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MORALITY BEFORE KNOWLEDGE

Application of machine learning and remote sensing in monitoring land use dynamics in tourism area

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ABSTRACT
Background: This study uses remote sensing and machine learning techniques to investigate the spatial-temporal changes in land use and land cover (LULC) within the Lake Toba tourism area over the past 35 years. Increasing tourism activities have significantly altered the region's landscape, particularly leading to a reduction in forest cover and an expansion of built-up areas. **Method**: By applying the Random Forest algorithm to satellite imagery data from Landsat 5, 8, and 9, and integrating Geographic Information System (GIS) technology, we analyzed and accurately predicted these changes. Additionally, indices such as NDVI and SAVI were used to monitor ecosystem health in detail, particularly for tracking the growth of invasive species like water hyacinths. **Findings**: LULC analysis of the Lake Toba tourism area reveals significant changes, including an increase in built-up areas, a decrease in vegetation, and the potential growth of water hyacinths. Surface temperature analysis indicates higher temperatures in built-up areas and cooler temperatures in natural vegetation. Using NDVI, SAVI, and MDWI indices also helped in monitoring water hyacinth growth, supporting improved ecosystem management for sustainability. **Conclusion**: This study highlights the environmental impacts of tourism and emphasizes the need for sustainable land management practices to balance development with ecological preservation. **Novelty/Originality of this Research**: This research demonstrates the effectiveness of combining machine learning with spatial technologies to support informed decision-making in land use planning.

KEYWORDS: land use and land cover (LULC); machine learning; tourism area.

1. Introduction

The tourism sector in Indonesia continues to play a vital role in supporting the national economy (Widari, 2020). The issue of land use and land cover (LULC) in the Lake Toba tourism area has become increasingly significant (Junef, 2017; Sinuhaji et al., 2019), particularly after Lake Toba's designation as a National Tourism Strategic Area (Kawasan Strategis Pariwisata Nasional or KSPN) (Marikena & Setiwannie, 2022; Yuli, 2022). The government's policy granting priority status to the development of this region underscores the critical need for meticulous land management to support sustainable tourism development (Sinaga, 2018; Siregar, 2018; Tanjung et al., 2024). As a tourism destination with potential for economic, socio-cultural, and environmental growth, changes in land use within this area have become a focal point in ensuring the sustainability of tourism development (Pardede & Suryawan, 2016; Tanjung et al., 2024).

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Despite its promising potential, the increase in tourist visits and tourism-related activities around Lake Toba has brought about numerous environmental challenges (Saputra, 2020; Hakim, 2024). These include the uncontrolled growth of settlements, inadequate waste management, and limited space allocation for tourism activities (Widhijanto & Tisnaningtyas, 2018). Addressing these challenges requires a comprehensive and sophisticated approach to land use management to ensure a harmonious balance between tourism development and environmental conservation (Safitri, 2021; Zaenal et al., 2016).

This balance is particularly essential given the interconnectedness of economic growth, environmental sustainability, and socio-cultural resilience in strategic tourism areas like Lake Toba (Delita etal., 2017; Hakim et a., 2024; Kartomihardjo et al., 2015; Sabon et al., 2018; Sihombing & Hutagalung, 2021). In this context, machine learning technology offers an effective solution for conducting in-depth and precise analyses of LULC changes (Navnath et al., 2022; Liu et al., 2023; Zhang et al., 2018, 2022). Through the integration of satellite imagery and advanced machine learning algorithms, patterns of land use change can be identified with high levels of detail (Bayona et al., 2021), while their impacts on environmental sustainability and tourism development can be accurately forecasted (Sedano et al., 2019; Tassi & Vizzari, 2020).

Spatial LULC analysis using a machine learning approach provides critical insights that aid decision-making processes related to the development and management of Lake Toba's tourism sector (Rimba et al., 2020; Belay et al., 2022). The application of such technology not only enhances our understanding of land use dynamics but also serves as an effective tool for designing management policies and strategies that are more adaptive and responsive to evolving environmental conditions and tourism demands (Fensholt et al., 2015; Jamali, 2020; Kuenzer et al., 209;).

Thus, spatial LULC analysis supported by machine learning has emerged as an essential instrument in ensuring the sustainability of Lake Toba's tourism region (Sihotang et al., 2012). It simultaneously strengthens the economic and social contributions of this area, reinforcing its status as one of Indonesia's premier tourism destinations. By harmonizing tourism growth with environmental conservation, this approach supports the long-term vision of sustainable development in the Lake Toba region (Hakim et al., 2024).

2. Methods

This Lake Toba area is located in North Sumatra Province which is surrounded by 7 seven districts that are Simalungun, Toba Samosir, North Tapanuli, Humbang Hasundutan, Dairi, Karo, and Samosir. The Lake Toba area is Lake Volcanic the largest in the world that has depth of about 450 m, 87 km long, and 27 km wide. Lake Toba is also known as lake deepest at a time lake the world's second largest lake, after Lake Victoria which is located in Africa (Sihotang et al., 2012). This is one of the reasons Lake Toba became a destination tourist priority in Indonesia and also became an area tour main one in North Sumatra Province (Rahma, 2020).

The Lake Toba area is also supported by many tourist destinations located in seven of the surrounding districts. This tourism potential showcases the uniqueness and distinctiveness of each region. Based on research data results, each district has tourism objects that serve as main attractions to highlight the diversity of the Lake Toba area.

Regency Simalungun includes the beautiful Simarjarunjung Hill, Parapat, Binangan Bolon Waterfall, Tanjung Camel, and Batu Gantung. Toba Samosir Regency features Bul-Bul White Sand, Situmurun Waterfall, Tourism of Faith, Gibeon Hill Baths, and TB Silalahi Museum. Regency North Tapanuli offers the View of Huta Ginjang, Muara Nauli Prayer Hill, and Toga Aritonang Monument. Regency Humbang Hasundutan includes Geosite Sipinsur, Culinary Tourism Tipang Mas, King Sisingamangaraja Palace, Promise Waterfall, and the Bakkara Valley. Regency Samosir presents Tomok Tour (Statue Sigale-gale, King's Cemetery, Batak Museum), Tuk Tuk Siadong, Batu Hoda Beach, Aek Sipitu Dai, Holbung Hill, Pusuk Buhit, Aek Rangat Pangururan, and Tele Tower. Dairi Regency includes Taman Iman, Puncak Sidiangkat, and Paropo/Tao Silalahi Beach. Lastly, Karo Regency features Sapo Juma Tongging Flower Garden, Tongging Beach, Simalem Park, and Sipiso-piso Waterfall.

Based on superiority index sensing far and analysis component main for accurate classification, research This based on the characteristics of the study area, classification image sensing far, and analysis characteristics spatial-temporal of change usage/closure land from 1985 to 2023. The details are as follows data collection is shown in Table 1.

Table 1. Landsat satellite image data used

Image Time	Satellite	Sensor	Spatial Resolution	Bands
1985 1990 1995 2000 2005 2010	Landsat 5	Thematic mapper (TM)	30 m	Band 1: blue (0.45–0.52 μm) Band 2: green (0.52–0.60 μm) Band 3: red (0.63–0.69 μm) Band 4: near-infrared (0.76–0.90 μm) Band 5: near-infrared (1.55–1.75 μm) Band 7: mid-infrared (2.08–2.35 μm)
2015 2020	Landsat 8	Operational land imager (OLI)	30 m	Band 1: coastal aerosol (0.43–0.45 μm) Band 2: blue (0.450–0.51 μm) Band 3: green (0.53–0.59 μm) Band 4: red (0.64–0.67 μm) Band 5: near-infrared (0.85–0.88 μm) Band 6: SWIR 1 (1.57–1.65 μm) Band 7: SWIR 2 (2.11–2.29 μm) Band 9: cirrus (1.36–1.38 μm)
2023	Landsat 9	OIL-2	30 m	Band 1: coastal aerosol (0.43–0.45 μm) Band 2: blue (0.450–0.51 μm) Band 3: green (0.53–0.59 μm) Band 4: red (0.64–0.67 μm) Band 5: near-infrared (0.85–0.88 μm) Band 6: SWIR 1 (1.57–1.65 μm) Band 7: SWIR 2 (2.11–2.29 μm) Band 9: cirrus (1.36–1.38 μm)

In the methodology study, the first image remote sensing the Landsat satellite covering the study area was obtained from GEE. The image data covering Landsat 5, Landsat 8, and Landsat 9 are available and processed without pixel cloud and already extracted according to the study area. Second, image overlay is processed based on the image sensing Far native, multi-feature index, and components main. Then, the classification image sensing Far implemented based on the Random Forest algorithm. Finally, the characteristics of spatial and temporal are explored from three perspectives: change of area, variation spatial, and transfer of use land.

3. Results and Discussion

3.1 Classification results land use

Regional development is not off from utilization space, but the availability of space in Lake Toba is very limited. Almost half of the KSN Lake Toba area is area forest so Lots of activity community, private sector, and government intersects with the problem forest. In the period time about 35 years based on Figure 1 results show land around the area of Lake Toba tourism which is dominated by forest cover land forests and grass, while built-up areas have also experienced change since around 1985 part north area of Lake Toba. The more years, the land woke up the more spread to the west and east area lake Toba was marked with a circle of red.

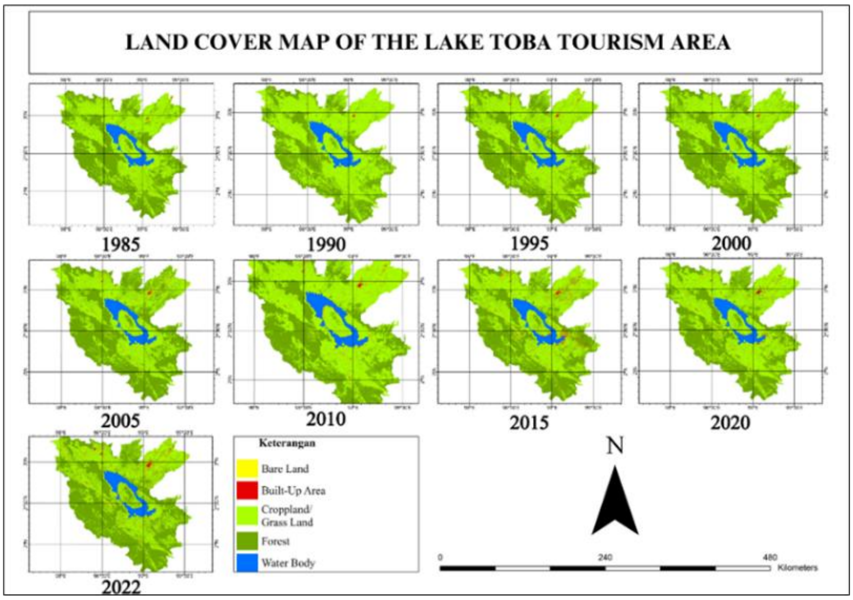

Fig. 1. Classification result maps

Appendix 1 shows the wide use land area of Lake Toba tourism based on type use land the biggest covering land vegetation (Cropland /Grass Land), forest, water body, built-up area, and land open (bare land). Of the five types use land mentioned, Figure 2 shows during almost 35 years experienced fluctuating changes in the type of land that woke up to a decline area land in 1990, 2000, and 2020. Likewise, land forests had time experienced a decline in 1990, 2010, and 2020.

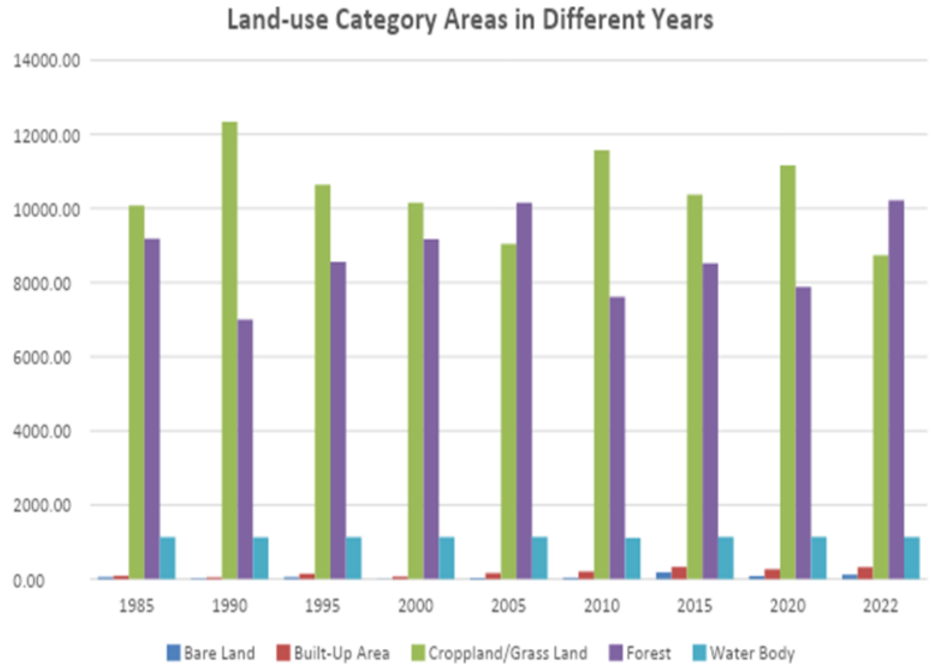

Fig. 2. Land-use category areas in different years

Based on the maps (Figure 3), land cover changes in the Lake Toba tourism area from 1985 to 2022 demonstrate significant dynamics. In the early period (1985-1990), the region was dominated by forests, indicated by the prevalence of green on the map. Over time, a gradual change is observed where yellow and orange areas, representing agricultural land and grasslands, begin to expand. The 1990-2000 period shows an increase in light yellow areas, indicating growth in agricultural land. From 2000 to 2010, there is an expansion of bright yellow areas, signifying an increase in open or built-up land. Dramatic changes are evident in the 2010-2020 period, where dark orange areas expanded significantly, suggesting the conversion of forests to agricultural land or other more intensive uses. The 2020-2022 period displays a more diverse pattern, with an increase in bright yellow areas indicating growth in built-up land or infrastructure.

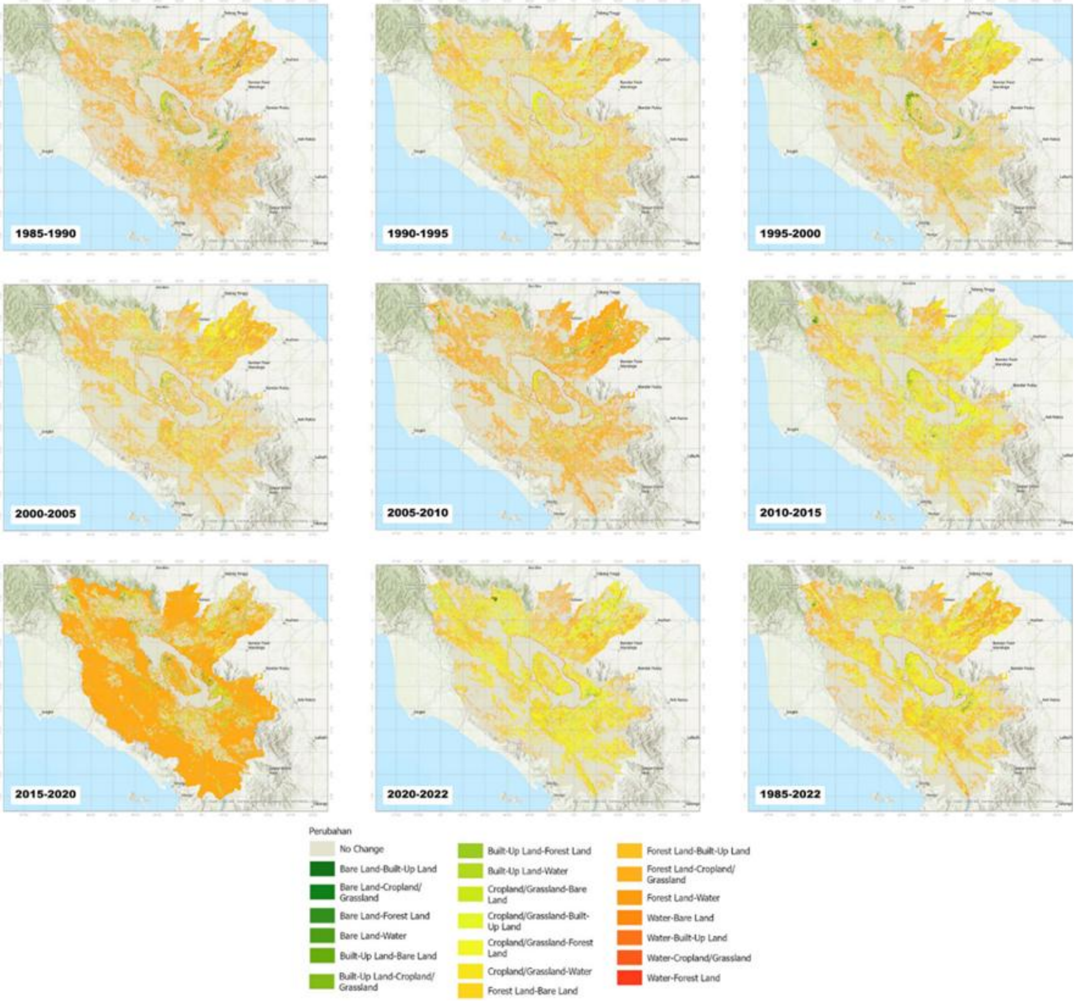

Fig. 3. Spatial distribution maps of land-use change Lake Toba tourism area

The pie charts reinforce this interpretation by showing changes in the proportion of each land cover type (Figure 4). From 1985 to 2000, the proportion of green (forest) gradually decreased, while other colors such as yellow and orange (agricultural land and grasslands) increased. The 2000-2010 period shows a significant increase in light pink areas, likely representing open or built-up land. The most drastic changes are seen in the 2015-2020 diagram, where the proportion of green sharply declines, replaced by increases in other colors, especially orange and yellow. This indicates a massive conversion from forests to agricultural and other land uses. The 2020-2022 diagram shows relative stabilization, albeit with a much smaller forest proportion compared to the initial period.

Overall, this visual analysis depicts a trend of deforestation and land use intensification in the Lake Toba tourism area. These changes reflect economic and tourism development in the region but also raise questions about environmental sustainability and potential long-term ecological impacts. The transformation from a predominantly forested landscape to a more diverse and intensively used area underscores the need for balanced development strategies that consider both economic growth and environmental conservation.

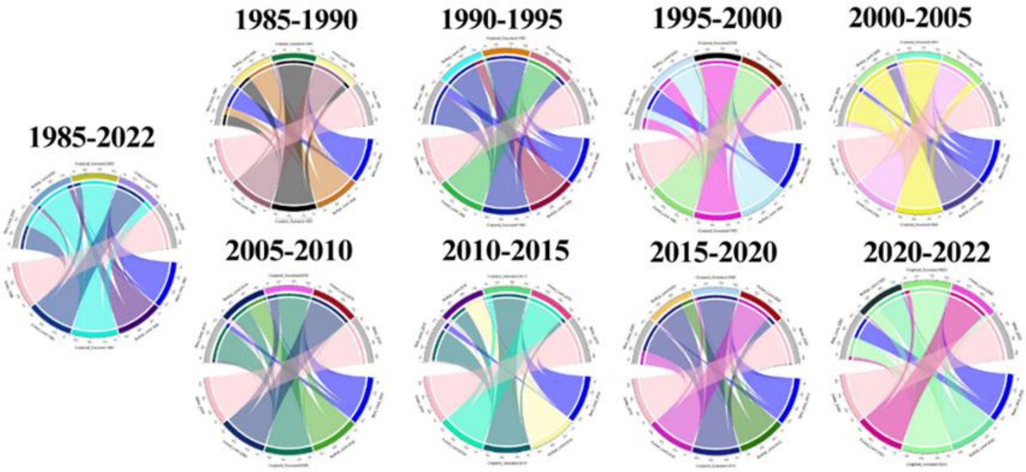

Fig. 4. Land-use type transfer chord diagrams
(Landsat Image Data Processing, 2024)

Apart from being done data processing and analysis cover the land as well as the changes, are also made calculation machine learning methods for see performance mark data accuracy includes Random Forest, Minimum Distance, and SVM. Of the three methods Table 2 shows the average results. Accuracy and kappa test 95.8% and the obtained method that has mark accuracy and kappa test tends to be the biggest namely Random Forest. This is due to RF tends effective in overcoming overfitting because using ensemble learning and can handle various types of features with good, including features that are not too useful.

Table 2. List of random forest, minimum distance, and SVM

Year	Random Forest		Minimum Distance		SVM	
	Accuracy	Kappa	Accuracy	Kappa	Accuracy	Kappa
1985	0.9842	0.9754	0.9381	0.9028	0.9759	0.9689
1990	0.9508	0.9215	0.9147	0.863	0.9401	0.919
1995	0.9342	0.8944	0.8917	0.8239	0.9215	0.8818
2000	0.9661	0.9449	0.9371	0.897	0.9617	0.9423
2005	0.9671	0.9462	0.9503	0.9184	0.9514	0.9191
2010	0.9711	0.9557	0.9332	0.8972	0.9528	0.9282
2015	0.9776	0.9633	0.9459	0.9111	0.9735	0.9612
2020	0.9751	0.9632	0.9347	0.8951	0.9572	0.9341
2022	0.9651	0.9444	0.9141	0.8621	0.9553	0.9445

3.2 Land Surface Temperature (LST) analysis

Land Surface Temperature (LST) estimation is carried out in time series, namely from 1985 to 2022 in the Lake Toba Tourism Area as seen in Figure 5. Processing in a time series manner is intended To describe change every year in a way clear. The LST estimation results were obtained from the average value of each image used every year. Then results of LST estimation are used For know and analyze trend change LST value.

Estimation results annually show LST values for several years namely 1985, 2000, 2005, 2015, and 20222 in the Lake Toba area have uniqueness Because the temperature Once reaches below 0 degrees. While the highest average value Once almost reached 40 degrees Celsius in 2000. This Of course also influenced by the existence of vegetation Because tends to absorb more Lots radiation sun and reduce the amount of energy that reaches the surface land. As a result, the temperature surface of the ground beneath vegetation is usually lower than in areas that are not closed vegetation.

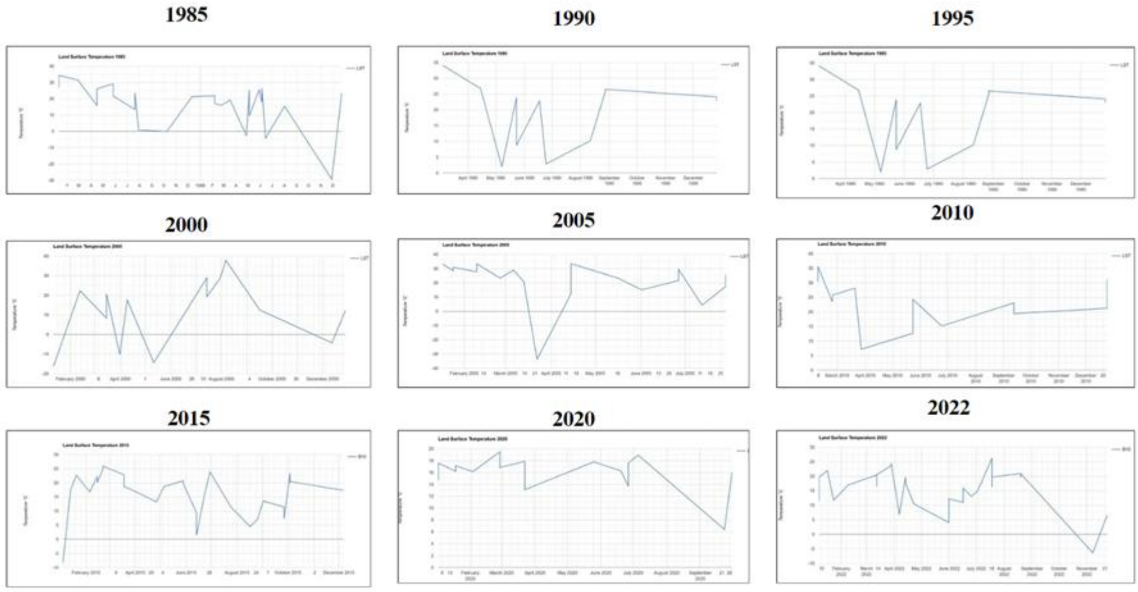

Fig. 5. Land surface temperature diagram

3.3 NDVI, SAVI, and MDWI analysis in management water hyacinth goiter

In the Lake Toba Tourism Area recently This population of water hyacinth goiter showed growth that is not controlled and in some parts place Already caused problems like disturbance means water transportation, disrupting beautiful nature, and clogging some channel irrigation. That needs existing management of water hyacinth goiter in the Lake Toba Tourism Area so that can utilized in a way maximum so that does not bother the ecosystem. The absence of information spatial in the Lake Toba Tourism Area becomes factor barrier to the monitoring and evaluation process management water hyacinth goiter. Even though spatial data can become sufficient tools For formulating management strategies for water hyacinth goiter.

One of method sensing far as can be used To estimate water hyacinth goiter that is with using NDVI (Normalized Difference Vegetation Index), Soil Adjusted Vegetation Index (SAVI), and Modified Normalized Difference Water Index (MNDWI) (Amliana et al., 2016). NDVI is one of the indexes of the most common vegetation used and calculated from the difference reflectance between light infrared near (NIR) and red in the spectrum electromagnetic (Fu et al., 2023; Sun et al, 2021). Increasing NDVI values usually show improvement in density and the presence of more vegetation. On growth water hyacinth goiter, increased NDVI value can show more growth and spread well from the plant. SAVI is a modification from NDVI that takes into account the impact of soil on reflectance. SAVI is usually better at overcoming the effect of background behind land, especially in areas that have different lands. In the case of the growth water hyacinth goiter, SAVI can give more estimates accurate about the density of vegetation and conditions of growth plant, especially in an environment with variation significant land. MNDWI measures relative water content from a certain area with utilise difference reflectance between NIR and area blue on the spectrum electromagnetic. Low MNDWI values show the presence of more water, while high values show a lack of water. Water hyacinth goiter usually grows in water, and therefore, areas with the growth of water hyacinth goiter tend to have higher MNDWI value Because plants Grow on water.

In the case of this article, in the Lake Toba Tourism Area, the distribution of water hyacinth goiter can seen around the edge of the lake in the middle. In the NDVI value, it can be seen from 1985 to 2022 occurred improvement water hyacinth marked goiter with color increasingly green dark from year to year around the edge lake. Then the SAVI value can be identified condition of the land on the water hyacinth hyacinth is a water hyacinth goiter often growing on the surface of colored water, so the reflectance of the land Can be different from plant other.

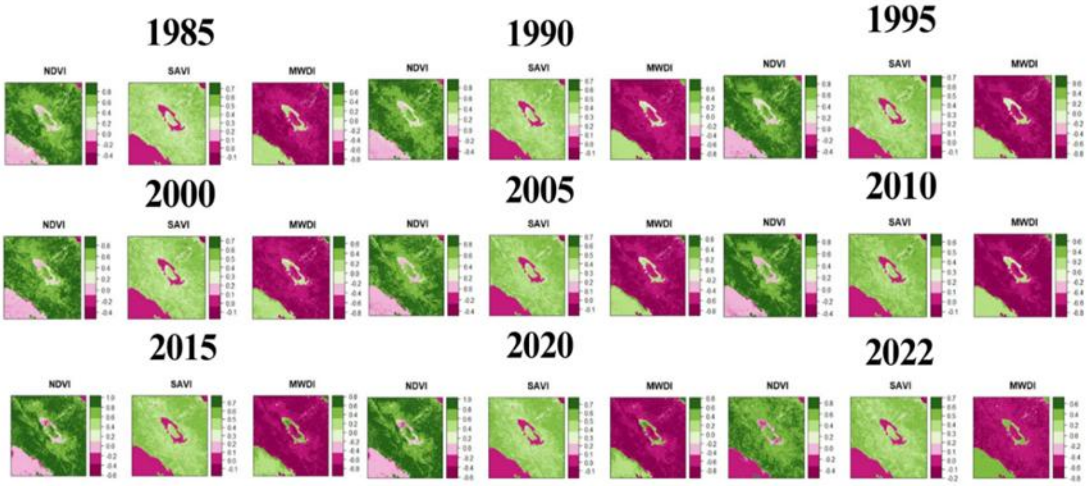

Fig. 6. Maps of NDVI, SAVI, and MDWI

From the results data processing shows SAVI value in color green young to signify its value is at an average of 0-0.2 meaning the existence of vegetation water hyacinth goiter not enough good. While the area with a higher MNDWI value and low possibility big is an ideal area for growth echinoderm goiter. Visible from 1985-2010 static changes are marked with the color of the water in the middle still green young, then continued in 2015-2022 starting happen improvement Where color green changed the more dark namely in the range MDWI value 0.2-0.4 means at 7 years final existence water hyacinth goiter located in a less than ideal area. However, MDWI is not fully effective in condition certain, such as areas with thick aquatic vegetation or dirty water conditions, which can blur the difference in reflectance between water and vegetation.

3.4 Discussion and future research

The research on the spatial analysis of Land Use Land Cover (LULC) in the Lake Toba tourism area presents several significant findings. The rapid development and increased tourism activities around Lake Toba have led to notable land use changes. As the area has been designated a National Tourism Strategic Area, there is an increasing need for more precise management of land resources to balance economic growth with environmental preservation. Remote sensing technology combined with machine learning, such as the Random Forest algorithm, has proven effective in monitoring and predicting LULC changes, providing accurate data for land management decisions.

The application of machine learning, particularly Random Forest, stands out due to its high accuracy and robustness in handling diverse data features. Over 35 years, this method has been instrumental in tracking shifts from forest cover to built-up areas, driven by tourism expansion. The findings indicate that the forested areas around Lake Toba have steadily decreased, while the construction of infrastructure and tourist facilities has expanded, particularly in the northern and western parts of the lake. These trends highlight the pressure on natural ecosystems and the need for sustainable land use policies (Kartamihardja et al., 2025).

Incorporating remote sensing and Geographic Information Systems (GIS) has allowed researchers to visualize and quantify these changes over time. Satellite imagery, including data from Landsat 5, 8, and 9, was used to classify different land types such as forests, grasslands, water bodies, and built-up areas. The use of the Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), and Modified Normalized Difference Water Index (MNDWI) further enhances the analysis by detecting vegetation health and water body changes. These indices provide a comprehensive view of environmental dynamics, especially in monitoring the spread of invasive species like water hyacinth (Eichhornia crassipes), which has become a problem in the lake.

One of the most concerning environmental impacts of land use change in the Lake Toba region is the rise in land surface temperature (LST). The research reveals that areas with increased built-up infrastructure experience higher LST due to the reduction of vegetative cover, which traditionally helps regulate temperature. The escalation in surface temperature may exacerbate climate-related issues, such as altered precipitation patterns and further degradation of ecosystems, necessitating careful environmental management and planning. The ongoing land use transformation around Lake Toba, primarily driven by tourism, reflects broader trends in developing regions where economic activities and urbanization take precedence over ecological sustainability (Perdiguero, 2023). The depletion of forest areas and expansion of built-up zones indicate a need for stricter regulations and better land use planning to ensure that tourism development does not compromise the ecological integrity of the region. The application of machine learning in LULC analysis offers a powerful tool for policymakers to monitor these changes in near real time and develop strategies to mitigate environmental harm. A key issue raised by the study is the uncontrolled growth of settlements and infrastructure, which could lead to long-term environmental degradation if not addressed. There is also a growing concern about water pollution and habitat disruption, exacerbated by tourism-driven activities. The research emphasizes the importance of adopting a balanced approach that aligns tourism growth with the conservation of natural resources, ensuring that Lake Toba remains both a viable tourist destination and an environmentally sustainable area.

The study's reliance on satellite data introduces certain limitations, such as the resolution constraints of Landsat imagery, which might miss smaller-scale land changes. While Random Forest provided high accuracy, other machine-learning algorithms could be explored to address overfitting issues and improve classification under complex conditions. Additionally, the temporal scope of the data (1985-2023) may not fully capture recent developments, necessitating continuous data updating for more accurate long-term predictions. Finally, the complexity of environmental interactions, particularly in ecologically sensitive areas like Lake Toba, suggests that machine learning models should be combined with ground-truthing techniques for better validation of satellite-derived data. A multidisciplinary approach involving ecologists, geographers, and local stakeholders would ensure that the findings are robust and actionable.

Future studies should focus on refining machine learning algorithms to enhance the accuracy of LULC predictions further. Additionally, integrating socioeconomic data with spatial analysis could provide a more comprehensive understanding of how land use changes affect local communities and biodiversity. Policymakers are encouraged to leverage these insights to implement stricter land management regulations, promoting sustainable tourism practices that prioritize environmental protection. Moreover, expanding the use of remote sensing techniques, including higher-resolution satellite imagery and drone technology, could improve monitoring efforts. Long-term environmental monitoring programs, incorporating public participation, could also help foster a shared responsibility for conserving the Lake Toba ecosystem. Investing in green infrastructure and promoting eco-tourism would mitigate the environmental impact of land use changes.

4. Conclusions

LULC analysis of the Lake Toba Tourism Area indicates a change significant with an increase in a built-up area, a decrease in vegetation, and a potential improvement growth of water hyacinth goiter. With the use of LST analysis, we can see an improvement in temperature surface in built-up areas and subsidence temperature in vegetation areas natural. The use of NDVI, SAVI, and MDWI helps in monitoring and controlling the growth of echinoderm goiter, by identifying vulnerable areas to growth. With the merged third index, management of the ecosystem in the Lake Toba Tourism Area can improved to support a sustainable environment and habitat protection.

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Author Contribution
Conceptualization, S.M., K.A.P. and P.S; Methodology, S.M. and K.A.P.; Data Curation, K.A.P. and P.S.; Writing – Original Draft Preparation, S.M.; Writing – Review & Editing, P.M.; Supervision, P.M.; Project Administration, S.M.

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Appendix 1. Land-use category areas in different years

Type	1984	1990	1995	2000	2005	2010	2015	2020	2022
Bare land	54.32	22.02	53.96	7.64	31.29	38.66	182.47	81.34	120.74
Built-up area grass	90.45	47.20	145.27	65.77	161.54	205.93	328.59	267.16	321.88
Land/cropplland	10,072.57	12,337.75	10,639.61	10,156.69	9,043.31	11,565.35	10367.17	11,167.72	8,734.20
Forest	9,180.11	6,997.01	8,560.65	9,167.94	10,157.81	7,609.07	8516.00	7,876.34	10,220.02
Water body	1,132.07	1,127.17	1,131.75	1,133.15	1,137.29	1,112.23	1136.87	1,138.68	1,134.01