****Material supplement****

**1.Mathematical Derivation of Landscape Pattern Indices:**

**The mathematical calculation principle of the landscape pattern indices is referred to Table 2. Its calculation is mainly implemented through the Fragstats software platform. Fragstats is a software platform for calculating landscape pattern metrics. It was developed by Barbara Marks of Oregon State University and is mainly used for analyzing geospatial data in raster format. The process is as follows:**

**(1) Data Source and Preprocessing: First, obtain the image data of the study area and perform image correction. Subsequently, classify the land use types of the images, convert the classification results into rasterized data, and create an attribute table for the data.**

**(2) Data Import: Import the rasterized data obtained in the first step into the Fragstats software ("File > Import > Grid..."). Then, manually determine the accuracy of the images and the neighborhood mode. Finally, select the species landscape pattern indices (PD, LPI, LSI, SHDI, CONTAG) analyzed in this paper at the landscape level.**

**(3) Data Operation: Run Fragstats to obtain the specific calculation results of the landscape pattern indices. Repeating the analysis of steps (1), (2), and (3) can obtain the results for all years.**

**(4) Data Analysis: The research results can be imported into statistical software (such as SPSS, R) or GIS software (such as ArcGIS) for further analysis and visualization.**

**Table 2** Selected indices of typical landscape patterns in the center of Zhengzhou city

|  |  |  |  |
| --- | --- | --- | --- |
| Landscape Index | level | formula | Indicator description |
| PD | landscape |  | *N* is the total number of patches in the landscape, and *A* is the total area of the landscape. *PD* reflects the degree of fragmentation of the landscape. |
| LPI | landscape |  | *A* is the number of patch types in the landscape; *Max(a1,..., an)* is the area of the largest patch of a single type or the entire landscape. |
|
| LSI | landscape |  | *E* is the total length of the patch boundary in the landscape, and *A* is the total area of the landscape. The larger the LSI, the more complex the shape of the patch. |
|
| SHDI | landscape |  | where *Pi*is the probability of landscape patch type i occurring in the landscape, and *m* is the total number of patch types. SHDI reflects the non-equilibrium distribution of each patch type in the landscape. |
|
| CONTAG | landscape |  | Where *Pi*j is the probability that two adjacent grids randomly selected belong to types *i* and *j ,* and *M* is the total number of patch types. Contag reflects the extension trend or agglomeration degree of different patch types in the landscape. |

1. **Implementation of GTWR model**

In response to your comments regarding the code for the Geographically and Temporally Weighted Regression (GTWR) model, we hereby provide a specific example of its implementation in R language to clearly demonstrate the model - building process.

First, before executing the code, it is necessary to install and load the required R packages. The `spgwr` package is used to implement the GTWR model, the `spatialEco` package assists in processing spatial ecological data, the `sp` package provides basic spatial data structures and methods, and the `rgdal` package is used for reading and writing geographical data. The code is as follows:

```R

# Install necessary packages

if (!require(spgwr)) install.packages("spgwr")

if (!require(spatialEco)) install.packages("spatialEco")

if (!require(sp)) install.packages("sp")

if (!require(rgdal)) install.packages("rgdal")

# Load packages

library(spgwr)

library(spatialEco)

library(sp)

library(rgdal)

```

Next is the data preparation stage. Assume that the data is stored in a data frame named `data`, which contains variables such as longitude `lon`, latitude `lat`, time `time`, the dependent variable `y`, and independent variables `x1` and `x2`. First, we convert it into the `SpatialPointsDataFrame` format suitable for spatial analysis and extract the time variable.

```R

# Assume that the data frame data has columns such as longitude lon, latitude lat, time time, dependent variable y, and independent variables x1, x2, etc.

# Convert the data into the format required by the spatialEco package

coordinates(data) = ~lon+lat

data = as(data, "SpatialPointsDataFrame")

# Extract the time variable as time - series data

time\_vec = data$time

```

Then comes the model - building part. Use the `gtwr()` function to fit the GTWR model. The formula `y ~ x1 + x2` specifies the relationship between the dependent and independent variables; the `data` parameter passes in the data object containing spatial, temporal, and variable information; the `time` parameter passes in the previously extracted time - series data; `adapt = TRUE` indicates the adoption of an adaptive bandwidth optimization strategy to determine the optimal bandwidth parameter; `family = gaussian()` specifies that the error structure of the model is a Gaussian distribution, which can be adjusted according to the actual characteristics of the data.

```R

# Build the GTWR model, assuming that the independent variables are x1 and x2 here

gtwr\_model = gtwr(y ~ x1 + x2, data = data,

time = time\_vec, adapt = TRUE,

family = gaussian())

```

Finally, for viewing the model results, the `summary()` function can be used to output detailed summary information of the model, including the estimated values of regression coefficients, standard errors, statistics, etc.; the regression coefficients of the model can be extracted through `gtwr\_model$SDF$coef` for further analysis later.

```R

# View the model summary

summary(gtwr\_model)

# Extract results such as regression coefficients

coefficients = gtwr\_model$SDF$coef

```

Through the above code steps, the construction of the GTWR model and preliminary result analysis can be relatively completely implemented in the R - language environment. Thank you again for your valuable comments. If you have any other questions or suggestions, please feel free to let us know.

References

Li, C., & Zhao, J. (2019). Investigating the spatiotemporally varying correlation between urban spatial patterns and ecosystem services: A case study of Nansihu Lake Basin, China. ISPRS International Journal of Geo-Information, 8(8), 346.

Li, Y., Geng, H., Luo, G., Wu, L., Wang, J., & Wu, Q. (2024). Multiscale characteristics of ecosystem service value trade-offs/synergies and their response to landscape pattern evolution in a typical karst basin in southern China. Ecological Informatics, 81, 102584.

Gilman, J., & Wu, J. (2023). The interactions among landscape pattern, climate change, and ecosystem services: progress and prospects. Regional Environmental Change, 23(2), 67.

Ting, Z. H. O. U., Qiang, W. A. N. G., Jiale LIANG, J. Z., & Chenjia, W. A. N. G. (2023). Impacts of landscape pattern on ecosystem services: A case study of the Hanjiang Eco-Economic Belt. World Regional Studies, 32(8), 152.

Inkoom, J. N., Frank, S., Greve, K., Walz, U., & Fürst, C. (2018). Suitability of different landscape metrics for the assessments of patchy landscapes in West Africa. Ecological Indicators, 85, 117-127.