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Vegetation cover dynamics of the Dniester basin under climate change influence in the 21st century

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Abstract. The increasing climate instability in the Carpathian Region of Ukraine highlights the need for long-term monitoring and quantitative assessment of vegetation cover changes in the Dniester River basin. The aim of this study was to analyse vegetation cover change trends in the Dniester basin within Ivano-Frankivsk Region during 2001-2024 and to identify relationships between these trends and key climate variables. Research methods included time series analysis of median summer vegetation index values based on MODIS satellite data, application of the Mann-Kendall test to detect monotonic trends, calculation of Pearson correlation coefficients to assess linear relationships, and use of Random Forest regression to model the nonlinear impact of temperature, precipitation, land cover types, and elevation on vegetation dynamics. The main results showed an overall positive trend in vegetation index growth, with the lowest value in 2003 and the highest in 2023. Statistically significant summer trends cover 43.2% of the territory, of which 38.8% are positive and 4.4% are negative trends. The most pronounced positive changes were observed at medium elevations in the Carpathian foothills, where broadleaf and mixed forests dominate. The Random Forest model achieved a coefficient of determination of 0.718, identifying temperature as the primary predictor of vegetation dynamics, followed by land cover type, precipitation, and elevation. The practical value of the study lies in providing a scientific basis for planning conservation measures, adapting forestry to climate change, and developing sustainable ecosystem management strategies for the Carpathian Region

Keywords: vegetation index; Mann-Kendall test; Pearson correlation coefficient; Random Forest; Carpathian Region; satellite remote sensing; ecosystems

Introduction

The Dniester River basin, which covers a significant part of western Ukraine, is characterised by high heterogeneity of vegetation cover – from mountainous forest ecosystems of the Carpathians to lowland agricultural landscapes. For the western region of Ukraine throughout the 21st century, substantial transformation of climatic conditions is expected: an increase in extreme precipitation and rain floods, reduction of snow cover, elevated risk of fire-hazardous weather and droughts (Glibovytska *et al.*, 2024). Scientists S. Krakovska & L. Kryshtop (2024) in their report on climate change impacts in Ukraine established that the cumulative threat from changing climatic factors in the region may reach 50-72.5% over the century. Such climate changes directly affect vegetation cover dynamics, as vegetation is

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sensitive to temperature fluctuations and moisture regime variations (Kravchynskyi *et al*., 2021).

To assess the impact of climate change on vegetation dynamics, it is necessary to conduct long-term analysis of large territories with high spatial and temporal coverage. Researchers S. Huang *et al*. (2020) noted that one of the most effective approaches for such monitoring is the use of satellite remote sensing data, particularly the Normalised Difference Vegetation Index (NDVI), which is calculated as the normalised difference between red and near-infrared spectral bands and serves as a sensitive indicator of photosynthetically active biomass. The authors emphasised that NDVI enables quantitative assessment of vegetation cover status and its changes over extended periods, making this indicator an indispensable tool for studying climate change impacts on ecosystems.

E. Sanz *et al*. (2021) investigated NDVI dynamics and its relationship with temperature and precipitation in arid pastoral ecosystems of south-eastern Spain for the period 2002-2019. Using correlation and regression analysis, the authors established that temperature is the most influential factor in NDVI dynamics, demonstrating a strong negative correlation under limited rainfall conditions and positive correlation during periods of high moisture. The researchers also identified time lags in vegetation response to changing climatic conditions (16-32 days), highlighting the importance of accounting for delayed climate effects on vegetation cover dynamics in arid regions.

L. Klimavičius *et al*. (2023) analysed seasonality and long-term NDVI trends in the eastern part of the Baltic Sea basin during 1982-2015, considering five land use types: croplands, pastures, wetlands, mixed and coniferous forests. The researchers found that temperature is the most important factor, while precipitation had significantly less influence on NDVI dynamics throughout the growing season. The authors established that the onset of the vegetation season became earlier by 3-4 weeks, and its duration increased by 6-7 weeks compared to the beginning of the study period, with these changes being statistically significant for all land use types. Maximum NDVI values were reached fastest in croplands and pastures, emphasising the importance of considering land use type when analysing phenological changes in vegetation.

L. Fathollahi *et al*. (2023) developed a global NDVI forecasting model based on deep neural networks using three climate variables: air temperature, soil moisture, and precipitation for the period 2017-2020. The model demonstrated high prediction accuracy with $R^2 = 0.86$ in temporal analysis and RMSE = 0.092, showcasing the effectiveness of applying machine learning methods for analysing relationships between climate and vegetation. This approach underscores the advantages of applying machine learning algorithms, such as Random Forest and deep neural networks, for modelling complex nonlinear dependencies between NDVI and climatic factors at global and regional scales, offering an alternative to traditional process-based models.

In Ukraine, there is a lack of contemporary research that would examine vegetation cover changes in detail within the context of climate change for the Carpathian Region. V.I. Lyalko *et al*. (2020) analysed long-term trends for the entire territory of Ukraine; however, the study employed indices aimed at detecting soil moisture and droughts. The scale of these investigations is quite large, and the level of detail remains low. V. Ivanyshyn & D. Kasiyanchuk (2024) conducted a local study of climate change impacts on vegetation in the Perehinsk territorial community, applying NDVI and NDWI indices along with correlation analysis. However, this study covers a short time period and a limited territory. In the research by O.S. Glukh *et al*. (2023), an investigation of NDVI changes for the Carpathian Region was also conducted for the period from 2000 to 2022. Nevertheless, the analysis was performed on only 15 images, which is insufficient for quality long-term analysis. In this regard, the aim of this study was a comprehensive examination of vegetation cover dynamics in the Dniester basin within Ivano-Frankivsk Region and determination of linear and nonlinear dependencies between vegetation changes, main climatic factors (temperature and precipitation), and vegetation types.

Materials and Methods

The study area is located within Ivano-Frankivsk Region of Ukraine and encompasses the Dniester River basin, which occupies the northern part of the region. The southern part of the region belongs to the Prut River basin. The relief of the study territory is characterised by considerable diversity. Elevation above sea level varies from 230 m in the Dniester River valley to 1,800 m in the mountainous part (Fig. 1). The hydrographic network of the territory is well-developed. Besides the main waterway – the Dniester River, the basin includes sub-basins of the Limnytsia, Lukva, Bystrytsia, Sivka, Svicha, Svirz, Vorona, and Hnyla Lypa rivers. This extensive river system significantly influences the natural and economic characteristics of the region (Matiyiv *et al*., 2022).

The land use structure of the region is heterogeneous: approximately 40% of the territory is occupied by forests, predominantly in mountainous and foothill zones. Croplands, as of 2023, constitute over 40% of the area (Fig. 2). In the lowland territories of the northern and eastern parts of the basin, agricultural lands prevail, represented by a mosaic of croplands and pastures. The mountainous part is characterised by the dominance of forest ecosystems, where coniferous species predominate at higher elevations and broadleaf and mixed forests in the foothills and at medium elevations (Rodriguez-Galiano *et al*., 2012). The spatial distribution of land cover types reflects the natural zonation of the region. In the southwestern high-mountain part, evergreen needleleaf forests prevail, which gradually transition to deciduous broadleaf forests with decreasing elevation. Mixed forests occupy an intermediate position and form a transitional zone between coniferous and broadleaf ecosystems (Prykhodko *et al*., 2023).

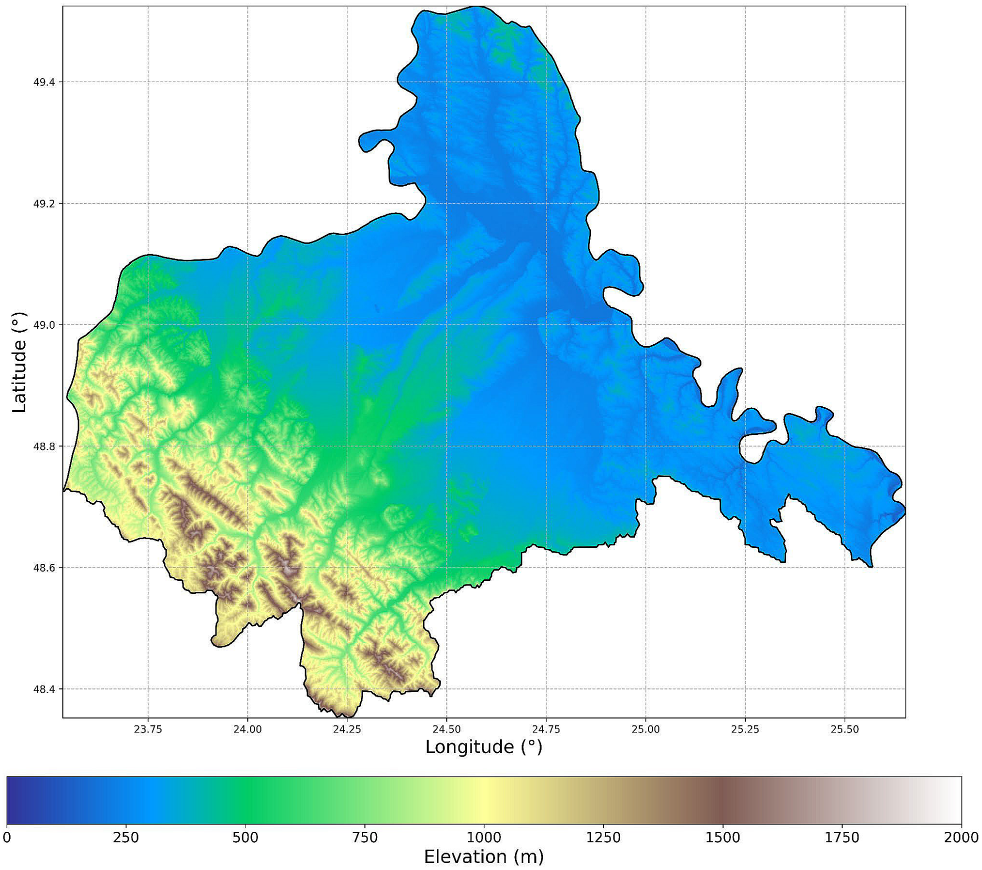

Figure 1. Digital elevation model of the study area of the Dniester basin within Ivano-Frankivsk Region
Source: created by the authors based on NASA SRTM digital elevation 30 m (n.d.)

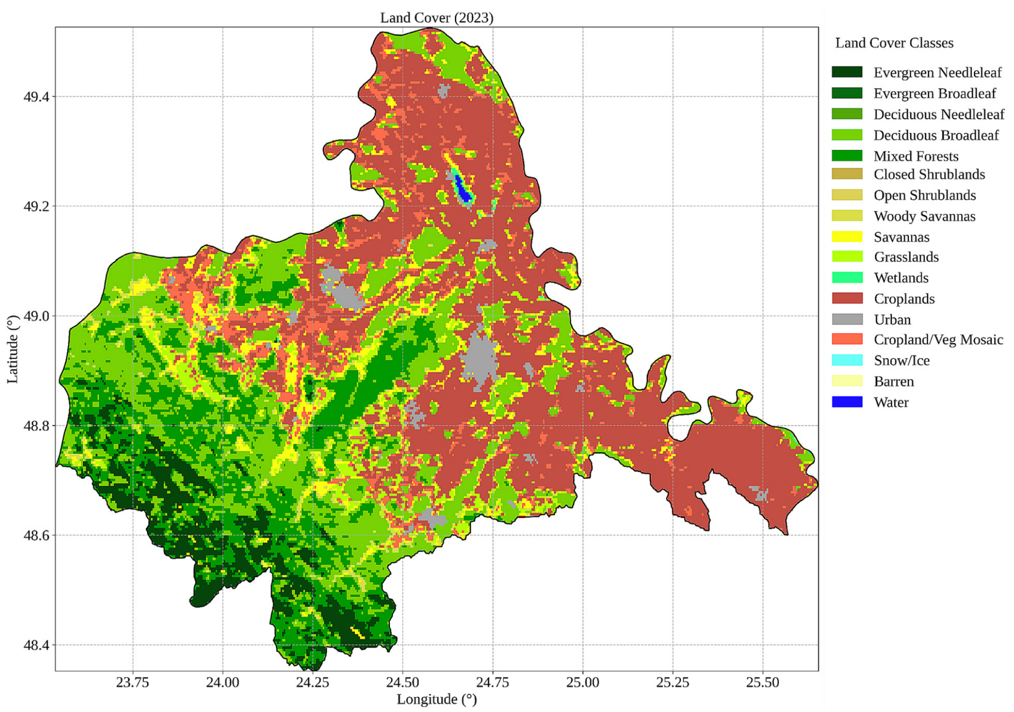

Figure 2. Spatial distribution of land cover types in the study area according to IGBP classification (2023)
Source: created by the authors based on M. Friedl & D. Sulla-Menashe (2022)

The study covered data for the period 2001-2024. All data for the research were obtained using the Google Earth Engine (GEE) platform. For NDVI data, the MODIS/061/MOD13Q1 collection was used (Didan, 2021). The spatial resolution of images in this collection is 250 meters. Images are provided at 16-day intervals, which are compositionally assembled from daily observations by satellites. The MODIS NDVI product is calculated based on atmospherically corrected bidirectional surface reflectances, for which masking of water bodies, clouds, heavy aerosols, and cloud shadows was performed. MODIS was chosen because, although it has somewhat lower image resolution compared to Landsat/Sentinel imagery, its advantage is that MODIS satellites have a revisit time of 1-2 days, unlike Landsat/Sentinel which have temporal coverage of 16 and 5 days respectively (Mao *et al.*, 2016). Low imaging frequency reduces the availability of cloud-free and distortion-free surface observation data, which can introduce greater uncertainty. Additionally, conducting long-term analysis at the river basin or regional level using high-resolution imagery such as Landsat or Sentinel requires substantial computational capacity and takes considerably more time, which also influenced the method selection.

Climate data were obtained from two different collections. Surface temperature data were taken from the MODIS/061/MOD11A2 collection (Wan *et al.*, 2021). The MODIS/061/MOD11A2 product provides average surface temperature compositionally calculated for 8-day periods. The collection resolution is 1000 meters. Precipitation data were obtained from Climate Hazards Center InfraRed Precipitation with Station (CHIRPS), collection UCSB-CHG/CHIRPS/PENTAD (CHIRPS Pentad…, n.d.). This is a quasi-global precipitation dataset spanning over 30 years. CHIRPS combines satellite imagery with 0.05° resolution with in-situ station data to create gridded precipitation time series for trend analysis. Land cover type data were obtained from the MODIS/061/MCD12Q1 collection, which provides global land cover types at annual intervals (Friedl & Sulla-Menashe, 2022). The collection resolution is 500 meters. For this study, the International Geosphere-Biosphere Programme (IGBP) classification was selected. The digital elevation model with 30-meter resolution was obtained from Shuttle Radar Topography Mission (SRTM) data. The collection identifier in GEE is USGS/SRTMGL1_003 (NASA SRTM digital elevation 30 m, n.d.).

The spatiotemporal variability of NDVI and temperature with precipitation was investigated using two methods (Satti *et al.*, 2024). The first method involved time series analysis over 24 years, with appropriate calculation methods applied for each parameter. For NDVI, time series were calculated based on median values, as the advantage of the median over the mean is its greater resistance to outliers, which frequently occur in NDVI values due to, for example, cloud cover. For constructing temperature time series, average values for the summer season were calculated. Time series for precipitation were built based on average precipitation sums for the summer season. The second method for investigating spatiotemporal variability consisted of detecting monotonic trends. For this purpose, the Mann-Kendall algorithm was used (Mann, 1945). The Mann-Kendall test is non-parametric; therefore, it is less sensitive to outliers and uneven data distribution compared to parametric tests. When studying trends using this test, statistically significant trends are conventionally considered those where the p value is less than 0.05, reflecting statistical significance at the 95% level or higher. To investigate the linear interaction between NDVI and climate indicators, Pearson correlation coefficients were calculated, as this method offers a quantitative measure of linear relationship between two variables.

To model the nonlinear impact of temperature, precipitation, land cover types, and elevation on NDVI, Random Forest regression was employed, implemented in Python using the Scikit-learn (n.d.) library. Random Forest was chosen due to its high noise resistance, automatic accounting for interactions between variables, and ability to handle categorical data, which is suitable for heterogeneous geospatial datasets. All input data were aggregated to an annual temporal scale with a spatial resolution of 0.0045° (~500 m), corresponding to the native resolution of land cover data, minimising interpolation errors for categorical data. NDVI, precipitation, temperature, land cover, and elevation data were combined into a one-dimensional array by stacking spatial (latitude, longitude) and temporal dimensions, followed by filtering to eliminate missing values by selecting common samples. Categorical land cover data were converted to numerical format using one-hot encoding – a method that represents each land cover type (e.g., forest or agricultural land) as a set of binary variables (0 or 1). This allows the Random Forest algorithm to effectively process discrete IGBP classes, because machine learning methods perform poorly with categorical data in their raw form, as they require numerical representations for mathematical computations.

Since this study used 7 of 17 possible land cover types, one-hot encoding was employed, providing compact data representation without significant increase in dimensionality. Continuous variables (precipitation, temperature, elevation) were used without normalisation, as Random Forest is insensitive to scaling. The Random Forest model, which creates an ensemble of many decision trees to predict NDVI based on input parameters, was optimised using GridSearchCV, testing combinations of hyperparameters (number of trees: 50, 100; maximum depth: 5, 10; minimum samples for split: 2, 5; minimum samples in leaf: 1, 2) using 5-fold cross-validation to ensure robust performance estimates. In Random Forest, each decision tree analyses a portion of the data and makes its own prediction, and their results are combined. GridSearchCV from the scikit-learn library automatically tests different model settings to find optimal ones, and 5-fold cross-validation divides the data into five parts, training the model on four and testing on the fifth, which was repeated five times to assess model stability.

All stages of the research, including data acquisition and preparation in GEE, were implemented programmatically using Python programming language version 3.11. The following Python libraries were used for research implementation. The "ee" library provided Python API for GEE. The "xarray" library enabled working with data as multi-dimensional arrays, where dimensions can be coordinates, temporal dimension, and any other arbitrary attributes; "xarray" provides the fundamental data structure and API and allows encoding information about how array values correspond to locations in space, time, etc. (Xarray, n.d.). The "xee" library, which is an extension to "xarray", enabled integration of GEE data (Google/Xee, n.d.). The "pymannkendall" library implements almost all known modifications of Mann-Kendall tests and the Theil-Sen slope coefficient (Hussain & Mahmud, 2019). The "scikit-learn" library for machine learning implemented algorithms for performing classification, regression, clustering, and other types of predictive data analysis. The "matplotlib" and "geemap" libraries were used for visualising graphs and maps.

Results

Analysis of changes in land use structure for the period 2001-2023 reveals significant transformations in the landscape structure of the basin (Fig. 3). The most pronounced tendency is the growth in cropland proportion from 20% to 34%, reflecting the intensification of agricultural production in the region. Simultaneously, a drastic reduction in the mosaic agricultural land category is observed, from 25% to 7%, indicating the transformation of mosaic agricultural-natural landscapes into continuous croplands. Among forest ecosystems, multidirectional changes are occurring: the area of broadleaf deciduous forests increased from 16% to approximately 22%, while the share of evergreen needleleaf forests slightly decreased from 9% to 6%. The area of mixed forests remained stable throughout the study period. The proportion of grasslands and steppes increased slightly from 3% to 4%.

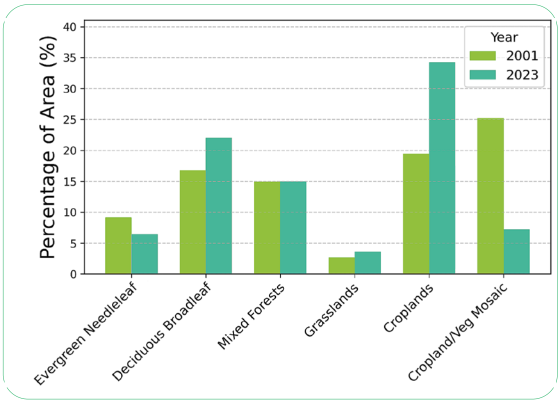

Figure 3. Spatial distribution of land cover types in the study area: 2001 and 2023
Source: created by the authors based on M. Friedl & D. Sulla-Menashe (2022)

Analysis of the median NDVI time series for the summer season in the studied territory of the Dniester basin within Ivano-Frankivsk Region demonstrates a positive tendency throughout the 24-year observation period. Although interannual fluctuations can be observed, the overall trend remains upward. The lowest value was recorded in 2003 (~0.75) and the highest in 2023 (~0.83) (Fig. 4).

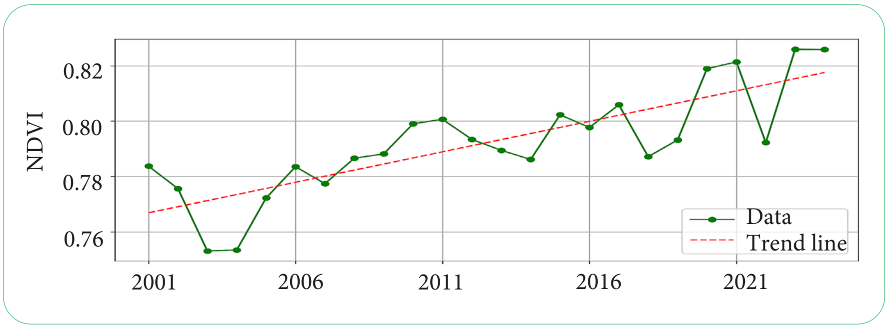

Figure 4. Dynamics of median NDVI values for the summer season in the study area (2001-2024)
Source: created by the authors based on data from GEE collection K. Didan (2021)

Results of the Mann-Kendall tests showed that NDVI changes for the summer season during the period 2001-2024 are distributed unevenly across the study territory (Fig. 5). Overall, statistically significant summer NDVI trends cover approximately 43.2% of the territory, of which 38.8% accounts for positive trends and 4.4% for negative ones. Positive changes nearly nine times outweigh negative ones, indicating overall improvement in vegetation condition in the region.

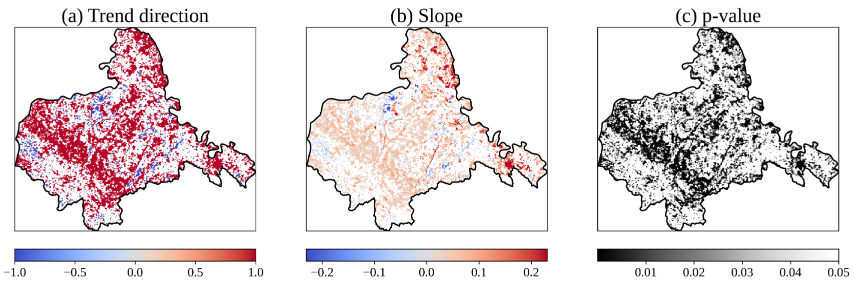

Figure 5. Results of NDVI trend analysis using the Mann-Kendall test
Note: a – trend direction; b – slope magnitude; c – statistical significance (*p* value)
Source: created by the authors based on K. Didan (2021)

Spatial analysis of trends shows that most statistically significant positive tendencies occur at medium elevations (500-800 meters above sea level) within the Carpathian foothills, where broadleaf and mixed forests dominate. In mountainous areas, statistically significant trends are practically not observed. Only in the western part of the mountainous territory can some negative tendencies be noticed, and in the southern part, minor positive trends. This is explained by the fact that broadleaf and mixed forests in highland landscapes are more resilient to global climate changes (Marod *et al*., 2025). For lowland territories, which are predominantly occupied by agricultural lands, the nature of changes is heterogeneous (Wang *et al*., 2023). Both negative processes are observed, largely caused by anthropogenic factors (forest exploitation, expansion of urbanised territories, increase in areas with hazardous geological processes, territories occupied by waste and dumps), as well as positive dynamics.

The average magnitude of statistically significant positive changes is 0.069 NDVI units, while for negative changes this indicator equals -0.072 NDVI units over 24 years. Some areas can be noted where the magnitude of changes stands out against others. Among them: negative dynamics in the area of Kalush City; increase in indicators in the valleys of the Limnytsia and Bystrytsia-Nadvirnianska rivers. Also, larger positive changes are observed in some areas in the northern and eastern parts of the territory, which are almost entirely occupied by agricultural lands. Average surface temperature for the summer season shows an upward tendency, although values vary quite strongly from year to year, and monotonic trends are not observed for practically the entire study territory (Fig. 6). The magnitude of change varies depending on the territory, averaging from +1°C to +1.6°C. Average precipitation sums for the summer season show an overall declining tendency, although, similarly to temperature, values vary substantially from year to year, and clear monotonic trends are not observed (Fig. 7).

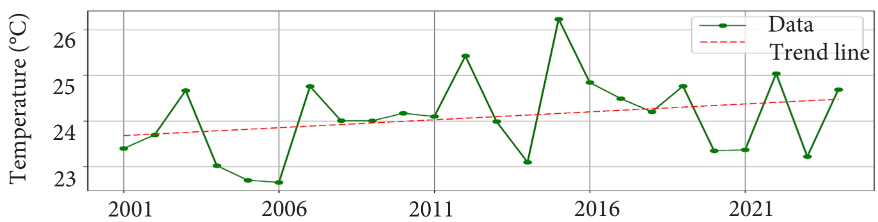

Figure 6. Dynamics of average surface temperature for the summer season in the study area (2001-2024)
Source: created by the authors based on Z. Wan *et al.* (2021)

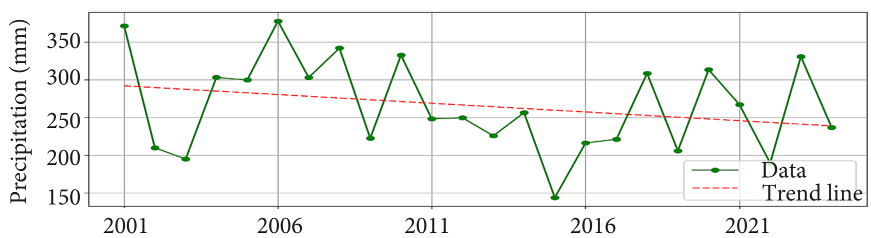

Figure 7. Dynamics of average precipitation sums for the summer season in the study area (2001-2024)
Source: created by the authors based on CHIRPS Pentad: Climate Hazards Center infrared precipitation with station data (Version 2.0 Final) (n.d.)

Pearson correlation test statistics showed a weak relationship between NDVI and climatic characteristics for the studied territory. The average correlation coefficient between NDVI and precipitation is 0.100, and between NDVI and temperature is -0.184. Analysing the spatial distribution of correlations (Fig. 8), it can be concluded that a stronger linear relationship between NDVI and climatic characteristics is observed in the lowland part occupied by agricultural lands, where the relationship with precipitation is positive, i.e., with increasing precipitation amount, NDVI values increase, and the relationship with temperature is negative, i.e., with increasing surface temperature, NDVI values decrease. With increasing elevation, the correlation dependency decreases to statistically insignificant values, which again confirms the greater resilience of highland landscapes to global climate changes.

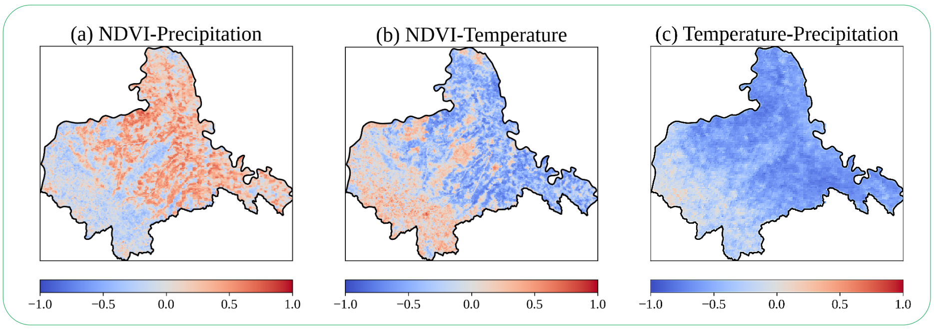

Figure 8. Spatial distribution of Pearson correlation coefficients

Note: a – NDVI and precipitation; b – NDVI and temperature; c – temperature and precipitation

Source: created by the authors based on K. Didan (2021), Z. Wan *et al.* (2021), CHIRPS Pentad: Climate Hazards Center infrared precipitation with station data (Version 2.0 Final) (n.d.)

To assess the nonlinear impact of temperature, precipitation, land cover types, and elevation on NDVI, a Random Forest regression model was applied. The model achieved a coefficient of determination $R^2 = 0.718$, RMSE = 0.038, and cross-validated $R^2 = 0.669 \pm 0.025$ with 5-fold cross-validation at a resolution of 0.0045° (~500 m) due to land cover detail, indicating relatively high prediction accuracy and moderate generalisation ability (Fig. 9).

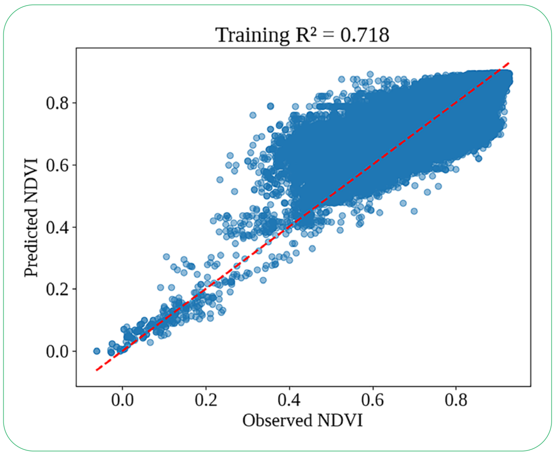

Figure 9. Results of NDVI modeling using Random Forest regression: relationship between observed and predicted values

Source: created by the authors based on NASA SRTM digital elevation 30 m (n.d.), CHIRPS Pentad: Climate Hazards Center infrared precipitation with station data (Version 2.0 Final) (n.d.), K. Didan (2021), Z. Wan *et al.* (2021), M. Friedl & D. Sulla-Menashe (2022)

Feature importance analysis showed that temperature is the primary predictor (55%), followed by land cover type (32%), precipitation (8%), and elevation (5%), emphasising the dominance of climatic factors and vegetation type, with a smaller but noticeable contribution from topography. The low relative importance of elevation is likely explained by its collinearity with temperature (decrease of 0.65°C per 100 m elevation), reflecting the law of altitudinal natural zonation and being partially accounted for through the temperature effect in the model.

Discussion

The overall tendency toward increasing NDVI values is consistent with the results of other studies for various regions. In particular, C. Eisfelder *et al*. (2023), when analysing seasonal NDVI changes for the European continent over a 30-year period, identified statistically significant positive trends in 22% of Europe's territory with an average change magnitude of 0.09. At the same time, the authors noted that for the summer season, changes are less substantial compared to other seasons and are characterised by regional specificity. For northern, central, and south-eastern parts of Europe, tendencies are predominantly positive, while in the western part, particularly in Spain and Ireland, changes are mainly negative in character. The researchers also noted that negative trends are mostly localised in agricultural areas, whereas forests demonstrate predominantly positive tendencies during the vegetation period and minor or positive trends during summer and autumn. The thesis regarding positive changes for forest ecosystems is also confirmed by the results of this study. Concerning negative dynamics for agricultural areas, no pronounced trends were detected within the studied territory, except for individual localised areas that require further analysis to establish the causes of such anomalies. It is assumed that such substantial changes are most likely caused by anthropogenic activity.

Research results by R. Prăvălie *et al*. (2022) for the territory of Romania also demonstrated overall dominance of positive NDVI tendencies. The authors note that positive changes cover 65% of the territory, predominantly in the Carpathian Region with moderate and high elevations, while 35% of negative changes are localised in lowland regions. Within the studied territory, positive dynamics were detected for 40% of the area. Differences in the obtained indicators may be caused by the heterogeneity of the studied territory, a significant part of which is occupied by agricultural lands. Overall, the obtained results are consistent with the conclusions of Romanian researchers. R. Prăvălie *et al*. (2022) also established that approximately 50% of NDVI changes correlate with temperature indicators, particularly forest ecosystems in mountainous environments demonstrate positive response to warming. These results are consistent with the conducted analysis, as the Random Forest model identified temperature as the main predictor (55% importance).

Results by X. Feng *et al*. (2023), obtained for the subtropical metropolitan region of Greater Bay Area (China), also confirm the dominance of positive vegetation cover trends over a 20-year period, which generally agrees with the upward NDVI dynamics identified in this study. The authors recorded EVI growth at a rate of 0.0045/year and significant prevalence of territories with vegetation condition improvement (over 65% of area), while degradation changes cover less than 6%. Such asymmetry between vegetation restoration and degradation processes resonates with results obtained within the Dniester basin, where positive tendencies also dominate, although occupying a smaller share of territory (approximately 39%). These differences can be explained by noticeably different intensities of anthropogenic impact, land use structure, and climatic conditions, as GBA is characterised by high humidity and powerful urbanisation pressure, while the studied territory combines mountainous, forest, and agricultural landscapes. An important distinction between the results of X. Feng *et al*. (2023) and this study is the spectrum of analysed climatic predictors. In the work of Chinese researchers, it was established that relative humidity and wind speed have the strongest relationship with EVI dynamics, while temperature plays a secondary role and is characterised by spatially mosaic influence. In the study, these climatic factors were not considered; instead, primary attention was focused on temperature and precipitation. Despite this, the identified dependencies partially correlate with the conclusions of X. Feng *et al*. (2023), since the Random Forest model in current case also determined temperature as a key factor explaining NDVI changes (55% importance), while precipitation plays a significantly smaller role.

The study by L. Chang *et al*. (2023), conducted for the Yuan River basin in China, also demonstrates the dominance of positive NDVI trends in long-term perspective, which corresponds to the general direction of changes identified within the Dniester basin. The authors note that vegetation cover improvement is most characteristic of rural and mountainous areas, while in urban zones weak NDVI growth or stability is observed, which they associate with increasing land use intensity. Similar spatially differentiated dynamics is observed in the research: mountainous forest landscapes of the foothills demonstrate the most pronounced positive trends, while lowland agricultural territories are characterised by mixed nature of changes. Importantly, L. Chang *et al*. (2023) identified temperature as a key factor most contributing to NDVI increase, while the influence of precipitation proved weaker and depended on local conditions. This agrees well with results of this study, according to which temperature also acts as the primary driver of interannual NDVI variability, while the relationship with precipitation is weak and spatially heterogeneous.

Research results by W. Zhang *et al*. (2020) conducted for the Yangtze and Yellow River basins also demonstrate a general tendency toward increasing vegetation indicators, which is consistent with this study. The authors recorded NDVI increase at a rate of 0.011 per decade and significant spatial heterogeneity of changes: the most intensive growth was observed in central parts of the basins, while degradation was noted in the eastern sector. Similar spatial trend mosaicity is characteristic of the Dniester basin, where positive changes are concentrated primarily in forest landscapes of medium elevations, while degradation is localised and predominantly associated with anthropogenic impact. At the same time, analysis at different temporal scales performed by the authors showed significant strengthening of NDVI correlation with temperature and precipitation in long-term trends (up to 93.6% and 81.5% respectively), indicating the dominance of climatic factors in interannual and multi-year vegetation variability. Current results demonstrate a similar tendency toward the key role of temperature, which the Random Forest model identified as the main predictor of

NDVI changes, but correlation dependencies for precipitation within the Dniester basin proved substantially weaker.

The study by L. Cui *et al.* (2022), conducted in the high-mountain Yarlung-Tsangpo basin, demonstrates clearly pronounced dominance of temperature as the key climatic factor determining NDVI sensitivity of different vegetation types, while the response to precipitation proved significantly weaker. Application of the Random Forest model showed that a temperature increase of 1.5°C causes NDVI growth of 1.6-4.68%, while a precipitation increase of 10% affects only 0.06-0.24%. Similar dominance of the temperature factor is consistent with current results: the Random Forest model within the Dniester basin also identified temperature as the primary predictor of NDVI variability, while the relationship with precipitation remained weak and spatially limited. Additionally, the authors indicate the presence of substantial delayed effects of temperature and precipitation, especially for forest formations, whereas within the Dniester basin such effects were not analysed, which constitutes a potential direction for further research.

Research results by K.M. Al-Kindi *et al.* (2023), conducted for the Dhofar Region in Southern Oman, demonstrate the importance of comprehensive accounting for both climatic and topographic factors in explaining spatiotemporal NDVI variability. Unlike this work, where temperature was identified as the main driver of NDVI changes, in the Omani Region, soils, elevation, slope, and precipitation amount received the highest importance in the Random Forest model, while temperature and humidity played a secondary role. Such a shift in dominant predictors can be explained by substantially different climatic conditions and significant dependence of vegetation productivity on intensive episodic precipitation, particularly rainfall events associated with frequent cyclones. At the same time, the study by K.M. Al-Kindi *et al.* (2023) confirms that NDVI remains sensitive to strong climatic anomalies, especially excessive precipitation in highland areas, which partially agrees with observations of increased sensitivity of lowland agricultural territories to changes in precipitation amount. However, unlike Dhofar, where NDVI responses had a pronounced local character and were clearly associated with cyclone impacts, in the Dniester basin, general tendencies were more stable, and negative or positive anomalies indicated predominantly anthropogenic influence.

Conclusions

The conducted study of vegetation cover dynamics in the Dniester basin within Ivano-Frankivsk Region for the period 2001-2024 enabled obtaining a comprehensive assessment of climatic factors' impact on the region's ecosystems and identifying key patterns of their spatiotemporal variability. Time series analysis of NDVI confirmed an overall positive tendency of vegetation cover growth, with statistically significant positive trends covering 38.8% of the territory. The most pronounced NDVI increases are observed in foothill forest ecosystems at elevations of 500-800 m. Simultaneously, high-mountain areas of the Carpathians show nearly stable NDVI values, indicating high vegetation resilience to global climate changes at these elevations.

Correlation analysis revealed a weak but statistically significant relationship between NDVI and climatic parameters, particularly temperature and precipitation, with the strongest linear dependencies recorded in lowland agricultural territories. The application of machine learning methods, specifically the Random Forest model, allowed identifying nonlinear relationships and establishing that temperature is the dominant factor, explaining 55% of NDVI variability. A secondary role is played by vegetation type, precipitation amount, and elevation above sea level, with precipitation influence being limited by spatial heterogeneity and localised predominantly in lowland zones with agricultural land use. Overall, spatial analysis revealed mosaicity of vegetation responses to climate changes: positive trends are concentrated in forest foothill massifs, while lowland agrolandscapes are characterised by more variable NDVI dynamics.

The obtained results allow making predictive conclusions regarding future vegetation dynamics in the Dniester basin within Ivano-Frankivsk Region. Promising directions for further research include: expansion of temporal frameworks to identify long-term cyclical changes, detailed analysis of extreme climatic events' impact on vegetation cover, assessment of relationships between NDVI changes and regional biodiversity, as well as development of forecasting models to evaluate the effects of different climate change scenarios. It is advisable to conduct similar studies in other parts of the Carpathian Region to create a comprehensive picture of vegetation cover changes in the Ukrainian sector of the Carpathians, which will contribute to effective nature conservation planning, forest and agricultural resource management, as well as assessment of ecosystem resilience to climatic risks.

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Динаміка рослинного покриву басейну Дністра під впливом кліматичних змін у 21 столітті

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Анотація. Зростаюча кліматична нестабільність у Карпатському регіоні України актуалізує необхідність довгострокового моніторингу та кількісної оцінки змін рослинного покриву басейну Дністра. Мета дослідження – аналіз тенденцій зміни рослинного покриву території басейну Дністра в межах Івано-Франківської області протягом 2001-2024 років та виявлення зв'язків між цими тенденціями й основними кліматичними змінними. Методи дослідження включали аналіз часових рядів медіанних значень індексу вегетації за літній сезон на основі супутникових даних MODIS, застосування тесту Манна-Кендалла для виявлення монотонних трендів, обчислення коефіцієнтів кореляції Пірсона для оцінки лінійних зв'язків та використання регресії Random Forest для моделювання нелінійного впливу температури, опадів, типів земного покриву та висоти над рівнем моря на динаміку рослинності. Основні результати показали загальну позитивну тенденцію зростання індексу вегетації з найнижчим значенням у 2003 році та найвищим у 2023 році. Статистично значущі літні тенденції охоплюють 43,2 % території, з яких 38,8 % припадає на позитивні та 4,4 % на негативні тенденції. Найвиразніші позитивні зміни спостерігаються на середніх висотах у передгір'ї Карпат, де домінують широколистяні та змішані ліси. Модель Random Forest досягла коефіцієнта детермінації 0,718, виявивши температуру як основний предиктор динаміки рослинності, за якою слідують тип земного покриву, опади та висота над рівнем моря. Практична цінність дослідження полягає в забезпеченні науковою основою для планування природоохоронних заходів, адаптації лісового господарства до кліматичних змін та розробки стратегій сталого управління екосистемами Карпатського регіону

Ключові слова: індекс вегетації; тест Манна-Кендалла; коефіцієнт кореляції Пірсона, Random Forest; Карпатський регіон; супутникове зондування; екосистеми