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Delineation of Nalwekomba Inland Valley Wetland in Eastern Uganda and Prediction of Future Landcover

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Abstract

Inland valley wetlands (IVWs) in Africa are potential hotspots for agriculture and artisanal fishing. They present good opportunities for the rural communities in mitigating against impacts of climate change due to their abundant water supply, diverse vegetation attributes and relatively fertile soils. Unfortunately, few small inland-valley wetlands in Sub-Saharan-Africa have been delineated, mapped and land cover (LC) information documented despite countries like Uganda having a strong wetland policy and inventory. The aim of this study was to delineate Nalwekomba IVW and catchment in Eastern Uganda, predict its future land use/cover changes (LULCC) by the year 2040, and quantify extent of LC losses and gains in the period. The Wetland Identification Model, an Arc Hydro toolset for predicting wetlands with remotely sensed data was utilized together with topographic indices as inputs to a machine learning algorithm (Random Forest) in the delineation of Nalwekomba wetland and future LULC prediction achieved using Land Change Modeler. Results reveal that Nalwekomba wetland covers 72.2 km^2 with a catchment of 216.24 km^2. In the year 2020, the catchment of Nalwekomba wetland had grassland as dominant cover (30.4%), followed by tree cover (29.1%), cropland (23.6%), shrubland (10.2%), built-up & settlement (4.3%), and open water (2.5%). Future LULC predictions reveal grassland will remain dominant LC but will be reduced by 4.6% to 28.9%, tree cover may reduce by 22.5%, and shrubs by 3.88%. Land cover-area increases are expected for built-up & settlement (71.9%); open water (48.4%), and cropland (17.2 %) by 2040. These results implicate human impacts on the wetland's land cover as the wetland's direct-use activities increase. In-depth ecosystem investigations in relation to human impacts are suggested to provide information for effective ecosystem management.

Key words: Ecological implications, land use impacts, sustainability, transition potential modelling, Wetland Identification Model

Introduction

Wetlands are unique and important ecosystems due to the functions and services provided to society and environment. They are recognized as great global biodiversity hotspots (Steinbach *et al.*, 2021) and areas for food production. Despite their vital ecological roles and ecosystem services; and contribution to the overall health of local, regional and global ecosystems (Bourgeau-Chavez *et al.*, 2009), wetlands are currently faced with unprecedented levels of degradation due to anthropogenic and climatic forces (Haidary *et al.*, 2013, Gabiri *et al.*, 2020). In Africa, wetlands are the most threatened ecosystems (Rebelo and McCartney, 2022). Decimation levels differ from country to country. These freshwater ecosystems are highly threatened and poorly protected (Deventer *et al.*, 2018, Steinbach *et al.*, 2021). Monitoring their integrity for sustainability is currently a global challenge.

Uganda has experienced high losses in wetland area from 15% of its land area in 1994 to the current 9% (MOWE, 2019) despite the wide geographic distribution and diversity. Inland valley wetlands constitute a large portion of Uganda's wetlands. They are normally small (Huising, 2002) and do not appear on most maps (Steinbach *et al.*, 2021). They are major agricultural (Gabiri *et al.*, 2018) hotspots, support artisanal fishing and livestock grazing. They are therefore key livelihood resources that require strategic management.

In 1994, an inventory approach to delineate Uganda's major wetland boundaries was done though digitizing topographic maps and in 2015 a National Wetland Atlas was a product of onscreen digitizing of wetland boundaries using Google Earth. Delineation of wetlands or watershed boundaries is important for identification of flow direction using elevation data (Nile Basin initiative, 2009). It has been achieved in Uganda through information derived from topographic maps, photographs, on-site measurements/ field surveys or satellite imagery done by Government Agencies (Busulwa *et al.*, 2009). A watershed (or catchment area) represents that land surface area where surface runoff eventually flows into the same outlet (Sit *et al.*, 2019). It may include other smaller wetlands that fill and spill into the subject wetland (McCauley *et al.*, 2014) i.e., includes lower order wetlands and their catchments. Thus, delineation of the watershed can be defined as finding the catchment area of a point of interest commonly river/stream outlet or wetland; or as it infiltrates into the groundwater (Bajjali, 2018). Globally, remote sensing data from various platforms has been commonly used for delineating major wetlands (Hartter and Southworth, 2009; Ndayisaba *et al.*, 2017; Darrah *et al.*, 2019; Fitoka *et al.*, 2020; Kabiri *et al.*, 2020). Drawbacks are associated with the high level of spatial detail required to adequately map wetland landscapes especially their seasonally flooded areas (Rebelo *et al.* 2011). For example, Landsat data has limitations of omission and commission errors in classification and may not suffice for small wetlands (Namakambo, 2008). Moderate Resolution Imaging Spectrometer (MODIS)-NASA (Asilo *et al.*, 2014; Li *et al.*, 2015) has limitations of cloud cover and this limits reusable repeat image acquisitions. Use of Light Detection and Ranging (LIDAR) in wetland delineation is good because of much higher temporal and spatial resolutions but very expensive and spatially limited in application and time-consuming in processing the large point cloud. Sentinel-1 products (dual satellite products) acquired by ESA that have a combined resolution of 5-6 days and spatial resolution of 20 m by 5 m and ground sampling distance of 10 m offer scientific detail for delineation of complex environments and are deemed appropriate. Utilizing DEMS (Goulden *et al.*, 2014) for example, from Shuttle Radar Topography Mission (SRTM), ASTER have been used in many studies for watershed delineation. They provide good input data especially if applied in conjunction with algorithms in Arc GIS version 10 for hydrologic modelling particularly for watershed delineation. This approach has the advantages of using parameters like flow direction, aspect, length, slope and accumulation for inclusion in the process of extraction of watershed area from the DEMS (Namakambo, 2008; James Gideon and Bernard, 2018; Obida *et al.,* 2019). Inaccuracies linked to use of DEMS include erroneous changes in elevation(sinks), that have some computation effects in flow direction and alignment in delineation.

Small wetlands make up more than 5-7% of Uganda's total wetland area (Sakané *et al.*, 2011) but are rarely included in surveys. Size definitions for small wetlands are varied but some studies indicate sizes that rarely exceeds 500 ha (Sakané *et al.*, 2011). In Uganda, wetland spatial information is needed for management (Denny, 1985; Busulwa *et al.*, 2009; Gabiri *et al.*, 2019). Nalwekomba wetland, one of the small inland valley wetlands in Uganda is under pressure of changing land use patterns due to infrastructural developments, fishing, livestock grazing, and wetland drainage for commercial and subsistence agriculture. While these activities support livelihoods improvement, unregulated and unabated use may impair wetland functionality. Information concerning Nalwekomba inland valley wetland in Eastern Uganda- its spatial spread and the land cover information have not been available to guide management and conservation. The study adopts the Wetland identification model and uses the optical indices for the three key wetland indicators in wetland delineation such as the Tendency to Water Index (TWI), Deep to Water Index (DTW)- a soil moisture index; Normalized Difference Vegetation Index (NDVI) for vegetation identification and the Normalized Difference Water Index (NDWI) for surface water and Soil Water Index, calculated by the multiple bands in the optical imagery, widely used to enhance the discrimination between open-water wetland areas and upland features (O'Neil *et al*., 2018). Basing on the Ramsar Convention on Wetlands (1971) definition for "wetlands", wetlands can be identified by common features, including the presence of hydrologic conditions that inundate the area, vegetation adapted for life in saturated soil conditions, and hydric soils. The land cover classification provided under the National biomass center, Uganda is modified and utilized for land cover classification in this study.

Wetland delineation and prediction of future land cover are prerequisites and crucial for wetland protection and conservation against degradation, and unplanned conversions. This is important to inform regional and local government planning, wetland managers and conservationists. The objectives of this study, therefore, are: 1) to delineate Nalwekomba IVW using remote sensing and GIS technology and 2) to predict its future land use and land cover by the year 2040.

Materials and methods

Study area

Nalwekomba wetland is located in Namasagali sub county of Kamuli district, south-Eastern Uganda traverses the parishes of Bwizza, Kisaikye, Kasozi and Namasagali (Fig. 1). The wetland lies 60 km north of Jinja town; with other districts like Kayunga in the west; Luuka in the South, Buyende on the north-east, and Lake Kyoga in the north. It is a tropical, inland freshwater vegetated valley swamp, in proximal connections and drained by Upper River Nile. It stands at an altitude of 1,082m above sea level. The wetland is part of the Victoria Nile catchment as the main wetland system which comprises- the Victoria Nile, Nalwekomba, Kiko and Nabigaga wetland systems covering almost 860km^2 of wetlands as part of Nile-lumbuye catchment (Victoria Nile-Lumbuye Catchment Management Plan- https://www.mwe.go.ug/sites). It lies 80km downstream of the Lake Victoria outfall. The wetland has an extensive catchment, served by numerous smaller first and second-order wetlands and their associated intermittent streams. These first- and second-order streams/wetlands are source of surface and sub-surface water flows through the wetland. The wetland exists as part of the larger Lake Kyoga basin complex which is majorly drained by River Nile; whose drainage basin is estimated to accommodate about 15 million people (Kayima *et al*., 2018). The wetland is currently highly altered with indications of degradation, the natural vegetation undergoing succession due to the myriad of human activities.

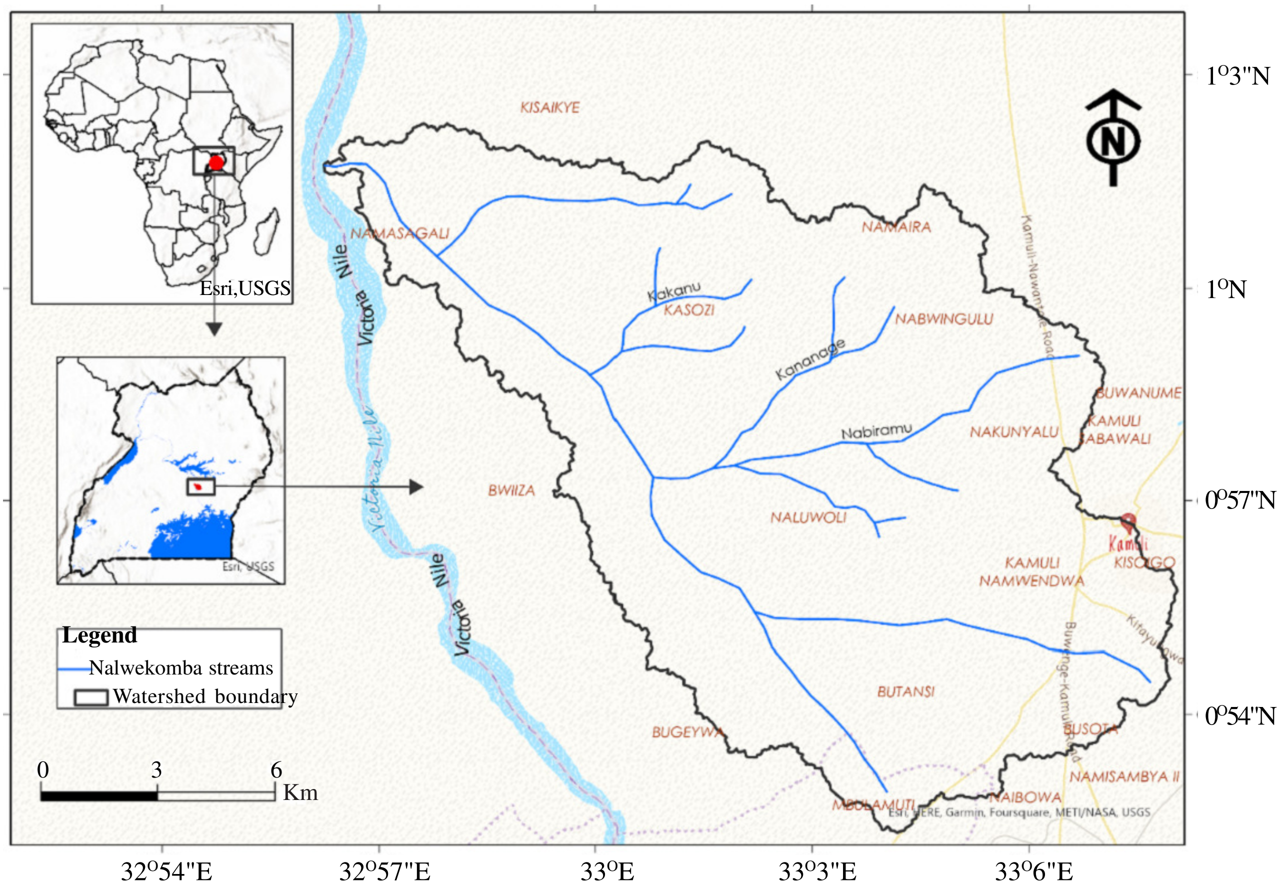

Figure 1. Nalwekomba wetland in Eastern Uganda (inset is Africa and Uganda in context)

Vegetation in the wetland is dominated with sedges (Cyperus *spp*.), Typha grass, water hyacinth (*Eichhornia crassipes*), *Leersia hexandra*, savanna grassland, *Miscanthus spp.*, and degraded forest with encroaching rice, sugarcane and subsistence farms. The upper part of the system has been developed for human settlements, and converted to arable land. Road constructions through the wetland have resulted in major alterations in some areas of the wetland. Fishing, raw materials (sand) mining for construction work, and cattle rearing are other major livelihood activities in the wetland. Tropical climate (sub-humid) characterised by two rain seasons is experienced in the study area, with peaks in March – June and August – November that synchronise with the wetland's bimodal flooding regimes. The average annual rainfall is 1,350mm with a mean monthly rainfall of 75 mm - 259 mm, mean (monthly) surface air temperatures of 24°C with minimum and maximum ranges of 14- 19 °C and 28- 36 °C, respectively. Proximity and drainage to River Nile lends a significant role to the ecology of this system.

Delineating of Nalwekomba Water Catchment Area (Watershed)

A Digital Elevation Model (DEM) generated by the Shuttle Radar Topography Mission (SRTM) was downloaded from USGS explorer in Geo TIF file format. Due to limitations of accuracy of its application with respect to hydrologic modelling of smaller systems, alternative elevation data from high-resolution depression-free Digital Elevation Model (DEM) raster data of the wetland sourced from the Alaska Data Facility (https://search.asf.alaska.edu/) (Sentinel 1) of the year 2015, with a spatial resolution of 12 meters was generated into a DEM by aid of GIS application tools. It has the capability of collecting cloud-free water and moisture specific data (Amler *et al*., 2015). Demarcation of the water catchment area for Nalwekomba wetland involved deriving the wetland's physiographic information i.e. configuration of the channel network - their length and slope, and location of drainage divides for the wetland through automated processes of watershed modelling, achieved through DEMS (Moore *et al*., 1991, Garbrecht and Martz, 2000) (Fig. 2). The Wetland Identification Model used in this process is an Arc Hydro toolset for predicting wetlands with remotely sensed data and machine learning (O'Neil *et al*., 2021). Generation of topographic information for Nalwekomba wetland to include surface water features within a watershed (Sit *et al*., 2019) and flow direction involved use of coordinates for sampling sites. These were picked physically in the field and recorded using GARMIN GPS (GPSMAP 64S) calibrated to WGS 84 coordinates reference system. They were imported into Microsoft Excel and saved as comma delimited text files (.csv). The elevation points and DEM files were exported to GIS software and converted to shape files, re-projected to WGS 84/UTM 36N, elevation

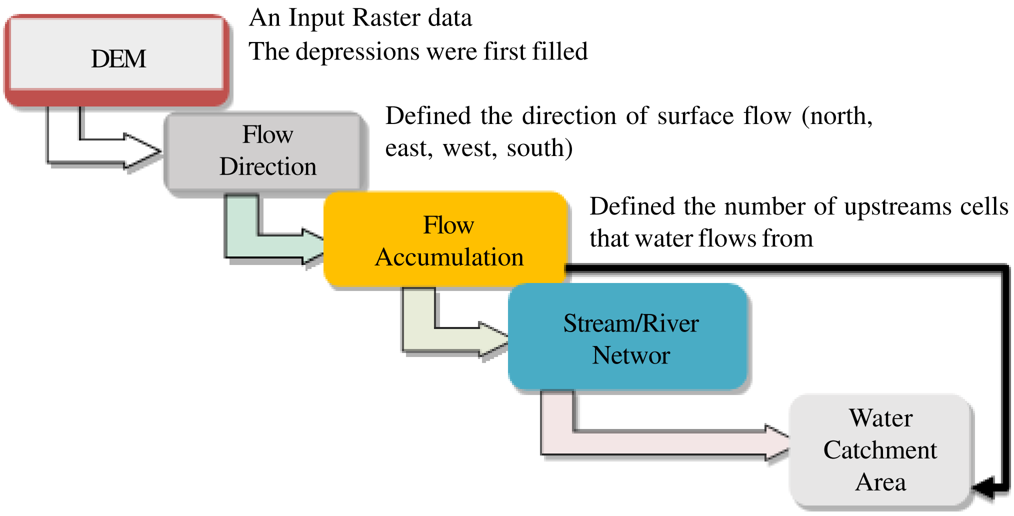

Figure 2. Procedures in generation of the water catchment area for Nalwekomba wetland.

values checked and outliers eliminated. UTM (Universal Traverse Mercator) is Uganda National Coordinate System that works almost with all GPS devices. It uses meters as its base unit, making it easier for conversions and measurements. TIN was generated using 3D catalyst tool in GIS and clipped to the extent of Kamuli area. The Fill sinks tool (Wang and Liu, 2007) was used to identify and fill surface depressions in the DEM. This tool preserves a downward slope along the flow path. A raster grid containing the information about flow directions (finds drainage networks) and drainage divides followed, and this was based on surrounding cells in the DEM (flow direction model). Flow accumulation function was performed on the resulting output of the flow direction raster to obtain cells that have high accumulation values (stream networks). The channel network was obtained by using the Channel Network Module in SAGA-GIS. The basin limits were obtained by using the UpSlope Area (Interactive) module, that helps to specify target cells, for which the upslope contributing area are identified (SAGA-GIS). A random point within the study area towards the outflow from the wetland was selected and a basin created. The created basin was then converted to a polygon (.shp file) using the polygonise tool. Finally, the pour point was established as the main outlet of the Nalwekomba stream into River Nile, which aided the delineation of the catchment area. ArcHydro Toolbox of ArcGIS software version 10.8 was used for generating the delineated watershed of the study area (see Fig. 6) based on methodology by Bajjali (2018). Tools in the software that were used included the following: - fill sink, flow direction, flow accumulation, conditional tool, stream link, watershed, and raster-to-polygon conversion tool.

Nalwekomba wetland boundary mapping

The process of mapping Nalwekomba wetland boundaries in the catchment was based on Landsat satellite imagery, soil moisture conditions, topographic maps, flood and surface water datasets through an automated process using Wetland Identification Model (WIM); an Arc Hydro toolset for predicting wetlands with remotely sensed data and machine learning (O'neil, 2021). The workflow (Fig. 3) involved preprocessing the input variable, classification and accuracy assessment. Both the Landsat imagery and high-resolution DEM were used as inputs to derive Normalized Difference Vegetative Index (NDVI), Normalised Difference Water Index (NDWI); and the predictor variables- topographic wetness index (TWI), curvature and cartographic Depth-To-Water Index (DTW), respectively. The perona-malik filter used for DEM smoothing estimates geomorphic feature boundaries to be where the slope is steeper than 90% of all slopes within the DEM (O'neil, 2021). Terrain variables derived from DEM data are important for mapping wetlands(Maxwell *et al.*, 2016).

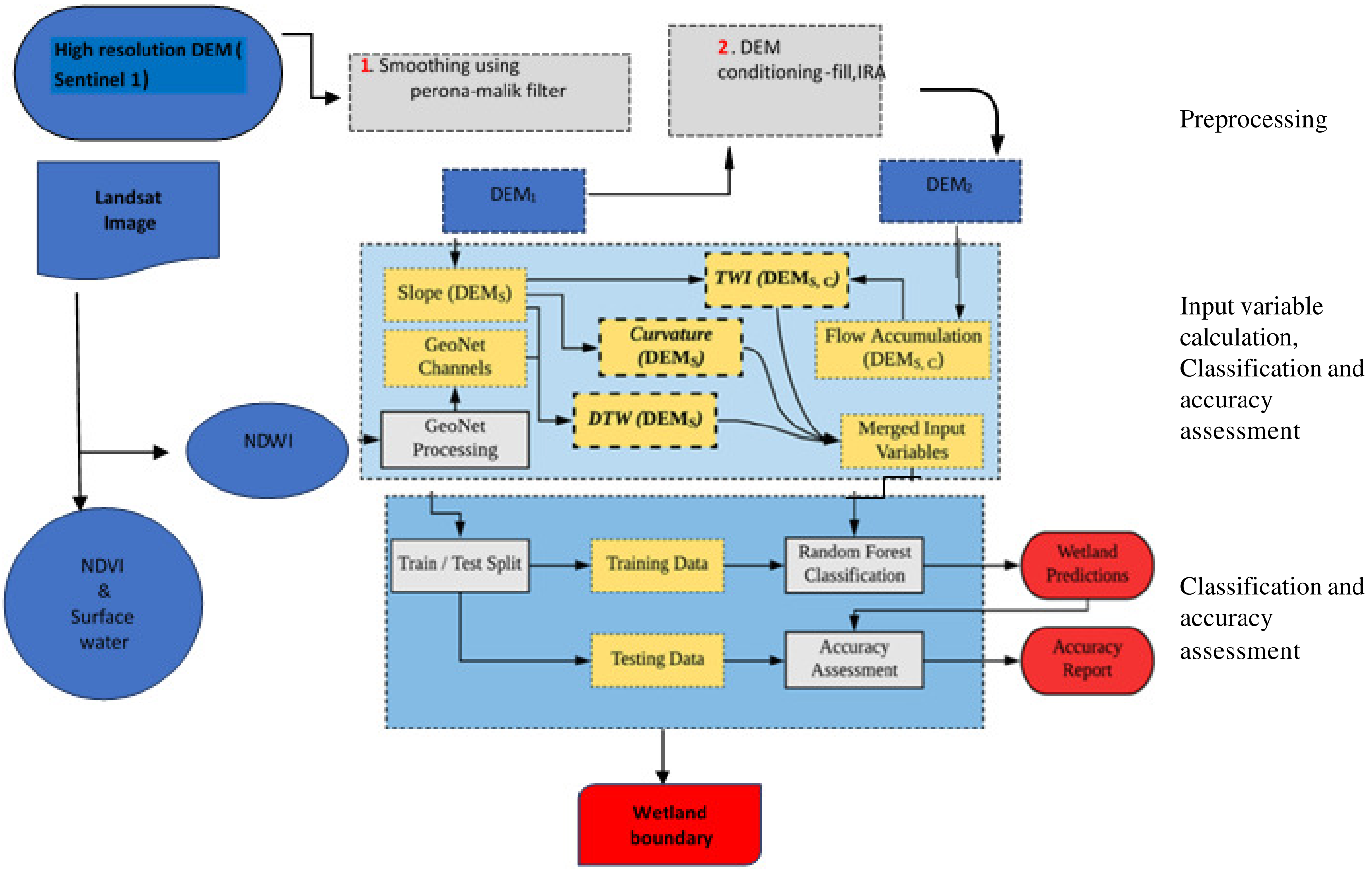

Figure 3. Workflow of the Wetland Identification Model.
Blue shapes indicate input data, grey shapes indicate processes, yellow shapes indicate intermediate output, and red shapes indicate final output. Source: Adopted and modified from (O'neil, 2021).

Curvature can be used to describe the degree of convergence and acceleration of flow (Moore *et al.*, 1991). NDVI and NDWI are the two most used indices for measuring the concentration of aquatic plants and delineating surface water features, respectively, and especially in classifying the contents within the wetland's boundaries (Kaplan and Avdan, 2017). NDVI is achieved through use of spectral bands (red and near infrared) that are most affected through absorption by chlorophyll in leafy green vegetation and by the density of green vegetation on the surface. It is calculated as a ratio between measured reflectivity in the red and near infrared portions of the electromagnetic spectrum from remotely sensed data to quantify the vegetative cover on the Earth's surface. It is in these two bands that the contrast between vegetation and soil is at a maximum. The resulting index value is sensitive to the presence of vegetation on the Earth's land surface and can be used to address issues of water extent, vegetation type, amount, and condition (Nile Basin initiative, 2009). The NDWI index can be effectively used for separating the water areas from the other land covers (Kaplan and Avdan, 2017). The NDWI threshold is known to be zero for Landsat images, where higher values from zero represent water pixels.

The TWI relates to the tendency of an area to receive water to its tendency to drain water. The index was calculated using equation 1 developed by Beven *et al.* (1979)

$$\mathrm{TWI} = \ln\left(\frac{\alpha}{\tan\beta}\right) \quad \text{…………………………………………………………………………….. (1)}$$

Where: α is the specific catchment area (contributing area per unit contour length) and $\tan(\beta)$ is the local slope derived from high-resolution DEM. This index represents the overall degree of wetness over the area as reflected by the image data (Thenkabail *et al.*, 2013).

The DTW, developed by Murphy *et al.* (2007), is a soil moisture index used as a predictor of wetland areas. It is based on the assumption that soils closer to surface water in terms of distance and elevation are more likely to be saturated (O'neil, 2021), the relationship is based on the equation 2 developed by Murphy *et al.* (2007);

$$\mathrm{DTW}\ (m) = \left[\sum\left(\frac{dz_i}{dx_i}\right)a\right]{}^{*}x_p \quad \text{…………………………………………………………………………… (2)}$$

Where: $\frac{dz}{dx}$ is the downward slope of pixel I, calculated along the least-cost (i.e., slope) path to the nearest surface water pixel; a is factor that is either 1 or "2 the pixel resolution (Murphy *et al.*, 2007). Figure SEQ Figure * ARABIC 5:

DTW calculation requires a slope grid to represent cost and depending on parallel or diagonal paths across pixel boundaries and x_p is a surface water grid to represent the source from which to calculate distance. The derived topographic indices were used as inputs to a machine learning algorithm (Random Forest) to predict and identify the areal extent of the wetland. Using both the training data (derived from the user-defined parameter indicating the proportion of wetlands and non-wetlands), and the merged input variables (predictor variables) (O'neil, 2021), the machine learning Random Forest (RF) model was trained. Following the procedures involved in the classification process, the wetland boundaries were delined and validated.

Prediction of future Land Use and Land Cover

The workflow for prediction of land use land cover change (LULCC) is shown in Figure 4. LULCC prediction considers historical rates of change and the transition potential model to predict a future specified scenario. Modelling spatial and temporal cover changes using the Markov chain analysis implemented within the Land Change Modeler (LCM) software was used in this study to assess the dynamics of land use change at different scales (Muller and Middleton, 1994). Future prediction of LULC changes utilized the transition potential model to predict future LULCC (Ghosh *et al*., 2017) by 2040. The Markov model is a stochastic model that forecasts change probability from one particular class to another, taking into account the LULC changes of the period under consideration. It works under the assumption of physics which state that the probability of a system being in a certain state at certain time can be determined if its state at an earlier time is known(Bell and Hinojosa,1977). LCM of Clark Labs (https://clarklabs.org/terrset/) determines how the variables influence future change, how much change took place between time 1 and time 2, and then calculates a relative amount of transition to the future date (Fig. 4). Three historical land use land cover maps of 1990, 2000 and 2010 were used for generation of the transition potential maps (Figs. 6a, b, and c); and statistics in the modelling to give the transition potential scenarios for various land cover as an output. The future land use scenarios were based on recent trends, historical land use information, and anticipated future changes. These utilized together with the output from change demand modelling, the future land cover was projected.

The model relied on developing a transition probability matrix of LULC change between two different dates. The resultant matrix -a product of transition potential, provided an estimate of the probability that each pixel of certain LULC class was transformed to another class or remained in its class (Eastman, 2009). It recognizes the potential spatial distribution of transitions (Wang *et al*., 2020). The LCM's robustness allows for the incorporation of constraints and incentives, such as zoning maps, and planned infrastructure changes, to include new roads or land cover

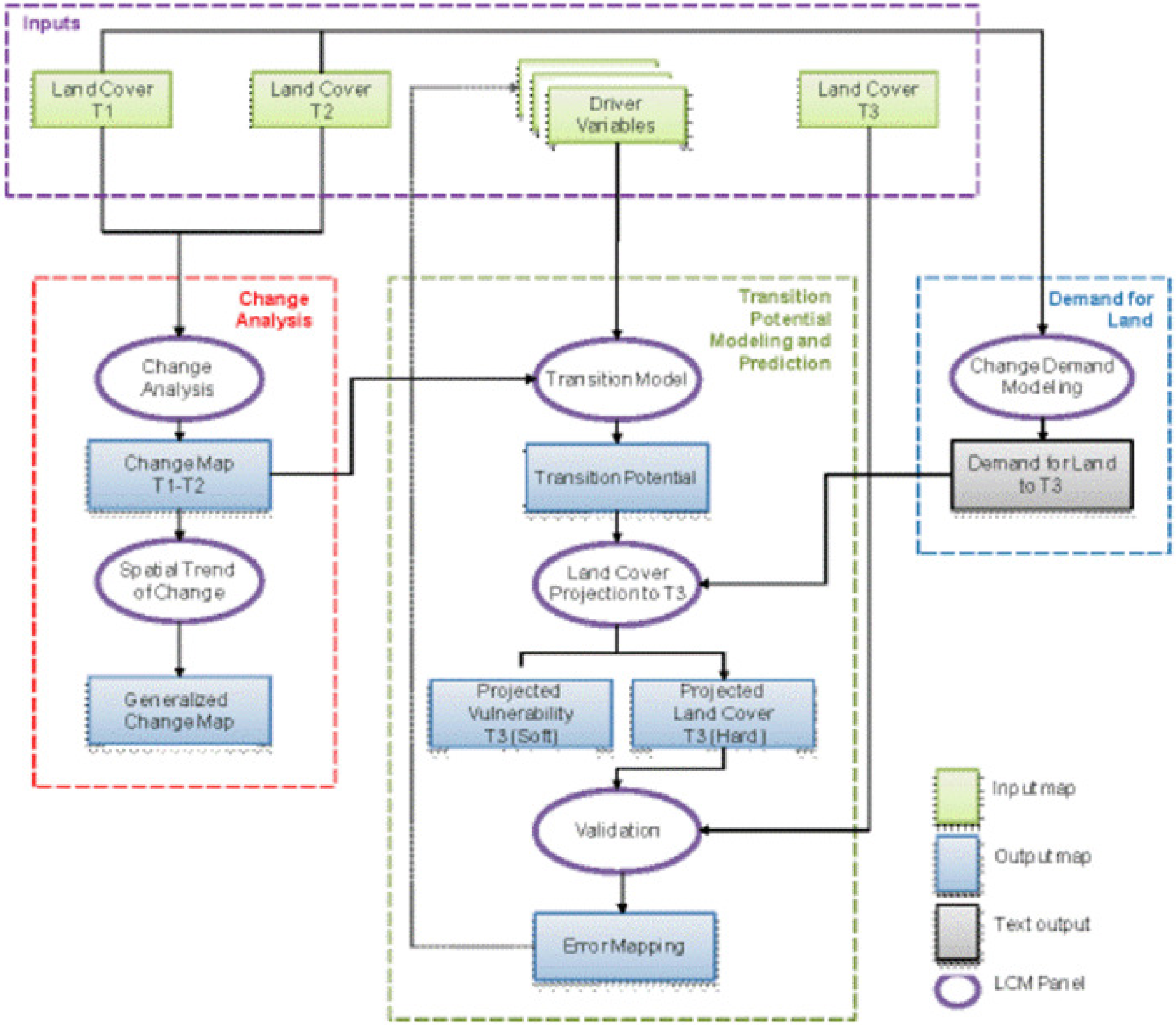

Figure 4. Methodological workflow of Transition Potential modelling for land use and land cover prediction for Nalwekomba wetland. (Source: https://clarklabs.org/terrset/)

development. During the analysis, three major drivers in the raster data formats were included in the model: Distance to roads, distance to urban center, and elevation data from Digital Elevation Model (DEM). Driver variables are factors considered important in affecting and influencing LULC change (Leta *et al*., 2021).The LULC map for the year 2020 was used for model validation. Automatic training and dynamic learning rate were adopted in model validation to generate skill measures and accuracy rate. This was achieved at 0.72 and 76% respectively. The minimum acceptable standard and range is from 65% to 89%.

Results

Results are presented in sections relating to wetland delineation, transition potential modelling as sub-outputs of the model for LULC prediction and modelled losses and gains.

Delineation of Nalwekomba wetland

Maps for topographic indices- NDVI and NDWI; TWI and DTW-the sub outputs utilized and derived in the Wetland Identification Model for wetland delineation are shown in Figures 5a (i and ii) and b (i and ii), respectively. Figure 6a shows the wetland polygon achieved by use of raster-to polygon conversion ArcGIS processing tool showing Nalwekomba wetland boundary map while Figure 6b is the delineated catchment map. Delineation of Nalwekomba wetland reveals a number of first and second order streams feeding the wetland with a final pour point established in River Nile (Fig. 6). Analysis of LULC statistics reveal that Nalwekomba wetland covers an area of 72.2 sq.km with a catchment 216.64 sq.km.

Transition potential modelling and LULC prediction

Transition potential maps used in determining the future change probability of a specific type of land use are presented in Figures 7a (forest cover), 7b (shrubland), 7c (grassland) 7d (cropland) 7e (built-up & Settlement), and 7f (open water), and the statistics (Table 1) as used to predict the future LULC types and changes in the wetland and its catchment. Values in the map legend provide possible ranges of map comparison and level or strength of agreement of the Kappa values where: values<0 =poor, 0.01-0.40 is slight; 0.41-0.60 is Moderate; 0.61-0.80 is Substantial and 0.81-1.00 is almost perfect.

Predicted and modelled land use and land cover map and trends for 2040

In the year 2020, the catchment of Nalwekomba wetland had grassland as dominant cover (30.4%), followed by tree cover (29.1%), cropland (23.6%), shrubland (10.2%), built-up & settlement (4.3%) and open water (2.5%) in descending order (Table 1). Future LULC predictions reveal grassland will remain dominant cover but

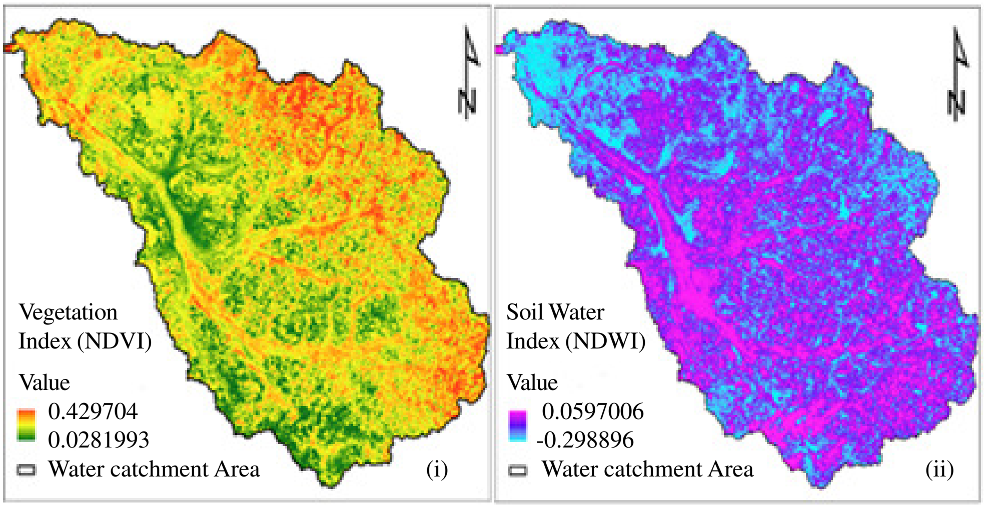

Figure 5a. (i) Vegetation Index and (ii) Soil Water Index

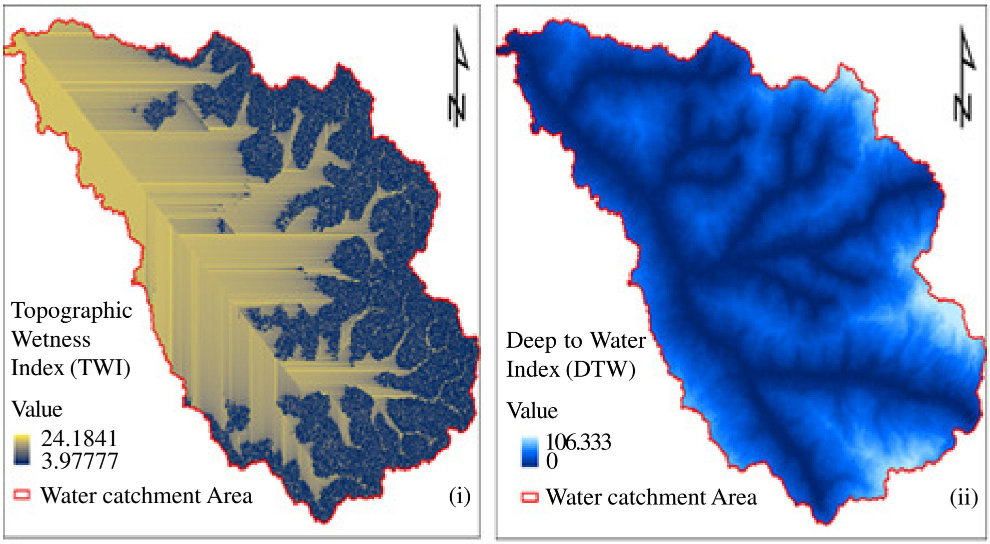

Figure 5b. Topographic Wetness Index (i) and Deep to Water Index (ii), respectively.

reduced by 4.6%. The LULC prediction results show high percentage expansions expected for built-up & settlement of 71.9 %, open water 8.4%, and cropland 15.4 %; and major percentage reductions for tree cover by 22.47%, grassland by 4.6% and shrubland by 3.88% (Fig. 8).

Predicted/Modelled losses and gains and LULC Net changes

Modelling land cover losses and gains (Fig. 9) in a wetland ecosystem provides a temporal synopsis of land use intensity affecting land cover and overall ecosystem

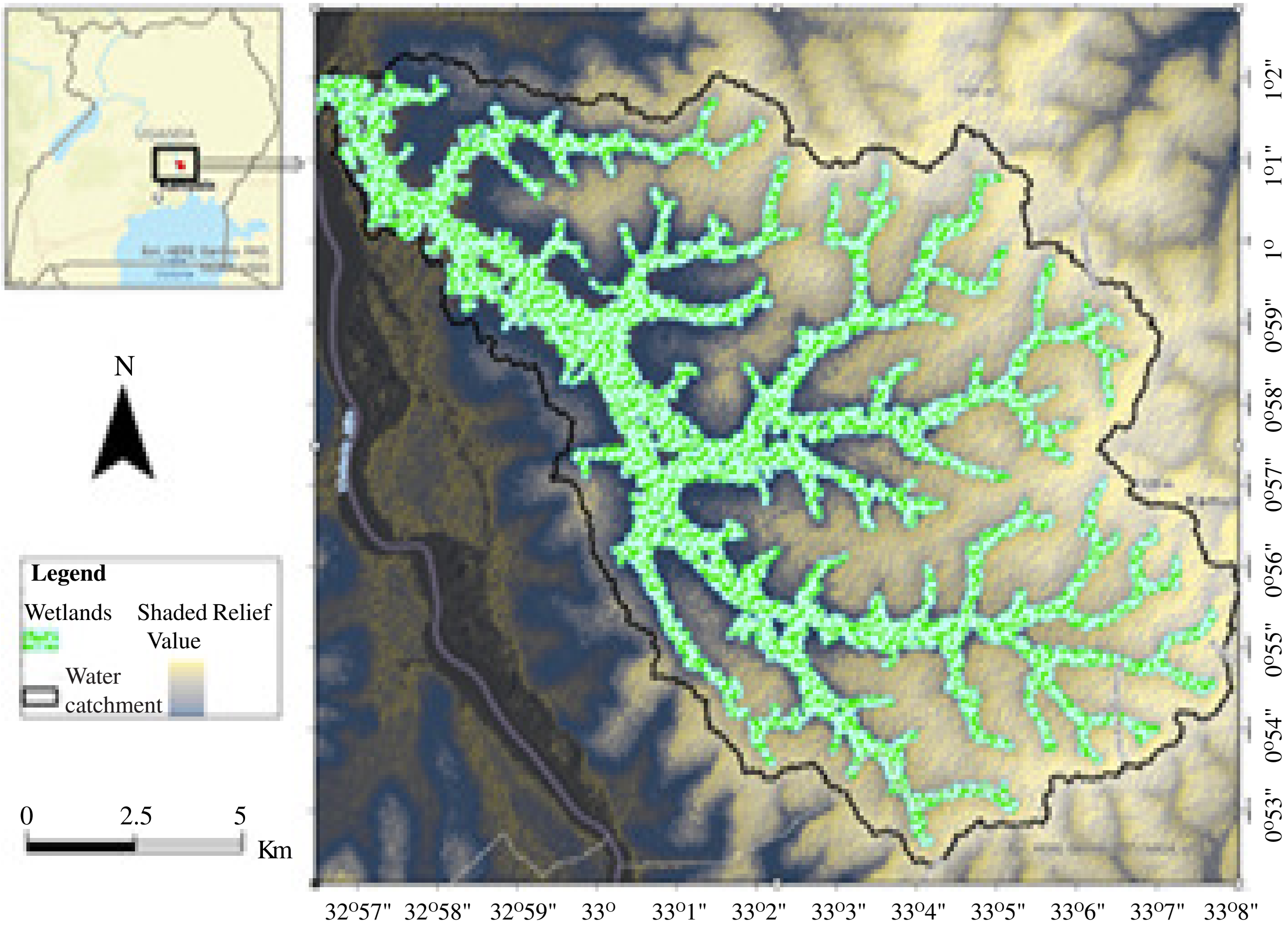

Figure 6a. Nalwekomba Wetland Boundary Polygon.

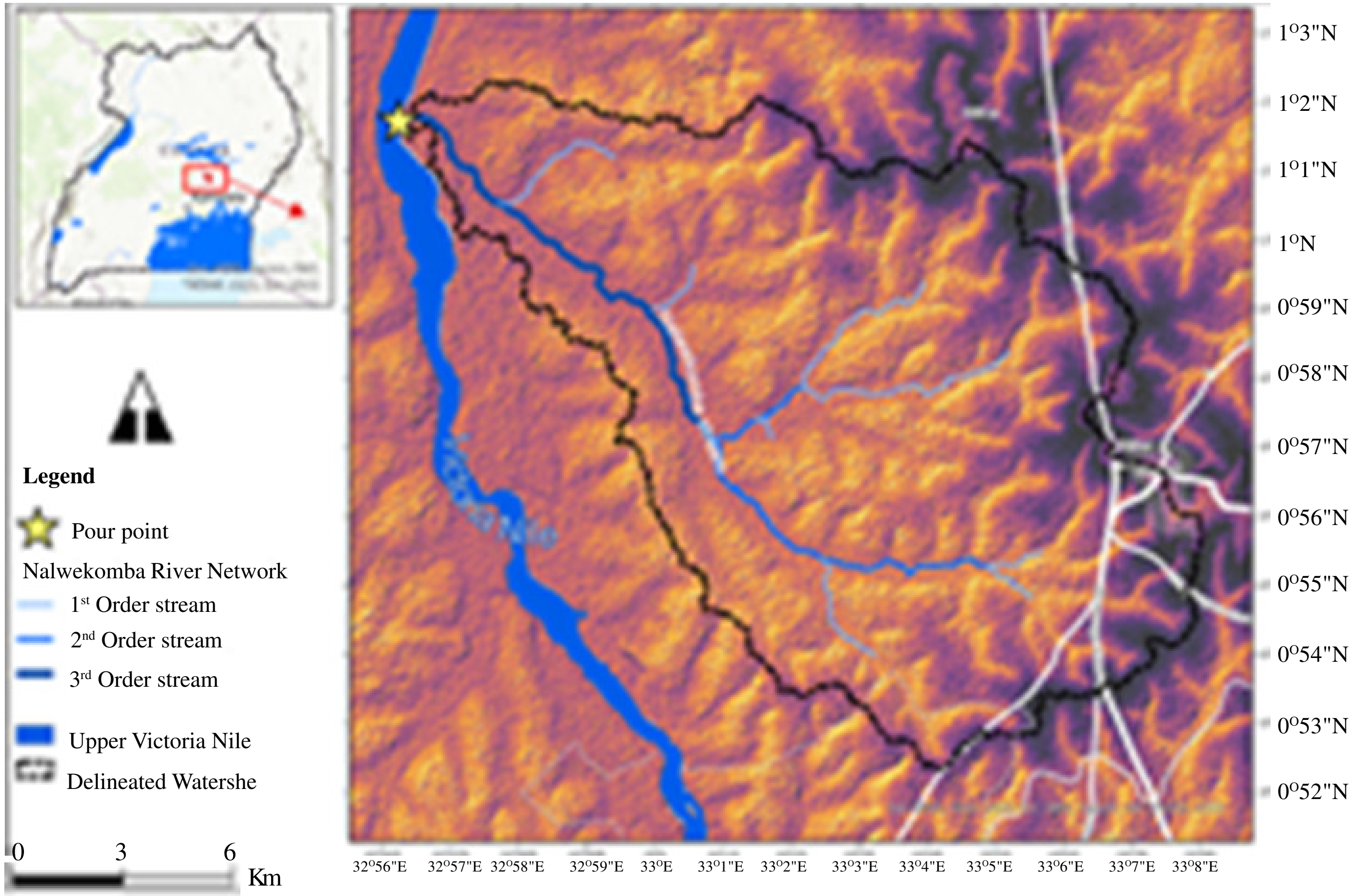

Figure 6 b. Delineated catchment map for Nalwekomba wetland.

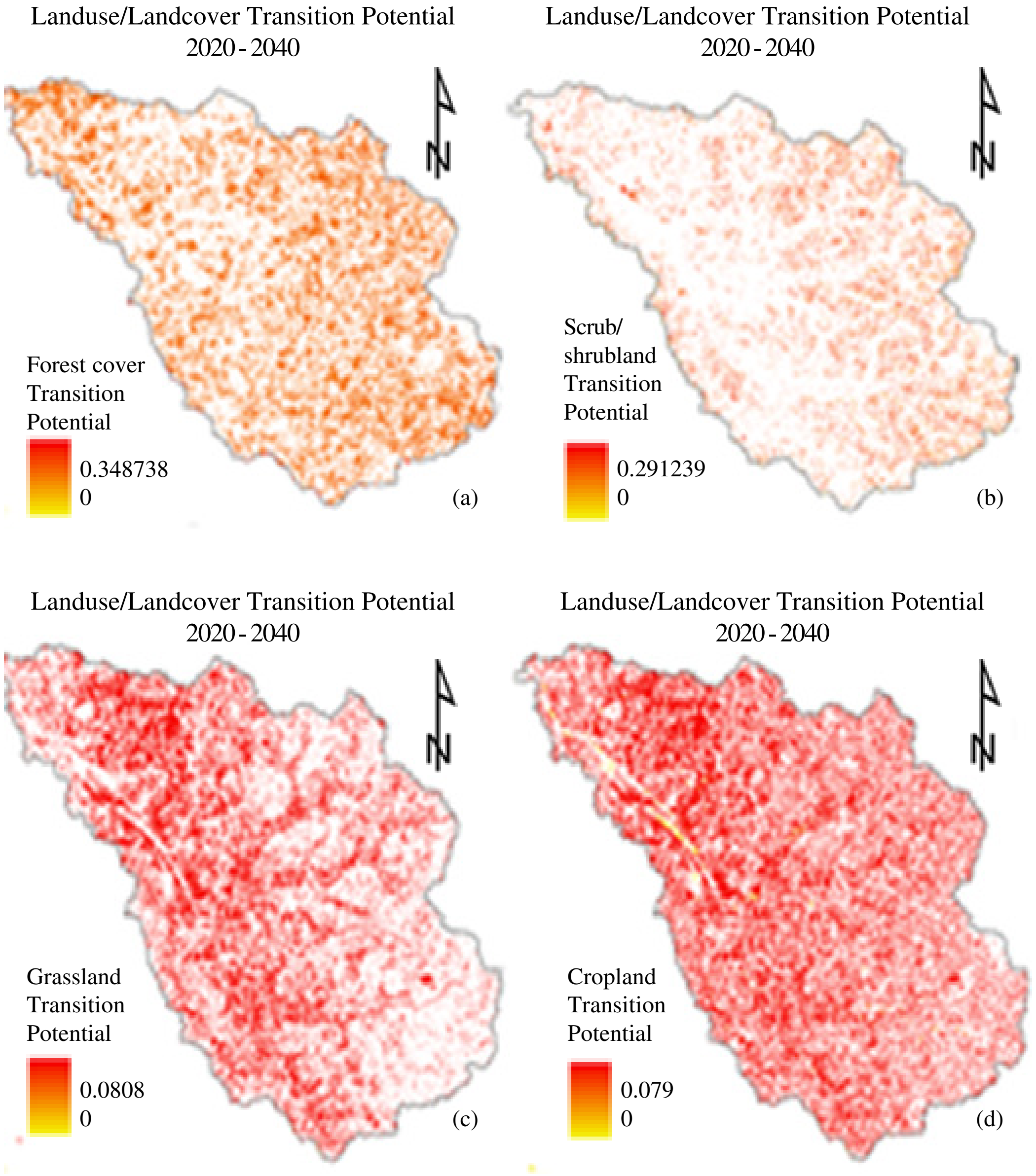

Figure 7. (a) Forest cover (b) Shrubland potential (c) Grassland and (d) Cropland potential transition map.

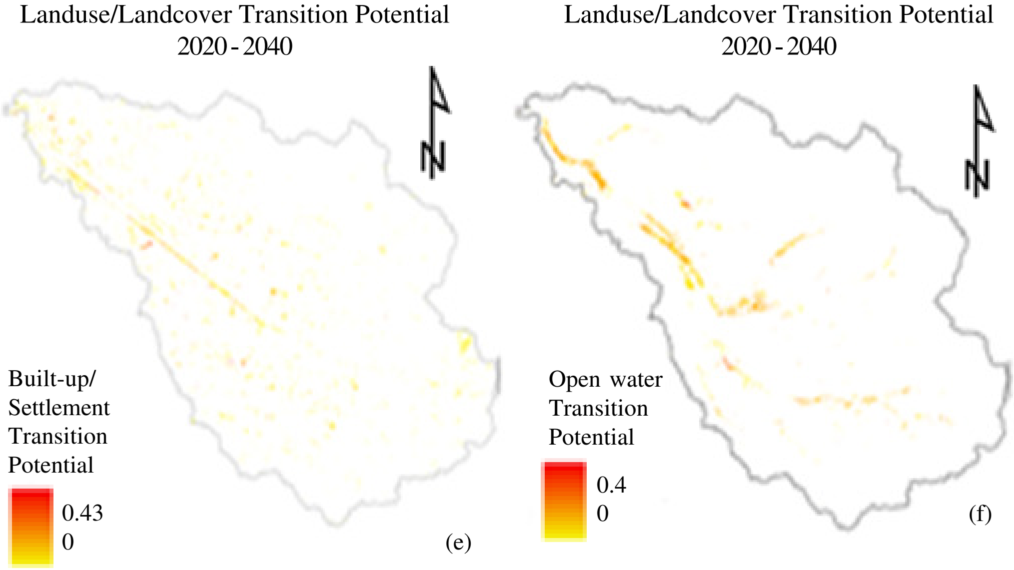

Figure 7 (e). Built-up and Settlement and (f) open water potential transition map.

Table 1. Predicted/Modelled Land use and Land cover statistics

CatchmentLand use & Land cover	Year 2020		Year 2040	
	Km^2	%	Km^2	%
Tree cover	62.97	29.1	48.82	22.5
Scrub/Shrubland	22.18	10.2	21.32	9.8
Grassland	65.76	30.4	62.71	28.9
Cropland	51.05	23.6	59.83	27.6
Open water	5.39	2.5	8.00	3.7
Built-up & Settlement	9.29	4.3	15.97	7.4

change. High temporal area changes are expected for tree cover (losses (-) of -45.25sq.km and gains (+) of 41.91sq.km; shrubland -44.13 and + 17.76; grassland -52.7 and +39.91 and cropland -13.18 and +44.09 (Fig. 9(i)). Figure 9 (ii) shows significant net changes in cover area over the period (2020-2040) where Shrubland will experience negative net changes in an area of 26.37 sq.km, grassland -12.79 sq.km followed by tree cover at -3.35 sq.km. Greatest positive net change in cover area will be experienced in cropland of 30.91sq. km followed by built-up & settlement at 13.5 sq.km. Open water for the wetland may experience a negative net area change of -1.89 sq.km over the period (Fig. 9 (ii).

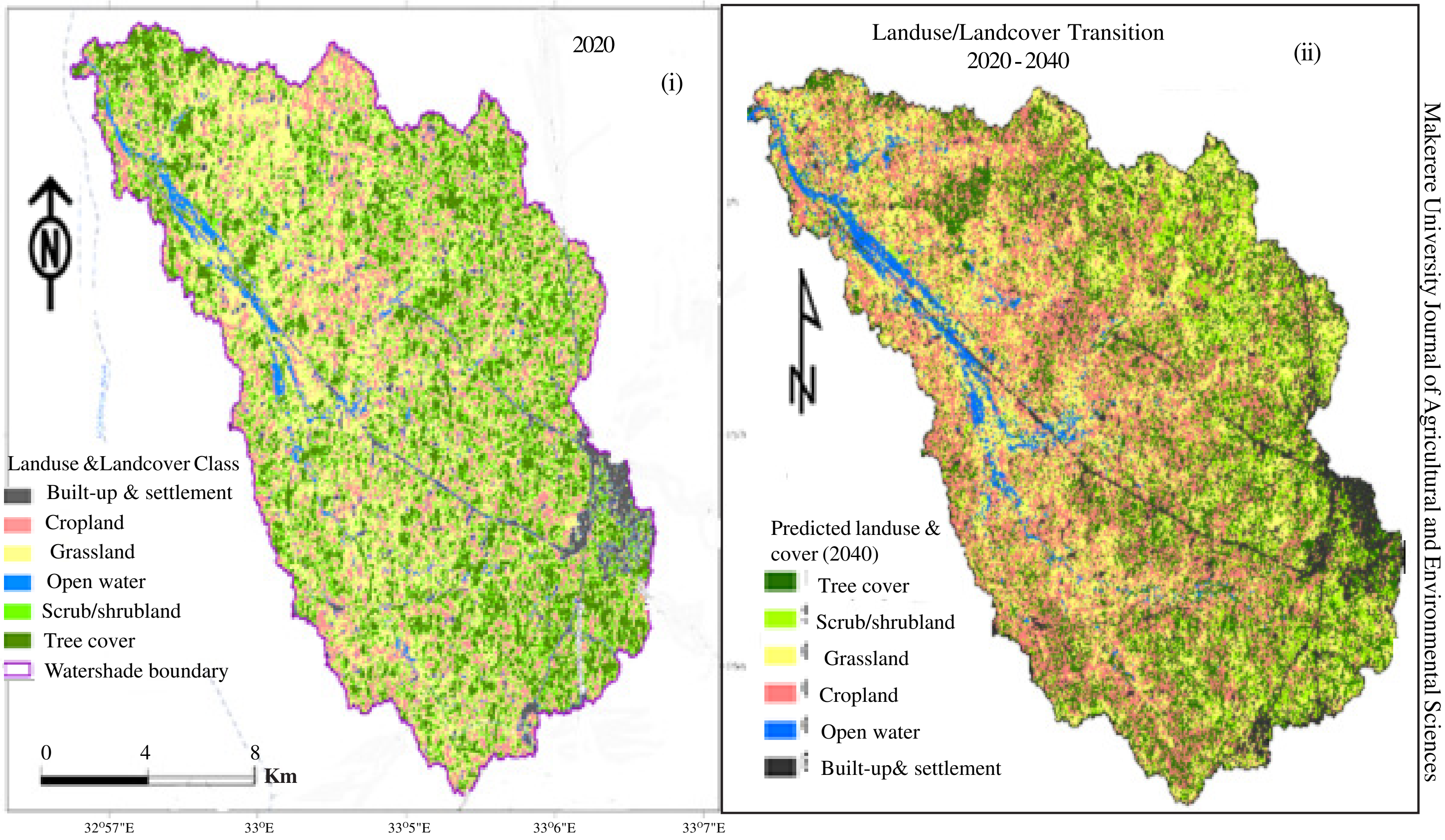

Figure 8 (i). Land use and Land cover map 2020; (ii) predicted for 2040.

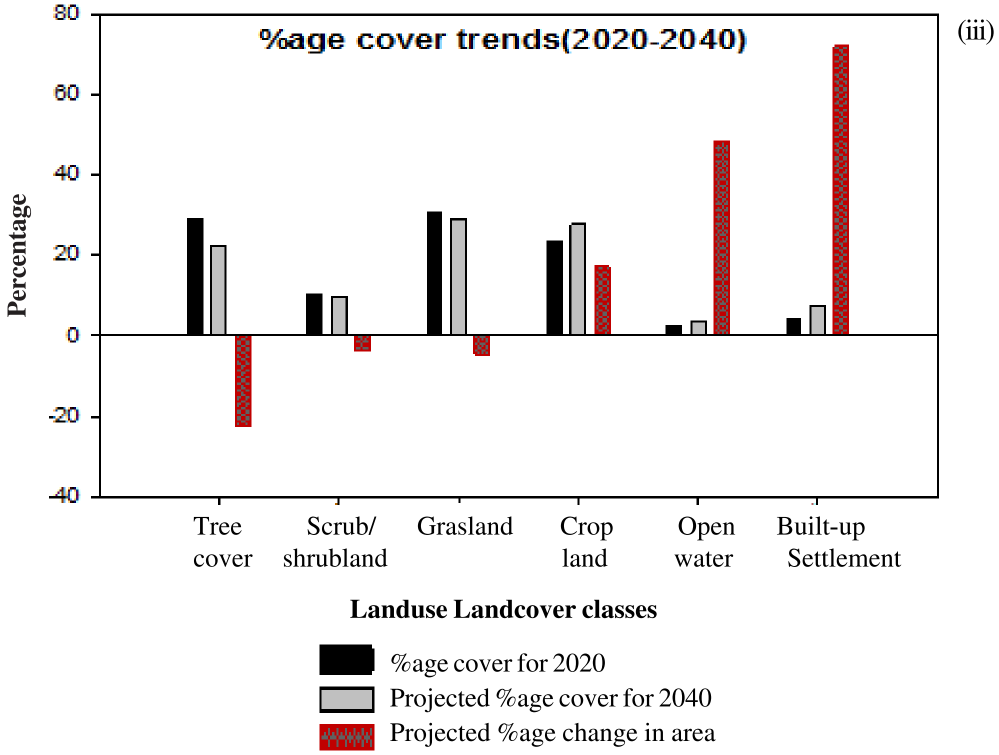

Figure 8 (iii). Graphical representation of the trends for 2020-2040 for Nalwekomba wetland and catchment

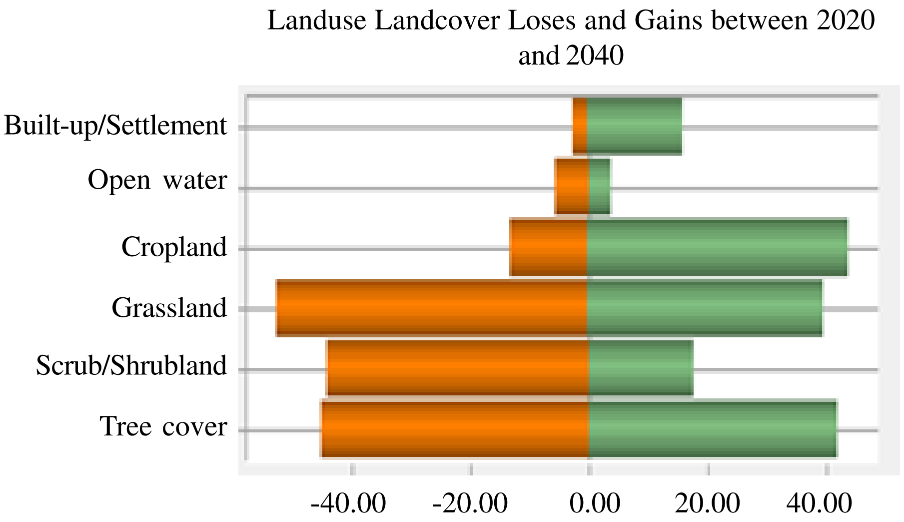

Figure 9 (i). Modelled losses and gains.

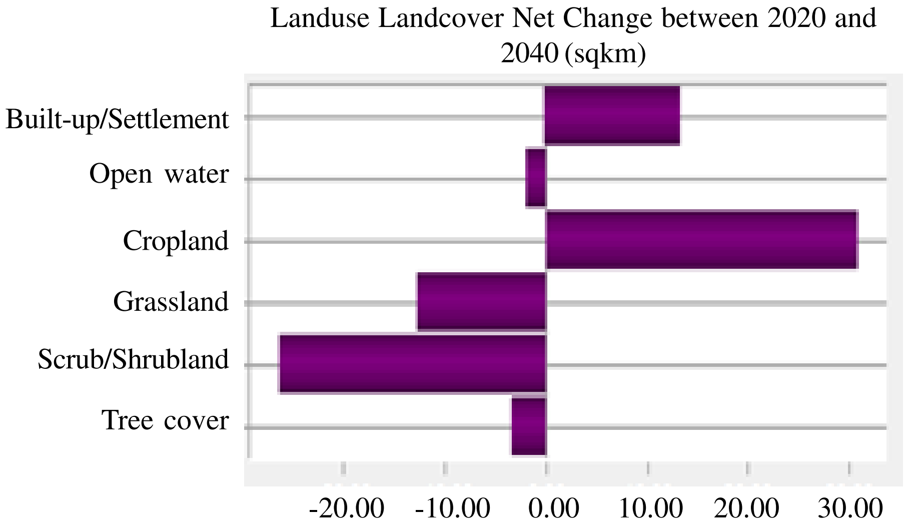

Figure 9 (ii). LULC Net changes between 2020 and 2040.

Discussion

Wetland delineation is important for strategic land use planning and ecosystem management and the study of future land use land cover (LULC) phenomena at local levels is crucial for understanding the negative impacts on environment (Mambo and Makunga, 2017). Though this study was not about effectiveness of DEM and their spatial resolution on delineation output and mapped features, studies (Goulden *et al.*, 2014) show that watershed area exhibits dependence on DEM spatial resolution due to landscape features which become identifiable at different DEM resolutions. The Sentinel 1 derived DEMs used in this study successfully and cost-optimally provided for modelling of the watershed extent revealing that Nalwekomba wetland (72.2km^2) is fed by numerous first and second order streams; has a catchment of 216.64km^2 with a pour point in Upper River Nile at Namasagali (Fig. 6). Much higher resolution DEMs are recommended to further elucidate these findings (Amler *et al.*, 2015).

The prediction results reflect an environmental effect signal of land use intensity on some of wetland's cover attributes. These results are consistent with predictions from other related studies (James Gideon and Bernard, 2018). Expected increase in cropland area portray the wetland's increasing importance in agricultural production for the rural households. This observation was also noted by Dossou-Yovo *et al.* (2017) on wetland encroachment in urban centers in Uganda.

Many studies predict future wetland land use will be impacted by climate change and population growth (anthropogenic activity). A projected >70% increase in built-up area and settlement may be a challenge that is in tandem with projected study area population increase (Kamuli District, Uganda) increasing demands for land for settlement and agriculture. Predictions from this study are supported by observations by Baig *et al.* (2022) who predicted similar occurrences that reveal persistent cover expansion for cropland and built-up area with increasing wetland land conversion due to population expansion. This assertion is further confirmed in studies by Maltby (2022) who observed that significant numbers of pristine wetlands experience immense pressure from human activities; the greatest wetland-human pressure being drainage for agriculture and settlement (Busulwa *et al.*, 2009). Reduction in tree cover, grassland, and shrubland are expected where land use activities entail vegetation clearance. They spur sequential and chronological effects on surface water processes, for example, increased runoff in the catchment.

Effects of the changing climate on aquatic ecosystems is envisaged in water quality and quantity changes. Water quality-related challenges are a product of increases in run-off, sedimentation, as well as changed natural flood cycles altered by agriculture activities (Maltby, 2022), and/or reduction in seepage or in the ground water recharge function that is highly promoted by the presence of vegetation. While increase in open water (surface water) is important for aquatic processes and functioning for the wetland and its catchment, anthropogenic-related changes in vegetation attributes (grassland, trees and shrub) may cause hydrologic changes. Gopal (2016) also reiterated that vegetation characteristics of the watershed are important in regulation of surface water levels where their predominance may provide mitigation against drastic fluctuations.

Diverse ecologic and economic implications of the expected increased surface water levels (open water) can be linked to the underlying causes within the ecosystem (McCauley *et al*., 2015; Thamaga, 2021). For example, ecosystem responses may be observed in changes in the wetland's hydrologic health affecting flooding regimes (Cherry, 2011), nutrient composition (Machado *et al*., 2015) leading to changes in wetland productivity. Also, the ground water recharge efficiency that result from changes in water holding capacity, changed residence times, and changed recharge potential for the wetland may be affected. Further envisaged implications from the projected scenarios of reduction in vegetative cover (grassland, trees and shrub) are effects on the wetland processes. Increased sedimentation associated with increased run-off (flooding) may result. Increased sedimentation reduces effective water depth. Shallow water depth may favour proliferation of succession in vegetation development. Reduction in wetland vegetation due to crop farming affects the wetland's physicalchemistry properties (Machado *et al.*, 2015) and changes in faunal populations (Willig 2017; Seki *et al.*, 2018b) weakening ecosystem resilience and retention potential (Mereta *et al.*, 2020).

In addition to environmental effect signals shown above, LULC changes carry socioeconomic signals. Temporal changes in tree cover, shrubland, grassland, and cropland may bring differentiated ecological effects on the wetland and catchment, and sustainability of wetland-dependent livelihoods. Wetland use (land use) and land cover changes constitute a disturbance for the wetland ecosystem. Minimal and intermediate disturbance is positive for the biodiversity of the wetland (Willig and Presley, 2017). LULC changes alter organic material inputs and exports for the wetlands and the resultant changed nutrient levels affect ecosystem processes and productivity. Aggravated disturbance through changes in land cover is a threat to biodiversity (Seki *et al.*, 2018b), and affects the hydrologic characteristics such as water depth, open-water surface to volume ratio that are responsible for the distribution of aquatic species. Wetlands exhibit resilience to disturbance but can be compromised with high degree of disturbance. This is negative for conservation actions. Land use management of inland valleys is therefore required at policy level to balance land requirements for agriculture and settlement and yet cater for the ecological concerns to preserve the wetland's essential characteristics that are important for wetland functioning. Further in-depth assessments are suggested to support future ecosystem management actions.

Conclusions

The delineation of Nalwekomba inland valley wetland revealed a rich hydrological network in the wetland's basin that covers 216.2 sq.km that can be utilized for water resources development in the area. Wetland land cover changes are inevitable occurrences both naturally and in anthropogenic environments and their assessments are important tools for natural resource management. Results highlight and confirm the increasing activities for built-up/ settlement and agriculture (cropland) in the small inland-valley wetlands and their catchments. Projected changes in land cover for Nalwekomba wetland and its catchment reveal higher net cover increases in built-up & settlement, open water and cropland, envisaged to replace shrubs, grasses and tree cover; which are crucial indicators pointing to wetland vulnerability to human actions.

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