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Quantifying synergistic multi-factor controls shaping spatiotemporal heterogeneity of cloud cover across China

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Abstract

Clouds exert a fundamental control on Earth's radiative balance and hydrological cycle. Despite growing understanding of cloud environmental regulators, the spatially heterogeneous and synergistic controls governing cloud cover over China remain insufficiently quantified. This study integrates the Optimal Parameters-based Geographical Detector (OPGD) and Robust Geographically Weighted Regression (RGWR) to characterize multi-factor synergies and spatially varying cloud-cover

controls, using 1984–2013 CLARA-A3 and ISCCP satellite cloud records, ERA5 meteorological fields, and multisource land surface datasets. Satellite observations reveal a prominent southeast-to-northwest gradient in total cloud cover, with high values prevailing over the eastern Tibetan Plateau, Sichuan Basin, and middle and lower Yangtze River basin, while low cloud cover dominates the Tarim Basin, North China, and Northeast China. Widespread cloud cover declines occurred across most of the study domain, with the most pronounced reductions over the Tibetan Plateau and arid northwestern China. Driving mechanisms exhibit strong regional dependence: atmospheric instability and thermal conditions primarily modulate cloud variations in arid climates, whereas moisture availability and land-atmosphere interactions govern cloud cover in humid regions. Interaction analyses show that bivariate nonlinear enhancement dominates factor coupling, highlighting pervasive synergistic effects among environmental regulators. The RGWR framework further uncovers notable spatial nonstationarity, in which both the magnitude and sign of driver impacts vary distinctly across climatic subregions. These findings clarify the spatially differentiated and synergistic controls on cloud cover, providing refined observational evidence for understanding regional cloud–climate interactions.

Keywords: Total cloud cover, spatiotemporal heterogeneity, multi-factor interaction, spatial nonstationarity, environmental drivers, China

1 Introduction

Clouds cover more than 60% of the global surface and constitute a fundamental component of the climate system, exerting substantial influences on the global radiation budget and hydrological cycle (Randall et al., 1991; Hartmann et al., 1992; Wielicki et al., 1992; Koren and Feingold, 2011; Zhao and Garrett, 2015). By reflecting incoming shortwave solar radiation while absorbing longwave radiation emitted from the global surface and atmosphere, clouds regulate the radiative balance of the land–atmosphere system (Alados et al., 2000; Huang et al., 2019; Ahamed et al., 2022; Müller and Pfeifroth, 2022). Variations in cloud distribution and cloud type produce substantial differences in radiative effects, thereby contributing to

pronounced regional disparities in the global energy balance (Kambeizidis et al., 2017). As a central component of climate feedbacks, cloud feedback remains one of the largest sources of uncertainty in climate change projections (Zelinka et al., 2017). Changes in cloud cover not only respond directly to global warming but also influence the rate of climate warming through radiative feedback processes.

Long-term variations in global cloud cover have attracted extensive scientific attention. Henderson-Sellers et al. (1992) reported that total cloud cover generally increased at most observational stations worldwide during 1900–1985, with particularly pronounced increases over North America and Australia. Subsequently, Warren et al. (2007) found that cloud cover decreased substantially over South America during 1971–1996, while slight declines occurred across Eurasia and Africa, with little overall change observed in North America, and winter and spring cloud cover increased over the Arctic. Based on global observations from 1971 to 2009, Eastman and Warren (2013) further showed that global mean total cloud cover exhibited a slight declining trend of approximately 0.04% per year, primarily attributable to reductions in middle-level and high-level clouds over the mid-latitudes. Over China, numerous studies have consistently documented an overall decline in cloud cover during recent decades (Kaiser, 2000; Endo and Yasunari, 2006; Qian et al., 2006; Zong et al., 2013; Wang et al., 2022). Using 6-hourly observations from the China Meteorological Administration, Kaiser (1998) found widespread decreases in total, high, and low cloud cover across most of China, with the largest declines occurring over eastern and northeastern China. Zhao et al. (2014) reported a slight decline in annual mean cloud cover over the Yangtze River Delta during 1982–2006, mainly driven by reductions in high clouds, whereas low cloud cover increased significantly during spring and summer. More recently, Shuai et al. (2022) showed that southeastern China remained persistently cloudy during 2001–2020, with cloud cover reaching approximately 75%, while cloud cover declined markedly across North China, particularly in arid and semi-arid regions where the annual decrease exceeded 0.5%. In contrast, cloud cover increased significantly over the middle and lower reaches of the Yangtze River. The long-term decline in cloud cover has been

90 closely linked to changes in surface radiation across China. Tang et al. (2017) and
91 Wang et al. (2021) reported increasing surface solar radiation over much of China in
92 recent decades. Norris and Wild (2009) estimated that surface solar radiation
93 increased by approximately 4.0 W m^{-2} per decade during 1990–2002, of which
94 reductions in cloud cover accounted for approximately 2.6 W m^{-2} per decade. More
95 recently, Wang and Yi (2025) found significant declines in net radiation fluxes at both
96 the top of the atmosphere and the surface during 2000–2023. Their results indicated
97 that radiation changes over the Tibetan Plateau were primarily controlled by
98 variations in middle-level and high-level clouds, whereas radiation changes over arid
99 and semi-arid regions resulted from the combined influences of cloud variations at
100 different altitudes, dust, and sulfate aerosols.

101 Cloud cover is jointly regulated by multiple processes, including atmospheric
102 dynamical and thermodynamic conditions, land surface characteristics, and human
103 activities, with dominant driving factors varying considerably across regions (Wang et
104 al., 2025). Land surface characteristics and anthropogenic activities influence cloud
105 formation primarily by modifying local hydrothermal and dynamical conditions.
106 Vegetation can promote cloud formation and persistence by regulating surface
107 moisture supply, net radiation, and latent heat fluxes, whereas urbanization alters local
108 ascending motion and sensible heat release through the urban heat island effect,
109 thereby affecting regional cloud cover (Jiang et al., 2017; Zhang et al., 2024).
110 Aerosols and large-scale atmospheric circulation represent two major categories of
111 factors driving cloud variability through distinct pathways. Aerosols modify surface
112 radiative forcing by scattering and absorbing solar radiation, thereby influencing
113 boundary-layer thermal structure and cloud droplet activation processes (Bellouin et
114 al., 2020; Li et al., 2019). Large-scale atmospheric circulation directly regulates the
115 spatial redistribution of water vapor through dynamical transport.

116 Previous studies (Inoue and Kimura, 2004; Eastman and Warren, 2013; Yang et
117 al., 2025) have identified meteorological conditions and land surface characteristics as
118 the primary controls on the spatiotemporal distribution of total cloud cover. However,
119 most existing studies have emphasized the independent effects of individual factors,

whereas the interactions among multiple driving factors and their spatial heterogeneity remain insufficiently understood (Jia et al., 2024). The Geographical Detector (GD) quantifies the explanatory power of individual factors and their interactions for spatial differentiation (Wang et al., 2010, 2016). The Optimal Parameters-based Geographical Detector (OPGD) optimizes the discretization of continuous variables and calculates explanatory power under different parameter combinations (Song et al., 2020; Song and Wu, 2021). OPGD has been applied to studies of urban heat islands, ecological drought risk, and other environmental problems (Yu et al., 2022; Wang et al., 2024; Chen et al., 2024). For example, Long et al. (2025) identified mean relative humidity and accumulated precipitation as the dominant global driving factors of vegetation cover across northeastern, northern, and northwestern China, while Liu et al. (2024) demonstrated that climate factors, particularly potential evapotranspiration, were the primary determinants of forest fire occurrence in the Panxi region. Meanwhile, Geographically Weighted Regression (GWR) has been widely employed to investigate spatial heterogeneity by capturing spatially varying relationships among variables (Bhowmick, 2025). Compared with conventional GWR, Robust Geographically Weighted Regression (RGWR) incorporates a robust estimation procedure that reduces the influence of outliers on local regression coefficients (Harris et al., 2010; Zhang and Mei, 2011).

Previous studies have identified regional differences in the environmental controls of cloud cover, but how multiple environmental factors interact to produce spatial heterogeneity remains unclear. It is also unclear whether the sign and magnitude of individual driving factors vary across climatic subregions. This study integrates OPGD and RGWR to quantify the independent and interactive effects of environmental driving factors and to characterize spatial nonstationarity in the relationships between cloud cover and environmental driving factors across China.

2 Data and Methods

2.1 ISCCP-H and CLARA-A3 Satellite Cloud Datasets

The International Satellite Cloud Climatology Project H-series (ISCCP-H) is one of the most widely used long-term global cloud climatology datasets. It integrates

observations from both geostationary and polar-orbiting meteorological satellites using visible and infrared channels, together with reanalysis data and radiative transfer retrieval algorithms, to derive key cloud properties, including cloud cover, cloud-top pressure, and cloud optical thickness (Young et al., 2018). Cross-calibration among different satellite platforms improves temporal consistency across the observational record. ISCCP has been used to investigate trends in cloud cover, cloud radiative effects, and interactions between clouds and the climate system (Devasthale and Karlsson, 2023). Over China, ISCCP has been used to characterize the spatial distribution and long-term evolution of cloud cover and to examine its relationships with monsoon activity, large-scale atmospheric circulation, and surface radiation changes (Lei et al., 2020; Zhong et al., 2021; Wang et al., 2024). This study employed the ISCCP-H HGG 3-hourly cloud product with a spatial resolution of $1^{\circ} \times 1^{\circ}$ for the period 1984–2013. The original 3-hourly observations were first aggregated into daily mean total cloud cover and subsequently resampled to $0.25^{\circ} \times 0.25^{\circ}$ using bilinear interpolation to ensure consistency with the other datasets.

The CM SAF cCloud, Albedo and surface RAdiation dataset from AVHRR data (CLARA) is a long-term climate data record produced by the Satellite Application Facility on Climate Monitoring (CM SAF) of EUMETSAT. It is derived from observations acquired by the Advanced Very High Resolution Radiometer (AVHRR) aboard NOAA and MetOp polar-orbiting satellites and provides cloud cover, cloud-top height, surface radiation, and related variables through improved cloud detection and radiative retrieval algorithms (Karlsson et al., 2023a). Compared with previous versions, CLARA-A3 incorporates improved sensor cross-calibration, orbital drift correction, and cloud detection consistency. CLARA-A3 has been widely applied to studies of long-term cloud variability, cloud radiative effects, and climate model evaluation (Karlsson et al., 2023b). Over China, it has demonstrated relatively high stability and consistency, particularly over regions with complex terrain (He et al., 2025; Wang et al., 2025). The present study used the daily total cloud cover product from CLARA-A3 at a spatial resolution of $0.25^{\circ} \times 0.25^{\circ}$, covering the period 1984–2013.

2.2 Environmental Driving Factors

Based on previous studies (Freedman et al., 2001; Teuling et al., 2017; Duveiller et al., 2021; Naud et al., 2023; Grise and Tselioudis, 2024; Yang et al., 2025), 15 environmental variables were selected as candidate environmental driving factors of total cloud cover.

Meteorological variables were obtained from the ERA5 fifth-generation atmospheric reanalysis produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) (Hersbach et al., 2020). ERA5 provides hourly data at a spatial resolution of $0.25^{\circ} \times 0.25^{\circ}$. The selected variables include: 10-m zonal wind (U10), 10-m meridional wind (V10), 2-m air temperature (T2M), 2-m dew-point temperature (D2M), surface pressure (SP), K Index (KX), Convective Available Potential Energy (CAPE), evaporation (E), surface sensible heat flux (SSHf), surface latent heat flux (SLHF), and volumetric soil water in the 0–7 cm soil layer (SWVL). ERA5 has been evaluated in previous studies for its representation of near-surface meteorological conditions, including temperature, wind fields, and pressure distributions (Liu et al., 2021; Zhang et al., 2025).

In addition, this study derived the 2-m Dew Point Depression (DPD2M), defined as the difference between T2M and D2M. DPD2M is defined as the difference between T2M and D2M and represents the degree of near-surface air dryness relative to saturation (Lawrence, 2005). Smaller DPD2M values indicate more humid conditions, whereas larger values indicate a greater moisture deficit and lower relative humidity (Theeuwes et al., 2019).

To characterize land surface conditions and topographic influences, four additional variables were incorporated: Normalized Difference Vegetation Index (NDVI), Leaf Area Index (LAI), Gross Primary Production (GPP), and Digital Elevation Model (DEM). LAI describes vegetation canopy density and is closely related to transpiration and moisture release, both of which promote cloud formation (Zhang et al., 2020; Wang et al., 2022). GPP represents ecosystem productivity and influences cloud formation through vegetation transpiration, surface energy exchange, and boundary-layer hydrothermal processes (Hoek et al., 2020; Kong et al., 2025).

NDVI characterizes vegetation cover and growth conditions and is widely used to represent land surface vegetation dynamics (Seneviratne et al., 2010; Zhang et al., 2015; Teuling et al., 2017). The corresponding datasets include: GLASS LAI (8-day, 0.05°×0.05°), GLASS GPP (8-day, 0.05°×0.05°), and GIMMS-3G+ NDVI (two observations per month, 0.0833°×0.0833°). These datasets have been used in studies of vegetation dynamics and climate change (Pinzon and Tucker, 2014; Liu et al., 2017).

To ensure consistency among datasets, all variables were harmonized to a common spatial resolution of 0.25°×0.25°. ISCCP-H was resampled from 1° using bilinear interpolation. GLASS LAI and GPP were resampled from 0.05°. GIMMS NDVI was resampled from 0.0833°. For temporal consistency, the 8-day LAI and GPP products were averaged to monthly values, while the two monthly NDVI observations were averaged to obtain monthly NDVI. To emphasize long-term spatial differentiation while minimizing the influence of interannual climate variability, monthly total cloud cover and all driving variables were averaged over the period 1984–2013 to construct long-term mean spatial fields, which were subsequently used in the OPGD and RGWR analyses.

2.3 Methods

2.3.1 Optimal Parameters-based Geographical Detector

OPGD, proposed by Song et al. (2020), extends the conventional GD by introducing an optimization framework for discretizing continuous variables, thereby improving the robustness and reliability of factor detection (Luo et al., 2021). GD is a statistical method for quantifying the explanatory power of driving factors for the spatial differentiation of a target variable. Its core statistic is the q-value, which ranges from 0 to 1. Larger q values indicate stronger explanatory power for spatial heterogeneity, whereas smaller values indicate weaker explanatory ability. The q-value is calculated using Equation (1),

$$Q = 1 - \frac{\sum_{h=1}^L N_h \sigma_h^2}{N \sigma^2} \quad (1),$$

in Equation (1), L denotes the number of strata after discretization, N is the total

number of samples, N_h represents the number of samples in stratum h , and σ^2 and σ_h^2 denote the overall variance and within-stratum variance of total cloud cover, respectively. When the within-stratum variance is substantially smaller than the overall variance, the corresponding factor exhibits stronger explanatory power for cloud cover heterogeneity.

Interaction detection evaluates whether the joint explanatory power of two driving factors is enhanced or weakened relative to their individual effects on the spatial differentiation of total cloud cover, thereby identifying the type of interaction between the factors. The interaction type is determined by comparing the q values of the two individual factors, $Q(X_1)$ and $Q(X_2)$, with the q value of their interaction, $Q(X_1 \cap X_2)$. Five types of interactions are identified based on the criteria presented in Table 1.

Interaction detection provides a quantitative framework for assessing whether pairs of driving factors exhibit enhanced or weakened explanatory power when acting jointly, thereby helping to identify important factor combinations associated with cloud cover heterogeneity.

Table 1. Classification criteria for interaction types in the OPGD interaction detection.

Interaction type	Criterion	Interpretation
Nonlinear weakening	$Q(X_1 \cap X_2)$ $< \min[Q(X_1), Q(X_2)]$	The combined explanatory power is lower than that of either individual factor
Univariate weakening	$\min[Q(X_1), Q(X_2)]$ $< Q(X_1 \cap X_2)$ $< \max[Q(X_1), Q(X_2)]$	The combined explanatory power exceeds that of the weaker factor but remains lower than that of the stronger factor

Bivariate enhancement	$Q(X_1 \cap X_2) > \max[Q(X_1), Q(X_2)]$	The combined explanatory power exceeds that of both individual factors
Nonlinear enhancement	$Q(X_1 \cap X_2) > Q(X_1) + Q(X_2)$	The combined explanatory power exceeds the sum of the individual q values
Independence	$Q(X_1 \cap X_2) = Q(X_1) + Q(X_2)$	The combined explanatory power equals the sum of the individual explanatory powers

256

257 2.3.2 Robust Geographically Weighted Regression

258 GWR is a local regression method designed to characterize spatially varying
259 relationships between variables. Conventional GWR estimates local regression
260 coefficients using ordinary least squares, making it highly sensitive to outliers and
261 large observational errors (Sugasawa and Murakami, 2022). RGWR extends GWR by
262 replacing the squared-error loss with the Huber loss function, thereby substantially
263 reducing the influence of outliers and improving estimation robustness (Huber, 1964;
264 Wulandari et al., 2019). In this study, RGWR was employed to identify spatial
265 nonstationarity by jointly considering residual distributions and adaptive bandwidth
266 adjustments, thereby avoiding excessive smoothing in areas affected by outliers. The
267 regression model is expressed as Equation (2),

268
$$Y_i = \beta_0(u_i, v_i) + \sum_{k=1}^p \beta_k(u_i, v_i) X_{ik} + \varepsilon_i \quad (2),$$

269 in Equation (2), i denotes the sampling location, k represents the explanatory
270 variable, Y_i is the observed total cloud cover, $\beta_0(u_i, v_i)$ is the local intercept,
271 $\beta_k(u_i, v_i)$ denotes the spatially varying local regression coefficient, X_{ik} is the

explanatory variable, and ε_i is the residual term.

A Gaussian kernel was adopted to calculate spatial weights,

$$w_i = \exp\left(-\frac{d_i^2}{2h^2}\right) \quad (3),$$

where w_i is the spatial weight of sample i , d_i is the spatial distance between the sample and the target location, and h is the bandwidth controlling the rate of distance decay (Liu et al., 2020).

3 Results

3.1 Spatiotemporal Characteristics of Total Cloud Cover over China

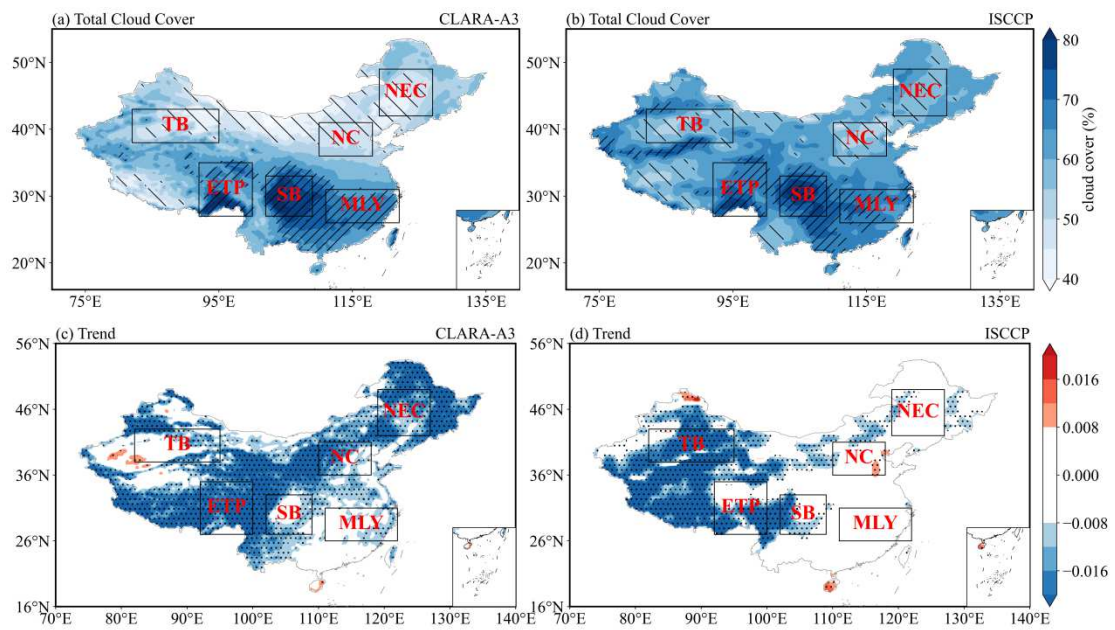


Figure 1. Spatial distribution of mean total cloud cover (a, b) and linear trends (c, d) over China during 1984–2013. Panels (a) and (c) show CLARA-A3, whereas panels (b) and (d) show ISCCP. Regions with cloud cover below the 25th percentile (right-hatched) represent regions with low cloud cover, including the Tarim Basin (TB), North China (NC), and Northeast China (NEC). Regions exceeding the 75th percentile (left-hatched) represent regions with high cloud cover, including the eastern Tibetan Plateau (ETP), the Sichuan Basin (SB), and the middle and lower reaches of the Yangtze River (MLY). Stippled areas indicate trends significant at the 95% confidence level.

The climatological mean total cloud cover derived from the CLARA-A3 and ISCCP datasets during 1984–2013 exhibits pronounced spatial heterogeneity across

China, with a clear southeast-to-northwest decreasing gradient (Fig. 1a, b). Both datasets consistently identify the eastern Tibetan Plateau (ETP), the Sichuan Basin (SB), and the middle and lower reaches of the Yangtze River (MLY) as regions with high cloud cover, whereas the Tarim Basin (TB), North China (NC), and Northeast China (NEC) represent the principal regions with low cloud cover. Based on these persistent spatial patterns, six typical regions were selected for subsequent analyses.

Despite minor differences in cloud cover values, the two satellite products show highly consistent large-scale spatial distributions. The SB and the ETP remain the regions with the highest cloud cover, whereas the TB contains a distinct center of minimum cloud cover. ISCCP generally reports slightly higher cloud cover values than CLARA-A3, but the differences are small relative to the overall similarity in spatial distribution.

Both datasets indicate a widespread decline in total cloud cover during 1984–2013 (Fig. 1c, d), with the strongest decreases occurring over the Tibetan Plateau and northwestern China, while trends are generally weaker across humid eastern regions. Compared with ISCCP, CLARA-A3 identifies a broader area of significant decreases extending into eastern Inner Mongolia and the NEC, whereas ISCCP shows stronger negative trends over the TB. Both datasets show a general decline in total cloud cover across much of China during the study period.

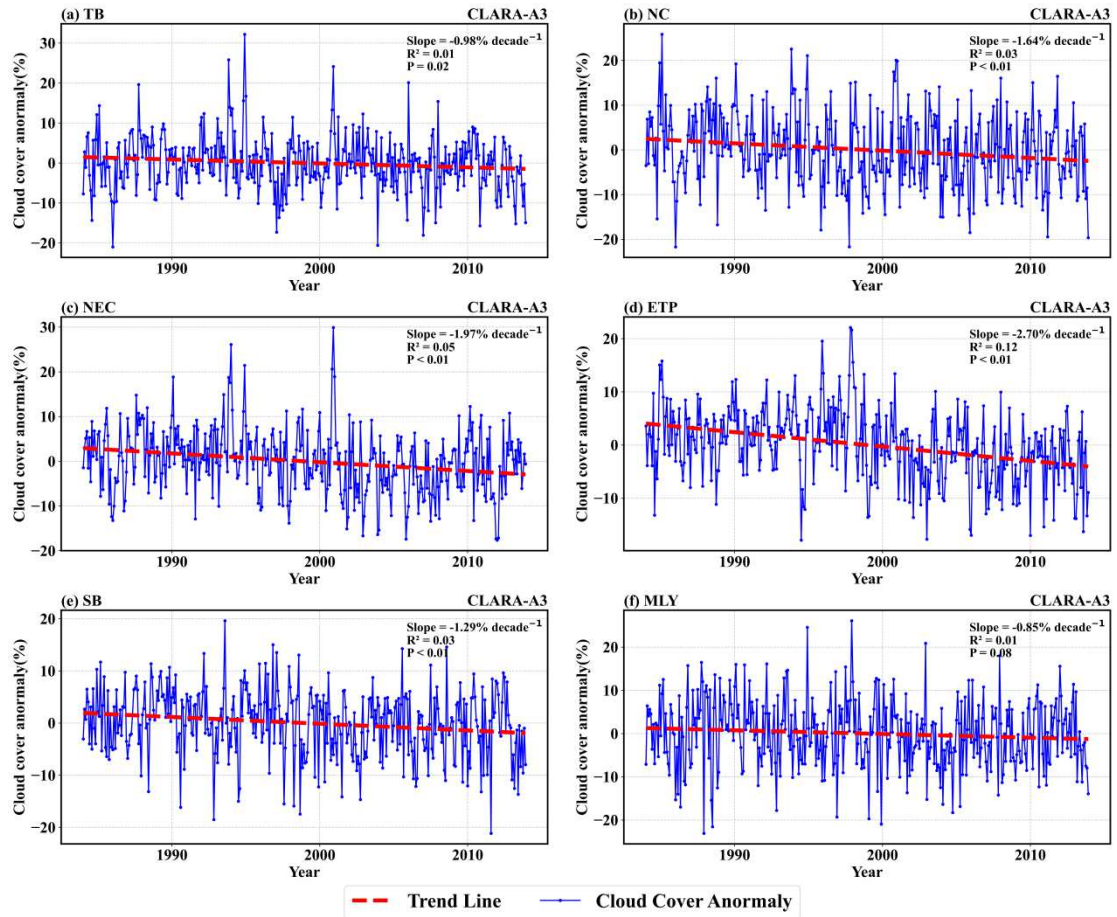


Figure 2. Monthly time series of total cloud cover anomalies and linear trends derived from CLARA-A3 for six representative regions of China during 1984–2013. Solid lines denote regional mean cloud cover anomalies, dashed lines indicate linear trends, and the annotated values represent the trend slope, coefficient of determination (R^2), and statistical significance (P-value).

The monthly anomaly time series derived from CLARA-A3 show that total cloud cover declined in all six typical regions during 1984–2013, although both the rate of decline and the magnitude of interannual variability differ substantially among regions (Fig. 2).

Among the regions with low cloud cover, the TB exhibits the weakest declining trend (-0.98% per decade), whereas the NC and the NEC experience more pronounced decreases. The regions with high cloud cover display stronger declining trends overall. The ETP experiences the largest decrease (-2.70% per decade), representing the most rapid decrease among the six typical regions. Previous studies

have attributed this decline primarily to reductions in middle level and high level clouds associated with a weakening of the South Asian High and enhanced Eurasian Rossby wave activity, which favors anomalous subsidence over the plateau (Ma et al., 2021; Wu et al., 2024). The SB also exhibits a substantial decline (-1.29% per decade), indicating a persistent reduction in cloud cover despite its humid climatic conditions. In contrast, the MLY displays the weakest decline among the regions with high cloud cover (-0.85% per decade), with relatively small changes in cloud cover during the study period.

Overall, the CLARA-A3 dataset indicates that all six typical regions experienced declining cloud cover during 1984–2013, consistent with previous studies documenting long term reductions in cloud cover across China (Xia, 2012; Liu et al., 2016). These declines may be associated with changes in feedbacks between moisture availability and convection under global warming, while both the direct and indirect effects of aerosols may contribute to regional differences in cloud cover evolution (Xia, 2010; Yang et al., 2021).

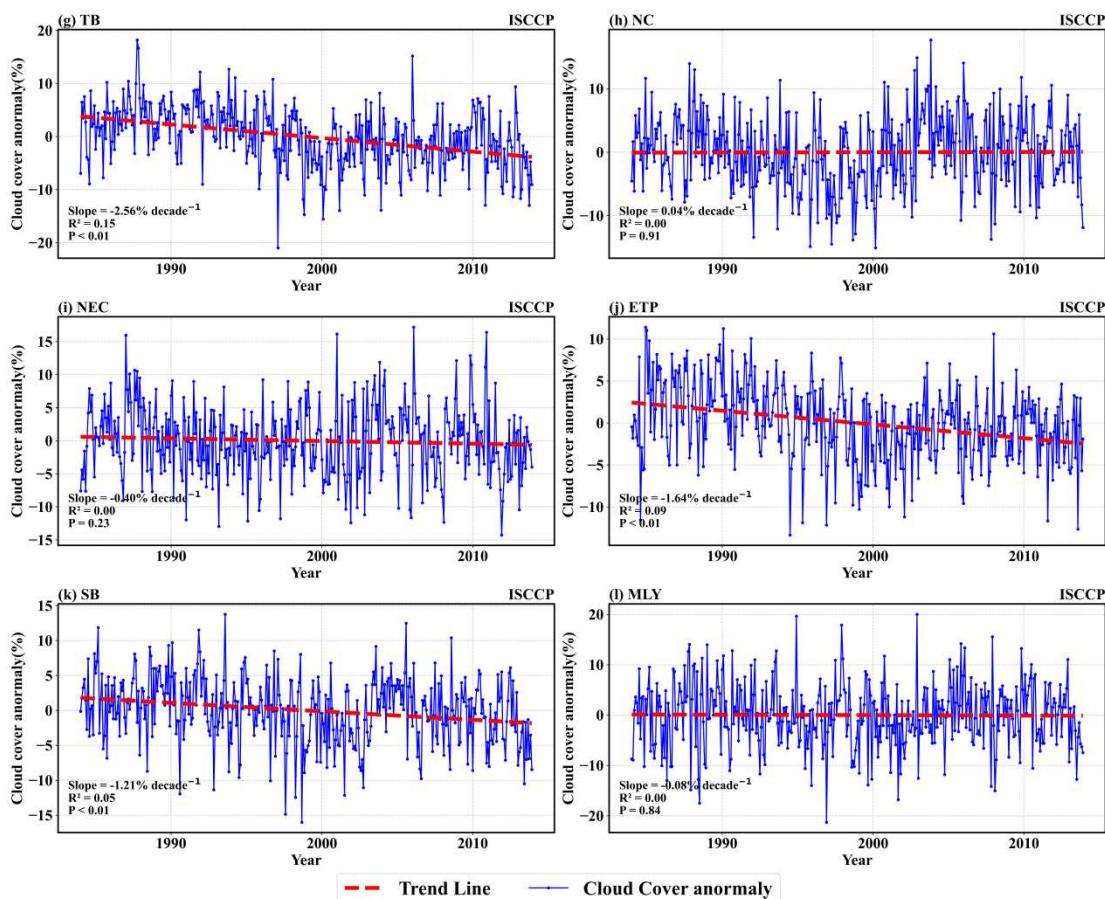


Figure 3. Monthly time series of total cloud cover anomalies and linear trends derived from ISCCP for six representative regions of China during 1984–2013. Solid lines denote regional mean cloud cover anomalies, dashed lines indicate linear trends, and the annotated values represent the trend slope, coefficient of determination (R^2), and statistical significance (P-value).

The ISCCP results broadly corroborate the principal findings obtained from CLARA-A3, showing that total cloud cover declined across all six typical regions during 1984–2013. The ETP and the SB consistently exhibit sustained reductions in cloud cover in both datasets, while the MLY shows the weakest long term decline (Fig. 3).

However, larger discrepancies emerge within the regions with low cloud cover. The TB exhibits a substantially stronger decline in ISCCP (–2.56% per decade) than in CLARA-A3, whereas the NC and the NEC show weaker declines in ISCCP than in CLARA-A3. Previous studies have suggested that such differences are closely related to uncertainties in cloud retrieval over arid and high-latitude regions, where high surface albedo and differences in the detection of thin and low clouds can affect long-term trend estimates derived from passive satellite observations (Noel et al., 2018; Devasthale and Karlsson, 2023).

Despite these differences in trend magnitude, both satellite datasets show a general decline in total cloud cover across the six typical regions during 1984–2013, with the ETP and SB showing relatively strong decreases and the MLY showing the weakest decline.

3.2 Spatial Distribution, Trends, and Driving Characteristics of Cloud Cover Driving Factors

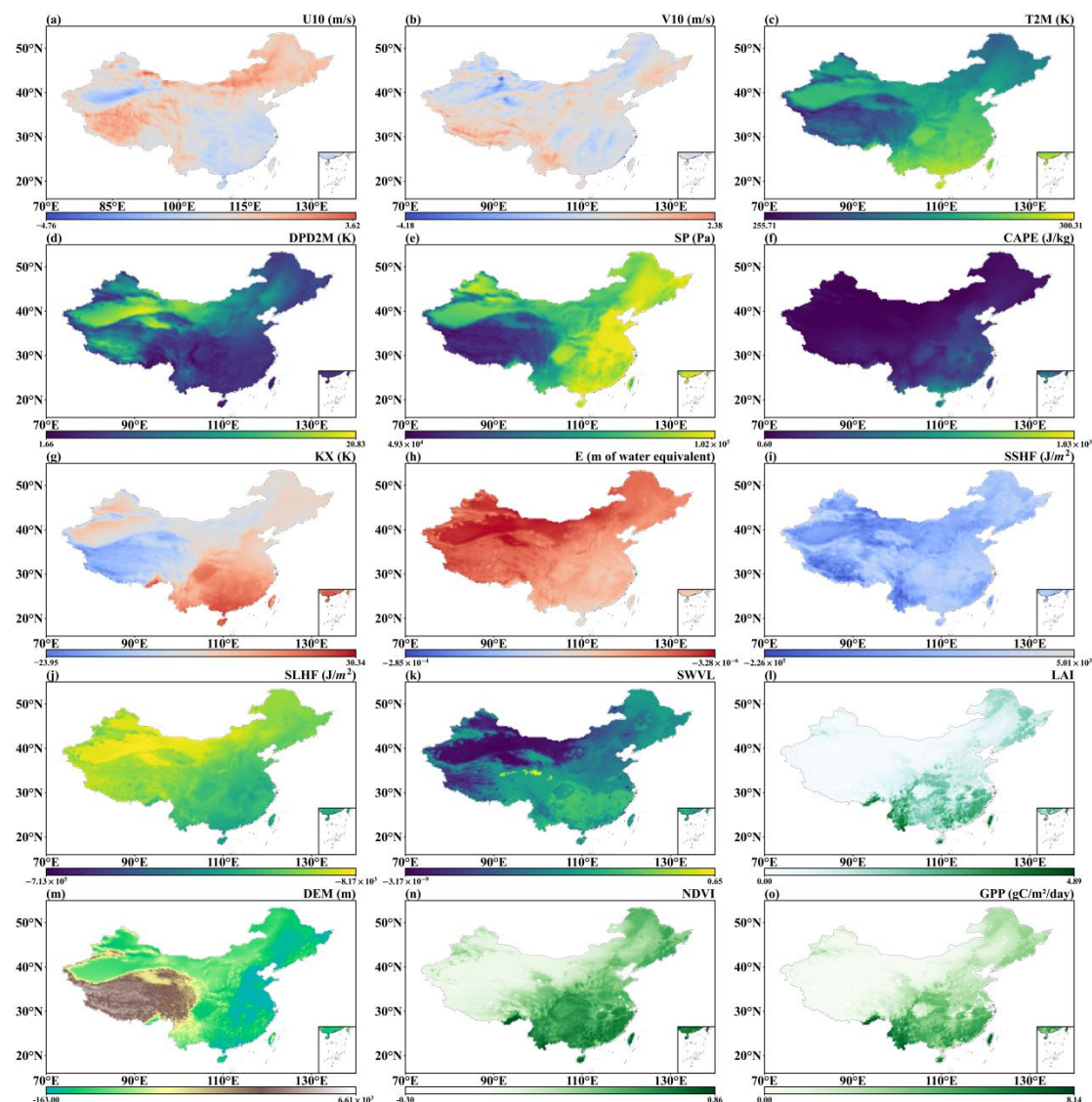


Figure 4. Long-term mean spatial distributions of meteorological and land surface variables across China during 1984–2013. (a) U10, (b) V10, (c) T2M, (d) DPD2M, (e) SP, (f) CAPE, (g) KX, (h) E, (i) SSHF, (j) SLHF, (k) SWVL, (l) LAI, (m) DEM, (n) NDVI, and (o) GPP.

Figure 4 illustrates the long-term mean spatial distributions of the 15 environmental variables considered as candidate environmental driving factors of total cloud cover during 1984–2013. The variables exhibit distinct regional patterns associated with climatic and topographic gradients across China.

The wind components U10 and V10 exhibit relatively large magnitudes over northwestern China and the Tibetan Plateau, whereas eastern plains and coastal regions generally experience weaker winds. T2M displays a pronounced south-to-north gradient, with higher temperatures over southern lowlands and lower

379 temperatures over the Tibetan Plateau. In contrast, In contrast, DPD2M reveals a clear
380 humidity gradient, with drier conditions across northwestern China and more humid
381 conditions throughout eastern and southern China. SP closely follows topographic
382 elevation, with the Tibetan Plateau characterized by substantially lower pressure than
383 the eastern lowlands. The atmospheric instability indicators CAPE and KX reach
384 relatively high values over southern China and eastern coastal regions, whereas
385 northwestern China and the Tibetan Plateau exhibit comparatively lower values.
386 Hydrological variables also show distinct regional contrasts. E and SWVL are
387 considerably higher across humid eastern China than over the northwestern arid
388 regions. SSHF is generally higher over dry regions, whereas SLHF is more
389 pronounced over humid areas with greater surface moisture availability. DEM
390 reproduces the three-step topographic gradient of China, while LAI, NDVI, and GPP
391 consistently show higher vegetation density and ecosystem productivity in eastern and
392 southeastern China.

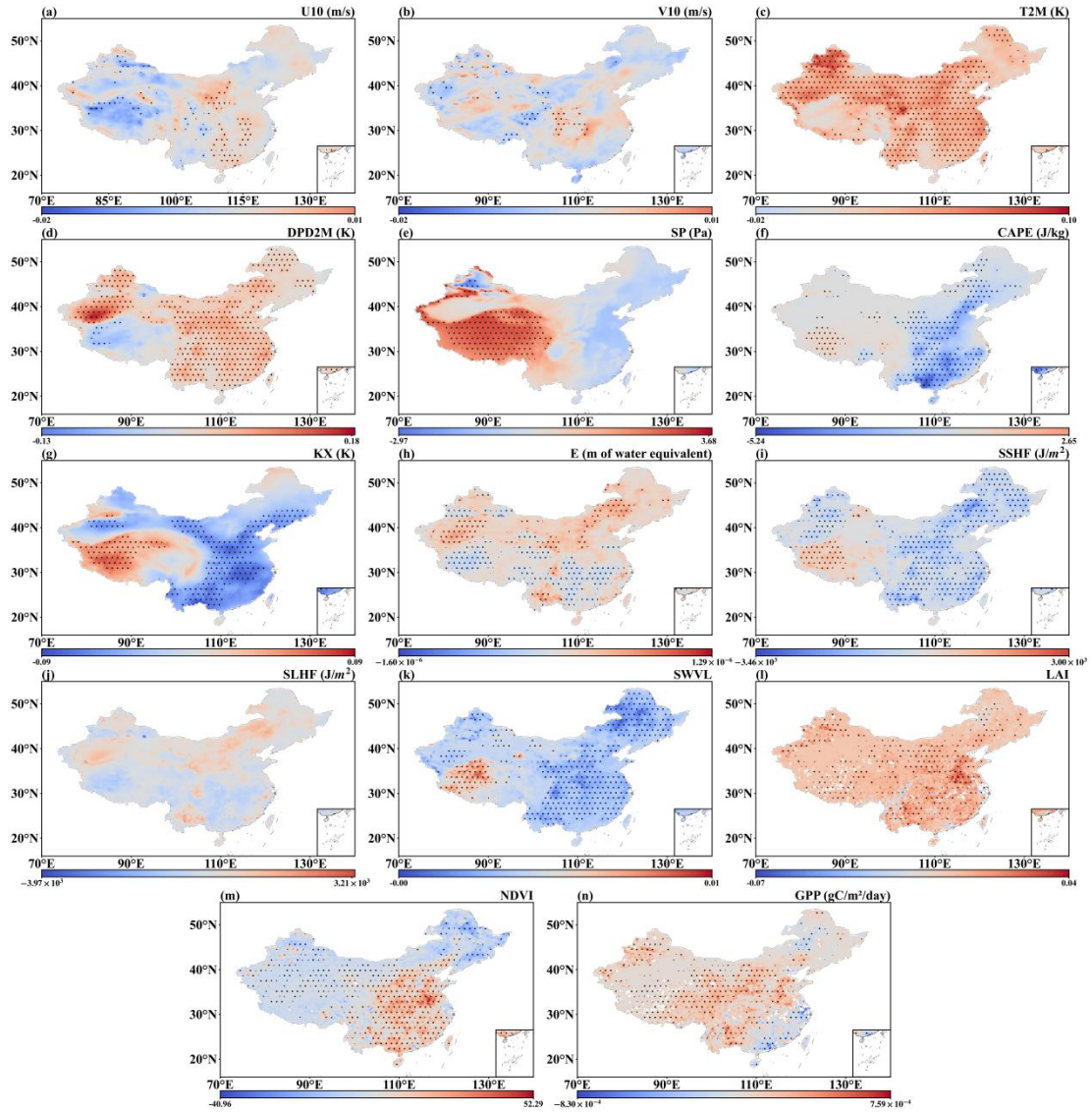


Figure 5. Linear trends of meteorological and land surface variables across China during 1984–2013. Panels (a–n) correspond to U10, V10, T2M, DPD2M, SP, CAPE, KX, E, SSHF, SLHF, SWVL, LAI, NDVI, and GPP, respectively. Stippled areas indicate trends significant at the 95% confidence level.

Figure 5 presents the long-term trends of the environmental variables during 1984–2013, revealing substantial regional differences in climatic and land surface evolution across China.

Neither U10 nor V10 shows coherent nationwide trends, implying that changes in near-surface winds remained largely localized throughout the study period. By contrast, T2M exhibits significant positive trends across most of China, with the most

405 pronounced warming over northwestern China, consistent with the well-documented
406 regional warming over recent decades. DPD2M also shows an increasing tendency
407 over most regions except the Tibetan Plateau. SP increases significantly over the
408 Tibetan Plateau, whereas CAPE decreases across parts of South China and the NC.
409 KX exhibits pronounced spatial heterogeneity, decreasing over the MLY, the NC, and
410 the western margin of the TB while increasing over western portions of the Tibetan
411 Plateau. E increases significantly within the TB but decreases over the Tibetan Plateau
412 and the Yangtze River basin. Surface heat fluxes display contrasting spatial pattern.
413 SSHF declines across eastern China and the TB but increases over western Tibet,
414 whereas SLHF shows relatively weak long-term changes nationwide. SWVL exhibits
415 a spatial pattern similar to that of SSHF, decreasing across eastern and northwestern
416 China while increasing over western Tibet. Meanwhile, LAI, NDVI, and GPP
417 consistently show widespread increases in vegetation growth and ecosystem
418 productivity, with the strongest increases occurring across eastern China.

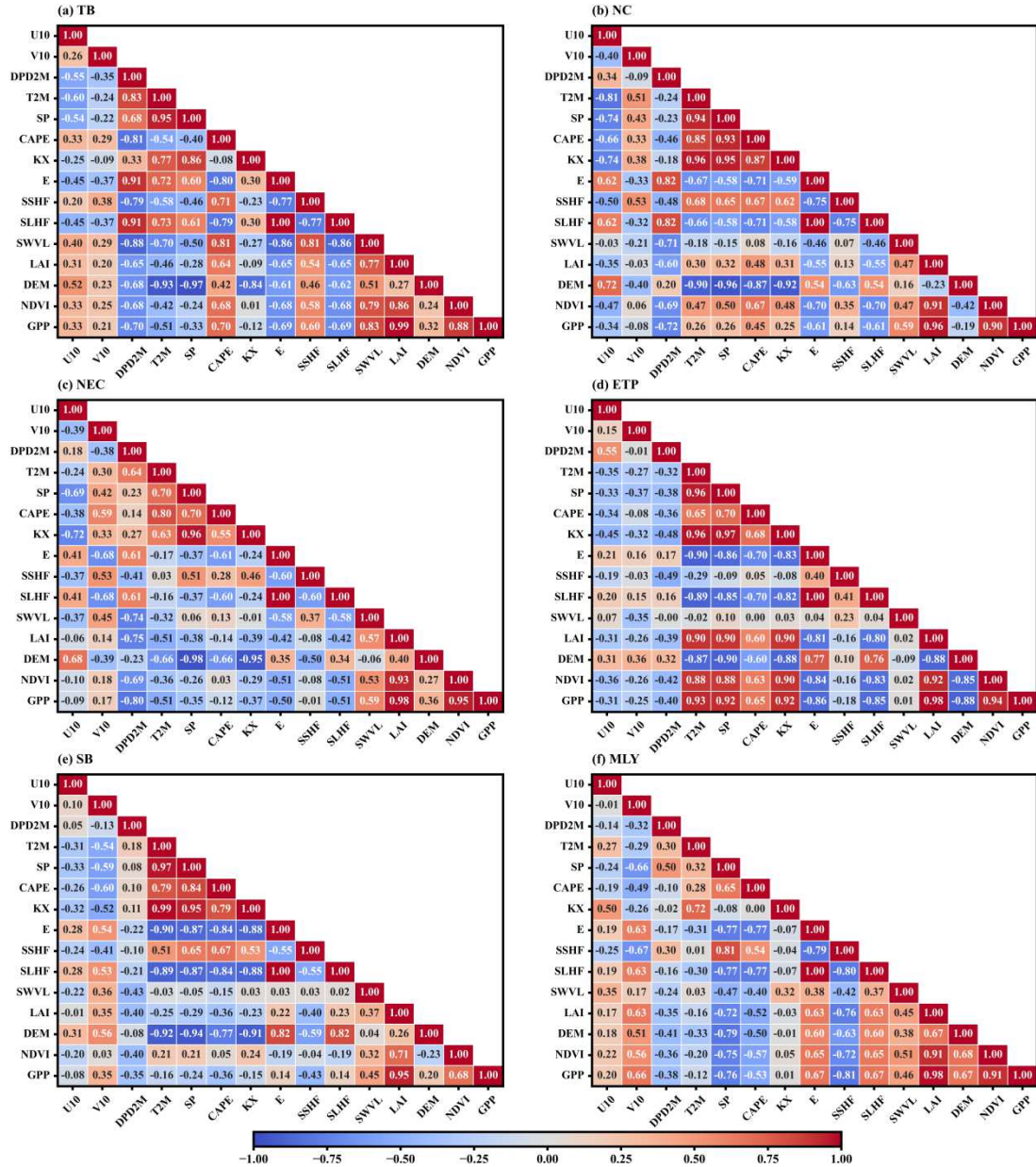


Figure 6. Pearson correlation matrices of candidate driving factors for six representative regions of China. (a) TB, (b) NC, (c) NEC, (d) ETP, (e) SB, and (f) MLY. Red and blue colors indicate positive and negative correlations, respectively.

Figure 6 presents the Pearson correlation matrices for the 15 candidate driving factors across the six typical regions. Most correlation coefficients remain below 0.70 in absolute value, whereas several strongly correlated variable groups occur consistently across the six typical regions.

Three correlation structures are particularly robust across the climatic regions.

First, DEM and SP exhibit strong negative correlations, reflecting the inverse relationship between elevation and atmospheric pressure. Second, NDVI, LAI, and GPP show strong positive correlations with one another. Third, T2M is positively correlated with both KX and CAPE.

Regional differences are also evident. Within the regions with low cloud cover, DPD2M shows stronger associations with E and SLHF over the TB, the NC exhibits stronger correlations between topographic and convective variables, and the NEC shows strong negative correlations between DPD2M and variables related to vegetation and soil moisture. Within the regions with high cloud cover, vegetation variables show strong correlations with thermal and pressure variables over the ETP. The SB exhibits strong correlations between convective instability and both T2M and SP, whereas the MLY shows strong correlations among soil moisture, evaporation, and vegetation variables.

These correlation patterns pinpoint major sources of multicollinearity for variable screening, and further reveal that inter-relationships among environmental driving factors differ substantially across climatic regions.

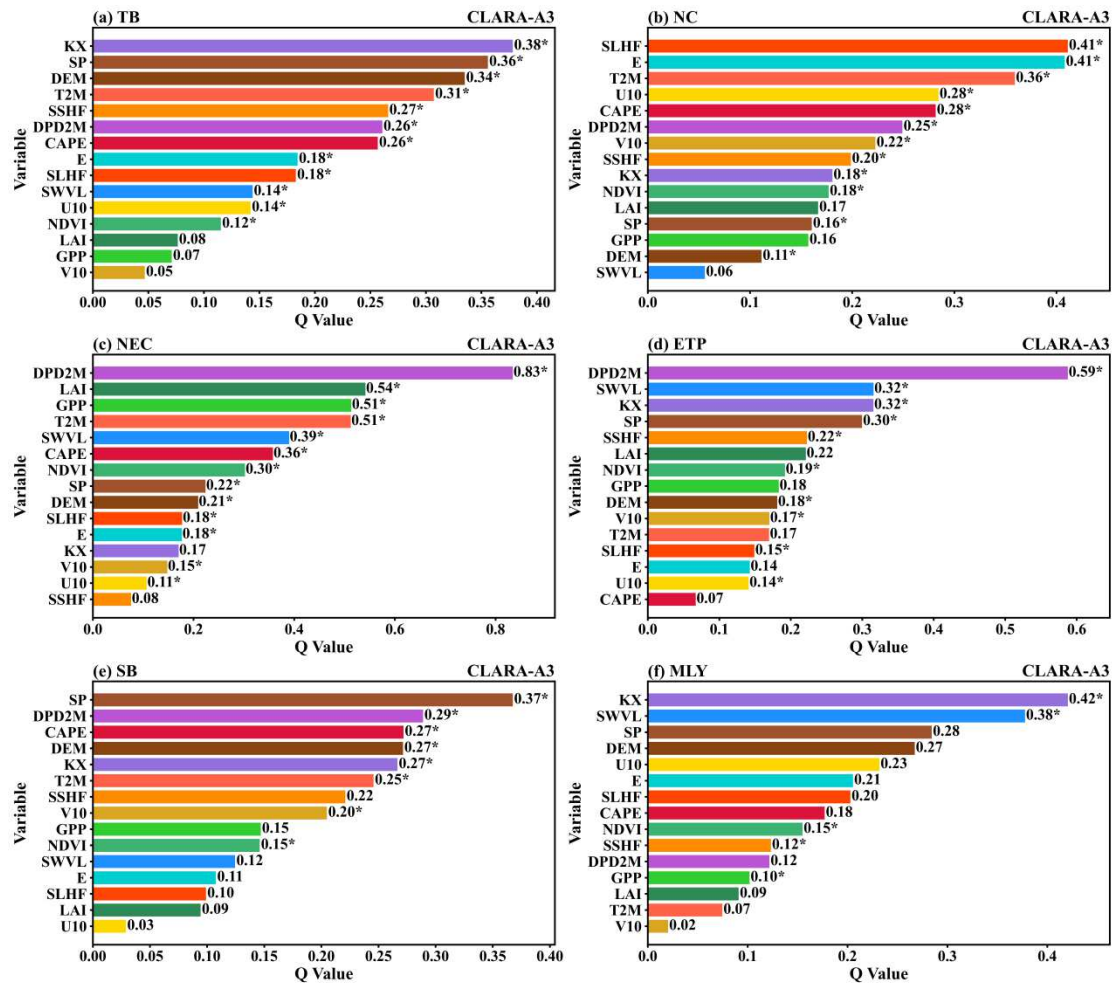


Figure 7. OPGD factor detection results (q values) for total cloud cover derived from CLARA-A3 during 1984–2013. Panels (a–f) correspond to TB, NC, NEC, ETP, SB, and MLY, respectively. Asterisks indicate statistical significance at the 95% confidence level.

The OPGD results derived from CLARA-A3 reveal substantial regional differences in the dominant controls of cloud cover heterogeneity (Fig. 7), indicating that different climatic regions are governed by distinct combinations of thermodynamic, moisture, and land surface processes.

Within the regions with low cloud cover, the TB is primarily controlled by KX ($q=0.38$) and SP ($q=0.36$), followed by DEM and T2M. These results indicate strong contributions from atmospheric instability, pressure conditions, topography, and near surface thermal conditions to the spatial differentiation of cloud cover in this arid region. Over the NC, SLHF and E exhibit the highest explanatory power, followed by T2M, highlighting the importance of moisture exchange between the land surface and

atmosphere and near surface thermal conditions. T2M can affect cloud formation through changes in atmospheric moisture holding capacity and boundary layer structure (Riemann-Campe et al., 2009; Trenberth, 2011; Teuling et al., 2017). In the NEC, DPD2M exhibits an exceptionally high explanatory power ($q \approx 0.80$), substantially exceeding that of all other variables. This indicates a strong spatial association between DPD2M and cloud cover in this region. The relatively high q values of LAI and GPP also indicate spatial associations between vegetation conditions and cloud cover, consistent with the effects of vegetation transpiration and surface energy partitioning on local moisture and thermal conditions (Bosman et al., 2019).

The regions with high cloud cover exhibit different combinations of dominant driving factors. Over the ETP, DPD2M remains the dominant driving factor, while SWVL and KX also exhibit relatively high explanatory power. The spatial differentiation of cloud cover is closely associated with near surface humidity, soil moisture, and atmospheric instability. Previous studies have similarly emphasized the importance of moisture transport, land evaporation, and thermal lifting in regulating cloud variability over the Tibetan Plateau (Fu et al., 2020; Ullah et al., 2021). Within the SB, SP provides the highest explanatory power, followed by DPD2M, CAPE, and DEM. The spatial distribution of cloud cover is closely associated with pressure conditions, moisture availability, atmospheric instability, and topographic forcing. Over the MLY, KX and SWVL emerge as the dominant driving factors. The humid monsoon environment allows soil moisture to affect cloud formation through surface evaporation and moisture supply to the boundary layer, while atmospheric instability favors convective development (Li et al., 2020; Zhang et al., 2025).

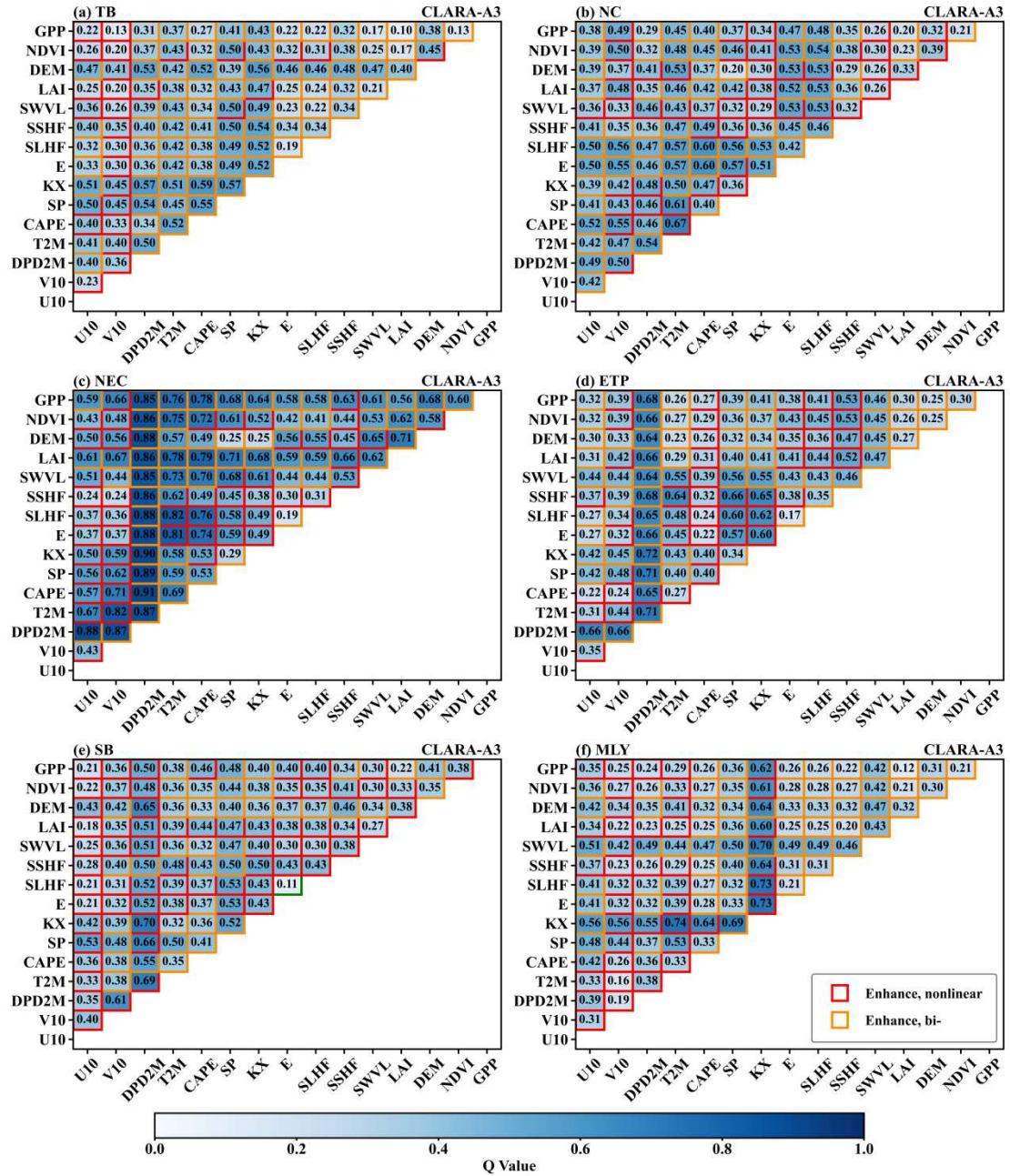


Figure 8. OPGD interaction detection results (q values) for total cloud cover derived from CLARA-A3 during 1984–2013. Panels (a–f) correspond to TB, NC, NEC, ETP, SB, and MLY, respectively. Colors represent interaction q-values, while border colors indicate interaction types: red for nonlinear enhancement, orange for bivariate enhancement, and green for univariate weakening.

The interaction detection results derived from CLARA-A3 show that bivariate enhancement and nonlinear enhancement are the dominant interaction types across the

493 six typical regions (Fig. 8). In most cases, the explanatory power of variable pairs is
494 substantially higher than that of the corresponding individual variables. The strongest
495 interactions involve different combinations of humidity, atmospheric instability,
496 surface energy exchange, and topographic variables across the climatic regions.

497 Within the TB, interactions involving KX produce substantial increases in
498 explanatory power, particularly when combined with DPD2M and CAPE, both of
499 which exhibit bivariate enhancement. In this extremely arid region, moisture
500 availability and atmospheric lifting conditions jointly constrain cloud development.
501 The spatial combination of atmospheric instability and humidity deficit produces
502 stronger differentiation in cloud cover than either factor alone. In the NC, CAPE
503 alone contributes relatively little to cloud cover heterogeneity, but its interaction with
504 T2M produces a pronounced nonlinear enhancement. Areas with higher CAPE largely
505 coincide with warmer conditions, allowing temperature and convective potential to
506 vary jointly across the region. In the NEC, the interaction effects are the strongest
507 among the regions with low cloud cover. Interactions involving DPD2M consistently
508 produce high q values, while interactions between T2M and V10, E, or SLHF all
509 exceed $q = 0.80$, with most classified as nonlinear enhancement. These interactions
510 indicate that temperature, moisture exchange, and horizontal wind conditions vary in
511 a coordinated manner across the region.

512 Over the ETP, the interaction between KX and DPD2M exhibits bivariate
513 enhancement with a substantial increase in explanatory power. The spatial
514 distributions of atmospheric instability and humidity differ across the plateau, and
515 their combined variation is associated with stronger differentiation in cloud cover. The
516 SB displays particularly strong nonlinear enhancement involving DPD2M, DEM, KX,
517 SP, and T2M. The enclosed basin and surrounding mountains create strong spatial
518 contrasts in moisture, temperature, pressure, and lifting conditions, resulting in
519 pronounced nonlinear interactions among these variables. The MLY exhibits similar
520 nonlinear enhancement involving KX, T2M, E, and SLHF. Under the East Asian
521 summer monsoon, surface evaporation, moisture supply, and atmospheric instability
522 vary substantially across the region. Their spatial co-occurrence is associated with

strong nonlinear enhancement in cloud cover heterogeneity (Shinoda and Uyeda, 2002; Li et al., 2020).

The CLARA-A3 interaction-analysis results demonstrate that spatial heterogeneity in total cloud cover across China stems from the spatial coupling of multiple environmental gradients, with non-linear amplification growing more prominent in regions where moisture supply and atmospheric instability co-occur.

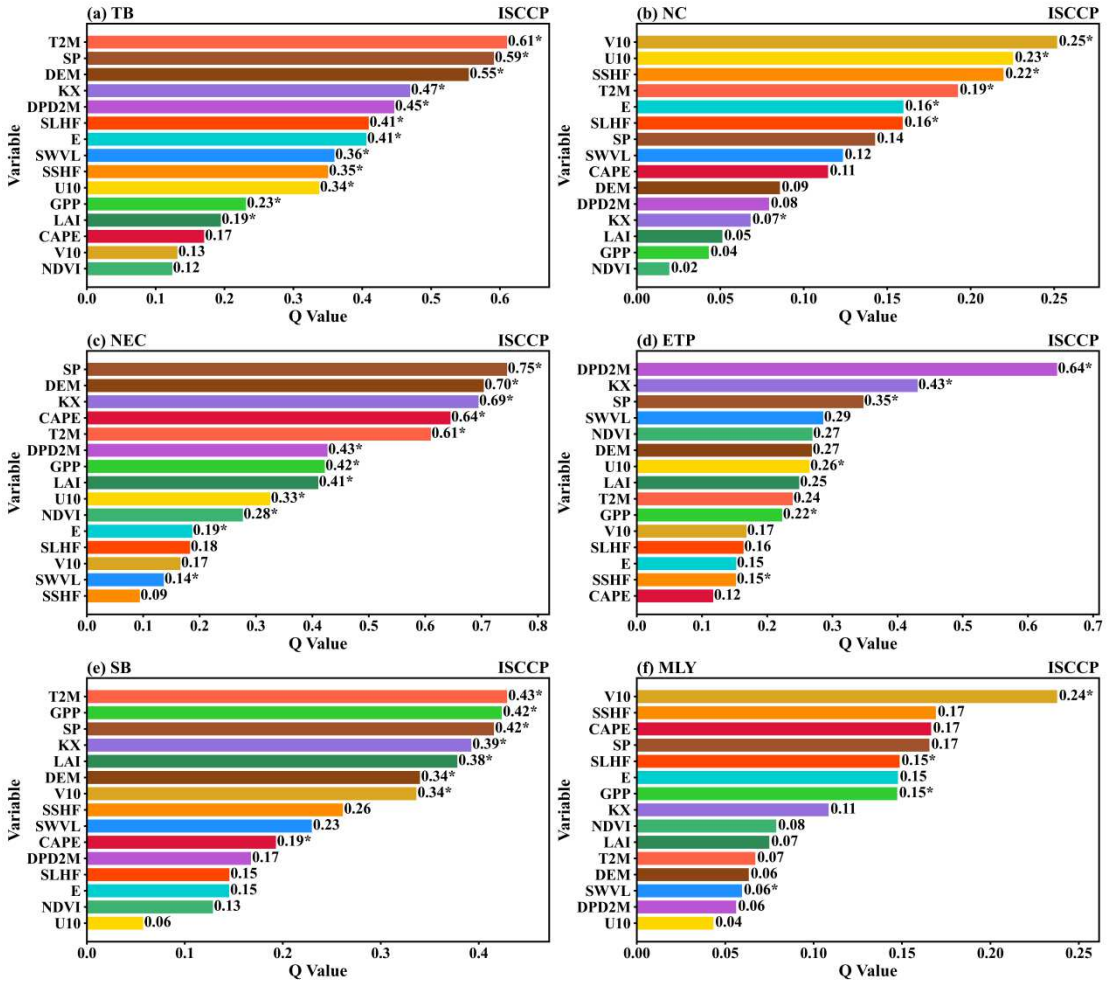


Figure 9. OPGD factor detection results (q values) for total cloud cover derived from ISCCP during 1984–2013. Panels (a–f) correspond to TB, NC, NEC, ETP, SB, and MLY, respectively. Asterisks indicate statistical significance at the 95% confidence level.

The ISCCP-based factor detection reveals regional differences in the relative importance of individual driving factors, with several differences from the CLARA-A3 results (Fig. 9).

Within the TB, T2M replaces KX as the dominant factor, whereas SP, DEM, and

KX remain among the strongest contributors. This difference indicates a greater association of ISCCP cloud cover with near-surface thermal conditions than with atmospheric instability in this arid region. In the NC, the dominant driving factors shift toward U10 and V10, indicating stronger associations with near-surface wind conditions than those identified by CLARA-A3, which instead highlights latent heat flux and evaporation. For the NEC, SP, DEM, and KX jointly explain cloud cover heterogeneity, while CAPE and T2M contribute more substantially than in CLARA-A3, indicating a greater association with thermodynamic variability.

The ETP exhibits the highest consistency between datasets, with DPD2M remaining the dominant factor in both cases. This indicates a strong spatial association between DPD2M and cloud cover in this region. Greater differences emerge over humid regions. In the SB, T2M becomes the leading factor, followed by GPP and SP, indicating a stronger association with thermal conditions than that identified using CLARA-A3. Over the MLY, V10 and SSHF dominate, with greater contributions from near-surface wind conditions and surface energy exchange than from atmospheric instability and soil moisture.

Although the relative importance of individual drivers differs across the two datasets, both consistently show that controls on total cloud cover vary substantially among climatic regions, further confirming strong spatial heterogeneity in the mechanisms governing Chinese cloud-cover variability.

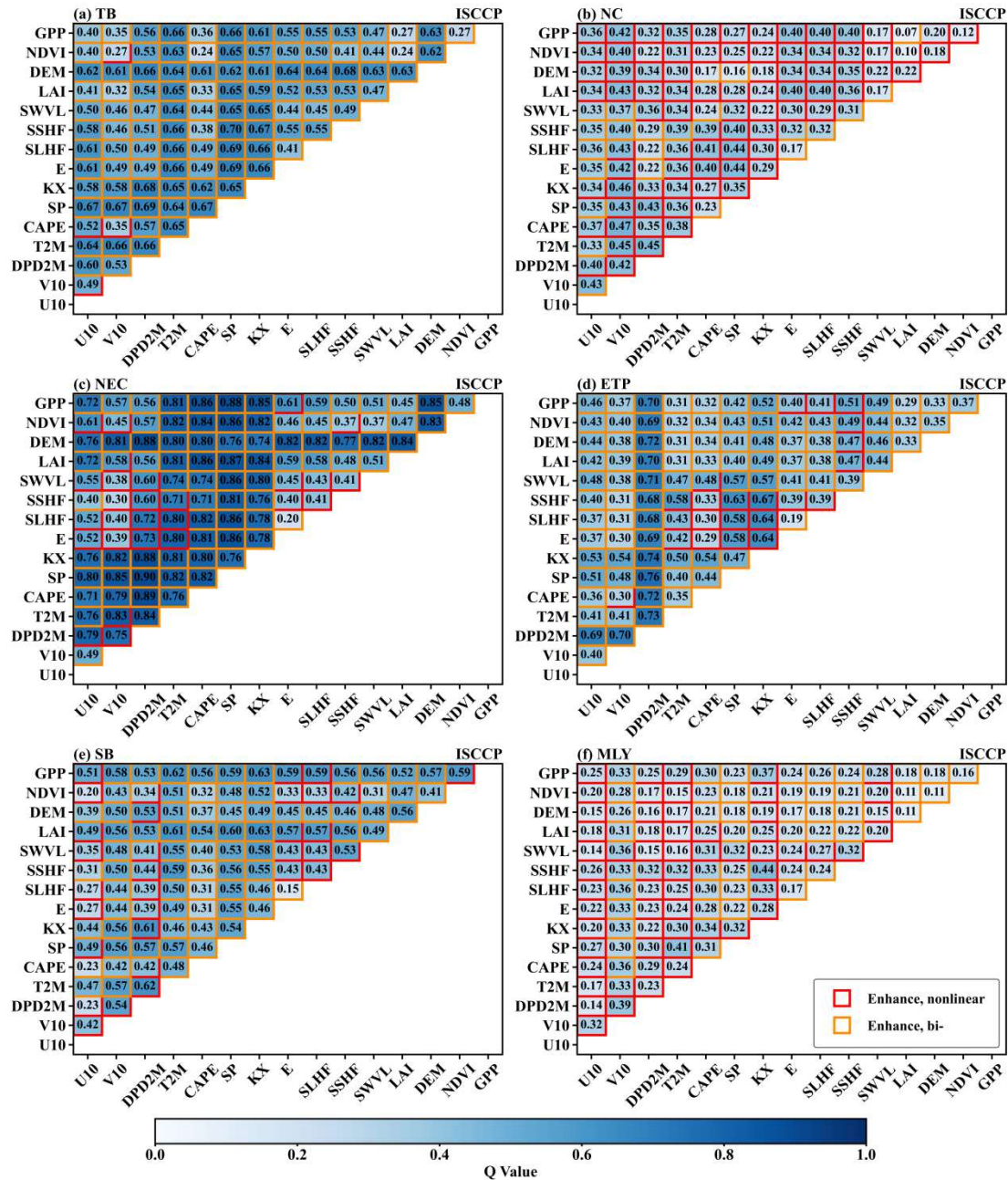


Figure 10. OPGD interaction detection results (q values) for total cloud cover derived from ISCCP during 1984–2013. Panels (a–f) correspond to TB, NC, NEC, ETP, SB, and MLY, respectively. Colors represent interaction q-values, while border colors indicate interaction types: red for nonlinear enhancement, orange for bivariate enhancement, and green for univariate weakening.

The interaction analysis based on ISCCP shows that bivariate enhancement and nonlinear enhancement are the dominant interaction types across the six typical regions (Fig. 10).

Within the regions with low cloud cover, enhanced interactions remain widespread despite differences in the dominant variable combinations. In the TB, interactions involving SP with SSHF, SLHF, and DPD2M exhibit relatively high explanatory power, indicating stronger interactions among atmospheric pressure, surface energy exchange, and humidity than those identified using CLARA-A3. For the NC, interactions between V10 and both CAPE and KX contribute most strongly, indicating strong interactions between near-surface wind conditions and atmospheric instability. In the NEC, interactions among DPD2M, KX, SP, and CAPE consistently produce high q values in both satellite products, involving combinations of humidity, atmospheric instability, and pressure conditions.

Within the regions with high cloud cover, the principal interaction structures remain largely consistent with those identified from CLARA-A3. Over the ETP, interactions between DPD2M and both SP and T2M remain particularly strong. The SB exhibits stronger interactions between SP and vegetation variables (GPP and LAI) than those identified using CLARA-A3. Over the MLY, multiple variable pairs display enhanced interactions, including combinations involving SP, T2M, SSHF, and KX, although the dominant combinations differ somewhat from those identified using CLARA-A3.

Despite these discrepancies, both satellite products consistently show that spatial heterogeneity in total cloud cover is predominantly shaped by synergistic interactions among environmental drivers. This corroborates that cloud-cover variability across China is fundamentally governed by coupled atmospheric and land-surface processes, rather than isolated effects of individual factors..

3.3 Spatial Heterogeneity of Cloud Cover Driving Mechanisms

Previous studies have demonstrated that the combination of GD and GWR provides an effective framework for identifying spatially varying environmental controls (Zhou et al., 2021). Building upon this methodological framework, the present study further integrates OPGD based factor screening with RGWR to quantify the spatial nonstationarity of driving factors of cloud cover across China's major climatic regions. Before constructing the RGWR models, candidate variables were

systematically screened to minimize the influence of multicollinearity while preserving both statistical significance and spatial independence. Following previous studies (Gong et al., 2025; Zhang et al., 2025), variables that passed the OPGD significance test ($p < 0.05$) were retained for further evaluation. Pearson correlation analysis was subsequently performed for each of the six representative regions (Fig. 6), followed by iterative removal of highly correlated variables using a Variance Inflation Factor (VIF) threshold of 7. Spatial autocorrelation tests and local collinearity diagnostics were further incorporated to address local collinearity associated with spatial nonstationarity. The resulting predictor sets represent region specific combinations of statistically significant variables with acceptable levels of global and local collinearity for RGWR modeling.

The selected variables show pronounced regional differences in their combinations across the six typical regions. For the CLARA A3 models, regions with low cloud cover are primarily characterized by combinations of thermodynamic, dynamical, and land surface energy variables. The TB retains U10, KX, SSHF, SWVL, and NDVI. The NC is characterized by V10, T2M, SSHF, SLHF, and LAI. The NEC retains U10, V10, T2M, DPD2M, SP, SWVL, and LAI. In contrast, the regions with high cloud cover contain a larger proportion of variables related to moisture availability. The ETP retains U10, V10, DPD2M, KX, SSHF, and SWVL. The SB retains V10, DPD2M, SP, and NDVI. The MLY retains KX, SSHF, SWVL, and NDVI.

The ISCCP models show broadly similar but not identical predictor combinations. T2M and GPP are retained in the TB, while the NC includes a greater number of wind related variables. In the SB, T2M and GPP are retained in addition to SP. The differences in selected variables indicate that the predictor combinations vary among climatic regions and between the two satellite cloud products.

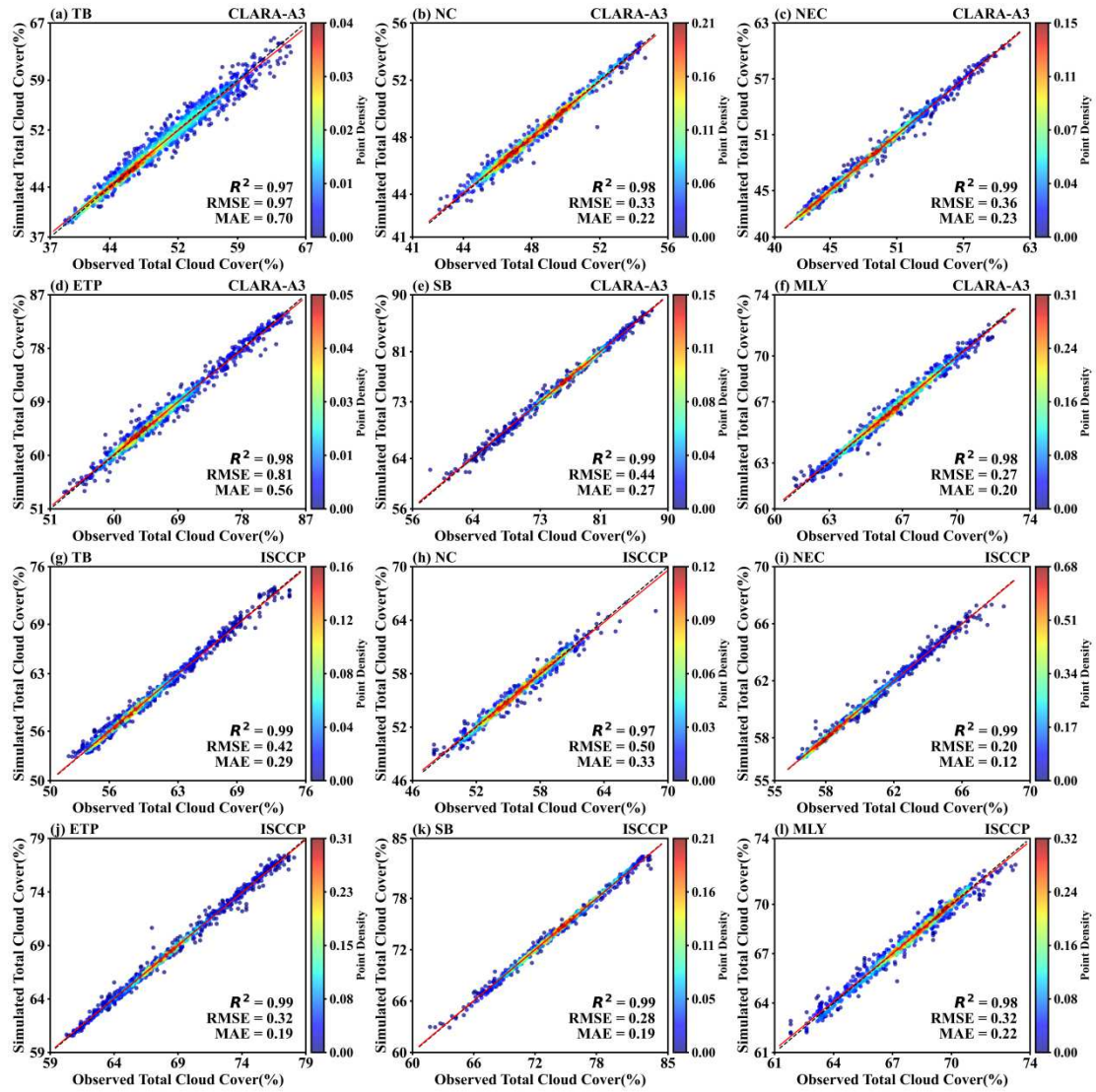


Figure 11. Scatter plots comparing observed and RGWR-simulated total cloud cover for six representative regions based on (a–f) CLARA-A3 and (g–l) ISCCP. Point colors indicate sample density, and solid lines represent fitted regression relationships.

The RGWR models exhibit strong performance across the six typical regions (Fig. 11). Unlike conventional global regression models that assume constant regression coefficients across space, RGWR allows model coefficients to vary among locations, thereby capturing spatially varying relationships between cloud cover and environmental driving factors (Comber et al., 2020). Overall, the CLARA-A3 based models exhibit consistently higher coefficients of determination than the corresponding ISCCP based RGWR models, indicating stronger spatial consistency between the CLARA A3 cloud product and the selected meteorological and land

surface driving factors.

Among the six typical regions, the SB and the NEC exhibit the highest model performance. In the SB, stable topographic forcing, abundant moisture availability, and persistent atmospheric instability produce relatively stable relationships between cloud cover and environmental driving factors. Similarly, the NEC benefits from relatively homogeneous land surface conditions and consistently strong humidity controls, enabling highly reliable local regression estimates. The TB, the NC, and the ETP exhibit intermediate model performance, whereas the MLY exhibits comparatively lower performance. In the MLY, the lower model performance is accompanied by greater spatial variability in the fitted relationships between cloud cover and the selected environmental driving factors.

Collectively, RGWR outputs show that controls on total cloud cover differ substantially across climatic regions, underscoring region-specific rather than spatially uniform environmental responses.

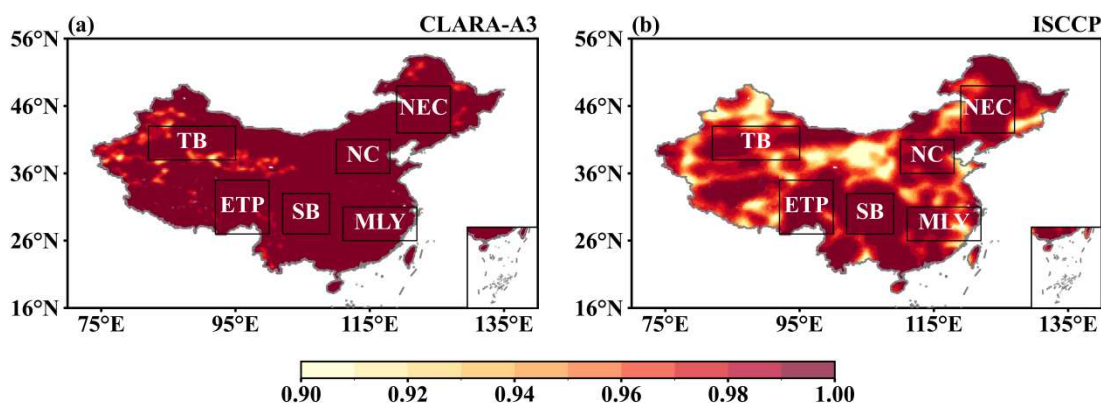


Figure 12. Spatial distribution of local coefficients of determination (R^2) derived from the RGWR models based on (a) CLARA-A3 and (b) ISCCP.

The spatial distributions of local R^2 values further characterize the spatial variability in model performance across China (Fig. 12). Both satellite driven models achieve generally high explanatory power, with most regions exhibiting R^2 values exceeding 0.90. The local R^2 distributions show clear spatial differences both among and within climatic regions. Despite minor numerical differences, the two satellite products produce similar large scale spatial patterns.

The SB, the NC, and the NEC consistently exhibit the highest local R^2 values, typically exceeding 0.95, with relatively uniform spatial distributions and few low performance patches. The TB and the ETP exhibit intermediate R^2 values with greater internal spatial variability. In the TB, local R^2 generally remains high across the central basin but decreases toward the northern and southern margins, whereas lower performance patches in the ETP are concentrated along its eastern boundary. The MLY displays the greatest spatial variability, with local R^2 values generally ranging from 0.75 to 0.90. Areas of lower performance occur primarily along coastal regions and southern hilly regions. Across China, the CLARA A3 model produces more spatially uniform R^2 distributions with fewer low performance patches, whereas the ISCCP model exhibits larger areas of reduced performance across northwestern China, the NC Plain, and western NEC.

These local R^2 patterns further illustrate the strengths of RGWR for resolving spatially varying relationships between total cloud cover and its environmental drivers. Regions with high model performance support reliable interpretation of local regression coefficients, while poorly fitted areas hint at additional cloud modulating mechanisms that require further investigation.

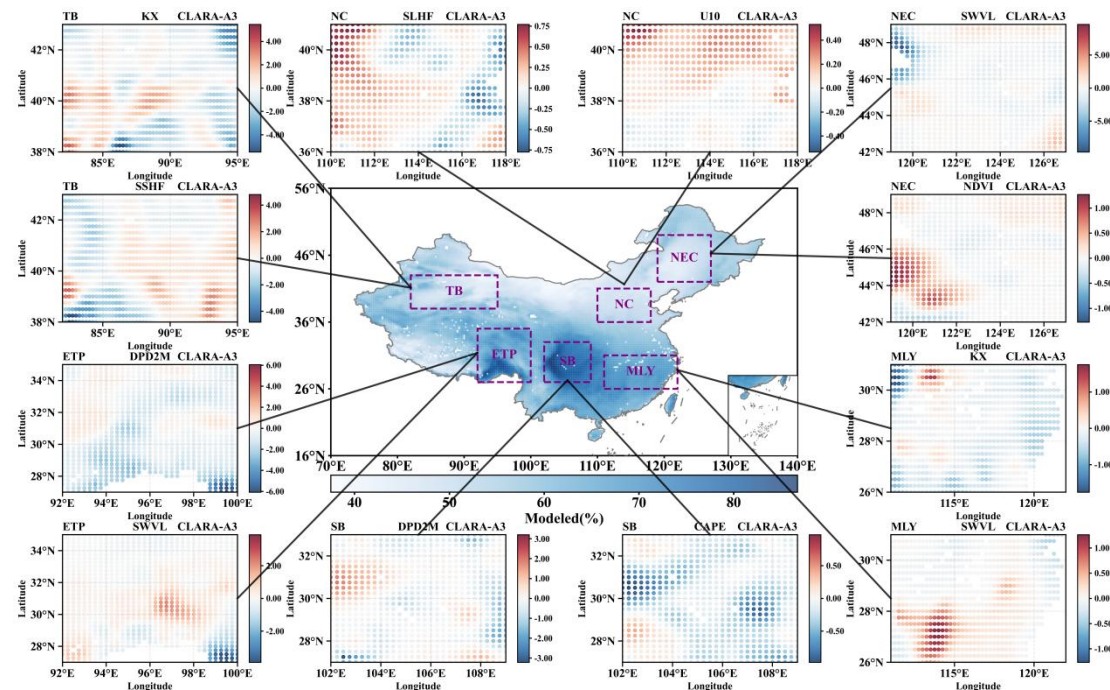


Figure 13. Spatial distributions of the local regression coefficients of the two most influential

driving factors identified by the RGWR model for six representative regions based on the CLARA-A3 cloud cover dataset. The dominant factor pairs are KX and SSHF for the Tarim Basin (TB), SLHF and U10 for North China (NC), SWVL and NDVI for Northeast China (NEC), DPD2M and SWVL for the eastern Tibetan Plateau (ETP), DPD2M and CAPE for the Sichuan Basin (SB), and KX and SWVL for the middle and lower reaches of the Yangtze River (MLY). The center panel shows the RGWR-simulated spatial distribution of total cloud cover across China based on CLARA-A3.

Figure 13 illustrates the spatial distributions of the local regression coefficients of the two dominant driving factors identified by the CLARA-A3-based RGWR model. The direction and magnitude of individual regression coefficients vary substantially among climatic regions and within individual regions, indicating spatially heterogeneous relationships between environmental driving factors and total cloud cover.

In the TB, the regression coefficient of KX exhibits a distinct east–west contrast. Negative coefficients dominate the central and eastern basin, indicating that enhanced atmospheric instability is associated with lower cloud cover under the limited moisture conditions of the region. Stronger instability may intensify boundary-layer vertical mixing, reduce near-surface moisture, and suppress the development of low clouds, resulting in a negative relationship between KX and total cloud cover (Abulimiti et al., 2023; Jin et al., 2024). By contrast, positive coefficients occur over the western basin, where relatively greater moisture availability allows atmospheric instability to favor cloud formation through enhanced lifting. The simultaneous long-term decline of both KX and cloud cover over western TB during 1984–2013 is consistent with this spatial relationship. Meanwhile, SSHF exhibits predominantly negative coefficients across southern TB, indicating that stronger sensible heat flux is associated with lower cloud cover, potentially through enhanced boundary-layer drying. In the NC, SLHF displays a clear south-to-north transition from negative to positive coefficients. Over the southern plains, enhanced latent heat flux is associated with reduced cloud cover, potentially because stronger turbulent mixing redistributes

near-surface moisture upward and modifies the saturation conditions required for low-cloud formation (Vial et al., 2016). In contrast, positive coefficients over northern mountainous areas indicate an association between enhanced evapotranspiration and increased cloud cover. U10 exhibits predominantly positive coefficients, indicating that stronger zonal winds are associated with higher cloud cover, potentially through orographic lifting and low-level convergence. In the NEC, the regression coefficients exhibit strong spatial contrasts. The coefficient of SWVL is positive along the western foothills of the Greater Khingan Mountains but gradually becomes negative toward the south. In relatively dry western areas, increased soil moisture enhances evapotranspiration and increases moisture availability near the surface, favoring cloud formation. Conversely, in the more humid eastern region, higher soil moisture may reduce sensible heating and modify boundary-layer development, resulting in negative coefficients. Meanwhile, NDVI exhibits positive coefficients in the south and negative coefficients in the north, indicating that vegetation is positively associated with cloud cover in southern areas but negatively associated with cloud cover in northern areas. These contrasting relationships may reflect differences in the relative effects of vegetation transpiration and surface thermal conditions (Bonan, 2008; Xu et al., 2022).

Within the regions with high cloud cover, cloud cover is primarily associated with spatial variations in moisture availability, orographic lifting, and thermal conditions. Over the ETP, DPD2M exhibits predominantly negative coefficients, with the strongest negative responses occurring along the Yarlung Zangbo River basin. This pattern indicates a strong negative association between humidity deficit and cloud cover across the plateau. The complex terrain over southeastern Tibet promotes upward motion under the influence of monsoonal moisture transport, favoring high cloud cover (Wang et al., 2015). The simultaneous increase in DPD2M and decrease in cloud cover during 1984–2013 further supports the dominant role of humidity limitation. Meanwhile, SWVL exhibits predominantly positive coefficients in the west and negative coefficients in the east. This spatial contrast indicates that increased soil moisture is positively associated with cloud cover over southwestern Tibet but

negatively associated with cloud cover over southeastern Tibet, potentially reflecting regional differences in the effects of evapotranspiration and surface energy partitioning on boundary-layer development. Within the SB, DPD2M maintains a strong negative relationship with cloud cover throughout most of the basin, confirming that moisture availability forms the fundamental basis for persistent cloud formation. By contrast, CAPE exhibits pronounced spatial variability. Negative coefficients dominate the central basin, whereas positive coefficients occur over western mountainous areas. These contrasting relationships indicate that the association between convective potential and cloud cover varies spatially, potentially reflecting differences in convective development, precipitation processes, and orographic lifting (Houze, 2012). Over the MLY, both KX and SWVL exhibit predominantly positive coefficients, indicating that atmospheric instability and soil moisture are positively associated with cloud cover under humid monsoon conditions. Higher KX coefficients over the northwestern portion of the region indicate a stronger positive association between atmospheric instability and cloud cover in this area. Positive SWVL coefficients across the central and southern areas indicate that higher soil moisture is associated with increased cloud cover, potentially through enhanced evapotranspiration and near-surface moisture supply.

RGWR results derived from CLARA-A3 clearly show that the same environmental drivers can produce opposite effects under different climatic backgrounds. This highlights the strong dependence of cloud formation on regional climatic context across China.

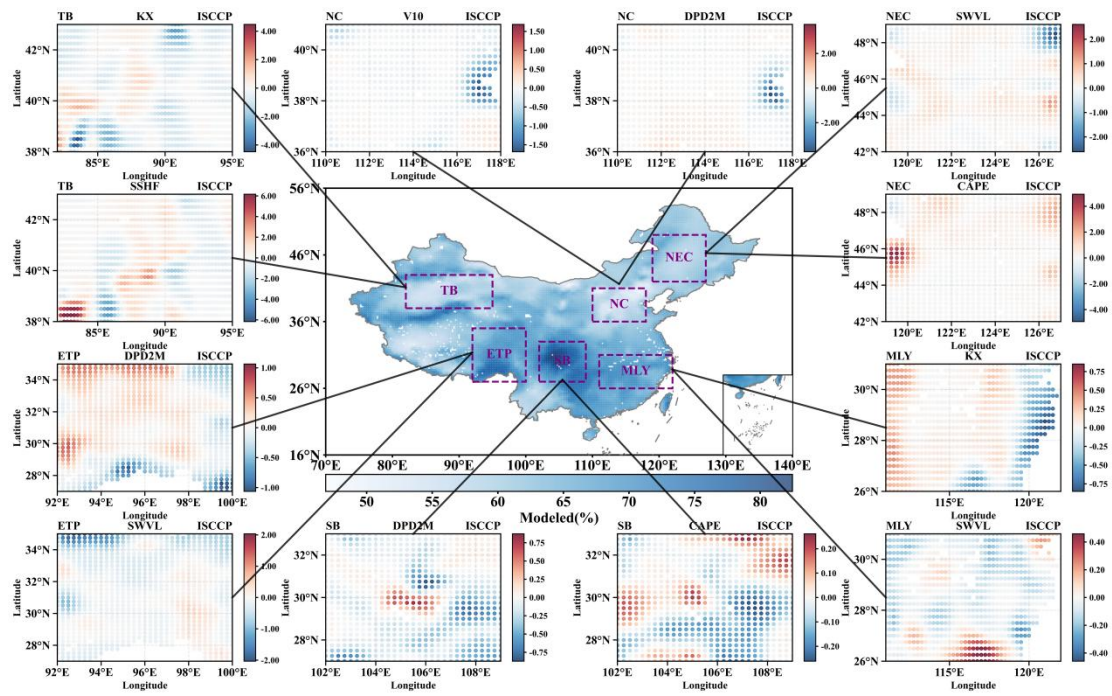


Figure 14. Spatial distributions of the local regression coefficients of the two most influential driving factors identified by the RGWR model for six representative regions based on the ISCCP cloud cover dataset. The dominant factor pairs are KX and SSHF for the Tarim Basin (TB), V10 and DPD2M for North China (NC), SWVL and CAPE for Northeast China (NEC), DPD2M and SWVL for the eastern Tibetan Plateau (ETP), DPD2M and CAPE for the Sichuan Basin (SB), and KX and SWVL for the middle and lower reaches of the Yangtze River (MLY). The center panel shows the RGWR-simulated spatial distribution of total cloud cover across China based on ISCCP.

The RGWR model based on the ISCCP cloud cover dataset reveals pronounced regional differences in the spatial distributions of the local regression coefficients of key driving factors across China's typical climatic regions (Fig. 14). These results indicate that cloud cover variability is controlled by different dominant driving factors in different regions, while both the direction and magnitude of individual driver effects exhibit considerable spatial heterogeneity within each region. Compared with the CLARA-A3-based RGWR results, the two satellite datasets show good agreement regarding the dominant driving factors, although noticeable differences remain in the strength of local responses and fine-scale spatial patterns, reflecting the sensitivity of the inferred relationships between environmental driving factors and cloud cover to

the choice of cloud dataset.

Within the TB, KX remains one of the dominant driving factors, and its spatial distribution closely resembles that obtained from the CLARA-A3-based model, indicating a stable relationship between atmospheric instability and cloud cover variability in this arid region. In the NC, the regression coefficients of V10 are predominantly positive, suggesting that enhanced southerly wind transport favors cloud formation through increased moisture advection. Compared with the CLARA-A3 results, ISCCP highlights a more pronounced spatial differentiation associated with the meridional wind field. Meanwhile, DPD2M exhibits predominantly negative coefficients throughout the region, indicating that the inverse relationship between near-surface humidity deficit and cloud cover remains consistent across both satellite products. In summary, the ISCCP results place greater emphasis on large-scale dynamical transport processes, particularly near-surface wind fields, whereas CLARA-A3 highlights the local influence of land surface moisture exchange through latent heat flux. In the NEC, SWVL retains the pattern of positive coefficients in the west and negative coefficients in the east identified in the CLARA-A3 analysis, indicating a consistent role of soil moisture in regulating cloud formation across both datasets. However, CAPE exhibits widespread positive coefficients throughout the region, suggesting that atmospheric instability exerts a substantially stronger positive influence on cloud formation in ISCCP than in CLARA-A3.

Within the ETP, DPD2M remains the primary driving factor, although its relationship with cloud cover is predominantly positive, in contrast to the negative relationship identified in the CLARA-A3-based model. This difference indicates that the relationship between near-surface humidity and cloud cover differs between the two satellite products. In the SB, the regression coefficients of DPD2M and CAPE continue to exhibit pronounced spatial heterogeneity, reflecting the important role of thermal contrasts between the basin interior and the surrounding mountainous terrain in modulating cloud cover variability. Over the MLY, both KX and SWVL exert substantial influences on cloud cover, although their spatial distributions remain highly complex. Considerable variations in both coefficient magnitude and sign occur

across the region, indicating that cloud cover variability is jointly regulated by thermodynamic processes and soil moisture under strong spatial nonstationarity.

The RGWR results from ISCCP and CLARA-A3 show broad agreement in the dominant driving factors identified for the six typical regions, but differences occur in the spatial distributions and magnitudes of local regression coefficients. ISCCP shows stronger associations with atmospheric circulation and instability variables, particularly V10, KX, and CAPE, whereas CLARA-A3 shows stronger associations with land surface hydrothermal and vegetation-related variables, including SLHF, SWVL, and NDVI. These differences are consistent with the distinct cloud detection and retrieval characteristics of the two satellite products, including their sensitivity to different cloud types and cloud properties.

4 Conclusion and Discussion

This study integrates OPGD and RGWR to investigate the spatial heterogeneity and environmental controls of total cloud cover over China during 1984–2013, using CLARA-A3 and ISCCP satellite data together with meteorological and land surface variables. By combining factor detection, interaction analysis, and spatially varying regression, this framework identifies how the relative importance and effects of environmental driving factors change across climatic regions.

Both satellite products show a pronounced southeast-to-northwest gradient in total cloud cover and widespread declining trends, with the strongest decreases over the ETP and northwestern China. A notable feature is the pronounced decline in total cloud cover over these regions despite substantial warming and humidification (Li et al., 2021; Zhang et al., 2021; Chen et al., 2023). This apparent decoupling indicates that increasing moisture availability does not necessarily result in increased cloud cover. In northwestern China, warming may enhance precipitation efficiency and accelerate the conversion of cloud condensate to precipitation, thereby shortening cloud lifetime (Sui et al., 2020; Li et al., 2022). Meanwhile, changes in atmospheric circulation can modify moisture transport and vertical motion, determining whether additional moisture contributes to persistent cloud development. The decline in total cloud cover thus reflects changes in the balance among moisture supply, condensation, precipitation, and

cloud persistence rather than a direct response to regional humidification. Over the ETP, the reduction is particularly associated with decreases in middle-level and high-level clouds, which have been linked to changes in the South Asian High and anomalous subsidence over the plateau (Ma et al., 2021; Wu et al., 2024). The stronger decline detected by ISCCP than by CLARA-A3 over the TB should be interpreted cautiously because cloud retrieval over bright desert surfaces remains subject to considerable uncertainty (Noel et al., 2018; Devasthale and Karlsson, 2023). Nevertheless, the overall decline over the plateau and northwest is consistent between the two datasets, indicating that cloud reduction in these regions cannot be explained by moisture availability alone.

The environmental controls of total cloud cover vary systematically among climatic regions. In regions where moisture is limited, atmospheric humidity strongly constrains the extent to which thermodynamic instability can translate into cloud formation. This is particularly evident in the NEC, where DPD2M has exceptionally high explanatory power, and in the TB, where KX exhibits contrasting effects across areas with different moisture conditions. Under severe moisture limitation, stronger instability may enhance boundary-layer mixing without producing sufficient condensation, resulting in negative relationships between KX and total cloud cover (Abulimiti et al., 2023; Jin et al., 2024). Where moisture availability is greater, the same instability can instead facilitate cloud development. Thus, the effect of atmospheric instability is conditional on the background moisture state rather than intrinsically positive or negative. In humid regions, the controlling processes shift toward stronger coupling among atmospheric instability, soil moisture, evaporation, and surface energy exchange. These contrasts indicate a systematic transition from moisture limitation in arid and semiarid environments toward stronger coupling between moisture and instability in humid monsoon regions.

The importance of DPD2M further demonstrates the role of atmospheric moisture constraints. Smaller DPD2M values indicate conditions closer to saturation and accordingly favor condensation and cloud persistence, whereas larger values represent stronger moisture deficits that inhibit cloud development (Lawrence, 2005; Theeuwes

et al., 2019). Its consistently negative relationship with total cloud cover over the NEC and the ETP indicates that near-surface humidity remains an important constraint across contrasting climatic and topographic environments. However, its varying relative importance among regions suggests that the strength of this constraint depends on the background hydrothermal state.

The interaction analysis demonstrates that cloud cover heterogeneity is fundamentally controlled by coupled environmental processes. Bivariate and nonlinear enhancements dominate across the six regions, indicating that the spatial effect of one factor depends strongly on the concurrent state of other factors. In the TB, interactions involving KX with DPD2M and CAPE indicate that atmospheric instability alone cannot readily promote cloud development under strong moisture limitation. In the SB, strong interactions involving DPD2M and DEM highlight the combined effects of moisture availability and lifting forced by terrain. In the MLY, interactions involving KX, E, and SLHF indicate close coupling between atmospheric instability and land surface moisture exchange under monsoon conditions. The prevalence of nonlinear enhancement suggests that these effects are not simply additive, but arise from the simultaneous regulation of moisture supply, thermal conditions, and dynamical forcing. This dependence on the background state is consistent with previous evidence that land surface moisture can exert contrasting effects on cloud development depending on the background atmospheric state (Chlond et al., 2014; Ryu and Salvucci, 2025).

The spatially varying RGWR coefficients provide further evidence that environmental controls are context dependent. KX in the TB and SWVL in the NEC and ETP exhibit opposite coefficient signs within individual regions. For SWVL, increased soil moisture may enhance evapotranspiration and boundary-layer moisture under relatively dry conditions, favoring cloud formation, whereas in humid environments it may reduce sensible heating and modify boundary-layer development, resulting in an opposite response. Similarly, the contrasting effects of KX across the TB indicate that atmospheric instability can either promote cloud formation or enhance turbulent mixing depending on local moisture availability. These sign reversals demonstrate that regional hydrothermal conditions influence not only the magnitude

but also the direction of cloud responses to environmental changes. Spatial nonstationarity is consequently a physical characteristic of relationships between clouds and their environment rather than merely a statistical feature of the regression model.

Differences between CLARA-A3 and ISCCP mainly reflect their distinct cloud retrieval characteristics and sensitivities to different cloud types. CLARA-A3 more clearly captures relationships involving SLHF and SWVL, whereas ISCCP places greater emphasis on V10 and CAPE. These differences may partly reflect the contrasting sensitivities of the two products to low, thin, middle-level, and high-level clouds (Karlsson et al., 2023a, 2023b). Importantly, the major regional patterns and spatially varying responses are reproduced by both datasets, indicating that the inferred environmental controls are not artifacts of a single satellite product, although their quantitative expression depends on the cloud retrieval characteristics.

The results show that cloud-cover variations across China arise from the coupled evolution of moisture availability, atmospheric instability, vertical motion, surface energy exchange, and topographic forcing. The marked cloud-cover decline over the eastern Tibetan Plateau and northwestern China illustrates that warming and humidification can co-occur with reduced cloud cover, as shifts in circulation and precipitation efficiency modify cloud persistence. More broadly, spatially variable coefficient signs and prominent interaction effects show that individual environmental drivers cannot be interpreted in isolation from prevailing climatic background conditions. Relationships between clouds and their environment therefore vary systematically along China's hydroclimatic gradient: in northwestern regions moisture acts as the primary limiting factor, whereas humid eastern China features tighter coupling among moisture, atmospheric instability, and land-surface processes. These findings underscore the necessity of accounting for regional context and multi-factor interactions when evaluating cloud responses to ongoing climate change.

Data availability

The ISCCP-H HGG cloud data are obtained from the National Centers for Environmental Information (NCEI) and are available at: <https://www.ncei.noaa.gov/products/international-satellite-cloud-climatology>. The CLARA-A3 cloud data are obtained from the EUMETSAT Satellite Application Facility on Climate Monitoring (CM SAF) and are available at: https://www.cmsaf.eu/EN/Home/home_node.html. ERA5 reanalysis data are obtained from the Copernicus Climate Change Service (C3S) Climate Data Store and are available at: <https://cds.climate.copernicus.eu/datasets/reanalysis-era5-single-levels?tab=overview>. The GIMMS-3G+ NDVI data are obtained from the NOAA National Centers for Environmental Information and are available at: <https://www.ncei.noaa.gov/data/land-normalized-difference-vegetation-index/access/>. The GLASS LAI and GPP products are obtained from the Global Land Surface Satellite (GLASS) product data service and are available at: https://glass-product.bnu.edu.cn/dload.html?utm_source=chatgpt.com. The DEM data are obtained from the Geospatial Data Cloud and are available at: <https://www.gscloud.cn/sources/accessdata/310?pid=302>.

Code availability

The code used for analysis in this study is available upon reasonable request.

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Author contributions

P.Z. conceptualized the study. J.W., P.Z. and J.L. designed the methodology. J.W., P.Z., and H.X. analyzed the data, created the figures, and wrote the first manuscript draft. J.W., P.Z., J.L., H.X., LY., and CZ contributed with ideas, interpretation of the results, and manuscript revisions.

Competing interests

The authors declare no competing interests.

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