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An advanced classification method for urban land cover classification

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SUMMARY

This manuscript presents a detailed comparative analysis of three advanced classification techniques that were used between 2018 and 2020 to classify land cover using Landsat8 imagery, namely Support Vector Machine (SVM), Maximum Likelihood Classification (MLSC), and Random Forests (RF). The study focuses on evaluating the accuracy of these methods by comparing the classified maps with a higher-resolution ground truth map, utilising 500 randomly selected points for assessment.

The obtained results show that, compared to MLSC and RT, the Support Vector Machine (SVM) approach performs better. The SVM model demonstrates enhanced precision in land cover classification, showcasing its effectiveness in discerning subtle differences in landscape features.

Furthermore, using the precise classification results produced by the SVM method, this study examines the temporal variations in land cover between 2018 and 2020. The results provide insight into dynamic land cover changes and highlight the significance of applying reliable classification techniques for thorough temporal analysis with Landsat8 images.

Keywords: *land cover classification; Landsat8; accuracy assessment; remote sensing; landscape dynamics*

INTRODUCTION

Classifying land cover entails mapping and classifying various surface features and materials across landscapes. It is a crucial aspect of remote sensing and geographical analyses (Hermosilla et al., 2022). It serves as a critical tool in understanding the distribution, dynamics, and changes in natural and anthropogenic environments, by utilizing satellite or aerial imagery coupled with advanced algorithms, such as Support Vector Machine (SVM), Maximum Likelihood Classification (MLSC), and Random Forests (RF) (Powell et al., 2010).

Selecting the best land cover classification method is crucial for environmental research and remote sensing applications. The method used has a major impact on the precision, dependability, and accuracy of land cover maps created from satellite images (Mohamed Abdi, 2019). Precise classification facilitates the identification and monitoring of changes in landscapes, hence empowering knowledgeable decision-making across multiple domains, such as agriculture, forestry, urban growth, and planning, and conservation efforts (Belenok et al., 2021). Moreover, it facilitates the understanding of ecosystem dynamics, the assessment of environmental impacts, and habitat mapping. Whether it's RF, MLSC, SVM, or another algorithm, choosing the best method has a direct effect on the quality of data that can be extracted from imagery. This increases the usefulness of land cover classification in addressing modern environmental challenges and directing sustainable resource management practices. (Jamali, 2021).

This paper provides a thorough analysis of three different classification techniques: SVM, MLSC, and RF. These techniques were used to classify land cover of Debrecen with Landsat8 satellite images for the years 2018 and 2020.

Evaluating the accuracy of classified maps is crucial in various fields and fundamental to remote sensing applications (Falkowski et al., 2009). Traditionally, overall accuracy (OA) and the Kappa coefficient have been the dominant metrics. However, recent studies have highlighted limitations associated with the Kappa coefficient, particularly its sensitivity to class prevalence. In scenarios where unbalanced class distributions exist, the Kappa coefficient can be misleadingly high, even if the model struggles to differentiate between specific, less frequent classes (Foody, 2020). Consequently, for a more robust assessment, in addition to Kappa index and OA our study incorporates the F1 score (Talha et al., 2023). The F1 score, derived from producer's and user's accuracy, provides a harmonic mean, balancing precision and recall, making it particularly suitable for imbalanced datasets (Yonaba et al., 2021). This combined approach using OA, kappa coefficient, and the F1 score offers a more comprehensive evaluation of our classified map's accuracy, especially when dealing with potentially uneven class distributions (Guizani et al., 2024).

Motivated by Debrecen's rapid urbanization and industrialization, this study investigates land cover changes between 2018 and 2020. This timeframe captures a critical period of urban sprawl and industrial development, as highlighted by the increasing suburban and periurban populations (Pénzes et al., 2023) and significant land cover modifications due to industrial investments (large water and labor-intensive automotive and battery industry facilities) (Iváncsics and Kovács, 2021). These changes, particularly the loss of valuable farmland, pose challenges for Debrecen's hydrology and resource management. This timeframe

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includes significant variations in land use, natural events, and human-caused alterations. Leveraging the precision of the selected classification technique, this study aims to dissect and interpret the nuanced alterations in land cover over for this two-year interval using Landsat8 imagery. By analyzing land cover changes between 2018 and 2020, we aim to establish a foundation for future land cover monitoring in Debrecen. This will be crucial for informing sustainable urban development strategies that balance economic growth with environmental protection.

In essence, this manuscript represents an extensive examination of sophisticated classification techniques for land cover characterization, assessing accuracy, and also examining the temporal dynamics of land cover changes from 2018 to 2020.

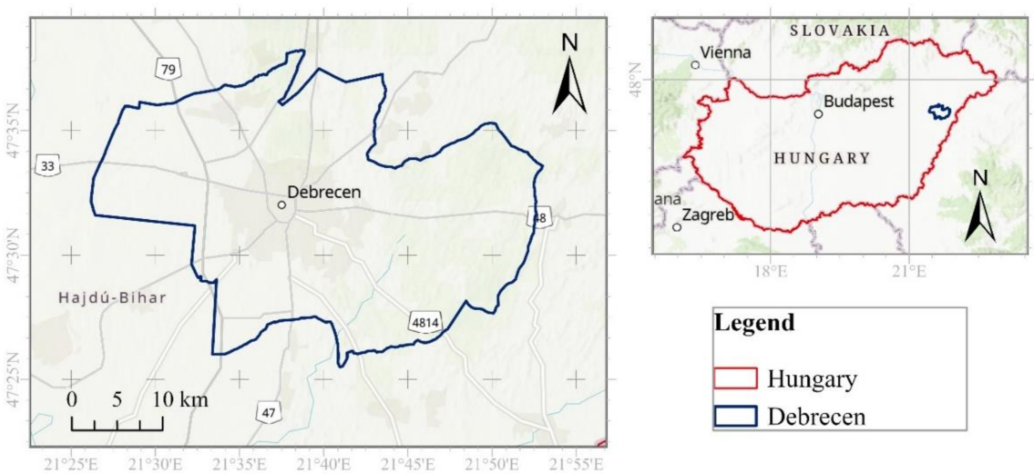
MATERIALS AND METHODS

Description of the study area

Debrecen, situated in eastern Hungary (*Figure 1*), present a diverse land cover types, characterized by a blend of urbanized areas, agricultural expanses, and natural features. The city serves as a regional hub amidst a landscape where urban zones, industrial sectors, residential areas, and commercial districts intermingle. While the city center showcases urban developments, including modern infrastructure and historic sites, the outskirts gradually transition into agricultural fields and green spaces. Surrounding the urban fabric, there are pockets of parks, natural areas, and woodlands, contributing to the city's ecological diversity.

Debrecen's land cover shows a harmonious combination of natural landscapes and human habitation. It includes cultivated lands for agriculture, encompassing fields for crops and pastures. Additionally, there are patches of green areas and forests, contributing to the city's environmental health and recreational spaces. Efforts in urban planning and land management in Debrecen aim to sustain this balance, emphasizing the preservation of green spaces, promoting sustainable land use practices, and addressing challenges related to urban growth while preserving natural habitats and agricultural lands (STRATEGY 24).

Figure 1. **Geographic location of Debrecen**



Satellite Data

In our study, we employed Landsat 8 satellite imagery captured during the years 2018 and 2020, specifically selecting images with less than 20 percent cloud cover. Leveraging these high-resolution satellite images provided us with comprehensive and consistent datasets to analyze land cover dynamics over the specified timeframe. The careful selection criteria ensured minimal interference from atmospheric conditions, enabling a clearer view of the landscape changes within our study area.

Landsat 8: Since 1974, the USGS National Land Imaging (NLI) Programme, of which the Landsat Programme is a part, has guaranteed data continuity, dependability, and comparability. The spatial resolution of Landsat is 30 meters (Bolton et al., 2020).

For accuracy assessment and analysis, we harnessed the power of Google Earth Engine, a robust platform that facilitated efficient processing, visualization, and analysis of the vast Landsat imagery datasets. This platform offered extensive computational capabilities, allowing us to perform sophisticated image processing techniques, classification algorithms, and accuracy assessments at scale. Google Earth Engine's tools and functionalities provided a streamlined and efficient workflow, enabling us to conduct a thorough and reliable evaluation of land cover classification accuracy across our study area at multiple points in time (Biswas et al., 2023).

These key methodologies, utilizing Landsat 8 imagery with limited cloud cover and leveraging the capabilities of Google Earth Engine for accuracy assessment, formed the cornerstone of our study, ensuring the reliability and robustness of our land cover classification analyses between 2018 and 2020.

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Methodological Framework for LULC Classification

This study employed ArcGIS Pro in conjunction with Landsat 8 imagery for the temporal periods of 2018 and 2020 to conduct Land Use and Land Cover (LULC) classification. Three distinct classification algorithms, namely SVM, MLSC, and RF, were implemented for each respective year. To validate the accuracy of the classification results, ground truth points sourced from Google Earth Engine were utilized (*Figure 2*). The LULC classes considered in this analysis comprised Forest, Developed/Urban areas, Crop covered areas, Grasslands, Surface water bodies, and bare ground (*Table 1*). The integration of these methodologies allowed for a comprehensive assessment and comparison of the classification outputs across both temporal and algorithmic dimensions, facilitating a robust understanding of landscape changes and land cover dynamics over the specified periods.

Figure 2. **Methodology of LULC classification using ArcGIS Pro**

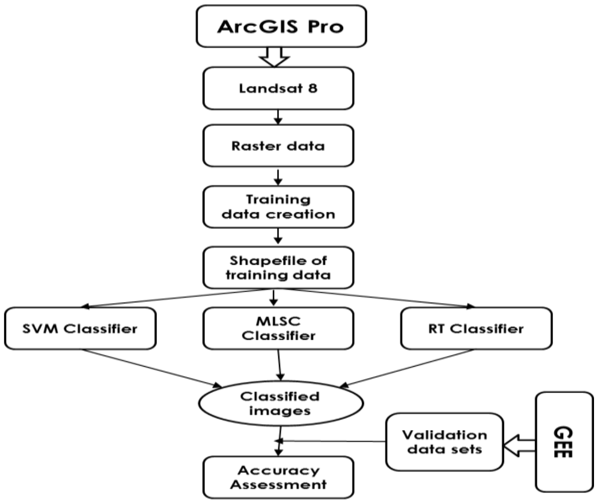


Table 1. **Name and description of LULC classes' scheme**
(Wang et al., 2023)

Class Name	Description of Class
Forest	Deciduous forest area, evergreen forest, mixed forest, residential forest
Developed/Urban	Residential, commercial, industrial, roads and transportation, communications, and utilities
Crop covered area	covered with herbage or grass, dominated by grass or grass-like vegetation
Grassland	covered with herbage or grass, dominated by grass
Surface water bodies	Lakes, and estuaries
Bare ground	Includes the soil or sand not covered by grass, sod, other live ground covers

Classification Methods

Using specific band combinations from Landsat 8 images, different training samples were obtained for every year in order to perform pixel-based supervised classification. In these training samples, every pixel was carefully defined into a particular LULC class. The LULC classification in this investigation was performed using the following classifiers:

- Support Vector Machine (SVM) is a supervised machine learning algorithm used for both classification and regression. Though we say regression problems as well its best suited for classification. The main goal of the SVM algorithm is to find the ideal hyperplane in an N-dimensional space that can distinct the data points in different categories in the feature space (Chi et al., 2008).
- Maximum likelihood classification assumes that the statistics for each category in each band are normally distributed and calculates the probability that a given pixel belongs to a specific class. All pixels are categorised unless a probability threshold is chosen. (Chowdhury, 2024).
- The Random Forest Classifier is a common machine learning method that was developed by Adele Cutler and Leo Breiman. This technique combines the output of multiple decision trees to reach a single result (Breiman, 2001).

Accuracy Assessment

The accuracy assessment of LULC classification using ground truth points involves comparing the classified data, originating from Landsat 8 satellite imagery using the three classification algorithms SVM, ML, and RF, with reference data derived from Google Earth Engine. (Foody, 1992).

- Ground Truth Data Collection: Collect 500 ground truth points from Google Earth Engine representing different land cover classes across our study area.

DOI: 10.34101/ACTAAGRAR/1/13652

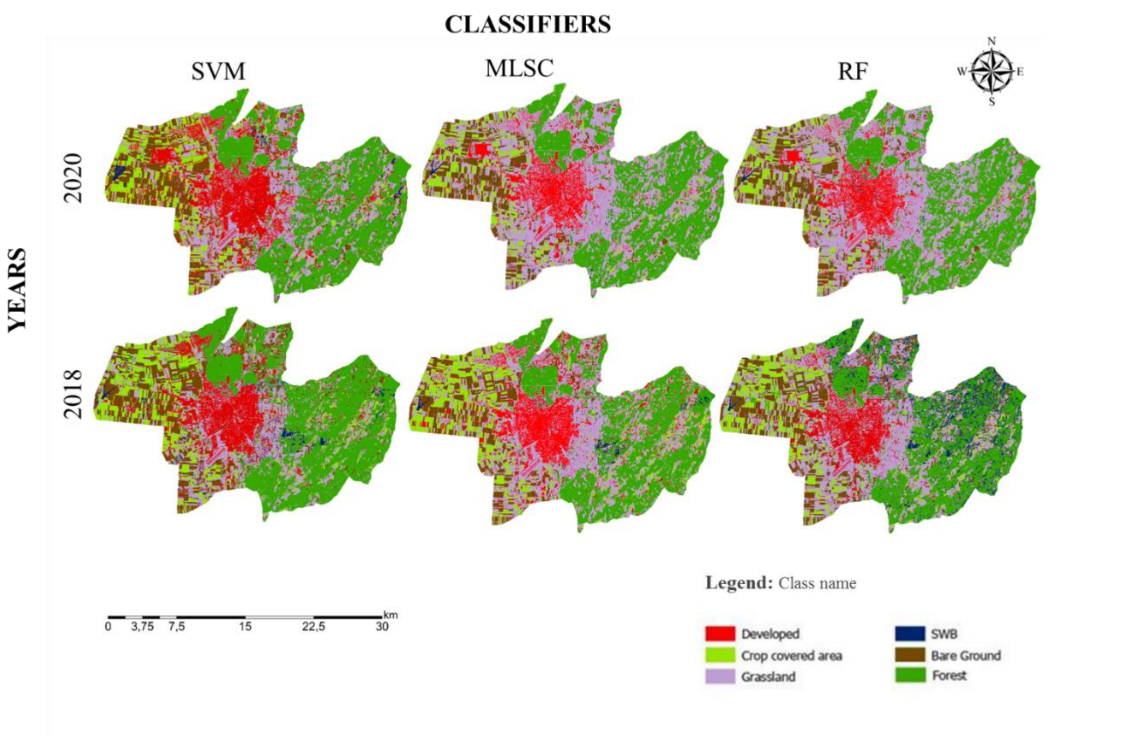
- Classification Using Remote Sensing Data: Using classification algorithms (SVM, ML, RF) to classify the Landsat 8 satellite image, creating a classified land cover map.
- Comparison with Ground Truth Data: Compare the classified land cover map with the ground truth points. Each ground truth point has a known land cover class.
- Error Matrix Calculation: Develop an error matrix or confusion matrix that summarizes the agreement and disagreement between the classified and ground truth data. This confusion matrix allows computation of various accuracy metrics, including Kappa index and the overall accuracy and F1 score.
- Calculation of Accuracy Metrics:
  – Overall Accuracy: This metric represents the percentage of correctly classified points over the total number of points.
  – Kappa Index: It evaluates the degree of agreement between the reference and classified data, taking into consideration any coincidental agreement. A higher Kappa index indicates better agreement beyond random chance.
  – F1 score: It is the metric used to assess the model performance by using harmonic mean of precision and recall together in single metric.
- Interpretation and Analysis: Analyze the accuracy metrics and error matrix to understand the performance of your classification methods. Identify areas of high accuracy and potential sources of errors, such as confusion between certain land cover classes or misclassifications.

RESULTS AND DISCUSSION

LULC Classification of Landsat 8 Imagery in ArcGIS Pro

The following *Figure 3* illustrates LULC maps created for the years 2018 and 2020 using Landsat 8 imagery and three distinct classification methods: SVM, MLSC, and RF. For 2018, the maps portray the classification outcomes for forest, crop-covered areas, developed regions, grasslands, surface water bodies, and bare ground using each respective method. Similarly, corresponding maps for 2020 exhibit the LULC classes delineated through SVM, MLSC, and RF methodologies. Each map provides a visual representation of the spatial distribution and extent of these six land cover categories, allowing for comparative analysis of the classification outputs across the two years and among the different classification algorithms employed.

Figure 3. **Land use land cover classification maps of Landsat8 images using SVM, MLSC, and RF classifiers for the years 2018 to 2020 in ArcGIS Pro**



Accuracy Assessment

The observed trend emphasizes SVM's robustness and effectiveness in handling the dataset over the two distinct time periods. The consistent higher Kappa index values of SVM, especially in 2020, suggest its enhanced capability to correctly classify instances compared to MLSC and RF. MLSC experienced a reduction in accuracy from 2018 to 2020, possibly indicating its sensitivity to changes in the dataset or specific characteristics within the later year. RF demonstrated marginal fluctuations but generally maintained its performance across both years.

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Across both years, SVM consistently demonstrated the highest Kappa index values, signifying its superior performance in accurately categorizing the data compared to MLSC and RF. In 2018, SVM yielded a Kappa index of 0.74, indicating substantial agreement, while MLSC and RF followed closely with 0.72 and 0.70, respectively. Notably, in 2020, SVM exhibited a further increase in accuracy, recording a Kappa index of 0.78, denoting substantial to almost perfect agreement, whereas MLSC showed a decrease to 0.64, and RF slightly increased to 0.73 (*Table 2*). In our analysis, we opted to calculate F1 scores for each land cover class across all classifiers (SVM, RF, and MLSC) for both 2018 and 2020 data. This decision stemmed from the recognized limitations of the Kappa coefficient for assessing accuracy in thematic maps, particularly when dealing with imbalanced class distributions commonly found in land cover datasets. F1 scores provide a more nuanced evaluation by considering both precision and user accuracy for each class, offering a superior measure of individual land cover class accuracy, detailed results of which can be found in *Table 2*.

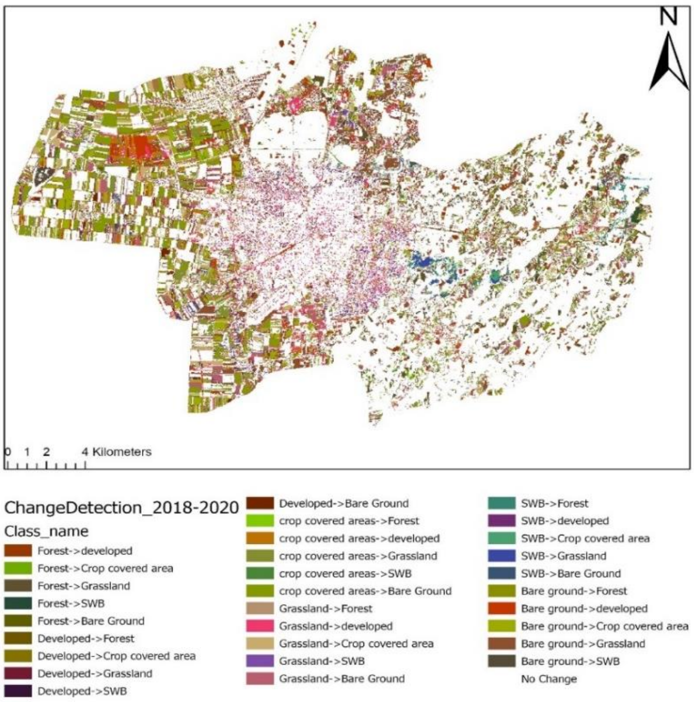
Table 2. **Overall Accuracy and F1 score (per Land cover class) of Landsat8 for SVM, MLSC, and RF classifiers using Arc GIS Pro**

Metrics used	Class Name	Years					
		2018			2020		
		Classifiers					
		SVM	MLSC	RF	SVM	MLSC	RF
F1 score	Forest	0,87	0,83	0,82	0,96	0,95	0,93
	Developed/Urban	0,88	0,67	0,77	0,75	0,44	0,71
	Crop covered area	0,75	0,78	0,73	0,63	0,52	0,52
	Grassland	0,72	0,80	0,76	0,88	0,67	0,84
	Surface water bodies	0,31	0,53	0,5	0,66	0,90	1
	Bare ground	0,87	0,78	0,86	0,70	0,72	0,69
Overall Accuracy (%)		**80**	**78**	**77**	**83**	**71**	**80**
Kappa Coefficient		**0.74**	**0.72**	**0.70**	**0.78**	**0.64**	**0.73**

Land use land cover Change Detection

The analysis of land use and land cover changes between 2018 and 2020 has revealed several significant alterations within the study area. Notably, these changes encompass shifts in the spatial distribution and extent of various land cover categories (*Figure 4*).

Figure 4. **Change dynamics between 2018 and 2020 using ArcGIS Pro**



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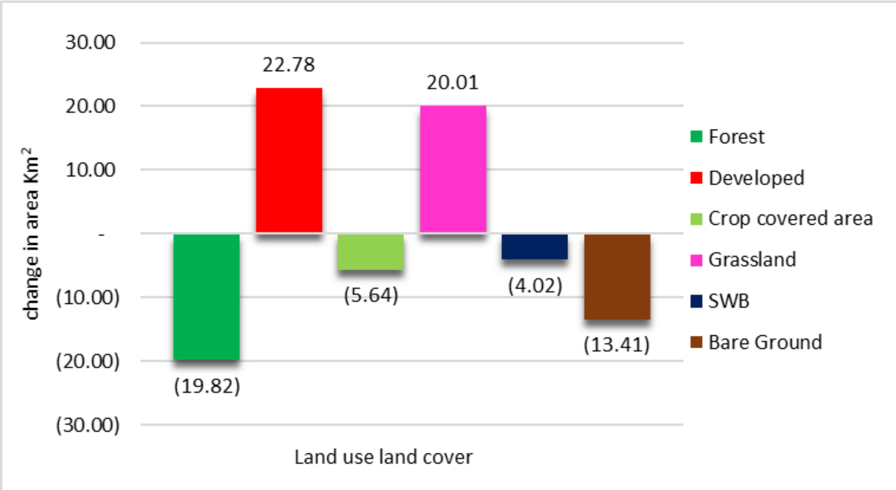
The recorded reduction of the forest cover by 19 km² within this timeframe signifies a concerning trend. Factors contributing to this decline could include anthropogenic activities like agricultural expansion or deforestation. The considerable increase in developed areas or urbanized by 22 km² indicates rapid infrastructural development or urbanization. The 4 km² decrease in surface water bodies indicates changes in hydrological patterns. Factors like land use changes impacting runoff, climate variability, or human activities affecting water bodies could contribute to this decrease. The decrease in bare ground areas by 13 km² might indicate land reclamation, vegetation regrowth, or changes in land management practices. Reduced bare ground could contribute positively to erosion control, soil stabilization, and ecosystem restoration. (*Figure 5*).

Figure 5. **Land cover change between 2018 and 2020**



CONCLUSIONS

Assessing land cover changes in Debrecen between 2018 and 2020 using ArcGIS Pro and Landsat 8 images proved enlightening. The ability to distinguish between land cover categories was demonstrated by testing the Support Vector Machine (SVM), Maximum Likelihood Supervised classification (MLSC), and Random Forests (RF) classification methods. SVM demonstrated robustness in accuracy, while MLSC and RF provided valuable insights despite minor variations. The combined approach facilitated a comprehensive understanding of land cover changing, emphasising the potential of using remote sensing methods for a comprehensive and precise land cover change analysis in the Debrecen region.

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REFERENCES

Belenok, V.; Noszczyk, T.; Liliia, H.B.; Sergiy, K. (2021): Investigating anthropogenically transformed landscapes with remote sensing. Remote Sensing Applications: *Society and Environment, 24*, https://doi.org/10.1016/j.rsase.2021.100635

Biswas, J.; Jobaer, M.A.; Salman F.; Haque, M.S.I.S.; Zamil A.L. (2023): Mapping and monitoring land use land cover dynamics employing Google Earth Engine and machine learning algorithms on Chattogram, Bangladesh. *Heliyon. 9*/11, https://doi.org/10.1016/j.heliyon.2023.e21245

Bolton, D.K.; Gray, J.M.; Melaas, E.K.; Moon M.; Eklundh, L.; Friedl, M.A. (2020): Continental-scale land surface phenology from harmonized Landsat 8 and Sentinel-2 imagery. *Remote Sens Environ, 240*, 111685, https://doi.org/10.1016/j.rse.2020.111685

Breiman, L. (2001): Random Forests. Kluwer Academic Publishers, *Machine Learning*, *45*, 5–32. https://doi.org/10.1023/A:1010933404324

Chi, M.; Feng, R.; Bruzzone, L. (2008): Classification of hyperspectral remote-sensing data with primal SVM for small-sized training dataset problem. *Adv. Space Res*, *41*, 1793–1799. https://doi.org/10.1016/j.asr.2008.02.012

Chowdhury, M.S. (2024): Comparison of accuracy and reliability of random forest, support vector machine, artificial neural network and maximum likelihood method in land use/cover classification of urban setting. *Environmental Challenges, 14*, https://doi.org/10.1016/j.envc.2023.100800

Falkowski, M.J.; Wulder, M.A.; White, J.C.; Gillis, M.D. (2009): Supporting large-area, sample-based forest inventories with very

DOI: 10.34101/ACTAAGRAR/1/13652

high spatial resolution satellite imagery. *Prog. Phys, Geogr, 33*/3, 403–423. https://doi.org/10.1177/0309133309342643

Foody, G. (1992): On the compensation for chance agreement in image classification accuracy assessment. *Photogramm. Eng. Rem. Sens, 58*, 1459–1460. http://pascal-francis.inist.fr/vibad/index.php?action=getRecordDetail&idt=4313997

Foody, G.M. (2020): Explaining the Unsuitability of the Kappa Coefficient in the Assessment and Comparison of the Accuracy of Thematic Maps Obtained by Image Classification. *Remote Sensing of Environment, 239*, Article ID: 111630. https://doi.org/10.1016/j.rse.2019.111630

Guizani, D.; Bódi, E.B.; Tamás, J.; Nagy, A. (2024): Enhancing water balance assessment in urban areas through high-resolution land cover mapping: Case study of Debrecen, Hungary. *Environmental Challenges. 15*, April 2024, 100906. https://doi.org/10.1016/j.envc.2024.100906

Hermosilla, T.; Wulder, M.A.; White, J.C.; Nicholas, C.C. (2022): Coops. Land cover classification in an era of big and open data: Optimizing localized implementation and training data selection to improve mapping outcomes. *Remote Sensing of Environment, 268*, https://doi.org/10.1016/j.rse.2021.112780

Jamali, A. (2021): Land use land cover mapping using advanced machine learning classifiers. *Ekológia* (Bratislava), *40*/3. https://doi.org/10.2478/eko-2021-0031

Mohamed Abd, A. (2019): Land cover and land use classification performance of machine learning algorithms in a boreal landscape using Sentinel-2 data. *GIScience & Remote Sensing, 57*/1, https://doi.org/10.1080/15481603.2019.1650447

Powell, S.L.; Cohen, W.B.; Healey, S.P.; Kennedy, R.E.; Moisen, G.G.; Pierce, K.B.; Ohmann. J.L. (2010): Quantification of live aboveground forest biomass dynamics with Landsat time-series and field inventory data: a comparison of empirical modeling approaches. *Remote Sens, Environ, 114*, 1053–1068. https://doi.org/10.1016/j.rse.2009.12.018

STRATEGY 24. (2022): Sustainable urban development strategy for Debrecen City 2021–2027. EDC Debrecen NGO, Available online: https://www.debrecen.hu/assets/media/file/hu/35689/fvs-megalapozo-debrecen-v02.pdf

Talha, M.; Farrukh, A.B.; Sajid, G.; Hamza, Z. (2023): ADU-Net: semantic segmentation of satellite imagery for land cover classification *Adv. Space Res., 72* (5) pp. 1780–1788. https://doi.org/10.1016/j.asr.2023.05.007

Wang, Y.; Sun, Y.; Cao, X.; Wang, Y.; Zhang, W.; Cheng, X. (2023): A review of regional and Global scale Land Use/Land Cover (LULC) mapping products generated from satellite remote sensing. ISPRS *Journal of Photogrammetry and Remote Sensing, 206*, 311–334. https://doi.org/10.1016/j.isprsjprs.2023.11.014

Yonaba, R.; Koïta, M.; Mounirou, L.A.; Tazen, F.; Queloz, P.; Biaou, A.C.; Niang D., Zouré C., Karambiri H., Yacouba H. (2021): Spatial and transient modelling of land use/land cover (LULC) dynamics in a Sahelian landscape under semi-arid climate in northern Burkina Faso. *Land Use Policy, 103*. Article 105305. https://doi.org/10.1016/j.landusepol.2021.105305.