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Using Gis and Remote Sensing to Map the Environmental Effects of Urban Expansion on Wetlands

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Abstract

This study uses remote sensing and geographic information systems (GIS) to examine how urban growth affects wetlands. The study is to analyze changes in land use and land cover within the study area by evaluating Landsat satellite pictures from MSS, TM, and ETM sensors spanning from 2018 to 2021. The goals are to measure the effects of urbanization on agricultural land and tree cover, analyze patterns of land cover alteration, and assess the accuracy of land cover classification using supervised techniques. The process comprised first correcting satellite images for altitude and geometry, then supervised classification with accuracy evaluations based on generic accuracy metrics and Kappa coefficients. The results show notable changes, such as a move from forest cover to built-up areas and residential areas. Urbanization and economic development are shown to be the main causes of these changes. Critical insights into the environmental effects of urban expansion on wetlands are provided by the study, which also highlights the usefulness of remote sensing for tracking land use patterns.

Keywords: Geographic Information Systems (GIS), Remote Sensing, Urban Expansion, Wetlands, Environmental Impact, Land Use Change.

1. INTRODUCTION

1.1 Overview of Urban Expansion and Wetland Degradation

Continual growth of cities and metropolitan areas is referred to as urban expansion. This growth is driven by factors such as population growth, economic development, and the requirements for infrastructure. For the purpose of housing a greater number of people and industry, this growth is necessary; yet, it comes at a tremendous cost to natural ecosystems, particularly wetland ecosystems. It is extremely easy for urban encroachment to occur in wetland habitats, which include marshes, swamps, bogs, and other water-saturated regions. To make room for residential, commercial, and industrial infrastructure, wetland regions are frequently drained, filled, or degraded as cities continue to grow.

Changes in water flow patterns as a result of changes in land use, increased pollution from construction operations, and the destruction of natural ecosystems are all consequences of urban expansion. In addition to contributing to long-term environmental damage, the deterioration of wetland areas affects the ecological functions that they provide, such as the purification of water, the control of flooding, and the support of biodiversity.

1.2 Importance of Wetlands in Environmental Sustainability

It is widely acknowledged that wetland ecosystems are among the most valuable ecosystems on the planet, as they provide several ecological, economic, and social advantages. Before surface water is allowed to join bigger bodies of water such as rivers and seas, they perform the function of natural water filters, eliminating pollutants and sediments from the water. In addition, wetland areas contribute to flood mitigation by soaking up surplus rainfall and regulating surface runoff, so lowering the likelihood of flooding in metropolitan areas that are close to the wetland.

The rich biodiversity of an area is enhanced by the presence of wetlands, which provide a home for numerous species such as fish, birds, and animals. They serve as breeding grounds for a wide variety of aquatic animals and as crucial resting places for migrating birds. The soil and vegetation of wetlands store a lot of carbon, which lessens the impact of global warming. Another important function of wetlands is carbon sequestration, which lessens the impact of global warming. In light of this, the preservation and restoration of wetland areas are absolutely necessary in order to ensure the continued viability of the ecosystem, particularly in light of the increasing urbanization.

1.3 Role of GIS and Remote Sensing in Environmental Monitoring

In order to map, analyze, and keep track of changes in the environment over time, modern technologies such as (GIS) and (RS) are utilized. Researchers are able to investigate the geographic patterns of urban expansion and the influence that it has on ecosystems because to the capabilities of (GIS), which enable the visualization and analysis of spatial data. On the other hand, remote sensing is the process of gathering information from satellite imaging or aerial photography in order to identify shifts in land use, vegetation, and existing bodies of water.

With the integration of (GIS) and Remote Sensing, strong tools are available for monitoring the degradation of wetland areas as a result of urbanization. Changes in land cover, evaluations of water quality, and tracking of shifts in wetland boundaries are all attainable through the utilization of these technologies. Additionally, (GIS) and (RS) make it possible to incorporate different datasets, such as topography, hydrology, and vegetation indices, which enable the provision of an all-encompassing perspective on the environmental impacts of urban expansion on wetland areas.

1.4 Scope and Significance of the Study

This study utilizes (GIS) and Remote Sensing technologies to enhance our comprehension of the environmental impacts caused by urban expansion on wetland areas. The region encompasses a geographical region in which increasing urbanization has had a substantial impact on the ecosystems of wetland areas. This allows for a temporal analysis of changes in land cover and wetland health, which is made possible by the fact that the study period extends several years. Through the identification of significant patterns of wetland degradation, the study offers essential insights into the relationship between urbanization and the preservation of wetland areas.

The significance of the study rests in the fact that it has the potential to educate politicians, urban planners, and environmentalists about the significance of making sure that wetland areas are preserved in the middle of urbanization. The findings have the potential to serve as a guide for the creation of sustainable urban policies that strike a balance between the need for development and the protection of extremely important ecosystems such as wetlands. Additionally, the research emphasizes the significant role that Geographic Information Systems (GIS) and Remote Sensing play in environmental monitoring and management, demonstrating their application in other locations that are confronted with difficulties that are comparable.

1.5. Objectives of the study

1. To examine changes in land cover and use in the area under study between 2018 and 2021.
2. To find patterns of land cover alteration by using Landsat satellite pictures from MSS, TM, and ETM sensors.
3. To evaluate the precision of classifying land cover through the use of supervised techniques, such as the maximum likelihood approach and training samples.
4. To assess how the area's tree cover and agricultural land are affected by urbanization and economic growth.
5. To determine and evaluate the general accuracy of classified land use maps as well as the Kappa coefficient.
6. To assess the pattern of land use changes and pinpoint important factors such population movement and urbanization

2. REVIEW OF LITERATURE

Ghosh, S., & Das, A. (2019) Wetlands benefit society and the environment in many ways, but recent human meddling puts the preservation of existing wetlands in jeopardy. The multiple negative environmental effects of fast urban expansion primarily affect wetlands that are near to megacities in South Asian countries. The East Kolkata Wetland, which is next to the megacity of Kolkata, is fighting for survival as a result of the city's rapid growth and transformation of its surroundings into urban landscapes. encroachment on communities found by land use change research, which increases the vulnerability of EKW. A vulnerability assessment is a necessary step in developing any conservation plans. The goal of this study is to locate the East Kolkata Wetland's vulnerable areas for wetland conversion. Several wetland conversion affecting elements and a knowledge-based method are combined with a well-established fuzzy multi-criteria decision-making approach. The outcome indicates that around 60% of the area is located in high to extremely high-vulnerability zones. Due to its high vulnerability, a plan for safeguarding this biologically significant wetland must be created very away. Wetland areas that are close to developed metropolitan areas fall into the category of high and extremely high vulnerability zones. To comprehend the applicability of the fuzzy MCDM technique and to create a suitable plan, the outcome must be validated. The results of this investigation are evaluated using Receiver Operating Characteristics (ROC). The area under the curve (AUC) accounts for 93.7%, indicating a high level of accuracy and dependability for the fuzzy MCDM. The study's findings require the local government to take immediate action to preserve this wetland.

Keshta, A. E., et.al., (2022) Burullus Lake, the second-largest lake on the northern side of the Nile Delta in Egypt, is a wetland that is internationally recognized for its importance. Fish, birds, animals, and herpetofauna all use it as a home while they migrate. Drainage and the transformation of the lake into fish farms and farmland are two major human impacts. Utilizing multispectral, moderate-spatial-goal (30 m2) Landsat satellite pictures, this study meant to survey how much bog that had been lost in Lake Burullus, Egypt, from 1985 to 2020. Rural lands, swamp, water, and unvegetated land surfaces, (for example, streets, ways, sand sheets, and rises) were the four essential land-use classes recognized in the Lake Burullus region. This was finished by applying Iterative Self-Organizing Data Analyses (ISODATA) unaided methods to satellite pictures from Landsat 5 Thematic Mapper (TM) and Landsat 8 Functional Land Imager-Thermal Infrared Sensor (OLI-TIRS). Overall, the categorization accuracy was assessed to be 96%, with a Kappa score of 0.95. Our research indicates that between 1985 and 2020, aerial coverage of marshes would decline significantly, falling 44.8%. In the western and southern parts of the lake, where the surface area rose by 103.2% from 2000 to 2020, most of the wetlands are drained and turned into farmland or fish farms. Water quality concerns and the loss of a vital wetland owing to the alarming loss of marshland should be brought to the attention of the communities living near Lake Burullus by environmental government agencies and those in charge of land-use policies.-services to the ecology.

Mao, D., et.al., (2018) Multiple ecosystem services provided by wetlands are beneficial to humans; nevertheless, because of increased urbanization, there has been a major global loss of wetlands. To assess the issue, we want to gauge the geological degree of wetland loss brought about by urbanization. In this review, we examined the sum and examples of wetland loss in China because of urbanization from 1990 to 2010 utilizing data from the China Public Land Cover Database (ChinaCover). Wetlands covering 2,883 km2 were lost to urbanization in China throughout the course of recent years. Of this aggregate, around 2,394 km2 were in the eastern regions (Upper east China, North China, Southeast China, and South China). In the period from 2000 to 2010, the pace of wetland loss because of urbanization was 2.8% more than the rate somewhere in the range of 1990 and 2000 (75 km2 yr−1). The most severely affected types of wetlands were marshes and reservoirs/ponds. Most of the wetland loss occurred as a result of urbanization, not industrialization or the expansion of transportation networks. Wetland loss owing to urbanization has been detected in four hotspots in China: the Yangtze River Delta, the Jianghan Plain, the Beijing-Tianjin metropolitan area, and the Pearl River Delta. More wetlands are expected to be swallowed up by the rapid expansion of small and medium-sized cities and urban transportation networks in the coming decades as China undergoes the ongoing impacts of industrialization and urbanization. China must prevent the further destruction of wetlands due to urbanization if it intends to achieve its sustainable development goals, notwithstanding the country's recent notable attempts to preserve wetlands.

Jamali, A. A., et.al., (2020) Salinity in the soil is one of the elements influencing soil degradation. Soil is a non-renewable and dynamic resource that provides the majority of human nourishment. The objective of this research was to forecast the increase in salinity on Golpayegan's plain by utilizing indices and spatial approaches to assess the reduction in wetland area and vegetation cover. From 1985 to 2016, the first 22 Landsat photos were chosen. The Landsat photos were processed to obtain two sets of maps: the Normalized Difference Vegetation Index (NDVI) and the Soil Salinity Index (SSI). Two indices were used in the process of classifying these areas. The Land Change Modeler (LCM) was used to populate these maps with six classifications, vegetation, and salinity. Using Multi-Layer Perceptron (MLP) Neural Networks, smart modeling advances further. Following model validation, transition potential probability maps were created. A forecast map for 2025 was produced by applying the Cellular Automata (CA) Markov technique. The findings indicated that the SSI6 was the most effective salinity index out of all of them. The terrain in the research region has shifted from low to high salinity, with the low salinity classes emerging first and the medium and high salinity classes emerging gradually. The density of vegetation and soil salinity are inversely correlated; when a marsh dries out and salinity rises, vegetation density falls. The management of drainage networks and the use of water resources by decision-makers is necessary to prevent the growth of salinity.

Hawash et al. (2021) provided a thorough analysis of the use of geographic information system (GIS) and remote sensing to analyze urban growth, with a particular emphasis on the Red Sea metropolis of Port Sudan. The authors talk on how important remote sensing technology is for tracking changes in land cover and use, particularly in places that are urbanizing quickly. They cite a number of seminal studies that have effectively employed satellite imagery to track patterns of urban growth, emphasizing the need of combining spatial and temporal data for precise change detection. The article also highlights how GIS is used in spatial analysis to help researchers map and measure urban expansion. The writers also discuss the difficulties in obtaining high-quality data and the resolution of satellite images, as well as the significance of these issues in enhancing environmental management and urban planning. Overall, the research shows that remote sensing and GIS are becoming more and more important tools for tracking urban sprawl, especially in places like Port Sudan where fast urbanization presents problems for the environment and development.

3. RESEARCH METHODOLOGY

Landsat satellite pictures from MSS, TM, and ETM sensors taken in 2018, 2019, 2020, and 2021 were combined with satellite data processing and interpretation software such as IDRISI, Arc GIS 10.1, and ERDAS Imaging to look into change trends in the examined area (Table 1). The satellite photos underwent pre-processing, which included geometric and altitude adjustments, for this reason. Roads and streams were recovered as vector layers from digital maps 1:50000 and superimposed onto satellite photos to examine the geometry of the images and make sure they are of the right geometry. The following method was used to perform geometric rectification on the images: The process of altering an image's component coordinate systems and matching them to comparable maps or previously corrected images is known as geometric correction.

Using the region's 1:50000 topographic maps, OLI sensor photos from 2018 were first geometrically corrected. To do this, 38 areas on the guide and picture with proper dissemination were picked, mathematical rectification was applied utilizing the first-request condition, and testing was completed utilizing the closest neighbor strategy. ETM Landsat pictures for 2021 were recorded on 2021 photos in the following phase. 35 land locations with appropriate distribution were chosen for this purpose. The image was changed into a land-based one by utilizing the nearest neighbor strategy and a first-request polynomial mathematical model. For the mathematical amendment of the TM sensor, 2019, and the MSS sensor, 2018, 32 and 35 land-control areas, separately, with appropriate conveyance, were chosen utilizing the closest neighbor approach and the first-request polynomial mathematical model, individually. Shown in Table 1 are the RMSE values for each picture. The Root Mean Square Error (RMSE) is a famous measurement for surveying the dissimilarity between the noticed and anticipated values in a model's current circumstance. Finding the (RMSE) is finished utilizing Condition (1):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{obs,i} - X_{model,i})^2}{n}}$$

where X_{obs} is observed values and X_{model} is modelled values at time/place i.
To extract patterns or interpret images, image enhancement refers to a conversion process that improves the quality of images to a more comprehensible level. One of the most important ways to improve photographs is by making them look like they have different colors. The three major colors (red, green, and blue) are assigned to their respective bands in the satellite image and three independent bands are blended to generate a false color image. Choosing appropriate bands for color photographs is done to maximize the usage of useful data and minimize the amount of worthless data.
A supervised classification technique was used to create the research area's land cover maps. A collection of levels or regions were chosen to act as training samples for each phenomena when employing supervised categorization. The data would then be arranged utilizing these examples. This strategy tracks down the quantity of changes and the connection between's the phantom upsides of unmistakable groups for test regions, as well as utilizing this component to correspond a pixel order with a ghostly example.
In order to create the land cover map, several training samples were created as polygons for each use by doing field operations and quality-checking the image to ensure that each polygon only contained pixels for that particular use. An effort was made to choose training samples that were evenly distributed. The next step was to use the maximum likelihood method to generate land cover maps for the following years after loading the program with the signature files containing the training samples. The images were classified into five sets: roadside, desert, city, farmland, and forest (Table 2). We choose the groups to group things into according to the detail in the satellite images and what we marked as features when we were in the research area. For a long time, this city was known as the home of nightingales and flowers. Other urban demands have supplanted the city's once-famous parks and gardens due to urbanization.
The accuracy of a created map determines its applicability. As a result, following classification, the classes need to be compared to reality and their accuracy needs to be estimated. The verification's objective is to evaluate how well the maps reflect actual land usage. Comparing each map pixel with its corresponding pixel in the real-earth map allows one to determine the number of pixels that have been successfully classified into different classes and the number that have been wrongly assigned.

Table 1: RMSE of each class of image

Image	No. OF Land control spots	RMSE
Landsat OLI sensor (2019)	40	0.48
Landsat ETM sensor (2018)	38	0.50
Landsat TM sensor (2020)	35	0.40
Landsat MSS sensor (2021)	40	0.45

Interpretation: The Root Mean Square Error (RMSE) results for geometric corrections of satellite images obtained from a variety of Landsat sensors over the course of several years may be found here. Landsat OLI sensor pictures from 2019 have a root mean square error (RMSE) of 0.48, and they contain forty land control spots, which indicates that the geometric correction is relatively accurate. The Landsat ETM sensor pictures from 2018 have a little greater root mean square error (RMSE) of 0.50 with 38 land control locations, which indicates a slightly less exact correction. The Landsat TM sensor photos from 2020, on the other hand, have the lowest RMSE of 0.40 with 35 land control locations, which reflects the highest geometric accuracy among the sensors that were included. With forty land control locations, the Landsat MSS sensor images from 2021 have an RMSE of 0.45, which demonstrates a fair level of precision. However, in comparison to the TM sensor, these images are significantly less exact. These RMSE values, taken as a whole, shed light on the fact that the accuracy of geometric correction varies across different Landsat sensors and years, with the TM sensor demonstrating the highest level of geometric precision.

Table 2: Classification of the Map of Land Cover

Category	Description
Agriculture	A combination of agriculture and farmland
Tree Cover	Parks and green spaces, orchards and gardens
Bare Land	Cleared areas, Solon Chak, feeble pastures, mountains, and undeveloped lands
Street	Street and Road
Urban	Residential, commercial, and industrial areas

One of the most popular and widely used ways to check if classified maps are accurate is to use an error matrix. Still another option is to make use of general accuracy, which is a measure for the precision of findings produced by different classification methods. General accuracy is one metric that can be used to evaluate the precision of classification. To do this, take the sum of all correctly identified pixels and divide it by the total number of reference pixels. Another tool for comparing classification results is the Kappa coefficient. The Kappa coefficient has a value that ranges from zero to one; the closer it is to one, the more accurate the map that is created from the classification is in comparison to the reality. The value one represents complete agreement (one hundred percent) between the classification map and the reality. General accuracy is not a valid metric for assessing the classification results, as stated in the theory of probability. This is because random factors play a significant effect in this metric. For this reason, the Kappa Index is frequently utilized in order to ascertain the degree of accuracy that can be attributed to the outcomes of various classification systems. We can define it as Equation (2).

$$K = (P_0 - P_e)/(1 - P_e) \quad (2)$$

where $PPee$ is the expected agreement when both annotators provide labels at random, and $PP0$ is the empirical probability of agreement on the label assigned to any sample (the actual agreement ratio). For this aim, seventy sites were selected at random, and field research, Google Earth software, and the relative cognitive ability of the examined area were used to evaluate the classification accuracy. An accuracy matrix for each map was created in accordance with the findings (Table 3). Fig. 2 shows the process flowchart for the entire methodology.

Table3: General land use map accuracy and the Kappa coefficient

Land use Map	Kappa Coefficient	General accuracy
OLI (2019)	0.75	91.2
ETM (2018)	0.80	90.2
TM (2020)	0.79	92
MSS (2021)	0.81	93.2

Interpretation: The Kappa coefficient and general accuracy for land use maps that were created from various Landsat sensors across a range of years are summarized in the table below. A Kappa coefficient of 0.75 and a general accuracy of 91.2% are both found on the Landsat OLI map from 2019, which indicates that there is a high level of agreement between the categorized map and the ground reality. The Landsat ETM map from 2018 has an even more impressive categorization performance, as seen by a Kappa coefficient of 0.80, which is somewhat higher than the previous year's value of 0.70. The Landsat TM map from the year 2020 has a Kappa coefficient of 0.79 and the highest general accuracy of 92%, which demonstrates that it has highly accurate classification. When compared to the other maps, the Landsat MSS map from 2021 has the greatest Kappa coefficient of 0.81 and the highest general accuracy of 93.2%, indicating that it has the best performance. In general, these measures suggest that the MSS sensor was the one that provided the most accurate categorization, while the other sensors also showed excellent levels of accuracy, but with some modest differences depending on the year.

4. DATA ANALYSIS

The majority of the land that was covered by trees has been converted into residential and artificial lands. Major contributors to these shifts include the expansion of the economy and the growth of urban areas, as well as the migration of people from rural areas to metropolitan areas. Further justification for the shrinking of agricultural fields can be found in this. One of the most important factors in this situation is the rising cost of residential land.

Table 4: Changes in the study region's area under different uses (2018–2021)

Land use and cover	2018		2019		2020		2021	
	ha	%	ha	%	ha	%	ha	%
Agriculture	4180.01	10	1432.90	3	4.1254.52	4.5	1025.26	2.6
Bare Land	3526.52	62.6	1425.60	42.3	1542.3	54.2	1525.65	40.3
Tree cover	3621.52	10	3569.25	8.2	3452.63	8.2	2465.2	7.2
Street and road	100.36	0.50	600.25	1.7	955.25	3.50	1085.30	2.9
Urban area	6536.63	17.45	1536.63	41.25	1745.28	45.21	1845.9	45.8

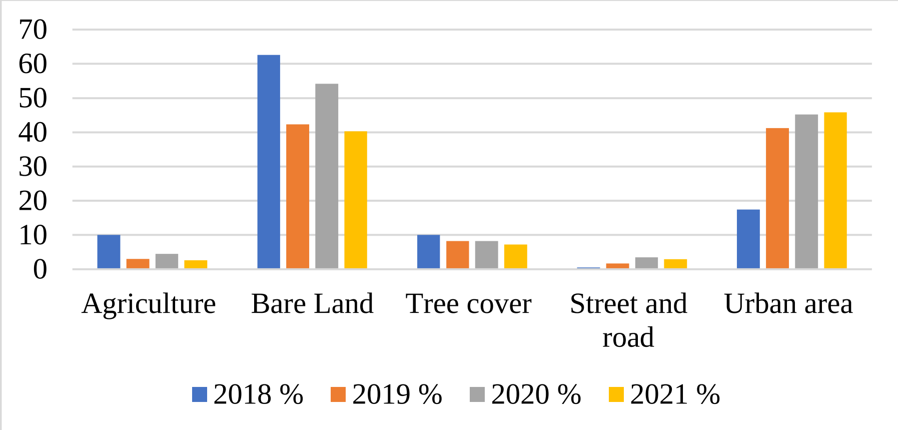

Figure: Percentage of land cover and usage changes

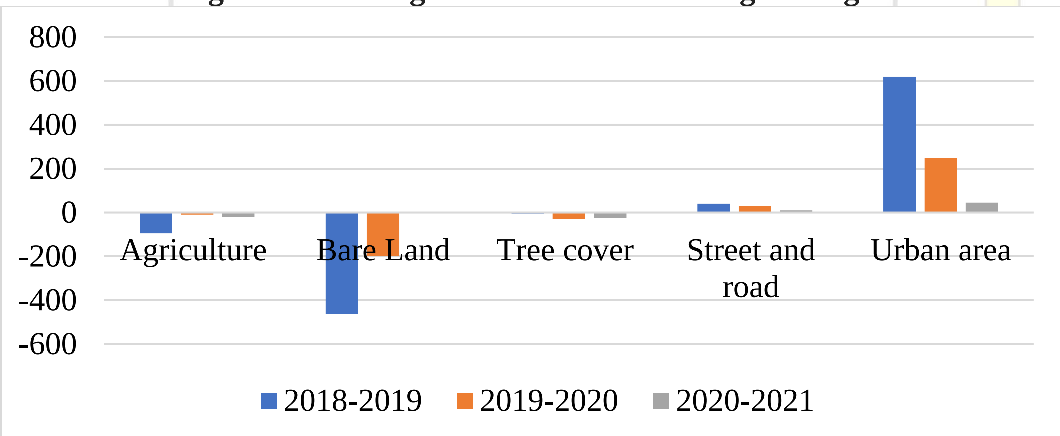

Figure 8. Annual changes in the three investigated periods' land cover and use

5. CONCLUSION

The study unequivocally shows that urban growth has significantly changed the patterns of land use in the investigated region, with a rise in residential and industrial areas and a large decrease in agricultural and tree cover. The key causes driving these changes are urbanization and economic expansion, according to an analysis of Landsat satellite pictures from 2018 to 2021. The dependability of the remote sensing data in evaluating land cover transformations is confirmed by the excellent accuracy of the classification maps, as demonstrated by Kappa coefficients and general accuracy metrics. The findings highlight the necessity of sustainable urban planning techniques in order to lessen the negative environmental effects that growing urbanization is having on wetlands and other natural ecosystems. This study provides a useful framework for upcoming environmental impact assessments by highlighting the importance of GIS and remote sensing technologies in monitoring and controlling changes in land use.

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