



Distinct spatiotemporal responses of soil-vegetation-hydrology to warming from 2005-2022 and predicting air temperature of provincial spatial scale using Kolmogorov-Arnold graph convolutional network in mainland China

Junjie Xu ^{1,2,3}, Yilei Yu ^{1,*}, Lihu Yang ², Xin Wei ⁴

¹ School of Eco-Environment, Hebei University, Baoding, Hebei, 071000, China

² Key Laboratory of Land Water Cycle and Surface Processes, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China

³ University of Chinese Academy of Sciences, Beijing 100049, China

⁴ College of Ecology and Environment, Institute of Disaster Prevention Science and Technology, Sanhe, Hebei, 065201, China

Correspondence: Yilei Yu (yuyilei1222@126.com)

Abstract. Under global warming, accurately predicting regional temperature and understanding the response mechanisms of multi-dimensional environmental variables are crucial for climate adaptation. This study integrates multi-source remote sensing, reanalysis, and ground observation data to construct a monthly provincial-scale environmental dataset for China covering 2005-2022.

5 Long-term trend analysis reveals a widespread increase in Mean Annual Temperature (MAT), which has enhanced vegetation activity, evidenced by rising NDVI and GPP, with rapid responses (0-1 month lag) especially in eastern humid regions. Conversely, deep soil moisture (100-289 cm) has declined in northern China, exhibiting lags of up to 5-6 months, indicating prolonged soil drying under sustained warming. Shallow soil moisture (0-7 cm) shows variable lags, concentrated
10 in the Yangtze River basin and Southwest China, while soil temperature responds within 0-3 months. Groundwater levels display weak direct correlation with air temperature. To capture complex spatial dependencies and non-linear interactions, we construct a provincial graph based on real geographic adjacency and develop a Graph Convolutional Network (GCN) coupled with Kolmogorov-Arnold Networks (KAN). The KAN-GCN model achieves state-of-the-art
15 performance on the 2021-2022 test period ($R^2=0.9889$, $RMSE=1.18^\circ C$), reducing MAE by 15%-30% in ecologically fragile regions such as Xinjiang and Qinghai compared to conventional MLP-GCN. Feature importance analysis consistently identifies surface soil temperature (0-7 cm) as the most critical predictor, highlighting the pivotal role of soil-atmosphere thermal coupling. Furthermore, Local Indicators of Spatial Association (LISA) error clustering confirms that
20 KAN-GCN eliminates the persistent high-error clusters observed with MLP-GCN over the Qinghai-Tibet Plateau, demonstrating superior spatial robustness and predictive reliability.



Keywords: Climate change; Soil-vegetation-hydrology system; Lag response; Graph convolutional network; Kolmogorov-Arnold network; Temperature prediction.

Highlights:

- 25 ● We reveal responses of China's soil-vegetation-hydrology system to warming.
 - We build a provincial adjacency graph and propose KAN-GCN for temperature prediction.
 - KAN-GCN outperforms MLP-GCN, with 15-30% lower MAE in China's fragile regions.
 - Surface soil temperature dominates as the key temperature predictor.
 - Long-term warming drives vegetation greening and deep soil drying in northern China.
- 30 **Software:**
- Name of software: MLP-GCN and KAN-GCN for provincial air temperature prediction
 - Developers: Junjie Xu
 - Contact: sherlockjjobs@163.com
 - Date first available: April 6, 2026
- 35 ● Software required: Python ≥ 3.10 ; PyTorch ≥ 2.0 (with CUDA support recommended); PyTorch Geometric ≥ 2.4 ; pykan (Kolmogorov-Arnold Networks); Additional dependencies: pandas, numpy, scikit-learn, geopandas, networkx, matplotlib, seaborn, libpysal, esda, joblib; All dependencies can be installed via the provided requirements.txt file. Docker support is optional but recommended for reproducibility.
- 40 ● Program language: Python
- Source code at: <https://github.com/sherlockjjobs/provincial-air-temperature-prediction>
 - Documentation: <https://github.com/sherlockjjobs/provincial-air-temperature-prediction/blob/main/README.md>
 - Data required for local installation and use of software is accessed through the cloud. See
- 45 Data Availability Statement.

1. Introduction

Against the backdrop of global climate change, the persistent rise in global mean temperatures has emerged as a core challenge facing both ecological environments and human societies (Hoegh-Guldberg et al., 2019). As one of the countries most profoundly impacted by

50 climate change, China possesses a vast territory, complex topography, and diverse climatic conditions, resulting in significant spatiotemporal heterogeneity in temperature variations. From 1961 to 2024, China's annual mean temperature exhibited a significant upward trend, increasing at an average rate of 0.31 °C per decade. The annual mean temperature in 2024 exceeded the



climatological norm by 1.0 °C for the first time, marking the warmest year since 1901 (Wang et al., 2025). Spanning from the cold-temperate zone of the northern Greater Khingan Range to the tropics of Hainan, and from the arid inland Northwest to the humid Southeast coast, rising temperatures have not only reshaped the structure and function of terrestrial ecosystems but have also triggered cascading responses in the hydrological cycle, soil processes, and vegetation dynamics (Yue et al., 2025). In some regions, warming has prolonged the vegetation growing season, for instance, the Growing Season Length (GSL) in the Mu Us Sandy Land of Inner Mongolia has extended by an average of 0.65 days year⁻¹ (Yang et al., 2022). Conversely, in other regions, it has exacerbated soil moisture deficits. Taking North China as an example, annual mean soil moisture showed a near-continuous decline from the 1960s to the 2010s. During the period of 1998-2017, the contribution of annual potential evapotranspiration to soil moisture variability increased by 26% compared to 1961-1997, with the contribution of summer potential evapotranspiration rising by as much as 45% (Li et al., 2021). A systematic understanding of the spatiotemporal patterns, response lag characteristics, and underlying mechanisms of these coupled variables is essential not only for diagnosing ecosystem vulnerability but also for laying the foundation to improve the predictive capability of regional climate models amidst continuous global change.

As a key indicator of climate change, air temperature is jointly regulated by multiple environmental factors, including vegetation cover, soil properties, hydrological processes, and geographical conditions (Li et al., 2022). The interactions between climate and the land surface are fundamentally non-linear and spatially heterogeneous. Vegetation indices, such as the Normalized Difference Vegetation Index (NDVI) and Gross Primary Productivity (GPP), typically exhibit rapid responses to temperature changes (Zeng et al., 2022). This is particularly evident in humid monsoon regions, where thermal conditions dominate the length of the growing season, rendering it highly sensitive to warming. In contrast, vegetation responses in arid and semi-arid regions are weaker or exhibit lag effects, highlighting the critical role of soil moisture as a mediating factor (Xu et al., 2023). In a warming experiment conducted in a semi-arid grassland in Wyoming, USA, the warming treatment increased the 6-year cumulative GPP by 29%, with this promoting effect being most significant in spring, reaching up to 129% (Ryan et al., 2017). Soil itself functions as both a reservoir and a conduit, while soil temperature closely tracks atmospheric fluctuations, soil water content integrates the cumulative effects of precipitation, evapotranspiration, and deep recharge processes across different time scales (Vereecken et al., 2022).

Regarding air temperature prediction methods, traditional approaches such as multiple linear regression and time series analysis often struggle to capture the complex spatial dependencies and



nonlinear relationships between temperature and environmental variables (Badugu et al., 2024).
90 Furthermore, they frequently lack interpretability and a foundation in physical mechanisms. Although machine learning models, such as Random Forest and Support Vector Machines, can reduce prediction errors by 10%-25% compared to traditional linear models by capturing nonlinearities (Sameh et al., 2023), they typically treat spatial units as independent entities. Consequently, they often overlook the geographic adjacency effects and spatial autocorrelation
95 inherent in temperature data (Wang et al., 2025). Recent advances in Graph Neural Networks (GNNs) have offered new perspectives for addressing these challenges. By explicitly encoding geographic adjacency relationships as topological connections between nodes, GNNs facilitate the joint modeling of spatial dependencies and multivariate interactions (Ding et al., 2024). Research indicates that GNNs performing 10-day forecasts on ERA5 reanalysis data at a resolution of
100 $0.25^\circ \times 0.25^\circ$ reduced the Root Mean Square Error (RMSE) by an additional 5%-8% compared to the ECMWF's HRES operational reforecasts, while significantly improving the detection hit rate for extreme high-temperature events (Shi et al., 2025). Graph Convolutional Networks (GCNs) can leverage the inherent spatial structure of Chinese administrative divisions, where adjacent provinces share similar climatic, soil, and ecological conditions, to enhance both prediction
105 accuracy and physical interpretability (Zhang et al., 2025). Despite these advantages, existing GCN-based studies on air temperature prediction typically employ fixed nonlinear activation functions (e.g., ReLU). Such fixed functions may be insufficient to adapt to the diverse and complex nonlinear patterns characterizing temperature-environment relationships across different regions and seasons (Wang et al., 2023). Emerging neural architectures, such as
110 Kolmogorov-Arnold Networks (KANs), utilize learnable spline functions to approximate nonlinear mappings. By adaptively fitting data-driven nonlinear relationships without presupposing activation forms, KANs offer a novel approach to this challenge and hold promise for better approximating the complex, non-monotonic relationships between eco-hydrological drivers and temperature (Panahi et al., 2025). In daily temperature forecasting experiments
115 conducted in Abidjan, Côte d'Ivoire, and Kigali, Rwanda, KANs achieved a further 6.4% reduction in RMSE compared to traditional Multi-Layer Perceptrons (MLPs), while providing a more accurate characterization of the non-monotonic humidity-temperature coupling processes (Akazan et al., 2025).

Despite continuous advancements in methodology, critical knowledge gaps remain to be
120 addressed. First, the lag response characteristics of various environmental variables to temperature, particularly their vertical stratification (e.g., shallow vs. deep soil) and regional differentiation across China, have not yet been systematically quantified at the provincial scale. Second, although Graph Convolutional Networks have demonstrated potential in spatial prediction tasks, there



remains a lack of clear understanding regarding the relative contributions of soil thermodynamic
coupling, vegetation status, and geographical background to temperature prediction. Finally, the
trade-off between model expressiveness and computational efficiency in real-world environmental
applications requires rigorous empirical evaluation. To address these issues, this study integrates
multi-source remote sensing, reanalysis, and ground observation data to construct a monthly,
multivariate environmental dataset covering provincial administrative units in China from 2005 to
2022. The primary objectives are to investigate the response characteristics of multidimensional
environmental variables to temperature in the context of global warming and to develop
high-precision provincial temperature prediction models based on GCNs. Specifically, the
objectives of this study are as follows: (1) to analyze the spatiotemporal patterns and long-term
trends of key environmental variables (climate, vegetation, hydrology, soil) in China from 2005 to
2022; (2) to identify the lag response characteristics and regional differentiation patterns of
eco-hydrological variables in response to temperature changes; (3) to construct a GCN prediction
model based on actual geographic adjacency relationships, compare the impact of different
readout heads (MLP vs. KAN) on model performance, and evaluate their effectiveness in
capturing complex spatial nonlinear relationships and their comparative predictive capabilities;
and (4) to reveal the key environmental factors influencing temperature prediction and the spatial
distribution characteristics of model errors through feature importance analysis, spatial error
autocorrelation analysis, and Local Indicators of Spatial Association (LISA) analysis. This study is
expected to deepen the understanding of the response mechanisms of China's land surface system
to climate change and provide new insights and empirical support for developing more accurate
and physically interpretable regional climate prediction techniques.

2. Materials and methods

2.1 Study area

Situated in eastern Asia on the western coast of the Pacific Ocean, China covers a land area
of about 9.6×10^6 km² (Li et al., 2023). Based on the natural geographical zoning data from the
Resource and Environment Data Cloud Platform of the Chinese Academy of Sciences and tailored
to specific research requirements, China is divided into seven major regions: Northwest, North,
Northeast, Southwest, Central, East, and South China (Zhou et al., 2024). China's topography is
characterized by a "high in the west, low in the east" gradient, exhibiting a three-step staircase
distribution (Xun et al., 2015). All five basic terrain types, plateaus, mountains, plains, hills, and
basins are distributed throughout the country (Wen et al., 2024). Due to its vast territorial expanse
and extensive longitudinal and latitudinal spans (spanning approximately 50° in latitude and 60° in
longitude), the combinations of temperature and precipitation are diverse, forming a complex and



varied climatic environment. The monsoon climate is particularly significant, which also contributes to the frequent occurrence of meteorological and geological disasters in China. The large latitudinal span results in significant spatial heterogeneity in temperature from north to south. South of the Qinling-Huaihe line, the region is primarily subtropical and tropical (Wang et al., 2024). The northern end of the Greater Khingan Mountains and its flanks are distributed in the cold temperate zone, while the middle temperate zone, situated between the warm temperate and frigid zones, covers a vast area (Zhao et al., 2016). The multi-year mean temperature ranges from -5 to 25°C from north to south. Vegetation types are abundant, primarily comprising grasslands, tropical rainforests, evergreen broadleaf forests, deciduous broadleaf forests, and coniferous forests (Zhao et al., 2009). Broadleaf forests are widely distributed across the temperate and warm temperate zones, whereas coniferous forests are mainly found in cold temperate regions. Soil types are complex and diverse, exhibiting a pattern of regular succession in response to changes in geographical location and topographic elevation (Zhang et al., 2022). This distribution manifests as horizontal zonality and is associated with vertical zonality and regional characteristics.

2.2 Data sources and preprocessing

This study constructs a multi-variable environmental dataset at the monthly scale for China's provincial administrative regions, covering the period from 2005 to 2022. This dataset is designed to systematically analyze the response mechanisms of eco-hydrological variables to air temperature in the context of climate warming and to support temperature prediction modeling driven by Graph Convolutional Networks (GCN). The dataset integrates multi-source information from remote sensing, reanalysis products, and ground-based observations (currently lacking data from Taiwan Province). Detailed information regarding the specific datasets is presented in Table 1.

Table 1. Summary of key environmental variable datasets used in this study.

Variable				
Category	Variable	Data Source	Temporal Coverage	Unit
Climate	2-m Air Temperature	ECMWF/ERA5-LAND/MON	2005-2022 (monthly)	°C
	(T2m)	THLY_AGGR		
Vegetation	Vegetation Index		2005-2022 (monthly)	g C m ⁻² month ⁻¹ mm
	(NDVI)	MODIS MOD13A3 v061		
	Gross Primary		2005-2022 (8-day →	
	Productivity (GPP)	CAS/IGSNRR/PML/V2_v018	monthly)	
Hydrology	Evapotranspiration		2005-2022 (8-day →	
	(ET = Ec + Es + Ei)	CAS/IGSNRR/PML/V2_v018	monthly)	month ⁻¹



		“Underground well water level observation grid dataset from 2005 to 2022” (Wang et al., 2025)		
Soil Properties	Groundwater Level (GWL)		2005-2022 (monthly)	m
	“A national soil organic carbon density dataset (2010-2024) in China” (Chen et al., 2025)			
	Soil Organic Carbon Density (SOCD)		2010-2024 (annual)	kg C m ⁻²
	Soil Moisture (SM)	ECMWF/ERA5-LAND	2005-2022 (monthly)	m ³ m ⁻³
Land Cover	Soil Temperature (ST)	ECMWF/ERA5-LAND	2005-2022 (monthly)	°C
	China Land Cover Dataset (CLCD v01) (Huang et al., 2023)			Categoric al (9 classes)
	Land Use/Land Cover (LULC)		2021	

Notes: All variables (except SOCD) are aligned to a monthly temporal resolution from 2005 to 2022. Spatial aggregation is based on FAO GAUL 2015 Level 1 administrative boundaries for mainland China’s 31 provinces (Hong Kong, Macao, and Taiwan excluded from modeling).

185 Missing values (<5%) were imputed using KNN. Seasonal cycles were explicitly encoded using sine/cosine transformations of month.

Air temperature (T2m) was derived from the ERA5-LAND monthly composite reanalysis products (~9 km spatial resolution), with provincial mean values extracted in Google Earth Engine (GEE) and converted from Kelvin to degrees Celsius. The vegetation index NDVI (from MODIS MOD13A3 v061, 1 km resolution) and both GPP and ET (from PML-V2 v0.1.8, 500 m resolution) were also processed in GEE to generate monthly composites and provincial spatial averages. GPP was used as monthly mean daily values, while monthly ET totals (mm month⁻¹) were obtained by aggregating (Ec+Es+Ei)×8 from each 8-day composite. Soil moisture (SM) and soil temperature (ST) were likewise sourced from ERA5-LAND and processed according to standard soil layer stratification (0-7 cm and 100-289 cm). Groundwater level (1 km resolution) was resampled to obtain provincial mean values. Soil organic carbon density (SOCD) was calculated by extracting annual mean values for the 0-30 cm and 30-100 cm soil layers and matching them to the provincial scale through spatial interpolation. Land cover (LULC) was represented by the 2021 CLCD v01 product (30 m resolution), employed as a static underlying surface characteristic.

200 **2.3 Graph convolutional network modeling**
2.3.1 Graph construction based on real geographical adjacency



To encode spatial dependencies among China's 31 provincial administrative units, we constructed an undirected adjacency graph using the GADM 4.1 Level-1 shapefile (Robbins et al., 2018). Each province was treated as a node, and an edge was established between two nodes if their administrative boundaries shared a non-trivial border, determined via geometric boundary intersection using shapely (Fig. 1). This ensures the graph reflects true geographical contiguity rather than arbitrary distance thresholds. The final graph contains 31 nodes and preserves the topological structure of mainland China's provincial layout.



Fig. 1. Adjacency graph of various provinces in China.

2.3.2 Data preprocessing and temporal encoding

We compiled a monthly environmental dataset spanning 2005-2022, integrating variables from remote sensing (e.g., NDVI, GPP), reanalysis products (e.g., ERA5-LAND for soil moisture/temperature and 2-m air temperature). Input features include: geographic coordinates (latitude, longitude), soil properties (soil_moisture and soil_temperature at 0-7 cm and 100-289 cm depths), vegetation indicators (NDVI, GPP), hydrological flux (ET), temporal encodings



(month_sin, month_cos, normalized year). Seasonal periodicity was modeled using sine/cosine transformations of the month variable. All continuous features were standardized using StandardScaler (Hernandez-Santiago et al., 2026). Only provinces present in every month were retained to ensure temporal completeness, resulting in a consistent set of 31 provinces across the entire time series.

The data were structured as a sequence of dynamic graphs, where each graph corresponds to one month and contains 31 nodes (one per province) (Peng et al., 2025). For month t , the node feature matrix $X_t \in \mathbb{R}^{31 \times F}$ ($F=12$) aggregates standardized environmental covariates, while the target vector $y_t \in \mathbb{R}^{31}$ contains observed 2-m air temperature. The edge index remains static across time, reflecting fixed geographical adjacency.

2.3.3 Dual model architectures: MLP-GCN and KAN-GCN

To investigate the impact of nonlinear function approximation on predictive performance, we implemented two graph neural network variants that share identical GCN encoders but differ in their readout heads (Fig. 2). Let $G=(V,E)$ denote the provincial adjacency graph, where each node $v_i \in V$ corresponds to a province and edges $(v_i, v_j) \in E$ represent geographical contiguity (Chen et al., 2024). For a given month, the input feature matrix is $X \in \mathbb{R}^{N \times F}$, where $N=31$ is the number of provinces and $F=12$ is the number of environmental covariates.

Both models first apply two layers of Graph Convolutional Network (GCN) to aggregate spatial information (Zhang et al., 2019):

$$H^{(1)} = \sigma(\tilde{A}XW^{(1)}), \quad H^{(2)} = \sigma(\tilde{A}H^{(1)}W^{(2)}) \quad (1)$$

where $\tilde{A} = D^{-1/2}(A+I)D^{-1/2}$ is the normalized adjacency matrix with self-loops, $w^{(l)}$ are learnable weight matrices, and $\sigma(\cdot) = \text{ReLU}(\cdot)$ is the activation function. The output $H^{(2)} \in \mathbb{R}^{N \times d}$ (with $d=64$) serves as the enriched node representation for all provinces.

The two models then diverge in their readout functions, applied independently to each node:

MLP: A standard Multi-Layer Perceptron (MLP) with fixed ReLU activations (Ta et al., 2026):

$$\hat{y}_i = f_{\text{MLP}}(h_i^{(2)}) = w_3^T \text{ReLU}(w_2 \text{ReLU}(w_1 h_i^{(2)} + b_1) + b_2) + b_3 \quad (2)$$

where $h_i^{(2)}$ is the i -th row of $H^{(2)}$, and the hidden dimensions are $R64 \rightarrow R64 \rightarrow R32 \rightarrow R$.

KAN: A Kolmogorov-Arnold Network (KAN) replaces fixed nonlinearities with learnable

univariate spline functions $\phi_{ij}^{(l)}$ (Qezelbash-Chamak et al., 2025):

$$\hat{y}_i = f_{\text{KAN}}(h_i^{(2)}) = \sum_{j=1}^{32} \phi_j^{(2)} \left(\sum_{k=1}^{64} \phi_k^{(1)}(h_{ik}^{(2)}) \right) \quad (3)$$



where each $\phi_k^{(1)}$ and $\phi_j^{(2)}$ is a trainable B-spline parameterized by grid points and coefficients. The KAN follows a width configuration of [64,32,1], with grid size 5 and spline order 3, enabling data-adaptive functional mapping.

Both models output a scalar prediction $\hat{y}_i \in \mathbb{R}$ for each province i . This shared encoder / divergent decoder design isolates the effect of the readout head's expressivity, allowing a fair comparison of fixed (MLP) versus learnable (KAN) nonlinearities in modeling the complex (Yu et al., 2024), nonlinear response of air temperature to eco-hydrological drivers under climate change.

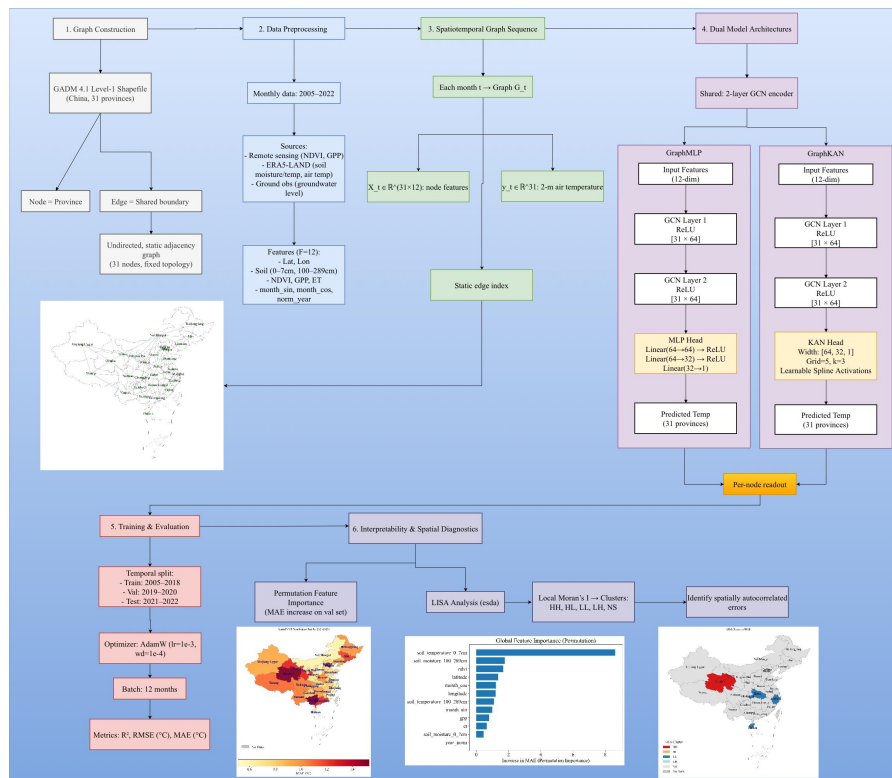


Fig. 2. Overall workflow of the GCN-based temperature prediction framework.

2.3.4 Training protocol with early stopping

Models were trained using the AdamW optimizer (learning rate= 10^{-3} , weight decay= 10^{-4}) with a batch size of 12 months (Alagiologlou et al., 2022). To prevent overfitting and ensure optimal generalization, we implemented an early stopping strategy based on validation performance (Mirdita et al., 2022). Specifically, training was monitored for up to 200 epochs, and the model with the highest coefficient of determination (R^2) on the validation set (2019-2020) was retained. If the validation R^2 did not improve for 20 consecutive epochs, training was terminated



early. This approach balances model convergence with computational efficiency and guards against overfitting to the training data. The dataset was partitioned into three non-overlapping temporal segments to rigorously evaluate model generalization under climate change: training set 2005-2018 (used for parameter optimization), validation set 2019-2020 (used for early stopping and model selection), test set 2021-2022 (held out for final, unbiased performance assessment). All random seeds were fixed (seed=42) to ensure full reproducibility.

Three standard regression metrics were employed: the coefficient of determination (R^2), the root mean squared error (RMSE), and the mean absolute error (MAE). These metrics evaluate model accuracy from complementary perspectives explained variance, sensitivity to large errors, and average prediction bias, respectively (Elmotawakkil et al., 2025). The model training and testing are both run on an Apple M2 Pro chip with 10 cores and 16GB of memory.

2.3.5 Model interpretability and spatial diagnostics

To interpret feature contributions, we computed permutation feature importance on the validation set: each input feature was randomly shuffled, and the increase in MAE relative to the baseline quantified its predictive relevance (Jing et al., 2023). Additionally, we performed Local Indicators of Spatial Autocorrelation (LISA) analysis on provincial MAE using the esda package. A Queen-contiguity spatial weights matrix, derived from the same GADM-based adjacency graph, was used to compute Local Moran's I. LISA clusters (HH, HL, LL, LH, NS) identified regions where prediction errors are spatially autocorrelated, revealing potential systematic model biases (Islam et al., 2022).

2.4 Response lag analysis based on correlation coefficient

This study employs a monthly-scale lagged Pearson correlation analysis to systematically identify the optimal response time lags of environmental variables relative to temperature. This method evaluates the strength of linear associations between temperature and each predictor across a range of temporal offsets, thereby revealing the intrinsic time-delayed dynamics within the land-atmosphere system (Wu et al., 2015).

Let $T(t)$ denote the monthly mean 2-meter air temperature (the target variable) in a given province at time t (in months), and let $X(t)$ represent the contemporaneous observation of an environmental variable (e.g., NDVI, soil moisture). For a predefined maximum lag window $L_{\max}$ (set to 6 months in this study), the lagged correlation between X and T at lag l ($l=0,1,2,\dots,L_{\max}$) is defined as:

$$r_l = \text{corr}(T(t), X(t+l)) \quad (4)$$

where $\text{corr}(\cdot, \cdot)$ denotes the Pearson correlation coefficient, computed as (Wang et al., 2022):



$$r_1 = \frac{\sum_{t=1}^{N-1} (T(t) - \bar{T})(X(t+1) - \bar{X}_1)}{\sqrt{\sum_{t=1}^{N-1} (T(t) - \bar{T})^2} \sqrt{\sum_{t=1}^{N-1} (X(t+1) - \bar{X}_1)^2}} \quad (5)$$

Here, N is the total length of the time series (in months), $\bar{T}$ is the mean of the full temperature series, and $\bar{X}_1$ is the mean of the lagged subsequence $\{X(1+1), \dots, X(N)\}$.

For each environmental variable X , the optimal lag l^* is determined as the lag that maximizes the absolute value of the correlation coefficient (Tian et al., 2024):

$$l^* = \arg \max_{l \in \{0, 1, \dots, L_{max}\}} |r_l| \quad (6)$$

The corresponding maximum correlation is denoted $r^* = r_{l^*}$. This criterion ensures the identification of the strongest linear relationship, irrespective of its direction (positive or negative).

The analytical workflow is as follows: for each province-variable pair, the correlation sequence is computed. Finally, the optimal lag l^* and its associated r^* are extracted and aggregated across provinces to reveal regional patterns of response timing.

2.5 Trend analysis

Sen's slope (also known as the Theil-Sen estimator) provides a robust estimate of the linear trend by computing the median of all pairwise slopes between time points (Shah et al., 2025). It is highly resistant to outliers and does not assume normality of the data. The MK test evaluates whether the detected trend is statistically significant without requiring assumptions about the underlying distribution. The test statistic Z is derived from the difference between the number of increasing and decreasing pairs in the sequence. For sample sizes $n \geq 10$, Z approximately follows a standard normal distribution. The null hypothesis H_0 states no trend, while the alternative hypothesis H_1 indicates a monotonic trend. A p -value below a chosen significance level leads to rejection of H_0 , confirming a significant trend (Aydin et al., 2025). Using Sen's slope β and the first observation (x_0, y_0) , the linear trend equation is constructed as:

$$\hat{y}(x) = \beta \cdot x + b, \quad \text{where } b = y_0 - \beta \cdot x_0 \quad (7)$$

3. Results

3.1 Spatiotemporal patterns and trends of eco-hydrological variables in China under a warming climate

From the perspective of the climate-vegetation system, mean annual temperature, NDVI, and GPP exhibit a high degree of spatial coherence (Fig. 3b-d). The eastern monsoon region, influenced by the summer monsoon, is characterized by favorable hydrothermal conditions, forming high-value zones where mean annual temperature exceeds 10°C, NDVI is greater than 0.6, and GPP surpasses 1000 g C m⁻² yr⁻¹. These zones correspond to the distribution of intensive cropland and dense forests (Fig. 3a). In stark contrast, the northwestern arid and semi-arid region,



due to its deep inland location, experiences an imbalanced hydrothermal regime. Here, mean annual temperature is generally below 10°C, NDVI is lower than 0.3, and GPP is less than 600 g C m⁻² yr⁻¹. Ecosystem productivity is strongly constrained by water stress, and land use is dominated by grassland and unused land. The Qinghai-Tibet Plateau constitutes a unique low-temperature-limited ecoregion. Although some alpine meadow areas receive relatively abundant precipitation, the mean annual temperature is generally below 0°C, leading to a short vegetation growing season. Consequently, both NDVI and GPP remain at low levels, indicating significant ecosystem vulnerability.

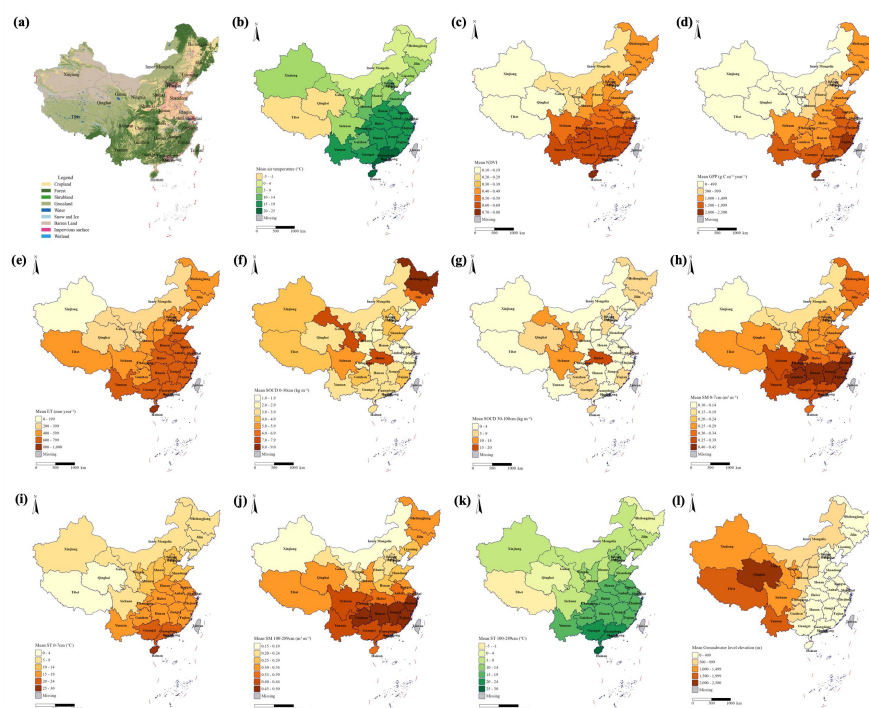


Fig. 3. Spatial distribution patterns of key environmental and ecological variables across China (2005–2022). (a) Land use in 2021; (b) Annual mean air temperature (°C); (c) Annual mean NDVI; (d) Annual mean GPP (g C m⁻² yr⁻¹); (e) Annual mean evapotranspiration (ET, mm yr⁻¹); (f) SOCD in the 0-30 cm layer (kg C m⁻²); (g) SOCD in the 30-100 cm layer (kg C m⁻²); (h) Soil moisture in the 0-7 cm layer (m³ m⁻³); (i) Soil temperature in the 0-7 cm layer (°C); (j) Soil moisture in the 100-289 cm layer (m³ m⁻³); (k) Soil temperature in the 100-289 cm layer (°C); (l) Mean groundwater level elevation (m).

Climatic patterns further shape the spatial differentiation of soil properties and groundwater resources. High-value areas of soil organic carbon density (SOCD) (>8 kg C m⁻²) are concentrated in the northeastern black soil region and the southwestern forest region. This is closely related to



345 the high organic matter input from dense vegetation cover and the slow decomposition rates due to
low temperatures (Fig. 3f-g). Accordingly, soil moisture content exhibits a decreasing gradient
from southeast to northwest. Surface soil moisture (0-7 cm) exceeds $0.3 \text{ m}^3 \text{ m}^{-3}$ in the humid
southeastern region, while it is mostly below $0.2 \text{ m}^3 \text{ m}^{-3}$ in the northwestern desert region, with
extremely arid areas like Xinjiang having values below $0.15 \text{ m}^3 \text{ m}^{-3}$ (Fig. 3h). The spatial
350 distribution of soil temperature closely follows that of air temperature. Surface soil temperature
exhibits stronger spatial heterogeneity, whereas deeper temperatures change more gently,
reflecting the soil's thermal buffering effect (Fig. 3i-k). As a comprehensive indicator of regional
hydrological conditions, groundwater depth is generally shallow in the eastern plains but deep in
the northwestern inland basins and the Qinghai-Tibet Plateau, reflecting significant differences in
355 water resource recharge conditions (Fig. 3l). In summary, these variables collectively delineate
China's eco-geographical gradients from southeast to northwest and from plains to plateaus,
revealing the intrinsic linkages among natural environmental factors and their regional response
mechanisms.

A comprehensive analysis of long-term trends reveals complex and regionally differentiated
360 responses of the ecosystem and hydrological cycle to persistent warming (Fig. 4). MAT, the most
direct climate indicator, shows a significant rising trend across the board, providing the
fundamental driver for changes in other variables. Consequently, vegetation dynamics have
responded positively, with concurrent increases in the NDVI and GPP observed in most provinces.
This trend suggests that longer growing seasons and improved thermal conditions have boosted
365 vegetation activity and carbon absorption. Nevertheless, this response is comparatively muted in
the water-limited Northwest, underscoring the controlling effect of water availability. The
feedbacks within hydrological and energy exchange processes are more intricate.
Evapotranspiration has risen in the humid South, driven by enhanced vegetation transpiration, yet
has declined in parts of the central region due to soil moisture stress, which reflects the non-linear
370 nature of hydro-thermal coupling. While soil temperature has increased broadly in line with air
temperature, a significant reduction in deep soil moisture in some northern provinces points to an
intensifying soil water deficit under long-term warming. Reflecting the combined impacts of the
surface water-heat balance and human activities, groundwater levels display stark spatial
heterogeneity, characterized by rises in the Northwest and North China and notable declines in the
375 South.

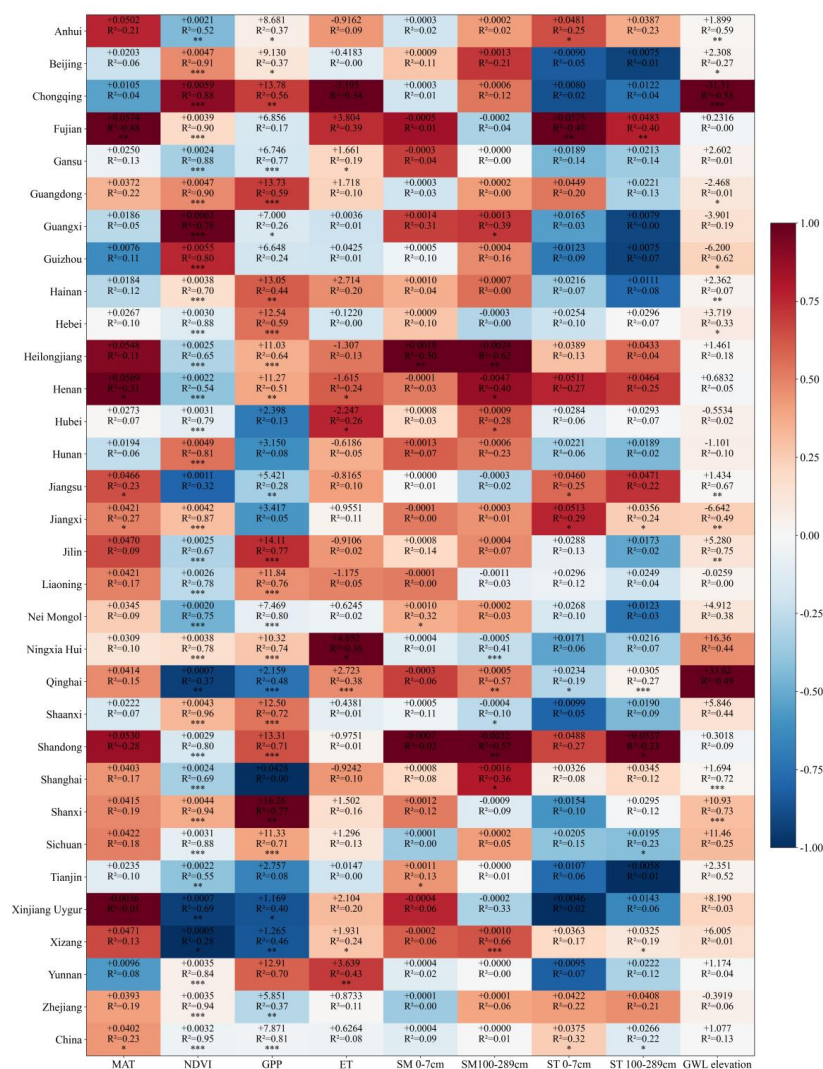


Fig. 4. China provincial multivariate trend heatmap: normalized Sen's slope, R^2 , and significance levels (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

3.2 Lag response patterns and regional differentiation characteristics of ecohydrological variables driven by temperature

380 The lagged responses of ecohydrological variables to temperature change in mainland China exhibit distinct southeast-northwest gradient patterns and vertical stratification characteristics. Vegetation indicators (NDVI, GPP) generally respond rapidly: the lag time of NDVI is ≤ 1 month in 72% of provinces, and 87% of provinces show a 0-month lag for GPP. This indicates that warming exerts an immediate driving effect on vegetation phenology and productivity,



385 particularly evident in the East Asian Monsoon Region (e.g., Zhejiang, Hubei). In contrast, soil
moisture exhibits significant lag effects on temperature with strong depth dependence: shallow
soil moisture (0-7 cm) has a large lag time range (0-6 months), with high-value areas concentrated
in the middle and lower reaches of the Yangtze River and Southwest China (e.g., Hubei, Anhui,
Jiangxi Provinces with a lag of ~6 months). This reflects the buffering effect jointly induced by
390 intense precipitation input and soil water-holding capacity. Deep soil moisture (100-289 cm)
presents a polarized pattern: lag times approach 0 in the humid southeastern regions (e.g.,
Zhejiang, Fujian), while most areas in northern and northwestern China (e.g., Shandong, Hebei,
Ningxia Provinces) show a lag of 5-6 months. This suggests that deep soil water circulation in arid
regions is dominated by slow vertical recharge processes. Soil temperature, regardless of depth,
395 generally has a lag time of 0-3 months, reflecting its physical nature as a direct receptor of air
temperature. The groundwater level exhibits the most complex response, with lag times ranging
from 1 month (e.g., Xinjiang, Heilongjiang) to 6 months (e.g., Shandong, Hainan), and its direct
correlation with air temperature is very weak. This highlights the combined impacts of natural
hydrological cycles and human activities.

400 Further summarized by geographical regions: humid eastern and southern regions (East
China, South China, Central China) are characterized by rapid vegetation responses and slow
shallow soil moisture responses, reflecting the priority of biological responses under hydrothermal
coordination (Table 2). Arid and semi-arid regions in northern and northwestern China generally
exhibit no vegetation lag, significant shallow SM lag, asynchronous responses of deep SM and
405 GWL, revealing the cross-seasonal support mechanism of deep water sources for surface
ecological processes. The Qinghai-Tibet Plateau (Tibet, Qinghai) shows short lag times for all
variables (1-3 months), embodying the synchrony and vulnerability of system responses under
low-temperature constraints. Northeast China (Heilongjiang, Jilin) is distinguished by extremely
short lags for SM and GWL, confirming the rapid hydrological activation driven by spring
410 snowmelt. Overall, lag processes are dominated by regional hydrothermal balance: water-limited
regions exhibit delayed responses and interlayer decoupling, while hydrothermally coordinated
(humid) regions show biological responses preceding hydrological processes.

Table 2. Lag time (in months) of eco-hydrological variables in response to air temperature at the provincial scale in China.

Geographical region	Province	NDVI	GPP	ET	SM 0-7	SM 100-289	ST 0-7	ST 100-289	GW L
Eastern China	Zhejiang	1	0	0	6	0	0	2	3
	Jiangsu	0	0	0	4	4	0	2	4
	Shandong	0	0	0	2	5	0	2	6



	Anhui	0	0	0	6	1	0	2	5
	Fujian	1	0	0	0	0	0	2	2
	Jiangxi	1	0	0	6	0	0	2	6
	Shanghai	0	0	0	6	0	0	2	1
Northern China	Tianjin	1	0	0	2	6	0	2	6
	Inner Mongolia	1	0	0	3	4	0	3	5
	Hebei	1	0	0	2	6	0	2	6
	Shanxi	1	0	0	4	6	0	2	6
	Beijing	1	0	0	3	6	0	2	5
Southwestern China	Guizhou	1	0	0	6	0	0	6	2
	Yunnan	6	1	0	4	6	0	6	6
	Chongqing	0	0	0	6	0	0	6	6
	Tibet	1	0	0	1	2	0	2	2
	Sichuan	1	0	0	2	6	0	6	1
Northwestern China	Shaanxi	1	0	0	1	3	0	2	3
	Gansu	1	0	0	4	5	0	2	3
	Qinghai	0	0	0	1	2	0	2	3
	Ningxia	1	0	0	4	6	0	2	6
	Xinjiang	0	0	0	6	1	0	3	1
Central China	Hunan	0	0	0	0	0	0	6	0
	Hubei	0	0	0	6	1	0	2	4
	Henan	0	0	0	3	6	0	2	6
Southern China	Guangxi	1	0	0	0	0	0	6	2
	Guangdong	1	1	0	0	1	0	2	3
	Hainan	1	0	0	1	5	0	2	6
Northeastern China	Jilin	0	0	0	0	3	0	3	0
	Liaoning	0	0	0	4	4	0	2	3
	Heilongjiang	0	0	0	0	3	0	3	1

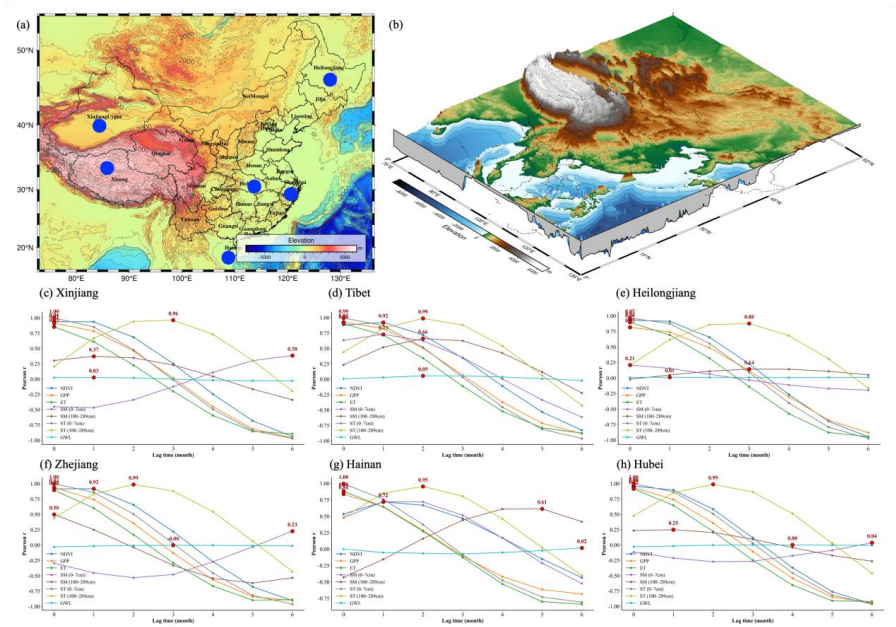


Fig. 5. (a) Plan topographic map of Chinese Mainland; (b) 3D Topographic Map of Chinese Mainland; (c)-(h) The time lag of ecohydrological variables to temperature changes in six provinces representing typical climatic zones of China, namely Xinjiang, Tibet, Heilongjiang, Zhejiang, Hainan and Hubei.

The lag characteristics of provinces in different climatic zones highlight the dominant role of climatic backgrounds (Table 3 & Fig. 5). In Xinjiang, surface SM lags by 6 months, deep SM by only 1 month, and GWL by 1 month, reflecting the regulation of water supply on soil moisture responses in arid regions. Tibet shows low lag times for all variables (1 month for NDVI, 1-2 months for soil moisture), as the low-temperature and short growing season weaken the driving effect of temperature on the ecohydrological system. In Heilongjiang, vegetation variables have no lag, and SM and GWL generally exhibit lags of 0-3 months, indicating a moderate temperature-driven effect under a cold temperate climate. Zhejiang has a 1-month lag for NDVI and 6-month lag for surface SM, reflecting the rapid vegetation response and delayed soil moisture response affected by precipitation distribution in the East Asian Monsoon Region. Hainan shows a 1-month lag for NDVI and 6-month lag for GWL, where sufficient tropical hydrothermal conditions coexist with slow GWL responses to temperature. Hubei has a 6-month lag for surface SM and 1-month lag for deep SM, indicating that soil moisture responses in the Central China Plain are significantly influenced by the coupling of agricultural water use and precipitation.

Table 3. Provincial climate and land-surface characteristics across representative regions of



435 China.

Province	Climate Type	Location Characteristics	Vegetation Type
Xinjiang	Temperate Continental Arid Climate	Northwest Inland	Desert/Green Oasis
Tibet	Plateau Mountain Climate	Qinghai-Tibet Plateau	Alpine Meadow/Grassland
Heilongjiang	Cold Temperate/Temperate Continental Monsoon Climate	Highest Latitude	Wetland/Mixed Broadleaf-Coniferous Forest
Zhejiang	Subtropical Monsoon Climate	Eastern Coastal	Evergreen Broadleaf Forest
Hainan	Tropical Monsoon Climate	Tropical Island	Tropical Rainforest
Hubei	Subtropical Monsoonal Humid Climate	Central Plain	Broadleaf Forest/Rice Paddy

Vegetation cover (NDVI) and productivity (GPP) exhibit a strong positive correlation across all regions (Fig .6). In the eastern humid region, mean annual air temperature (MAT) is strongly positively correlated with vegetation indicators (NDVI: 0.90, GPP: 0.85), corroborating the promotional role of temperature on vegetation growth. Conversely, a strong negative correlation (-0.71) between groundwater level (GWL) and soil temperature in the northwestern arid region indicates the regulatory effect of groundwater on surface thermal conditions. In the northeastern cold-temperate zone, the high correlation (0.94) between soil temperatures at different depths demonstrates the soil's thermal conduction properties. Significant spatial heterogeneity is observed in the multicollinearity among variables. VIF values are consistently high in the northwestern, central, and northeastern regions (VIF for evapotranspiration in the northeast reaches 26.2), suggesting a high degree of coupling among variables in arid, transitional, and cold zones. In contrast, the humid southwestern mountainous areas, attributable to their complex topography, demonstrate greater variable independence (VIF < 10).

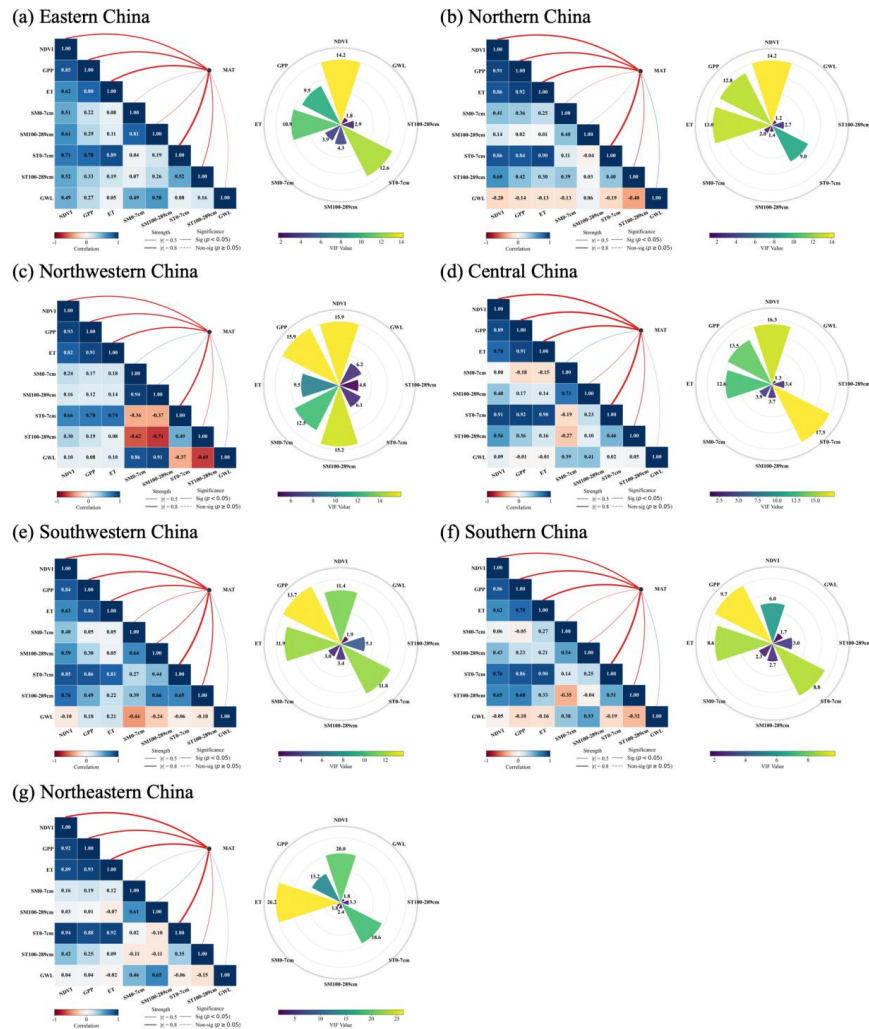


Fig. 6. Correlation and multicollinearity spatial differentiation characteristics of ecological-climate variables in the seven major geographical regions of China.

3.3 Model performance evaluation

For the training set, the MLP-GCN model recorded an R^2 of 0.991, while the KAN-GCN model performed better with an R^2 of 0.9956 (Table 4). During the validation phase (2019-2020), the MLP-GCN R^2 was 0.9858, and the KAN-GCN model improved this to 0.9916. On the test set (2021-2022), serving as the final evaluation of generalization ability, the KAN-GCN model maintained its lead, with $R^2=0.9889$, $RMSE=1.1818$ °C, and $MAE=0.9188$ °C. These results indicate that the KAN-GCN model consistently outperformed the MLP-GCN model across all



three datasets, demonstrating a stronger ability to capture complex relationships between environmental variables and temperature. Regarding training efficiency, the MLP-GCN model took 3 minutes, stopping early at epoch 156. In contrast, the KAN-GCN model took 6 hours and 38 minutes, stopping at epoch 189. This shows that the KAN-GCN model has stronger generalization and higher precision. However, this performance came with high computational costs, the KAN-GCN training time of 6 hours and 38 minutes far exceeded the MLP-GCN's 3 minutes, reflecting the complexity of parameter optimization in the KAN architecture.

Table 4. Model performance statistical indicators.

	MLP-GCN			KAN-GCN		
	R ²	RMSE	MAE	R ²	RMSE	MAE
Train (2005-2018)	0.991	1.0778	0.8267	0.9956	0.7492	0.5539
Validation (2019-2020)	0.9858	1.3112	0.9876	0.9916	1.0111	0.7588
Test (2021-2022)	0.9805	1.5613	1.1523	0.9889	1.1818	0.9188
Early stop	at epoch 156			at epoch 189		
Time	3 minutes			6 hours 38 minutes		

Fig. 7 shows the spatial distribution of prediction errors for both models. In the MLP-GCN model (Fig. 7a-b), provinces like Xinjiang and Tibet had relatively higher MAE. Conversely, the KAN-GCN model (Fig. 7c-d) showed lower MAE in most provinces, leading to more consistent and accurate predictions. Seasonal error heatmaps further revealed that the KAN-GCN model had smaller errors across different seasons, proving its robustness to seasonal temperature changes. This indicates that the KAN architecture offers greater adaptability and robustness in handling seasonal nonlinear patterns.

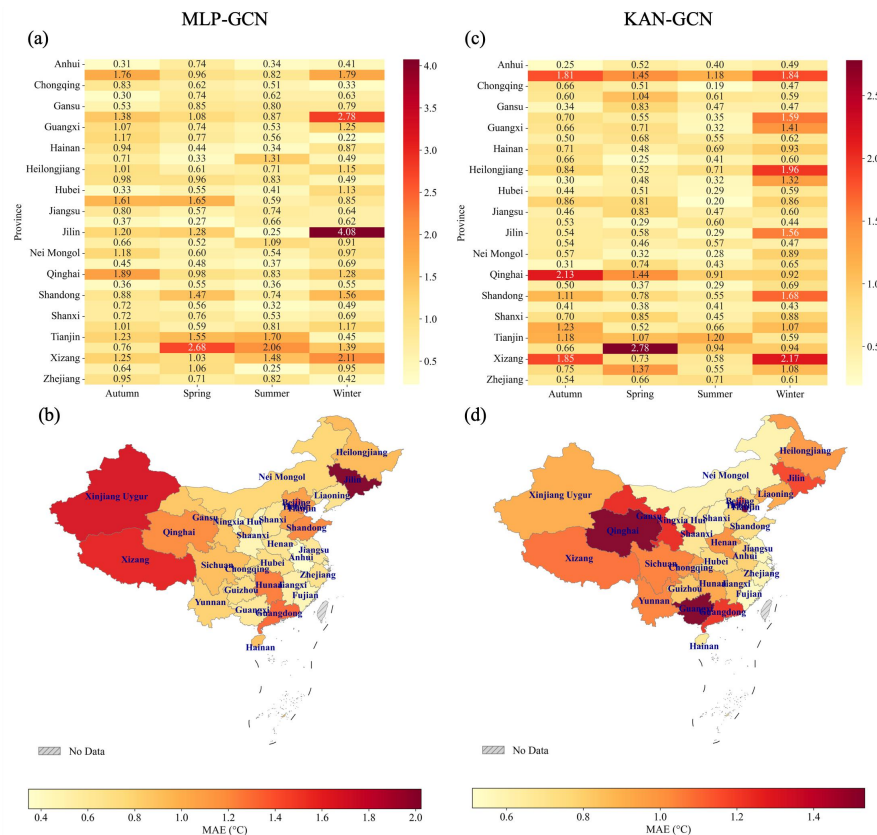


Fig. 7. Map of air temperature prediction model errors across Chinese provinces and seasonal comparison heatmaps for selected provinces. (a)-(b) represent the errors of the MLP-GCN model. (c)-(d) represent the errors of the KAN-GCN model.

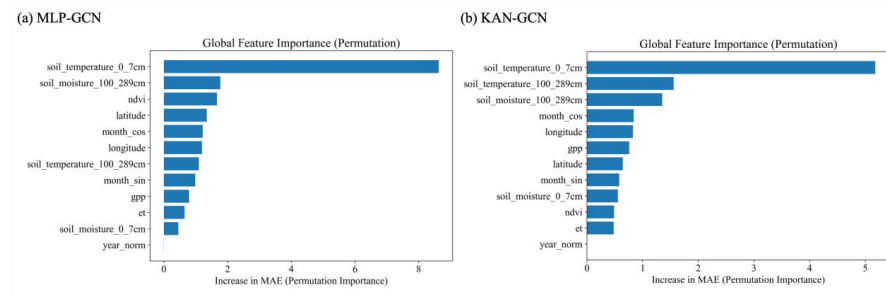


Fig. 8. Comparison of feature importance.

The results of the feature importance analysis (Fig. 8) reveal both commonalities and disparities in the identification of key influencing factors between the two models, with both underscoring the pivotal role of soil thermal conditions in air temperature prediction. For the



MLP-GCN model, soil_temperature_0_7cm emerged as the most critical feature, evidenced by the highest increase in MAE upon permutation. This was followed by deep soil moisture (soil_moisture_100-289cm) and the vegetation index (NDVI), while geographic and temporal variables such as latitude, month cosine (month_cos), and longitude also occupied significant positions. This suggests that the MLP-GCN model relies primarily on direct associations among soil, vegetation, and geographical space for air temperature prediction, demonstrating a high sensitivity to surface soil heat exchange and deep-layer moisture conditions. In contrast, the feature importance ranking for the KAN-GCN model exhibits a stronger focus on soil thermodynamic processes, soil_temperature_0_7cm and soil_temperature_100-289cm jointly claimed the top two positions, with deep soil moisture following closely behind. Furthermore, both models assigned relatively low importance to the normalized year (year_norm), indicating that over the 2005-2022 period, the linear trend of long-term climate warming contributed less to monthly air temperature prediction than the combined effects of underlying surface factors (soil, vegetation, and geographical patterns) and short-term temporal rhythms. Finally, eco-hydrological variables such as GPP and ET ranked lower in importance, reflecting that the driving force of air temperature on these variables is stronger than the reverse feedback effect.

3.4 Error space autocorrelation analysis based on LISA

The Local Indicators of Spatial Association (LISA) method was employed to conduct a spatial clustering analysis on the MAE of both the MLP-GCN and KAN-GCN models using the test set (2021-2022). The LISA cluster maps classify spatial relationships into four types: High-High (HH) clusters, High-Low (HL) clusters, Low-High (LH) clusters, and Low-Low (LL) clusters, while also identifying Not Significant (NS) regions where no significant spatial autocorrelation is observed.

As illustrated in Fig. 9a, Qinghai Province is identified as an HH cluster, indicating that the model exhibits high prediction errors in this region. Furthermore, a L-L cluster is formed across central and eastern regions, including Shaanxi, Hubei, and Zhejiang provinces. This suggests that prediction errors in these areas are generally low and spatially consistent, reflecting the model's robust performance in regions with relatively homogeneous geographical and climatic conditions. Additionally, Hainan Island stands out as an isolated L-L cluster point, demonstrating high prediction accuracy. In contrast, the spatial distribution of errors for the KAN-GCN model is more balanced, demonstrating stronger spatial robustness (Fig. 9b). Its H-H cluster areas have virtually disappeared, with only a small-scale H-L cluster appearing in Shandong Province. This indicates that while the prediction error in Shandong is higher than that of its neighboring provinces, it has not formed a large-scale area of systematic high error. This corroborates previous findings that the



515 KAN-GCN model possesses superior generalization capabilities and lower prediction bias overall. Meanwhile, the Qinghai region presents as a L-H cluster, implying that although the error in this area is lower than its surroundings, it differs significantly from the error levels of its neighboring provinces. Provinces such as Zhejiang and Hainan remain LL clusters, consistent with the results of the MLP-GCN model, which reflects the stability of the KAN-GCN model in these regions. Similarly, the majority of provinces are classified as NS, showing no significant spatial autocorrelation. The LISA analysis indicates that, compared to the MLP-GCN model, the KAN-GCN model effectively reduces the occurrence of H-H clusters.

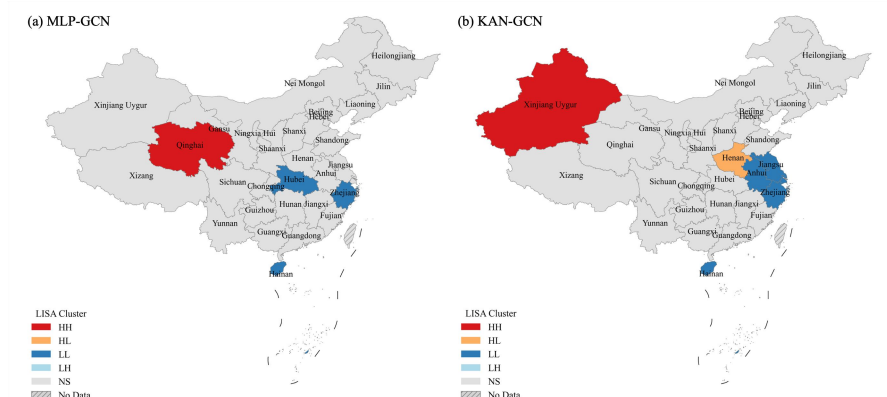


Fig. 9. LISA cluster map of prediction MAE.

4. Discussion

4.1 Nonlinear responses and regional heterogeneity of eco-hydrological variables under climate warming

525 Eco-hydrological systems across different regions of China exhibit highly differentiated response patterns. These disparities stem not only from the inherent gradients in climatic backgrounds but are also profoundly modulated by surface process regulation mechanisms. In the eastern humid region, vegetation responds almost synchronously to rising temperatures, indicating that heat availability is the primary factor limiting the length of the growing season and photosynthetic efficiency (Chen et al., 2022). Conversely, in the arid northwest, despite significant warming, vegetation activity has not intensified to a comparable degree, underscoring the critical modulation of water availability on ecosystem sensitivity (Yang et al., 2025). The lagged behavior of soil moisture further elucidates the memory effects of hydrological processes in response to climate change. In the middle and lower reaches of the Yangtze River, the response lag of shallow soil moisture to temperature variations can extend up to six months, this is likely attributable to buffering mechanisms resulting from the combined effects of abundant precipitation, high



water-holding capacity, and agricultural irrigation (Ren et al., 2025). In contrast, while deep soil moisture in the northern arid region also exhibits a prolonged lag, the underlying cause is more closely associated with slow vertical recharge processes. Given the infrequency of precipitation inputs, the replenishment of deep soil moisture relies primarily on seasonal rainfall or limited infiltration, resulting in a significantly delayed response to atmospheric warming (Dang et al., 2022). The Qinghai-Tibet Plateau, characterized as a low-temperature-dominated ecosystem, generally exhibits rapid responses across various variables to temperature changes. This suggests that in energy-limited environments, even minor thermal perturbations can trigger relatively synchronous chain reactions throughout the system. Overall, the response of China's eco-hydrological systems to climate warming does not follow a single trajectory, rather, it presents a pattern characterized by rapid biological responses and slow hydrological responses.

4.2 The pivotal role of soil-atmosphere thermal coupling in air temperature prediction

Feature importance analysis clearly indicates that surface soil temperature is the primary factor influencing the accuracy of air temperature predictions, irrespective of the model architecture employed. This finding profoundly reveals the critical role of soil-atmosphere thermal coupling within land-atmosphere interactions (Wu et al., 2025). Acting as a regulator of surface energy distribution, soil temperature directly dictates the intensity of sensible and latent heat flux exchanges between the land surface and the atmosphere, serving as the most direct and effective underlying surface variable affecting near-surface air temperature (Li et al., 2023). The importance of deep soil moisture reflects its regulatory effect on soil heat capacity and thermal conductivity, the wetness of deep soil influences surface temperature via thermal conduction, thereby affecting air temperature (Wang et al., 2024). On a seasonal scale in particular, this memory effect is paramount. The relatively low importance of the normalized year variable, which represents the long-term warming trend, indicates that during the 2005-2022 study period, the dominant driver of monthly air temperature variability was not the linear warming trend. Instead, it was a complex nonlinear combination shaped by the status of the underlying surface (soil and vegetation), geographical patterns, and intra-seasonal fluctuations. This implies that when constructing high-precision regional climate prediction models, it is essential to place high emphasis on and accurately characterize the dynamics and spatial heterogeneity of soil thermodynamic and hydrological processes, rather than relying solely on atmospheric circulation or global warming trend signals (Chen et al., 2023).

4.3 The superiority of Graph Convolutional Networks in regional air temperature prediction stems from joint modeling of spatial dependencies and nonlinear mechanisms



575 KAN-GCN achieved higher test accuracy and reduced MAE by 15-30% in geographically marginal or ecologically fragile regions like Xinjiang and Qinghai. This advantage stems from the core characteristics of the KAN architecture, whose trainable B-spline basis functions can adaptively fit complex nonlinear mappings between inputs and outputs without the need for preset activation forms (Rigas et al., 2024). For instance, in arid regions, the relationship between deep soil temperature and surface air temperature may exhibit threshold effects or saturation responses, traditional ReLU networks struggle to capture such non-monotonic behaviors, whereas KAN can model them flexibly through the local adjustment of spline nodes (An et al., 2025).

580 Feature importance analysis further reveals the differences in interpretation logic between the two architectures. MLP-GCN relies more heavily on surface variables and shallow soil states, reflecting its preference for direct correlations. In contrast, KAN-GCN places greater emphasis on the synergistic effects of multi-layer soil heat conduction processes, implying its ability to identify physical coupling mechanisms across different depths. This capability is also reflected in the spatial structure of errors. LISA analysis shows that MLP-GCN formed significant High-High (HH) error clusters in Qinghai, indicating systematic overestimation or underestimation in low-temperature and low-vegetation-coverage areas. Conversely, KAN-GCN almost eliminated such clusters, with an error distribution closer to randomness, proving its stronger generalization robustness in heterogeneous geographical units.

590 However, the performance improvement of KAN comes with a significant computational cost. Under identical hardware conditions, training KAN-GCN took 6 hours and 38 minutes, far exceeding the 3 minutes required for MLP-GCN. This is primarily due to the requirement to optimize spline parameters (grid points+coefficients) for every neural connection in KAN, leading to a substantial increase in parameter count and gradient calculation complexity (Liu et al., 2024). Additionally, KAN is more sensitive to hyperparameters, resulting in higher tuning costs (Somvanshi et al., 2025). Therefore, in practical applications, a trade-off must be made based on task requirements. If the goal is to pursue the highest prediction accuracy and physical interpretability, KAN-GCN is the superior choice. Therefore, if the focus is on real-time performance, deployment efficiency, or small-sample scenarios, MLP-GCN still holds practical value.

600 4.4 Potential and sources of uncertainty in integrated modeling of multi-source environmental variables

Despite integrating remote sensing, reanalysis, and ground observation data to construct a provincial monthly multi-variable dataset covering the period 2005-2022, several sources of uncertainty in this study remain worthy of discussion. First, soil organic carbon density data



605 contains missing values for certain years and is available only on an annual scale, which may
attenuate its explanatory power regarding short-term air temperature fluctuations. Secondly,
groundwater level data remain limited in sparsely monitored western regions, potentially
compromising the accuracy of the lag characteristics associated with groundwater level.
Furthermore, Variance inflation factor (VIF) analysis revealed high multicollinearity ($VIF > 20$)
610 among variables in regions such as the Northwest and Northeast. This suggests that in arid or cold
ecosystems, the climate-soil-vegetation system is highly coupled, making it difficult for any single
variable to independently explain variations in air temperature. Although GPP and ET ranked
lower in feature importance, this does not negate their ecological significance. Rather, it reflects
that, on a monthly timescale, they function more as responders to air temperature rather than
615 drivers. Future work could incorporate causal inference methods to further distinguish between
driving and feedback pathways, and integrate hydrological isotope data. This would enhance the
physical consistency and interpretability of the model, particularly in regions subject to intense
anthropogenic interference.

5. Conclusions

620 This study systematically investigates the spatiotemporal response characteristics of
vegetation, soil, and hydrological variables to temperature changes in China within the context of
global warming. Furthermore, a high-precision provincial temperature prediction model is
constructed based on Graph Convolutional Networks (GCN). By integrating multi-source data
spanning 2005-2022, including remote sensing, reanalysis, and ground observation data, lag
625 response analysis, trend analysis, and GCN modeling were conducted.

Long-term trend assessments reveal a pronounced upward trajectory in Mean Annual
Temperature (MAT), which elicits favorable growth feedbacks from vegetation, characterized by
NDVI and GPP indices. Vegetation responses in the arid northwestern areas are relatively muted,
primarily constrained by water availability. The decline in deep soil moisture observed in certain
630 northern provinces indicates a worsening deficit of soil water resources amid prolonged warming.
Vegetation metrics generally exhibit rapid responses to temperature variations, with a lag period
ranging from 0 to 1 month. This phenomenon is particularly evident in the humid eastern regions.
In contrast, soil moisture responses to temperature fluctuations are marked by significant time lags
and vertical stratification effects. Surface soil moisture (0-7 cm) shows a lag of 0-6 months, with
635 high-value zones concentrated in the middle and lower reaches of the Yangtze River as well as the
southwest region. For deep soil moisture (100-289 cm) in arid northern areas, the lag period
extends to 5-6 months. Soil temperature responds with a shorter lag (0-3 months), while the direct
correlation between groundwater levels and air temperature remains weak. Humid regions are



dominated by rapid biological responses to warming, whereas arid regions depend on
640 cross-seasonal deep soil water to maintain surface ecological processes. On the Qinghai-Tibet
Plateau, most eco-hydrological variables display relatively short lag times, typically falling within
the range of 1-3 months.

Graph Neural Networks possess advantages in integrating spatial dependencies and nonlinear
mechanisms. KAN-GCN model achieved optimal performance on the test set (2021-2022), with
645 an R^2 of 0.9889 and an RMSE of 1.18°C. In marginal or ecologically fragile provinces such as
Xinjiang and Qinghai, MAE was reduced by 15-30% compared to the MLP-GCN model. Local
Indicators of Spatial Association (LISA) error clustering analysis further confirmed that
KAN-GCN model effectively eliminates the systematic high-error clustering phenomenon existing
in the MLP-GCN model in regions such as the Qinghai-Tibet Plateau. Specifically, KAN-GCN
650 resolved the High-High (HH) error clustering found in the MLP-GCN model in Qinghai, resulting
in a more balanced error distribution and demonstrating superior spatial robustness.
Soil-atmosphere thermal coupling is identified as the core physical mechanism for temperature
prediction. Feature importance analysis consistently indicates that surface soil temperature (0-7
cm) is the most critical factor influencing prediction accuracy. This finding emphasizes that in
655 regional climate prediction modeling, it is necessary to prioritize the detailed characterization of
the dynamic changes and spatial heterogeneity of soil thermal-hydrological processes. Future
research should incorporate causal inference methods to distinguish between driving and feedback
pathways and integrate process-based data such as hydrological isotopes. This will further
enhance the physical consistency and interpretability of models, particularly in areas with intense
660 anthropogenic disturbance. Furthermore, exploring model generalization capabilities at higher
spatial resolutions and under complex underlying surface conditions will help to continuously
improve regional climate prediction capabilities in the context of climate change.

Author contributions

JX: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software,
665 Validation, Visualization, Writing-original draft, Writing-review & editing; **YYL**: Funding
acquisition, Project administration, Supervision, Writing-review & editing; **LHY**: Investigation,
Resources, Supervision; **XW**: Investigation, Resources, Visualization.

Declaration of competing interest

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



Acknowledgement

This work was supported by The Basic Research Program of the Science and Technology Plan of Qinghai Province, China (Project No.: 2024-ZJ-910).

Data availability

675 The reanalysis and remote sensing data used in this study are freely available online via the Google Earth Engine Data Catalog (<https://developers.google.com/earth-engine/datasets>). The code and dataset to replicate this work are available in the open-access repository <https://github.com/sherlockjjobs/provincial-air-temperature-prediction>.

References

- 680 Wang Q, Zhai P, Zhang Q, 2025. Regional patterns of climate change and extreme events in China since 1961[J]. *Journal of Meteorological Research*, 39(3): 688-697.
- Yang M H, Jin X Y, Wang T, 2022. Vegetation Phenology Change of Mu Us Sandy Land and Its Response to Climate Change[J]. *Bulletin of Soil and Water Conservation*, 42(2): 242-249.
- Li X, Ren G, You Q, et al., 2021. Soil moisture continues declining in North China over the regional warming slowdown of the past 20 years[J]. *Journal of Hydrometeorology*, 22(11): 685 3001-3015.
- Ryan E M, Ogle K, Peltier D, et al., 2017. Gross primary production responses to warming, elevated CO₂, and irrigation: quantifying the drivers of ecosystem physiology in a semiarid grassland[J]. *Global Change Biology*, 23(8): 3092-3106.
- 690 Sameh B, Elshabrawy M, 2023. Seasonal autoregressive integrated moving average for climate change time series forecasting[J]. *American Journal of Business and Operations Research*, 8(2): 25-35.
- Shi J, Shirali A, Jin B, et al., 2025. Deep learning and foundation models for weather prediction: A survey[J]. *arXiv preprint arXiv:2501.06907*.
- 695 Akazan A C, Mbingui V R, N'guessan G L R, et al., 2025. Localized Weather Prediction Using Kolmogorov-Arnold Network-Based Models and Deep RNNs[J]. *arXiv preprint arXiv:2505.22686*.
- Hoegh-Guldberg O, Jacob D, Taylor M, et al., 2019. The human imperative of stabilizing global climate change at 1.5 C[J]. *Science*, 365(6459): eaaw6974.
- 700 Yue T X, Zhao N, Shi W J, et al., 2025. Surface Modelling of Ecosystems and Ecological diversity[M]//*Eco-Environmental Informatics*. Singapore: Springer Nature Singapore: 243-287.



- Li M, Ma Z, Wu P, et al., 2022. Ecological response to climate change across China from
combined soil temperature and moisture changes[J]. *Earth and Space Science*, 9(12):
705 e2022EA002640.
- Zeng Y, Hao D, Huete A, et al., 2022. Optical vegetation indices for monitoring terrestrial
ecosystems globally[J]. *Nature Reviews Earth & Environment*, 3(7): 477-493.
- Xu L, Gao G, Wang X, et al., 2023. Distinguishing the effects of climate change and vegetation
greening on soil moisture variability along aridity gradient in the drylands of northern
710 China[J]. *Agricultural and Forest Meteorology*, 343: 109786.
- Vereecken H, Amelung W, Bauke S L, et al., 2022. Soil hydrology in the Earth system[J]. *Nature
Reviews Earth & Environment*, 3(9): 573-587.
- Badugu A, Arunab K S, Mathew A, 2024. Predicting land surface temperature using data-driven
approaches for urban heat island studies: a comparative analysis of correlation with
715 environmental parameters[J]. *Modeling Earth Systems and Environment*, 10(1): 1043-1076.
- Wang Y, Yang M, Wang M, et al., 2025. A novel potential outlier recognition approach
considering local heterogeneity enhancement to improve the quality of soil datasets[J].
Geoderma, 454: 117200.
- Ding J, Liu C, Zheng Y, et al., 2024. A Comprehensive Survey on Artificial Intelligence for
720 Complex Network: Potential, Methodology and Application[J]. *arXiv preprint
arXiv:2402.16887*.
- Zhang R J, Ji X H, Xie Y H, et al., 2025. A novel graph convolutional neural network model for
predicting soil Cd and As pollution: Identification of influencing factors and
interpretability[J]. *Ecotoxicology and Environmental Safety*, 292: 117926.
- 725 Wang X, Wang X, Yin X, et al., 2023. Distributed LSTM-GCN-based spatial-temporal indoor
temperature prediction in multizone buildings[J]. *IEEE Transactions on Industrial
Informatics*, 20(1): 482-491.
- Panahi S, Moradi M, Bollt E M, et al., 2025. Data-driven model discovery with
Kolmogorov-Arnold networks[J]. *Physical Review Research*, 7(2): 023037.
- 730 Li Z, He W, Cheng M, et al., 2023. SinoLC-1: The first 1-meter resolution national-scale
land-cover map of China created with the deep learning framework and open-access data[J].
Earth System Science Data Discussions, 2023: 1-38.
- Zhou H, Tao F, Chen Y, et al., 2024. Climate change reduces agricultural total factor productivity
in major agricultural production areas of China even with continuously increasing
735 agricultural inputs[J]. *Agricultural and Forest Meteorology*, 349: 109953.
- Xun H Z, Zhong L W, Fang H H, et al., 2015. Terrain evolution of china seas and land since the
indo-china movement and characteristics of the stepped landform[J]. *Chinese Journal of*



- Geophysics, 58(1): 54-68.
- 740 Wen H, Wang T, Zhang T, et al., 2024. Footprint of soil erosion effects on pedodiversity at different hierarchical levels: A study across China's water erosion-prone areas[J]. Journal of Environmental Management, 372: 123152.
- Wang F, Gao M, Liu C, et al., 2024. Uniformly elevated future heat stress in China driven by spatially heterogeneous water vapor changes[J]. Nature Communications, 15(1): 4522.
- 745 Zhao H, Gong L, Qu H, et al., 2016. The climate change variations in the northern Greater Khingan Mountains during the past centuries[J]. Journal of Geographical Sciences, 26(5): 585-602.
- Zhao Y, Yu Z, Chen F, et al., 2009. Vegetation response to Holocene climate change in monsoon-influenced region of China[J]. Earth-Science Reviews, 97(1-4): 242-256.
- Zhang J, Zhu L, Li G, et al., 2022. Distribution patterns of SOC/TN content and their relationship 750 with topography, vegetation and climatic factors in China's north-south transitional zone[J]. Journal of Geographical Sciences, 32(4): 645-662.
- Chen Z, Chen L, Lu R, et al., 2025. A national soil organic carbon density dataset (2010–2024) in China[J]. Scientific Data, 12(1): 1480.
- Wang M, Yao J, Chang H, et al., 2025. Underground well water level observation grid dataset 755 from 2005 to 2022[J]. Scientific Data, 12(1): 728.
- Huang X, Yang J, 2023. The 30 m annual land cover datasets and its dynamics in China from 1985 to 2022[J]. Earth Syst. Sci. Data, 13: 3907-3925.
- Robbins J C, Titley H A, 2018. Evaluating high-impact precipitation forecasts from the Met Office Global Hazard Map (GHM) using a global impact database[J]. Meteorological 760 Applications, 25(4): 548-560.
- Hernandez-Santiago E, Tello-Leal E, Jaramillo-Perez J M, et al., 2026. Development of an Ozone (O₃) Predictive Emissions Model Using the XGBoost Machine Learning Algorithm[J]. Big Data and Cognitive Computing, 10(1): 15.
- Peng X, Liu Z, Zhang P, et al., 2025. Adaptable graph region for optimizing performance in 765 dynamic system long-term forecasting via time-aware expert[J]. Nature Communications, 16(1): 10213.
- Chen Q, Ding R, Mo X, et al., 2024. An adaptive adjacency matrix-based graph convolutional recurrent network for air quality prediction[J]. Scientific Reports, 14(1): 4408.
- Zhang S, Tong H, Xu J, et al., 2019. Graph convolutional networks: a comprehensive review[J]. 770 Computational Social Networks, 6(1): 1-23.
- Ta H T, Thai D Q, Rahman A B S, et al., 2026. Fc-kan: Function combinations in kolmogorov-arnold networks[J]. Information Sciences: 123103.



- Qezelbash-Chamak J, Hicklin K, Kim M., 2025. KANBalance: Kolmogorov-Arnold network mitigates class imbalance[J]. Pattern Recognition: 112325.
- 775 Yu R, Yu W, Wang X, 2024. Kan or mlp: A fairer comparison[J]. arXiv preprint arXiv:2407.16674.
- Alagialoglou L, Manakos I, Heurich M, et al., 2022. A learnable model with calibrated uncertainty quantification for estimating canopy height from spaceborne sequential imagery[J]. IEEE Transactions on Geoscience and Remote Sensing, 60: 1-13.
- 780 Mirdita M, Schütze K, Moriwaki Y, et al., 2022. ColabFold: making protein folding accessible to all[J]. Nature methods, 19(6): 679-682.
- Elmotawakkil A, Moumane A, Ait Youssef A, et al., 2025. Machine Learning and Remote Sensing for Modeling Groundwater Storage Variability in Semi-Arid Regions[J]. Intelligent Geoengineering.
- 785 Islam S M S, Islam K M A, Mullick M R A., 2022. Drought hot spot analysis using local indicators of spatial autocorrelation: An experience from Bangladesh[J]. Environmental Challenges, 6: 100410.
- Jing H, He X, Tian Y, et al., 2023. Comparison and interpretation of data-driven models for simulating site-specific human-impacted groundwater dynamics in the North China Plain[J].
- 790 Journal of Hydrology, 616: 128751.
- Wu D, Zhao X, Liang S, et al., 2015. Time-lag effects of global vegetation responses to climate change[J]. Global change biology, 21(9): 3520-3531.
- Wang L, He Y, Li L, et al., 2022. A novel approach to ultra-short-term multi-step wind power predictions based on encoder-decoder architecture in natural language processing[J]. Journal
- 795 of Cleaner Production, 354: 131723.
- Tian J, Wang G, Xiang D, et al., 2024. Causality analysis and prediction of riverine algal blooms by combining empirical dynamic modeling and machine learning techniques[J]. Water Resources Research.
- Shah A, Sugathan A, Malghan D, et al., 2025. Spatiotemporal changes in heat stress exposure in
- 800 India, 1981-2023[J]. Nature Communications, 16(1): 9496.
- Aydin H, Yenigun K, Isinkaralar O, et al., 2025. Hydrological low flow and overlapped trend analysis for drought assessment in Western Black Sea Basin[J]. Natural Hazards, 121(2): 1833-1863.
- Chen A, Meng F, Mao J, et al., 2022. Photosynthesis phenology, as defined by solar-induced
- 805 chlorophyll fluorescence, is overestimated by vegetation indices in the extratropical Northern Hemisphere[J]. Agricultural and Forest Meteorology, 323: 109027.
- Yang Y, Yin J, Slater L J, et al., 2025. Global vegetation dynamics under decreased terrestrial



- water storage: Insights into water stress response[J]. *Agricultural and Forest Meteorology*, 368: 110549.
- 810 Ren R, Zhang B, Xu Q, et al., 2025. Forest age and precipitation magnitude affected the contribution rate of rainfall to soil water[J]. *Plant and Soil*, 512(1): 121-135.
- Dang C, Shao Z, Huang X, et al., 2022. Assessment of the importance of increasing temperature and decreasing soil moisture on global ecosystem productivity using solar-induced chlorophyll fluorescence[J]. *Global change biology*, 28(6): 2066-2080.
- 815 Wu R, Wang Z, Meng F, et al., 2025. Strengthening coupling between vegetation and soil-atmosphere compound drought over the past two decades[J]. *Earth's Future*, 13(8): e2025EF006311.
- Li Z L, Wu H, Duan S B, et al., 2023. Satellite remote sensing of global land surface temperature: Definition, methods, products, and applications[J]. *Reviews of Geophysics*, 61(1).
- 820 Wang J, Zheng J, Deng J, et al., 2024. Effect of moisture content, temperature, and microstructure on the thermal conductivity of loess and its prediction model[J]. *Bulletin of Engineering Geology and the Environment*, 83(5): 206.
- Chen S, Long G, Jiang J, et al., 2023. Foundation models for weather and climate data understanding: A comprehensive survey[J]. *arXiv preprint arXiv:2312.03014*.
- 825 Rigas S, Papachristou M, Papadopoulos T, et al., 2024. Adaptive training of grid-dependent physics-informed kolmogorov-arnold networks[J]. *IEEE Access*.
- An S, Zhang L, Li X, et al., 2025. Global-Local Feature Fusion of Swin Kansformer Novel Network for Complex Scene Classification in Remote Sensing Images[J]. *Remote Sensing*, 17(7): 1137.
- 830 Liu Z, Wang Y, Vaidya S, et al., 2024. Kan: Kolmogorov-arnold networks[J]. *arXiv preprint arXiv:2404.19756*.
- Somvanshi S, Javed S A, Islam M M, et al., 2025. A survey on kolmogorov-arnold network[J]. *ACM Computing Surveys*, 58(2): 1-35.