INTRODUCTION

Modern methods used for the study of ecosystems and their conditions include remote sensing of environment. The capacities of this technique are used in precision agriculture [Seelan et al., 2003] and ecology for determination of flora conditions, e.g., forest [Morales et al., 2008], wetlands [Martínez-López et al., 2014], grasslands [Marsett et al., 2006] status, through the implementation of various spatial vegetation indices. Two of them have become mostly implemented both by scientists and practitioners: normalized difference vegetation index (hereinafter referred as NDVI) and enhanced vegetation index (hereinafter referred as EVI).

Two of them have become mostly implemented both by scientists and practitioners: normalized difference vegetation index (hereinafter referred as NDVI) and enhanced vegetation index (hereinafter referred as EVI).

NDVI was firstly proposed in 1974 [Rouse et al., 1974]. The calculation of the index is based on the ratio (1):

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$$  \(1\)

where: Red and NIR represent the spectral reflectance, measurements obtained in the red and near-infrared regions (Gutman 1991).

EVI is an improved version of NDVI, which is introduced as a replacement for NDVI. The index is less dependent on soil and atmospheric influences; however, some studies reported about the difficulties in creation of long EVI time-series [Jiang et al., 2008]. Standard EVI is calculated as follows (2):
\[
\text{EVI} = G \times \frac{(\text{NIR} - \text{Red})}{(\text{NIR} + C_1 \times \text{Red} - C_2 \times \text{Blue} + L)}
\]  

(2)

where: Red, Blue and NIR represent the corrected surface reflectance, 
L is the canopy adjustment argument (in Moderate Resolution Imaging Spectroradiometer it is taken as 1.0),  
C1 and C2 are the adjustment coefficients to diminish the distortion related to the influence of aerosols (in Moderate Resolution Imaging Spectroradiometer they are taken as 6.0 and 7.5, respectively),  
G is the gain factor (it is taken as 2.5) [Matsushita et al., 2007].

Vegetation cover conditions monitoring and control is an important part of the environmental studies directed to conservation of biodiversity. Annual and long-term observations for vegetation provide valuable information on the patterns of flora reaction to human activities and natural changes on the response of vegetation to the changes in climate conditions. While direct observation and measurements remain the most precise way of obtaining information on the status of vegetation [Lykhovyd, 2020], the use of spatial indices provides an opportunity for fast assessment of vegetation conditions on a large area [Kim et al., 2010], which is impossible using direct on-land methods. This is the main reason for their use in large-scale ecological monitoring and modeling.

The main aim of the study was determination of annual and long-term dynamics in spatial vegetation indices, which indirectly represent the dynamics in the vegetation cover status, strength and direction of climate factors impact on vegetation through the interconnection of spatial NDVI and EVI to air temperature and precipitation amounts to better understand the patterns of flora reactions to climate and its dynamics under the pressure of its change.

**MATERIALS AND METHODS**

MODIS NDVI and EVI 250 m smoothed time series 16-day terrain data for the period from 01/01/2012 to 01/01/2020 for Kherson oblast of Ukraine (Fig. 1) provided by the University of Natural Resources and Life Sciences (Vienna) were used in the study.

Square screens of Kherson oblast were cut using GDAL raster cutting engine within QGIS 3.10 software by the mask of vegetation cover of the region (Fig. 2) obtained at NEXTGIS Data service to exclude distortion in the values of the studied indices connected with accounting the areas, which are free from vegetation, e.g., sands, lakes, buildings, etc.

The data were processed using QGIS 3.10 raster statistics function to calculate mean values.
of NDVI and EVI by each month. The results were generalized annually (Table 1, Table 2).

Regional climate data for the period from 01/01/2012 to 01/01/2020, including air temperature and precipitation amounts, were recorded at the Kherson hydrometeorological station, and generalized (Table 3, Table 4).

The connection between the meteorological and vegetation indices was estimated using statistical analyses: linear Pearson correlation [Zou et al., 2003], multiple linear regression [Seber & Lee, 2012] with calculation of mean absolute percentage error (MAPE) [De Myttenaere et al., 2016]. All the statistical calculations were performed using BioStat v7 add-in within Microsoft Excel 365. Coefficient of variation (CV) for the studied vegetation indices were calculated by generally accepted methodology [Everitt, 1998]. Trend lines for the vegetation indices with a polynomial regression forecast were built by the

**Figure 2.** The mask of Kherson oblast used to cut the screens of the region to extract only the information on vegetation cover (the mask was purchased at NEXTGIS Data)

| Year | Mean | CV (%) |
|------|------|--------|
| 2012 | 0.34 | 16.02  |
| 2013 | 0.39 | 8.05   |
| 2014 | 0.35 | 10.53  |
| 2015 | 0.36 | 15.55  |
| 2016 | 0.39 | 14.02  |
| 2017 | 0.38 | 11.90  |
| 2018 | 0.41 | 9.94   |
| 2019 | 0.40 | 10.65  |

**Table 1.** NDVI values for the vegetation cover of Kherson oblast for the period of 2012–2019

| Year | Mean | CV (%) |
|------|------|--------|
| 2012 | 0.14 | 23.78  |
| 2013 | 0.19 | 28.93  |
| 2014 | 0.20 | 21.32  |
| 2015 | 0.16 | 15.43  |
| 2016 | 0.15 | 9.71   |
| 2017 | 0.16 | 10.65  |
| 2018 | 0.18 | 20.06  |
| 2019 | 0.17 | 4.82   |

**Table 2.** EVI values for the vegetation cover of Kherson oblast for the period of 2012–2019

| Year | Mean | CV (%) |
|------|------|--------|
| 2012 | 0.14 | 16.02  |
| 2013 | 0.39 | 8.05   |
| 2014 | 0.35 | 10.53  |
| 2015 | 0.36 | 15.55  |
| 2016 | 0.39 | 14.02  |
| 2017 | 0.38 | 11.90  |
| 2018 | 0.41 | 9.94   |
| 2019 | 0.40 | 10.65  |
means of Microsoft Excel 365 prediction tool [Heiberger et al., 2009]. All statistical analyses were performed for the probability level of 95%.

RESULTS AND DISCUSSION

Annual dynamics of vegetation cover in Kherson oblast

As any biological system, flora also has its fluctuations in time [Tsimring, 2014]. Annual dynamics in vegetation cover are well-known and seem to be evident. It is known by the local inhabitants that in Kherson oblast, grass starts to grow in early spring, trees blossom during the late spring and summer time, fruits appear in the late summer and autumn, and at the end of the autumn period gradual senescence and death of most vegetation, except evergreens can be observed. However, this evidence and knowledge based on common wisdom cannot be considered as a reliable source for the scientific knowledge of the processes, which take place in ecosystems. As a results of 8-year MODIS NDVI and EVI data generalization, the main annual trends in the vegetation growth in the region were determined (Fig. 3).

It was determined that the peak in the vegetation growth in the region is reached in the May–July period that is proved by the highest values of spatial vegetation indices at this time span: NDVI is 0.53–0.54, EVI is 0.31–0.32, respectively. The winter period (December–February) is characterized by the least live vegetation (average NDVI for the period is 0.39, and EVI is 0.18, respectively), which is represented by evergreens only. The spring period (March–May) is characterized by a substantial increase in the indices from 0.43 to 0.54 for NDVI and 0.22 to 0.31 for EVI, testifying about the regrowth of most vegetation in the studied region. The peak of vegetation growth is in the summer (June–August), when the average values of spatial indices reach 0.52 for NDVI and 0.30 for EVI, respectively. However, August (the end of summer) is a turning-point in the vegetation development. The flora comes into the period of gradual senescence, which continues through all the autumn period (September–November) and finishes (reaches the minimum) in January, which is simultaneously the coldest month of a

### Table 3. Air temperature in Kherson oblast for the period of 2012–2019, Celsius degrees

| Year | I | II | III | IV | V | VI | VII | VIII | IX | X | XI | XII |
|------|---|----|-----|----|---|----|-----|------|----|---|----|-----|
| 2012 | -1.3 | -7.2 | 2.4 | 12.8 | 20.5 | 23.3 | 26.4 | 23.9 | 19.2 | 14.9 | 7.0 | -0.4 |
| 2013 | 0.1 | 2.5 | 3.3 | 11.6 | 20.5 | 23.0 | 23.6 | 24.2 | 15.1 | 9.3 | 7.5 | 0.5 |
| 2014 | 1.1 | 0.0 | 6.8 | 11.0 | 18.1 | 20.8 | 25.0 | 24.5 | 18.4 | 9.3 | 3.3 | 0.4 |
| 2015 | -0.4 | 0.9 | 5.2 | 9.4 | 17.0 | 21.3 | 23.5 | 24.1 | 20.9 | 9.6 | 7.4 | 2.6 |
| 2016 | -3.1 | 3.9 | 6.2 | 12.7 | 16.3 | 22.1 | 24.3 | 24.9 | 18.0 | 8.4 | 4.0 | -1.2 |
| 2017 | -4.7 | -0.8 | 7.0 | 9.3 | 16.3 | 22.0 | 23.4 | 25.4 | 19.9 | 11.3 | 5.4 | 5.9 |
| 2018 | -0.3 | -0.2 | 1.5 | 14.1 | 19.5 | 22.9 | 24.2 | 25.5 | 18.7 | 13.5 | 2.7 | 0.1 |
| 2019 | -0.6 | 1.4 | 5.9 | 10.5 | 18.0 | 23.8 | 23.2 | 23.4 | 18.1 | 11.6 | 7.1 | 4.3 |
| Mean | -1.2 | 0.1 | 2.4 | 11.4 | 18.3 | 22.4 | 24.2 | 24.5 | 18.5 | 11.0 | 5.6 | 1.5 |

### Table 4. Precipitation amounts in Kherson oblast for the period of 2012–2019, mm

| Year | I | II | III | IV | V | VI | VII | VIII | IX | X | XI | XII |
|------|---|----|-----|----|---|----|-----|------|----|---|----|-----|
| 2012 | 56.2 | 15.1 | 26.7 | 18.7 | 65.4 | 25.6 | 19.0 | 49.1 | 3.5 | 22.4 | 7.3 | 31.2 |
| 2013 | 39.8 | 22.2 | 41.3 | 8.0 | 12.0 | 70.1 | 48.1 | 12.4 | 43.7 | 53.9 | 1.0 | 3.7 |
| 2014 | 39.5 | 7.8 | 17.7 | 23.6 | 42.6 | 85.9 | 18.6 | 24.8 | 65.1 | 31.1 | 19.0 | 45.5 |
| 2015 | 32.2 | 39.9 | 57.7 | 57.8 | 44.8 | 60.6 | 64.2 | 25.7 | 3.8 | 19.1 | 50.7 | 5.2 |
| 2016 | 61.1 | 28.5 | 24.2 | 55.0 | 82.6 | 72.6 | 19.4 | 34.2 | 33.2 | 74.4 | 34.2 | 26.3 |
| 2017 | 27.5 | 20.3 | 5.1 | 87.9 | 25.6 | 35.2 | 10.3 | 39.8 | 4.8 | 0.7 | 12.0 | 40.6 |
| 2018 | 24.1 | 33.3 | 61.0 | 1.6 | 35.7 | 23.1 | 90.8 | 0.0 | 42.8 | 9.6 | 31.1 | 56.3 |
| 2019 | 23.0 | 9.8 | 7.3 | 56.0 | 72.8 | 92.6 | 48.7 | 22.1 | 12.1 | 10.4 | 37.9 | 26.3 |
| Mean | 37.9 | 22.1 | 30.1 | 38.6 | 47.7 | 55.1 | 43.6 | 21.6 | 25.6 | 29.1 | 28.1 | 28.7 |

Mean 37.9 22.1 30.1 38.6 47.7 55.1 43.6 21.6 25.6 29.1 28.1 28.7 408.3
year (the only month with an average air temperature that is below zero).

The dynamics of the decrease in spatial vegetation indices starting from the August period can also be attributed to the fact that most crops cultivated on agricultural lands of the region have been already harvested before this period or are entering into the stage of ripening when green biomass is wilting.

Surprisingly, the senescence of vegetation in Kherson oblast is not completed in November or December, as it was usually stated by local hydro meteorologists and agricultural scientists who claim that usually cessation of vegetation at the beginning of November [Ushkarenko, 1994]. It could be attributed to the increase of air temperatures in these months over the last years, resulting in better conditions for continuous growth of some cold-resistant flora species.

Long-term (2012–2019) dynamics of the vegetation cover in Kherson oblast

The study of the long-term dynamics of the flora conditions in Kherson oblast showed that there is a strong tendency towards the improvement of vegetation growth conditions in the region, which is proved by the gradually increasing values of both studied spatial vegetation indices (Fig. 4, 5).

Polynomial regression trend lines testify about the highly likely ($R^2 > 0.80$) further increase in the vegetation indices, i.e., further enhancement of vegetation in the region [Taylor, 1990]. There are numerous factors affecting vegetation, e.g., climate, soil, biological interactions within ecosystems, anthropogenic activities (especially, on agricultural lands), etc. The next stage of the study was to define the role of climate impact on the vegetation cover conditions in Kherson oblast.
Dependence of vegetation cover in Kherson oblast on climate

Monthly air temperature and precipitation amounts were applied as the indices of climate characteristics in the study. The connection between the vegetation indices and climatic indices was determined by the linear Pearson correlation and multiple linear regression analysis. It was found out that both NDVI and EVI are closely related to the air temperature (linear Pearson correlation coefficient R values were 0.77 and 0.85, respectively), and at the same time there was almost no connection between the vegetation indices and precipitation amounts (correlation coefficient R values were 0.24 and 0.28, respectively).

Multiple linear regression analyses resulted in the determination of stronger connection between the climatic indices and EVI (Table 5), while their inter-connection with NDVI was considerably lower (Table 6).

Regression equations (3), (4) describing the dependence of the studied vegetation indices on climate inputs confirm the above-mentioned statement that the greatest impact on vegetation cover is made by air temperature, while precipitation amounts have very slight effect on it.

\[
NDVI = 0.3903 + 0.0050 \times A + 0.0004 \times B \tag{3}
\]

where: \(NDVI\) is a value of the spatial vegetation index,

| Regression statistics criteria | Values of criteria |
|-------------------------------|--------------------|
| Multiple correlation coefficient (R) | 0.7893 |
| Mean square (MS) | 0.1165 |
| Mean square error (MSE) | 0.0015 |
| Multiple determination coefficient (R²) | 0.6230 |
| Adjusted R² | 0.6149 |
| Root mean square error (RMSE) | 0.0394 |
| Mean absolute percentage error (MAPE) | 6.7064 |
| F value | 76.8292 |
| Multiple determination coefficient for the prediction (R²) | 0.6019 |

Table 5. Multiple linear regression analysis results for the model “air temperature; precipitation amounts – EVI” in Kherson oblast for the period of 2012–2019

| Regression statistics criteria | Values of criteria |
|-------------------------------|--------------------|
| Multiple correlation coefficient (R) | 0.7497 |
| Mean square (MS) | 0.1165 |
| Mean square error (MSE) | 0.0008 |
| Multiple determination coefficient (R²) | 0.7647 |
| Adjusted R² | 0.7596 |
| Root mean square error (RMSE) | 0.0282 |
| Mean absolute percentage error (MAPE) | 9.5655 |
| F value | 151.0948 |
| Multiple determination coefficient for the prediction (R²) | 0.7497 |

Table 6. Multiple linear regression analysis results for the model “air temperature; precipitation amounts – NDVI” in Kherson oblast for the period of 2012–2019
\[ EVI = 0.1711 + 0.0050 \times A + 0.0005 \times B \tag{4} \]

where: \( NDVI \) is a value of the spatial vegetation index, 
\( A \) is air temperature in Celsius degrees, and 
\( B \) is precipitation amounts in mm.

The developed models, in particular the model for EVI, can be proposed as a reliable tool for the climate-based prediction of the vegetation cover status in Kherson oblast (prediction accuracy of the EVI model is 75% with MAPE of 9.57% < 10%) [Moreno et al. 2013].

**DISCUSSION**

\( NDVI \) is an easy and commonly used index for characterizing vegetation, especially, in precision agriculture systems [Oliver, 2010]; however, doubt on its usefulness for the determination of subsequent changes in vegetation cover and estimation of the dynamics in vegetation was cast [Elmore et al., 2010], mainly because of its tendency towards distortion due to soil reflection ability and cloudiness [Huete, 1988; Koslowsky, 1993; Hobbs, 1997]. EVI seems to be more reliable and less dependent on the above-mentioned hindrances, although it can be distorted by topography [Matsushita et al., 2007]. It was found that both \( NDVI \) and \( EVI \) trends on annual and long-term scales are remarkably close. However, it seems that \( NDVI \) tends to somewhat overestimate the livelihood of vegetation cover in the cold season of a year, maybe, because of the above-mentioned dependence on the soil reflection abilities, which cause some distortions in the winter period, as it is reported by the scientists [Lange et al., 2017]. Notwithstanding the fact that \( NDVI \) imaginary is subjected to additional noise under the conditions of high (exceeding 3.0) leaf area index [Gao, 1996], under different sunshine peculiarities [Huete et al., 1999], it is still widely used for vegetation cover estimation [Miura et al., 2019]. Besides some errors occurring due to the imperfection of the calculation algorithm, it should also be kept in mind that \( NDVI \) is mainly dependent on the chlorophyll content in green mass of vegetation and is less sensible to the area of canopy cover [Lillesæther, 1982]. All these drawbacks seem to be replaced in the \( EVI \) computation algorithm [Matsushita et al., 2007]. Although this statement is quite debatable [Wardlow & Egbert, 2010], the performed study showed that \( NDVI \) is considerably less variable by the years and inter-annually than \( EVI \) (see CV values presented in Tables 1, 2) that drives us into the idea of its less reaction to seasonal changes, thus making \( NDVI \) less suitable for the estimation of fluctuations in vegetation cover depending on the internal and external factors of effect. All in all, the authors agree with [Karkauskaite et al., 2017; Qiu et al., 2018] that \( EVI \) is slightly better choice in case of studying the vegetation cover dynamics.

The study of long-term trends in spatial indices revealed a strong tendency towards their increase. The discovered trends have high reliability at the probability level of 95% (\( p < 0.05 \)), representing the idea of a positive effect of climate changes, the main tendency of which is an increase in the average annual air temperature [Lykhovyd 2018; Vozhehova et al., 2018], on the vegetation cover in Kherson oblast. This conclusion is supported by the report on the results of long-term (for the periods of 2051–2060 and 2090–2098) vegetation cover changes modelling due to the climate changes. The modelling provided the results that vegetation cover will be considerably dense (by 21% and 36% for the periods of 2051–2060 and 2090–2098, respectively) because of the changes in climate, especially, this statement is true for the middle and northern latitudes of the Earth [Jiang et al., 2011]. However, scientists emphasize the inequality in vegetation feedback on global warming, pointing out that it will have a positive effect for the higher latitudes, and an adverse effect, which mainly will manifest itself through thinning of vegetation cover and gradual desertification of land, for the lower latitudes [Woodward et al., 1998].

Another debatable question is the dependence of the spatial indices on precipitation amounts. While the current study results showed almost no dependence of \( EVI \) and \( NDVI \) on the rainfall, there are several research works claiming the opposite. Statistically significant dependence of the studied indices on precipitation was proven in the studies of Zoungrana et al. [2015], Wang et al. [2003]. This contradiction was resolved by Schultz & Halpret [1993], who have drawn the
conclusion that the NDVI dependence on air temperature and precipitation amounts variates by the climate zones, because the importance of rainfall and temperature for growth of vegetation varies in different regions of the world. For example, in cold regions with high rainfall, NDVI will mostly correlate with temperature, and in hot arid regions, this index will mainly depend on rainfall [Schultz & Halpert, 1993]. This conclusion is also supported by the work [Ding et al., 2007], showing that the NDVI correlation with rainfall is different in different years and areas of the Tibetan Plateau.

Statistical evaluation of the relations between climate and spatial vegetation indices revealed that EVI reacts on climate changes more than NDVI; thus, EVI will be better for the prediction of vegetation cover changes depending on climate conditions. It may result from less atmospheric noise in EVI [Wang et al., 2003]. Better performance of EVI for the estimation of agricultural land was also proven by previous studies [Lijun et al., 2008]. However, some reports on the worse performance for prediction of vegetation cover status of EVI-based models compared to the NDVI -based ones were found. For example, the study conducted in Northern Hebei Province of China testified about a significant advantage of the NDVI-based vegetation prediction over the EVI-based [Li et al., 2010]. Better performance of NDVI for vegetation cover evaluation and mapping was proven by the study conducted in Brazil, where NDVI outscored EVI in classification accuracy and showed better performance in the assessment of seasonal fluctuations of the regional flora [Eduarda et al., 2007]. Although there are a number of reports claiming better NDVI performance for vegetation cover assessment, it should be mentioned that the different feature of the performed study is an additional linkage of spatial vegetation indices to climate indices, and in this relation it was found significant benefit of EVI-based estimation of the vegetation in the studied region. Besides, EVI can be much more accurately predicted by air temperature and precipitation amounts, which makes this index more suitable for vegetation cover status forecasting. Similar attempts for EVI-based forecasting of vegetation cover changes were successfully made by other scientific groups using other techniques and inputs for the models [Gurung et al., 2009].

In order to support the results of current study, it should be mentioned that Moreira et al. have also proven strong correlation between climate indices, viz., air temperature and rainfall, and EVI [Moreira et al., 2019]. They also discovered that EVI–temperature and EVI–rainfall correlation is dependent on the El Nino and La Nina events.

Taking into account all the above-mentioned scientific statements and the results of current study, it is evident that it is too early to answer the questions on investigation of vegetation cover through spatial vegetation indices and their linkage with climate. Great discrepancies and serious contradictions between the results of the studies conducted under different climate conditions using different techniques for statistical analysis testify about the necessity of conducting further robust studies in this field to improve the current knowledge on the patterns of the “climate–vegetation” interactions both on local and global scales.

CONCLUSIONS

On the basis of the results of the current study it was found out that:
1. Annual dynamics in vegetation cover of Kherson oblast, studied by means of spatial vegetation indices, is characterized with a peak in the May–July period, gradual senescence since August and active regrowth since March;
2. There is a strong tendency towards the improvement of vegetation conditions in the region, which is proven by the gradually increasing values both of EVI and NDVI on the long-term scale of the studied (2012–2019) period;
3. Spatial vegetation indices and, hence vegetation cover of the region, strongly depend on air temperature and had a slight correspondence to rainfall; therefore, precipitation amounts cannot be considered as a major force for the improvement of vegetation status in the studied area;
4. Both EVI and NDVI could be predicted with sufficient accuracy by the climate indices; however, for this purpose, it is much better to apply the proposed modelling technique to EVI than NDVI because of higher forecasting precision.

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