forests

Supplementary Materials

S1. Research Methods

S1.1. Land Use Degree Comprehensive Index (LDCI)

The land use types were quantified with the land use degree comprehensive index (LDCI)[1]. The equation as follows:

$$LDCI_a = 100 \times \sum_{i=1}^{n} A_i \times C_i \quad (S1)$$

where $LDCI_a$ is the land use degree index; Ai is the land use classification index and the quantitative values are 4, 3, 2, 2, 2 and 1 for construction land, cropland, forest land, water bodies, grassland, and unused land; C_i is the area percentage of different land use types in one unit.

S1.2. Significance test of vegetation NDVI slope

The significance of vegetation NDVI slope was expressed using the F test [2], Based on the results of significance tests, the trends of NDVI changes were classified into six classes, including extremely significant increase (P < 0.01, Slope > 0), significant increase (0.01 < P < 0.05, Slope > 0), insignificant increase (P > 0.05, Slope > 0), insignificant decrease (P > 0.05, Slope < 0), significant decrease (0.01 < P < 0.05, Slope < 0), and extremely significant de-crease (P < 0.01, Slope < 0). Table S1 shows the trend of vegetation improvement or degradation in different regions.

Table S1. The area ratio of improvement or degradation trend of vegetation NDVI (%).

Classes / Region	Extremely significant decrease	Significant decrease	Insignificant decrease	Insignificant increase	Significant increase	Extremely significant increase
AKC	3.02	1.60	13.01	38.39	13.77	30.21
K-AKC	2.07	1.36	11.31	33.04	13.07	39.16
NK-AKC	3.36	1.69	13.63	40.38	14.04	26.90
SC	1.3	0.66	5.98	24.22	13.97	53.87
K-SC	1.32	0.68	5.45	20.85	13.03	58.67
IP	3.73	2.00	15.92	44.27	13.69	20.4
K-IP	2.92	2.14	18.02	46.81	13.05	17.07
CLV	7.06	3.67	22.11	39.44	10.22	17.49

Note: AKC: Asian karst concentration distribution area; SC: Southwest China; IP: Indochina Peninsula; K-AKC: Karst area of AKC; NK-AKC: Non-Karst area of AKC; K-SC: Karst area of SC; K-IP: Karst area of IP; CLV: Cambodia, Laos and Vietnam.

S1.3. Spatial Aggregation of Vegetation NDVI Slope

In order to find spatial clusters that explain the dynamics of the vegetation, this study uses the global spatial autocorrelation Moran's Index(I) (I_g) and local spatial autocorrelation Moran's I (I_l) [3]. I_g is calculated as follows:

$$I_g = \frac{n \sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij} \sum_{i=1}^{N} (x_i - \bar{x})^2} \quad (S2)$$

where I_g is in the range of [-1, 1]. When its value is greater than 0, it indicates that there is spatial positive correlation in the study area, and the closer the value is to 1, the stronger the spatial positive autocorrelation is, and the value of the study object is clustered; when its value is less than 0, it indicates that there is spatial negative correlation in the study area, and the closer the value is to -1, the stronger the spatial negative autocorrelation is, and the value of the study object is distributed as a discrete mutual exclusion (exclude the high value around the high value, and exclude the low value around the low value); when it is closer to 0, the value of the study object is randomly distributed, and no autocorrelation exists. I_l is calculated as follows:

$$I_l = \frac{n^2(x_i - \overline{x})\sum_{j=1}^{N} w_{ij}(x_j - \overline{x})}{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}\sum_{j=1}^{N}(x_j - \overline{x})^2} \tag{S3}$$

In this study, x means vegetation NDVI slope. Subject to the specified level of significance, $I_l > 0$ means that x has positive local spatial autocorrelation, with municipal or provincial administrative districts with similar values clustered together; otherwise, it has negative local spatial autocorrelation, with municipal or provincial administrative districts with dissimilar values clustered together. x_i and x_j mean the value of variable x in location i and location j ; $\overline{x}$ means the mean value of variable x. Figure S1 shows the value and aggregation degree of Moran 's I. Global Moran's I and Z-score of 0.27 and 11.3, respectively, with strong spatial aggregation.

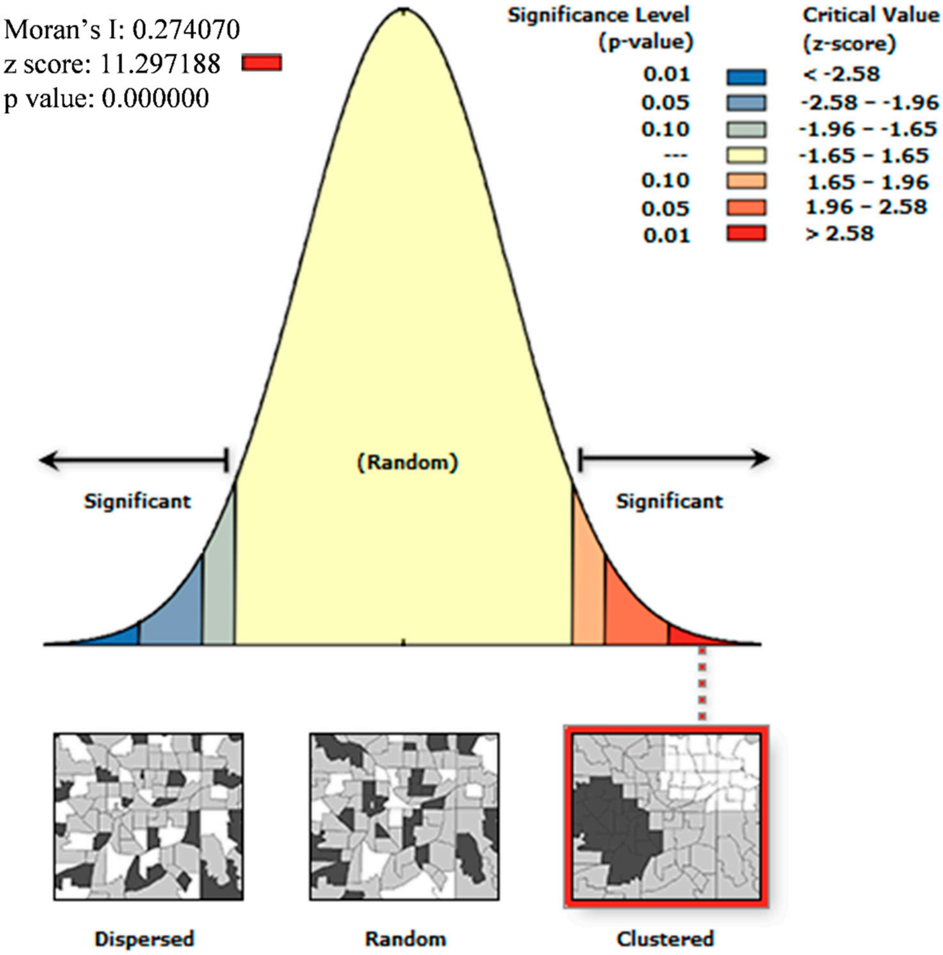

Figure S1. The value and aggregation degree of Moran 's I.

S1.4. Optimal parameters-based geographical detector (OPGD)

In this study, the vegetation NDVI slope from 2000 to 2020 was used as the dependent variable, and the six comprehensive factors were used as explanatory variables. All six comprehensive factors are continuous variables, so they must be layered by discretization before they can be used in geographical detector. In this study, the optimal parameters-based geographical detector (OPGD) [4,5] was used to select the best category based on the five classification methods of equal interval (equal), natural breakpoint (natural), quantile, geometric interval(geometric), and standard deviation (sd). The best categories and methods of each comprehensive factor are shown in the following Figure S2-S5, and different factors in different regions are classified.

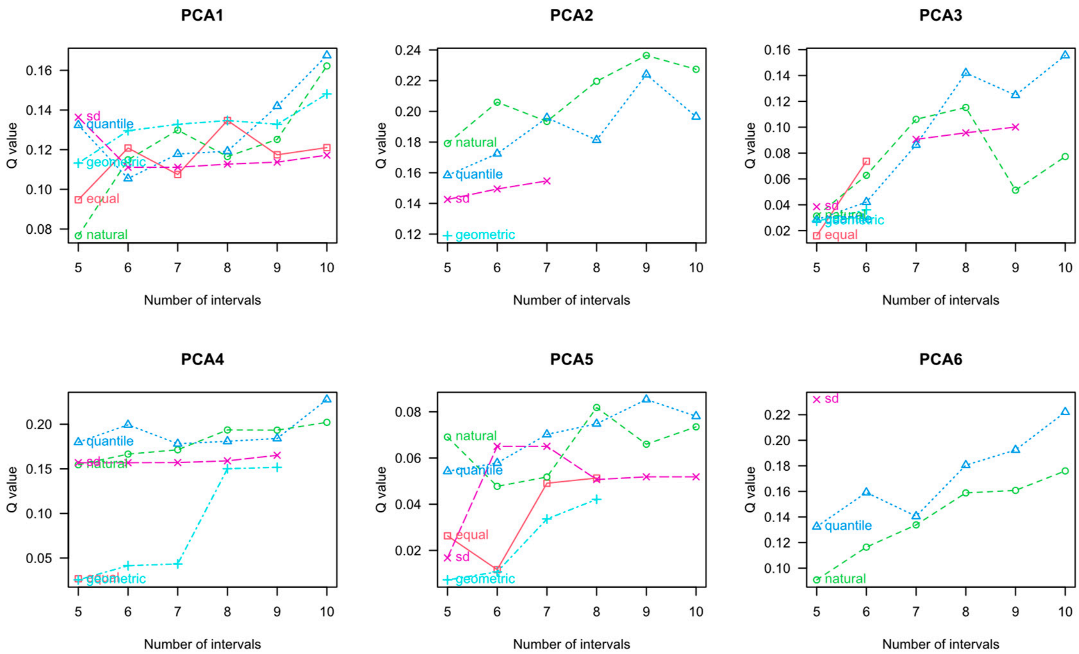

Figure S2. The best category with the largest Q value in AKC.

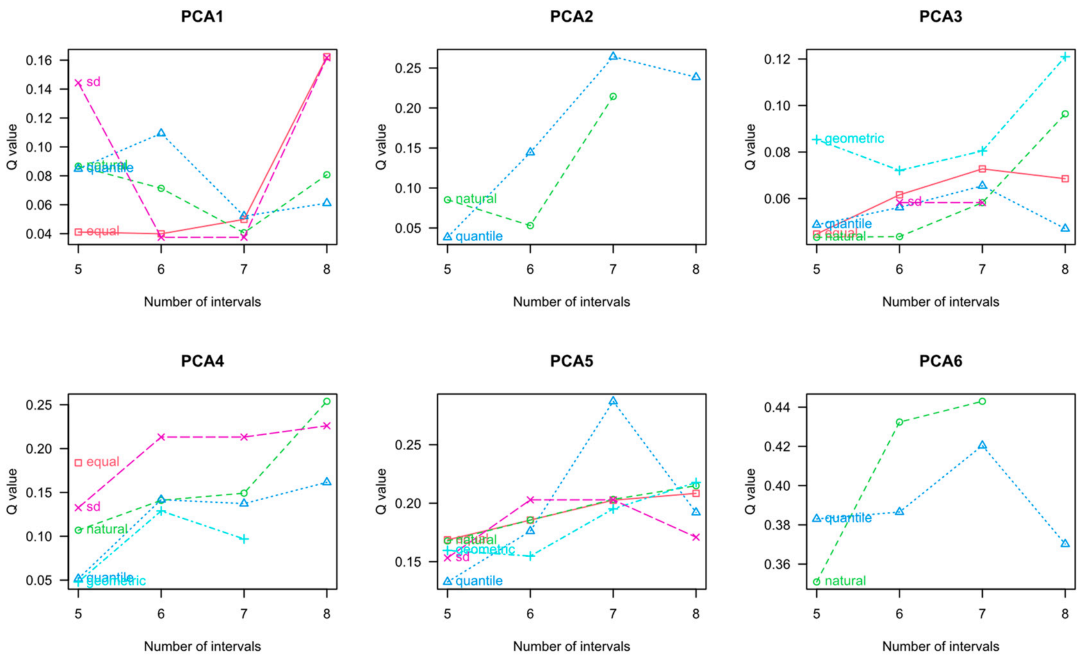

Figure S3. The best category with the largest Q value in SC.

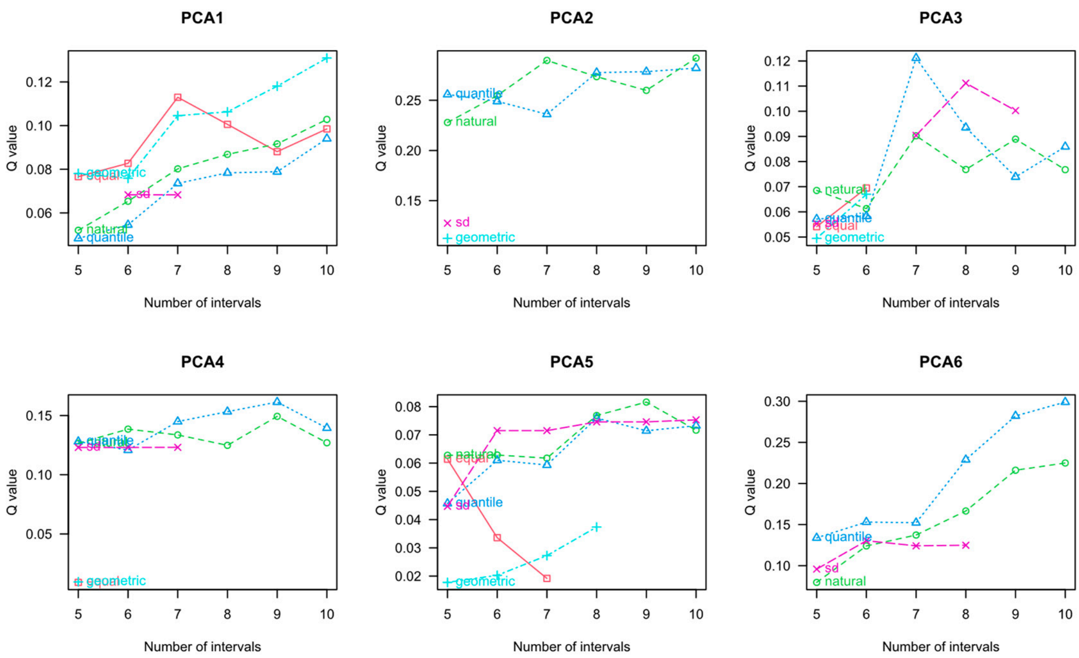

Figure S4. The best category with the largest Q value in IP.

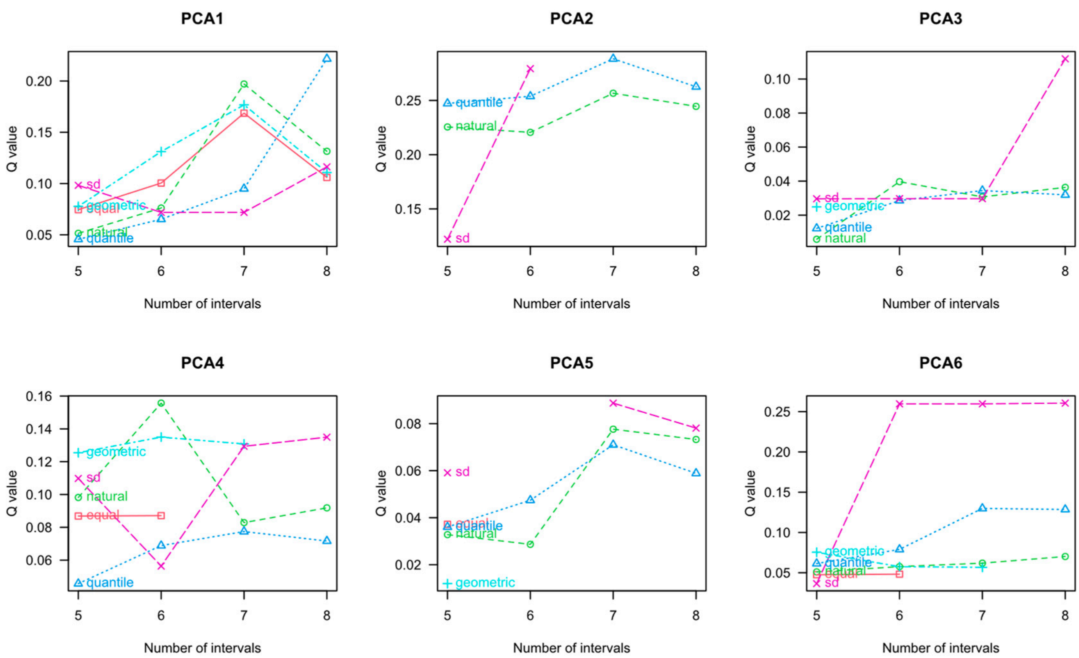

Figure S5. The best category with the largest Q value in CLV. Note: PCA1: Thermal condition; PCA2: Urban economic development; PCA3: Soil condition; PCA4: Agricultural economic development; PCA5: Water condition; PCA6: Human activity intensity. AKC: Asian karst concentration distribution area; SC: Southwest China; IP: Indochina Peninsula; CLV: Cambodia, Laos and Vietnam.

OPGD can also test if the interaction between two factors impacts on the explanatory power of vegetation NDVI (in this study interaction is symbolized by ∩). As shown in Table S2 [6].

Table S2. Types of two factor interactions.

Basis of determination	Interaction
Q(X1∩X2) < Min[Q(X1), Q(X2)]	Weaken nonlinear
Min[Q(X1), Q(X2)] < Q(X1∩X2) < Max[Q(X1), Q(X2)]	Weaken unifactor
Q(X1∩X2) > Max[Q(X1), Q(X2)]	Enhanced bifactor
Q(X1∩X2) = Q(X1) + Q(X2)	Independent
Q(X1∩X2) > Q(X1) + Q(X2)	Enhanced nonlinear

S1.5. Coefficient of Variation (CV)

The coefficient of variation (CV) is a statistical metric derived by dividing the standard deviation of raw data by the mean of the raw data [7]. In this study, we employed CV as a tool to gauge the stability of NDVI changes. The formula used for this calculation was as follows:

$$CV_{NDVI} = \frac{1}{x}\sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n-1}} \tag{S4}$$

where n represents the study period; x_i represents the NDVI value in the i year; and $\bar{x}$ represents the average NDVI during the study period. A higher CV value signifies greater variability within the time series, whereas a lower value indicates less pronounced fluctuations.

Can be divided into these categories: Low volatility (CV < 0.05), Relatively low volatility (0.05 < CV < 0.1), Medium volatility (0.1 < CV < 0.15), Relatively high volatility (0.15 < CV < 0.2), High volatility (CV > 0.2).

As shown in Figure S6, although the annual average NDVI value presents a skewed distribution, we can find that it is approximately a normal distribution, and the value on the left half is infinitely close to 0, so it can be used to calculate the CV, and the CV has no Assumption requirements on the shape of the distribution, so it can be used to describe our data.

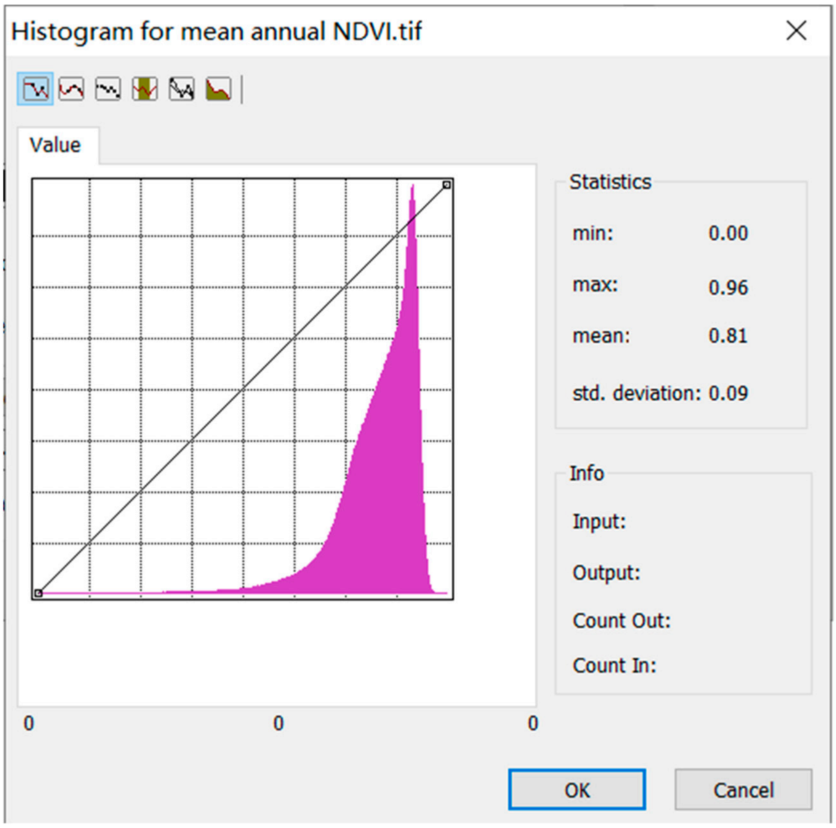

Figure S6. Data distribution of annual average NDVI.

References

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