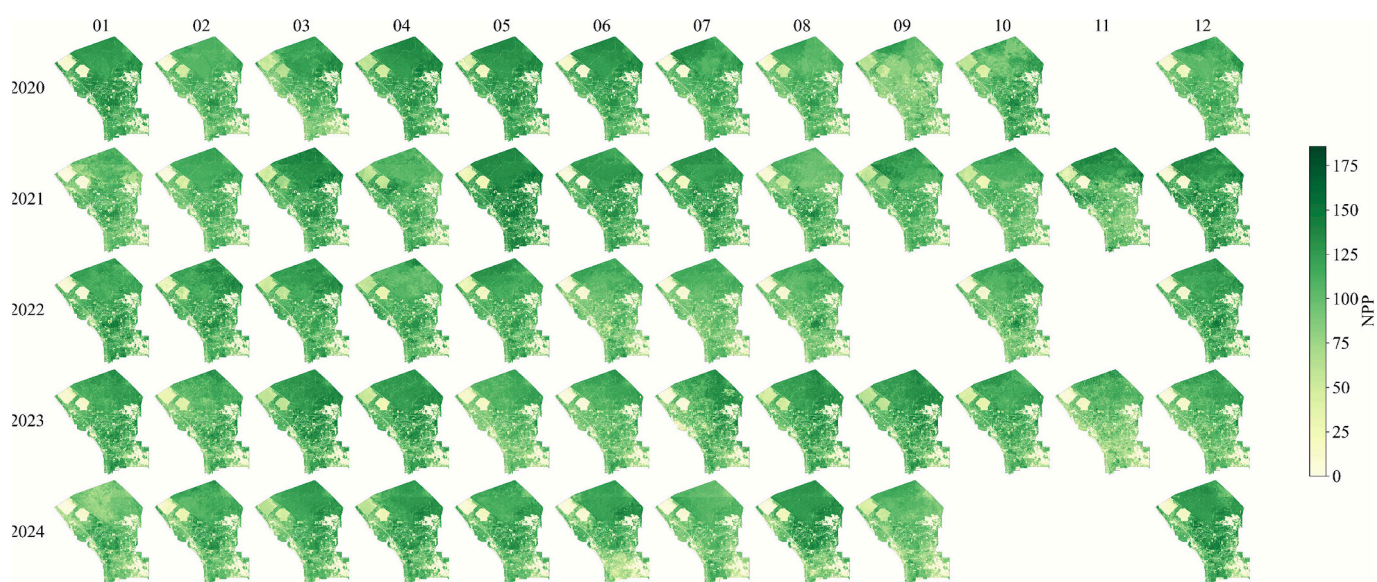


Fig. 10. Monthly NPP maps at 10 m resolution for 2020 to 2024 ($\text{g C m}^{-2} \text{ month}^{-1}$).

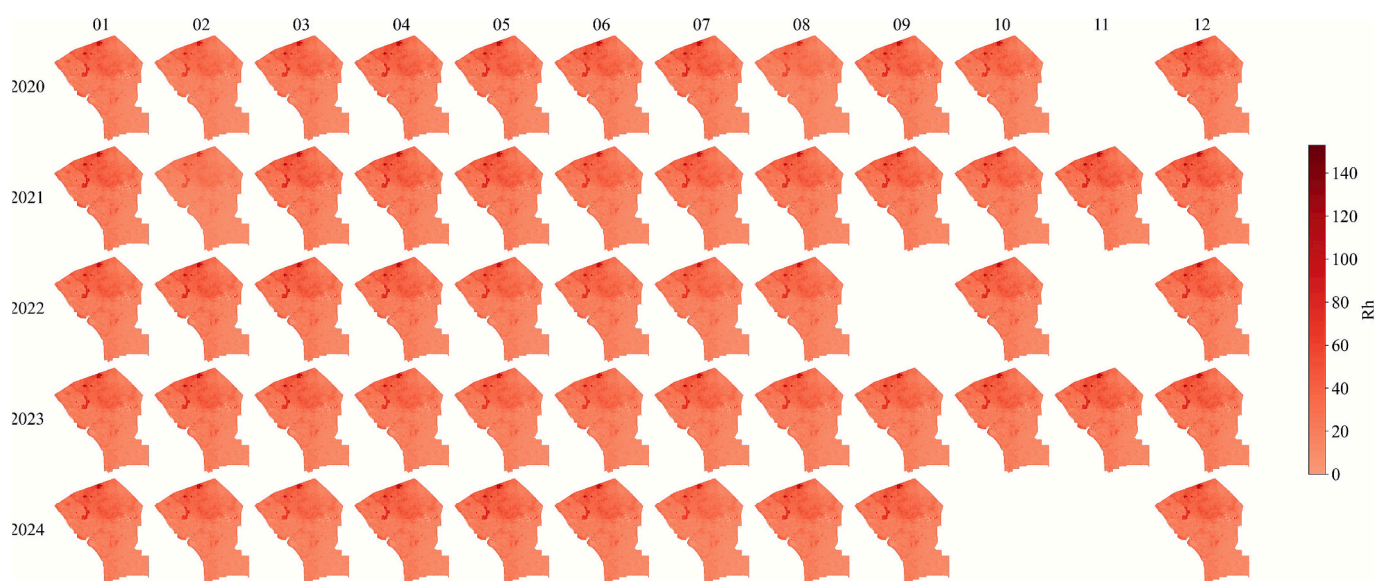


Fig. 11. Monthly Rh maps at 10 m resolution for 2020 to 2024 ($\text{g C m}^{-2} \text{ month}^{-1}$).

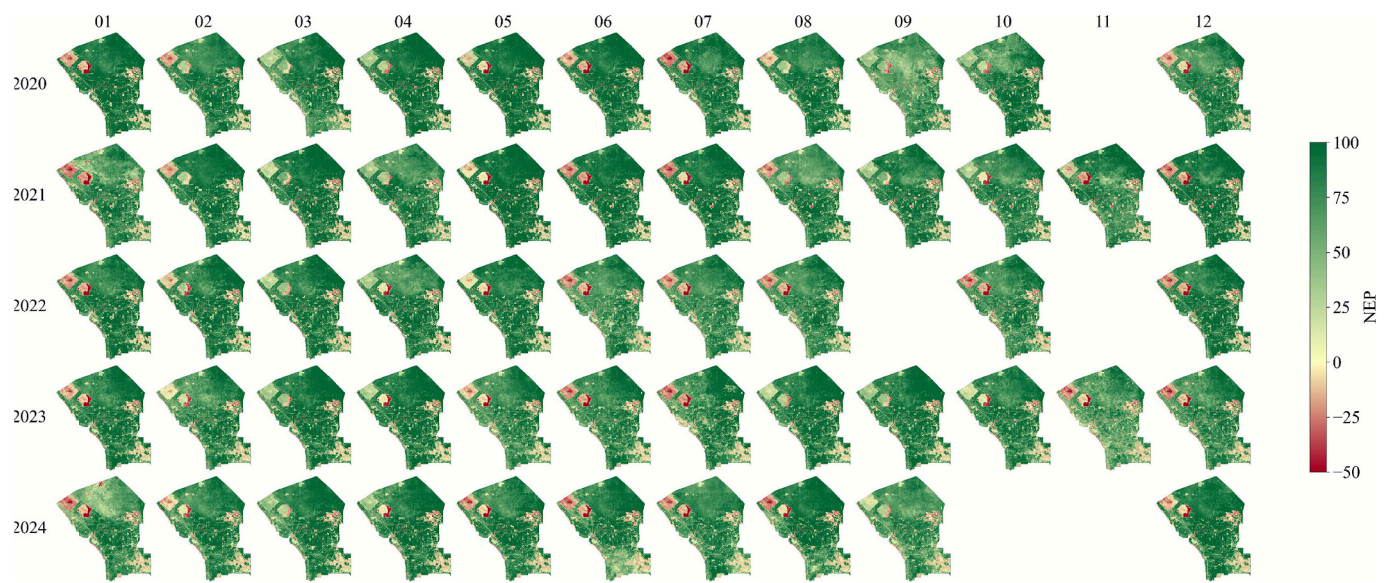


Fig. 12. Monthly NEP maps at 10 m resolution for 2020 to 2024 ($\text{g C m}^{-2} \text{ month}^{-1}$). Color convention: red indicates carbon source (negative NEP) and green indicates carbon sink (positive NEP). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

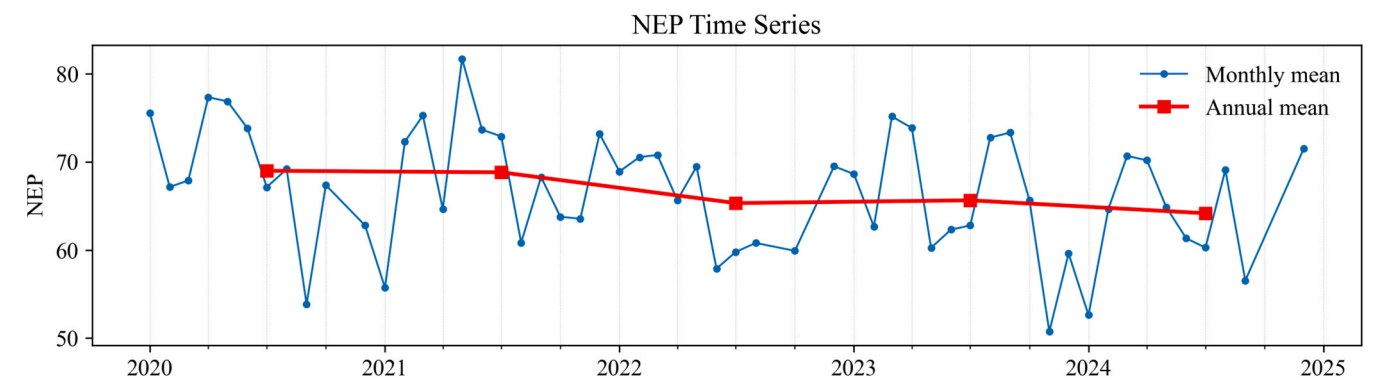


Fig. 13. Monthly and annual mean NEP time series for 2020–2024 ($\text{g C m}^{-2} \text{ month}^{-1}$).

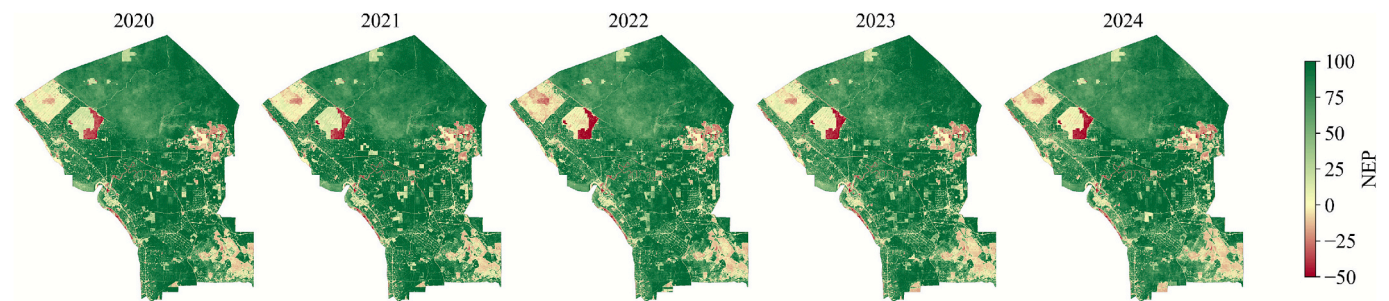


Fig. 14. Annual NEP for 2020 to 2024 (report as annual cumulative, $\text{g C m}^{-2} \text{ yr}^{-1}$).

slopes.

Overall, consecutive La Niña events suppressed photosynthetic production by reducing available sunlight, prolonging soil saturation, and altering redox conditions. These changes triggered short-term increases in heterotrophic respiration during extreme years, further contracting sink capacity. Agricultural fluctuations could be mitigated through slope water conservation, organic matter input, and conservation tillage. In mangroves, tidal regulation, salinity management, and replanting are needed to restore strong sink capacity. The high-resolution NEP series provides detailed evidence of sink–source dynamics under

Table 7		
Landscape classification thresholds of monthly NEP ($\text{g C m}^{-2} \cdot \text{month}^{-1}$).		
Class	NEP threshold	Ecological interpretation
1	≤ -8.3	Strong carbon source (degraded cropland, disturbed bare land)
2	$-8.3-0$	Weak carbon sink or mild carbon source
3	$0-8.3$	Moderate carbon sink
4	$8.3-16.7$	Relatively high carbon sink
5	>16.7	High carbon sink (mature forests, mangroves)

monsoon–ENSO interactions and delivers robust inputs for regional carbon neutrality strategies and carbon budget models.

3.3. Landscape pattern analysis of carbon flux

To further examine the spatial heterogeneity of carbon sink functions and the structural mechanisms driving them, monthly NEP data for 2020–2024 were classified into five ecological levels (Table 7). Thresholds were based on the 25th and 75th percentile distributions of global carbon-cycle models (Running et al., 2004), the classification criteria for ecosystem carbon budgets from the (Intergovernmental Panel on Climate Change IPCC, 2023), and the observed carbon flux ranges of tropical ecosystems (Pan et al., 2011; Saatchi et al., 2011). This framework combines ecological benchmarks with statistical distribution, enabling identification of both strong carbon sources and stable carbon sinks. Four landscape metrics were then calculated: number of patches (NP), mean patch area (AREA_MN), largest patch index (LPI), and edge density (ED). These metrics were further analyzed by land cover class to reveal patch-level differences in carbon dynamics (Mills et al., 2023).

From the classification results (Fig. 15), the NEP landscape displayed a three-tiered pattern of high sink, moderate sink, and source. Northern hill forests and estuarine mangroves consistently maintained Class 5 patches, forming the primary regional sinks. Under strong La Niña conditions in 2022, Class 5 patches contracted markedly, especially in sugarcane–grass slopes. At the same time, extensive Class 2 weak sink patches emerged, and some zones shifted to Class 1 carbon sources. In 2024, carbon source expansion occurred along degraded mangrove margins, indicating an increased risk of sink-to-source transitions under prolonged hydroclimatic variability.

At the land use level (Fig. 16), carbon sink fluctuations varied significantly across ecosystem types. Forests and mangroves sustained consistently high NEP with limited interannual variation, reflecting their buffering capacity against hydrothermal stress. Grasslands and shrublands showed moderate sinks but responded sensitively to both drought and excessive rainfall. Croplands displayed alternating phases of carbon gain and loss, with short-term sink peaks during sowing and regrowth followed by temporary source phases after harvest and tillage. Built-up areas and sparsely vegetated lands persistently exhibited negative NEP, confirming their role as stable carbon sources. These contrasts highlight both the intrinsic productivity differences among ecosystems and the influence of human management on regional carbon

budgets.

Landscape metrics provided further insights into the morphological drivers of carbon sink dynamics (Figs. 17–20). From 2020 to 2021, forests and mangroves exhibited high LPI above 40 percent, low NP, and low ED, indicating dominance of large, well-connected patches with weak edge effects. In 2022, extreme rainfall caused rapid fragmentation of high-sink patches, with NP increasing by about 30 percent, LPI dropping below 30 percent, and ED rising sharply—signaling increased patch segmentation and edge complexity. In 2023, El Niño conditions enhanced radiation and reduced rainfall, which supported short-term recovery of patch connectivity but also introduced drought-related stress. In 2024, another neutral year, localized patch tearing occurred in cropland and degraded mangrove edges, leading to renewed fragmentation in specific areas. This fragmentation–integration–re-fragmentation cycle closely tracked ENSO-driven hydrothermal variability, underscoring the dependence of regional sink capacity on landscape structure under climatic anomalies and human disturbance.

Overall, the results demonstrate that regional carbon sink capacity is shaped by both patch connectivity and edge complexity. Forests and mangroves maintained stable high carbon sinks through cohesive patches with low edge densities. In contrast, croplands and degraded slopes experienced frequent fragmentation, which increased the likelihood of carbon source emergence. These findings point to three management priorities:

- (i) consolidating core sink zones through restoration of degraded forests and mangroves;
- (ii) promoting low-disturbance crop rotations and ecological corridors in cropland–grassland mosaics to buffer NEP variability during ENSO events; and
- (iii) strengthening green infrastructure in urban fringes and coastal zones to mitigate emissions under compound stressors such as storm surges and urban heat.

This integrated analysis of structure and function provides a scientific basis for refining regional strategies of emission reduction and sink enhancement, and for optimizing landscape design to support long-term carbon neutrality.

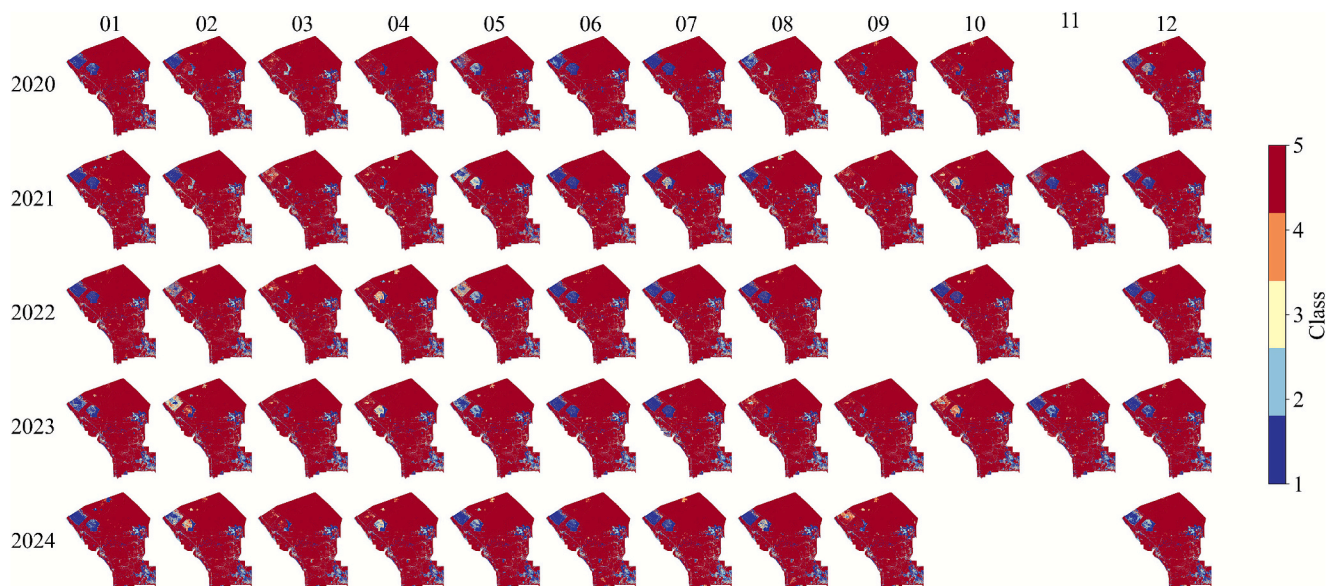


Fig. 15. NEP classes (1–5) derived from monthly NEP thresholds ($\text{g C m}^{-2} \text{ month}^{-1}$), 2020–2024.

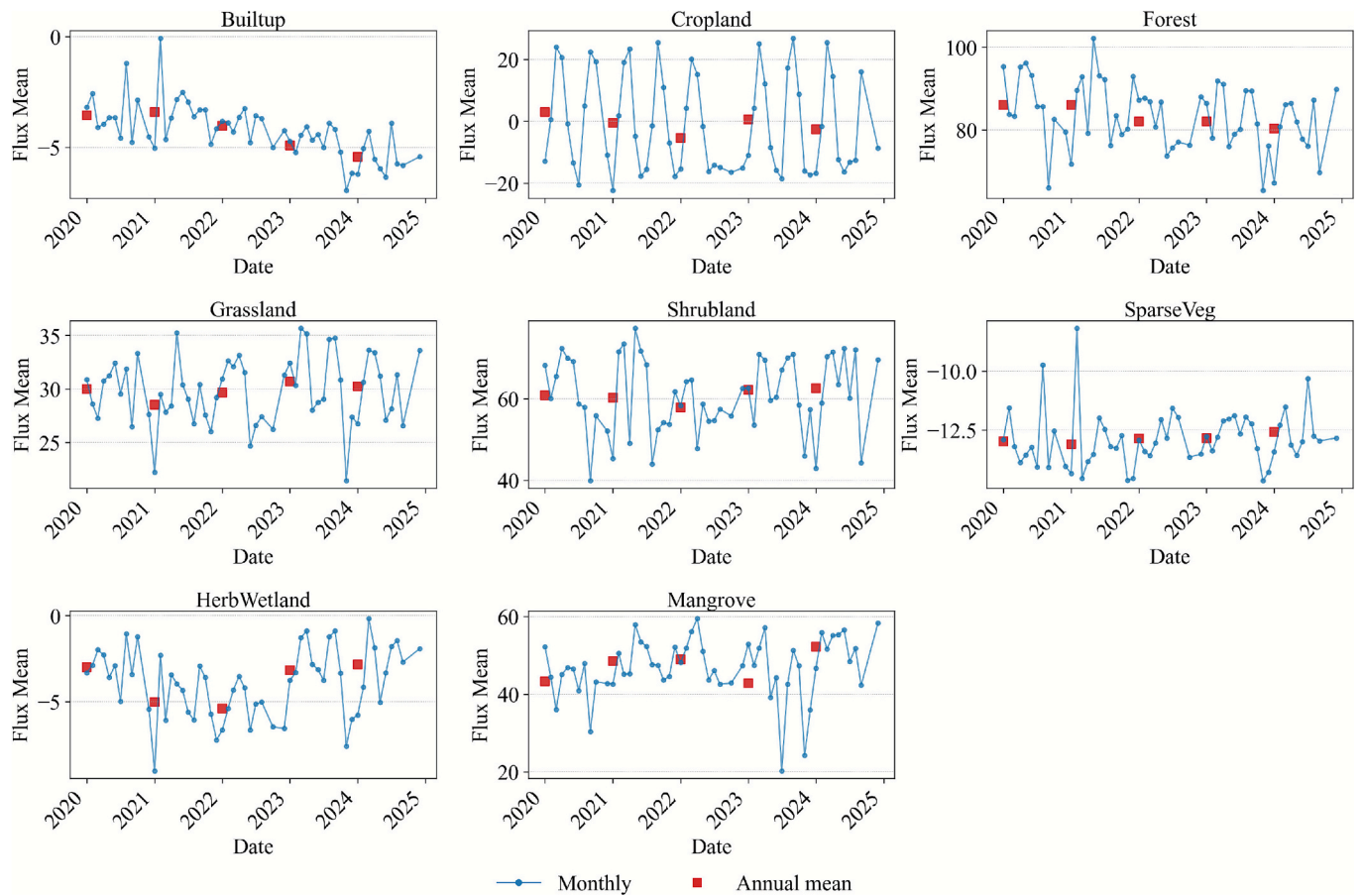


Fig. 16. NEP dynamics by land cover class: monthly means and annual summaries.

4. Discussion

4.1. Comparison of CRFNet and other methods

For baseline comparison, two state-of-the-art radar–optical NDVI reconstruction models, MCNN-Seq (Zhao et al., 2020) and BRIOS (Y. Chen et al., 2024), were reproduced strictly according to the algorithm configurations reported in the original studies. To ensure comparability, all models—including the proposed CRFNet—were trained and validated on the same dataset constructed with the unified preprocessing pipeline described in Section 2.2. This design eliminates differences caused by inconsistent input preparation and isolates the contribution of model architectures. The year 2020, characterized by a strong La Niña event with frequent cloud–rainfall interference, was selected as a representative test period to highlight the robustness of each method under extreme tropical conditions. Reconstruction accuracies are summarized in Table 8, while spatial and temporal distribution maps are presented in Fig. 21.

From Table 8, it is evident that CRFNet substantially outperformed both baselines. CRFNet achieved an R^2 of 0.824 with RMSE of 0.117 and MAE of 0.082, while MCNN-Seq collapsed under persistently cloudy conditions, producing negative R^2 values (−1.588) and large residuals (RMSE = 0.540). BRIOS yielded moderate results (R^2 = 0.746, RMSE = 0.140, MAE = 0.106) but still fell short of CRFNet. This demonstrates that conventional convolution–recurrent architectures either fail to generalize to tropical monsoon regions (MCNN-Seq) or tend to oversmooth vegetation trajectories (BRIOS), while CRFNet maintains stable accuracy and reduced error. Even under extremely cloudy conditions, CRFNet preserved robust performance, confirming its clear advantage over existing radar–optical fusion approaches.

The spatial comparison in Fig. 21 further highlights these differences. Reconstructions by MCNN-Seq exhibited strong artifacts and unrealistically uniform fields, whereas BRIOS produced blurred vegetation gradients and underestimated canopy recovery after rainfall. In contrast, CRFNet preserved fine-grained heterogeneity, including vegetation regrowth in croplands and stable high NDVI patches in mangroves and hill forests. The seasonal trajectory captured by CRFNet also aligned more closely with the expected “rapid growth–slow decay–recovery” rhythm of tropical vegetation, confirming the advantage of integrating Bi-LSTM for long-term dependencies and attention mechanisms for key temporal states.

These improvements are not only methodological but also ecologically meaningful. By providing more reliable NDVI inputs, CRFNet enabled pixel-level estimation of NPP, Rh, and NEP at 10 m resolution. This made it possible to reveal the inhibitory effect of consecutive La Niña years on photosynthetic production and the emergence of carbon source patches in cropland and degraded mangrove zones. Compared with previous methods, CRFNet therefore provides a more credible technical path for high-resolution carbon flux monitoring in persistently cloudy tropical regions.

4.2. Carbon flux dynamics under ENSO influence

The reconstructed NEP showed pronounced seasonal and interannual variability. Between 2020 and 2024, mean annual NEP decreased by about 7.4 % with a linear trend of $-1.26 \text{ g C m}^{-2} \text{ yr}^{-1}$. Seasonal fluctuations followed the tropical monsoon rhythm, with peaks in February and July and troughs in November and December. ENSO anomalies strongly modulated these dynamics. During La Niña years (2020 and 2022), reduced radiation and prolonged soil saturation limited NPP and occasionally enhanced Rh, resulting in weaker sinks. In

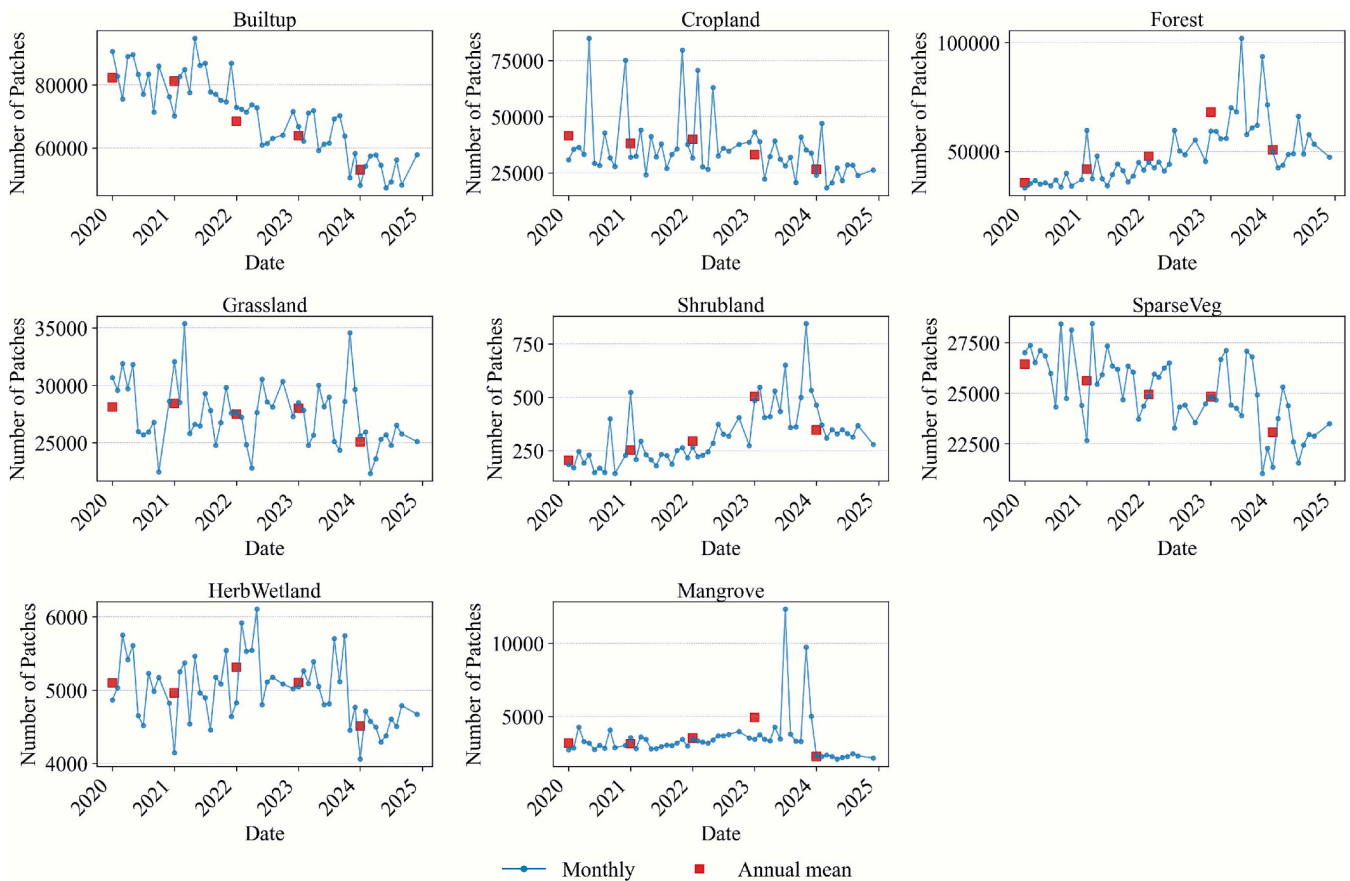


Fig. 17. Trends in the number of NEP patches (NP) by land cover type (2020–2024).

contrast, El Niño conditions in 2023 increased radiation and lowered rainfall, which temporarily supported vegetation recovery but also induced drought stress. Neutral years (2021 and 2024) exhibited intermediate behavior. The complementary NPP and Rh fields confirmed these mechanisms, providing component-level support for the reconstructed NEP series. Recent studies corroborate these findings: [Ke et al., \(2025\)](#) documented a global decline in land carbon sink strength during the 2023/24 El Niño event; [Heinrich et al., \(2023\)](#) reported that tropical forests in Malaysia and Indonesia show strong sensitivity of GPP and heterotrophic respiration to climatic anomalies; and [Takamura et al., \(2023\)](#) demonstrated that radiation, rainfall, and soil moisture variability during ENSO phases exert direct control on carbon–water coupling in Southeast Asian rainforests; and [Bennett et al., \(2023\)](#) found that South American tropical forests experienced sharp reductions in carbon uptake during the 2015–16 El Niño drought. Together, these lines of evidence strengthen the ecological plausibility of our NEP estimates under ENSO-driven hydroclimatic variability.

4.3. Landscape structure and ecosystem heterogeneity

Landscape analysis at 10 m resolution revealed robust structure–function coupling in carbon flux dynamics. High-sink zones in hill forests and mangroves consistently exhibited cohesive spatial configurations, with largest patch index (LPI) values generally exceeding 40 % and edge density (ED) remaining below 20 m ha⁻¹. These conditions coincided with relatively low interannual variance of NEP ($\pm 5\text{--}8\text{ g C m}^{-2}\text{ month}^{-1}$) and stable seasonal amplitudes, indicating that strong connectivity buffered against hydroclimatic fluctuations. By contrast, cropland mosaics and degraded slopes displayed frequent fragmentation, with patch number (NP) often doubling relative to forested areas, LPI declining to below 30 %, and ED increasing to more than 25 m ha⁻¹.

Such structural patterns were associated with larger temporal variance in NEP, exceeding $\pm 15\text{ g C m}^{-2}\text{ month}^{-1}$ during La Niña years.

Hydroclimatic stress amplified these contrasts. In 2022, for example, extreme rainfall coincided with a $\sim 30\%$ increase in NP, a sharp decline of LPI to 28 %, and an ED surge above 30 m ha⁻¹ in high-sink classes, reflecting rapid patch segmentation and weakened dominance of core sinks. This fragmentation corresponded with a measurable reduction in mean NEP of $\sim 10\text{ g C m}^{-2}\text{ month}^{-1}$ at the landscape scale. Conversely, in 2023, partial reintegration was observed: LPI recovered to $\sim 37\%$ and ED fell below 22 m ha⁻¹, consistent with short-term restoration of patch connectivity and a rebound in sink strength. However, localized re-fragmentation in 2024 re-emerged along cropland and degraded mangrove margins, underscoring the instability of disturbed landscapes.

Two mechanistic inferences arise from these findings. First, large, cohesive patches act as stabilizers of carbon flux by maintaining contiguous photosynthetic surfaces and dampening edge-driven variability in respiration and soil moisture. Second, edge proliferation amplifies vulnerability to climatic extremes, heightening the probability of sink-to-source transitions in intensively managed or disturbed ecosystems. These dynamics mirror recent empirical evidence that fragmentation magnifies the sensitivity of tropical forests to ENSO-driven hydroclimatic variability ([Bennett et al., 2023](#)).

The consistent co-variation between NEP and landscape metrics (NP, LPI, AREA_MN, ED) thus provides independent structural validation of the reconstructed NEP series. It strengthens confidence in the ecological realism of the 10 m NEP maps and highlights their utility for identifying vulnerability hotspots and prioritizing interventions. Practically, the results emphasize that stabilizing large, connected patches and reducing edge complexity—especially in cropland–wetland–mangrove ecotones—are central to maintaining carbon sink capacity in tropical monsoon regions.

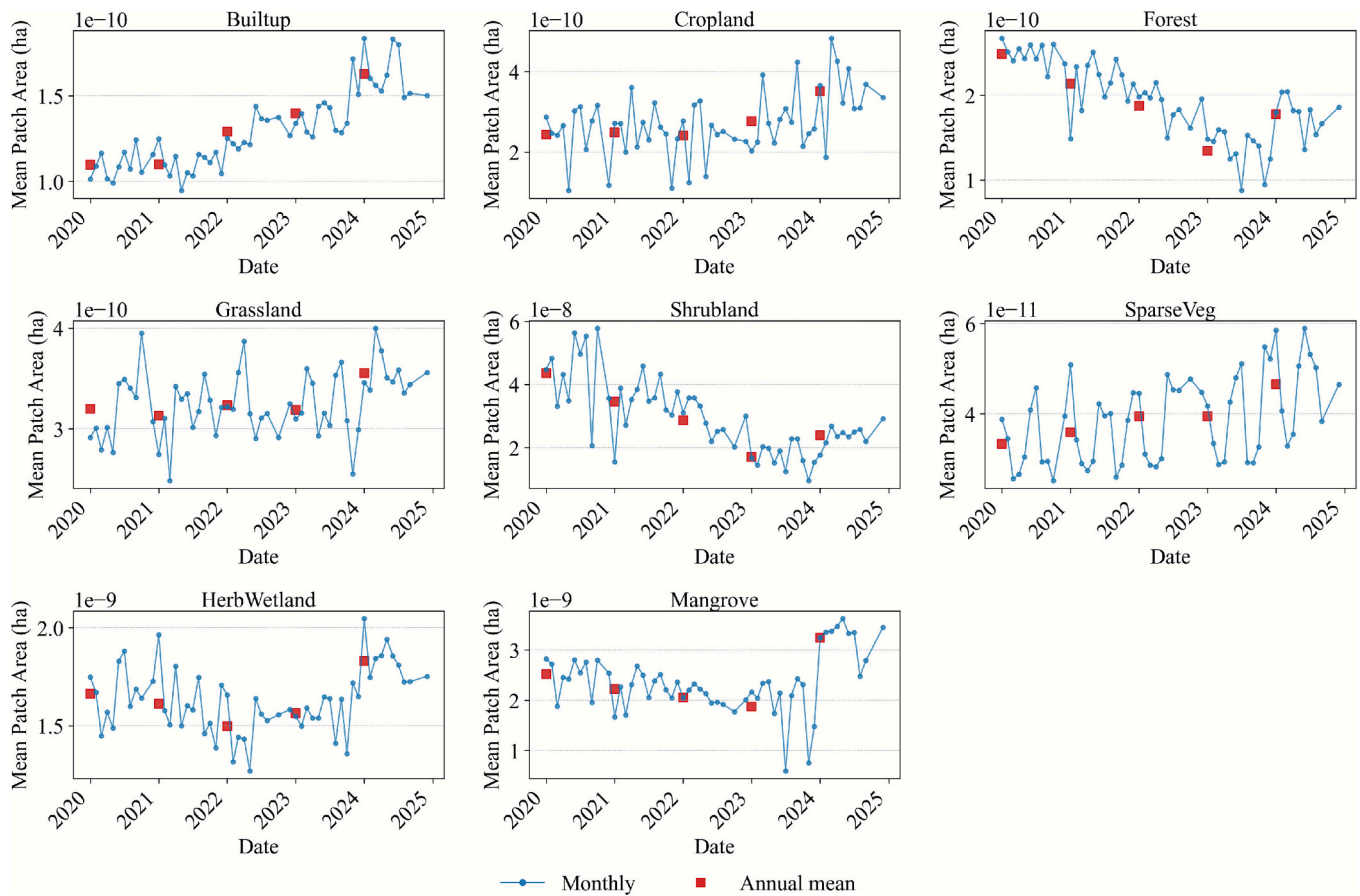


Fig. 18. Trends in mean NEP patch area (AREA_MN) by land cover type (2020–2024).

4.4. Limitations and uncertainties

Despite the advances of CRFNet and the ecological insights obtained, several limitations should be recognized.

- (1) Scale mismatch. Auxiliary drivers had coarser resolutions than the 10 m NDVI baseline: precipitation (~5 km, CHIRPS), temperature and radiation (~10 km, ERA5-Land), soil moisture (~10 km, FLDAS), soil organic carbon (~250 m, OpenLandMap), and terrain (~30 m, SRTM). All were resampled to 10 m for pixel alignment, which inevitably smoothed fine-scale variability and may have introduced block effects. This scale harmonization was necessary for integration but may bias NEP magnitudes in heterogeneous zones such as farmland–wetland–mangrove ecotones.
- (2) Static land cover. ESA WorldCover 2020 was used as a static layer, and land-use change during 2020–2024 was not represented. This omission may underestimate the effects of urban expansion, crop rotation, and mangrove degradation on carbon fluxes.
- (3) Validation constraints. Flux tower data were not available in the study area, preventing direct validation of NEP. As a partial substitute, NPP and Rh component maps were compared, which indirectly supported NEP estimates but cannot fully replace ground-based observations.
- (4) Model assumptions and training strategy. NEP estimation relied on a light-use efficiency formulation for NPP and an empirical temperature-driven Rh model, both subject to uncertainties in reanalysis inputs and parameterization. In addition, CRFNet training used a ± 7 -day Sentinel-1/2 pairing window and a mask-weighted MSE loss, which may not fully account for phenological shifts or noisy supervision in fast-changing tropical vegetation.

Hyperparameters were optimized through limited tuning due to computational constraints, leaving the possibility that more advanced training strategies could further improve robustness.

- (5) Data availability. CRFNet requires at least some usable optical observations. Months with complete optical loss remain unrecoverable, explaining the small gaps observed in the NDVI and NEP series.

These limitations highlight the need for finer-resolution auxiliary drivers, dynamic land cover products, more sophisticated training strategies, and indirect validation methods in future work.

4.5. Future work

Building on the limitations identified above, several directions can further enhance the robustness and ecological applicability of high-resolution carbon flux estimation in tropical monsoon regions:

- (1) Advancing NDVI reconstruction models. Although CRFNet achieved stable performance under persistent cloud cover, it still relies on limited optical supervision and may underperform when no usable Sentinel-2 inputs are available. Future work could incorporate multimodal features—such as multi-orbit Sentinel-1 backscatter, SIF, or VOD—to further reduce optical dependence and enhance model generalization. Extending CRFNet with transformer-based temporal encoders or uncertainty-aware loss functions may also improve robustness during extreme climate events. These extensions were not attempted here due to computational constraints and the need to first establish a baseline framework tailored to humid tropical conditions.

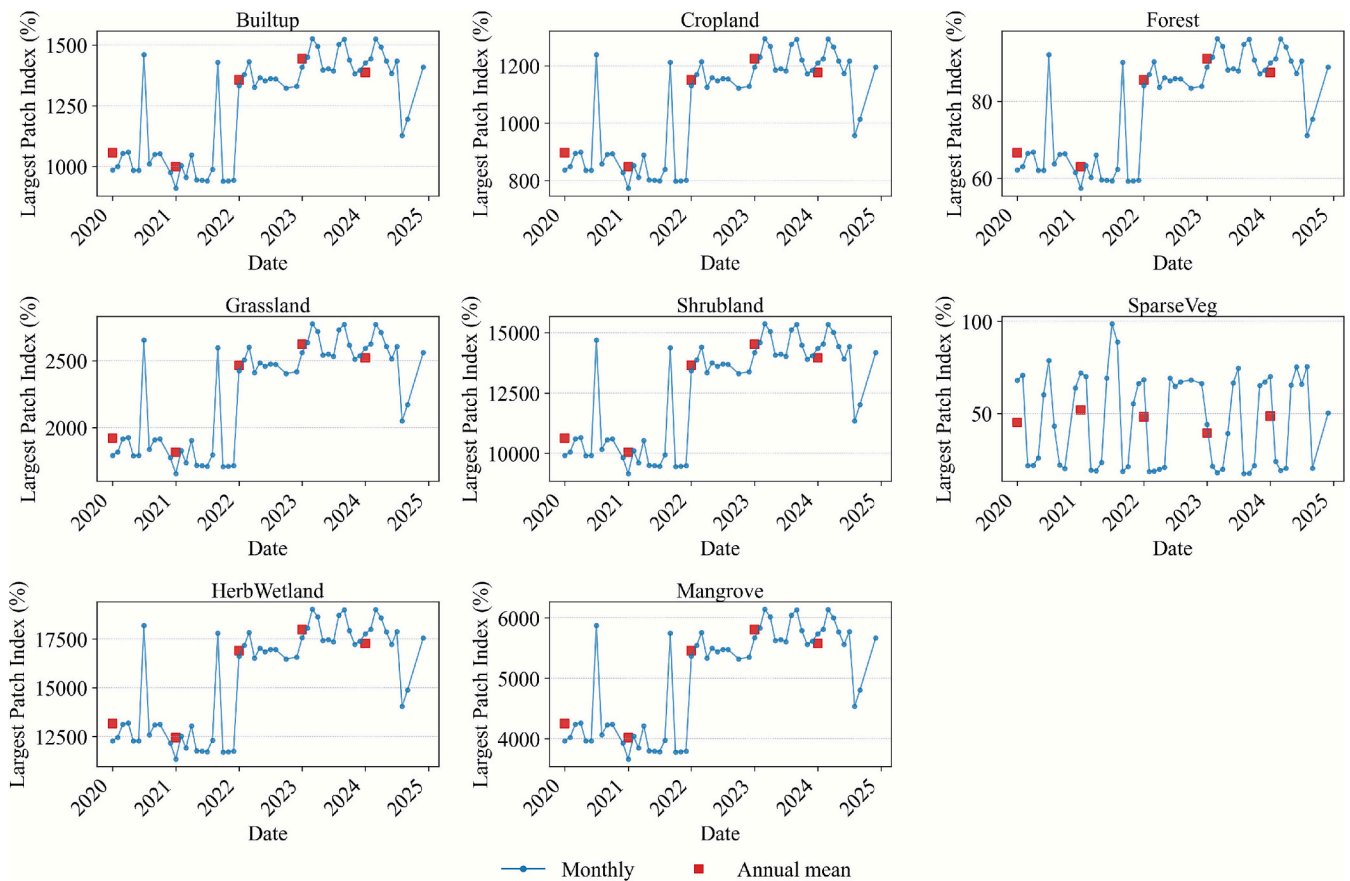


Fig. 19. Trends in largest patch index (LPI) of NEP by land cover type (2020–2024).

- (2) **Dynamic land cover products.** This study relied on the static ESA WorldCover 2020 dataset, which does not reflect land-use changes during 2020–2024. While necessary given current data availability, this assumption may underestimate the effects of urban expansion, crop rotation, and mangrove degradation. Future work could construct annually updated land cover products by combining multi-temporal Sentinel-2 classification with radar-based mapping to overcome cloud contamination. Although building such datasets is a major undertaking in the tropics, even partial updates for key classes (cropland, mangroves) would reduce parameter bias and improve the ecological realism of landscape indicators.
- (3) **Finer-resolution auxiliary drivers.** The present analysis harmonized precipitation (~5 km), climate (~10 km), soil moisture (~10 km), terrain (~30 m), and soil carbon (~250 m) datasets to the 10 m NDVI baseline. This step ensured spatial alignment but inevitably smoothed local variability. Future studies could integrate emerging high-resolution products—such as sub-kilometer precipitation downscaled from GPM, finer soil maps, or vegetation proxies (SIF, VOD)—to provide more ecologically relevant drivers for NPP and Rh estimation.
- (4) **Indirect validation strategies.** The absence of flux towers in Kuala Selangor precluded direct NEP validation. This study partially addressed this by cross-checking NPP and Rh components and by linking NEP patterns with landscape metrics. Future validation could be strengthened by indirect yet feasible approaches, such as cross-regional comparisons with published flux studies in similar tropical basins or consistency checks against satellite-based GPP products (e.g., SIF-derived GPP). These strategies, although less direct than tower validation, are achievable under current data

constraints and provide independent ecological support for reconstructed NEP.

- (5) **Transferability and generalization.** While this study focused on Kuala Selangor, testing CRFNet across other tropical basins with contrasting hydrological regimes, vegetation mosaics, and disturbance pressures would provide stronger evidence of its robustness. Such cross-regional transfer not only validates generalization but also helps identify which model components (e.g., attention mechanisms, mask-weighted loss) contribute most to stability, thereby refining the framework for broader application.

5. Conclusion

This study developed a cloud-adaptive deep learning framework (CRFNet) that integrates Sentinel-1 SAR and Sentinel-2 optical data to reconstruct 10 m NDVI in a persistently cloudy tropical monsoon region (2020–2024). CRFNet achieved stable accuracy (R^2 above 0.82, RMSE below 0.11) under prolonged cloud cover and heavy rainfall, demonstrating clear advantages over existing radar–optical fusion models. Using the reconstructed NDVI, the light use efficiency (LUE) model was applied to estimate spatiotemporal NEP. Results showed a regional decline of about 7.4 % in mean annual NEP from 2020 to 2024, with La Niña years exhibiting stronger reductions due to combined light deficits and soil oversaturation. Degraded mangroves and sloping croplands were identified as sensitive zones of sink-to-source transition. Landscape analysis revealed that high carbon sink levels were associated with cohesive large patches (high LPI, low ED), while fragmentation and edge proliferation increased carbon source risk. The findings verify that coupling deep learning with ecological process models enables refined monitoring of carbon fluxes under complex tropical climate regimes.

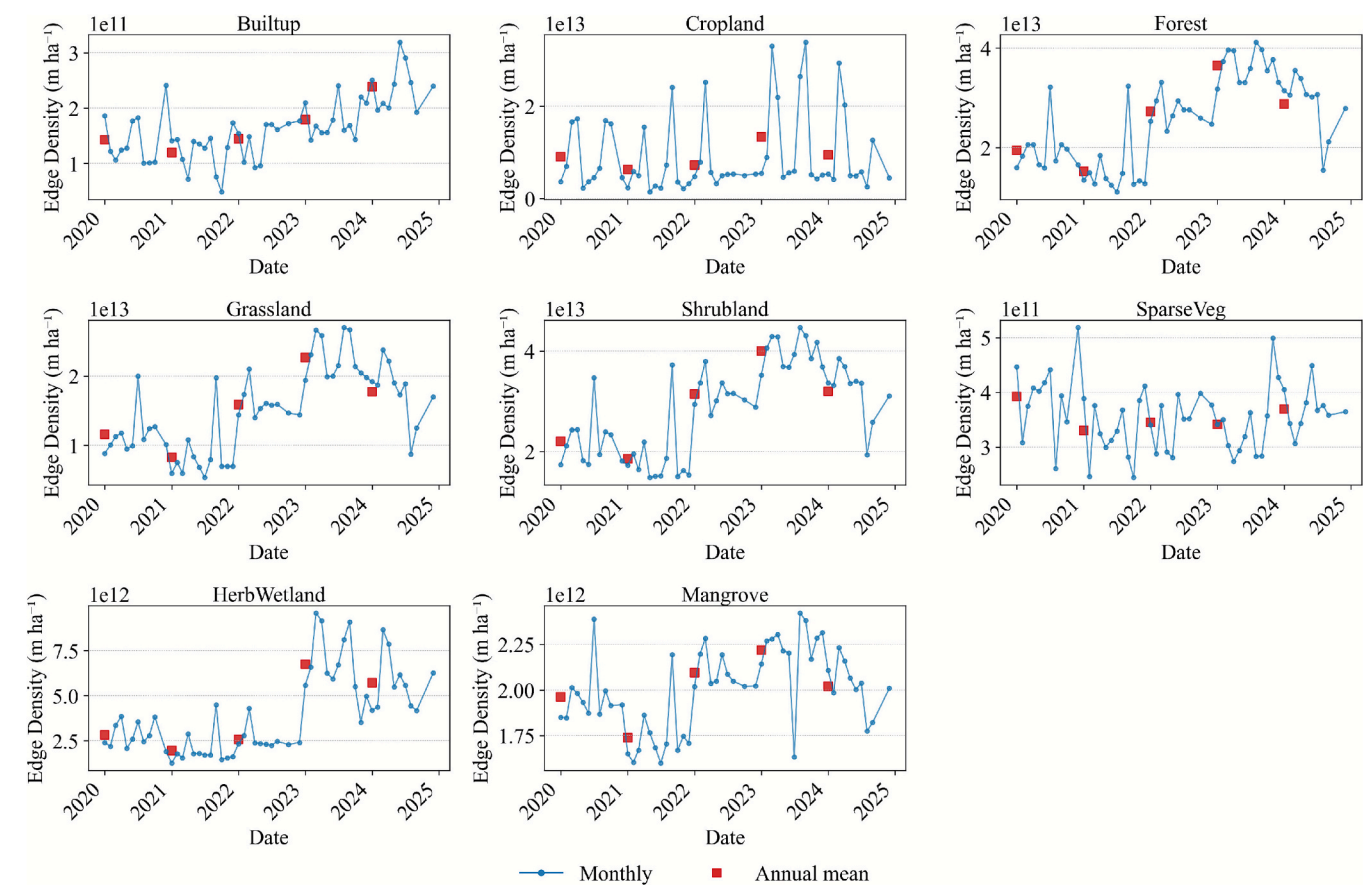


Fig. 20. Trends in edge density (ED) of NEP by land cover type (2020–2024).

Table 8
NDVI reconstruction accuracy in 2020 (La Niña).

Model	R ²	RMSE	MAE
MCNN-Seq	-1.588	0.54	0.422
BRIOS	0.746	0.14	0.106
CRFNet	0.824	0.117	0.082

The 10 m NEP dataset produced here offers a valuable basis for carbon budget assessment, ecosystem management, and carbon neutrality planning in monsoon regions. Future research should incorporate dynamic land cover data, richer multi-source observations, and broader cross-regional testing to further enhance generalizability and ecological relevance.

CREDiT authorship contribution statement

Pengfei Jia: Writing – original draft, Validation, Resources, Methodology, Data curation, Conceptualization. **Helmi Zulhaidi Mohd Shafri:** Writing – review & editing, Supervision, Project administration, Formal analysis. **Shengrui Yu:** Visualization, Software. **Zhi Zheng:** Visualization, Validation, Formal analysis. **Shiqing You:** Writing – review & editing, Visualization, Software. **Abdul Rashid Mohamed Shariff:** Writing – review & editing, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

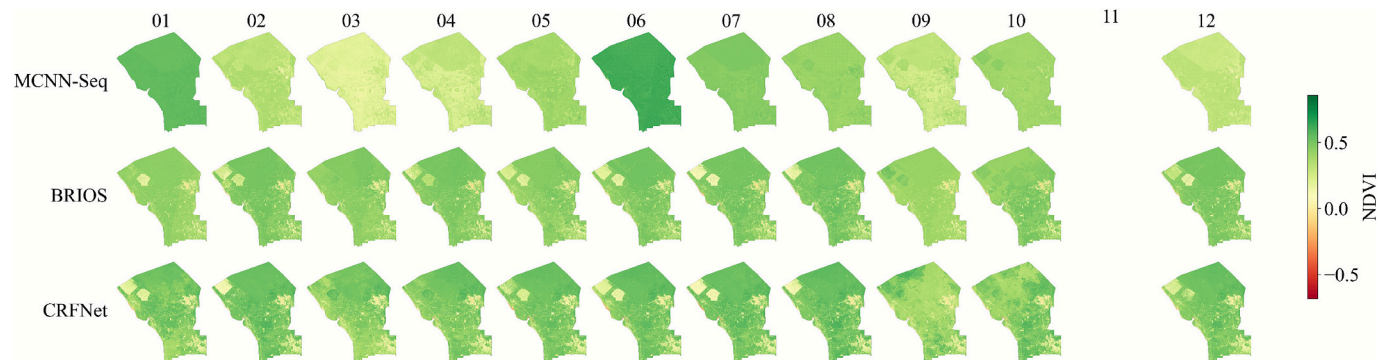


Fig. 21. Monthly NDVI reconstructions in 2020 by MCNN-Seq, BRIOS, and CRFNet.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jag.2025.104966>.

Data availability

CRFNet code is shared in [Supplementary Materials](#) and on GitHub: <https://github.com/Madao97/CRF-Net>. Due to size, datasets can be requested from jiapengfei97@gmail.com.

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