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THE EFFECT OF LAND USE CHANGE ON WATER TURBIDITY USING REMOTE SENSING AND GIS TECHNIQUE

RICKY ANAK KEMARAU[1]*, OLIVER VALENTINE EBOY[2] AND ZAINI SAKAWI[1]

[1]*Earth Observation Centre, Institute of Climate Change, Universiti Kebangsaan Malaysia, 43600 Bangi, Selangor, Malaysia.*
[2]*Geography Program, Faculty of Social Science and Humanities, Universiti Malaysia Sabah, Jalan UMS, 88400 Kota Kinabalu, Sabah, Malaysia.*

**Corresponding author: rickykemarau@ukm.edu.my*
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Abstract: In the context of escalating freshwater pollution and diminishing rainwater collection areas, this investigation utilises remote sensing and GIS to examine the impact of land use and cover (LULC) transformations on water turbidity at Kelalong Dam, Bintulu, Sarawak. Using Landsat 5 Thematic Mapper (TM) and Landsat 8 Operational Land Imager (OLI) plus Thermal Infrared Sensor (TIRS) imagery collected during the lower-rainfall southwest monsoon season (April to September) of 2007 and 2021, the study explores the relationship between LULC shifts and turbidity. The study aims to address the gap in research evaluating the long-term effects of land use on water turbidity, particularly within the Malaysian context. Through the Normalised Difference Turbidity Index (NDTI) and meticulous LULC classification, the repercussions of LULC evolution on water turbidity were analysed. The findings reveal significant LULC alterations over the span, including an increase in built-up areas (25.9 km²), plantations (9.63 km²), and bare lands (0.49 km²), alongside a decline in forests (35.9 km²). These changes correspond with elevated water turbidity levels, highlighting the tangible effects of LULC dynamics on water quality. This study underscores the critical need for enhanced water quality surveillance and prudent LULC management to mitigate river basin pollution.

Keywords: Water turbidity, land use change, remote sensing and GIS, sustainable water management.

Introduction

Rapid industrialisation and urbanisation have significantly influenced global land use and land cover (LULC) patterns, profoundly impacting water bodies' ecological and chemical characteristics (Ganaie *et al*., 2021). Water turbidity, a critical indicator of water quality, is affected by such changes, as turbidity levels are often elevated by increased runoff from altered landscapes (Zhang *et al*., 2022).

The relationship between land use changes and water quality parameters such as turbidity has been extensively studied (Kibena *et al*., 2014; Hua, 2017; Xiong *et al*., 2022; Zhang *et al*., 2023; Li & Xia, 2023). These changes often lead to increased sedimentation and nutrients in water bodies, which can cause significant shifts in turbidity and overall water quality (Bhateria & Jain, 2016). For instance, deforestation and urban development increases surface runoff, exacerbating sediment loading in rivers and lakes (Wang *et al*., 2024).

Furthermore, integrating Geographic Information Systems (GIS) with remote sensing provides a powerful tool for analysing the spatial distribution of turbidity and its correlation with LULC patterns (Zhang *et al*., 2022). This integrative approach enables researchers to perform detailed temporal analyses of environmental data, enhancing the understanding of ecological dynamics over time (Kemarau & Eboy, 2023; Kemarau *et al*., 2023).

Despite the advancements in remote sensing technologies and methodologies, the specific impacts of different types of land use on water turbidity in the Malaysian context, particularly over extended periods, have not been adequately addressed. This study aims to fill these research gaps by applying the NDTI in a long-term analysis of LULC changes and their impacts on water turbidity at Kelalong Dam, Sarawak, thus contributing novel insights into sustainable land and water resource management in rapidly developing regions. Despite the growing body of research, the long-term impact of LULC changes on water turbidity, particularly in biodiverse areas like Borneo, remains underexplored.

Recent studies emphasise the utility of remote sensing techniques in monitoring environmental changes, providing comprehensive spatial and temporal data that are invaluable for managing and mitigating the impacts on water bodies (Mahrad *et al*., 2020). The Normalised Difference Turbidity Index (NDTI), developed from remote sensing data, has been validated in various geographical contexts (Garg *et al*., 2017; Ouni *et al*., 2019; Elhag *et al*., 2021), but its application in Malaysian ecosystems is not well-documented, marking a significant gap in local environmental studies.

The unrestrained population and demanding land use practices impact the water quality in water reservoirs (Hutchins *et al*., 2018). Turbidity is an important indicator of river water quality and hydrological conditions. As a measure of water transparency, turbidity is related to total suspended sediment concentration and other impurities in the water (Robert *et al*., 2016; Zheng *et al*., 2018). It is usually monitored by on-site measurements and hydrological station observations, which are typically time-consuming and limited to discrete stations. With wide coverage and low-cost advantages, remote sensing provides an alternative method for monitoring turbidity on different temporal and spatial scales (Song *et al.,* 2014).

Integrating in-situ measurements and remote sensing data allows for consistent quantification of turbidity changes, especially in the remote and wide study area. Although there have been many studies on the impact of logging and alternative land use on the yield of suspended sediments (Douglas, 1999; Walsh *et al*., 2011). However, there has been a gap in evaluating the impact of land use on water quality for a longer time over longer time scales. This study determines the impact of land use change on turbidity between 2007 and 2021. Besides that, there are still fewer studies in Malaysia that applied the Normalised Difference Turbidity Index (NDTI), which is one remote sensing index for studying one water quality parameter. Toriman *et al.* (2018), Al Mamun *et al.* (2016), and Wan *et al.* (2015) applied GIS analysis to assess the impact of land use on water quality, flash floods, and water quality. This study wants to explore the effect of land-use change on NDTI between 2007 and 2021 at Kelalong Dam, Bintulu.

The research results are important because it studies the impact of land-use changes on sedimentation and turbidity. The study site Kelalong Dam was built to supply water to the Bintulu population. It is very important to monitor turbidity every year. This paper explores the hypothesis that the impact of land use increases with turbidity disturbances to resolve such research gaps. This study is important because it can guide the responsible parties to take appropriate action to maintain the quality of water that will be supplied.

Materials and Methods

Kelalong Dam is a water supply dam for the Bintulu District located about 20 km northeast of Bintulu. The total reservoir storage capacity is 33,700 ML. The location of Kelalong Dam is Bintulu, Sarawak, Malaysia (Figure 1).

This study uses data from Landsat 5 TM and 8 OLI TIRS satellites as shown in Table 1 to achieve the objective of the study. Landsat 5 TM and 8 OLI TIRS data was downloaded from the USGS website. The Landsat used is captured during the southwest monsoon season (April until September), which is mainly dry and has a smaller amount of rain than the northeast monsoon season (Kemarau & Oliver, 2021).

In long-term environmental change studies, satellite images from two distinct time points can provide valuable insights into land use and land cover (LULC) changes and their impacts

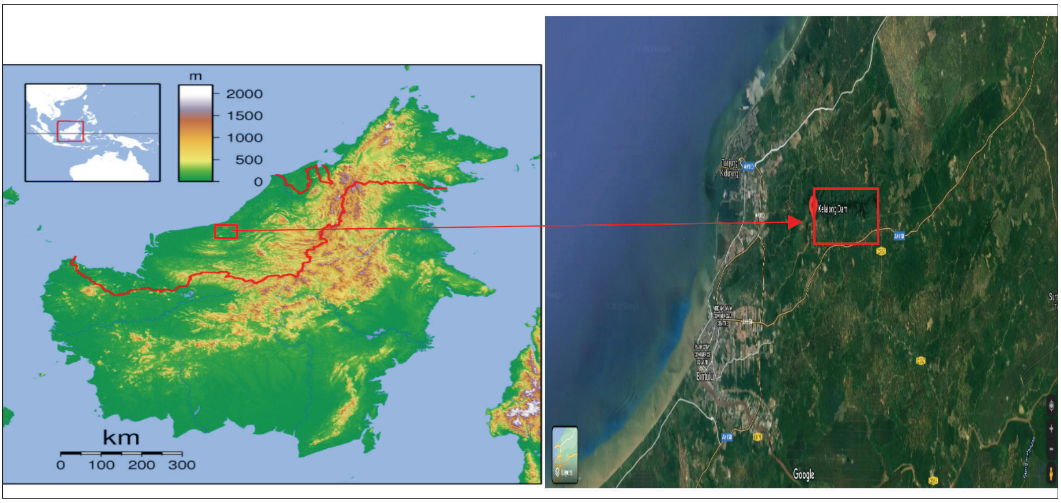


Figure 1: Location of Kelalong Dam, Bintulu, Sarawak

Table 1: Information on the dataset

Sensor	Data Level	Data Acquisition	Cloud Cover
Landsat 5 Thematic Mapper (TM)	Level 1	25 May 2007	Less than 10%
Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS)	Level 1	21 August 2020	Less than 10%

on water turbidity. This approach is predicated on several methodological considerations and supported by previous remote sensing and environmental monitoring research. The selection of two-time points, 2007 and 2021, was strategically chosen to capture significant LULC changes over an extended period. This allows for analysing gradual changes rather than short-term variations, providing a clearer picture of sustained trends and impacts (Jensen, 2015). Long-term studies often use such temporal endpoints to identify and analyse change (Lambin & Meyfroidt, 2011).

Landsat 5 TM and Landsat 8 OLI/TIRS are motivated by their availability and the continuity of the data they provide, which is crucial for long-term environmental monitoring (Wulder *et al*., 2019). Both sensors are well-calibrated and have been extensively used for environmental monitoring, offering a consistent basis for comparative analysis over time (Roy *et al*., 2014). This methodology is common in environmental studies where two-time points (a baseline and a follow-up) are used to understand the extent and impact of environmental changes. By analysing data from these two points, we can directly assess the impact of interventions and changes in land use policies or natural environmental changes over the study period (Kennedy *et al.,* 2014). The use of Normalised Difference Indices (like NDTI) derived from these images is a proven method for assessing specific environmental parameters such as turbidity in water bodies. These indices are sensitive enough to detect significant environmental changes over time and have been validated in numerous studies (Pettorelli *et al*., 2014). The provider has done the geometric correction for both data. The detailed flow of the method will be discussed in the next sentence (Figure 2).

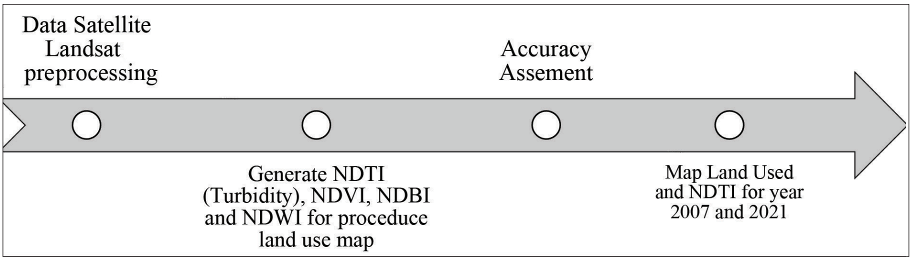


Figure 2: Workflow steps towards achieving the study's objective

Figure 2 shows the flow step required to achieve the objective of the study. The first data needed, Landsat 2007, and 2021 preprocessing were geometric, radiometric, and atmospheric correction. The next data applied needs to generate NDTI to gain the parameter water quality turbidity and generate the Normalised Difference Vegetation Index (NDVI), Normalised Difference Bare Index (NDBI), and Normalised Difference Water Index (Table 2), which was applied by Ricky and Oliver (2021) to generate land use maps 2007 and 2021.

The detailed method generates NDTI, NDBI, NDVI, and NDWI following the formula in Table 2. Table 3 shows the bands available in Landsat 5 TM applied in this study.

Table 4 shows the available wavelength Landsat 8 OLI and TIRS were applied to achieve the objective study.

This study was classified into five different land-use categories: Built-up human, plantation, vegetation, bare land, and water bodies using the NDBI, NDWI, and NDWI index for the years 2007 and 2020.

Table 2: Formulas for generating NDTI, NDVI, NDBI, and NDWI

Index	Formula	Source
NDTI	(Red – Green) / (Red + Green)	Elhag *et al.* (2019)
NDVI	(Near-infrared – Red) / (Near-infrared + Red)	Ding *et al.* (2014)
NDBI	(Short infrared – Near-infrared) / (Short infrared – Near-infrared)	Guha *et al.* (2018)
NDWI	(Near-infrared – Short infrared) / (Near-infrared + Short infrared)	Guha *et al.* (2020)

Table 3: Information of Landsat 5 TM

Landsat 4-5 TM	Wavelength Detailed	Wavelength (Micrometres)	Resolution (Metres)
Band 1	Visible – Blue	0.43 – 0.45	30
Band 2	Visible – Green	0.45 – 0.61	30
Band 3	Visible – Red	0.53 – 0.59	30
Band 4	Near-infrared	0.64 – 0.67	30
Band 5	Short-wave infrared 1	0.85 – 0.88	30
Band 6	Thermal band	1.57 – 1.65	60
Band 7	Short-wave infrared 2	2.11 – 2.29	30
Band 8	Panchromatic	1.50 – 0.68	15

Table 4: Information for Landsat 8 OLI and TIRS

Landsat 8 OLI and TIRS	Wavelength Detailed	Wavelength (Micrometres)	Resolution (Metres)
Band 1	Coastal aerosol	0.45 – 0.52	30
Band 2	Blue	0.52 – 0.60	30
Band 3	Green	0.63 – 0.69	30
Band 4	Red	0.76 – 0.90	30
Band 5	Near-infrared	1.55 – 1.75	30
Band 6	Short-wave infrared	10.40 – 12.50	60
Band 7	Short-wave infrared	2.08 – 2.35	30
Band 8	Panchromatic	0.50 – 0.68	15
Band 9	Cirrus	1.36 – 1.38	30
Band 10	Thermal infrared 1	10.6 – 11.19	100
Band 11 Thermal	Thermal infrared 2	11.50 – 12.51	100

The result found the mapped results at an accuracy of 92.6%, indicating that they can be used to fulfil the mapping objective reliably. The results of the accuracy assessment are shown in Table 5.

Results and Discussion

The map of land use contained five types of land use, namely water bodies, forests, plantations, built-up (housing, commercial, industrial, and transportation), and bare soil (land areas that are unprotected soil and barren areas influenced by humans) as shown in Figure 3 shows the land use map in 2007 and 2021. Based on Figure 3 displays the change in the pattern of land use between 2007 and 2021. In 2007, Figure 3 shows that almost all study areas covered forests transformed into plantations in 2021.

Table 5: Accuracy assessment

Indices	Land Cover	2007	2020
User accuracy (%)	Water body	97	97
	Built-up	94	96
	Plantation	95	99
	Vegetation	97	98
	Bare land		
Producer accuracy (%)	Water body	96	99
	Built-up	100	97
	Plantation		
	Vegetation	92	97
	Bare land	99	99
Overall accuracy (%)		98	98
Kappa coefficient (%)		98	98

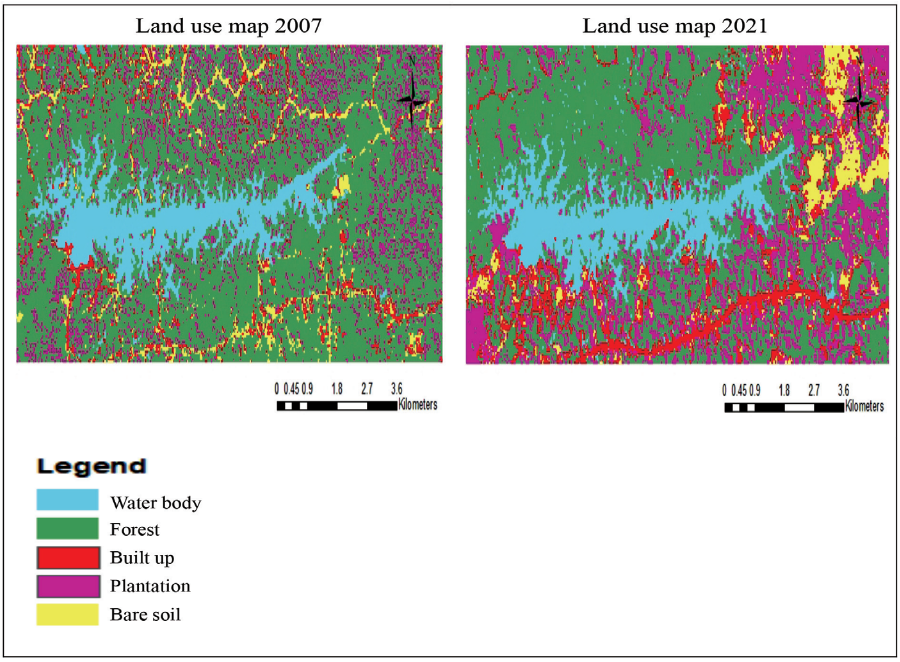
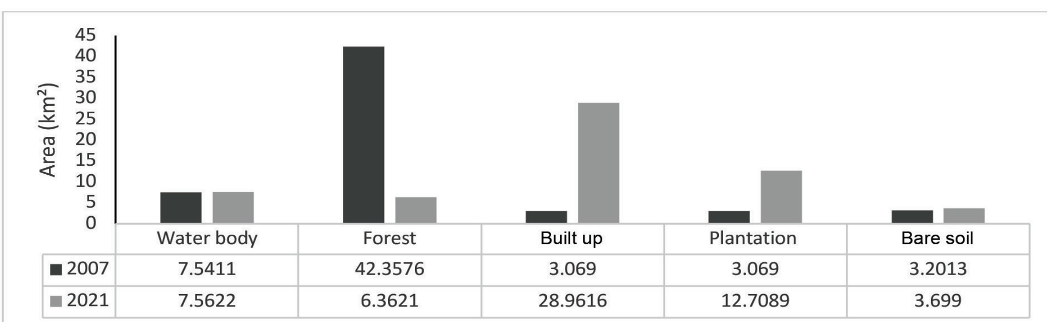


Figure 3: Land use map for 2007 and 2021

The details of settling the change in land use area between 2007 and 2021 will be explained using Figure 4.

Figure 4 shows the land-use area in 2007. The vegetation area (forest) has the widest area of 42 km² followed by the air body area of 7.54 km². The bare soil area is the second largest area of 3.21 km², and the third area is 3.069 km². However, in 2021, the built artificial area has a larger area of 28.9 km², second the plantation area of 12.70 km², and the air body area of 7.56 km² in 2021. These results clearly show the land-use change between the year 2007 and 2021 in study areas, which will be described in Figure 5.

Figure 5 shows the areas of the vegetation area experienced the largest decrease in 35.99 km². The second is built-up human-developed land-use area increased by 25.89 km, plantations by 9.63 km, and bare land 0.49 km².



	Water body	Forest	Built up	Plantation	Bare soil
2007	7.5411	42.3576	3.069	3.069	3.2013
2021	7.5622	6.3621	28.9616	12.7089	3.699

Figure 4: Land use area in 2007 and 2021

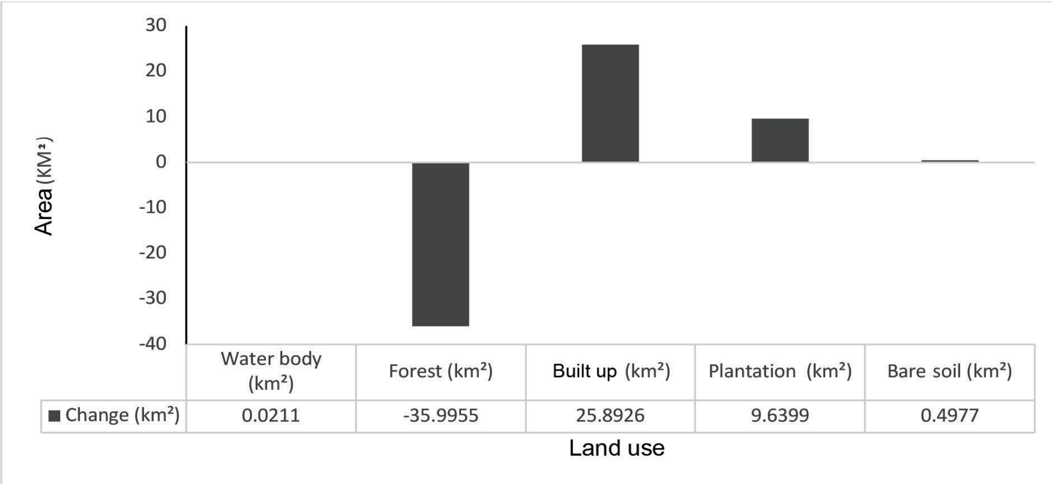


Figure 5: Alterations in land use areas from 2007 to 2021

Figure 6 shows the NDTI distribution map in 2007 and 2021. Looking at Figure 7, the value of NDTI between 2007 and 2021 increases for mean, maximum, and minimum values. The minimum of NDTI is a negative (-) 1 and the maximum value of NDTI is a positive (+) 1. The explanation of the classification of NDTI value is based on Table 6.

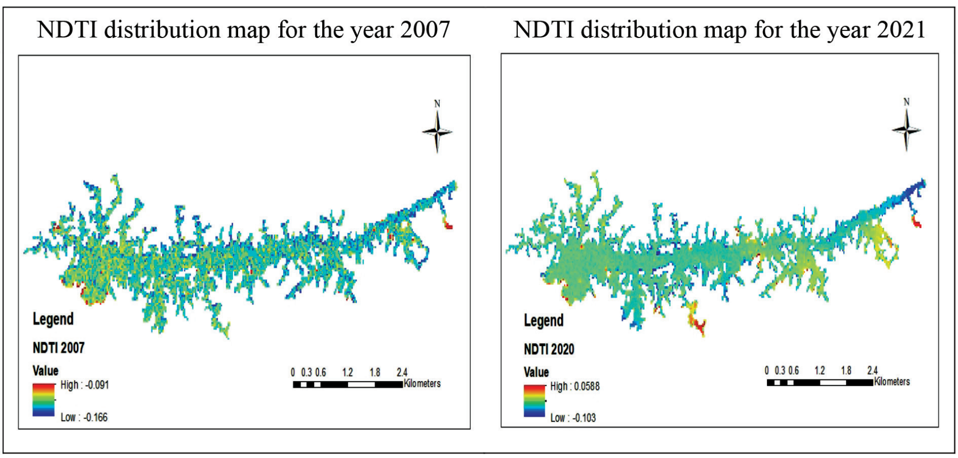


Figure 6: NDTI distribution map for 2007 and 2021

Table 6: NDTI value classification

NDTI Value	Turbidity Level
-1 until 0	Clearwater/slightly turbidity
0 until 0.25	Fairly turbidity
0.25 until 0.50	Rather turbidity
0.50 until 0.75	Turbidity
0.75 until 1	Very turbidity

Figure 6, which represents the NDTI distribution map in the years 2007 and 2021, found that the turbidity level of water in the study area is clearwater/slightly turbidity which has a value below 0. However, there is a maximum, mean, and minimum NDTI of value increase in the study area between 2007 and 2021. The value maximum, minimum, and mean of NDTI value increase are strongly influenced by the land-use change factor in the use area. These developed lands namely built-up, plantation and bare land, provide overflow to the air catchment area. Figure 7 illustrates the increase in the minimum, maximum, and mean value of NDTI between 2007 and 2021.

Figure 7 shows the change in NDTI between 2007 and 2021. The study varied from 0.02 for the NDTI of 2007 and 2021, 0.076 for the maximum value between 2007 and 2021, and 0.063 for the minimum value of NDTI. The increase in the value of NDTI is a factor of land-use change from vegetation to developed areas, plantations, and bare land with a total of 35 km². Natural growing areas are active as filters flowing during rain and air flowing to catchment areas related to man-built land uses, plantations and vacant land where any land surface is exposed during rain will provide rainwater runoff moving to the rainwater catchment area. This led to total deferred sediment that caused slight turbidity to water in the study area.

Based on Figure 8, the study found a major change in land use from agriculture and bare soil in the east of the study area. The change of land use in the east of the study areas indirectly caused the value of NDTI in the eastern area to be higher, which is 0.050 in the year 2021, compared to 2007 in the same area with an NDTI value below 0. This matter clearly shows the activity of land use change from forest to agricultural activities and bare land, giving the value of NDTI higher between the years 2007 and 2021 because the exposure of the land (soil) surface during the rains causes surface adjustment activities that bring the eroded soil to the river during the rains.

It was found from Figure 9 that the land use type gives the mean value of NDTI. The results of the study of Figure 9 were obtained on the NDTI distribution map in 2021 by identifying the maximum value of NDTI obtained based on the type of land use close to the water body. For example, in the area of the black circle in Figure 8, which shows that the area is built, the

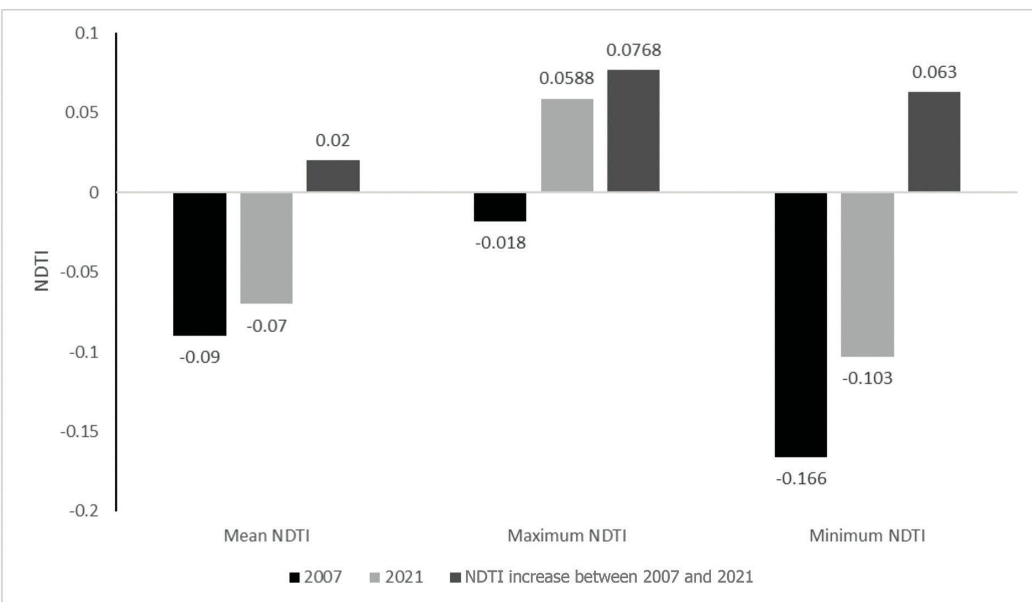


Figure 7: Changes in NDTI values between 2007 and 2021

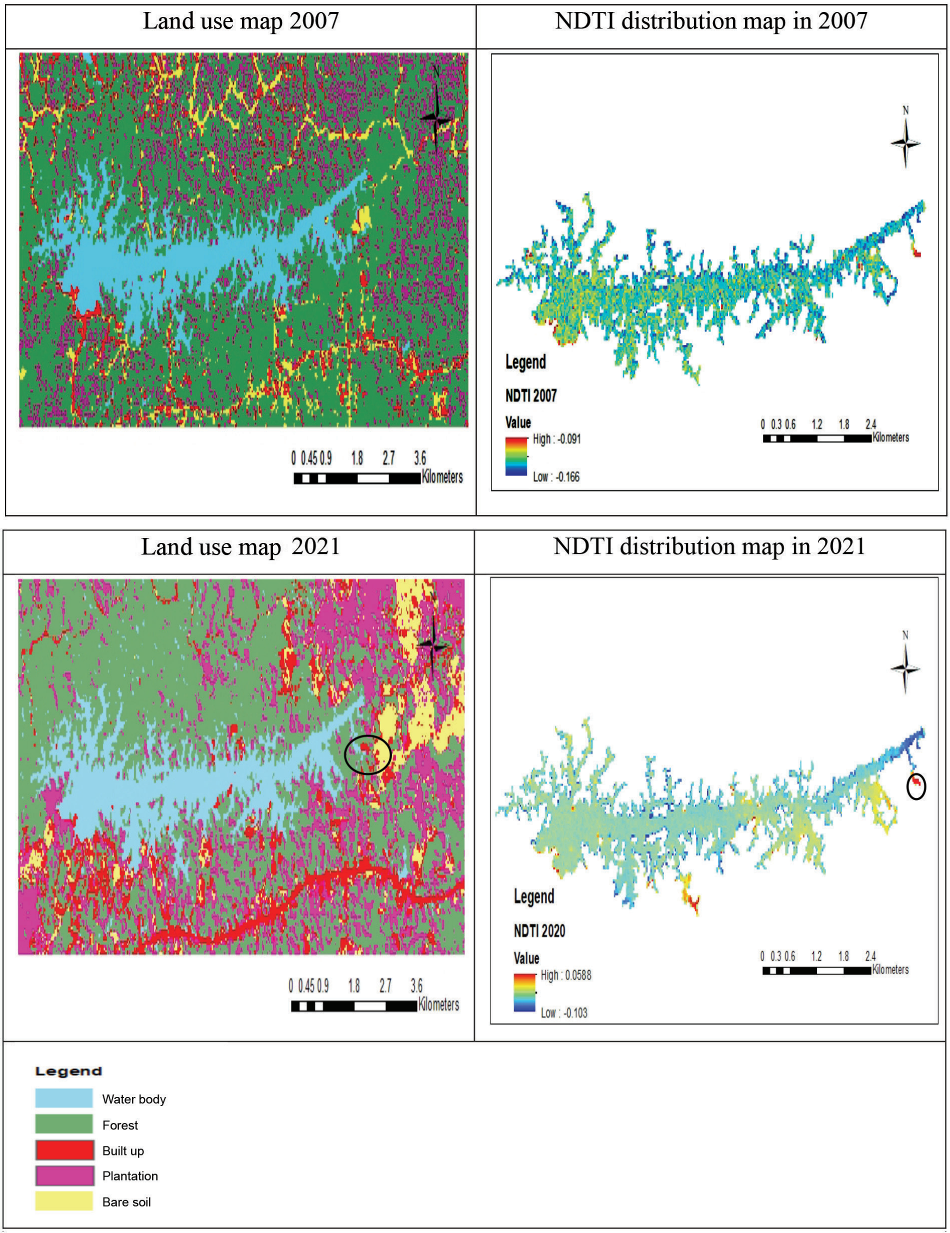


Figure 8: Comparison of land use and turbidity rate distribution between 2007 and 2021

mean value of NDTI is 0.038. This study found that the mean value of NDTI in areas close to empty land (bare soil) because of clearing activities has the highest NDTI which is 0.058, followed by built-up areas, third agricultural areas, and then the lowest mean value of NDTI in forest areas. Areas proximate to bare land have the highest average because those areas do not have vegetation covering the bare soil, which causes higher erosion rates during rain compared to built-up areas, agriculture, and forest areas. The clearing activities of land (bare soil) can lead to increased salinity, sediments, and the decomposition of organic matter in streams, leading to acidity problems in the catchment (Camara *et al*., 2019). The water

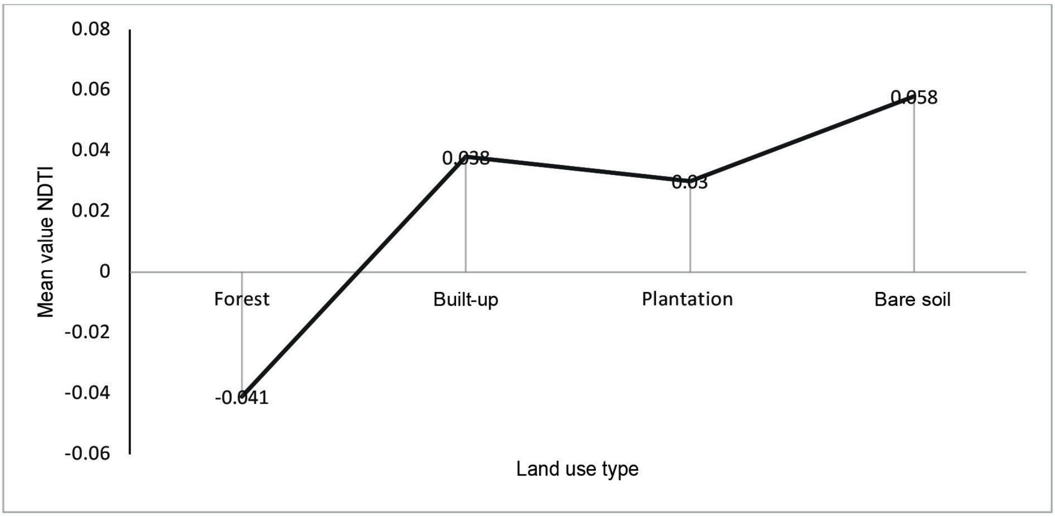
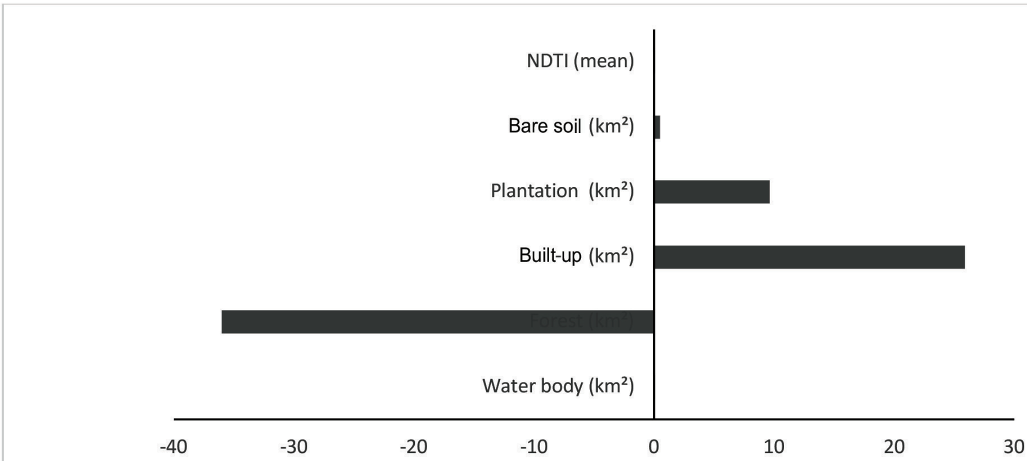


Figure 9: The mean value of NDTI is based on the proximity of each type of land use to water bodies



	Water body (km²)	Forest (km²)	Built-up (km²)	Plantation (km²)	Bare soil (km²)	NDTI (mean)
■ Change (km²)	0.0211	-35.9955	25.8926	9.6399	0.4977	0.02

Figure 10: The effect of changes in land use aea on the mean NDTI value in 2007 and 2021

bodies surrounding forest areas denote a -0.041 value of NDTI because Nainar *et al.* (2017) highlighted the contributions of rainforests to protecting water quality, particularly turbidity by reducing water runoff activities during rain and decreasing erosion. The researchers believe that the water turbidity level would have increased had it not been for the monitoring of development around the Kelalong Dam.

This study found that land use changes in the Kelalong Dam area for 2007 and 2021 directly affect air quality through the turbidity parameter represented by NDTI. Land use from forest areas to bare land, built, and plantation areas caused the value to change from -0.07 in 2007 to -0.09 in 2021. Forest areas experienced a decline of 35.99 km² to built, plantation, and bare land areas, which explains the increased value average NDTI between 2007 and 2021 of 0.02. This explains the positive relationship between the increase in the use of built-up land and bare land with the mean value of NDTI and the relationship between the song and the decrease in the forest area with the mean value of NDTI. The results of this study have similarities with Camara *et al*. (2019), who explained that the increase in built-up (urban) areas, agriculture, and vacant land causes an increase in physical changes (turbidity) with a Spearman correlation value of 0.53 (urban parameters with physical water bodies) and 0.70 (parameter land used for agriculture with physical water bodies). Air quality monitoring is important because the deposition of dead vegetative matter and suspended sediments can cause a reduction in reservoir capacity (Bishwakarma & Støle, 2008), thus contributing to a decrease in power generation capacity and an increased cost of freshwater treatment.

The transformation in land use observed between 2007 and 2021 at the Kelalong Dam area is profound, with significant shifts from forested regions to built-up, plantation, and bare lands. As shown in Figure 3, the forest area decreased dramatically by 35.99 km², which was largely converted into built-up areas (increased by 25.89 km²) and plantations (increased by 9.63 km²). These changes are critical as they directly influence the hydrological and sediment dynamics of the region (Foley *et al*., 2005; Lambin *et al*., 2013).

The Normalised Difference Turbidity Index (NDTI) maps for 2007 and 2021 (Figure 6) reveal an increasing trend in turbidity levels coinciding with land use changes. The NDTI values, classified from -1 (clear water) to 1 (very turbid), show a marked increase, particularly in areas where forest cover was replaced by anthropogenic land uses. This shift indicates increased runoff and sediment transport due to reduced vegetation cover, corroborating findings by Turner and Rabalais (2003) that link land use changes to water quality degradation. The conversion of forests to less permeable surfaces (e.g., urban and agricultural lands) enhances surface runoff, reducing the land's natural ability to filter and retain water and sediments (Defries & Eshleman, 2004). This process was particularly evident in the eastern sectors of the study area, where intensive agricultural activities and bare soil exposure led to higher NDTI values in 2021 compared to 2007, as detailed in Figures 7 and 8.

These findings underscore the need for integrated land and water management strategies that consider the impact of land use on water bodies. The increased turbidity affects water quality and poses challenges for water treatment and biodiversity conservation (Postel & Richter, 2003). Monitoring and managing these changes is vital for sustainable water resource management, especially in regions facing rapid developmental pressures. This study contributes to the scientific understanding of the spatial dynamics of turbidity in response to extensive land use changes. By employing remote sensing techniques over a 14-year interval, the study highlights the long-term impacts of anthropogenic activities on water quality. Moreover, it utilises the NDTI, an innovative approach in the Malaysian context, providing a replicable methodology for similar ecological assessments in other regions (Okin *et al*., 2004).

Conclusions

This study has effectively demonstrated the significant relationship between land use and land cover (LULC) changes and the increased water turbidity at Kelalong Dam from 2007 to 2021. Employing remote sensing data and the Normalised Difference Turbidity Index (NDTI), our findings substantiate that transformations from forested areas to built-up, plantation and bare lands have led to marked increases in turbidity. This correlation highlights the pressing need for proactive environmental management practices.

The transition observed underscores the urgent requirement for integrated land and water management strategies to mitigate the environmental impacts of urban and agricultural expansion. Effective monitoring and sustainable land management policies are imperative to safeguard water quality. Local authorities and stakeholders should prioritise establishing protective measures around sensitive water catchments to prevent further degradation.

Furthermore, this research paves the way for future studies to adopt similar methodologies in different geographical contexts, exploring adaptive management strategies that balance developmental needs with environmental preservation. Ensuring the sustainability of water resources in the face of developmental pressures is crucial for environmental health and the socio-economic well-being of the community relying on these water bodies. In essence, the insights gained from this study advocate for a holistic approach to land use planning and water quality management, reinforcing the need for thoughtful consideration of environmental impacts in developmental policies and practices.

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Conflict of Interest Statement

The authors declare that they have no conflict of interest.

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