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Research article

Evaluating the spatial and temporal variations of aquatic weeds (Biomass) on Lower Volta River using multi-sensor Landsat Images and machine learning

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ABSTRACT

Aquatic invasive weeds affect hydrological, ecological, and socio-economic activities on freshwater ecosystems. On the Lower Volta River (LVR) of Ghana, invasive aquatic weeds have been known to be nuisance to fishing, navigation, aquaculture, hydropower production and other agricultural practices in the area. While information on the spatial and temporal distribution of aquatic weeds would be beneficial in improving weed management and control measures on the river, such information is very scanty. Also, these aquatic weeds are also biomass resources, that can be transformed to bioenergy. Thus, this study evaluated the spatial and temporal variations of aquatic weeds on the Lower Volta River, and assessed their potential biomass for bioenergy production.

Random Forest (RF) algorithm and Landsat images were used to map the distribution of the weeds in 1975, 2003, and 2020, respectively. Accuracy assessment results showed mean Overall Accuracy (OA) of 83.44% and mean User Accuracy (UA) of 79.24%. The results indicated that as of 1975, aquatic weeds covered only 1495 ha and appeared in some specific locations such as Kpong and Ada. However, by 2003, the weeds had spread to most parts of the river covering 5600 ha, which was an increase of approximately 4-fold within a period of 28 years. The area covered by the weeds, however declined by 1505 ha between 2003 and 2020. Thus, in 2020, water hyacinth covered about 36% of the aquatic weeds relative to 28% in 2003. The results showed that, the quantity of the water hyacinth biomass per unit area was 21.5 kg/m^2. This result can also be used as the basis for resource assessment as well as determination of its viability for bioenergy production and strategies for its modern utilisation. The conversion of water hyacinth into bioenergy remains one of the best aquatic weed management strategies that must be adopted in LVR.

1. Introduction

Freshwater covers only about 3% of the earth's surface (Central California Area Office, 2020), yet remains one of the most important resources, providing numerous socio-economic and ecological benefits for households, farms, and industries (Thamaga and Dube, 2018). The Volta River system is the biggest freshwater systems in Ghana. It supplies water for domestic, agricultural, and industrial uses, serves as habitat for diverse aquatic species, a recreational area, navigable waterway between the northern and southern parts of the country, and a climate modulator for the tropical region (Ghansah et al., 2016). Among the recent economic activity on the river is aquaculture in small units along the banks of the river (Ainoo-Ansah, 2013).

The Akosombo and Kpong hydroelectric dams are, by far, the most significant economic project constructed on the river, producing electricity for many parts of Ghana and some neighbouring Countries (Andah

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et al., 2003). The constructions of the dams, however brought about hydrological and ecological changes on the Volta Lake, especially along the Lower Volta River (LVR) stretch. Hydrologically, the flow of the river is regulated throughout the year, curtailing flooding, resulting in high loads of sediments during the rainy season (Pabi and Akpabey, 2017). Ecologically, the dams promote the growth of native aquatic weeds and infestation of highly invasive aquatic weeds particularly, water hyacinth (Pierce and Opoku, 1971; Pabi and Akpabey, 2017). These aquatic weeds have been known to be nuisance to fishing, navigation, aquaculture, and other farming activities. The weeds also harbour reptiles, serve as breeding ground for mosquitoes, induced eutrophication, and other water quality deterioration concerns (Pabi and Akpabey, 2017). While some aquatic weeds control measures and management practices have been rolled out by the Volta River Authority (VRA) and other agencies ("Volta River Authority | News," April, 2015), the weeds are still in abundance, mainly due to their high re-infestation rate, as well as inadequate knowledge of their spatial and temporal variations. Although, there have been calls for the intensification and effective management efforts in curtailing the spread of the aquatic weeds, information about the spatial and temporal variations would be useful in order to fully understand and appreciate the evolution as well as other infestation behaviour of the weeds. Such information can also be used to estimate the quantity of weeds, as a potential biomass resource, for other economic purposes. However, there are scanty information about the spatial and temporal variations of the aquatic weeds on the LVR, due to the few studies that have been conducted about the weeds in this area.

Odei (1987) assessed the proliferation of aquatic weeds as well as other ecological changes due to the construction of the dams on the Volta River. However, this study (Odei, 1987) was limited to only the Ada area of the river and thus, did not provide information about the spatial and temporal trends of the weeds. The study also used traditional field surveying methods in mapping the proliferation of the weeds. This method is laborious, time consuming and expensive if a complete variation of the weeds on the Lower Volta River needs to be mapped. Also, Pabi and Akpabey (2017) used high resolution satellite images to map the extent of aquatic weeds at the LVR area, the results provided a baseline information about the spatial extent of the weeds at that time. However, no study has mapped the variations in the distribution of the aquatic weeds at different points in time. Thus, a good understanding of the evolution of aquatic weeds in the LVR is still lacking. Also, information about the impact of weeds control and management practices is still inadequate. Access to timely data that can provide information about the spatial and temporal variations of the weeds is therefore imperative.

Satellite sensors with high spectral and spatial resolution provide data to monitor aquatic weeds variations and spread, thus enabling an assessment of areas of severe infestation and allow for timely interventions (Shekede et al., 2008). In respect of this, studies that assessed the spatial and temporal variations of aquatic weeds have found satellites with long temporal coverage particularly useful, as sensors onboard these satellites offer opportunity to combine images captured at different times to assess the evolution of weeds. For example, Shekede et al. (2008) combined the Landsat Multispectral Scanner (MSS), Thematic Mapper (TM) and Enhanced Thematic Mapper (ETM) to map the spatial and temporal variations of aquatic weeds on Lake Chivero in Zimbabwe. The study noted that the availability of a long period of satellite data helped to assess information about the variations, infestation level and rate of spread of aquatic weeds in the 1970s and 1980s when ground information were not available. Other studies have assessed the capabilities of newer sensors to mapping water weeds, to the extent of assessing the abilities of these sensors to specific species of aquatic weeds. For example (Dube et al., 2017), and (Thamaga and Dube, 2018) used Landsat 8 Operational Land Imager (OLI) and Sentinel-2 Multispectral Instrument (MSI) respectively, to map water hyacinth species. Thus, these presents opportunity to use remotely sensed images for mapping the spatial and temporal trends of the aquatic weeds on the Lower Volta.

In addition to satellite data, the development of machine learning (ML) algorithms and evolution of personal computers with high processing capacities offers opportunity for accurate and improved mapping of water weeds. Recent studies that utilized ML to classify aquatic weeds have reported high accuracies of the maps produced. For example, when (Dube et al., 2017) used Discriminant Analysis (DA) and Partial Least Squares Discriminant Analysis (PLS-DA) ML algorithms to map water hyacinth, both algorithms obtained Overall Accuracy (OA) and User Accuracy (UA) over water hyacinth of 90% and above. Similarly, when Chabot et al. (2018) used the Random Forest (RF) ML algorithm to map emergent and submerged invasive water soldier (*Stratiotes aloides*), the algorithm produced UAs of 84% and above over all the different species of the aquatic weeds. There is an added opportunity to explore the use of machine learning in mapping aquatic weeds on the Lower Volta. Thus, this study evaluated the spatial and temporal variations of aquatic weeds on the LVR, over a 45-year period. This study further classified 1975 Landsat MSS, 2003 Enhanced Thematic Mapper Plus (ETM+) and 2020 OLI images with RF ML algorithm to produce Land Use and Land Change (LULC) maps for the respective years. There was an evaluation of the gains and losses within the time intervals. Also, there was an assessment of the spatial and temporal changes of the aquatic weeds as well as the amount of the other LULCs that contributed to net changes in aquatic weeds. The study further estimated the current biomass potential of water hyacinth in the area using pre-determined wet weight and surface area covered by the weeds on the 2020 Landsat image. The results provided further understanding of the evolution of aquatic weeds and impact of weeds control practices on the Lower Volta River.

2. Materials and method

2.1. Study area

The Lower Volta River is a part of the Volta River Basin in Ghana. The study areas stretch from Akosombo dam to the Kpong dam which is located about 25 km downstream of the Akosombo dam, extending to the estuary where it joins the sea (Gulf of Guinea). It is located between Latitudes 5° 47′ and 6° 18′, and Longitudes 0° 03′ and 0° 5'. The course of the river passes through 7 districts in the Volta Region of Ghana, from Asuogyman through North and Central Tongu, to Lower Manya, Shai-Osudoku and Ada East districts (GOG, 2019), as shown in Figure 1. There are several notable communities located along the river including Atimpoku, Senchi, Kpong, Akuse, Torgome, Asutsure, Sogakopke, Agordome, Big Ada and Ada Foah. Major occupations of the people in the area fishing and farming. The Lower Volta river, which is one of the largest man-made lake in the world and has the Akosombo dam as the most important structure built on the basin. The river is located in the Southern Savannah climatic zone of Ghana and the area experience bi-modal rainy seasons from March to November with peaks in May/-June. The area records a mean annual rainfall of 870.4 mm and mean annual potential evapotranspiration of 1600 mm. Additionally, the mean annual temperature for the area is about 27.9 °C with the relative humidity ranging between 74 % and 94 %. The major source of water supply for the people in the area is mostly from the streams and ground water. The Dahomian describes the geological formation (Okra et al., 2016) with gneiss as the major rock type in the area. However, the formation has a low groundwater potential of about 36 % (Dapaah-Siakwan and Gyau-Boakye, 2000). The vegetation in the area is dominated by grassland and shrub with scrubby mangrove vegetation along the coastal fringes (Logah et al., 2017).

2.2. Data sets

2.2.1. Field survey

Before the field survey, existing literature and Google Earth images were used to conduct a desktop study to learn about the LULC, of the area. Dominant LULC of the area included water weeds (such as *Vossia sp.*

Figure 1. Map of the Lower Volta and riparian districts.

association, Vallisneria sp. and Ceratophyllum sp., and the invasive species, water hyacinth - Eichhornia crassipes), water, settlement and farmlands, the latter which comprised of different cropland types and gallery vegetation. Some of the aquatic weeds management projects and recent economic activities such as aquaculture have taken place. Field survey was conducted to confirm and obtain GPS locations of the different aquatic species and other LULC of the area. The field survey took place between 6th and 19th December 2020. Two teams used canoes to navigate the course of the river, with one heading downstream and the other upstream from the Kpong fishing market, thereby covering the whole stretch of the river (Figure 1). Each team used a Garmin handheld GPS of accuracy between 0.3-3 m to record point locations of aquatic weeds. Also, other LULC including farmlands, settlements, water were collected. In all, a total of 3601 points locations were collected using the handheld GPS devices, which were used as training samples to classify the 2020 image.

Simultaneously, the field teams recorded extra 804 GPS coordinates of the water hyacinth. These coordinates were used to determine the range of NDVI values of water hyacinth. Training data for the other remaining years, 2003 and 1975 were selected through visual interpretations of Google Earth images and on the individual Landsat images.

The description of the LULC identified in the area and data used for the classification have been shown in Table 1.

Table 1. Types of the LULC classes and the number of training samples per class used the classification.

LULC	1975	2003	2020
Farmland/gallery vegetation	242	1355	1354
Aquatic weeds	155	1584	1585
Settlement	382	685	1212
Water	405	450	450

2.2.2. Landsat images and pre-processing

Three dry season Landsat images that covered the study area were downloaded from the Earth Explorer website (https://earthexplorer.usgs.gov/). They are 1975 Landsat Multispectral Scanner (MSS) image, a 2003 Landsat 7 Enhanced Thematic Mapper Plus (ETM+) image and a 2020 image from the Landsat 8 Operational Land Imager (OLI). Four main pre-processing steps were undertaken, namely: atmospheric correction, resampling, image registration, and normalization. The first was atmospheric correction, which sought to remove haze, non-target effects as well as convert the Top-of-Atmosphere (TOA) spectral radiances to Bottom-of Atmosphere (BOA) to spectral reflectance. This was performed using the Dark Object Subtraction (DOS1) technique in the Semi-Automatic Classification tool in the QGIS software 3.14. The second pre-processing step, resampling, was done using the bilinear interpolation method. This algorithm was chosen because it produces smoother interpolation and enhances image quality compared to nearest neighbour which is commonly used (Bovik, 2009; Stam and Fung, 2011). All the image pixels were resampled to 30 m at this stage. The third step was image-to-image registration using the OLI image as the reference image. The process was undertaken using 18 coordinate points selected from a topographical map. The OLI image was used as reference to reorient the other two images. This step ensured that pixels in each image geometrically matches with the corresponding pixel in the other images. The fourth pre-processing step was normalization of the images pixels and was executed using the *norm* function in R software. Normalization aided the reduction of in-between scene variability as a result of potential differences in atmospheric conditions during satellite scene acquisition (Shekede et al., 2008). The corrected images were clipped to the boundary polygon of the Lower Volta River. The characteristics of the images used are shown in Table 2.

2.3. Method

This study used multi-sensor Landsat images and field training samples to produce LULC maps for the three years. The current surface area covered by water hyacinth was extracted from NDVI from the 2020 image. The quantity of water hyacinth was then estimated by multiplying the estimated area by the biomass per square meter, which was collected

Table 2. Characteristics of Landsat images used in the study.

Sensor	Date	Path	Row	Resolution (m)
Landsat 1 MSS	28-12-1975	207	56	60
Landsat 8 OLI	12-02-2003	193	56	30
Landsat 8 OLI	02-01-2020	193	56	30

in-situ. The general approaches used in this study have been summarized and shown in Figure 2. Furthermore, the detailed description of the methods, which were applied, have been presented in the subsequent sub-sections.

2.3.1. LULC classification with Random Forest

Random Forest (RF) supervised image classifications were performed on the pre-processed Landsat images to map the spatial and temporal variations of aquatic weeds on the Lower Volta from 1975 to 2020. RF is an ensemble learning method for classification and regression that works by creating a number of decision trees during training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees (Ho, 1995). Each tree in the forest is independently constructed using a unique bootstrap sample of the training data (Breiman, 2001). Additionally, RF predicts a response from a set of predictors by creating multiple decision trees and aggregating their results (Forkuor et al., 2017). They are non-parametric models that do not require variables to be normally distributed (Mullainathan and Spiess, 2017).

The model was built and trained with the *train* function in the *caret* package (Kuhn, 2015). The field samples were split into training set (66%) and test set (44%) using the *sample.split* function in the *caTools* package. Tuning of the data was done by growing a number of trees (*ntrees*) in the forest and setting the number of variables randomly sampled at each stage (*mtry*) (Janitza and Hornung, 2018; Probst and Boulesteix, 2017). Cross validation, which determines how the model will generalize to an independent dataset, was performed using K-fold cross-validation. After building the model, classification was executed on the pre-processed images. Accuracy assessments were performed on the classified images to assess the results of the classification. A confusion matrix was used to compute the Overall Accuracy (OA), Producer's Accuracy (PA), User Accuracy (UA) and Kappa coefficient.

2.3.2. Estimation of water hyacinth biomass

A Field survey was carried out on the Volta lake to collect samples of water hyacinth. An in-situ destruction measurement and inference from remote sensing was applied in the estimation of the biomass. In all, 20 sample plots were randomly selected on the volta lake to collect the water hyacinth. The point intercept method was used to acquire water hyacinth samples from the study site and measure them in the field. The importance of the point intercept is to take measurements at regular intervals or defined locations and avoid subjective selection of locations in the field (Madsen, 1999). The points were generated at 300 m interval and a Germain GPS was use to locate the points on the lake. Quadrants made from polyvinyl chloride (PVC) measuring 1 m by 1 m summing up to an area of 1 m^2 was used, from which the water hyacinth was collected. The wet weight of the water hyacinth for each plot was weighed with a mass scale and the average biomass from the 20 plots were determined. The Normalized Difference Vegetation Index (NDVI) is one of vegetation indices that are used to identify physiological characteristics of vegetation and has been used to estimate vegetation parameters such as chlorophyl content, biomass, and canopy cover (Frampton et al., 2013). NDVI is a non-linear function which varies from -1 to 1, depending on amount of greenness (chlorophyl) in the surface/feature.

Typical NDVI values for vegetation ranges from 0.1 to 7. According to Pabi and Akpabey (2017), water hyacinth on the Volta River has the highest NDVI compared to the other floating and submerged aquatic weeds. In this study, the NDVI was used to calculate the amount of water hyacinth in each of the images. The range of NDVI values for water hyacinth was first identified by superimposing the representative sample points of the water hyacinth on the NDVI of the 2020 image. The corresponding NDVI values from the Landsat pixels were then computed. The pixels within this range were then separated and the surface area covered by water hyacinth was computed from the total count of the number of pixels.

3. Results

3.1. Accuracy assessment of LULC classification

Tables 3, 4, and 5 show the accuracy matrix for the three classifications. Among the three classifications, the 1975 classification results produced an OA of 86.54%, being the highest among the three classifications. The 2003 and 2020 classifications had OAs of 79.08% and 84.7%, respectively. The highest PA (96.09%) was produced from water class on the 2020 image, while water produced the highest UA of 100% on the 1975 image. Farmland/gallery vegetation had the lowest PA (66.67%) and lowest UA (73.33%) from all the three classifications. Within the individual years, PAs and UA were generally moderate in the 2003. The water class had the highest performance, across the three classifications. The classifications showed moderate UAs for aquatic weeds between 76.19 from the 1975 image to 83.82% from the 2020 image. PAs for aquatic weeds were relatively higher than the UAs ranging between 81.15% from the 2003 image to 89.38% from the 2020 image. In general, the 2020 image had the highest performance in terms of UA and PA.

3.2. Changes in LULC in the Volta River

The Figure 3 shows the area of coverage of each LULC for the periods of study; 1975, 2003 and 2020. Water was the most dominant class of the study area throughout the years of study. It covered a surface area of 11122 ha (45%) in 1975, 7906 ha (32%) in 2003 and 8809 (40%) ha in 2020. This shows a decrease of 13% in water surface area between 1975 and 2003 and slight increase of about 8% between 2003 and 2020. The farmland/gallery vegetation formed the second dominant LULC in area, occupying a surface area of 9940 ha (40%) in 1975, 7368 ha (30%) in 2003 and then 7109 ha (29%) in 2020. The trend of changes in surface area of farmland/gallery vegetation was somehow different from that of water since there was a slight decrease in area between 2003 and 2020 for the farmland/gallery vegetation, while water area increased within this period. However, the extent of changes between 1975 and 2003 were larger than those between 2003 and 2020 for both LULC classes. Settlement showed progressive increase in area throughout the years of study. It changed from a coverage of 1,829 ha (7%) in 1975 to 3,590 ha (14%) in 2003 to 4,452 ha (18%) in 2020, corresponding to an increase of 2,623 ha, which was almost 45% increase within the 45 years of study. Aquatic weeds also showed considerable changes during the years of study, increasing in surface area between 1975 and 2003, but decreasing between 2003 and 2020.

The gains and losses of each LULC are also shown in Figures 4a and 5a. Between 1975 and 2003, farmland/gallery vegetation lost 7767 ha of their original area but gain 3518 ha of new areas. Water also lost 6321 ha of their original area but gained 3156 ha of new areas. Settlements and aquatic weeds had the least losses, of 1400 and 944 ha respectively, but then gained new areas which were about 2-folds and 7-folds respectively higher than their loses. Aquatic weeds on the other hand had the highest loss of area between 2003 and 2020, losing 2931 ha of area but gaining 1426 ha, that is 50% net loss. Farmland/water weeds had the second largest loss among the classes but also made the largest gain. The loss was however larger than the gain, resulting in a net loss of 259 ha. Both settlement and water had net gains between the time interval, with settlements gaining 862 ha additional area whiles water gained 903 ha additional area. Figures 4b and 5b, c show the gains and losses (transitions) of the LULC for the periods 1975–2003, 2003–2020 and 1975 to 2020.

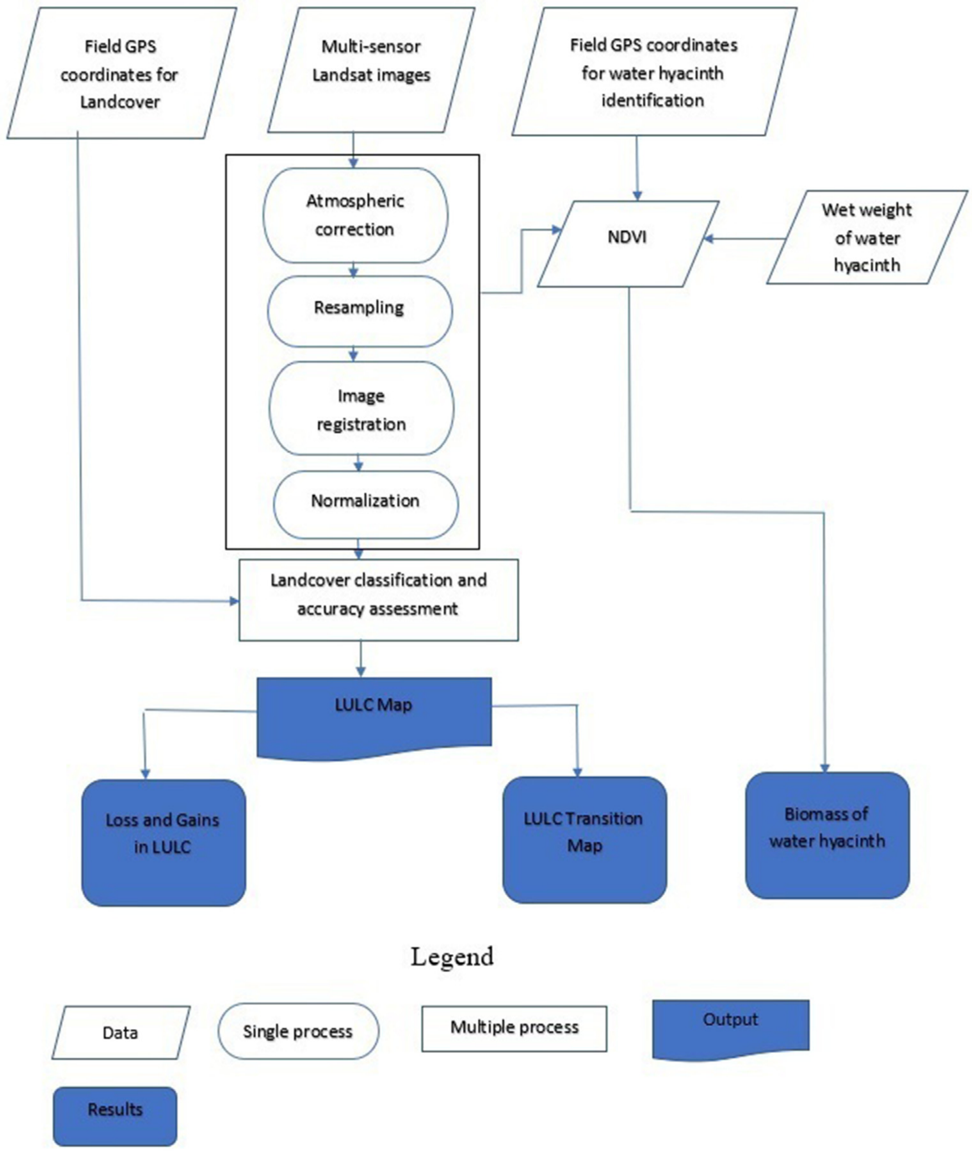

Figure 2. Flowchart of methodology used in producing LULC maps and estimation of the quantity of water hyacinth.

Table 3. Accuracy assessment results for the 1975 classification.

	OA = 86.54%			Kappa = 0.8128		
	Aquatic weeds	Farmland/gallery vegetation	Settlement	Water	Total	User Accuracy (%)
Aquatic weeds	32	9	1	0	42	76.19
Farmland/gallery vegetation	7	44	9	0	60	73.33
Settlement	0	13	88	3	104	84.62
Water	0	0	0	106	106	100.00
Total	39	66	98	109	312	
Producer Accuracy (%)	82.05	66.67	89.80	97.25		

3.3. Spatial temporal variations of aquatic weeds

The 1975 classification (Figure 6) showed that, indeed aquatic weeds have existed in the Lower Volta even before 1975, occurring around some defined areas of the river, mostly close to the communities along the river. The weeds occurred near the Akuse section of the river, close to the location where the facade of the Kpong dam is currently situated. It is however worth noting, that the Kpong reservoir did not exist around this time. The water and farmland/gallery vegetation classes were dominant in this area as compared with the aquatic weeds. Another area where the

Table 4. Accuracy assessment results for the 2003 image classification.

	OA = 79.08			Kappa = 0.7097		
	Aquatic weeds	Farmland/gallery vegetation	Settlement	Water	Total	User Accuracy (%)
Aquatic weeds	366	77	2	26	471	77.71
Farmland/gallery vegetation	61	295	37	1	394	74.87
Settlement	6	13	154	1	174	88.51
Water	18	0	0	100	118	84.75
Total	451	385	193	128		
Producer Accuracy (%)	81.15	76.62	79.79	78.13		

Table 5. Accuracy assessment results for the 2020 image classification.

	OA = 84.7			Kappa = 0.7856		
	Aquatic weed	Farmland/gallery vegetation	Settlement	Water	Total	User accuracy (%)
Aquatic weed	404	66	8	4	482	83.82
Farmland/gallery vegetation	42	291	45	0	378	76.98
Settlement	3	28	289	1	321	90.03
Water	3	0	0	123	126	97.62
Total	452	385	342	128		
Producer accuracy (%)	89.38	75.58	84.50	96.09		

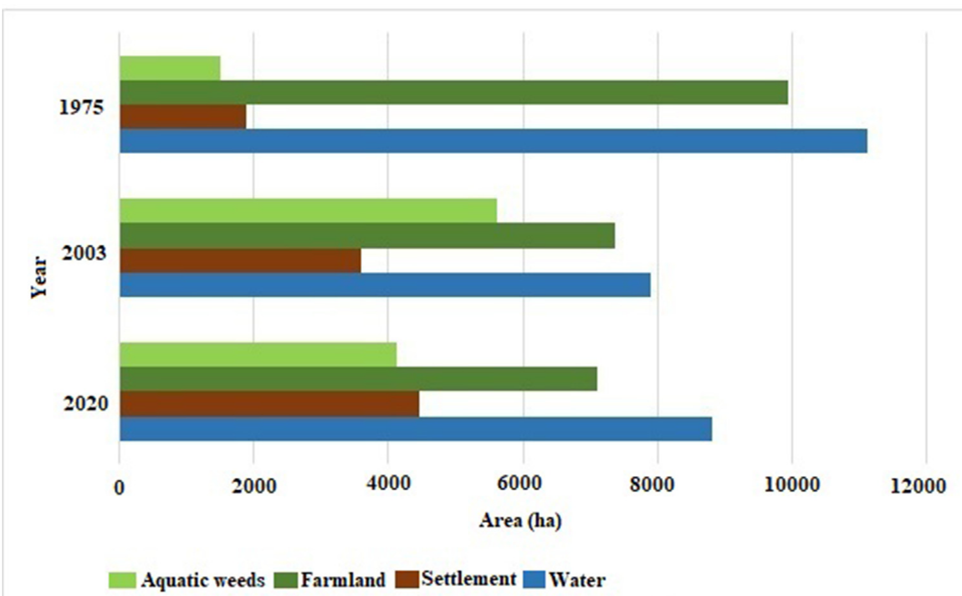

Figure 3. Area covered by each LULC within the study years.

weeds existed was near the Adidome community, almost midway along the stretch of the river. Aquatic weeds also occurred around Ada and Ada Foah, within the delta. Aquatic weeds were however, less conspicuous around the Atimpoku community, and most of the other sections of the river. Water and farmland/gallery weeds were however dominant along these other sections.

The 2003 classification (Figure 7) had a different narrative of the weeds, in terms of the spatial variations. From the results of the classification, aquatic weeds were present along the whole stretch of the river and conspicuous near major communities. Cluster of the weeds appeared at Atimpoku section of the river, where they were distributed at both sides of the river as well as around the islets. Compared to the 1975 image (Figure 6), the weeds covered most of the smaller channels of the river at this section, with the water only visible along the central course. Cluster of aquatic weeds also appeared in Kpong, covering some distance from the bank into the river. Additionally, aquatic weeds had spread along the stretch between the Kpong township and the river, reaching the point where the intake of the Ghana Water Company is currently located, and has also spread to the other bank of the river. Other new area location of the weeds included Agordome and Agotaga communities. The weeds also became widespread within the delta, covering most of the islets. The results also showed an expansion of the Kpong, Big Ada and the Ada Foah communities (Figure 7).

The results of the 2020 classification (Figure 8) showed some similarities in the distribution of weeds when compared with the 2003 classification (Figure 7). However, there were some reductions in the

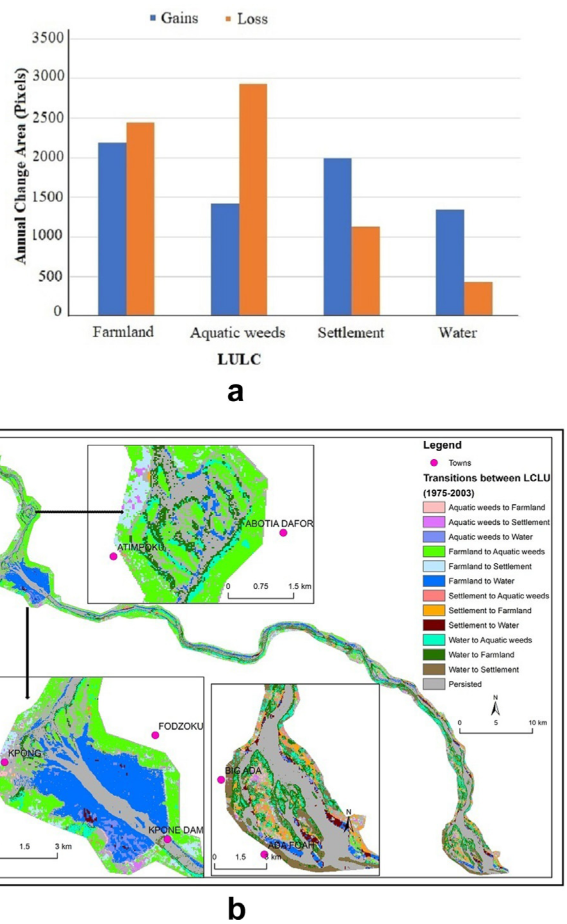

Figure 4. a: Gains and Losses between the LULC between 1975 and 2003. b: LULC change map between 1975 and 2003.

cluster of the weeds along some of the locations. For example, the left bank of the river at Atimpoku show less distribution of weeds on the 2020 image compared to the same area in the 2003 image. Also, isolated weeds found on the main river course around the same area visibly disappeared, uncovering the water beneath (Figure 8). A similar observation can be found within the delta of the river, where some of the weeds gave way to water. There was also reduction in weeds around Agordome and Agotaga communities when the 2020 image is compared with 2003 image.

3.4. Net gains and loss in aquatic weeds

The results show that aquatic weeds had a net gain of 4122 ha between 1975 and 2003 (Figure 9) but a loss 505 ha between 2003 and 2020 (Figure 10). The gain in area can be attributed to the construction of the Kpong dam, which caused a major ecological change in the LVR area. Increased anthropogenic activities including settlements and markets around the river have also been found to contribute to ecological changes that favours the growth of the aquatic weeds (Andah et al., 2003). The decrease in area of aquatic weeds can, however, be attributed to the Weed Management Activities being undertaken on river. These operations of the weed managers reflected in the direct gain in area by water, as the weeds were removed from some area of water they covered in the previous image. From Figure 9, the farmland/gallery vegetation contributed about 3500 ha in the net gain for aquatic weeds, while water contributed 1925 ha and settlement 281 ha. The net loss of water needs between 2003 and 2020 mostly transited to water (896 ha) and farmland/gallery vegetation (455 ha).

3.5. Coverage of water hyacinth biomass

Water hyacinth can grow up to a meter length and hold in sediment making the plant static (Omondi et al., 2019). The reproduction rate is rapid and the seeds are versatile, thus may remain dormant even in harsh conditions up to about 20 years. Casco et al. (2014) found that, in a year, a single plant can cover up to 0.06 ha. The assessment performed in this study indicated that NDVI of water hyacinth ranged between 0.6259 and 0.7156, with a total count of 16610 pixels. This covers a total area of 1, 495 ha representing 36% of all the aquatic weeds in 2020. This represents a significant increase in the coverage of water hyacinth. Considering that Pabi and Akpabey (2017) found that water hyacinth covered 28% of all the floating water weeds when they used NDVI from high resolution Geo-eye images to map aquatic weeds on the river. The biomass estimated from water hyacinth in 2020 image was 21.5 kg/m^2. Management of the weeds has been somewhat successful but expensive, considering the current methods and strategies being implemented.

Therefore, the management and control of the weeds can be complemented by using sustainable approaches by first considering the weeds as biomass resources and secondly, implementing modern techniques to convert them to bioenergy. In view of the fact that water hyacinth cannot be completely eradicated, the continuous bioenergy production from the water hyacinth could reduce the over reliance on the use of fossil fuel sources, reduce the high costs associated with the management of the weeds and enhance other socio-economic activities in the communities along the Volta river. This could therefore be achieved through anaerobic degradation processes, coupled with associated benefits such as utilization of the digestate as biofertilizer to enhance crop production.

4. Discussion

The study utilized the RF machine learning algorithm and Landsat images to map the spatial and temporal changes of aquatic weeds on the Lower Volta River. The RF algorithm was consistent on all the images from the three sensors, achieving OAs of 80% and above and kappa coefficients of 0.7 and above. These accuracies underscore the robustness of RF in mapping aquatic weeds with RF as found by other studies. For example, (Chabot et al. (2018) produced OA and kappa of 92% and 0.88 respectively, when they applied the RF algorithm on unmanned aerial vehicle (UAV) images to monitor emergent and submerged invasive aquatic weeds in shallow waters of the Trent-Severn Waterway in Ontario, Canada. Similarly, Singh et al. (2020) produced OAs of above 80% when RF was used to map the variations of water hyacinth on different water bodies in South Africa. The UAs of water weeds obtained in this study (84–87%), were also within the range of accuracies obtained by these studies (Chabot et al., 2018; Singh et al., 2020).

The successful discrimination of aquatic weeds from other vegetation and different LULCs indicate the ability of the three Landsat sensors to provide primary data for mapping aquatic weeds. Despite having only four spectral bands, the MSS performed accurately in unison with the performances ETM+ and OLI that have greater number of bands. This shows the capabilities of the MSS as part of the continuity of the Landsat programme. Other studies that used the ETM+ and OLI for mapping aquatic weeds also mentioned the added advantage of the extra bands, which helped to discriminate different species of aquatic weeds (Dube et al., 2017).

In addition to the primary bands, derivatives of these sensors such as NDVI have been successful in estimating vegetation parameters, particularly biomass as has been performed in this study. Shekede et al. (2008) also utilized NDVI from different Landsat sensors to estimate biomass over Lake Chivero in Zimbabwe.

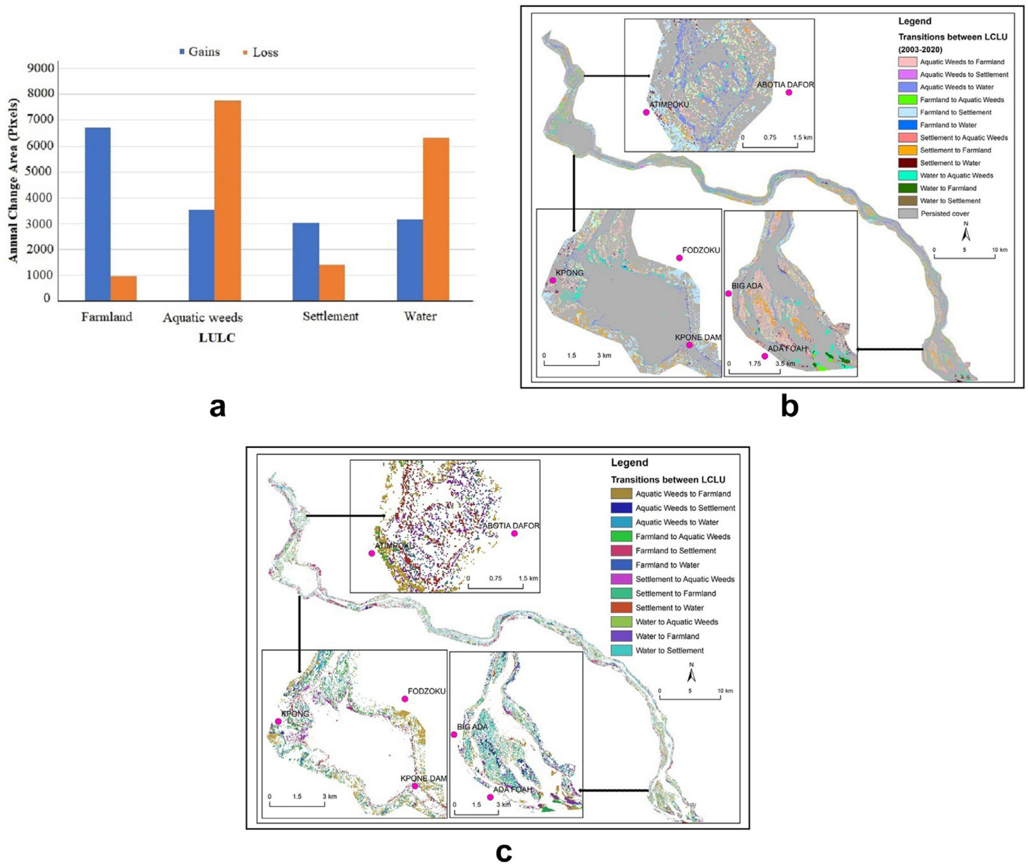

Figure 5. a: Gains and Losses between the LULC between 2003 and 2020. b: LULC change map between 2003 and 2020. c: LULC change map between 1975 and 2020.

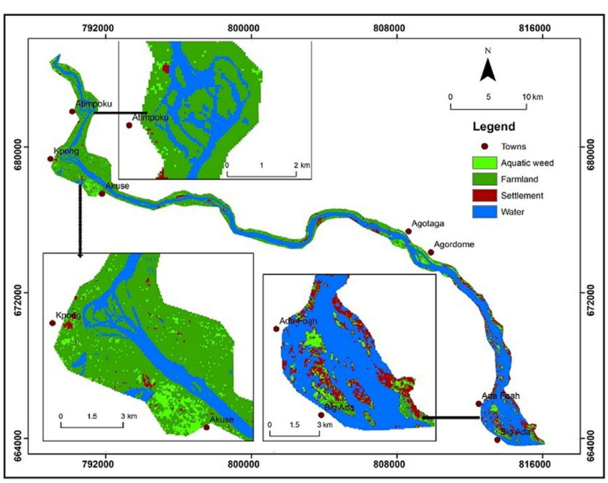

Figure 6. Spatial distribution of Aquatic weeds in 1975.

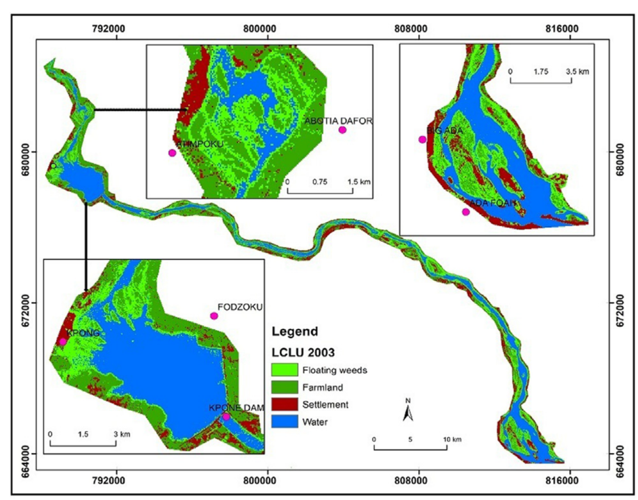

Figure 7. Spatial distribution of Aquatic weeds in 2003.

Aquatic weeds started becoming dominant on the Volta River after the construction of the Akosombo Dam in 1965 (Pierce and Opoku, 1971) and this study indicated the weeds covered an area of about 1400 ha 10 years later. According to Odei (1987), the weeds were dominant at the estuary at Ada, within the delta where the river meets the sea. This observation was captured by the classification of the 1975 satellite image which indicated clusters of aquatic weeds within the delta. VRA (2015) indicated that, the problem of aquatic weeds became a menace around 1998, with the spread of water hyacinth around the Kpong reservoir and other areas. This account was corroborated by findings from this study, which showed that aquatic weeds had increased in area by 375% between 1975 and 2003 and 275% between 1975 and 2020.

Earlier studies that assessed the growth and spread of aquatic weeds on the water indicated farming and expansion of settlements as some of the LULC factors that contributed to the increase in the spread of water weeds (Odei, 1987; Pabi and Akpabey, 2017).

On the other hand, analysis from this study showed that the coverage of aquatic weeds had declined by 1500 ha (26%) between 2003 and 2020. This reduction could be attributed to the many aquatic weeds management activities that have been rolled out in recent times. For example, VRA (2015) indicated that glyphosate was being used as

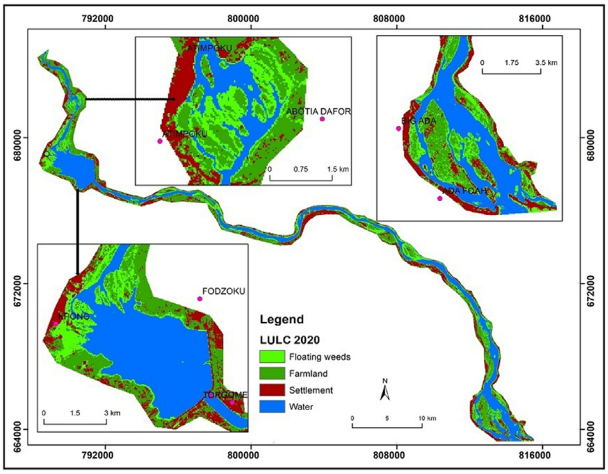

Figure 8. Spatial distribution of Aquatic weeds in 2020.

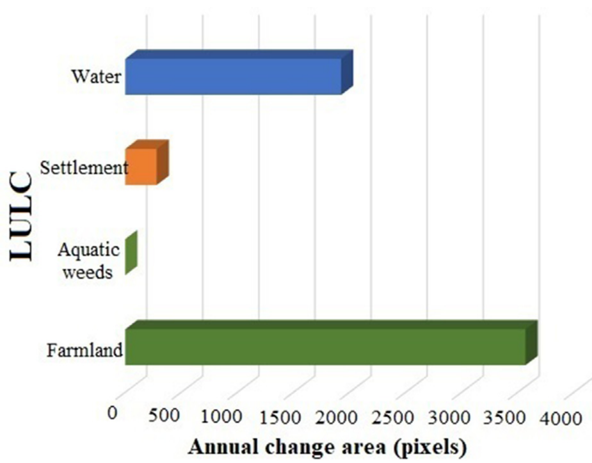

Figure 9. Contribution of the net changes in aquatic weeds between 1975 and 2003.

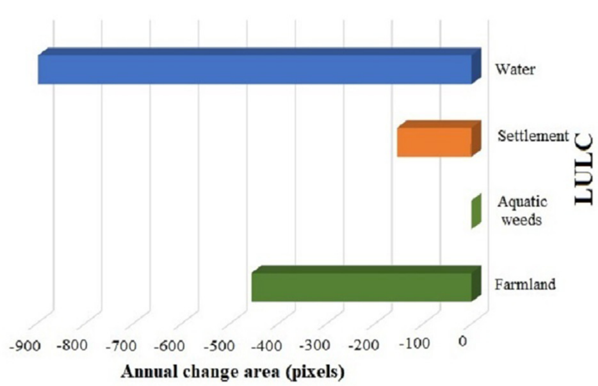

Figure 10. Contribution of the net changes in aquatic weeds between 2003 and 2020.

chemical control of water hyacinth in the Lower Volta, and expected to reduce the intensity of infestation of water hyacinth. The VRA also indicated the initiation of a mechanical dredging and harvesting system to control the spread of weeds. Some observations made during the data collection were that manual removal of aquatic weeds also do take place regularly, especially around the Kpong area. These management practices have accounted for the gradual decline in the aquatic weeds on the water, although these methods appear to be unsustainable.

5. Conclusion

In summary, the study has demonstrated the capabilities of a combined remote sensing data and machine learning in generating information about the spatial and temporal distribution of aquatic weeds such as water hyacinth on the Lower Volta River. The results show that, the 1975 classification produced the highest OA of 86.54 %, this was followed by the 2020 classification attaining an OA of 84.7 % with 2003 being the least with an OA of 79.08 %. The water class attain the highest PA and UA of 96.09 % and 100 % for 2020 and 1975 image respectively. Additionally, the LULC classification show that water covers an area of 45 %, 32 % and 40% in 1975, 2003 and 2020 respectively. The aquatic weed experienced a net gain of 4122 ha between 1975 and 2003 but net loss of 505 ha between 2003 and 2020. Interestingly, the water hyacinth represents 36 % of the total aquatic weeds in the study area and the biomass estimated from the water hyacinth was 21.5 kg/m^2. Such information will be beneficial to both ongoing and near future management of the weeds by using sustainable strategies. The findings can be used in planning out the scale of resources, such as estimation of biomass, which will be required for the application of a specific control measure at a given location and point in time as well as assessment of progress being made by existing weeds management programs. It could consequently help in time-based assessment with regards to the efficiency and effectiveness of a control program. Furthermore, the results of this study, and its methodological approach can be used to monitor LULC activities that impact on the growth and variations of aquatic weeds such as water hyacinth, especially crop farming, settlements and provide supporting information related to activities of fish farming on the Volta river.

Declarations

Author contribution statement

Richard Arthur: Contributed reagents, materials, analysis tools or data; Wrote the paper.

Clement Nyamekye: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Wrote the paper.

Samuel Anim Ofosu: Performed the experiments; Wrote the paper.

Gabriel Osei: Analyzed and interpreted the data; Wrote the paper.

Linda Boamah Appiah: Performed the experiments; Analyzed and interpreted the data; Wrote the paper.

Samuel Kwofie and Dieter Bryniok: Contributed reagents, materials, analysis tools or data.

Benjamin Ghansah: Analyzed and interpreted the data; Wrote the paper.

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Data availability statement

Data will be made available on request.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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