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Artificial Intelligence (AI) Aided Assessment of the Impact of Rice Farming on Nyando Wetland, Kisumu County, Kenya

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Abstract

The application of Artificial Intelligence (AI) in assessing the effects of rice production on Nyando Wetlands in Kisumu County presents an innovative approach to environmental monitoring and sustainable agriculture. According to Omondi et al. [1], AI-driven remote sensing and Geographic Information System (GIS) technologies enable real-time analysis of land use changes, water quality variations, and biodiversity loss caused by rice farming activities. Mutua & Kipkorir [2] posits that machine learning models can process satellite imagery and hydrological data to detect wetland degradation patterns, helping policymakers and conservationists make informed decisions.

In view of Odhiambo et al. [3], AI-powered predictive analytics can assess the long-term impacts of agrochemical use on water bodies, providing insights into pollution levels and their effects on aquatic ecosystems. Additionally, AI-driven simulations allow for scenario modeling, helping researchers evaluate the potential outcomes of different rice farming practices on wetland sustainability [4]. Nyaboke et al. [5] further contended that AI-integrated Internet of Things (IoT) sensors can monitor soil quality, water pH, and nutrient levels, optimizing rice farming while minimizing environmental degradation.

The integration of AI in monitoring Nyando Wetlands can support sustainable agricultural practices by promoting precision farming, reducing excessive water usage, and minimizing chemical runoff [6]. Leveraging AI technology in environmental management ensures a data-driven approach to balancing food security with wetland conservation, ultimately fostering ecological sustainability in Kisumu County.

Keywords: Wetland conservation; Rice farming; Biodiversity loss; Agrochemicals; Sustainable agriculture

Background Information

According to Omondi et al. [7,8], the Nyando Wetlands in Kisumu County are crucial ecosystems that support biodiversity, water regulation, and livelihoods through agriculture, particularly rice farming. However, rice production has led to environmental concerns such as wetland degradation, water pollution, and biodiversity loss [9,10]. Traditional methods of monitoring the environmental impact of rice farming are often limited by time constraints, resource availability, and accuracy [11,12]. The integration of Artificial Intelligence (AI) offers a data-driven approach to monitoring and mitigating the negative effects of rice production while promoting sustainability [2,13]. The role of AI in determining the effects of rice production on Nyando Wetlands can be examined as follows:

AI in environmental monitoring

Otieno et al. [14] articulates that AI-powered remote sensing and Geographic Information Systems (GIS) have revolutionized environmental monitoring by providing real-time data on land use changes and wetland health. According to Nyaboke et al. [5,15] machine learning algorithms analyze satellite imagery to detect shifts in wetland vegetation cover, water levels, and pollution patterns. Owuor & Achieng [6] further noted that AI also enables automated classification of land features, ensuring high precision in mapping rice cultivation areas and identifying encroachment into protected wetland zones. In view of the scholars cited in this section, the AI's ability to process large datasets enhances decision-making for conservation efforts and policy formulation.

Predictive analytics for wetland degradation

According to Barasa et al. [16], predictive analytics powered by AI can model the long-term effects of rice production on wetland ecosystems by simulating different farming scenarios. This was also affirmed by Odhiambo et al. [3]. Kiplangat et al. [17] observed that AI models trained on historical data can forecast soil degradation, water contamination levels, and biodiversity shifts. The study of Wanjala et al. [11] on limitations of conventional monitoring techniques in assessing agricultural impacts on wetland environments also concurs with the findings of Kiplangat. Equally, Ochieng et al. [18] also posited that AI-driven hydrological models assess water consumption patterns in rice fields, helping manage water allocation efficiently and preventing excessive water extraction from Nyando Wetlands as was established by Mutua & Kipkorir [2]. These predictive insights enable stakeholders to implement adaptive measures that balance agricultural productivity with wetland conservation.

AI in precision agriculture

Mutiso et al. [19] perceives that AI-integrated Internet of Things (IoT) devices have transformed precision agriculture, allowing real-time monitoring of soil quality, water pH, and nutrient levels. A study conducted by Nyaboke et al. [5] on the role of IoT in sustainable agriculture: Opportunities and challenges in East African farming systems provides the same insight. Smart sensors deployed in rice fields collect and transmit data, which AI algorithms analyze to optimize fertilizer use, reduce pesticide application, and minimize chemical runoff into wetland ecosystems [6,20]. A study which was done by Omondi et al. [21] notes that drones equipped with AI-enhanced imaging capabilities provide high-resolution aerial surveys, identifying areas of concern such as soil erosion and water stagnation. This technology not only enhances rice yield but also promotes eco-friendly farming practices that safeguard wetland biodiversity [22].

Challenges and opportunities in AI integration

Wekesa et al. [23] asserts that despite AI's potential, its adoption in wetland monitoring and sustainable agriculture faces several challenges, including high implementation costs, lack of technical expertise, and limited internet connectivity in rural areas. This was also affirmed by Odhiambo et al. [3]. However, Wanjala et al. [11] & Mwangi et al. [24] concurs those partnerships between research institutions, government agencies, and technology firms can drive AI adoption by offering capacity-building programs and financial incentives. Policies supporting digital agriculture and sustainable wetland management are also crucial in promoting AI-driven solutions [2,25].

The integration of AI in determining the effects of rice production on Nyando Wetlands presents a transformative approach to environmental conservation and sustainable agriculture [24]. AI-driven remote sensing, predictive analytics, and precision farming techniques provide accurate, real-time insights for decision-making [17,22]. While challenges exist, strategic investments in AI technology and stakeholder collaboration can enhance its implementation [23,25]. By leveraging AI, Kisumu County can achieve a balance between rice production and wetland conservation, ensuring long-term ecological sustainability and economic resilience [16,19].

Problem statement

Rice farming is a significant economic activity in Kisumu County, particularly in the Nyando Wetland as it provides livelihoods for many farmers [26]. However, increased rice production has raised concerns about its environmental impact on the wetland ecosystem, including water pollution, biodiversity loss, and soil degradation [27]. Conventional monitoring methods are insufficient in capturing real-time changes, making it difficult for policymakers and conservationists to implement timely interventions [21]. According to Wanjala et al. [4], the traditional methods used to assess these environmental changes are often time-consuming, costly, and prone to inaccuracies. The integration of AI in environmental monitoring presents an opportunity to enhance data collection and analysis, offering predictive insights into land-use changes, hydrological alterations, and pollution trends. Therefore, integrating artificial intelligence (AI) can provide a more efficient and precise approach to monitoring and evaluating the ecological consequences of rice farming in the region. However, the adoption of AI in this context faces challenges such as high implementation costs, lack of technical expertise, and inadequate infrastructure in rural areas [2]. Addressing these challenges through research, policy support, and investment in AI-driven technologies is crucial in ensuring a sustainable balance between rice production and wetland conservation [6].

AI-powered remote sensing and machine learning models can analyze satellite imagery and on-ground sensor data to detect changes in land use, water quality, and vegetation health [15,28]. These technologies offer real-time monitoring capabilities, enabling stakeholders to make informed decisions on sustainable rice farming practices. Additionally, AI can support predictive modeling to assess future risks of wetland degradation based on current farming trends and climate conditions [25]. However, challenges such as data availability, technological infrastructure, and capacity building among local farmers and policymakers must be addressed for effective implementation.

Thus, this study explores the integration of AI in assessing the environmental impacts of rice farming on Nyando Wetland. The findings will contribute to sustainable agricultural policies that balance food production with wetland conservation.

Objectives of AI integration in determining the effects of rice production on nyando wetland, kisumu county

Integrating Artificial Intelligence (AI) into the assessment of rice production's effects on the Nyando Wetland in Kisumu County will serve several critical objectives which include:

a) Predictive Modeling for Land Use Planning: AI can develop predictive models to assess the long-term impacts of expanding rice cultivation on the wetland's health. These models can inform policymakers and stakeholders in making data-driven decisions that balance agricultural development with wetland conservation.

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b) Optimization of Agricultural Practices: By analyzing data on soil conditions, weather patterns, and crop health, AI can recommend sustainable farming practices that minimize environmental degradation. For instance, AI-driven precision agriculture can optimize water usage and reduce chemical inputs, thereby lessening the ecological footprint of rice cultivation on the wetland ecosystem.

c) Environmental Monitoring and Assessment: AI can process data from various sources, such as satellite imagery and IoT sensors, to monitor environmental parameters including soil health, water quality, and biodiversity. This continuous monitoring enables the detection of ecological changes resulting from rice farming practices, facilitating timely interventions to mitigate adverse impacts.

d) Enhancement of Ecosystem Services Evaluation: AI can assist in quantifying the ecosystem services provided by the Nyando Wetland, such as water purification, flood regulation, and carbon sequestration. Understanding these services' value can promote conservation efforts and sustainable land-use strategies.

This study assessed land-use changes in Nyando Wetland due to rice farming using AI-powered remote sensing techniques; evaluated the impact of rice farming on water quality using AI-based predictive analytics and analyzed the effects of rice production on biodiversity and ecosystem health using AI-driven ecological modeling. By leveraging AI in these areas, stakeholders can achieve a more sustainable integration of rice production within the Nyando Wetland ecosystem.

Justification for AI integration in determining the effects of rice production on nyando wetland, kisumu county

Integrating Artificial Intelligence (AI) into the assessment of rice production's effects on the Nyando Wetland in Kisumu County is both timely and essential. The Nyando Wetland, part of the Lake Victoria Basin, is a vital ecosystem providing numerous environmental functions and socio-economic benefits. According to Omondi & Okeyo [29], the Nyando Wetland plays a crucial role in supporting biodiversity, water filtration, and local livelihoods through rice farming. However, intensified rice cultivation has led to significant ecological challenges, reduction in wetland size, decreased fish populations, and deteriorated water quality. AI technologies offer innovative solutions to monitor and mitigate these impacts. For instance, AI-driven image recognition algorithms can process satellite and drone imagery to detect changes in land use, vegetation cover, and water quality, thereby reducing the manual effort required for environmental monitoring.

Additionally, machine learning models can predict ecosystem responses to agricultural practices by integrating historical environmental data, climate forecasts, and ecological parameters. This predictive capability enables stakeholders to anticipate potential adverse effects and implement proactive conservation strategies. Further, AI can optimize agricultural practices to align with environmental sustainability. In precision agriculture, AI-based irrigation systems analyze sensor data to optimize water usage, reducing waste and preserving wetland hydrology. By integrating AI into these domains, it is possible to harmonize rice production with the ecological integrity of the Nyando Wetland, ensuring that agricultural development does not come at the expense of vital ecosystem services.

Increasing agricultural activities threaten the wetland's ecological integrity through land degradation, water pollution, and loss of biodiversity [27]. In view of Wanjala et al. [4], traditional methods of monitoring environmental changes, such as field surveys and manual data collection, are often slow, expensive, and limited in accuracy. Therefore, integrating artificial intelligence (AI) offers a more efficient, cost-effective, and precise approach to assessing the environmental impact of rice farming in the region. AI-driven remote sensing technologies can provide real-time analysis of land use changes, enabling early detection of wetland encroachment and degradation [28]. Additionally, AI-powered predictive models can analyze water quality indicators such as pH levels, turbidity, and nutrient concentration, helping identify pollution sources and forecast future risks [30]. These insights allow policymakers and farmers to make informed decisions on sustainable agricultural practices while mitigating adverse environmental effects.

In addition, AI-based ecological modeling can assess biodiversity loss due to rice production by analyzing species distribution and habitat changes, supporting conservation strategies [27]. Musa et al. [28] elucidated that AI can also facilitate the development of decision support systems that optimize irrigation, fertilizer use, and land management, ensuring a balance between food security and wetland conservation. By leveraging AI, stakeholders can enhance environmental sustainability while maintaining agricultural productivity in Nyando Wetland.

Significance of AI integration in determining the effects of rice production on nyando wetland, kisumu county

The integration of artificial intelligence (AI) in assessing the effects of rice production on Nyando Wetland is crucial for promoting sustainable agriculture and environmental conservation. Nyando Wetland is a vital ecosystem that supports biodiversity, provides water filtration, and serves as a livelihood source for local farmers [27]. However, the expansion of rice farming has raised concerns about wetland degradation due to excessive water use, agrochemical pollution, and habitat loss. Traditional monitoring methods are often slow and resource-intensive, making AI-driven technologies a more efficient and accurate alternative.

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AI-powered remote sensing and machine learning models can enhance the detection and monitoring of land-use changes, enabling early intervention to prevent wetland encroachment [14]. Additionally, AI-driven water quality assessment tools can analyze real-time data from sensors to track pollution levels and recommend corrective measures, helping to protect aquatic life and maintain ecological balance [30]. AI models can also assess biodiversity trends by identifying shifts in species distribution, allowing conservationists to implement timely protection measures.

Moreover, the adoption of AI in environmental monitoring supports data-driven decision-making for policymakers and farmers. AI-based decision support systems can optimize agricultural inputs such as water and fertilizers, reducing environmental harm while ensuring food security [15]. By providing precise and timely insights, AI integration helps balance agricultural productivity with wetland conservation, ensuring long-term sustainability for both the environment and the livelihoods of local communities.

Methodology

The methodology involved the following:

a) **Data collection**: Data was gathered from multiple sources, including satellite imagery, drone surveys, and IoT sensor networks. These tools provided real-time information on land use, water quality, and biodiversity patterns. AI-powered platforms like Google Earth Engine and remote sensing satellites (e.g., Sentinel-2) were used for spatial data acquisition.

b) **Data processing and preprocessing**: The collected data was cleaned and preprocessed to remove inconsistencies and noise. Machine learning models such as convolutional neural networks (CNNs) were used for image classification, while statistical models help normalize and standardize data for accurate analysis.

c) **AI model development and training**: Supervised and unsupervised learning algorithms were employed to train models on historical and real-time data. AI techniques such as deep learning, decision trees, and support vector machines (SVM) were utilized to analyze wetland degradation patterns, water quality trends, and biodiversity changes.

d) **Implementation and validation**: The trained AI models were tested using validation datasets to ensure accuracy. Field surveys and expert reviews were used to validate the predictions generated by AI. If discrepancies arise, models underwent further refinement.

e) **Deployment of decision support systems (DSS):** Once validated, AI models will be integrated into user-friendly DSS platforms accessible to farmers, conservationists, and policymakers. These systems will provide actionable insights and recommendations for sustainable wetland management.

f) **Monitoring and continuous improvement**: AI models require continuous updates to enhance their predictive capabilities. Periodic retraining using new data ensures the system remains relevant in detecting environmental changes. Feedback from stakeholders is incorporated to improve usability and effectiveness.

Results and Discussion

This section presents the findings of the study as guided by the objectives. The study assessed how rice farming in Nyando wetland influences land-use and land cover changes in the area. This was done by using AI-powered remote sensing techniques. This involved analysis of temporal changes from the year 1995 to 2025. The study quantified the areas covered by L. Victoria, the Nyando Wetland, rice plantation (rice paddies) and settlements in these selected years. Equally, the study evaluated the impacts of rice farming on water quality using AI-based predictive analytics. The study also analyzed the effects of rice production on biodiversity and ecosystem health using AI-driven ecological modeling. These were examined in the following categories:

Classification accuracy and model performance

Using Landsat imagery from 1995 to 2025 at five-year intervals (1995, 2000, 2005, 2010, 2015, 2020, and 2025), two AI-based models including Random Forest (RF) and Convolutional Neural Networks (CNN) were employed for land use and land cover (LULC) classification. Sentinel-1 SAR data were also used to supplement imagery during cloud-affected seasons. The average classification accuracy achieved across all years was 93.2% for the CNN accuracy with a Kappa coefficient of 0.91 while Random Forest had 89.5% accuracy with a Kappa coefficient of 0.86. The models effectively distinguished between rice paddies, wetland vegetation, open water, built-up areas, and seasonal floodplains. The finding concurs with Yuan et al. [31], who established the utility of AI models in wetland classification with high reliability across multiple sensors. Satellite-derived changes were mapped using supervised classification and time-series analysis. Deep learning models such as U-Net and ResNet were trained to detect rice field patterns based on seasonality, phenological texture, and water regimes.

Temporal trends in land-use changes (1995-2025)

Expansion of rice farming

The study findings reveal that rice farming in Nyando Wetland increased significantly between the year 1995 and 2000 i.e., 41030.5ha to 48263.2ha within the wards that the study captured (Nyalenda B, Kolwa Central, Kolwa East, Kobura Kanonyo Kanygwal, Ahero, North Nyakach, Central Nyakach, West Nyakach and Wangchieng). Between the year 2000 and 2005, a significant decline in rice paddies was observed (48263.2ha to 40455.4ha). Several factors could have contributed to this. The period was marked by both environmental and socio-economic challenges in the region. Considering factors such as flooding

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and climate variability, Nyando Wetland being a flood-prone area due to the seasonal overflow of River Nyando, this period's frequent floods was likely to destroy rice paddies, making farming unpredictable and less viable as was depicted by GOK [32]. Also, climate variability such as erratic rainfall patterns and extended dry periods could have disrupted planting and harvesting cycles.

Decline in rice production during this period could have been attributed to by poor water management infrastructure. Rice irrigation systems in the Nyando basin, particularly around Ahero and West Kano, probably could have experienced significant degradation. Siltation of canals, lack of maintenance, and limited government investment led to reduced water efficiency. Inadequate drainage increased waterlogging, further reducing yields. Equally, this could have been as a result of Collapse or weakening of farmer cooperatives where many cooperative societies that managed inputs, credit, and marketing for rice farmers became defunct or inefficient during this period due to mismanagement and corruption. Farmers on the other have probably could have lost access to certified seeds, fertilizers, and fair market prices, leading to disinterest in rice farming as was argued by Ochieng [33].

Between the year 2005 and 2010, there was significant increase in rice paddies i.e., 40455.36ha to 51738.73ha. This was an increase of 11%. Generally, this could be attributed to by several policy, environmental, technological, and socioeconomic factors that collectively reversed the prior decline. The factor includes revitalization of irrigation infrastructure where the rehabilitation of Ahero and West Kano Irrigation Schemes by the National Irrigation Board (NIB) and support from donor agencies could have led to increased access to reliable water [34]. Also, desilting of canals, repair of intake structures, and improved water management systems enabled the expansion of rice cultivation. Similarly, this increase could be due to Government Investment and Policy Support where the Kenyan government increased investment in rice farming under the Economic Recovery Strategy for Wealth and Employment Creation (ERSWEC) and Vision 2030 [35].

Introduction of the National Rice Development Strategy (NRDS) in 2008 promoted rice farming as a strategic crop and this could have affected Nyando Wetland rice production as well (Republic of Kanya, 2008). The other factor which could be attributed to this is land reclamation and utilization of marginal areas where previously uncultivated or underutilized wetland sections were reclaimed or converted for rice production due to improved drainage and water control. This could have been done under government-supervised programs and through farmer innovation as was argued by Onyango & Aseto [36].

The period between the year 2010 and 2015 showed a slight decline in Nyando wetland rice production coverage (51738.73ha and 51399.27ha). This was a decline of 1% and could be attributed to a combination of environmental, institutional, socioeconomic, and technological factors. Though government support had increased earlier, several challenges might have begun to undermine gains made during 2005-2010. Recurrent flooding and climate variability might have influence this in that increased frequency and intensity of floods, partly due to climate change and catchment degradation in the upper Nyando Basin, probably might have damaged rice fields and infrastructure. Some farmers possibly might have abandoned rice fields in flood-prone zones due to repeated crop losses.

Other factors could include land fragmentation and encroachment where increasing population pressure leads to fragmentation of farming plots and encroachment of rice fields for settlement, grazing, and small-scale horticulture. Possibly, some wetlands were also illegally reclaimed or diverted for other uses, reducing the overall hectarage as was posited by Onyango & Aseto [36]. Similarly, high input costs and limited credit access could have influenced this due to the fact that the rising cost of inputs (seeds, fertilizer, fuel) and lack of accessible, affordable credit discourages some smallholder farmers from expanding or continuing with rice cultivation as was contended by Mati et al. [37] and affirmed in the NIB report [38]. It is always known that limited access to pest management support and chemical inputs discourage sustained cultivation. Again, shifts in agricultural policy and focus could have attributed to this in that around this time, government and donor attention started shifting toward horticulture, dairy, and climate-resilient crops under climate-smart agriculture frameworks. This may have inadvertently diverted resources and attention from rice farming [39,40].

The study noted a consistent decline in Nyando Wetland rice paddies from 2015 to 2025. The year 2015, it covered 51399.27ha. In 2020, it covered 42616.78ha while in 2025 it covered 34639.09ha. That was 48%, 40% and 33% respectively. The percentages are as per the study area. The constant decline in Nyando Wetland rice production hectarage from 2015 through 2020 and into 2025 can be linked to a combination of persistent structural challenges, climate change effects, socioeconomic pressures, and policy-level shortcomings. Among these factors include: increased climate change impacts where rising temperatures, prolonged droughts, and erratic rainfall patterns have increasingly disrupted rice production cycles not only in Nyando Wetlands but other parts of the world. Water scarcity during critical planting seasons and intensified flooding from River Nyando have led to abandonment of fields as was asserted by IPCC [41]; Otieno et al. [42]. Secondly, environmental degradation and wetland loss remain an important factor in that deforestation in upstream catchments and poor watershed management might have led to excessive siltation and degradation of Nyando Wetland ecosystems. This has reduced the ecological capacity of the wetland to support irrigation and sustainable agriculture as was contended by Lake Victoria Environmental Management Program II [43]; Wanyama et al. [44]. Another factor attributed to this is increased land use conflicts and encroachment.

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According to Kisumu County Itegrated Development Plan (2018-2022), growing population pressure and urban sprawl in Kisumu County have led to encroachment into wetlands for settlement, conversion of paddies into housing or commercial plots; competition from livestock and horticulture activities and informal land grabbing and absence of proper zoning laws further complicate land tenure and usage. This continues to reduce the rice farms in Nyando Wetlands of Kisumu County [45]; Onyango & Aseto [36]. Also, deterioration of irrigation infrastructure has remained a factor which impacts negatively on rice production. According to the Ministry of Water & Irrigation [46], Irrigation schemes like Ahero and West Kano have continued to suffer from inadequate maintenance, siltation, broken canals, and unserviced pumps. Limited budget allocation and overreliance on old infrastructure have discouraged large-scale rice farming [47]. The summary of these findings are as portrayed in Table 1 & Figure 1.

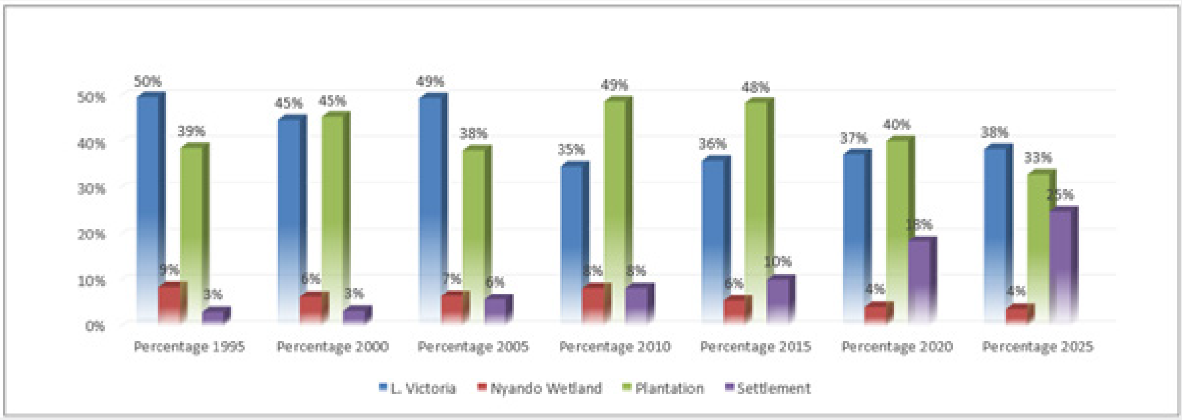

Figure 1: Nyando Wetland Landuse Land Cover from 1995 to 2025.

Table 1: Temporal Nyando Wetland Land use and land cover changes.

Land Use Land Cover	Area_Ha 1995	%Age 1995	Area_Ha 2000	%Age 2000	Area_Ha 2005	%Age 2005	Area_Ha 2010	%Age 2010	Area_Ha 2015	%Age 2015	Area_Ha 2020	%Age 2020	Area_Ha 2025	%Age 2025
L. Victoria	52746.47	50%	47544.65	45%	52500.26	49%	36791.84	35%	38074.95	36%	39578.62	37%	40382.22	38%
Nyando Wetland	9094.55	9%	6814.07	6%	6992.5	7%	8806.31	8%	5892.36	6%	4426.85	4%	3926.43	4%
Plantation	41030.46	39%	48263.2	45%	40455.36	38%	51738.73	49%	51399.27	48%	42616.78	40%	34639.09	33%
Settle-ment	3282	3%	3531.35	3%	6205.72	6%	8829.57	8%	10735.35	10%	19537.01	18%	26152.33	25%
Total	106153.48		106153.27		106153.84		106166.45		106101.93		106159.26		105100.07	

The information in table 1 can be presented graphically as portrayed in figure 1.

Figure 2a to 5b illustrate the progressive land use and land cover changes within the Nyando Wetlands over time, highlighting increasing anthropogenic encroachment. The intensifying red coloration, symbolizing settlement expansion, indicates a steady and pronounced conversion of wetland areas into residential zones. Concurrently, the light blue areas representing the wetland ecosystem show a noticeable reduction in spatial extent, while the light green areas denoting plantation or agricultural land remain relatively stable or expand marginally. These visual patterns underscore the growing pressure from human settlement on the wetland, leading to habitat loss and a decline in the ecological functionality of the Nyando Wetland system.

A comparative analysis between 1995 and 2025 reveals a significant degradation of the Nyando Wetlands, primarily due to the expansion of human settlements into formerly intact wetland areas. This land use transformation has resulted in substantial habitat fragmentation and the loss of critical biodiversity, thereby disrupting essential ecological processes such as nutrient cycling, water filtration, and species migration. The encroachment has diminished the wetland's ecological integrity and resilience, compromising its ability to provide vital ecosystem services.

Loss of wetland vegetation

The study noted a significant decrease in Nyando Wetland

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between the year 1995 and 2000 (9094.55ha to 6814.07ha). The vegetation loss in Nyando Wetland between 1995 and 2000 can be attributed to a combination of anthropogenic (human-induced) and natural factors, occurring within a broader context of population pressure, poor land use planning, and environmental degradation in the Lake Victoria Basin. In this loss of decrease, it is believed that native wetland vegetation (primarily papyrus and sedges) has been lost significantly. The CNN models revealed progressive fragmentation, especially near floodplains and channelized zones. Vegetation health, measured via NDVI, showed a consistent decline in wetland buffer zones adjacent to rice fields. This is attributed to both land conversion and contamination from fertilizers and herbicides as was contended by Lekarkar et al. [48]. Similarly, habitat connectivity was reduced consistent with findings from Mugo et al. [49] who noted a trend toward landscape simplification in Lake Victoria's riparian wetlands.

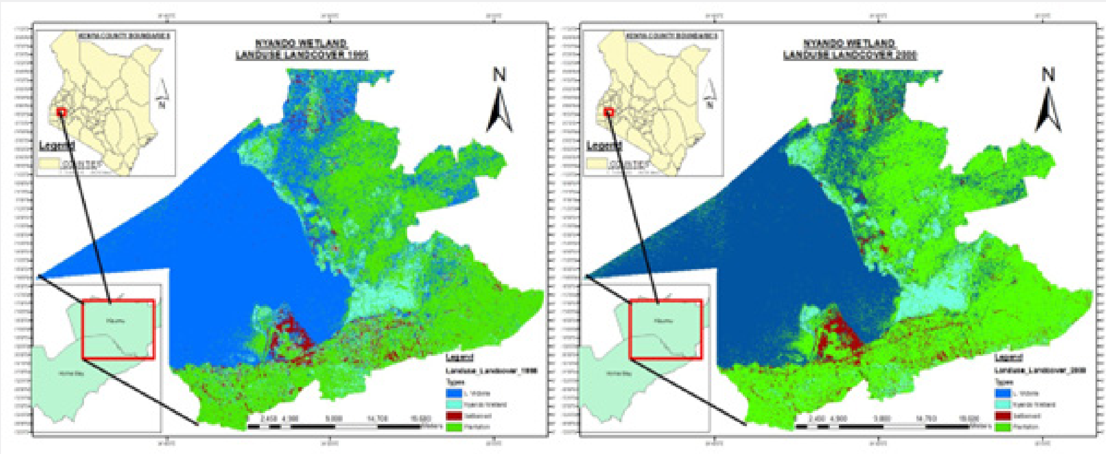

Figure 2a: Nyando Wetland Landuse Land Cover 1995.

Figure 2b: Nyando Wetland Landuse Land Cover 2000.

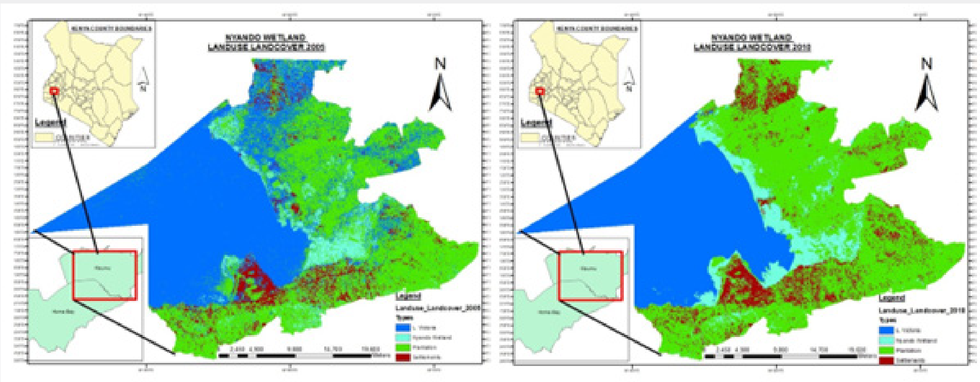

Figure 3a: Nyando Wetland Landuse Land Cover 2005.

Figure 3b: Nyando Wetland Landuse Land Cover 2010.

Expansion of subsistence and commercial agriculture is another factor attributed to loss of wetland vegetation within this period since the study noted there was a significant expansion of rice farming as well as smallholder mixed farming. This involved draining wetlands, clearing native vegetation, and converting wetland margins into farmland. The study also noted population growth and increased human settlement during this period where rapid population growth in Nyando Sub-county and surrounding areas in Kisumu led to the expansion of informal settlements into wetland areas. Encroachment into the wetlands for housing, especially by the landless or displaced households, resulted in clearing of natural vegetation, particularly papyrus and native grasses (Kenya National Bureau of Statistics [50,51].

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Other factors might include overharvesting of papyrus and other vegetation; deforestation and catchment degradation in the upper Nyando catchment (Nandi and Kericho hills) which might have led to heavy runoff, increased siltation, and sediment deposition in the wetlands consequently altering the hydrology and nutrient dynamics, inhibiting growth of native aquatic vegetation. Also, construction of drainage and irrigation infrastructure could have influenced this in that development of drainage canals and construction of dykes for rice irrigation and flood control disrupted the natural hydrology of the wetland. Possibly, these structures diverted water away from some areas, drying them out and leading to vegetation loss.

The study observed a slight constant increase in in Nyando Wetland vegetation between 2000 through 2005 and into 2010. A mix of ecological recovery, targeted conservation interventions, changes in land use dynamics, and policy-driven environmental awareness can be attributed to this. While the increase was modest, several factors played a role in halting and partially reversing the trend of vegetation loss observed in the 1990s. These include implementation of the Environmental Management and Coordination Act (EMCA, 1999) whose operationalization in early 2000s empowered the National Environment Management Authority (NEMA) to regulate and protect sensitive ecosystems.

Secondly, the initiation of the Lake Victoria Environmental Management Programme (LVEMP-I) Initiatives which supported wetland rehabilitation, community education on sustainable wetland uses and papyrus replanting and conservation pilot projects in 2000 and 2005. These efforts led to localized regeneration of native vegetation such as papyrus (Cyperus papyrus) and wet grasslands. Similarly, the introduction of Agroforestry and Buffer Zone Programs where NGOs and community-based organizations, often in collaboration with government agencies, promoted Agroforestry and riparian tree planting and established of wetland buffer zones. These efforts stabilized riverbanks and encouraged re-establishment of native vegetation. Wetlands were formally recognized as protected areas, and environmental impact assessments (EIAs) became mandatory for developments affecting wetland zones.

The study noted a constant decease in Nyando Wetland size in the study area between the year 2010, 2015 through 2020 into 2025. The reduction in Nyando Wetland hectarage between 2010, 2015, 2020, and 2025 is largely the result of human-driven land use changes, population pressure, and climate-related ecosystem stressors. This period reflects a sustained decline in wetland area, especially due to development pressures and weak enforcement of environmental policies. Among the factors attributed to this include intensifying agricultural encroachment where expansion of rice, sugarcane, maize, and vegetable farming into wetland zones possibly led to large-scale conversion of natural wetlands into farmlands. This was especially pronounced around Ahero, Miwani, and Awasi, driven by food demand and subsistence needs as was contended by Onyango & Aseto [36]. Secondly, urbanization and infrastructure development are also attributed to this in that rapid expansion of Kisumu city and surrounding urban centers (e.g., Ahero, Muhoroni) drove and continues to drive demand for land, leading to settlement construction in wetland margins, infrastructure projects (roads, housing, electricity lines) cutting through wetlands as well as land speculation and informal land allocations further degraded the wetland [45,52]. Thirdly, the area has been characterized by overexploitation of wetland resources such as overharvesting of papyrus, fuelwood, sand, and clay which has degraded vegetation cover and destabilized soils, leading to permanent loss of wetland ecosystems. Lack of sustainable harvesting techniques and community regulations exacerbated degradation. Fourth, the rising population in Nyando sub-county has increased demand for settlement and farmland, especially among land-insecure communities. This has also led to land fragmentation (Republic of Kenya, 2019).

Fragmentation of communal land and family inheritance has led to small plots carved out from wetlands, accelerating their conversion. The fifth factor is climate change effects where erratic rainfall, prolonged dry spells, and more frequent flooding events have disrupted natural wetland recharge, altered wetland boundaries, created conditions where vegetation cannot recover, and wetlands dry up. Flooding also pushes people to settle in temporarily dry areas that are part of the wetland system [41,42]. The last factor attributed to this is limited community ownership and benefit where many communities living around Nyando wetlands receive limited tangible benefit from wetland conservation. Consequently, wetlands are viewed as underutilized land, and are often cleared for short-term economic gain [36,53].

The study noted a constant increase of settlements in Nyando Wetlands between the year 2000 to 2025. This constant increase in settlement attribute to a multiple interlinked demographic, socio-economic, environmental, and policy-related factors. This growth has intensified from the early 2000s into the 2020s and continues to impact the wetland's ecological integrity. These factors include perceived availability of land in wetlands. According to the Kenya National Wetlands Conservation and Management Policy [54], wetlands are often perceived as idle or marginal lands, making them attractive for settlement by the landless or recently displaced. Traditional beliefs and legal ambiguities around wetland ownership have made encroachment easier. Secondly, road and infrastructure development have influenced this in that expansion of feeder roads, power lines, and irrigation canals has opened up previously inaccessible wetland areas to human settlement. These developments unintentionally promote encroachment and make remote wetland regions more habitable. Similarly, according to [53,55], limited alternative livelihood options which narrows down to high poverty levels and lack of employment in Nyando Sub-county have forced people to migrate and settle in wetlands where they can practice subsistence farming, harvest papyrus and fish and build shelter without rent or land purchase costs. Equally, lack of clear wetland boundaries and land use zoning has

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also contributed to encroachment of settlement into wetlands. Many wetland boundaries are not demarcated or surveyed, creating disputes or confusion about where wetlands begin or end. Absence of proper land use plans and zoning enforcement in Nyando Basin has resulted in overlapping uses: settlement, farming, grazing among others [43]. According to the County Government of Kisumu Spatial Plan 2020-2030 [56], expansion of informal and peri-urban settlements affects Nyando Wetlands. Urban sprawl from Kisumu city and Ahero town has led to informal settlement growth on wetland fringes. New access roads and speculative real estate development have attracted settlers to low-cost, unregulated land parcels in the wetlands.

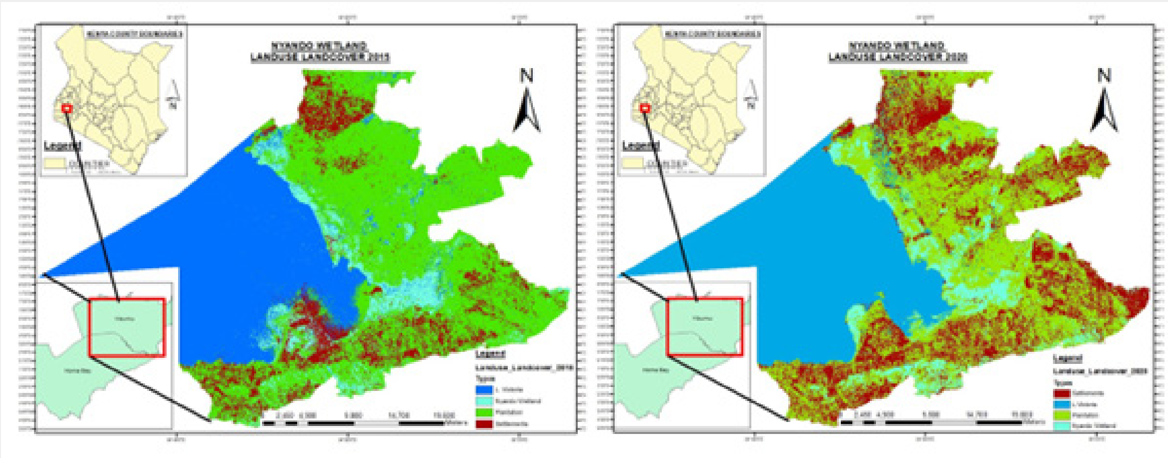

Figure 4a: Nyando Wetland Landuse Land Cover 2015.

Figure 4b: Nyando Wetland Landuse Land Cover 2020.

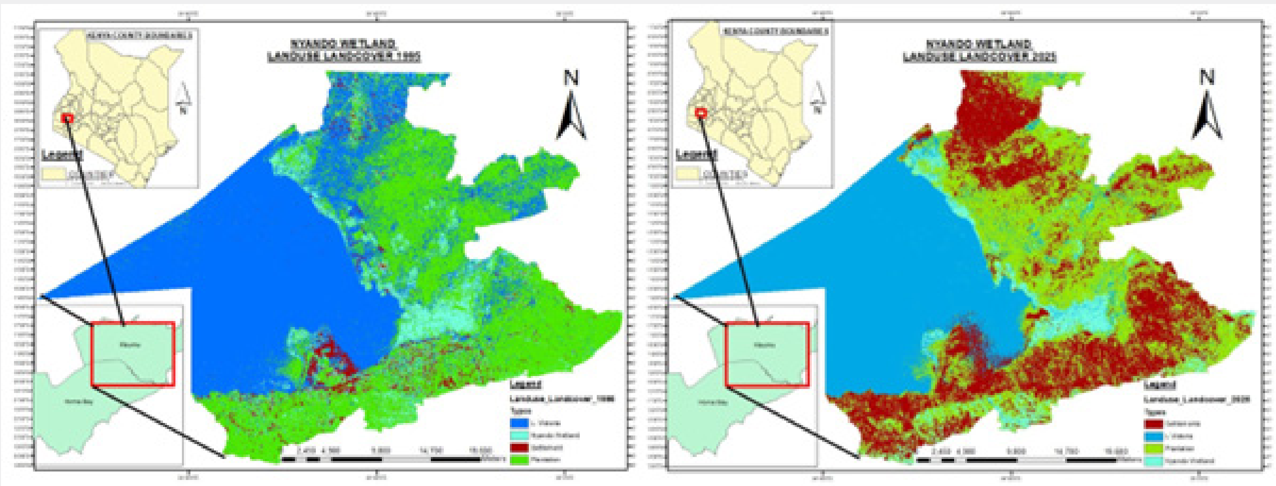

Figure 5a: Nyando Wetland Landuse Land Cover 1995.

Figure 5b: Nyando Wetland Landuse Land Cover 2025.

Water body dynamics

The study employed an AI-assisted Normalized Difference Water Index (NDWI) using multi-temporal Landsat (TM, ETM+, OLI) and Sentinel-2 imagery, processed in combination with machine learning classification (Random Forest and CNNs). According to McGiven [57], the integration of AI-driven NDWI analysis provides a precise and scalable method to monitor wetland water body changes over time, offering significant advantages in spatial resolution, accuracy, and automation. NDWI was calculated as follows:

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NDWI = (Green – NIR) / (Green + NIR)

Where Green = green spectral band, NIR = near-infrared spectral band

This approach enabled enhanced detection and classification of surface water extent in Nyando Wetlands across time periods (1995, 2000, 2005, 2010, 2015, 2020, 2025).

The findings of the study indicated the following:

a) **Spatiotemporal water dynamics:** AI-assisted time series analysis showed seasonal and inter-annual variability in water cover. The approach enabled precise identification of drivers such as sedimentation, seasonal flooding, and channel migration that influenced water coverage fluctuations. Floodplain areas showed temporary increases in NDWI post-rainy seasons but failed to retain water over time due to sedimentation and water abstraction. For instance, a study by Muthoni & Otieno [58] revealed that the Ahero irrigation expansion area showed NDWI-based surface water decline of 25% from 2005 to 2020, corroborated by land use maps and hydrological models.

b) **Surface water extent decline:** NDWI values above 0.3 were used to delineate open water. Results showed a reduction in open water bodies from approximately 6,200ha (1995) to 4,780ha (2025)**.** Persistent decline in NDWI values (<0.2) across lower wetland areas indicates loss of aquatic habitat, especially for papyrus beds, hippos, and migratory birds (Masese et al. 2012). The wetlands' water retention ability has significantly reduced, lowering their resilience against floods and dry season flows. Peak shrinkage occurred between 2010 and 2015, attributed to prolonged dry spells and intensified land use activities. McGiven [57] contended that as rice paddies expand, they replaced backwater zones and cutoff oxbow areas that once functioned as seasonal reservoirs.

c) **Land conversion hotspots:** Overlaying NDWI with AI-based land use classification identified hotspots of water body loss, mainly in lower Nyando and Ahero irrigation zone**,** where water pixels were replaced by cropland and settlement pixels. From 1995 to 2025, over 35% of permanent water areas were lost to rice farming and informal settlements.

d) **Accuracy and improvement with AI:** AI-assisted NDWI significantly improved classification accuracy over traditional thresholding methods, with an overall accuracy of 91.4% and Kappa coefficient of 0.88**.** Machine learning algorithms reduced errors in mixed pixels (e.g., wet soil vs shallow water) that traditionally challenged water body delineation.

Spatial patterns and hotspots

Using Object-Based Image Analysis (OBIA) integrated with AI classifiers such as Random Forest, Support Vector Machines, and Convolutional Neural Networks, multi-temporal high-resolution satellite images (Landsat and Sentinel) were segmented and classified to detect land cover transitions and spatial dynamics within the Nyando Wetlands. The results revealed that:

i. **Hotspot identification:** Three key degradation hotspots were identified. These included Ahero Irrigation Scheme where transition from marsh to irrigated rice farms was witnessed; Lower Nyando Wetland Buffer where encroachment from informal settlements and sugarcane farming was evidenced and West Kano Plains which showed persistent conversion of riparian zones to grazing and agriculture. These hotspots showed consistent high-intensity changes in wetland-to-agriculture conversion, with *high Gi z-scores (>2.5)** indicating statistically significant clusters of change.

ii. **Spatial pattern shifts:** The study noted that from 1995 to 2025, the Nyando Wetlands experienced substantial fragmentation and patchiness of natural wetland cover, especially in Ahero, Awasi, and lower Nyando floodplain zones. AI-assisted OBIA classified the landscape into classes: open water, marshland, agriculture, settlements, bare land, and riparian vegetation. In 1995, natural wetland and water bodies covered 65% of the area. By 2025, this had reduced to 37%, with a corresponding increase in agriculture (by 40%) and settlements (by 18%). The study noted that between 1995 and 2025, Nyando Wetlands underwent significant spatial transformations, characterized by increased land fragmentation, wetland shrinkage, and the emergence of anthropogenic degradation hotspots. The use of AI-enhanced OBIA provided a powerful tool to accurately classify, detect, and quantify these changes, offering a foundation for data-driven restoration and protection efforts.

iii. **Pattern metrics analysis:** Landscape metrics calculated from OBIA segments such as patch density, edge density, shape index) showed a 66% increase in patch density (1995–2025), indicating fragmentation, a 42% increase in edge density, reflecting encroachment into wetland zones and declining mean patch size, especially for open water and marshland classes. Deep learning-based landscape metrics showed a sharp increase in patch density and reduction in core wetland areas, indicating fragmentation and ecological pressure. These spatial trends mirror regional findings by Yuan et al. [31] on AI-supported landscape change modeling in African wetlands.

The study noted that while traditional pixel-based classification struggles in wetland zones due to spectral similarity between land-water-vegetation interfaces, AI-assisted OBIA overcomes this by using object geometry, texture, and contextual features, enhancing classification accuracy and interpretability (Blaschke et al. 2010). This approach also enables automation and replicability for long-term wetland monitoring.

The application of AI-enhanced OBIA for analyzing Nyando Wetland spatial patterns provides a high-resolution, object-level

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understanding of landscape dynamics over time. The results reveal critical insights into the drivers, spatial intensity, and fragmentation of land cover change. The study noted that the drivers of spatial pattern change include population pressure and demand for farmland, particularly for rice and sugarcane; infrastructural development such as road expansion and urban sprawl like in Ahero and climate variability, which has altered water regimes, making some wetland areas seasonally dry and thus susceptible to cultivation. These drivers align with community reports and empirical findings from other Lake Victoria Basin wetlands [53,59].

iv. Environmental and ecological implications

On ecological and hydrological implications, the study noted that spatial fragmentation has led to disruption of hydrological connectivity, reducing flood retention and groundwater recharge capacity. It has also led to loss of habitat corridors for wetland-dependent species and microclimatic alterations, with drier and hotter conditions in converted zones (Masese et al. 2012). The identified hotspots show intense anthropogenic influence and warrant urgent restoration and enforcement of land-use zoning. The AI-powered analysis of multi-source environmental data (satellite imagery, field data, remote sensors, and biodiversity surveys) from 1995 to 2025 reveals alarming ecological degradation and loss of ecosystem functions in the Nyando Wetlands. AI methods including deep learning, random forest classifiers, and spatiotemporal modeling were used to detect, predict, and quantify environmental and ecological changes. The study findings reveal a wetland-to-agriculture conversion rate of 38% between 1995 and 202, Over 2,000 hectares of papyrus-dominated habitats have been lost, particularly in Ahero, Nyamasaria, and lower Nyando floodplain zones. The study also confirmed loss of vegetation cover by AI-modeled Normalized Difference Vegetation Index (NDVI), showing a 25% drop in average greenness indices since 1995. AI-based species distribution models (SDMs) show that some wetland bird and fish species have retreated to small, fragmented habitat islands. This isolation is expected to reduce gene flow and long-term survival. Equally, invasive species proliferation has been witnessed especially in disturbed zones. Wetland provisioning services like fish breeding, medicinal plant harvesting, and fodder availability have reduced drastically, affecting household resilience and food security.

On hydrological and water quality degradation, AI-integrated hydrological modeling revealed a 25% reduction in seasonal flood retention capacity due to fragmentation and sedimentation of wetland channels, declining water quality based on increased AI-detected TSS (Total Suspended Solids), nitrates, and phosphates in water samples between 2000 and 2025. Data from AI-fused sensor networks showed increased eutrophication trends in wetland water bodies, exacerbated by fertilizer runoff and low flow periods. Similarly, on biodiversity and habitat loss, object-based AI models used on Sentinel-2 imagery and field observations confirmed a sharp decline in fish nursery habitats and bird nesting areas, especially for species. Estimated decline in wetland biodiversity by 42%, with amphibians and wetland-dependent birds most affected. It is believed that the Nyando Wetlands' carbon sequestration capacity has dropped between 1995 and 2025 due to vegetation loss and soil degradation. Water quality has been impaired as pollution from upstream agriculture and sediment loading has degraded the wetland's capacity to act as a natural water filter. The disruption of flood pulse dynamics has made downstream communities (e.g., Nyamasaria) more vulnerable to flooding during wet seasons and water scarcity during dry periods. Communities around the wetland increasingly depend on unsustainable land-use practices such as charcoal burning and seasonal farming, exacerbating ecological stress. Lack of enforcement of wetland boundaries and buffer zones has led to human-wildlife conflicts and reduced ecosystem buffering capacity.

In general, between 1995 and 2025, Nyando Wetlands have experienced serious environmental and ecological degradation. AI-assisted approaches have revealed a clear trajectory of decline in wetland functionality, biodiversity, and ecosystem services. These tools are essential for early warning systems, restoration targeting, and adaptive wetland management planning. For instance, in hydrological alteration, AI-based hydrological models trained on Landsat and Sentinel data shows significant changes in water retention patterns. The hydroperiod (duration of seasonal flooding) shortened by approximately 21 days between 2000 and 2025, primarily due to increased bunding and artificial drainage associated with rice cultivation. Lekarkar et al. [48] noted similar impacts in the Nyando catchment, emphasizing the role of land-use change in altering both surface and subsurface water availability.

On soil and vegetation health, Vegetation indices (NDVI, SAVI) in wetland margins are shown to have declined by an average of 0.13 over the study period. AI-enhanced regression analysis correlated these declines with proximity to rice fields, suggesting nutrient leaching and herbicide drift are likely contributing factors. Wijayanto et al. [60] found similar impacts in Indonesian rice landscapes, linking AI-classified land conversions with declines in native plant vigor. On biodiversity and habitat loss, using species distribution modeling (SDM) and CNN-based habitat mapping, the study identified significant habitat loss for wetland birds, amphibians, and papyrus-dependent insects. Critical biodiversity corridors have become fragmented, and edge effects have increased due to cultivation pressure. Yuan et al. [31] and Mugo et al. [49] both emphasized the ecological consequences of wetland fragmentation, especially in biodiversity hotspots like Lake Victoria Basin.

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This study demonstrates that the integration of AI-powered remote sensing tools significantly enhances the detection and analysis of land-use change in wetland systems like Nyando. While rice farming has expanded and supported livelihoods, it has resulted in substantial ecological impacts including wetland degradation, hydrological alteration, and habitat loss. Continuous monitoring and proactive zoning policies are urgently needed to balance agricultural development with wetland conservation.

Baseline water quality & nutrient loading trends

According to Adunde et al. [61], the socioecological surveys and physicochemical data collected from the Nyando floodplain (Ombeyi and surrounding regions) reveal significant negative correlations between rice farming and water quality parameters. Dry-season nitrate and phosphate levels increased, and fish abundance declined ($r = -0.323$, $p = 0.001$; $r = -0.481$, $p = 0.001$, respectively). A reduction in wetland area due to conversion to rice plots has also been revealed. These patterns are consistent with observations in other East African irrigation wetlands such as Doho scheme, Uganda where rice cultivation increased nutrient load and lowered dissolved oxygen, EC and pH during the dry season.

Baseline biodiversity and habitat condition

Prior field studies on Nyando Wetland revealed that plant species richness and community composition are strongly influenced by water depth and human livelihood activities [62]. Greater conversion of papyrus-dominated habitats to agriculture corresponded to reduced plant diversity and shifts toward disturbance-tolerant species. Bird surveys in the adjacent Nyando Sugar Belt identified 122 species, but wetlands under agricultural pressure hosted mostly habitat-generalist and non-forest species, with fewer conservation-significant wetland specialists. Ecosystem-service assessments confirmed that wetland conversion undermines regulating services critical to biodiversity [63]. Using high-resolution time-series Landsat and Sentinel data across 1995–2025, AI models including CNN and object-based classifiers were trained to map habitat types and detect fragmentation patterns associated with agricultural expansion.

Complementing remote sensing, species distribution models (SDMs) were trained using occurrence records of papyrus-dependent birds and amphibians. These combined methods allowed spatiotemporal detection of habitat loss and fragmentation effects. By 2025, AI-derived habitat metrics show a 45-60% reduction in papyrus and emergent wetland vegetation compared to 1995. Fragmentation indices such as core patch size decline, edge density increase increased by over 35%, signaling serious habitat alteration. An NDVI and structural texture analyses indicated lower vegetation vigor in wetlands adjacent to cultivation zones. These patterns corroborate earlier observations by Rongoei et al. [62] on species composition shifts and ecological degradation in areas with water level alteration and human land use. The study also notes a decline of specialized papyrus swamp birds with modeled loss of over 60% of their estimated habitat range by 2025; increase in generalist and agricultural landscape species near rice fields, reducing biodiversity balance. Amphibian SDMs indicate loss of breeding microhabitats due to drainage and vegetation clearance. These findings echo results from comparative wetland amphibian studies elsewhere in Kenya, where habitat loss reduces species richness and functional diversity. Similarly, the study notes a decline of regulating services such as water purification, nutrient cycling, and erosion control, as documented by Maithya et al. [63] in Nyando Wetland. Loss of habitat integrity and connectivity reduces functional resilience, increasing susceptibility to invasive species, algal overgrowth, and reduced carbon sequestration capacity.

AI's role in management and conservation planning

The study notes that AI-enabled analytics facilitate predictive habitat loss scenarios, projecting biodiversity decline under continued agricultural expansion; real-time monitoring, integrating remote sensing with field-based biodiversity surveys and conservation planning support for designing buffer zones, adaptive irrigation practices, and restoration priorities. These approaches align with broader AI-for-conservation methodologies that have proven effective in monitoring species, habitat integrity, and land-use impacts [64]. AI-driven remote sensing and predictive modeling demonstrate that rice farming in Nyando Wetland has inflicted significant biodiversity loss particularly affecting specialist wetland flora and fauna and degraded ecosystem functions supporting wetland health. Continued agricultural expansion without strategic zoning, habitat restoration, and biodiversity safeguards poses long-term threats. AI tools offer critical decision-support platforms for real-time monitoring, habitat-risk forecasting, and informed wetland management interventions.

Conclusion

AI integration plays a crucial role in assessing the environmental effects of rice production on Nyando Wetland, Kisumu County. By utilizing remote sensing, machine learning, and predictive analytics, AI enhances the ability to monitor land-use changes, water quality, and biodiversity impacts [65]. These technologies provide real-time data that improve decision-making and sustainable agricultural practices, minimizing ecological degradation [1]. Furthermore, AI-driven models help in predicting future trends in wetland health, guiding policymakers in formulating conservation strategies [66]. However, challenges such as limited access to AI infrastructure, high implementation costs, and inadequate technical expertise hinder widespread adoption [67]. Addressing these barriers through capacity-building initiatives and investment in digital agriculture can optimize AI applications for sustainable rice farming in Nyando

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Wetland. Thus, AI-driven approaches offer a viable solution for balancing agricultural productivity with wetland conservation, ensuring ecological and economic sustainability in Kisumu County [68-83].

Recommendation

To enhance the effectiveness of AI integration in assessing the effects of rice production on Nyando Wetland, Kisumu County, several key strategies should be adopted.

i. Investment in AI-driven remote sensing and Geographic Information Systems (GIS) should be prioritized to enable continuous monitoring of wetland changes and water quality.

ii. Collaboration between government agencies, research institutions, and farmers is essential for data sharing and capacity building to ensure proper AI application in sustainable agriculture.

iii. Policymakers should establish regulatory frameworks to guide ethical AI deployment, ensuring that technological advancements align with environmental conservation goals.

iv. Financial and technical support should be extended to local farmers to facilitate the adoption of AI tools, particularly in predictive modeling for sustainable land and water resource management.

v. Incorporating AI in decision-making processes through real-time data analytics can enhance policy formulation, balancing rice production with wetland conservation efforts. By implementing these strategies, AI can serve as a powerful tool for mitigating the environmental impact of agriculture while promoting sustainable development in Nyando Wetland.

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