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ASSESSING WATER REDUCTION DYNAMICS IN THE CHAI RIVER, DAKUK, IRAQ USING REMOTE SENSING AND GIS TOOLS

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Abstract
Water erosion is a major environmental issue in the globe today, contributing to sedimentation and degrading agricultural lands. The study objectiveis to probe the dynamics of water erosion in the Chai River basin, Dakuk, Iraq. Geographic Information System (GIS) and remote sensing are genuinely employed to detect and quantitative the changes in water of Chai River relative to barren and vegetation features. Maximum Likelihood classification method is applied to classify the Sentinel Satellite images from 2015 to 2014. Change detection analysis is employed to detect the changes in landcover classes between the selected years. The results were revealing that soil dominated the landscape in 2015, followed by water and plants. By 2024, the water class expanded, reaching 3.7559 km², primarily at the expense of soil. The study found that 2.0445 km² of soil was converted to water and plants, indicating a decrease in soil cover. The water class gained 1.3800 km², while vegetation remained stable. This suggests potential hydrological or environmental changes. Because the sand class side of the river increased because of the recent decline in rainfall rates, the boundaries Chai River and water level dropped between 2015 and 2024.

Keywords: Change detection, GIS, Remote sensing, Soil erosion, Water reduction

Introduction

One major environmental issue facing the world today is water erosion, which exacerbates sedimentation and degrades agricultural lands. The dynamics of water erosion in the Jay River Basin are still not well understood, despite the fact that this problem is urgent and poses a threat to natural resources. The main cause of this knowledge gap is the region's severe lack of research, which is made worse by the use of antiquated, constrained, and frequently insufficient techniques for erosion process monitoring. Therefore, the creation and application of more accurate and effective instruments for land use management and thorough water erosion monitoring in this susceptible region is essential.

In dry and semi-arid regions, water erosion of soil is an operation of ongoing degradation of the land (soil, vegetation cover), and it is regarded as a damaging form of environmental degradation that affect productive pasturelands (Alalwanya,A.A.M.,Ghani,E.A.,Ali,K.A., &

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Al-Bayati, 2021). Water erosion mostly happens when soil particles that have been separated by raindrop impact (also known as splash erosion) and runoff are transported by overland flow, frequently creating distinct channels like gullies or rills (Symposium & Erosion, 2019). Soil erosion is the biggest negative environmental concerns in the globe. It is undesirable because it results in many substantial off-site environmental problem such flooding, water siltation, and pollution in addition to depriving soil nutrients and degrading land (Issaka & Ashraf, 2017).
Traditional field measuring methods, while thorough and reliable at plot scales, might be challenging or even unfitting to apply at levelsof catchment due to the significant amount of labor, expense, and time required (Phinzi & Ngetar, 2019). The spectrally complex nature of erosion levels and adjacent regions may make it difficult to map soil erosion using this conventional parametric technique (Sepuru & Dube, 2018).
Remote sensing is a method of collecting data about the surface of the Earth without contacting with it. The information acquired in remote sensing is accurately gathered by sensors attached on platforms like satellites, planes, and drones(Mirzakarimova, 2023). The past decade has seen remarkably great improvements in remote sensing technologies, which significantly enhance the ability to map erosion processes and precisely quantify them(Glendell et al., 2017). The application of RS methodologies in a GIS framework offers greatly promising potential to effectively exploit the capabilities of modern software tools and technologies to efficiently improve the process of locating and mapping erosion processes and thoroughly assessing soil loss owing to water erosion (Polovina, S., Radić, B., Ristić, R., & Milčanović, 2024).). The effectiveness and cost-efficiency of quantitative spatial and temporal analysis concerning changes in waterways are successfully achieved through the integration of remote sensing data with Geographic Information Systems (Langat et al., 2019). During the last two decades, Geographic Information Systems (GIS) have been widely and consistently used to accurately assess, analyze, and represent coastal hazards (Jadidi, A., Mostafavi, M. A., Bédard, Y., Long, B., & Grenier, 2013). The aim of this research is to thoroughly study the dynamics of water erosion in the Chai River basin, Dakuk, Iraq, using remote sensing and GIS techniques. Its main objectives are the careful identification of erosion-prone sites, systematic monitoring of changes, and holistic assessment of the impacts of environmental conditions and human activities. The study will ultimately provide data-based evidence to decision-makers for the actively promoted adoption of sustainable land management and conservation practices that could effectively reduce soil erosion and environmental degradation in the territory.

MATERIALS AND METHODS

The methodology adopted employing remote sensing and GIS tools to male an analysis that is spatial and temporal patterns of soil erosion. Sentinel 2-L2A was processed to make up land use and land cover maps, with supervised Maximum Likelihood classification technique extracted the classes of land cover. Change detection analysis was used to pinpoint the changing of classes over time between 2015 and 2024. Kappa coefficient and total precision was applied to ensure the accuracy of the taxonomy results. The final outputs, including thematic maps and spatial changing analyses, provide insights into land cover changing. Figure 1 illustrates the flowchart of the current paper.

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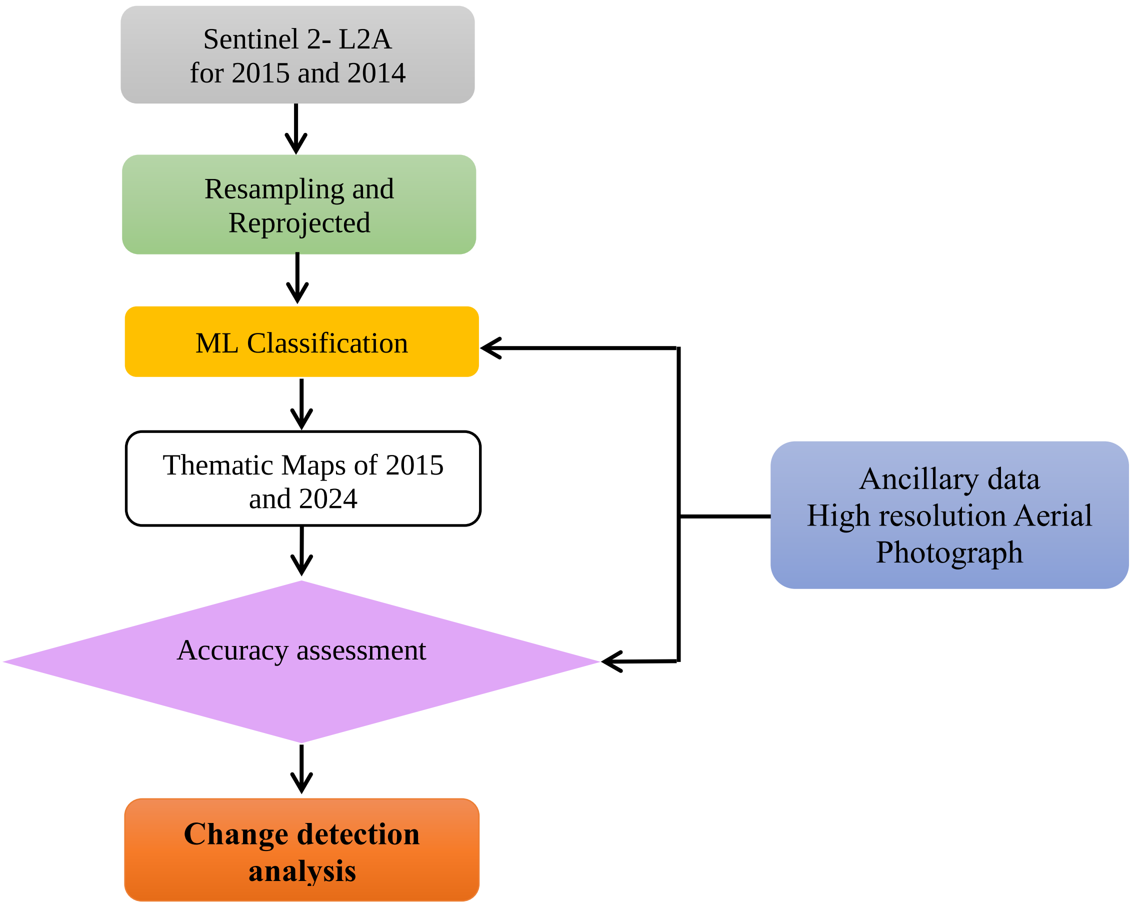

Figure 1: Workflow of the procedures for the study

Study area

The geography of Dakuk is largely flat, with heights ranging from 200 to 300 meters above sea level. This flat topography encourages sluggish water movement and soil absorption, which increases agricultural output. Erosion is minor due to low surface runoff, but some slow erosion occurs along riverbanks. Geologically, the area is made up of clay and sandy soils, with clay being more susceptible to erosion.

This research focuses on the Chai River watershed in the Dakuk region, which is located southeast of Kirkuk Governorate in Iraq. The basin is circumscribed by latitudes34°44'30''-35°35'49''Nand longitudes44°17'39''-45°28'16''E (Beg et al., 2023). Dakuk is economically

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significant, with a semi-arid environment that features hot, dry summers and cold, wet winters. The region's natural features include fertile agricultural plains, low hills, orchards, and irrigated rivers. The area receives 300 to 500 mm of rainfall per year, which supports a diverse range of plant and animal life and allows for a basic agricultural existence.

Agriculture, cattle rearing, and grazing are the principal land uses, however urban development is underway, with new residential and public amenities being built. Dakuk is extremely rich in natural resources, particularly oil, necessitating long-term land management strategies to safeguard the ecosystem and preserve biodiversity. Figure 2 illustrates the study area (Chai River, Dakuk District, Kirkuk, Iraq).

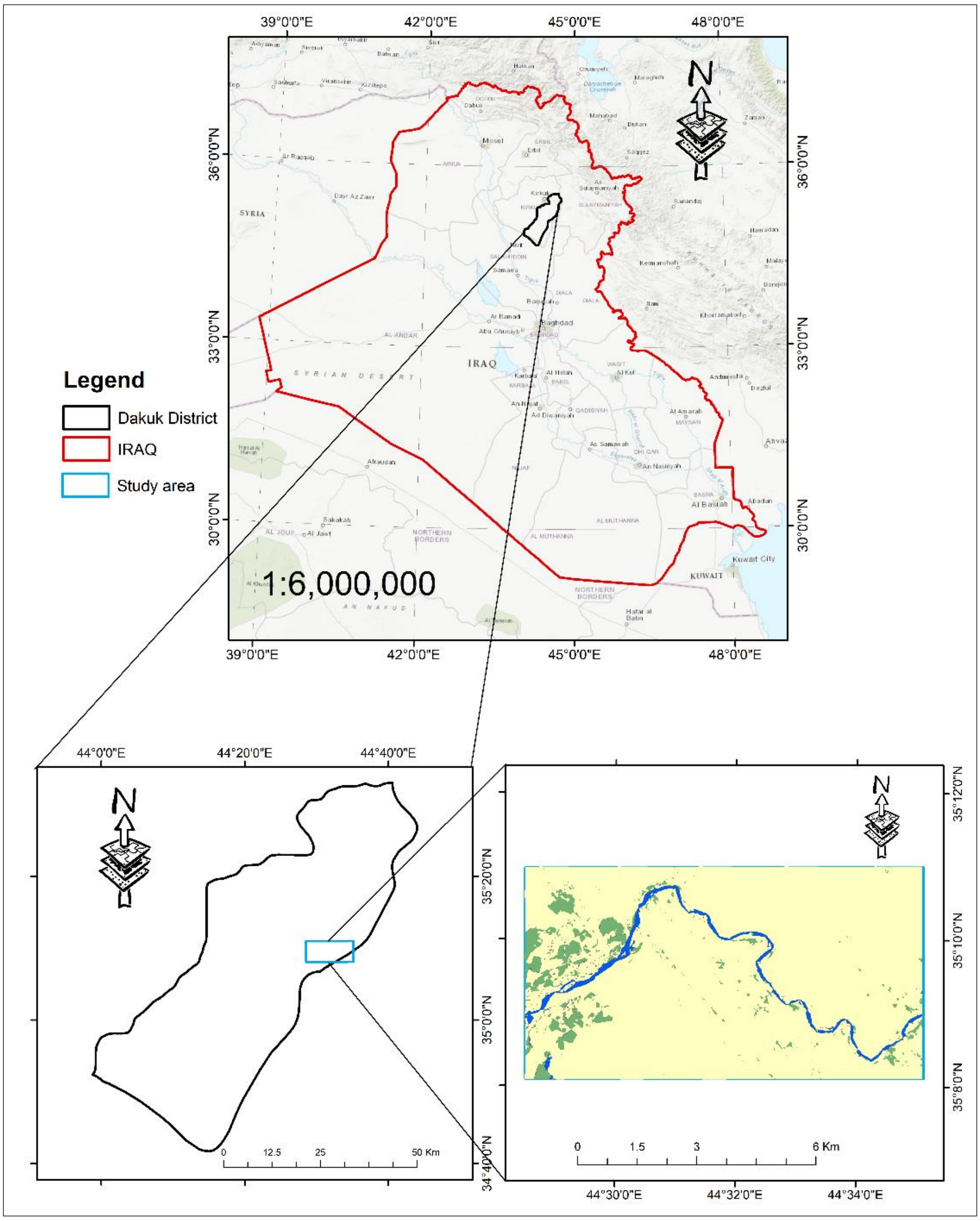

Figure 2: Study area of current research (Chai River, Dakuk)

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Data used

This study employed Level-2A (L2A) Sentinel-2 multispectral data from 2015 to 2024 to examine changes induced by water erosion during a nine-year period. The Sentinel-2 mission consists of dual satellites, Sentinel-2A and Sentinel-2B, every single one is manned with an optical image sensor MSI (Multi-Spectral Instrument). The MSI attempts to measure mirrored radiance in 13 spectral bands spanning from the Visible and Near Infrared (VNIR) to the Short Wave Infra-Red (SWIR) spectrum (Main-Knorn et al., 2017). Two satellites produce images with 10- to 60-meter spatial resolution, 13 spectral bands, and a 5-day return frequency at the equator. (Astola et al., 2019). The L2ABOA imagery is taken after a series of atmospheric modifications from the L1C imagery (Medina-Lopez, 2020). Table 1 describe the particulars of sentinel data in this paper.

Table 1: the details of Sentinel L2A satellite images

Data	Source	Description
Satellite images (Sentinel L2A)	https://dataspace.copernicus.eu/	Spatail resolution 10 m, 20 m, 60 m GRANULE/L2A_T38SMD_A035868 & 02663 Acquisition Date January 18, 2024 December 26, 2015

In this study, we carefully adopted two satellite images from 2015 and 2024 to thoroughly examine how soil loss and vegetation degradation, primarily caused by water erosion, have severely affected erosion-prone locations such as riverbanks and agricultural land. The multispectral data effectively enabled the delineation of diverse landcover types, like bare soil, vegetation, and waterbodies. The use of these two independent datasets over a nine-year period allowed researchers to systematically study the extent of water erosion and its notable consequences on the landscape, ultimately providing vital insights into the ongoing environmental changes in these highly sensitive places.

Preprocessing

Sentinel-2 **reliably** provides 13 multispectral bands, including three red-edge bands that **specifically** enhance vegetation detection. It also includes four **commonly** used conventional bands—red, green, blue, and near-infrared—that **effectively** offer a 10-meter spatial resolution. (Wang et al., 2018). Nevertheless, pre-processing enhances image quality by eliminating errors related to collecting data (Phiri et al., 2020). This method frequently involves a series of steps aimed at improving the data for future study. Subsetting, resampling, and re-projection are some of the important preprocessing procedures in SNAP (Sentinel Application Platform), and they are explained below:

Subsetting

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This preprocessing step is designed to reduce dataset size by focusing on a specific area of interest (AOI). Sentinel-2 photos span large areas, and analyzing the entire scene can be computationally intensive.

Resampling

The input products include 13 spectral bands at three distinct spatial resolutions (10 m, 20 m, and 60 m). Many operators do not accept goods with bands of varying sizes, so it was required to resample the bands to an equivalent resolution of 10 meters (Kovács, 2019).

Reprojection

The UTM zone related to the overlaying Sentinel-2 granlues can be matched by choosing and possibly setting the target Coordinate Reference System (CRS). The operator permits the target pixel spacing in the target CRS and the selection of imagine resampling technique (Taha & Ibrahim, 2021). The reprojected positions normally be among Sentinel-2 pixel sites, so nearest neighbor resampling was used because it is computationally efficient, preserves the input image pixel values, and allows for quantification of geometric resampling chnages (Roy et al., 2016). There are two ways to correctly illustrate area when calculating zonal statistics employing WGS84 datasets: reprojecting the datasets to an equalizing land projection or weighting pixels depending on latitude (Goodman et al., 2019).

Land use/ land cover classification

One of the most significant environmental issues endangering both developed and developing nations is land use/cover (LCLU) (El-Tantawi,A.M.,Bao,A.,Chang,C.,&Liu,2019). Despite their common usage, the phrases "land use" and "land cover" are better described as distinct concepts. "Land use" describes how the biophysical characteristics of the land are altered as well as the motivation for such alteration. The biophysical condition of the Earth's surfaces and the near subsurface is referred to as land cover (Macarringue et al., 2022) Land use classification is important since it offers data utilizable as input for modeling, which is specifically those coping with the environment, like models tackling with climate change and policy developments (Rwanga&Ndambuki,2017). Satellite images provide several benefits of multi-temporal availability and maximum spatial coverage for LULC mapping (Talukdar,S.,Singha,P., Mahato,S.,Pal,S.,Liou,Y.A.,&Rahman,2020). The approach results in a map-like representation after classifying land use using remotely sensed data. Image classification thus serves as a key technique for examining digital photos. This classification tool allows us to create our own representation of land use/land cover data (Devi, M. R., & Baboo, 2011).

Supervised classification

Supervised classification has been deeply investigated within the scope of systems based on machine learning (Silva, 2017). Among the most prominent and widely used approaches for studying this data are supervised classification methods, which necessarily require labeled reference data to train learning models (El-Tantawi,A.M.,Bao,A.,Chang,C.,&Liu,2019). The

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primary determinants of classification accuracy in managed land cover taxonomy are carefully selected classifiers, reliably integrated auxiliary data, and appropriately chosen training samples (Li et al., 2021). Notable examples of classifiers include the maximum likelihood classifier (MLC), support vector machines (SVMs), and decision trees (DTs), which are **frequently** applied in land cover studies (Otukei & Blaschke, 2010). The kappa coefficient and error matrix are now **commonly** and **effectively** used to **accurately** evaluate the performance of image classification.
(Rwanga & Ndambuki, 2017).

Maximum Likelihood Classification

Maximum likelihood classification (MLC) could ultimately and maximally be the most widely adopted supervised classification technique and undoubtedly is used in numerous applications (Sisodia et al., 2014). The maximum likelihood decision rule remarkably counts on a normalized (Gaussian) estimate related to the probability distribution function for each class (Mingguo, Z., Qianguo, C., & Mingzhou, 2009). This approach extnesively employed most frequently and widely in remote sensing, where a pixel is allocated to the appropriate class with the ultimate probability (Mondal et al., 2012). The Bayes technique was used to determine the pixel class in an image using the maximum likelihood ratio testing (Abbasi, A., & Fahlgren, 2017). The foundation of MLC is Bayes classification, which assigns pixels to classes based on their likelihood of falling into a specific class (Sisodia et al., 2014).

Accuracy assessment

Accuracy assessment is **critically** important to the conceptualization of remotely sensed data (G. Foody, 2008). The objective desirable of accuracy assessment is to **precisely** quantify how well pixels have been gathered into the correct land cover classes (Rwanga & Ndambuki, 2017). Additionally, the objectives of accuracy assessment include **effectively** comparing maps, **accurately** describing the quality of the maps, and **thoroughly** assessing changes in land cover (Zhen et al., 2013). Accuracy assessment is vital for the classification process (Ismail, M. H., & Jusoff, 2008). The ultimate commonly used accuracy estimation technique for evaluating the classification precision of remote sensing images is the confusion matrix, which can **easily** summarize the classification data and **clearly** evaluate the overall and class accuracy (Yi & Zhang, 2012). Overall accuracy refers to the percentage of events (e.g., pixels or measuring units) that are **correctly** identified.
(Shao et al., 2019).
The difficultie in precise assessment mustn't be overlooked, and authors were requested to take attempt to address them. This includes the creation of error corrected estimations of classification accuracy and associated variables such as occurrence (G. M. Foody, 2023).
Accuracy assessment or validation is a crucial phase in the analysis of remote sensing data (Rwanga & Ndambuki, 2017). It is true that the actual application of remote sensing data and outcomes is dependent on their dependability, which must be assessed (Kerr & Fischer, 2015).

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Change detection analysis

Distant-controlled sensing change detection approaches boost conservation capacities by monitoring changes in environmental state, and they may assess management efficacy without causing additional damage the landscape (Willis, 2015). Change detection using satellite imagery is an **incredibly** essential method for identifying vicissitudes on the Earth's surface and has an **extensively** wide variety of apps, including urban development, environmental monitoring, agricultural studies, disaster evaluation, and map updating (Shi et al., 2020). Change detection **systematically** uses multi-temporal satellite images to **accurately** identify geographic changes triggered by natural or human-made phenomena. It is **particularly** crucial for land use and land cover change detection, environmental monitoring, and remote sensing (Asokan & Anitha, 2019). Understanding the **complex** connections and interactions between natural and human occurrences is **critically** important for improving decision-making. This can be **effectively** achieved through **precise** detection of change of Earth's surface features (Lu et al., 2004). Change detection methods are **frequently** integrated with pre-processing techniques that **carefully** extract information or **significantly** reduce data dimensionality. These methods are then **successfully** applied to the stream of extracted features (Carrera, D., & Boracchi, 2018). A **remarkably** wide range of change detection approaches were developed, and many have been **thoroughly** compiled and examined.(Lu et al., 2004). Detecting change and non-change typically serves as the first step in assessing the amount and spatial sequence of changed areas in a research area during a change detection interval (Lu et al., 2014). The comparable efficiency of different change detection strategies in diverse situations must be quantitatively analyzed in order to gain knowledge of tried and tested change detection procedures in a flexible way. This allows one to get the best outcomes whilst monitoring changes in a certain environment (Goswami et al., 2022). It is particularly critical to decide on the change detection approach counting on the type of application that it will be employed (Asokan & Anitha, 2019).

Results
Classification result of 2015

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Figure 3 states the taxonomy of landcover in 2015, the land cover was categorized into three primary classes: Soil, Vegetation, and Water. Soil formed the largest class of the land cover occupying the largest area of 58.5343 km². Little movement was observed between class changes; there was 1.3563 km² that changed to water and 0.5681 km² that changed to vegetation. Vegetation cover was less with total of 1.7877km². A small area of only 0.0237 km² of the vegetation underwent conversion from water class. The least represented class of land cover was the water which occupied an area of 0.2568 km². There were no transition trends between other classes and water during this year. Classification done in 2015 identified soil as the dominant land cover class followed by vegetation and water resources. This shape clarifies a primary passageway for evaluating fluctuations in ground cover in the future.

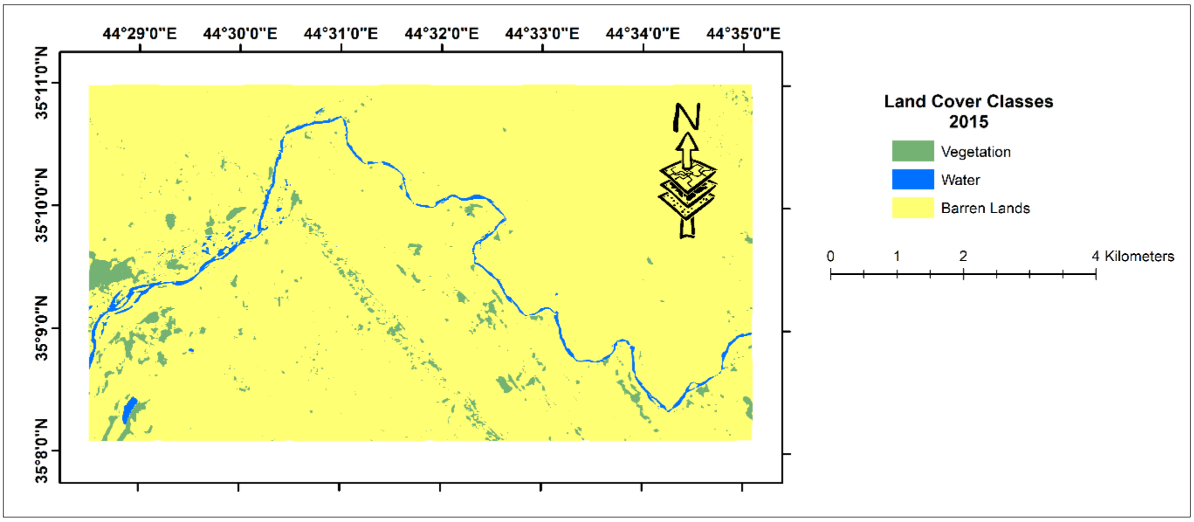

Figure 3: Land cover classes for study area in 2015

Classification result of 2024

Figure 4 illustrates the land cover classification in 2024, the land cover was categorized into three main classes: Soil, Vegetation, and Water. Soil was still the highest density in the land cover class with an area of 58.5343 km². A few transitions were noted; about 1.3563 KM2 of soil area switched to water and about 0.5681 KM2 shifted to vegetation, which was an appreciable change but signifying mere reshuffling in the land use pattern. Forest or other wooded land occupied an area of 1777 hectares; this, did not change from the previous year's size of 1777 hectares. Other classes compensate for small losses, and therefore total area does not change significantly. Water land use raised dramatically to 3.7559 km² from the previous level, making it the most rapidly changing class of the study's land cover. This increase was mainly attributed by change of 1.3800 Square kilometer of soil and 0.0237 Square kilometer vegetation to water.

The dynamics related to land cover according to the classification in 2024 essentially changed: water areas increased for the most part of soil, and vegetation did not change and remained constant by sharing its transitions. These shift are still consistent with the current environmental and land use changes in the region.

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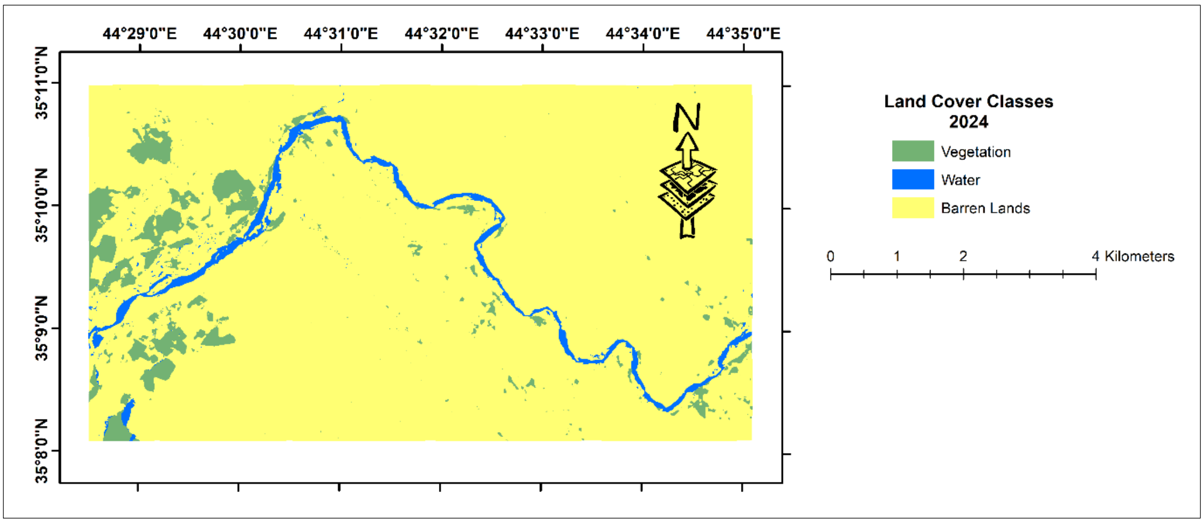

Figure 4: Land cover classes for study area in 2024

Change detection results

Figure 5 shows the change detection of land covers that occurs between 2015 and 2024 over the Chai River. A comparison of the land cover pattern of the research area between the years 2015 and 2024 captures an ever-evolving of the distribution pattern of soil, vegetation and water. In each of these classes, there was some degree of change and these changes could be environmental and possibly anthropogenic. The analysis further shows that soil is still by far the most widespread cover across the two years of 2015 and 2024. Nevertheless, its total area has even decreased for the several years. As for the soil class, the area covered in 2015 was 60.5788 units and in the year 2024 it was 60.4587units thus having a loss of 0.1201 units. This change indicates little change in either conversion of soil to other land cover types like vegetation or water. However, at this level of review, the proportion of the total land area occupied by soil remains by far the highest. Land use showed a change in vegetation cover as it equally revealed new important changes in cover. Where vegetation found was 0.8171 units in 2015, it had risen to 2.0598 units in 2024 meaning an overall gain of 1.2427 units. This rise could be due to afforestation, the expansion of agriculture practices or decline in desertification. Its growth shows the increasing greener coverage of the land use which may be good for the environment and ecological systems. Water bodies had the strongest rate of decline of the three land cover classes. The area by water in 2015 was 3.7559 units, while in 2024 it was 2.6333 units thus meaning a decline of 1.1226 units. This may be as a result of decrease in water bodies due to factors like climate change, or change in rainfall pattern as well as human activities including drainage for development. The problem of the decreased water area can be a cause for alarm concerning hydrological equilibrium and local habitats, which deserve more research.

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Soil is relatively constant with only slight decreases, while vegetation points to large improvements, including positive land use or even natural restoration. However, the decline in the proportion of water area might indicate certain environmental pressure that can harm stability over the long run. T These findings will be useful for the decision-makers to initiate more policies on the usage and availability of the land partition where water resources are to be protected and vegetation cover, and sustainable soil health are to be promoted. Table 2 describes the changing in land cover classes between two years which are 2015 and 2024.

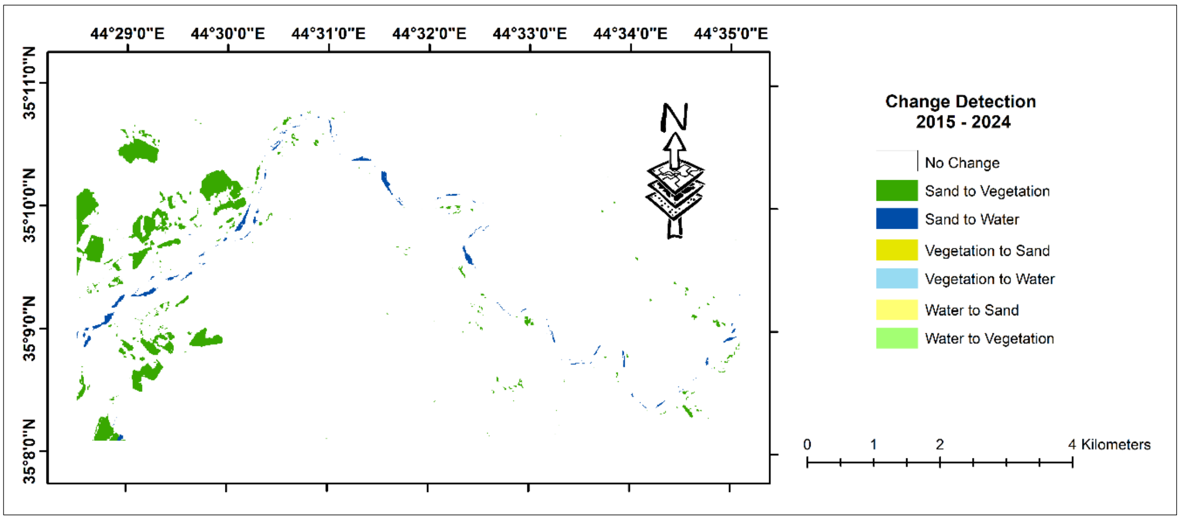

Figure 5: Change detection of land cover classes between 2015 and 2024

Table 2: The confusion matrix of change area between 2015 and 2024

Area Counts (Km^2)						
		2015				
		Soil	**Vegetation**	**Water**	**Row total**	**Class total**
2024	**Soil**	58.5343	0.5681	1.3563	60.4587	60.4587
	Vegetation	1.7877	0.2484	0.0237	2.0598	2.0598
	Water	0.2568	0.0006	2.3759	2.6333	2.6333
	Class total	60.5788	0.8171	3.7559	0	0
	Class changes	2.0445	0.5687	1.3800	0	0
	Image difference	-0.1201	1.2427	-1.1226	0	0

Conclusion

The current study presents important insights into soil, vegetation, and water distribution by highlighting the dynamic changes in land cover within the study region between 2015 and 2024. With an area of 58.5343 km², soil dominated the landscape in 2015. Water came in second with 0.2568 km² and plants with 1.7877 km². Although the general extents of the soil and vegetation remained unchanged by 2024, the water class significantly expanded, reaching 3.7559 km², mostly at the expense of the soil.

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The change detection examination indicated that 2.0445 km² of soil changed to water and plants, suggesting a decrease in soil cover. The water class had the most significant alteration, with a net gain of 1.3800 km² from soil and vegetation, while vegetation remained stable as gains from other classes compensated losses. This expansion indicates possible hydrological or environmental changes in the region.
These results give insights to the signifcance of observing land cover changes with consideration to the long term sustainability of the earth's resources. The cumulative extent and number of water areas, along with relatively slight shifts in plant cover, requires deeper investigation into the factors behind such changes – climatic, hydrological or anthropogenic. Development of a sound framework for planning and sustainable management of land use will be important in balancing the natural environment with the need to support development in the region.

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