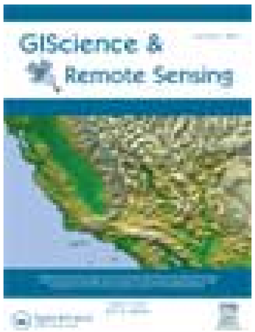

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NDVI dynamics as reflected in climatic variables: spatial and temporal trends – a case study of Hungary

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Understanding climate change and revealing its future paths on a local level is a great challenge for the future. Beside the expanding sets of available climatic data, satellite images provide a valuable source of information. In our study we aimed to reveal whether satellite data are an appropriate way to identify global trends, given their shorter available time range. We used the CARPATCLIM (CC) database (1961–2010) and the MODIS NDVI images (2000–2016) and evaluated the time period covered by both (2000–2010). We performed a regression analysis between the NDVI and CC variables, and a time series analysis for the 1961–2008 and 2000–2008 periods at all data points. The results justified the belief that maximum temperature (TMAX), potential evapotranspiration and aridity all have a strong correlation with the NDVI; furthermore, the short period trend of TMAX can be described with a functional connection with its long period trend. Consequently, TMAX is an appropriate tool as an explanatory variable for NDVI spatial and temporal variance. Spatial pattern analysis revealed that with regression coefficients, macro-regions reflected topography (plains, hills and mountains), while in the case of time series regression slopes, it justified a decreasing trend from western areas (Transdanubia) to eastern ones (The Great Hungarian Plain). This is an important consideration for future agricultural and land use planning; i.e. that western areas have to allow for greater effects of climate change.

Keywords: climate change; trend; CARPATCLIM; principal component analysis; topographic variables; MODIS

1. Introduction

Identifying climate change clues and realizing the consequences they will bring in various landscapes are crucial tasks for the future. One of the most relevant phenomena of these changes is drought, which has an increasing relevance in several countries around the world, from Africa (e.g. Tanzania, Nigeria) to Australia, the Americas and Europe. Drought is

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a limiting factor for agriculture and has caused problems for plant cultivation since the beginnings of agricultural production (Barger and Thom 1949; Bhuiyan et al. 2017; Ray et al. 2015). It can also have effects on the composition of habitats (Menzel et al. 2006; Török et al. 2018; Valkó et al. 2014), the appearance of invasive species (Hellmann et al. 2008; Parmesan and Yohe 2003), and wildfires (Deák et al. 2014). Although drought is a natural phenomenon in many regions around the world, the area under discussion is increasingly related to climate change (Wilhite, Hayes, and Svoboda 2000).

Accordingly, European countries – especially Hungary with its location in the middle of the Carpathian Basin – and Mediterranean countries are also affected by the increase in the length of drought periods (Kern, Marjanović, and Barcza 2016; Blanka, Mezősi, and Meyer 2013; Bradford 2000; Szalai, Szinell, and Zoboki 2000). The global warming of the past decades has been reported by the IPCC (2014) and climate scenarios (e.g. ALADIN and REMO) have also predicted an increase in the frequency, duration and intensity of these drought periods (Mezősi et al. 2016; Spinoni et al. 2015b; Kertész and Mika 1999; Molnár and Mika 1997). Furthermore, an increase in the number of extremely warm days (i.e. heat waves) is predicted for the Carpathian Basin (Mika 2013).

Studies usually use long-term datasets of temperature, precipitation or other climate variables. Indices of drought (e.g. PaDI, Pálfai Drought Index; Pálfai and Herczeg 2011; PDI, Palmer Drought Index; Guttman 1998; VegDRI, Vegetation Drought Response Index for Canada; Tadesse et al. 2017), aridity (AI, Aridity Index; Arora 2002; UNESCO 1979) or anomaly (Blanka, Mezősi, and Meyer 2013) are also popular tools for revealing trends and severity. A recently developed possibility is to apply satellite-based data to perform such analyses. Measuring climatic variables requires a large network of meteorological stations, and the collected data is usually not freely available. Although there are freely available data sources, such as the CARPATCLIM database (Spinoni et al. 2015a; Szentimrey et al. 2012a) and the E-OBS database (Haylock et al. 2008), their time range or spatial resolution may not be appropriate for following spatial processes.

Changes in climate have direct effects on the land cover as the intensity of heat waves, and the length of drought periods increases and the amount of precipitation decreases with an unbalanced temporal distribution (extreme rainfalls causing damages). Satellites provide information about land cover and we can monitor changes in selected categories. We also can estimate the biomass quantity using spectral indices such as the Normalized Difference Vegetation Index (NDVI, Rouse et al. 1974). The relationship between different types of vegetation is described in Sellers et al. (1992). However, the available data is often not appropriate to compile a continuous and equidistant time series, due to the satellites' long revisiting intervals (i.e. long orbits) and the existence of clouds. Thus, the only satellite data which can be used is that which provides enough data after filtering out cloudy periods, i.e. daily data must be captured (e.g., MODIS, AVHRR). Both MODIS (Lhermitte et al. 2011; Verbesselt et al. 2010; Wallace et al. 2017) and AVHRR (Pettorelli et al. 2005) were used in the time series analyses. Besides, we can find successful examples of the application of satellite images with better spatial but worse temporal resolution (i.e. Landsat images; a time series of 30 years: Tran et al. 2017; or on a smaller time scale within a year: Rao et al. 2017). Although, as Pettorelli et al. (2005) pointed out, NDVI data products can contain noise due to mixed pixels, mis-registration or cloud-cover effects, all of which potentially introduce caveats, the same researchers also found that NDVI datasets are useful tools in research into spatial and temporal trends in vegetation changes or even wildfires. Studies have revealed strong correlations between NDVI and climate variables, e.g. precipitation (Wang, Rich, and Price

2003), or large-scale climatic indices (based on the middle troposphere geopotential height; Gong and Shi 2003). These results justify the belief that in spite of the relatively short period of satellite image acquisition, both meaningful relationships and trends can be found for climatic processes.

As regards Hungary, several studies have proved the climate is changing and have predicted the increasing temperature, aridification, and decreasing precipitation with extreme rainfall intensities (e.g. Kis, Pongrácz, and Bartholy 2018; Bartholy, Pongrácz, and Kis 2015; Pongrácz et al. 2009, Pongrácz, Bartholy, and Kis 2014). However, a spatial-based landscape scale change perspective has not yet been performed. Using 1038 points of measured climatic data with 50 year datasets and a 10 year normalized vegetation data set (NDVI) we intended (1) to reveal the relationship between the climatic variables and the NDVI (based on regression coefficients of bivariate linear regressions); (2) to quantify temporal trends using time series analysis; (3) to explore the spatial heterogeneity of the determination coefficients and regression slopes by landscape regions, land cover and topography.

2. Methods

2.1. Study area

The study area was Hungary, but given the climatic data available, the western part of the country was not included in the analysis. Hungary has a relatively small area (93,000 km^2), with the investigated area covering ~87,021 km^2 (Figure 1). There are

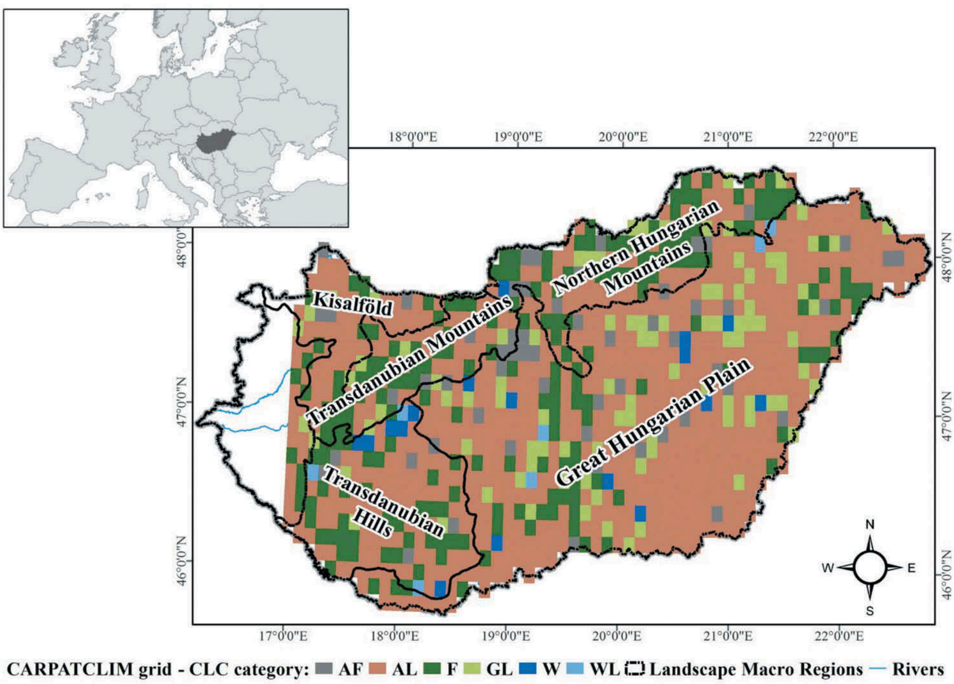

Figure 1. Location of Hungary and the analyzed data points by macro-regions and land cover types; AF – artificial surfaces; AL – arable land; F – forest; GL – grassland; W – water; WL – wetland.

six macro-regions in terms of topographical features: two thirds of Hungary's area is a plain (The Great Hungarian Plain and The Kisalföld); there is a hilly region (The Transdanubian Hills) and three ranges of hills/mountains (The Transdanubian Mountains, The Northern Hungarian Mountains and the Alpokalja, or Alpine Foothills). The Alpokalja was omitted from the analyses due to its low case number in the climatic database. Plains are flat surfaces with minimal relief located at 80–120 m a.s.l., while the highest peaks in the upland areas are between 600 and 900 m. In spite of the small area, three types of climatic effects can be identified: there are oceanic effects in the west, Mediterranean effects in the east, and given that there is an enhancing continental feature moving from the west to the east, the continental features are enhanced. Consequently, the Great Hungarian Plain is the warmest and driest region of Hungary. Arable land represents the dominant land cover type, representing about 62% of the total land area; forests cover just over 20%, and grasslands cover ~11% of the whole country (CLC 2012).

2.2. Datasets

We applied various data sources in the study, including satellite data, climatic and topographic variables, and also thematic maps which have been used as factors in spatial analysis (Table 1).

2.2.1. Climatic data

We used the CARPATCLIM (CC) dataset (Spinoni et al. 2015a; Szalai et al. 2013) as climatic data. This set is an initiative designed to improve the data availability of the Carpathian Region in order to track climatic changes. CC is a gridded spatial database (10 km × 10 km; data points were referred to in the study as Points of Interest, POIs) interpolated from data from meteorological stations. The dataset was homogenized with the Multiple Analysis of Series for Homogenization (MASH) (Szentimrey 2011; Szentimrey et al. 2012b; Bihari and Szentimrey 2013), a procedure used to enable missing data completion and to harmonize the participating partners' (10 organizations from 9 countries) meteorological data (Lakatos et al. 2013). Following this, the homogenized data was interpolated with the Meteorological Interpolation based on the Surface Homogenized

Table 1. Satellite based, climatic, topographic variables and spatial factors.

Variable	Source	Sensor	Spatial resolution	Reference
Vegetation density (NDVI)	MOD13Q1 NDVI	MODIS	250 m	(Didan 2015)
Climatic data	CarpatClim	-	10 km	Szalai et al. (2013)
Topographic data	SRTM	radar interferometry, C-band and X-band	30 m	Jarvis et al. (2008)
Land cover	CLC (2012) v18	-	250 m	CLC (2012)
Macro-regions	Inventory of the Natural Micro-regions of Hungary	-	vector	Dövényi (2010)

Data Basis (MISH) method (Szentimrey and Bihari 2007). The final database is a 48-year data set, covering temperature, precipitation, aridity, radiation, humidity, and air pressure, collected on a monthly basis. In this study we used the aridity index (ARI), potential evapotranspiration (PET), precipitation (PREC) and maximum air temperature (TMAX) datasets as climatic variables.

2.2.2. NDVI data

Terra and Aqua satellites carrying the MODIS sensor were launched in 1999 and 2002, respectively, and data is available from February 2000. It has one a day revisiting period and 36 spectral bands. Most of the bands have a spatial resolution of 1000 m, but some distinguished ranges have resolutions of 500 and 250 m (Justice et al. 1998). The NDVI is derived from the two 250 m spatial resolution bands, the red (620–670 nm) and the near infra-red (841–876 nm). We used the MOD13Q1 NDVI 250 m products (Didan 2015), compiled as 16-day composites (excluding the pixels from cloud cover and off-nadir sensor views) as gridded level-3 data (Solano et al. 2010).

The NDVI is a normalized ratio of the red (RED) and near infra-red (NIR) bands (1).

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{1}$$

It is a normalized measure of vegetation density, ranging from -1 to +1; i.e. the denser the vegetation, the higher its value, and, given the spectral profile of bare soils and rocks (and also artificial surfaces), these objects have negative values.

2.2.3. Environmental variables

We used the CORINE Land Cover (2012) raster dataset to include land cover as environmental data (CLC 2012). Its spatial resolution (250 m) was appropriate to combine it with the NDVI and climatic variables. Although we aggregated its 43 categories into six simplified land cover classes – arable land, artificial surfaces, forests, grasslands, wetlands and water bodies -, we omitted the wetlands and water bodies from further analysis given their low case number. Furthermore, as a base for topographic variables we incorporated the SRTM digital surface model (Jarvis et al. 2008) and used its surface height data and also derived the slope and aspect coverages. A map of the macro-regions of Hungary was vectorized from the Inventory of the Natural Micro-regions of Hungary (Dövényi 2010).

2.3. Data preparation

The spatial resolution of the NDVI data is 250 m, but the CC only has a grid of 10 km × 10 km; thus, NDVI images allowed an appropriate background to be sampled with the data points of the coarser CC. Furthermore, given the temporal resolution of MODIS NDVI composites (there were two in each month), we first filtered out the unreliable pixels (due to cloud cover) based on the Quality Assurance (QA) layer, and then calculated monthly averages for the NDVI data. Unreliable QA data affected only 2% of the whole dataset and so did not bias the statistical analysis.

Altogether, 203 MODIS NDVI images were included in the analysis, and sampled and paired with the CC grid. Data preparation was performed in ArcGIS 10.3; we developed an extension in Python to arrange the CC data into a geodatabase.

2.4. Statistical analysis

2.4.1. Relationship between the NDVI and climatic variables

The relationship between NDVI and CC variables was analyzed with bivariate linear regression analysis of the period between 2000 and 2010 (from the beginning of the MODIS data capture to the end of the CC dataset). The NDVI was paired spatially (by POIs) with all the CC data, and the determination coefficients of the regressions were collected into a single file by data points; i.e. all 1038 of the POI time series for Hungary were included in the regression analyses with the 1038 data points of the NDVI dataset, and R^2 values were determined (see the workflow in Figure 2). We filtered out the influential data points, based on Cook's distance.

Determination coefficients reflected the explained variance of NDVI using the independent CC variables, and the map indicated the spatial distribution but did not provide information on the spatial pattern. Accordingly, we performed Principal Component Analysis (PCA) on the determination coefficients of the regression between the NDVI and CC variables. PCA helped to reveal the correlation structure and also to visualize the dissimilarity or similarity of the applied groups (macro-regions) in the multivariate space with biplot diagrams. Model fit was tested with the Root Mean Square Residuals (RMSR) and the Adjusted Goodness of Fit Index (AGFI). RMSR values of <0.1 indicate good fits, and those below 0.05 very good fits; AGFI values reflect a good fit if the value is more than 0.9, and a very good fit if it is above 0.95 (Basto and Pereira 2012). Accordingly, we applied hypothesis testing with a robust Analysis of Variance (rANOVA) with a 0.2 trim value to test the null hypothesis (H_0: there was no difference in the R^2 means of the independent variables: macro-regions). The Tukey HSD was applied as a post hoc test. Next, we also examined the effects of land cover; however, to retain our focus on the spatial pattern, we applied the two-way ANOVA. This approach ensured the common evaluation of land cover and macro-regions and revealed whether land cover can bias the linear relationship between NDVI and TMAX. The effect of topographic variables (elevation and aspect) was analyzed with correlation analysis.

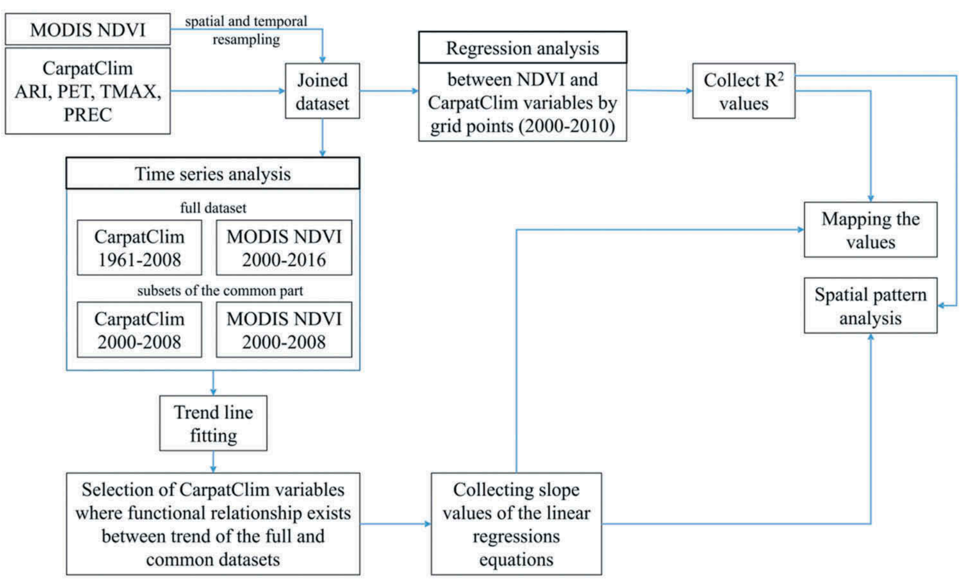

Figure 2. The workflow of the data processing.

2.4.2. Time series analysis of the NDVI and climatic variables

We fitted a trend line onto the time series (using the monthly CC and NDVI datasets) and determined the equation of fit; the slope (β) of the equation indicated the magnitude and the direction of the trend. As 2009 and 2010 were reported as outliers having unusually greater precipitation compared to the previous years (Spinoni et al. 2015a; Móring 2011), we omitted the data for these years to ensure that the general trend is not biased by the temporary fluctuation. Slope values were determined (1) for the whole period of the CC data (1961–2008), and (2) also for the common period of the CC and NDVI data (2000–2008). β-values indicated the changes in the dependent variable (both for NDVI and CC variables) by time units, i.e. the monthly change. Their sign showed the direction of the changes (increasing or decreasing) and the value itself reflected the magnitude, with larger values indicating a larger change. We compared the slope (β) values of the different data periods to reveal whether there is only a slightly different trend in the time series and the 8 years of the common period of the NDVI, and the CC variables are appropriate to describe this, or whether it is too short a period to draw conclusions from, and we have to find other data sources. Finally, we repeated the analysis by splitting the years into the four seasons involving 3 months at a time (according to the meteorological seasons of the northern hemisphere) to reveal the seasonal trends.

All statistical analyses were performed in R 3.3.3 (R Core Team 2017) using the ggplot2 (Wickham 2009), multcomp (Hothorn, Bretz, and Westfall 2008), ggfortify (Tang, Horikoshi, and Li 2016), psych (Revelle 2017), FactoMineR (Husson, Le, and Pagès 2010) and walrus (Love and Mair 2017) packages.

3. Results

3.1. Determination coefficients

Determination coefficients between the NDVI and the CC variables were distributed over a large range (Table 2). The best R^2 values were experienced with the TMAX; the mean was 0.58 and the maximum was 0.85. The PET had a strong relationship with the NDVI, too, with its values almost as high as in case of TMAX. ARI's R^2-values indicated a weaker relationship, but the weakest relationship was found with precipitation (PREC), with the mean only 0.09 and the maximum below 0.3 (Figure 3).

3.2. β-values of trend line fitting

β-values indicated a positive trend, considering the variables involved. Data for the two periods reflected that there were variables that did not change much (PET, TMAX; Table 3), and variables where values changed considerably, even in the case of mean values (ARI, PREC; Figure 4).

Table 2. Basic descriptive statistics of the determination coefficients (R^2) of the linear regressions performed on the NDVI and the CARPATCLIM variables by POIs (in the period 2000–2010).

Independent variable	Mean	Sd	Min	Max
ARI	0.30	0.09	0	0.56
TMAX	0.58	0.19	0.01	0.85
PREC	0.09	0.04	0	0.27
PET	0.52	0.19	0	0.83

Table 3. Basic descriptive statistics of the CARPATCLIM variables and the NDVI, considering the β-values of the trend lines calculated by POIs for the periods 1961–2008 and 2000–2008.

	Mean	Sd	Median	Min	Max
Variables	full time period (1961–2008)				
ARI	0	0	0	−0.01	0
PET	0.01	0	0.01	0	0.01
PREC	0.01	0.01	0.01	−0.01	0.02
TMAX	0	0	0	0	0
	common time period (2000–2008)				
ARI	0.05	0.01	0.04	0.01	0.11
PET	−0.01	0	−0.01	−0.02	0
PREC	0.2	0.04	0.19	0.12	0.4
TMAX	0	0	0	−0.01	0
NDVI	0.95	3.87	0.92	−23.13	18.42

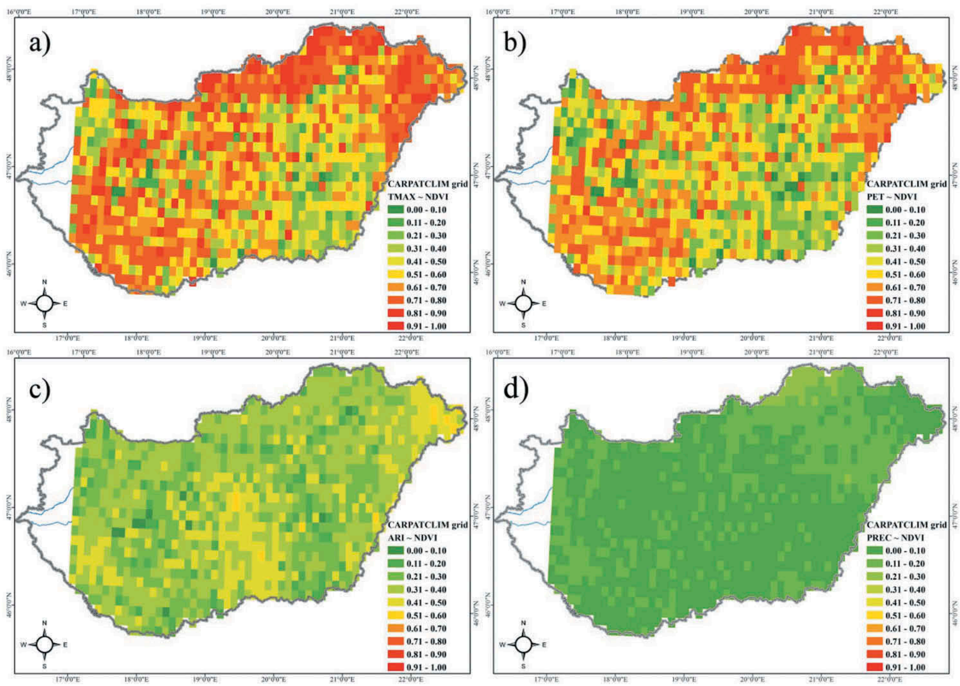

Figure 3. R^2-values of the CC variables: a – TMAX; b – PET; c – ARI; d – PREC.

The most important issue was to find whether the shorter period can also provide information on the long trends. Regression analysis for the periods 2000–2008 and 1961–2008 revealed that in the case of TMAX, the short period can indeed reflect the trend of the 50 year dataset (Table 4), with R^2 indicating a strong relationship. We repeated the analysis by subsetting the dataset by seasons and found lower R^2-values: for autumn the value was 0.07, but for winter, it was 0.61. However, considering the PET, ARI and PREC, the shorter period did not follow the long-term trend at all.

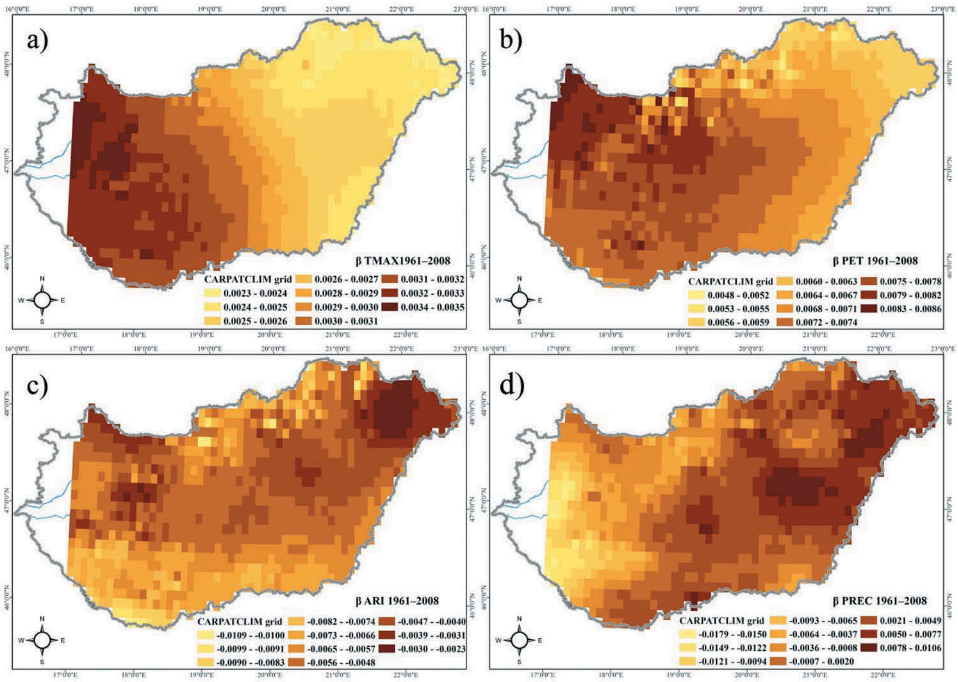

Figure 4. β-values of CC variables by POIs for the period 1961–2008; a – TMAX; b – PET; c – ARI; d – PREC.

Table 4. Determination coefficients of the regression analyses between the β-values of the trends (dependent variable: β-values for the period 1961–2008, independent variable: β-values for the period 2000–2008) ($p < 0.05$ is highlighted in bold).

	Year	Spring	Summer	Autumn	Winter
ARI	0.04	0.13	0.05	0.10	0.05
PET	**0.23**	**0.42**	**0.34**	**0.27**	**0.13**
PREC	0.12	0.00	0.05	0.06	0.00
TMAX	**0.84**	**0.39**	**0.30**	0.07	**0.61**

3.3. Analysis of spatial pattern

3.3.1. Analysis of the determination coefficients by macro-regions and land cover classes

PCA performed on the R^2 values was justified by the RMSR and AGFI (which were 0.03 and 0.91, respectively, indicating that the quality of the adjustment was excellent, and the fit was very good); the result explained 89% of the total variance. PC1 accounted for 68.5% and was in strong correlation with the TMAX, PREC and PET, while PC2 accounted for 21.0% of the variance and correlated with the ARI. Accordingly, we were able to evaluate the variables in the multivariate space. Considering the macro-regions, most of the PC values were distributed in the same part of the ordination diagram; only the Northern Hungarian Mountains (f category in Figure 5) region was discriminated along the vertical axis, which corresponds to ARI; however, there were no differences along the horizontal axis.

R^2-values averaged by macro-region revealed spatial variations: the largest variations occurred in the Northern Hungarian Mountains, while the lowest were usually on the Kisalföld (Table 5). According to Table 2, the largest belonged to the TMAX and PET, and the lowest to the PREC. Hypothesis testing performed on the PC1 of the PCA by macro-regions (we omitted the Alpokalja macro-region because it had only 7 POIs) revealed that the smaller R^2-values of the plains (Great Hungarian Plain and Kisalföld) significantly differed from the Transdanubian Hills and from both mountain regions. There were no significant differences between the two plains, the Transdanubian Hills and the two mountain regions, or between the two mountain regions themselves (Figure 6).

3.3.2. Analysis of the β-values by macro-regions

For easier interpretation we recalculated the β-values, so we can refer to the change in terms of a hundred-year period. The rank of the regression slopes (β) revealed that – assuming a linear trend for the period 1961–2008 – the largest increase (expressed in the change in TMAX over

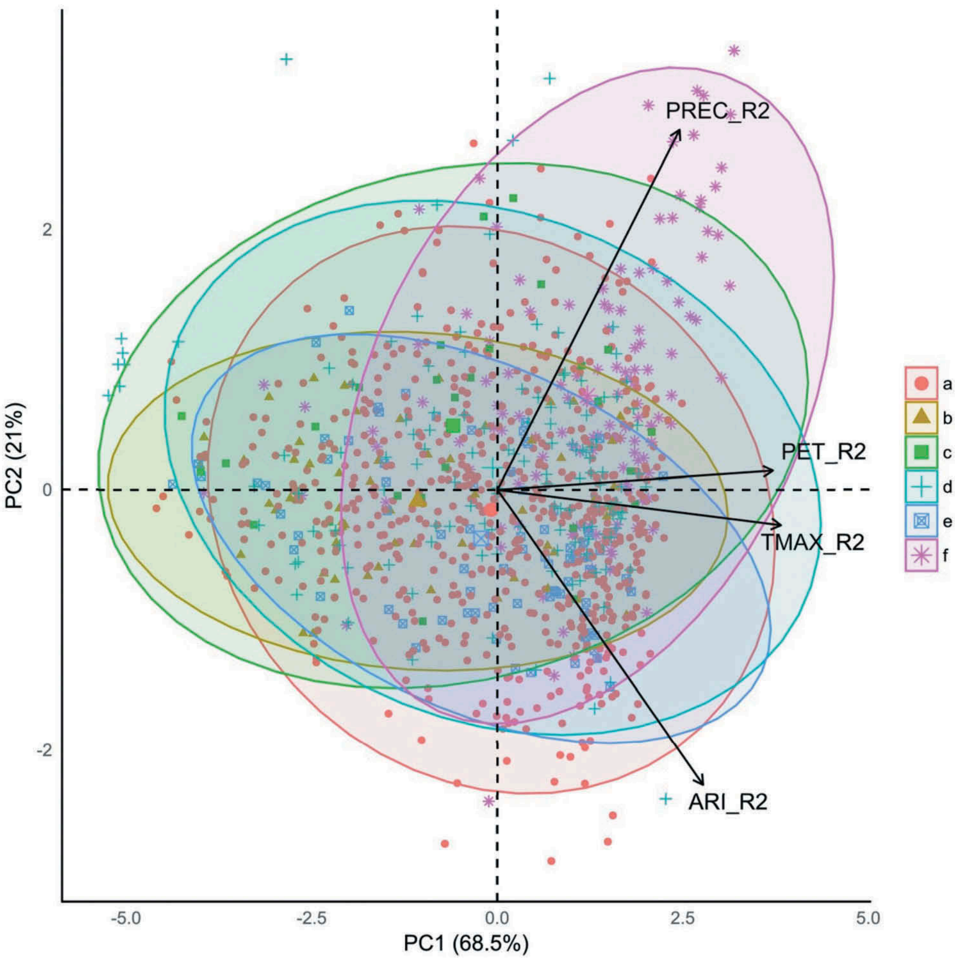

Figure 5. Ordination diagram of the PCA performed on the R^2-values of CARPATCLIM variables and the NDVI, by macro-region.

Table 5. Averaged R^2-values of regressions between the NDVI and climatic variables by macro-regions (2000–2008).

Macro-region	TMAX	PET	PREC	ARI
Great Hungarian Plain	0.545	0.481	0.083	0.340
Kisalföld	0.482	0.421	0.082	0.296
Northern Hungarian Mountains	0.724	0.668	0.136	0.322
Transdanubian Hills	0.622	0.582	0.089	0.307
Transdanubian Mountains	0.631	0.573	0.070	0.320

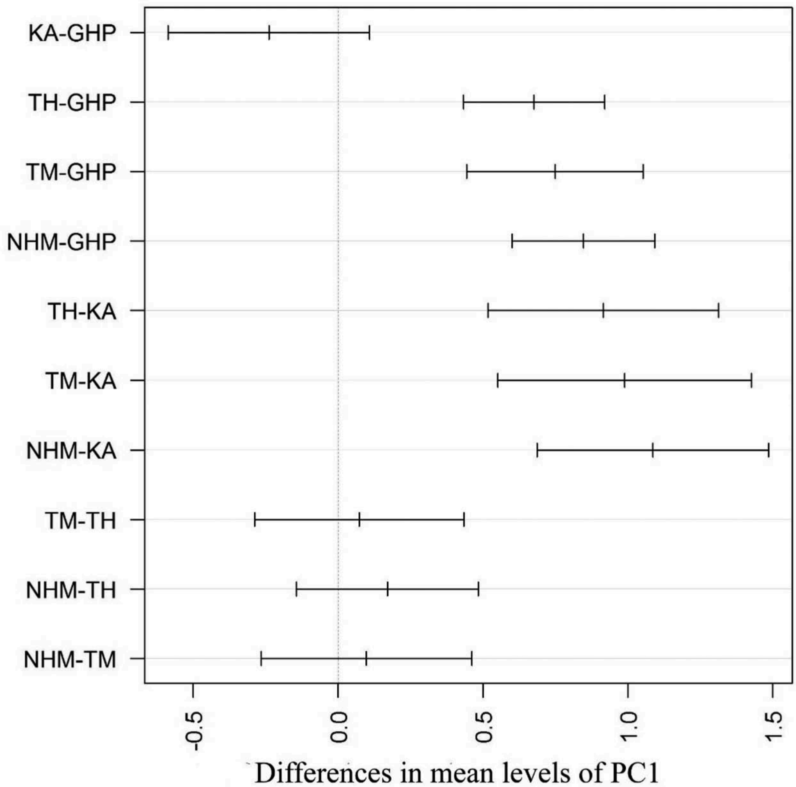

Figure 6. Means with 95% confidence intervals of pairwise analysis of PC1 values (corresponding to R^2 between the TMAX, PET and PREC and NDVI) by macro-region (confidence intervals including 0 are of non-significant differences, $p > 0.05$; GHP: Great Hungarian Plain, KA: Kisalföld, TH: Transdanubian Hills, TM: Transdanubian Mountains, NHM: North Hungarian Mountains).

100 years) can be expected in the Transdanubian Hills (3.74℃), followed by the Kisalföld (3.70℃), the Transdanubian Mountains (3.63℃), the Great Hungarian Plain (3.24℃) and the Northern Hungarian Plain (2.97℃). The spatial patterns revealed by ANOVA were completely different from the R^2-values; in this case the pattern reflected the similarity of the Transdanubian region (the Kisalföld, the Transdanubian Hills and the Transdanubian Mountains) while all the other macro-regions showed significant ($p < 0.05$) differences. Usually, the Great Hungarian Plain had low values, causing larger differences (Figure 7),

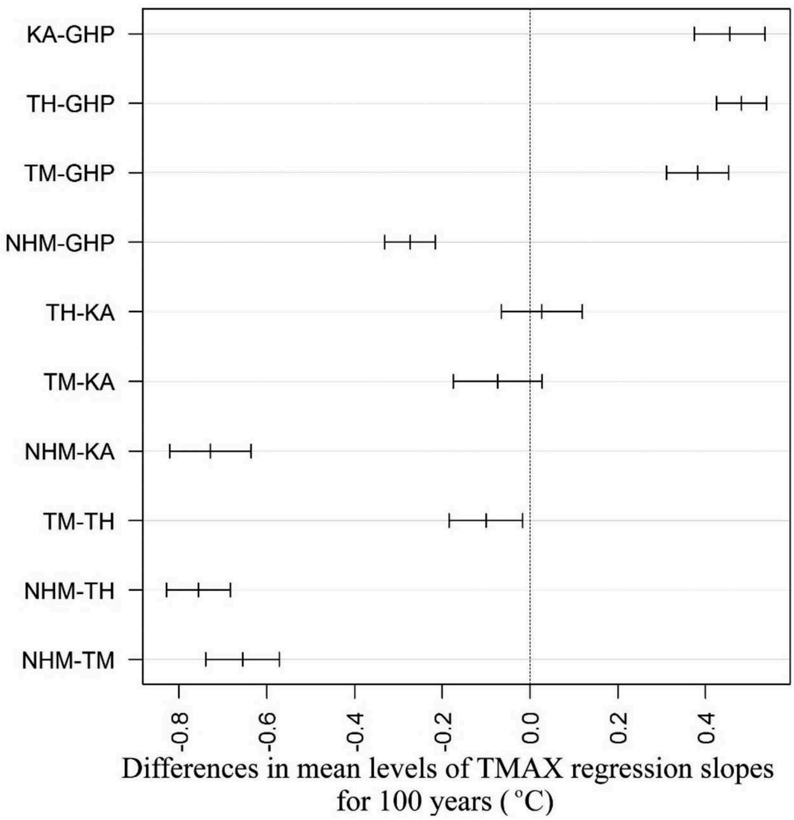

Figure 7. Means with 95% confidence intervals of pairwise analysis of TMAX regression slope (β) values by macro-regions; slope values were multiplied by 100 referring to a wider period (confidence intervals including 0 are of non-significant differences, $p > 0.05$; GHP: Great Hungarian Plain, KA: Kisalföld, TH: Transdanubian Hills, TM: Transdanubian Mountains, NHM: North Hungarian Mountains).

and indicating a smaller increase in the future. As the Northern Hungarian Mountains had the lowest mean βs, differences were also the lowest compared to the other macro-regions.

3.3.3. Effects of land cover on determination coefficients

Two-way ANOVA revealed that both macro-regions and land cover classes had a significant effect ($p < 0.001$; adjusted $R^2 = 0.297$) on the R^2-values of the regression between the NDVI and TMAX. Although their interaction was not significant ($F[4,3] = 1.593$; $p = 0.088$), its value and the interaction plot (Figure 8) indicated a weak bias to land cover: there were interactions between arable land and grasslands, and artificial surfaces and grasslands. This refers to the fact that both macro-regions and land cover classes had significant effects on the model on their own ($p < 0.001$ for both factors), and through their interaction: involving both factorial variables were important in the model, resulting in a smaller residual error (0.025 instead of 0.030). Forests had the highest average R^2-values in each macro-region, with values ranging between ~0.7 and 0.8, but all the other macro-regions had lower values and their variances were larger, up to double those of the forests. The Northern Hungarian Mountains had the greatest R^2 for each land cover class.

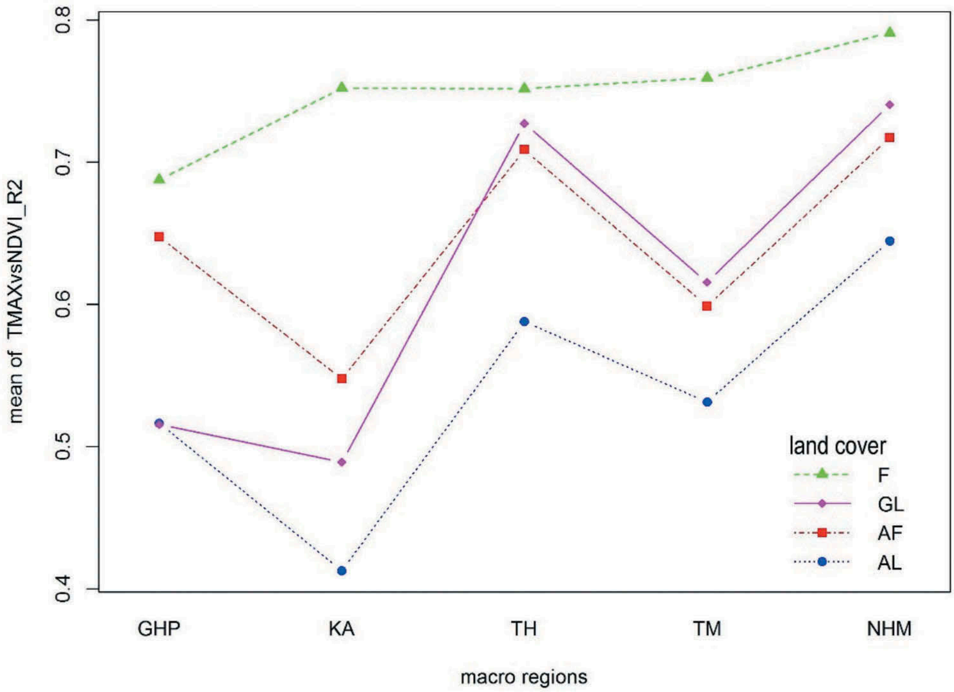

Figure 8. Interaction plot of R^2 of NDVI and TMAX by macro-regions and land cover (macro regions are ranked by the average terrain height, GHP: Great Hungarian Plain (101 m), KA: Kisalföld (128 m), TH: Transdanubian Hills (164 m), TM: Transdanubian Mountains (254 m), NHM: North Hungarian Mountains (258 m); F: forests, GL: grasslands, AF: artificial surfaces, AL: arable land; when lines are intersected, interaction plot indicates statistical interaction between two factorial variables, the macro-regions and land cover classes – ordinal rank is a prerequisite for this type of plot).

3.3.3. Effects of topography on R^2 and β-values

The R^2 of the ARI and NDVI regressions did not have any statistical relationship (i.e. dependence) with the topographic variables, but surface elevation was in weak correlation with TMAX, PREC and PET. Aspect did not have any connection with the R^2 in the pattern of climatic variables (Table 6).

The statistical relationship with the β-values indicated that only TMAX was in a weak but significant correlation with elevation (Table 7). The trends of all other variables were independent of topography.

4. Discussion

The occurrence of drought periods can be a natural phenomenon; however, it is also a consequence of climate change; i.e. the frequency, intensity and the length of these periods has increased in recent decades in several locations around the world (Loukas, Vasilides and Tzabiras 2008; Vicente-Serrano et al. 2014; Farkas, Hoyk, and Rakonczai 2017). Hungary is one of these places and previous studies have also identified these intensified extremities in terms of drought periods, heat waves or rainstorms (Mika 2009; Horváth, Solymosi, and Gaál 2009; Kertész 2016; Vári and Ferencz 2006). On a national

Table 6. Correlation (r) between the determination coefficients (R^2) and topographic variables by POIs ($p < 0.05$ is highlighted in bold).

R^2 values	Slope (degree)	Aspect (azimuth)	Elevation (m)
ARI	0.07	0.17	0.01
TMAX	**0.38**	0.12	**0.37**
PREC	**0.20**	0.13	**0.21**
PET	**0.39**	0.11	**0.40**

Table 7. Correlation (r) between the regression slope parameter (β) and topographic variables by POIs ($p < 0.05$ is highlighted in bold).

β-values	Aspect (azimuth)	Elevation (m)
ARI	−0.01	−0.05
TMAX	−0.07	**−0.31**
PREC	0.02	−0.13
PET	−0.03	0.04
NDVI	0.01	0.02

level, local differences in the trends have not yet been reported, and we have revealed several significant differences on a regional scale.

4.1. Spatial pattern of NDVI and climatic variables

We have found a strong relationship between the NDVI and the climatic variables, TMAX and PET, while ARI had only a weak relationship, and PREC did not show any correspondence with it. The R^2 of NDVI–TMAX and NDVI–PET were spatially clustered; using macro-regions (i.e. plains, hills, and mountains) as grouping factors we were able to delineate the different areas of the correspondence. We found that with the help of NDVI, TMAX is the climatic variable that can be described with the best performance: the average R^2 was 0.58, but it reached its maximum in the Northern Hungarian Mountains (0.72) while the lowest value occurred in the Kisalföld (0.48). Differences between the R^2-values justified the spatial pattern on the level of macro-regions: plains were similar, and mountains were also similar, but plains, hills and mountains differed from each other. Schultz and Halpert (1993) described a high correlation between temperature and NDVI (in the Northern Hemisphere) and Hao et al. (2012) also found a strong correlation between temperature (maximum and minimum) and precipitation (R^2 were >0.87), but their study area was completely different: the stations investigated were located at a height of 1800–3500 m. Due to orography and high relief, biomass and precipitation followed a spatial pattern, which can be functionally described. In contrast, Hungary's POIs ranged between 76 and 1014 m, and 84% of them are found below 200 m a.s.l., which meant that vertical variance was not great enough to reveal a relationship for this region. Besides the relatively small diversity of orography, precipitation also has a relatively narrow range, between 500 and 800 mm, but 70% of the whole area has less than 650 mm (Szalai et al. 2004) and, according to our query carried out on the CC database, 74% of the area is below 200 m and has precipitation below 700 mm. Thus, in the case of Hungary, the range of these environmental factors results in relatively low R^2-

values with NDVI. Schultz and Halpert (1993) also found that vegetation response has limitations in different climatic regions: there can be a delay in time in the response when the wet season arrives suddenly with great intensity, or the amount of precipitation has to be within a certain range for the observable response (and in the temperate zone it is has only moderate effect). Our results strengthen the importance of the need for a greater data range for larger effects.

The greatest average R^2 which occurs in the Northern Hungarian Mountains can be explained by the high proportion of forest: although there are differences between the different types of forests, their NDVI is quite high and similar in the same periods of the year. Thus, when we compare them to the climatic variables (i.e. TMAX), the biomass variability is not affected by large deviances. Arable land, on the other hand, can have the greatest differences in biomass. The NDVI varies by plantations (e.g. dense cereal plantations have a higher NDVI compared to cucumber, pumpkin or water melon) or even by regions for the same type of plants (according to seed-time, climatic differences, soil quality or available nutrients). Accordingly, the variation in the NDVI can be high, which influences the relationship with climatic factors. Hao et al. (2012) also found a stronger connection between the NDVI and forests, compared to grasslands. In terms of our results, the best R^2-values also occurred with the POIs of forests.

4.2. Spatial pattern of trends

The regions of the Carpathian Basin are at different levels of risk brought about by the detrimental tendencies of climate change. The direction and the magnitude of these changes can also be different, but on the country level, focusing on Hungary, the trend showed a monotonous increase in temperature (Figure 4). Our analysis, performed with regression slopes reflecting the temporal trend and magnitude, has demonstrated the presence of spatial heterogeneities. Although regression is a simple method of time series analysis, our results (on average we predicted 2.97–3.74℃) corresponded to the study by Bartholy et al. (2009). The spatial trend reflected a decrease in the regression slopes from the west to the east (from the Kisalföld to the Great Hungarian Plain, according to the ANOVA; Figure 6). This result does not reflect the highest measured TMAX values (especially in the eastern part of the country which has the highest maximum temperatures), but it predicts the possible trend. Accordingly, in areas where the temperature was high, the level of further increase will be smaller compared to colder areas in the western part of the country. Spatial patterns in the macro-regions reflected that the Great Hungarian Plain stood out in terms of its lowest β-values, which justified the decrease in β-values. The greatest increase in TMAX can be expected in Transdanubia, especially in the Transdanubian Hills and the Kisalföld.

While the macro-regions had a significant effect on the relationship between the NDVI and climatic data, we found only a weak connection with the topographic variables. However, macro-regions can be regarded as ordinal data of surface height, since plains, hills and mountains have different average heights (Great Hungarian Plain: 101 m; Kisalföld: 128 m; Transdanubian Hills: 164 m; Transdanubian Mountains: 254 m; Northern Hungarian Mountains: 258 m, derived from the coordinates of POIs from SRTM). Thus, the influence of surface height can be identified only at a regional level, because the regression is biased by the large variance of both the vegetation and terrain. We also have to note that CC variables are interpolated values and there can be deviations from measured data, i.e. interpolation can influence the statistical relationships. Nevertheless, the CC database is freely available and homogenized, so it offers a regional alternative both for spatial and temporal analyses and may replace the datasets of meteorological stations (the representativeness of the data is 70–85%; Szentimrey et al. 2012b). Besides, it is obvious that height is just one variable; the real determining factors are related to other environmental variables (e.g. relative position in terms of increasing continental climate and, accordingly, increasing aridity, land cover and land use practices). We cannot reject the relevance of surface height (there was a weak correlation), but we should interpret it jointly with other environmental factors. The results were similar in the case of regression slopes of time series, too: we found only weak correlations with the surface height.

4.3. Novelties and limitations

There are novelties and limitations when we apply regression determination coefficients (R^2) and regression slopes (β). The batch statistical analysis of all measuring points of the database (where each point represents a unique database of climatic variables and the NDVI) provides possibilities for bivariate regression, principal component and time series analysis. The quantified data of the relationships and the trends of the changes with supplementary environmental variables (landscape regions, land cover, topography) resulted in a dataset for further spatial analysis. Although we found valuable outcomes with the NDVI dynamics and trends, results were not in correspondence with all previous studies. In the case of Hungary, the relatively small area and relief are limiting factors: if the input data do not vary, correlations can be lower than expected (such as in the case of terrain height). Overall, determining and mapping the coefficients is far beyond the simple univariate evaluations or comparisons of different variables or maps, because using the whole dataset helps in exploring the spatial pattern and finding the important influencing factors of time series trends or NDVI dynamics.

5. Conclusions

In this study we aimed to reveal the climatic trends and relationship between the NDVI dynamics and climatic variables. The results are compiled from the determination coefficients of 1038 regression analyses conducted on the NDVI and climatic data. We revealed that there is a functional relationship between the MOD13Q1 NDVI products and temperature maximum, potential evapotranspiration and the aridity index. The spatial pattern of determination coefficients between the NDVI and climatic variables reflected the relevance of surface height, i.e. macro-regions of Hungary: plains differed significantly from mountains. The strength of the relationship is biased by the land cover, forested areas provided the best R^2-values, and arable lands showed a large variance, which caused a deterioration in the results and reduced the R^2-values. Regression slopes (β), as measures of change in the maximum monthly temperature between 1960 and 2010, can reflect the long-term changes in a measuring point (POI), and if we are able to repeat the analysis for each available data point considering the whole range of the time series, the spatial pattern appears in the maps in a quantified and examinable form. We demonstrated a decreasing trend in maximum temperature from west to east. Spatial analysis justified the western-eastern difference, with the smallest increase expected in the Great Hungarian Plain and the largest in the Transdanubian Hills. Topographic variables did not have a large effect, neither on the relationship between NDVI and climatic data, nor on the regression slopes of the time series; however, the reason for this is the lack of large differences in the relief and the dominant extent of the plains (more than two thirds of the whole area).

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