Data Article

Dataset for landscape pattern analysis from a climatic perspective

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Abstract

Revealing the driving forces of changes in landscape pattern is a key question of landscape ecology and landscape analysis. Temperature and precipitation as climatic variables have a dominant role in triggering vegetation changes; thus, a database, which contain their interaction, can support the understanding of spatio-temporal changes in vegetation patterns even on a large scale. The dataset provided in this article contain the R-squared values of bivariate linear regression analysis between the Normalized Difference Vegetation Index (target variable; as a general quantitative descriptor of surface greenness) of the TERRA satellite’s MODIS sensor and the climatic variables of the CarpatClim database (predictor variables; maximum monthly temperature, aridification index, evapotranspiration and precipitation). Environmental variables are also included to support further analysis: terrain height, macro regions, land cover classes. The dataset has a spatial projection (i.e. maps) and covers the area of Hungary. Tabular version provides the possibility of traditional statistical analysis, while maps allow the investigation to involve the spatial characteristics of absolute and relative position of the data points. This data article is related to the paper “NDVI dynamics as reflected in climatic..."
variables: spatial and temporal trends — a case study of Hungary” (Szabo et al., 2019).
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1. Data

Landscape change and landscape pattern analysis is a key issue of landscape ecological research. Usually, landscape change can consider only a few dates with maps of field surveys or classified satellite
Pattern is also important, but we often lack the appropriate data to analyse, and the classified maps also contain thematic errors [1,2]. Using a time series of vegetation and climatic data, determining their relationships and to visualize the result on maps is a new approach to provide a solution to demonstrate spatially the climatic effects on the vegetation. This approach enables to study the spatial pattern and to involve the strength of correlation into a deeper analysis with topographic, biogeographic or even social factors.

Our database reflects the relationship of climatic variables with the vegetation (NDVI); i.e. how the vegetation cover is determined by the climatic factors (Fig. 1). Supplementary environmental factors help to reveal the patterns of this relationship (Table S1). It can also be useful for the exploration of the regions where NDVI has a high dependence on aridity, evapotranspiration, precipitation or monthly maximum temperature. As it is a spatial dataset, the relationships can also be studied with measures of spatial indices such as autocorrelation or pattern analysis (e.g. is the data isotropic or anisotropic; is there a stationarity) [3].

2. Experimental design, materials, and methods

Climatic data was represented by the CarpatClim (CC) database of nine Central-European countries [4,5]. It is a database containing several climatic variables in daily, monthly or yearly basis from 1960 to 2010. All data is based on measurements of meteorological stations and presented in a regular grid of 10 km × 10 km. Data, at first, were homogenized using the Multiple Analysis of Series for Homogenization method (MASH) [6−8] and then were interpolated by the Meteorological Interpolation based on Surface Homogenized Data Basis (MISH) [9]. Homogenization ensured the harmonization of the different measurement technologies of the countries involved in the program and managed the missing data completion. The interpolation technique was developed directly for climatic data using

![Fig. 1. R-squared values of the bivariate regression analyses between a: NDVI and monthly temperature maximum, b: NDVI and potential evapotranspiration; c: NDVI and aridification index; d: NDVI and precipitation.](image-url)
long-term observations (i.e. time series) beside the spatial parameter [9]. The application of the MASH and MISH approaches resulted in a reliable spatial prediction: representativeness of the data was between (70–85%) [7].

Normalized Difference Vegetation Index (NDVI) data were provided by the MOD13Q1 16-days product with 250 m spatial resolution [10]. NDVI reflects the greenness of the surface, i.e. has a direct relationship with the vegetation cover [11]. Its values are calculated using the formula in Eq. (1).

\[
\text{NDVI} = \frac{\text{infra red} - \text{red}}{\text{infra red} + \text{red}}
\]  

(1)

Where infrared: is the infrared range of the electromagnetic spectrum (620–670 nm in case of MODIS sensor); red: is the red spectrum of the electromagnetic spectrum (841–876 nm in case of MODIS sensor).

As NDVI is a normalized index, it ranges between −1 and +1. We extracted the data to fit into the 10 × 10 km grid of the CC.

As supplementary data, we also involved topographic data into the dataset using the SRTM digital surface model [12] with terrain height, slope and aspect. Besides, nominal data, as factors for further analysis, were added: (1) land cover data from CORINE Land Cover [13] database with the CLC codes and with aggregated categories (arable lands, grasslands, forests, wetlands, water bodies and artificial surfaces); and (2) macro regions of Hungary (Great Hungarian Plain, Kisalföld, Transdanubian Mountains, North-Hungarian Mountains, Alpokalja, Transdanubian Hills; according to Dövényi [14]). All supplementary data were extracted for the 10 × 10 km grid of the CC.

Bivariate linear regression analyses were performed for the CC-variables (fix factors) and the NDVI scores (dependent variable) in each CC-grid (1038 points). Influential data, which can distort the results, were filtered out based on the Cook’s distance (D), excluding cases where \( D > 4/n \) (n: number of cases) [15]. We reported the R²-values for each point of the CC-grid (Fig. 1).

Statistical analysis was performed in R 3.4 [16].

Acknowledgments

The publication was supported by the National Research Development and Innovation Office [NKFIH 108755]. The research was supported by the European Social Fund in the project of TAMOP 4.2.4. A/2-11-1-2012-0001 ‘National Excellence Program’ project, and the Higher Education Institutional Excellence Programme of the Ministry of Human Capacities in Hungary, within the framework of the 4th thematic programme of the University of Debrecen. The project was supported by the Bolyai János Research Scholarship of the Hungarian Academy of Sciences (BD). BD was supported by the NKFI KH 130338 project. SS was supported by the TUDFO/51757/2019-IT Thematic Excellence Project of the University of Debrecen (Space Science programme).

Conflict of interest

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

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.dib.2019.104187.

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