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# THE MANAGEMENT OF LAND USE CHANGES IN PERI-URBAN AREA OF TIMISOARA CITY USING GIS AND REMOTE SENSING TECHNOLOGIES

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***Abstract***

*Land cover and Land use monitoring is a very complex process for a better understanding of the dynamics of the landscape over a long period of time. Such monitoring cannot be performed without using geospatial methods in the field of remote sensing and Geographic Information Systems (GIS). In this paper was analysed the use of land in the Periurban area of Timisoara in the period 1990-2018 based on data provided by the Copernicus program of the European Union. From the analysis of the data from 1990 to 2018, based on the GIS spatial analyses, it can be concluded that approximately 5,700 hectares have changed their destination. The most significant changes were those in the category Pesterers in Non irrigated arable land (21.8% - 1,256 ha) and the change in the category Non irrigated arable land in Discontinuous urban fabric (18.9% - 1,087 ha), leading to the conclusion both of the urbanization of this periurban area of Timisoara Municipality, but also of the development of the agricultural field. Also, in this study were analysed 3 remote sensing indices determined based on Landsat 8 images, data that can be the basis for a monitoring of urban expansion in western Romania.*

***Key words**: GIS , Land cover, index, Normalized Difference Vegetation Index (NDVI), Normalized Burn Ratio (NBR), Normalized Difference Build up Index (NDBI), remote sensing*

## INTRODUCTION

A series of communes that border the Municipality of Timișoara have experienced, in recent times, a significant development, becoming the "suburbs" of the municipality due to the development of facilities, utilities and infrastructure.

The urban development of the Timisoara Metropolitan area from 1990 until now has led to substantial changes in the communes in the immediate vicinity of the Municipality of Timisoara, so that there have been significant changes in the use of land. In this context, the periurban area of Timisoara Municipality represents an area of major interest for a healthy sustainable development and to satisfy the needs of all those involved. Thus, a correct management is required to support the community in the periurban area [23].

Land use and land cover are 2 terms that are very often used [20]. Land cover refers to the physical characteristics of the earth's surface: the distribution of vegetation, water, soil and other physical features, including those determined by human activities [15]. Land use - refers to the way in which the land area has been used by people, for example the functional role of land for various economic activities [4].

In conclusion, Land cover and Land use is the result of natural, socio-economic factors and land use by people in time and space [16]. Land cover and Land use monitoring is a very complex process for a better understanding of the dynamics of the landscape over a long period of time. Such monitoring cannot be performed without using geospatial methods in the field of remote sensing and Geographic Information Systems (GIS). Recent studies have looked at how Land cover has undergone major changes in recent years, based on data from modern remote sensing systems. Landsat 8, Sentinel 2, Rapid Eye, World view, etc. systems were used in such studies. Information from remote sensing systems [6], [13] together with field data led to an objective classification of land cover.

Remote sensing techniques are the basis of the process of mapping large areas, and the information contained in the spectral bands of remote sensing images is of real use in monitoring and managing the earth's surface.

Integrating in a Geographic Information System [10], [11] data on the use and coverage of land, statistical data on the population of communes in the periurban area of Timisoara, respectively topo-cadastral data from field measurements, the decision-making process regarding the urban development of Timisoara Municipality and its adjacent communes can be improved [7], [14], [18]. Some studies also analyzed the agricultural areas in the Periurban perimeter of Timisoara in order to assess spatial and temporal variability [19].

## MATERIALS AND METHODS

The peri-urban area of Timișoara Municipality consists of 12 territorial administrative units, Fig.1 and 26 localities, Fig. 2. According to the statistical yearbook [9], the data on the surface and the number of inhabitants are presented in Table 1.

Table 1. Demografic data – Periurban Area of Timisoara iIty

| No. | Administrative Territorial Unit - ATU | Surface ha | Number of inhabitants |
|---|---|---|---|
| 1. | Dumbravita | 1,896 | 10,984 |
| 2. | Ghiroda | 3,412 | 7,188 |
| 3. | Mosnita Noua | 6,912 | 9,095 |
| 4. | Giroc | 5,200 | 14,037 |
| 5. | Sanmihaiu Roman | 7,530 | 7,865 |
| 6. | Sacalaz | 11,951 | 9,314 |
| 7. | Sanandrei | 9,253 | 7,147 |
| 8. | Giarmata | 7,169 | 7,469 |
| 9. | Remetea Mare | 7,286 | 2,639 |
| 10. | Sag | 3.495 | ,631 |
| 11. | Dudestii Noi | 5,394 | 3,509 |
| 12. | Bechicherecu Mic | 4,668 | 3,207 |

Source: Data's from NIS.

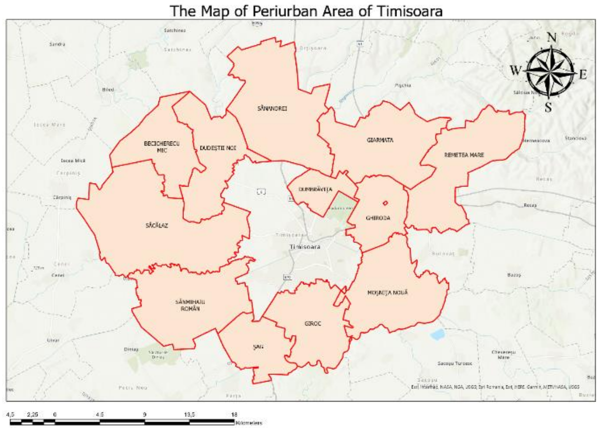


Fig. 1. The map of Periurban area of Timișoara
Source: original image, based on GIS data.

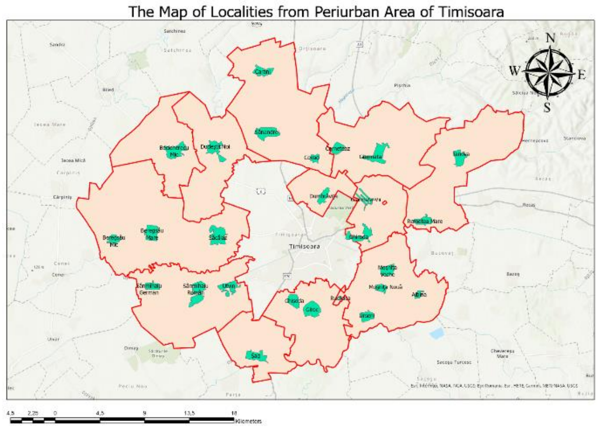


Fig. 2. The map of Localities from Periurban area of Timișoara
Source: original image, based on GIS data.

In this paper were used vector and raster data, available free of charge for the entire territory of Romania, Table 2.

Table 2. Data used and data source

| Data | GIS data type | Source |
|---|---|---|
| Land Cover | Raster | [3] |
| Administrative Territorial Units - ATU | Vector | [1] |
| Localities | Vector | [1] |
| Digital Elevation Model | Raster | [22] |
| Remote sensing images (2014-2018) | Raster | [12] |

Source: original data.

Data on how to use land cover (Land Cover) are part of the Corine Land Cover Project which is a European project that highlights the dynamics of land cover on a European scale [3].

Based on this project, Land Cover data are updated approximately every 6 years and are available free of charge on the website of the European platform Copernicus [21], which is a platform managed by the European Environment Agency.

The Corine Land Cover - CLC data are in GIS format of the vector type and the attributes of the polygons contain the information regarding the characteristics of the land cover type. The classification of the lands was made on 3 hierarchical levels, namely: Level 1: 5 classes Level 2: 15 classes Level 3: 44 classes


Fig. 3. Legend of Corine Land Cover Classes
Source: https://land.copernicus.eu

The classification of the land cover was made based on a process of visual photointerpretation and images obtained from remote sensing systems: Landsat TM and ETM, SPOT, IRS P6, RapidEye, Sentinel-2 and Landsat-8. These data were supplemented with auxiliary data (aerial photographs, thematic maps). All CLC (Corine Land Cover) data layers are available on the internet [3], Figure 3.

In order to better understand how to change the land cover, a series of remote sensing satellite scenes from the Landsat 8 system were also used in this study. For this purpose, satellite scenes were downloaded between 2017 - 2020, July-August, and analysed the evolution of remote sensing indices: Normalized Difference Vegetation Index (NDVI) [17], Normalized Burn Ratio (NBR), [2], [5], [8] and Normalized Difference Build up Index (NDBI) [24].

The NDVI value varies from -1 to 1. Higher the value of NDVI reflects high Near Infrared (NIR), means dense greenery. Generally, NDVI has the following values: from -1 to 0 and NDVI represents Water bodies, from -0.1 to 0.1 NDVI represents Barren rocks, sand, or snow, from 0.2 to 0.5 NDVI represents Shrubs and grasslands or senescing crops and from 0.6 to 1.0 NDVI represents Dense vegetation or tropical rainforest.

The NBR index is defined to highlight areas that have burned and to index the severity of a burn and the NDBI value lies between -1 to +1. Negative value of NDBI represent water bodies where as higher value represent build-up areas. NDBI value for vegetation is low.

The calculation formulas of these indices are described in equations (1), (2) and (3).

$$NDVI = (NIR - R)/(NIR + R) \qquad (1)$$

where: NDVI – Normalized Difference Vegetation index, NIR – Near Infrared Band, R – Redd band

$$NBR = (NIR - MIR)/(NIR + MIR) \qquad (2)$$

where: NBR – Normalized Burn Ratio, NIR – Near Infrared Band, MIR – Middle Infrared Band

$$NDBI = (SWIR - NIR)/(SWIR + NIR) \qquad (3)$$

where: NDBI – Normalized Difference Build up Index, SWIR – Shortwave Infrared Band, NIR – Near Infrared Band

## RESULTS AND DISCUSSIONS

Based on the GIS solutions used (Arc GIS software) 5 thematic maps of the studied area were accomplish, and the maps are represented in Figure 4.

The GIS Maps are representing the land cover in the Periurban area of Timisoara in the period 1990 - 2018. From a statistical point of view, CLC (Corine Land Cover) data in the period 1990 - 2018 are presented in Tables 3 and 4.

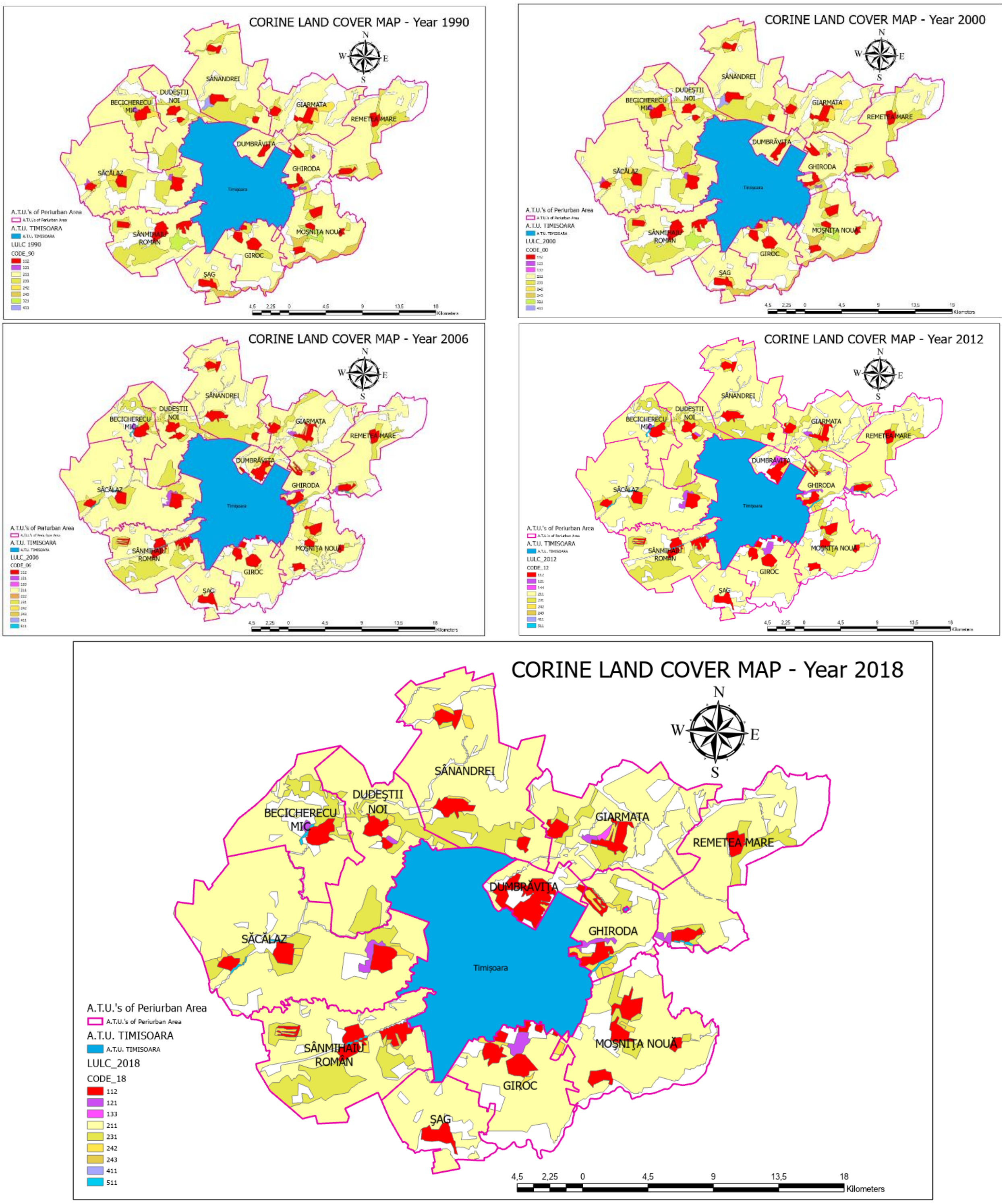


Fig. 4. The maps of Land Cover from 1990 - 2018
Source: original images based on Corine Land Cover.

The thematic maps are suggestive and express in a visual and concrete form the way in which the Periurban area of Timisoara City experienced a considerable development in the period 1990 - 2018 from an urban point of view.

In this context, GIS maps correlated with remote sensing images can support the precision agriculture for sustainable land management, regardless of their use category, by creating spatial databases containing their characteristic attributes.

From an economic point of view, the use of GIS and Remote sensing imagery is a major advantage over the use of classic cartographic material because it can provide a real-time situation regarding the use and exploitation of the parcels at the level of an Administrative Territorial Unit (ATU).

Based on the data presented, it can be stated that the highest increase in the period 1990 - 2018 was Discontinuous urban fabric 1.89% (1,129 ha) and Non-irrigated arable land of 2.05% (496 ha) and the decrease was felt. most at Pastures -1.91% (1,335 ha) and Land mainly occupied by agriculture, with significant areas of natural vegetation -2.02% (1,300 ha). The situation of the changes at the level of the study area, for the period 1990 - 2018 is presented in Table 5.

Table 3. Distribution in hectares of Land Cover for the period 1990 - 2018

| CLASS | LAND COVER | ARIA(ha) 1990 | ARIA(ha) 2000 | ARIA(ha) 2006 | ARIA(ha) 2012 | ARIA(ha) 2018 |
|---|---|---|---|---|---|---|
| 112 | Discontinuous urban fabric | 4,020 | 7,216 | 8,321 | 8,285 | 5,148 |
| 121 | Industrial or commercial units | 117 | 117 | 273 | 484 | 498 |
| 133 | Construction sites | | 33 | 1 | 109 | 43 |
| 211 | Non-irrigated arable land | 49,704 | 389,947 | 395,759 | 392,280 | 50,200 |
| 222 | Fruit trees and berry plantations | 0 | 0 | 48 | 0 | 0 |
| 231 | Pastures | 7,785 | 9,773 | 7,731 | 7,216 | 6,449 |
| 242 | Complex cultivation patterns | 689 | 748 | 628 | 753 | 777 |
| 243 | Land principally occupied by agriculture, with significant areas of natural vegetation | 1,339 | 5,170 | 38 | 38 | 38 |
| 321 | Natural grasslands | 588 | 594 | 0 | 0 | 0 |
| 411 | Inland marshes | 100 | 141 | 52 | 52 | 9 |
| 511 | Water courses | 0 | 0 | 177 | 177 | 136 |

Source: Data's from CLC 1990, 2000, 2006, 2012 and 2018.

Table 4. Percentage distribution of Land Cover for the period 1990 - 2018

| CLASS | LAND COVER | ARIA(%) 1990 | ARIA(%) 2000 | ARIA(%) 2006 | ARIA(%) 2012 | ARIA(%) 2018 |
|---|---|---|---|---|---|---|
| 112 | Discontinuous urban fabric | 6.25 | 1.74 | 2.01 | 2.02 | 8.13 |
| 121 | Industrial or commercial units | 0.18 | 0.03 | 0.07 | 0.12 | 0.79 |
| 133 | Construction sites | 0.00 | 0.01 | 0.00 | 0.03 | 0.07 |
| 211 | Non-irrigated arable land | 77.25 | 94.25 | 95.82 | 95.82 | 79.31 |
| 222 | Fruit trees and berry plantations | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 |
| 231 | Pastures | 12.10 | 2.36 | 1.87 | 1.76 | 10.19 |
| 242 | Complex cultivation patterns | 1.07 | 0.18 | 0.15 | 0.18 | 1.23 |
| 243 | Land principally occupied by agriculture, with significant areas of natural vegetation | 2.08 | 1.25 | 0.01 | 0.01 | 0.06 |
| 321 | Natural grasslands | 0.91 | 0.14 | 0.00 | 0.00 | 0.00 |
| 411 | Inland marshes | 0.16 | 0.03 | 0.01 | 0.01 | 0.01 |
| 511 | Water courses | 0.00 | 0.00 | 0.04 | 0.04 | 0.21 |

Source: Data's from CLC 1990, 2000, 2006, 2012 and 2018.

In order to better understand how to change the land cover, a series of remote sensing satellite scenes from the Landsat 8 system were also used in this study.

For this purpose, satellite scenes were downloaded between 2017 - 2020, July-August, and analysed the distribution of NDVI indices, Figure 5, NBR, Figure 6 and NDBI, Figure 7.

From the analysis of the data from 2018, a high correlation was identified between NBR, NDBI and NDVI indices.

Regarding the statistical accuracy of the experimental analysis of the data, it was performed by appropriate mathematical and statistical methods (p, R2, test F).

To assess the interdependencies between NBR, NDBI and NDVI remote sensing indices, regression analysis was used which resulted in polynomial functions with related precision parameters.

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Table 5. Area change from 1990 -2018

| | **Change (1990 - 2018)** | **Area Change (ha)** | **Area Change (%)** |
|---|---|---|---|
| 1 | Complex cultivation patterns - Discontinuous urban fabric | 50,720 | 0.881 |
| 2 | Complex cultivation patterns - Non-irrigated arable land | 376,829 | 6.548 |
| 3 | Complex cultivation patterns - Pastures | 76,037 | 1.321 |
| 4 | Complex cultivation patterns - Water courses | 25,029 | 0.435 |
| 5 | Discontinuous urban fabric - Complex cultivation patterns | 132,446 | 2.301 |
| 6 | Discontinuous urban fabric - Construction sites | 0,669 | 0.012 |
| 7 | Discontinuous urban fabric - Industrial or commercial units | 33,817 | 0.588 |
| 8 | Discontinuous urban fabric - Inland marshes | 1,001 | 0.017 |
| 9 | Discontinuous urban fabric - Land principally occupied by agriculture | 2,293 | 0.040 |
| 10 | Discontinuous urban fabric - Non-irrigated arable land | 37,019 | 0.643 |
| 11 | Discontinuous urban fabric - Pastures | 28,116 | 0.489 |
| 12 | Discontinuous urban fabric - Water courses | 19,228 | 0.334 |
| 13 | Industrial or commercial units - Complex cultivation patterns | 50,258 | 0.873 |
| 14 | Industrial or commercial units - Discontinuous urban fabric | 3,647 | 0.063 |
| 15 | Industrial or commercial units - Pastures | 1,245 | 0.022 |
| 16 | Industrial or commercial units - Water courses | 4,324 | 0.075 |
| 17 | Inland marshes - Discontinuous urban fabric | 20,891 | 0.363 |
| 18 | Inland marshes - Non-irrigated arable land | 1,647 | 0.029 |
| 19 | Inland marshes - Pastures | 24,724 | 0.430 |
| 20 | Land principally occupied by agriculture - Complex cultivation patterns | 29,104 | 0.506 |
| 21 | Land principally occupied by agriculture - Discontinuous urban fabric | 20,691 | 0.360 |
| 22 | Land principally occupied by agriculture - Industrial or commercial units | 4,700 | 0.082 |
| 23 | Land principally occupied by agriculture - Non-irrigated arable land | 242,168 | 4.208 |
| 24 | Land principally occupied by agriculture - Pastures | 0,697 | 0.012 |
| 25 | Land principally occupied by agriculture - Water courses | 53,845 | 0.936 |
| 26 | Natural grasslands - Discontinuous urban fabric | 37,214 | 0.647 |
| 27 | Natural grasslands - Land principally occupied by agriculture | 1,001 | 0.017 |
| 28 | Natural grasslands - Non-irrigated arable land | 171,257 | 2.976 |
| 29 | Natural grasslands - Pastures | 340,681 | 5.920 |
| 30 | Non-irrigated arable land - Complex cultivation patterns | 361,933 | 6.289 |
| 31 | Non-irrigated arable land - Construction sites | 42,076 | 0.731 |
| 32 | Non-irrigated arable land - Discontinuous urban fabric | 1,087,295 | 18.893 |
| 33 | Non-irrigated arable land - Industrial or commercial units | 200,505 | 3.484 |
| 34 | Non-irrigated arable land - Inland marshes | 7,606 | 0.132 |
| 35 | Non-irrigated arable land - Land principally occupied by agriculture | 33,721 | 0.586 |
| 36 | Non-irrigated arable land - Pastures | 538,487 | 9.357 |
| 37 | Non-irrigated arable land - Water courses | 7,016 | 0.122 |
| 38 | Pastures - Complex cultivation patterns | 144,386 | 2.509 |
| 39 | Pastures - Discontinuous urban fabric | 159,790 | 2.777 |
| 40 | Pastures - Industrial or commercial units | 102,302 | 1.778 |
| 41 | Pastures - Land principally occupied by agriculture | 1,431 | 0.025 |
| 42 | Pastures - Non-irrigated arable land | 1,256,844 | 21.839 |
| 43 | Pastures - Water courses | 20,224 | 0.351 |

Source: original data obtained after GIS spatial analysis.

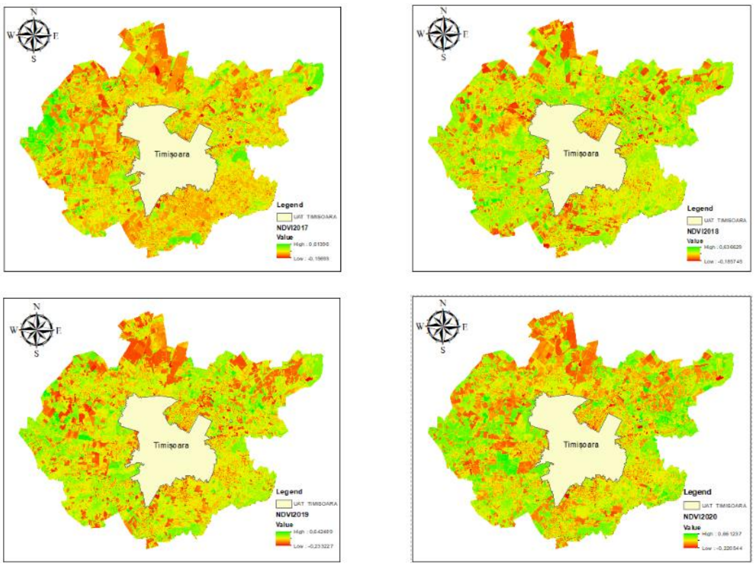


Fig. 5. The maps of NDVI 2017 -2020
Source: original images based on Landsat 8 Imagery.

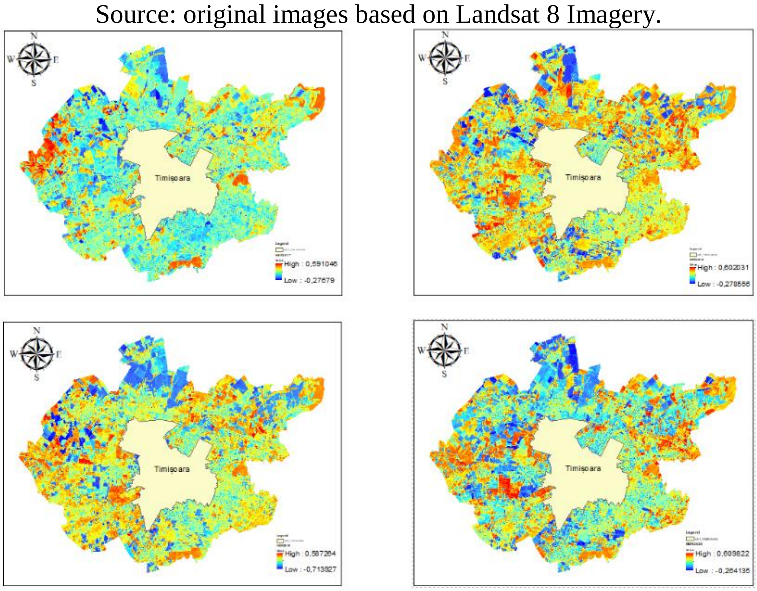


Fig. 6. The maps of NBR 2017 -2020
Source: original images based on Landsat 8 Imagery.

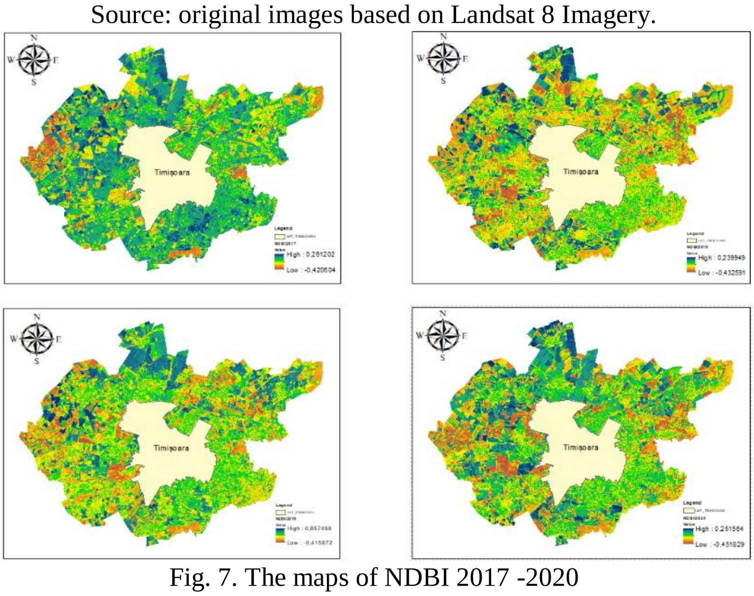


Fig. 7. The maps of NDBI 2017 -2020
Source: original images based on Landsat 8 Imagery.

Table 6. Remote sensing index values

| CLASS | NBR 2018 | NDBI 2018 | NDVI 2018 |
|---|---|---|---|
| 112 | 0.259186 | -0.12143 | 0.327436 |
| 121 | 0.234976 | -0.10488 | 0.280786 |
| 133 | 0.284165 | -0.11584 | 0.336997 |
| 211 | 0.286317 | -0.12514 | 0.348214 |
| 231 | 0.370533 | -0.17661 | 0.425699 |
| 242 | 0.303872 | -0.1427 | 0.362165 |
| 243 | 0.336919 | -0.1711 | 0.396058 |
| 411 | 0.446249 | -0.27733 | 0.45946 |
| 511 | 0.405585 | -0.232 | 0.429187 |

Source: original data obtained after calculated the remote sensing indexes.

The NDVI index, used to characterize the vegetation, had average values between 0.28078 - 0.45946. The NDVI index recorded minimum values for category 121 - Industrial or commercial units and reached maximum values for category 231 - Pastures and category 411 - Inland marshes.

The NBR index used to evaluate the combustion potential based on multispectral satellite data had values between 0.23497 - 0.44624. The minimum values recorded for the NBR index were recorded in the land cover category 121 - Industrial or commercial units to reach the maximum values in category 411 - Inland marshes and 231 - Pastures.

The NDBI index used to map the built-up urban areas had values between -0.2773 - -0.10488. The minimum values recorded for the NDBI index were recorded in the land cover category 411 - Inland marshes to reach the maximum values in category 121 - Industrial or commercial units.

The statistical correlation analysis revealed the high level of correlations between NBR, NDBI and NDVI indices for the periurban area of Timișoara Municipality. High correlations were identified between NBR, NDBI and NDVI indices, namely -0.97351 between NBR and NDBI, 0.977785 between NBR and NDVI and -0.92114 between NDBI and NDVI. Given the high level of correlations between the analysed index, the regression analysis was used to evaluate the predictive relationship of each index based on the spectral values of the other 2 indices.

Prediction for NDVI values based on spectral data recorded for NBR and NDBI was possible with high statistical accuracy: $R2 = 0.985$; $p <= 0.001$ for NBR, equation (4), respectively $R2 = 0.942$; $p <= 0.001$ for NDBI, equation (5).

$$NDVI_P = -2.363x^2 + 2.412x - 0.1503 \quad (4)$$

where: $NDVI_P$ – predicted NDVI; x - NBR.

$$NDVI_P = -6.36x^2 - 3.307x + 0.02324 \quad (5)$$

where: $NDVI_P$ – predicted NDVI; x - NDBI.

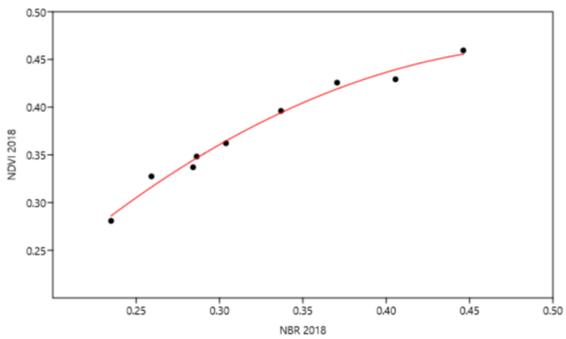


Fig. 8. Relation of dependence between NDVI - NBR for the study area

Source: original graph based on data from Table 6.

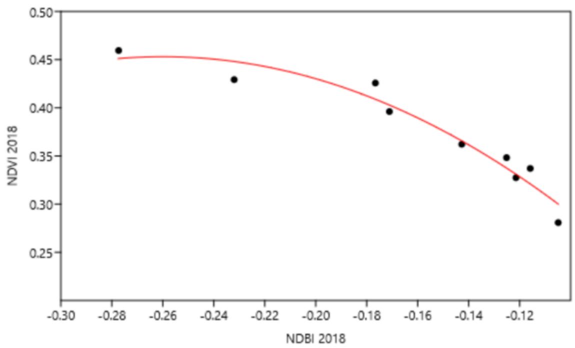


Fig. 9. Relation of dependence between NDVI – NDBI for the study area

Source: original graph based on data from Table 6.

The PCA analysis of the distribution of NDVI classes, for the studied area, according to NDBI and NBR, is shown in Figure 7. PC1 explained 97.507% of variance, PC2 explained 2.2792% and PC3 explained 0.21412% of variance. The multivariate analysis facilitated the grouping of the results according to the calculated remote sensing indices and the land cover categories in the peri-urban area, based on Euclidean distances, figure 8, with a high statistical precision, cophenetic index value being 0.7298.

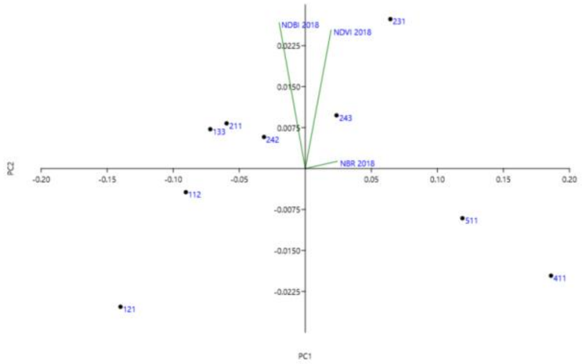

Fig. 10. PCA scatter diagram
Source: original image based on experimental data.

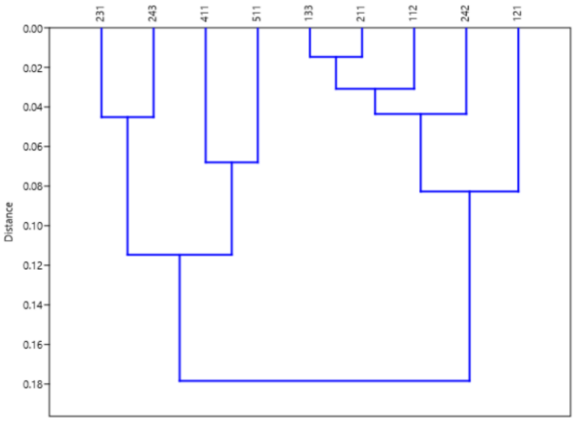

Fig. 11. Dendrogram of cases studied based on Euclidean distances
Source: original image based on experimental data.

## CONCLUSIONS

From the analysis of the data from 1990 to 2018, based on the GIS spatial analyses, the following conclusions could be drawn: About 5,700 hectares have changed their destination. The most significant changes were the change from the category of Pesterers in Non irrigated arable land (21.8% - 1,256 ha) and the change from the category Non irrigated arable land to Discontinuous urban fabric (18.9% - 1,087 ha) this leading to the conclusion of urbanization to this periurban area of Timisoara Municipality, but also to the development of the agricultural field.

The science of the Geographic Information Systems together with the Remote sensing imagery can be used by the local administrations of the periurban localities of the major cities of Romania in order to monitor how the use of the land is changing and to predict the future directions of development of these areas.

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