THESIS OF DOCTORAL (Ph.D.) Dissertation

HydroGIS-based watershed management using land cover mapping and hydrological modeling for urban water balance assessment

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1- The antecedents and the objectives of the doctoral dissertation

Water is a fundamental natural resource that sustains ecosystems, drives economic activities, and supports public health and food systems (Michelle et al., 2021). Despite covering over 70% of the Earth's surface, usable freshwater is scarce and non-equally distributed, often leading to regional water scarcity (Frank & Benon, 2016). Over recent decades, increasing population, intensified agriculture, and especially rapid urbanization have intensified pressures on water availability and quality (Kintu et al., 2019). Climate change compounds these challenges by altering precipitation patterns, accelerating extreme events, and shifting hydrological regimes (Caldwell et al., 2012). Urbanization significantly modifies the natural hydrologic cycle. In the process of urbanization, permeable surfaces such as soil and vegetation are replaced by impervious materials that disrupt key hydrological parameters. The modification leads to increased surface runoff (RO), reduced infiltration, and altered evapotranspiration (ET) processes, causing urban flooding, groundwater depletion, and poor water quality (Weng & Lu, 2008). Also, impermeable cover affects the time of concentration (time it takes for runoff to reach the watershed outlet) leading to faster, more intense peak flows and an increased risk of flash flooding (Guizani et al., 2022). These implications call for better urban planning and water management approaches anchored to reliable and timely land cover (LC) information. Some traditional LC datasets like the Urban Atlas and Corine Land Cover (CLC) can provide helpful regional baselines; however, given their low temporal and infrequent updates, their application is less effective in a constantly changing urban environment (Poleman, 2018). To do this, combining remote sensing (RS) and GIS-based hydrological modelling provides an effective scalable and higher-resolution framework for monitoring LC alterations as well as assessing water-related affects (Schott, 2002; Chemak et al., 2022). The increasing availability of high-resolution satellite imagery from Landsat 8 (L8) and Sentinel-2 (S2), along with advanced machine learning classifiers: such as Maximum Likelihood Classification (MLC), Random Forest (RF), and Support Vector Machine (SVM), has enabled more accurate and efficient LC classification in urban contexts (Al Kafy, 2023). These tools allow for multi-temporal analysis to detect and quantify LC change, which is essential for assessing urban impacts on hydrological processes such as runoff generation, infiltration loss, and ET variation (Qingyan et al., 2021).This dissertation focuses on the second-largest city in Hungary, Debrecen, which serves as a regional development center and has experienced considerable urbanization and industrialization since 2018. Investments in construction have recently altered the land surface by building new factories, commercial areas, and residential areas (Tamás et al., 2019; Guizani et al., 2024). As natural and agricultural lands continue to be constructed upon, built-up areas have lost parcelized such that forests, wetlands, and agriculture are today predominantly impervious surfaces, dramatically altering drainage networks, soil and water quality, and contributing to flood risk. Conclusions, actions to mitigate and adapt in areas where construction is replacing natural and agricultural lands will require detailed hydrologic assessment that amalgamates LC classification and watershed-scale modeling. At an equal level, Debrecen's urban development is resulting in the loss of productive crop-covered land and food security in the process. As urbanization of agricultural land occurs, it threatens to hinder the city's capacity to provide areas for local food production (Molnár & Kozma, 2018; Pénzes et al., 2023; Iváncsics & Kovács, 2021). Furthermore, knowledge of the morphometric and physiographic characteristics of watershed parameters in order to understand the conceptual mechanisms by which urbanization changes hydrological responses (Guizani et al., 2022). These parameters alter the way rainfall is converted to surface runoff and modify the speed of water as it is conveyed through each part of the system. The analysis of Debrecen's sub-watersheds improves hydrological simulations and can improve estimation of the urban water balance. In summary, this dissertation presented an integrated framework developed through analyzing LC classification, multi-sensor RS, ML, watershed morphometry, hydrological modeling, and urban agriculture that can address the multi-faceted issues of urbanization, hydrology, and food security. Although the focus of the research was Debrecen, the methodology is transferrable and scalable to any fast-growing urban area that is experiencing similar water pressures. In this context, the research is guided by the following aims:

1. To develop and test a robust and adaptable framework for rapid and quasi-real-time LC mapping in fast-developing urban environments, using Debrecen as a model city.
   - Design a replicable LC mapping workflow based on the MLC method.
   - Evaluate the adaptability and transferability of the proposed framework to other urban contexts.

2. To assess the effectiveness of multi-sensor remote sensing data combined with machine learning algorithms in enhancing the accuracy of LC classification in dynamic urban landscapes.
    - Investigate the contribution of multi-sensor satellite data to enhancing the accuracy and spatial detail of LC classification in urban environments.
    - Compare the performance of various machine learning algorithms and identify the most suitable classification method in enhancing classification outcomes across dynamic urban areas.
3. To develop an integrated hydrological modeling framework by assessing watershed characteristics and incorporating LC dynamics for enhanced urban water balance estimation in the Debrecen region.
    - Evaluate the morphometric and physiographic attributes of the Debrecen watershed and its sub-watersheds to strengthen hydrological modeling and analysis.
    - Integrate classified LC maps into pixel-scale hydrological modeling in order to refine water balance estimation temporally and spatially across urban and peri-urban landscapes.
4. To quantify LC changes and related hydrological and crop yield parameters in Debrecen, with a particular focus on urban expansion and the associated decline of agricultural areas, in response to rapid urbanization dynamics observed between 2018 and 2022.
    - Conduct multi-temporal LC change detection to identify and map spatial patterns of urban expansion and agricultural land loss between 2018 and 2022.
    - Quantify the extent and rate of LC transitions, highlighting the impact of urban growth on the surrounding agricultural landscape.
    - identifying yield loss due to urbanization

2. MATERIAL AND METHODS

2.1. Description of the research areas

Geographic and Urban Characteristics

With a surface area of 461.25 km² and a population of over 200,000 residents, Debrecen is Hungary's second largest city. Debrecen is located in the Northern Great Plain region of Hungary, close to the eastern edge of the European Union, and has the central functions of administration, commerce, and education (Tamás et al., 2019). The recent dominant trend of industrialisation within the region since 2019 has expanded urban landuse significantly to include over 1200 ha of newly designated land (Molnár & Kozma, 2018). Most estimates predict an increase of 30,000–50,000 additional people to the urban centre by 2050 (STRATEGY 24). These expansions will significantly change land cover and hydrology.

Climate and Environmental Conditions

Debrecen exhibits a humid continental climate, with average annual precipitation of 546 mm, and considerable seasonal variability. The warmest months are July–August, and the coldest is January. Solar radiation is higher than 680 MJ/m² during summer, and the average yearly wind speed is 3.03 m/s (Szász et al., 2013). Climate data from 1991–2022 show hot temperature events and rainfall variability were increasing, which impact urban water balance, RO generation, and ET.

Topography and Soil Properties

A low hill and parabolic dunes are in the eastern part of an alluvial fan plain. Elevations range from 97 to 161 m (ASTER, 2013). The soil texture in the study area consists of loam, sand, clay and peat with loam and sand being the dominant forms (Bakacsi et al., 2014). Soil properties landforms are a key influence on water infiltration and retention, which was vital in hydrological parameterisation and RO modelling.

2.2 Watershed Parametrization

The time of concentration (Tc) is an important hydrological measure that indicates how quickly runoff from the furthest distance takes to travel to the watershed outlet (Welle & Woodward, 1986). Tc incorporates characteristics of the terrain, LC, and slope, with values nearer to zero indicating steeper basins or those with intensive urban LC. For the purposes of this study, Tc was calculated from Kirpich's empirical equation that was deemed appropriate for small to medium ungauged basins (Edris et al., 2016). This method requires 2 inputs: flowing length (L) and elevation difference (H). Both of these inputs were assessed from a high resolution DEM derived from GIS tools. The watershed compactness co-efficient (Kc) was also calculated in this study. Water moves and reacts differently depending on the configuration of the basin. Compact basins (low Kc) tend to react faster than elongated basins (high Kc). In this study, Tc and Kc were calculated for each sub-watershed.

2.3. Method for Rapid and quasi real time LC mapping framework

2.3.1 Design of a Replicable LC Mapping Workflow Using the MLC Method

To assess Debrecen’s water balance, L8 imagery (2013–2019) was integrated with Urban Atlas and CLC datasets. Scenes from WRS path/row 186/27 (cloud cover <35%) were selected during peak vegetation (Jun–Sep) for classification accuracy (Yan et al., 2023). L8 (30 m, 16-day revisit) and S2 MSI (10 m, 13 bands) were used due to their complementary spectral-spatial advantages (Acharki, 2022). Pre-processing included layer stacking, NDVI masking (threshold: 0.3), and composite generation (Lemenkova, 2014). MLSC was applied to L8 data (Ali et al., 2018; Medina and Beatriz, 2018). Based on prior studies, 210 training samples from 7 LC classes were selected using ROIs and NDVI support (Zhou et al., 2022). Urban Atlas helped differentiate sealed vs semi-sealed surfaces (Barranco et al., 2014). MLSC's efficiency in structured datasets and its long usage history supports its continued relevance despite noted limitations (Daba and You, 2022).

2.3.2 Evaluation of Framework Adaptability and Transferability

Validation of classification

After selecting training points, samples were assigned to LC classes and processed in ENVI v5.3 (Bruse & Fleer, 1998). Spectral separability was assessed using Jeffries–Matusita (JM) and Transformed Divergence (TD) indices (Padma & Sanjeevi, 2014), which range from 0 (no separability) to 2 (perfect separation) (Kavzoglu & Mather, 2000; Jia & Richards, 1999). TD and JM helped verify class distinction and minimize overlap. Values >1.9 indicate strong separability (Jensen, 2005). For the 2019 LC map, 70% of the points were used for training and 30% for testing. The high separability scores confirmed the quality of the ROIs and classifier reliability, supporting water balance modeling.

Accuracy Assessment of Classification

In evaluating classification reliability, confusion matrix-derived metrics were used: Overall Accuracy (OA), Kappa (K), F1 Score, Producer's (PA) and User's Accuracy (UA), and disagreement metrics (Q and A) (Pontius & Millones, 2011). A stratified random sampling was used, with 770 validation points ensuring class balance and at least ≥500 m between points to reduce the effects of spatial autocorrelation (Su et al., 2020). The availability of high-resolution reference data from Google Earth and the CLC allowed for visual assessment. We used OA and K, which are standard practice, but are typically biased due to the frequency of the classes; therefore, we also used Q and A disagreement, which are meant to consider errors in composition and location as agreed on. Evaluation was through TP, TN, FP, and FN (Sim et al., 2024).

2.4 Application of Machine learning algorithm in LC classification

2.4.1 Data sources

This research study incorporated multi-temporal L8 (OLI) and S2 (MSI) imagery from 2018, 2020, and 2022, respectively, obtained from the USGS Earth Explorer and Copernicus Open Access Hub. These data sources provided high spectral resolution and temporal resolution which was appropriate for LC classification. Major pre-processing tasks included atmospheric correction (LaSRC for L8, Sen2Cor for S2), cloud/shadow masking (CFMask, SCL), and geometric correction to ensure spatial consistency. The image sets were selected for summer months (June–September) and had minimal cloud percentage (<35%) and WRS path/row: 186/27. The standardized pre- and post-processing protocol provided consistent, spatially coherent datasets for classification using ML methods.

2.4.2 Training Data and Validation

2018, 2020, and 2022 all used a consistent training methodology, incorporating the validated process used for the 2019 L8 classification. After stratifying and labeling points few of the sample points, they were split into 70% for training and 30% for validation, which is common practice to prevent bias when validating the model with the separate sample point testing (Martinez-Sanchez et al., 2024). The spectral band combinations for S2 and L8 provided the best separation for classes comparatively. There were two indices used to objectively test spectral separability: J–M and TD, with set thresholds that were also consistent across the years. The methodology and standards across the years allow for dependable LC classifications and a relatively comparable result as best as possible temporally (Guizani et al. 2024).

2.5 Integrated Tool Development and Hydrological Coefficient Analysis for Improved Urban Water Balance Estimation in Debrecen

2.5.1 Description of the tool developed.

In order to calculate urban water balance, a simplified, pixel based approach enables hydrological coefficients to be derived in relation to LC class. For RO coefficients, region-based RO coefficients were instead used. For ET, Turc's empirical method was used. Then, infiltration could be derived through the water balance equation. This has allowed the integrated tool to be used as a framework to allow water resource analysis for urban contexts in Debrecen with spatially explicit estimates of RO, ET and infiltration (Turc, 1961; Diouf et al., 2016).

3.5.2. Calculation of hydrological coefficients.

Evapotranspiration

To assess evapotranspiration, the study utilized Turc’s empirical method which only uses two variables: mean annual temperature and precipitation. The precipitation input was calculated using the Precipitation Median Method (PMM), which takes the minimum and maximum annual precipitation recorded in the area and averages them. In Debrecen, the median precipitation was approximately 589.9 mm, while the mean annual temperature ranged from 11.1 °C to 12.5 °C. These climatic inputs were then used for deriving the average annual reference evapotranspiration for the study area (Turc, 1961; Osorio et al., 2014). Following this, the reference ET was adapted to each given LC category according to crop coefficients that consider differences in surface characteristics, vegetation types, and land use type. Forest areas were assigned values of 1, indicating full evapotranspiration activity, and sealed surfaces such as roads or buildings were assigned low coefficients, close to zero, as they have little involvement in ET activity. The semi-sealed surfaces have coefficients given according to an average of the type of surface they include, which would be parks and mixed-use (Tallis et al. 2013).

By multiplying the reference ET by the crop coefficient of each LC class, the final ET values were determined for each category. This approach allowed for a detailed spatial representation of evapotranspiration behavior across Debrecen's landscape, tailored to the local climate and surface conditions.

Runoff

Runoff coefficients were calculated using the Kenessey method (1928, 1930), based on three landscape factors: slope (α_1), soil permeability (α_2), and vegetation cover (α_3). Each of these factors is one of the physical characteristics that help generate RO. The slope factor (α_1) measures the water flow due to terrain steepness. Generally, the steeper the slope, the larger the RO. Soil permeability (α_2) measures the infiltration capacity of soil based on its characteristics and structure. Soils with greater permeability allow greater infiltration into the soil and less RO. The last factor is vegetation cover or sterility (α_3) and describes surface conditions. The litter and components of, herbaceous, shrub, and tree vegetation will usually be higher than other surfaces; therefore lower RO. On the other hand, bare earth areas or impervious surfaces will usually be higher in RO than vegetated surfaces. Values for these factors were gathered from available datasets and reference tables prepared and standardized for conditions in this region of Eastern Europe. This was intended to provide some level of relevance to the geomorphology and land use close to Debrecen. The total RO coefficient for each LC class was derived from the sum of those three α values (it was designed to be a physically based measure of RO control and location specific for Debrecen).

Infiltration

Infiltration is highly influenced by soil texture and urban soil compaction, is a complicated and variable factor that can be challenging to measure directly. To resolve this issue, infiltration was estimated in an indirect way through a water balance approach. Infiltration could be treated as an unknown in the water balance. Total precipitation was divided into three parts: RO, infiltration, and ET that was related to each of the LC classes. RO and evaporation rates were estimated based on the land use specific coefficients, while infiltration was calculated as a residual of the water balance. The method follows the approach of Batelaan and De Smedt (2001), wherein infiltration is calculated as the difference between total precipitation and the sum of RO and ET calculated for each LC class based on the average amount of constituent coefficients and respective surface areas for each land use class. The study developed fair relative indicators of hydrologic processes across the watershed based on land use specific coefficients for spatially explicit estimates of infiltration without needing direct soil measurement of infiltration.

2.6 Method to detect LC change and its impact on crop yield

2.6.1 LC Classification and Change Detection

Despite the rapid urban and industrial expansion of Debrecen (Pénzes et al., 2023), LC change research is still limited (Szilassi, 2017). There are multiple methodologies for detecting changes in LC, the process of comparing multi-temporal satellite images remains a feasible and effective solution to support LC change research (Boriah, 2010). This study quantified the urban expansion that occurred between 2018 and 2022, and the best performing LC maps were selected based on accuracy assessments. Transitions from non-urban to urban LC classes were the primary focus of mapping and measuring the implications of industrialization on urban sprawl. During the study, we engaged trajectory analysis from Bilintoh et al. (2024) to help conceptualize and characterize LC changes over time, whereby transitions between LC classes were classified as Gain, Loss, Stability, and Alteration on a pixel-wise basis. This informed not only the discoveries of continued development, but also changes in development. The analysis was conducted through the free access Trajectories R package to clarify the time-stamped LC changes associated with long- and short-term urban change to help raise the level and quality of evidence for planning.

2.6.2 Crop Yield Data and Trend Analysis

To understand the interactions between urbanization and agricultural output, crop yield statistics were obtained from the Hungarian Central Statistical Office for Hajdú-Bihar County. The dataset spans from 2000 to 2024, and the critical indicators for wheat and maize were harvested area (ha), production (tons) and yield (kg/ha). Crop yields were based on county statistics, as data for Debrecen was not available; however, the relationship between urban expansion and the agriculture trends seen in the region within Hajdú-Bihar County likely reflects changes in landscape characteristics influencing agricultural trends within Debrecen much more closely than rural areas in Hajdú-Bihar. The dataset was characterized descriptively to visualize the trends over time in yields, production and area seeded; and the yield and area of cultivated cropland were then compared with the LC change data to observe influences of urban expansion on agricultural products over time. This comprehensive spatial-statistical method provides a good approach to understanding how landscape changes may be affecting regional agri-food systems.

3. Results and Discussion

3.1. Watershed Parametrization and Morphometric Analysis

3.1.1 Delineation and Division of Sub-Watersheds

Utilizing a 30 m DEM and ArcGIS hydrological tools we delineated 9 sub-watersheds in the Debrecen region from flow direction and accumulation analysis. These units have a total area of 1488 km² and serve as the basis for monitoring water quality, hydrological modelling, and morphometric analysis. We derived key physical characteristics area (A), perimeter (P), and length (L) using zonal statistics and spatial statistics to perform simulations of RO and watershed response. Table 1 provides a summary of the physiographic features of each sub-watershed, which are important information for the calculation of compactness, shape, and time of concentration.

Table 1. Physiographic characteristics of the 9 sub-watersheds.

Id	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
P (km)	69.7	28.97	45.53	144.09	221.57	46.56	113.22	25.03	59.351
A (km^2)	50.34	12.85	46.57	214.56	710.34	44.30	324.19	12.238	72.83
L (km)	14.19	3.1	9.59	50.35	69.19	11.93	34.37	1.39	14.8

3.1.2 Morphometric Characterization: Gravelius Compactness Index and Basin Form

The GC was employed to provide an understanding of the determined areas and perimeters of the 9 sub-watersheds in Debrecen, which were obtained by using ArcGIS. GC = 1 signifies a circular basin, and higher values indicate more elongated shapes. SB-5, which accounts for 48% of area (SB-5 has the longest main channel, 69.19 km), followed by the smaller sub-watersheds, SB-2 and SB-8 (<13 km² in size). All GC values which exceed 1.77 indicate rectangular or elongated geometry. This type of geometry tends to slow runoff concentration means lower peak flow, and lagging flood times. These results are also important for future consideration and management of urban water and agricultural water systems.

3.1.3 Estimation of Time of Concentration for Sub-Watersheds

The Tc is an important parameter because it reflects the time it takes for a watershed RO to reach the outlet, and will affect peak flow and risks associated with flooding. Tc for the nine delineated sub-watersheds in the City of Debrecen was estimated used the Kirpich which is suited for watersheds of small to medium size. Key parameters used for inputs were mainstream length, slope and elevation drop, which were extracted and determined from an analysis of DEM in ArcGIS software. Of the presented sub-watersheds, SB-5 had the longest Tc (28.09 hrs) due to its area and mainstream length. The shortest Tc for SB-2 and SB-8 (1.94 and 0.94 hrs respectively) both indicated rapid RO due to intensified slopes and compact nature of the areas. Shorter Tc values equal faster onset for flood risk, whilst longer values are more gradual but prolonged RO time. Understanding these values should help with flood control, drainage design, and help with urban planning.

Table 2. Time of Concentration for Each Sub-Watershed

Id	Area (km^2)	Perimeter (m)	H (m)	Tc
1	50.344	69.704	15.100	7 h 7 min
2	12.853	28.970	4.610	1 h 56 min
3	46.570	45.537	108.000	2 h 7 min
4	214.569	144.095	94.831	15 h 8 min
5	710.347	221.579	49.390	28 h 5 min
6	44.309	46.563	8.830	7 h 9 min
7	324.192	113.224	51.030	12 h 22 min
8	12.238	25.030	2.750	0 h 56 min
9	72.830	59.351	19.800	6 h 43 min

3.2 Rapid and Quasi-Real-Time LC Mapping in Urban Environments Using L8 Imagery and Machine Learning-Based MLSC for the Year 2019

3.2.1. Training data quality assessment of the mapping

To evaluate the spectral separation of the LC classes from the training dataset, we employed two pairwise separability measures, namely the J-M and TD indices that measure the amount of separation between different LC types in multi-dimensional spectral space. Our results indicated excellent spectral separation, being that the J-M values for all class pairs were either equal to or extremely close to the maximum of 2.0 with the TD values also equal to the maximum of 2.0, this suggests that the training samples have a strong statistical separation which ultimately leads to reliable classification performance. The greatest overlap occurred between semi-sealed surfaces and other classes such as bare ground, forest and lawns and pasture (J-M = 1.9), even so, there was still robust spectral separation overall. Looking further into the spectral reflectance signatures derived from L8 data confirmed our observations. In the visible bandwidth, we noted subtle differences within most of the LC types. For example, crop covered and semi-sealed areas had higher relative reflectance among most of the LC types. Conversely, the forest and surface water bodies resembled each other closely in the visible area bandwidth, particularly the red band. We also observed that some better distinguishing among the LC types occurred in the NIR and SWIR areas. While surface water bodies were clearly low, even in band 5, we noted that crop areas had a high reflectance in both the SWIR bands. Given these explainable upper and lower boundaries for surface water bodies and crop LC, we noted that some overlap still existed - that bare ground and semi-sealed surfaces ('barren land') were spectrally similar in the SWIR1 bands, and that lawns and pasture overlapped with bare ground information in the SWIR2 bands. So in addition to the LC types, we calculated standard deviation to understand the variability in the surface cover data. Semi-sealed surfaces had some of the highest variability (SD 200–1269), which likely indicates urban variability, while water bodies had the lowest variability (SD 12–23), indicating similar spectral characteristics.

3.2.2. Validation and LC mapping in Debrecen

The LC map's classification accuracy was tested not only by OA, but Kappa coefficient, and F1-scores per class. The model produced an OA of 81.2% and a Kappa score above 0.78, indicating strong agreement and a good model classification, with such grade indicating a reliable classification performance; as K values above 0.75 are generally regarded as great models (Sajjad et al., 2022). The highest F1-scores were found in the class of Forest (0.97), Semi-sealed surfaces (0.94), and SWB (0.90), reasonable balanced, reliable classification scores. In comparison, the lowest F1-scores were found in the Crops Cover, Lawns, and Pastures (0.65-0.67), where it was relatively easier to misclassify the classes, demonstrating issues with creating confusion with the spectral cover as well as a mixed signals with the croplands. Besides classification errors, other factors such as sample quality, interpretation uncertainties, registration inaccuracies, and radiometric or atmospheric conditions also influence overall accuracy (Lu et al., 2008). A sample LC map in 2019 has been displayed to highlight some of the spatial variations, thus allowing further hydrologic analysis.

3.3 Accuracy Enhancement of LC Classification Using Multi-Sensor RS and ML

3.3.1 Training data and Validation

The performance of the training data from both L8 and S2 (2018, 2020, and 2022) datasets was confirmed through spectral separability analysis using J-M and T-D indices. The training data showed that excellent spectral separability among class pairs was observed: (1) J-M indices were all greater than 1.9; and (2) T-D values were all the maximum of 2.0. These results demonstrate that the training data were representative and captured the distinct spectral characteristics of each class that resulted in reliable and accurate classification for all datasets.

3.3.2 ML based LC classification

The performance of three ML algorithms (SVM, MLC, and RF) were compared using L8 and S2 imagery for the years 2018, 2020, and 2022. Overall, S2 data coupled with SVM classifier provided the highest accuracy for all LC classes and years. For example, the SVM-S2 coupling achieved an OA of 90% and a Kappa of 0.87 in 2020. This combination provided the best classification results in forests (F1=0.98), developed areas (F1=0.77), and grasslands (F1=0.92) classification. SVM-S2 produced higher F1 scores in comparison to other classifiers and sensors, including 0.93 for forest and 0.85 for crop-covered areas. Higher accuracy may be attributable to the high spatial and spectral resolution of S2 imagery in combination with SVM's ability to capture more complex class boundaries. Conversely, MLC had relatively weak accuracy, particularly for developed and crop-covered classed, while RF performed moderately well, but whenever possible SVM was better in the majority of categories for the other algorithms (Figure 1). In addition to traditional accuracy metrics, we also explored the use of disagreement metrics (Q%, A%, and D %) as another means to assess classification quality. The lowest disagreement values were achieved by using the SVM-S2 combination, with the total disagreement equal to 12.6% in 2020, the lowest of any classifier- sensor pair (e.g., L8+SVM had a 17.7% D %). Lowest disagreement values indicate that we had good percentage estimate of class proportions and spatial alignment of land coverage classes, with Q% as low as 4.2% (2022), and A% around 7% (2020). This reflects the validity of SVM especially as it works well with high resolution S2 imagery, for a reliable spatially accurate land cover map of urban-natural areas in Debrecen.

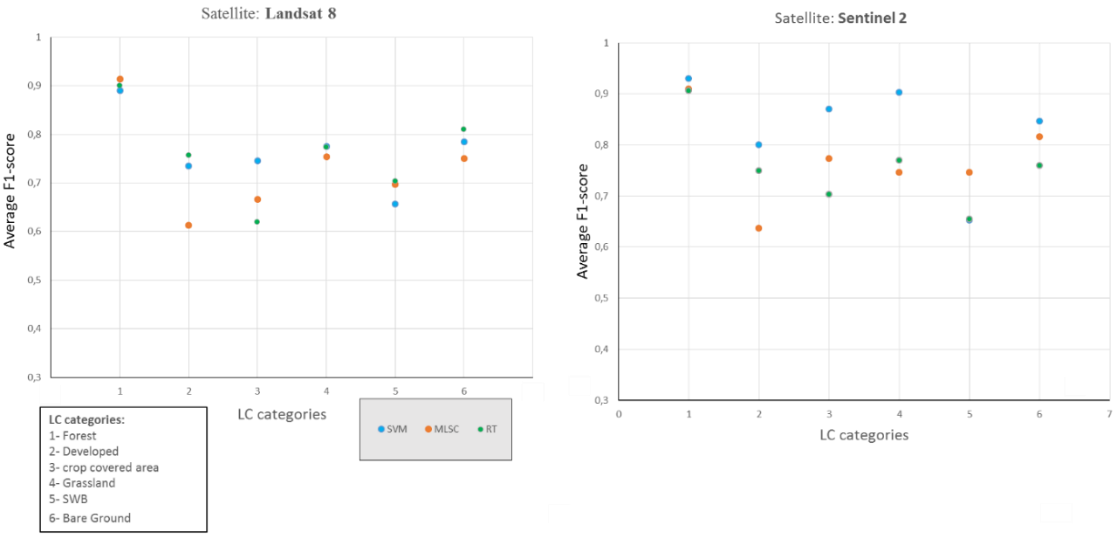


Figure 1. Average F1-score distribution per categories

3.3 Hydrological Modeling Integration with LC Dynamics for UWB Analysis

In the flat Debrecen basin, LC strongly influences hydrological variable ET, RO, and I measured as percentages of annual precipitation (Table 3).

Table 3 presents the detailed hydrological ratios by land cover.

LC class	ET Ratio	I Ratio	RO Ratio
	Average [%]	Average [%]	Average [%]
SWB	85.99	-	-
Grassland	59.65	12.35	28
Forest	71.68	17.32	11
Semi sealed surface	18.59	15.40	66
Area with crop cover	56.12	21.87	22
Bare ground	7.165	61.83	31
Sealed surface	7.127	10.87	82

SWB show the highest ET (86%) due to direct solar radiation, with no infiltration calculated. Forests have high ET (72%) and infiltration (17%) but low runoff (11%), highlighting vegetation's role in water retention. Crop areas and grasslands show moderate ET and infiltration with reduced runoff. Urban surfaces differ sharply: sealed areas have very low ET (7%), low infiltration (11%), and the highest RO (82%). Semi-sealed surfaces follow a similar trend. Bare ground has low ET but relatively high infiltration and moderate runoff. These patterns demonstrate vegetation's importance in enhancing infiltration and reducing runoff, while impervious urban surfaces increase RO significantly. This highlights the need for managing RO and improving infiltration to support groundwater recharge.

3.4 Spatiotemporal Analysis of LC Change and Urban Growth in Debrecen (2018–2022)

3.4.1 LC Dynamics and Transformation Patterns

Between 2018 and 2022, Debrecen saw significant land cover changes: surface water decreased by 0.89 km^2, forests declined by 9.8 km^2 due to drought and urbanization, barren land dropped by 67 km^2, while grassland and cropland grew by 34 km^2 and 9.8 km^2. Developed areas expanded by 33 km^2, reflecting rapid urban growth. Urban change occurred through three main processes shown in Figure 2**:** permanent gain (~5%), bidirectional exchange (~10%), and alternation (>10%) indicating land-use instability. Figure 3 details developed land trends, with over 10% permanent gain, about 5% permanent loss, and more than 5% alternation, highlighting fluctuating urban development. These results stress the need for trajectory analysis to accurately capture urban dynamics and support sustainable planning. Between 2018 and 2022, Debrecen experienced substantial LC changes: surface water decreased by roughly 0.89 km^2; forests decreased in area by 9.8 km^2 because of drought and urban growth; barren land (which may occur naturally or because of urbanization) decreased in area by roughly 67 km^2 while grassland and cropland increased in area by 34 km^2 and 9.8 km^2, respectively; Developed areas expanded by ~33 km^2 which demonstrated considerable urban growth. Urban change occurred through three main processes, indicated in Figure 2: development by permanent gain (~ 5%), by bidirectional exchange (~10%), and alternation (>10%) which indicates instability in land-use. Figure 3 presents trends of developed land which include not only over 10% permanent gain, but also roughly 5% permanent loss, and over 5% alternation which would represent some fluctuation in urban development. The results reinforce the consideration of trajectory analysis in order to assess urban growth and change accurately, and in order to promote sustainability and responsible planning.

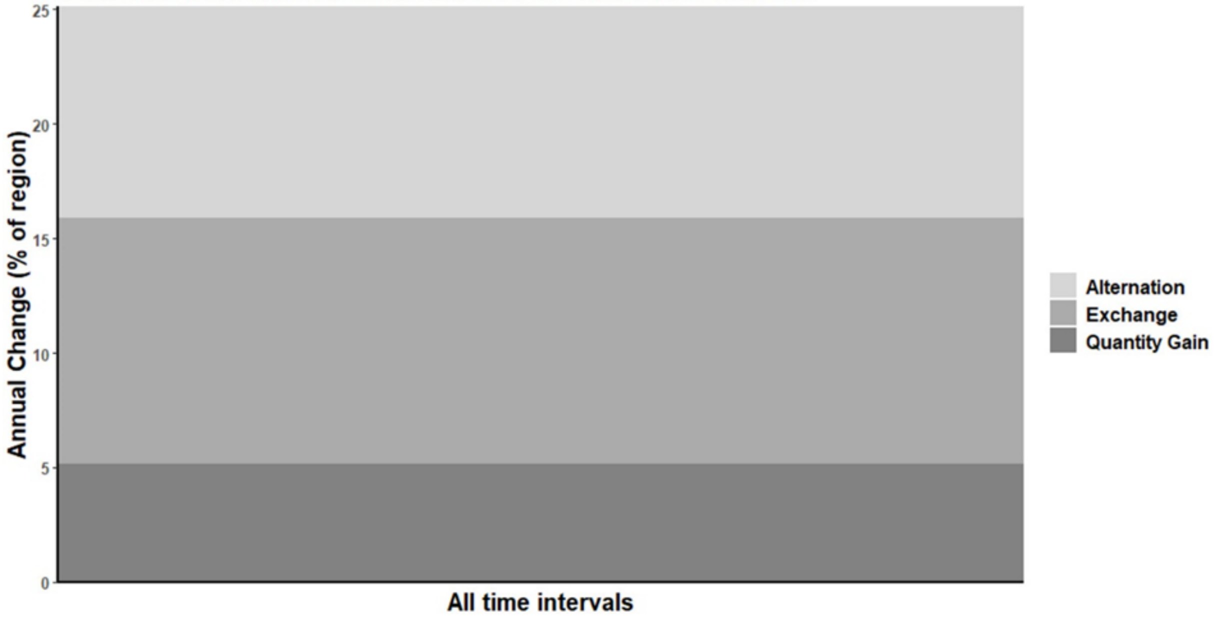


Figure 2. Three components of change during the temporal extent expressed as the annual percentage of the unified size.

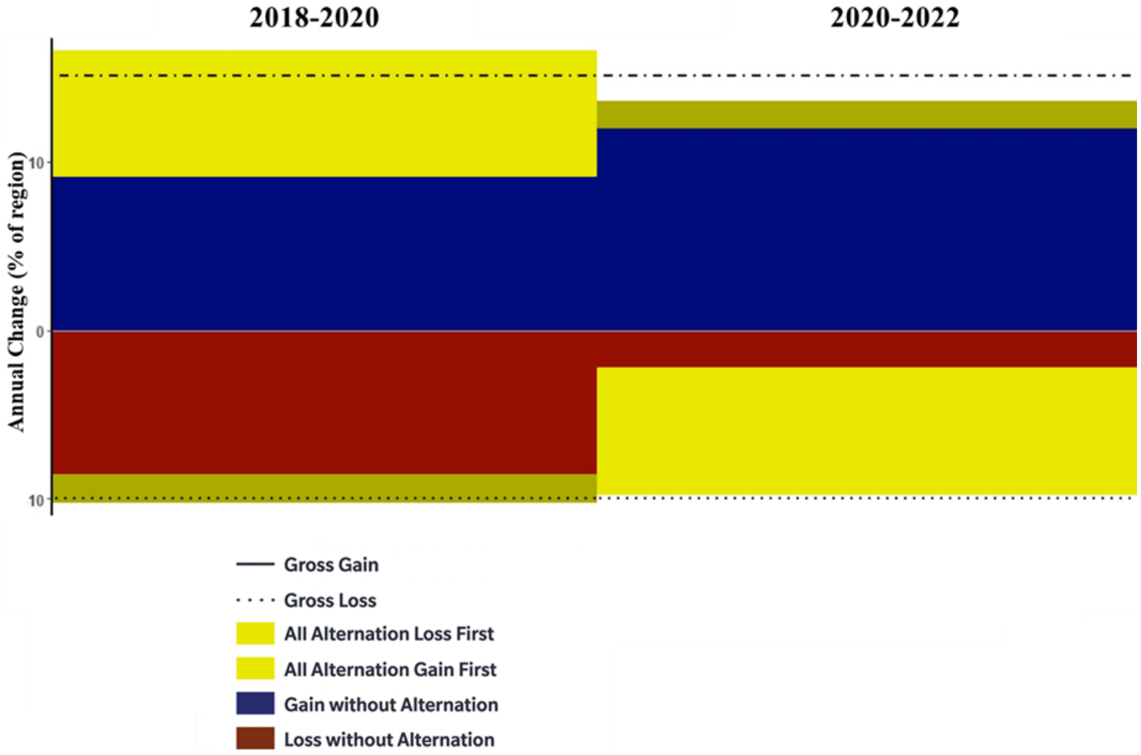


Figure 3. Annual Gain and Loss for developed area category during two time interval.

3.4.2 Mapping Urban Expansion and Development Trajectories

Between 2018 and 2022, Debrecen underwent significant LC change, mainly from urban occupiers or industrial development. In total, grasslands experienced the most land use change, with 28.89 km² converting to developed land. This is followed by bare ground (16.96 km²), and cropland (12.21 km²). Industrial expansion occurred rapidly since 2019, and was fueled by a number of new factories that wanted a large flat area that was easily accessible, often on the edge of urban or suburban settlement. The vegetation classes of forested area (4.17 km²), and surface water (0.44 km²) will not experience as much change in those periods, which may demonstrate successful environmental protection or a general unsuitability for development. A substantial portion of land (369 km²) remained otherwise stable. The developed area trajectories for both periods (2018-2020, 2020-2022) are demonstrated in Figure 4. Generally, compact urban cores remained stable while suburban growth was along major transport routes, and areas outside of core urban development experienced unstable change patterns due to redevelopment or ground cover change. The presented trajectory analysis captures the urban dynamic of Debrecen, which is useful in the context of understanding urban change, urban transitions and planning sustainability for land use from agricultural to urban LC.

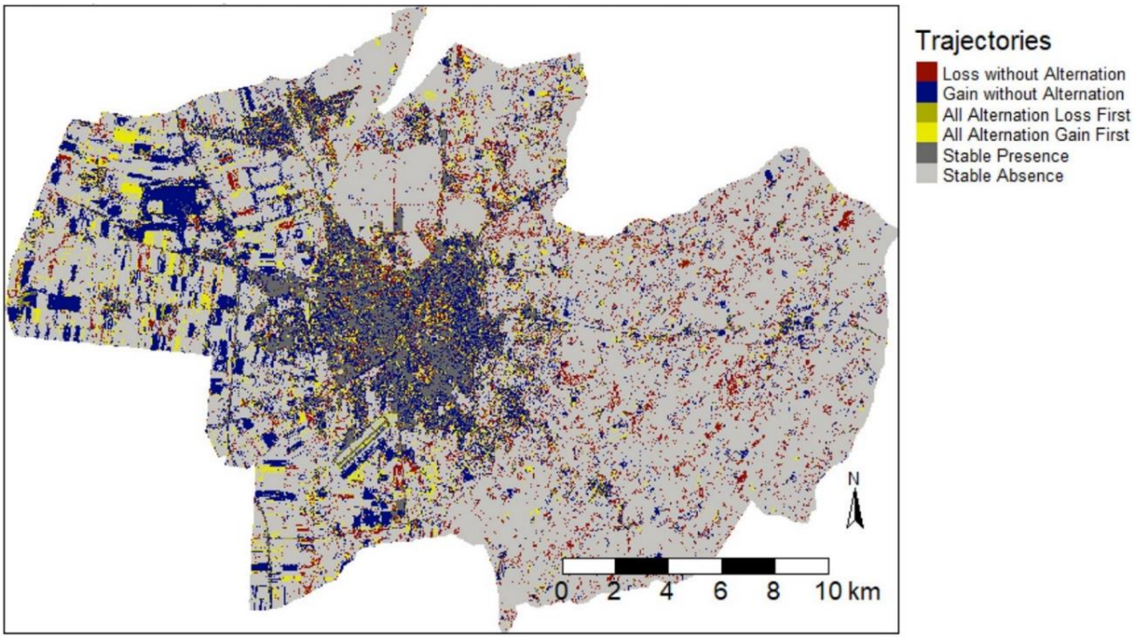


Figure 4. Developed area Trajectories for two time intervals (2018–2022).

3.4.3 Identification and Analysis of Urban Change Hotspots

Figure 5 compares urban development intensity in four key zones (BMW Industrial Complex, Józsa residential area, Battery Production Park, and Urban Commercial Area) highlighting diverse land-use changes. Classification accuracy improved over time, with S2 and SVM yielding an OA of 88% and strong F1 scores, especially for grasslands (0.90). These enhanced LC maps provide a reliable basis for integrating hydrological models to support sustainable urban planning and water resource management in Debrecen. Since 2019, urban expansion surrounding Debrecen has taken place primarily in previously existing urban patterns that represented metropolitan growth patterns, where the urban area has expanded over grasslands and cropland and affected virtually no forest or water. Figure 5 shows the different patterns of landuse change and development intensity in the four nodes examined in the study (BMW Industrial Complex, Józsa residential area, Battery Production Park, and Urban Commercial Area). The classification accuracy increased over time, as found in the classification process - S2 and SVM produced an OA of 88% and identified a high F1 score values (grasslands = 0.90). Furthermore, the expected LC maps identified by S2 and SVM over recent years are solid indications for the eventual use for functional hydrological modelling (to inform on sustainable urban planning), through the integration of hydrological types of models in Debrecen.

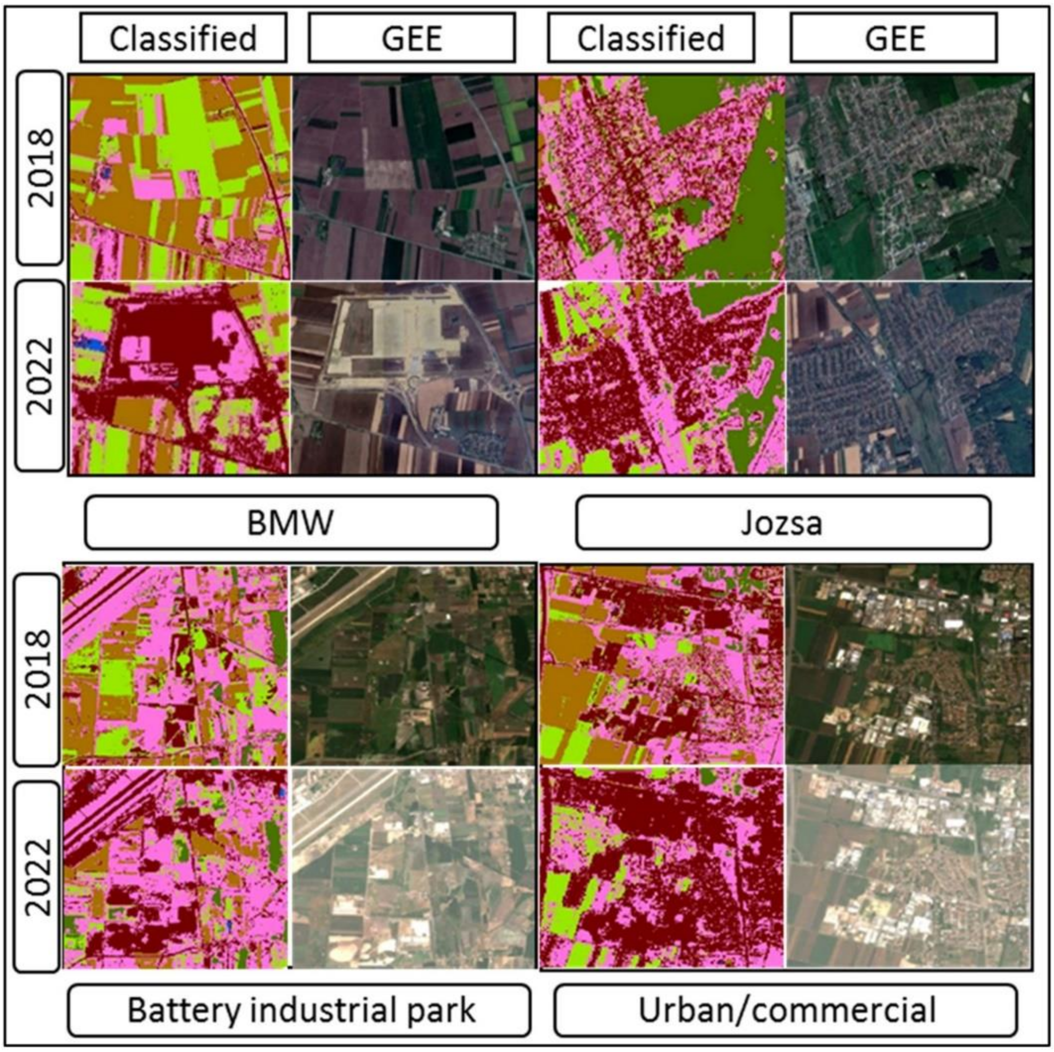


Figure 5. Four sample areas represent the change in urban development intensity between 2018 and 2022.

3.4.4 Impact of Urban Expansion on Agricultural Land Dynamics and Crop Yield Loss in Debrecen (2018–2022)

Significant LC changes in Debrecen affected agricultural lands, with bare ground and forests decreasing by 67 km² and 9.8 km², respectively, while crop-covered areas increased slightly by 9.8 km². Despite some stability in cropland within the city, the overall trend in Hajdú-Bihar County shows a decline in agricultural area. Wheat and maize, the region's staple crops, experienced substantial reductions in harvested area (wheat from 58,459 ha to 48,334 ha, and maize from 95,585 ha to 54,698 ha) alongside variable yields influenced by climatic conditions. Notably, 2022 marked a sharp decline in yields, coinciding with a dry year, underscoring the vulnerability of crop production to climate variability. Using LC change data, approximately 29.17 km² of previously bare or cropland was converted to urban use. Estimations based on average yields show potential annual losses of 21,687 tonnes of maize, 15,512 tonnes of wheat, and 8,326 tonnes of sunflower production on this lost agricultural land. These findings highlight the critical trade-offs between urban development and agricultural productivity, stressing the need for integrated land-use planning to preserve crop yields and regional food security in Debrecen and its surroundings.

4. NEW CONTRIBUTION TO ACADEMIC KNOWLEDGE

1. I developed a rapid, quasi-real-time LC classification framework for Debrecen using L8 OLI imagery and MLC. The framework resulted an OA of 81.2% and a Kappa coefficient of 0.78, and the best performed with the highest F1-scores class-levels for forest (0.97), semi-sealed areas (0.94), and surface water (0.90) in LC classification., while crop cover and grassland classes showed lower F1-scores (0.647 and 0.668), likely due to spectral mixing.

2. I integrated multi-sensor RS data with ML algorithms to classify urban LC. S2 imagery combined with the SVM classifier yielded the highest and most consistent performance (OA: $88 \pm 2.1\%$; Kappa coefficient: 0.84 ± 0.03), particularly for forest (F1-score: 0.93 ± 0.05), developed areas (F1-score: 0.80 ± 0.07), and grassland (F1-score: 0.90 ± 0.02). This combination also achieved the lowest total disagreement values (12.6% in 2020 and 13.1% in 2022), highlighting its reliability for accurate urban LC mapping.

3. I developed an LC-based hydrological framework for Debrecen to estimate ET, I, and RO at the pixel level with spatial resolution 10 m. By linking classified LC types with reference Kc and applying the Kenessey method for RO estimation, the model captured spatial water balance patterns across the city. Results showed highest ET in SWB (86%) and forests (72%), while sealed surfaces had the lowest (~7%). Infiltration was highest in crop-covered areas (22%) and lowest in sealed zones, where RO reached 82%. This adaptable and replicable approach supports high-resolution hydrological modeling in urban environments, offering a practical tool for climate-resilient water management.

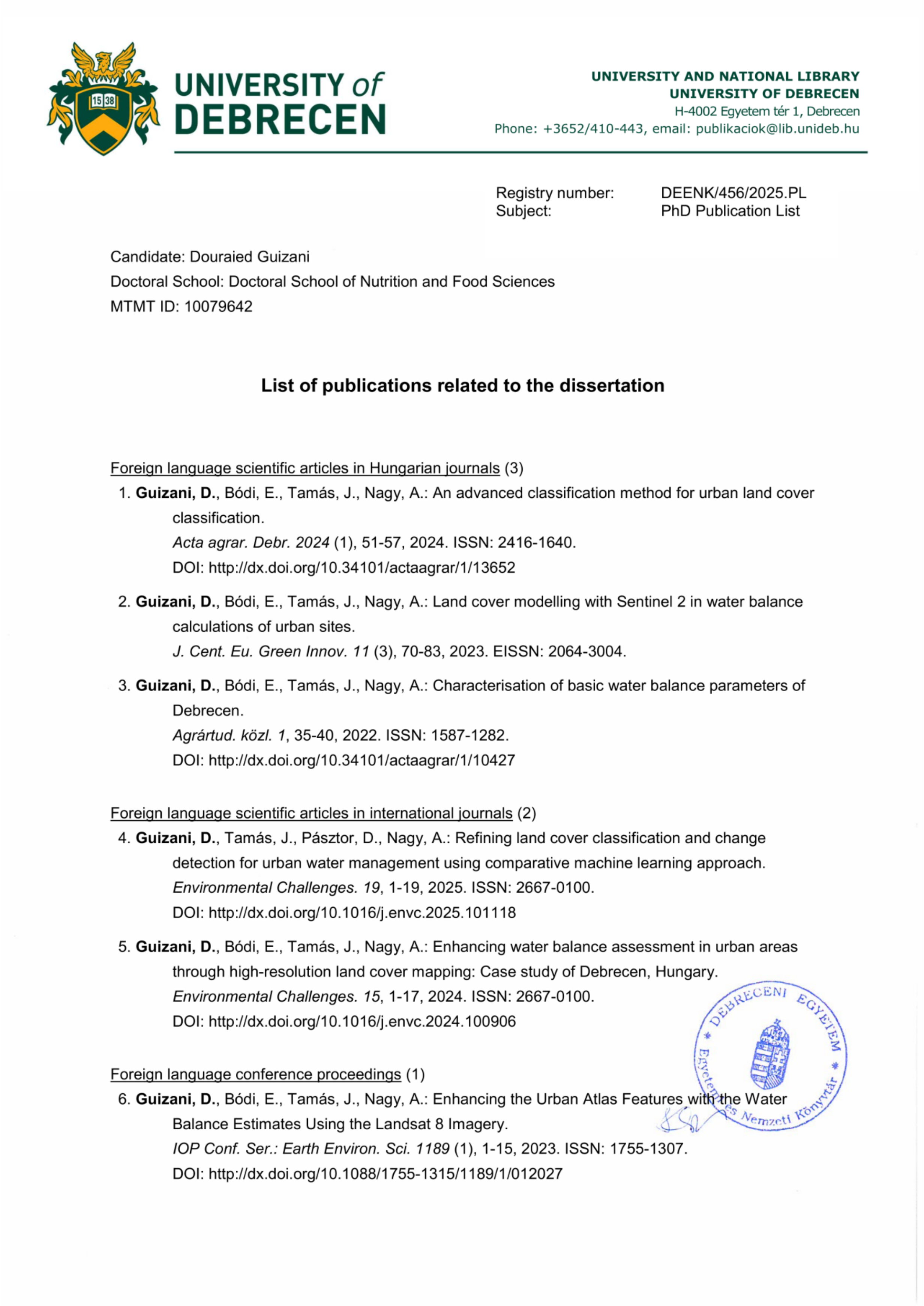
4. Between 2018 and 2022, Debrecen's urban area expanded by 33 km^2, mainly replacing cropland (12.21 km^2) and bare ground (16.96 km^2). Grasslands increased by 34 km^2, while bare ground and forest areas declined by 67 km^2 and 9.8 km^2, respectively, reflecting the impacts of urbanization and climatic factors. Urban growth was concentrated in suburban zones and industrial hubs, notably the BMW Complex and JÓZSA area. This land transformation coincided with sharp agricultural declines in Hajdú-Bihar County, where wheat and maize areas dropped by 17% and 43%, and yields fell by 34% and 72%, respectively. The conversion of 2,916.8 ha of cropland led to estimated annual losses of ~21,693 t maize, 15,500 t wheat, and 8,320 t sunflower. These findings highlight the

trade-offs between urban expansion and agricultural productivity in rapidly developing regions.

5. PRACTICAL USE OF THE RESULTS

1. The developed LC classification framework using L8 and MLC enables rapid generation of LC maps for urban areas. It supports near-real-time monitoring of vegetation and land transformations with minimal input. The method is adaptable for other cities by adjusting training data and thresholds, making it ideal for planners and GIS specialists needing fast urban mapping tools.
2. The integration of S2 imagery with SVM classifier provides highly accurate LC classification results for urban areas, especially in differentiating developed, agricultural, and forested zones. This supports municipalities in tracking urban growth and land use changes, allowing timely decision-making for zoning, infrastructure planning, and environmental assessments.
3. The LC-based hydrological model offers a pixel-level estimation of ET, I, and RO, using RS and LC-specific Kc values. It enables urban water managers and hydrologists to simulate water balance under changing land use conditions. The method is easily transferable to other urban regions with similar topography and climate.
4. LC change analysis from 2018–2022 revealed urban expansion patterns in Debrecen and their impacts on agriculture. These spatial insights can guide regional authorities in urban planning to minimize cropland loss. The results can support agricultural policies to compensate for or adapt to productivity decline in peri-urban zones.

6- CERTIFIED PUBLICATIONS



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Candidate: Douraied Guizani
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List of publications related to the dissertation

Foreign language scientific articles in Hungarian journals (3)

1. **Guizani, D.**, Bódi, E., Tamás, J., Nagy, A.: An advanced classification method for urban land cover classification.
   Acta agrar. Debr. 2024 (1), 51-57, 2024. ISSN: 2416-1640.
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2. **Guizani, D.**, Bódi, E., Tamás, J., Nagy, A.: Land cover modelling with Sentinel 2 in water balance calculations of urban sites.
   J. Cent. Eu. Green Innov. 11 (3), 70-83, 2023. EISSN: 2064-3004.
3. **Guizani, D.**, Bódi, E., Tamás, J., Nagy, A.: Characterisation of basic water balance parameters of Debrecen.
   Agrártud. közl. 1, 35-40, 2022. ISSN: 1587-1282.
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Foreign language scientific articles in international journals (2)

4. **Guizani, D.**, Tamás, J., Pásztor, D., Nagy, A.: Refining land cover classification and change detection for urban water management using comparative machine learning approach.
   Environmental Challenges. 19, 1-19, 2025. ISSN: 2667-0100.
   DOI: http://dx.doi.org/10.1016/j.envc.2025.101118
5. **Guizani, D.**, Bódi, E., Tamás, J., Nagy, A.: Enhancing water balance assessment in urban areas through high-resolution land cover mapping: Case study of Debrecen, Hungary.
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Foreign language conference proceedings (1)

6. **Guizani, D.**, Bódi, E., Tamás, J., Nagy, A.: Enhancing the Urban Atlas Features with the Water Balance Estimates Using the Landsat 8 Imagery.
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   DOI: http://dx.doi.org/10.1088/1755-1315/1189/1/012027

Foreign language abstracts (2)

7. **Guizani, D.**, Tamás, J., Nagy, A.: Sustainable urban development in Debrecen: addressing water scarcity, agricultural decline, and industrial expansion through community-based hydroponic solutions.
   In: Abstract Book of the 8th International Scientific Conference on Water, Magyar Agrár-és Élettudományi Egyetem, Gödöllő, 35, 2025. ISBN: 9789636231156(pdf)

8. **Guizani, D.**, Bódi, E., Tamás, J., Nagy, A.: Identification of water balance properties of urban atlas using Landsat 8 data.
   In: Book of abstract XXII Conference of PhD Students and Young Scientists : Interdisciplinary topics in mining and geology. Szerk.: Jan Blachowski, Wrocaw University of Science and Technology Publishing House, Wrocaw, 41-42, 2022. ISBN: 9788374932202

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1. **Guizani, D.**, Bódi, E., Tamás, J., Nagy, A.: An advanced classification method for urban land cover classification.
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7. **Guizani, D.**, Tamás, J., Nagy, A.: Sustainable urban development in Debrecen: addressing water scarcity, agricultural decline, and industrial expansion through community-based hydroponic solutions.
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