Journal of the Indian Society of Remote Sensing
https://doi.org/10.1007/s12524-020-01107-6

RESEARCH ARTICLE

Detecting Spatiotemporal Expansion of Water Hyacinth (*Eichhornia crassipes*) in Lake Tana, Northern Ethiopia

Tewachew Asmare[1] · Biadgilgn Demissie[2,4] · Amare Gebremedhin Nigusse[2] · Abraha GebreKidan[3]

Received: 28 August 2019 / Accepted: 28 January 2020

Abstract

In the Northern Ethiopia, Lake Tana has serious problems related to the alien water hyacinth invasive weed. The weed species grows in and swims over water and expands very quickly. The purpose of this study is to detect the spatiotemporal trend of the weed during 2013, 2015 and 2017. Landsat 8 satellite images captured in December were used to assess the rate of expansion of the water hyacinth. Training samples were collected for supervised classification of the satellite images and accuracy assessment. Image preprocessing and image enhancement was carried out before classification. The expansion and distribution of the water hyacinth was analyzed using decision tree and maximum likelihood classification techniques. The classification accuracy assessment result for 2017 reported 99.5% overall accuracy and 98% of kappa coefficient. The result depicted that in 2013, water hyacinth coverage was very small in its coverage and was estimated to be 112.1 ha (0.17%) of the study area. In 2015, the coverage of the weed showed little significant change as of 2013 and grew up to 168.7 ha (0.25%). However, after two years, its aerial coverage was dynamically expanded to 1512 ha (2.25%) of the study area in 2017. The result indicated that there was rapid expansion of the weed species from 2015 to 2017s. The coverage increased by 50% in the period between 2013 and 2015 and by 82% in the period between 2015 and 2017. Since the expansion of the weed is extremely fast and endangers the existence of the water, appropriate intervention mechanisms should be urgently introduced.

Keywords Water hyacinth · Lake Tana · Northern Ethiopia · Image classification · Weed

Introduction

Water hyacinth is a plant which expands very fast and claimed to be indigenous to the Amazon basin (Barret and Forno 1982; Piyaboon et al. 2016). It is a plant which causes conservation challenges and socioeconomic problems due to its fast growth and horizontal expansion. It has been known for introducing major problems to stream flow, navigation and recreational activities and causes disruption to aquatic systems (Téllez et al. 2008). The water hyacinth is also known for disrupting aquatic ecosystems and habitats by mainly adversely affecting water quality, causing tropical diseases to aquatic creatures. Water hyacinth is most widespread and damaging aquatic plant species identified as toxic plant in some African countries (UNEP 2013). Threats caused by invasive alien species like water hyacinth, such as biodiversity, deteriorating water quality, economic development and human well-being, are not easily managed and difficult to reverse (UNEP 2013). It is described as the most troublesome weed worldwide as well (Ndimele et al. 2011). Sometimes, it brings about a decline in dissolved oxygen causing a death of significant number of fish and other aquatic life (Téllez et al. 2008).

Ethiopia, though known as having huge water resources (Goshu et al. 2010), mainly depends on inland water resources. Lake Tana, the largest lake in Ethiopia, accounts

✉ Biadgilgn Demissie
biadgilgnd@gmail.com

1 Amhara Design and Supervision Works Enterprise, Bahir Dar, Ethiopia

2 Institute of Geo-Information and Earth Observation Sciences (I-GEOS), Mekelle University, Main Campus, P.O. Box: 231, Mekelle, Ethiopia

3 Department of Chemistry, Mekelle University, Mekelle, Ethiopia

4 Department of Geography and Environmental Studies, Mekelle University, Mekelle, Ethiopia

for 52% of the inland water surface area and 33% of the total volume of inland water resource (88 billion m^3) which is more than half of inland water resource of the country (Goshu et al. 2010). However, recently the lake is being threatened by many problems, such as poor waste management and/or pollution, silt load and the occurrence of invasive alien species like water hyacinth (*Eichhornia crassipes*). Currently, expansion of water hyacinth is among the most prominent threats of the lake which is getting a wide media coverage and concern (Fig. 1).

According to Asmare (2017), water hyacinth incidence in Lake Tana was recognized in 2011. Starting from its recognition, it continues to flourish year after year. Even if several efforts have been made by different parties to control and eradicate the plant, it has become difficult to manage it. In order to control aquatic weeds and managed lakes effectively, comprehensive and accurate long-term water quality monitoring programs are needed and accomplished systematically (Hestin et al. 2008; McCullough et al. 2012; Lugo et al. 1998). For the last 5 years, several actions are undertaken by different bodies, governmental, non-governmental and local communities to tackle the expansion of the weed, yet it regenerates and expands year by year despite these efforts.

Understanding the expansion and seasonal and annual variation of water hyacinth is important for managing and maintaining lake ecosystem balance (Julien et al. 2001; Villamagna and Murphy 2010). Similarly, understanding the spatial distribution and configuration of aquatic plants, such as water hyacinth, is important for proper management and sustainable monitoring of lake water (Rai and Munshi 1979; Rommens et al. 2003; Brendonck et al. 2003). However, due to various reasons, such as lake inaccessibility, shortage of finance and human capacity, it has become difficult to obtain information on the spatial distribution, configuration and evolution of aquatic plants in less developed countries like Ethiopia (Dube et al. 2017).

Different studies were carried out in the area regarding the increasing expansion of the weed and give recommendations on the monitoring methods. According to Adgo et al. (2016), if the expansion of the water hyacinth continues, particularly toward the southern part of Lake Tana, it is highly probable that it invades the Blue Nile River from its source and hence the Great Ethiopian Renaissance Dam (GERD) reservoir. On the other hand, Asmare (2017) studied that the presence of water hyacinth affects the fishing environment, which results in a negative impact on the living communities; this in turn will impose an adverse effect on sustainability of the lake and the country as a source of transportation, recreation and source of fish. Despite the severity of the expansion, its spatiotemporal distribution, the extent and trend of expansion of the weed are not well known except recent wide media coverage. The spatial extent and the rate of expansion of the water hyacinth needs to be investigated.

Hence, the aim of this study was to detect the spatiotemporal distribution and expansion of the water

Fig. 1 Water hyacinth invasion of the Lake Tana, Northern Ethiopia

hyacinth in the northeastern part of Lake Tana, Northern Ethiopia. The outputs of the study will be important for decision makers to understand the spatiotemporal dynamics of the weed and have an implication for better monitoring and intervention activities. The findings of the study will also be useful for future lake resource planning and water quality monitoring in the country.

Methodology

Study Area

Lake Tana is located in the basaltic plateau of northwestern highlands of Ethiopia with 11° 35′ N to 12° 17′ N and 36° 59′ E to 37° 37′ E (Fig. 2). It is a highland fresh water lake. It is also the largest lake in Ethiopia and the third largest lake in the Nile basin (Kebede et al. 2006), with around 3032 km^2 area coverage and with a mean elevation of 1800 m.a.s.l. It is approximately 80 km long and 68 km wide and has a shoreline length of around 427 km, with a mean of 9 m and maximum of 14 m depth (Ligdi et al. 2010; Vijverberg et al. 2009; Lemma et al. 2017). It is the shallowest highland lake in the country. It has an elevation of about 1785 m a.s.l. (Poppe et al. 2013).

The areas around the lake are pre-dominantly farmlands used for crop cultivation. It is bordered by a flood plain of the Gumara and Rib River in the east and the Megech River in the north (Lemma et al. 2017), whereas in the west and northwest, it is surrounded by mountainous areas that do not rise more than 2000 m a. s. l. edges of the lowlands beyond it in the west. The major soils of the Lake Tana basin include Chromic Luvisols, Eutric Cambisols, Eutric Fluvisols, Eutric Leptosols, Eutric Regosols, Eutric Vertisols, Haplic Alisols, Haplic Luvisols, Haplic Nitisols and Lithic Leptosols (Heide 2012).

In terms of climate, Lake Tana, including northeastern parts, is characterized by bimodal rainfall distribution with a main rainy season from June to October and small rainy season from February to March. The long-term mean

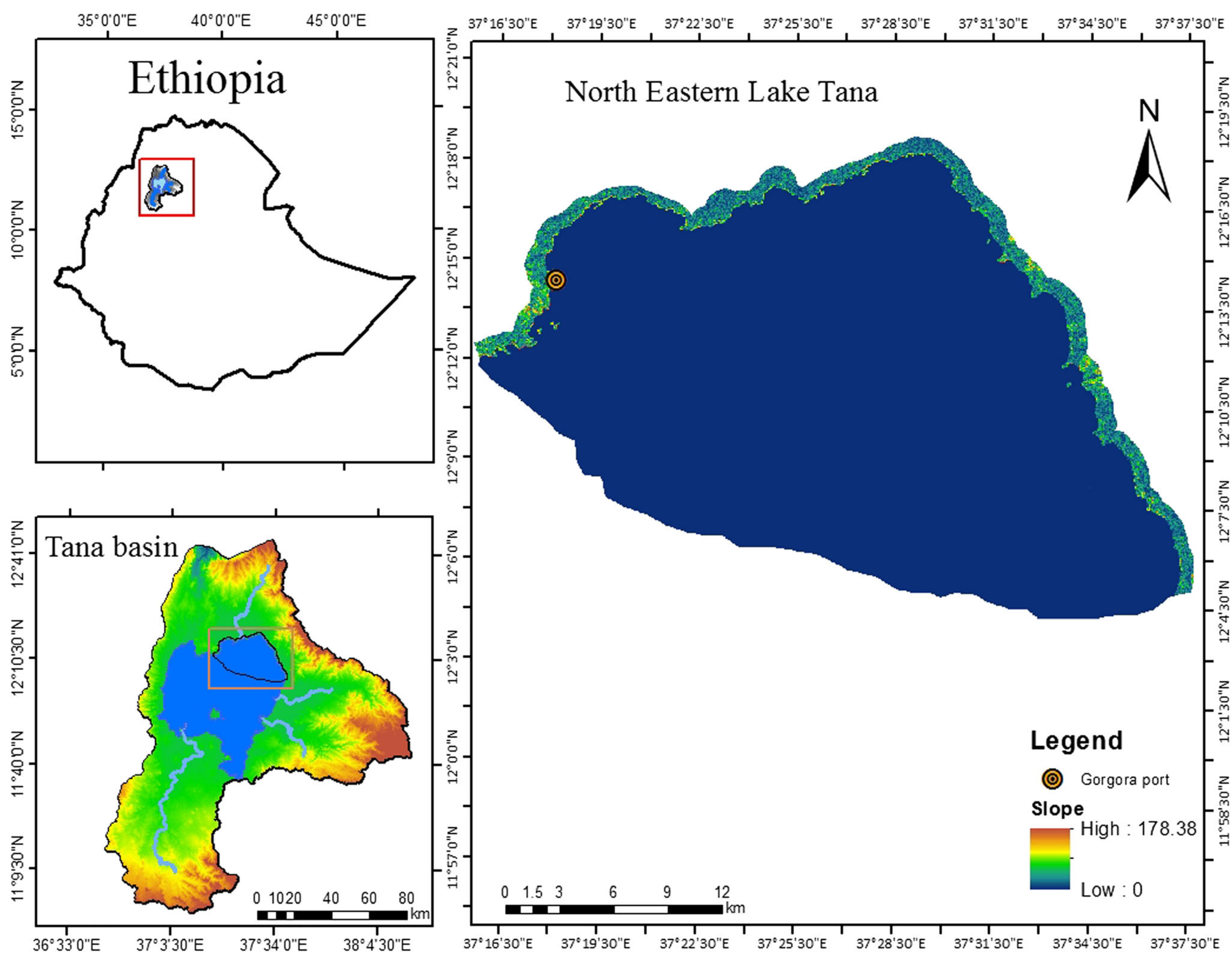

Fig. 2 Location of the study area

rainfall of Bahir Dar, Debre Tabor and Gondar meteorological stations ranges from 680 to 2400 mm (Sisay et al. 2016). The mean annual rainfall (2006–2013) is 1600–2400 mm in the south, 1250–1500 mm in the east and below 1100 mm in the north and west (Lemma et al. 2017) of Lake Tana. Temperature varies between 6 and 30 °C. The annual lake level fluctuates with an average of level of 1.5 m. The minimum level takes place in June (end of the dry season), whereas it reaches maximum level in September (end of the rainy season). The lake is characterized by warm climate with 1564 mm mean annual rainfall; the highest rain receipt happens between July and August (Goshu et al. 2010). The water temperatures varies slightly, the lowest temperature recorded in January and the highest in May, and declines through the rainy season between July and August (Ligdi et al. 2010).

Lake Tana is fed by seven permanent and 40 seasonal rivers. The main feeders are Gilgel Abay, Gumara, Rib and Megech which contribute more than 90% of the inflow (Kebede et al. 2006; Dessie et al. 2014). The study site is part of the Megech watershed which drains to the lake in the northeastern direction. The Blue Nile River in the southern part is the outlet of the lake.

According to Heide (2012), about 3 million people live in Lake Tana watershed, of which 89% are rural settlers whose livelihood is dependent on agriculture. The economy of the region is mainly dependent on a subsistence mixed agriculture, consisting of both crop production, and livestock rearing like most of the Ethiopian highlands. Fishery is an alternative source of livelihood of the local communities living near to the lake.

For this study, the northeastern part of the lake is selected deliberately based on the amount of water hyacinth coverage, ecological condition and accessibility. The area is having more water hyacinth coverage as compared to the other peripheries of the lake. Another best opportunity of the area is its accessibility. This is helpful for taking samples and training areas and making timely observations in the study area.

Materials and Methods

Satellite Image Acquisition

Three Landsat 8 satellite images with consecutive 2-year difference (2013, 2015 and 2017) were used to assess the rate of expansion of the water hyacinth cover in the last 5 years period (Table 1). Landsat 8 satellite images were downloaded from the United States Geological Survey Global Visualization Viewer (GloVis) (https://earthexplorer.usgs.gov/web-link). The downloaded Landsat images were formatted as Geo-TIFF and projected to Universal Transverse Mercator, World Geodetic System 1984, and Zone 37. All scenes were from Worldwide Reference System 2 Path 170, Row 52, and were selected based on minimal scene cloud cover. The scenes that were captured during the dry season were selected to reduce confusion with the growth of seasonal grass and herbaceous plants. Closeness of the date of the scene to the date of the actual field data collection was also taken into account. The satellite images had 30 m spatial resolutions (Ruelland et al. 2011).

Table 1 Description of Landsat satellite images used

Satellite image	Sensor	Acquisition date	Source
Landsat 8	OLI	Dec 15/2013	USGS
Landsat 8	OLI	Dec 21/2015	USGS
Landsat 8	OLI	Dec 26/2017	USGS

The geometric correction was applied by the provider (USGS) with an accuracy of 0.2 pixels

Training Sample Collection

Field observation and/or training sample collection were carried out for the image classification and accuracy assessment. For a successful classification, sufficient numbers of training samples were needed. The first step for supervised classification is selecting training sites (Ismail et al. 2009). In order to get good representative data for land cover classification, the training data should be evenly distributed over the study area in a random pattern. Hence, training sites were decided and classified on the basis of field observation supported with image interpretation. Extensive field survey was carried out in the month of December (similar to the time of image acquisition) to record training data. Ground control points (GCPs) were collected using a global positioning system (GPS) for each land cover type. Along with training data collection, site observations were carried out with transect walks, and the observations were important for refining the training sites and verification after image classification. In terms of coverage, samples were collected from four major land cover types, namely water hyacinth-covered areas, water body areas, bare land/plowed areas and cultivated/shrub-covered areas. According to Mather and Koch (2011), a minimum of 30 points/features per class are needed for supervised classification. Intensive field site survey was carefully carried out to get a detail understanding of the study area. A total of 120 training samples were collected, 30 training samples for each land cover class. According to Hsiao and Cheng (2016), the accuracy of land use/land cover classification highly depends on the amount of samples and accuracy of training data used. These training data were used to discover potentially predictive relationships between features, and they were inputs for classifying as well as result validation/accuracy assessment. The training samples comprised GPS readings and type of coverage (land cover). Among the samples collected, two-third were used for classification, whereas one-third of the samples were used for validation (accuracy assessment).

Image Preprocessing

Radiometric and geometric corrections radiometric and geometric corrections are mandatory for satellite images used for change detection analysis (Caprioli et al. 2006). Radiometric distortion is caused due to atmospheric effect like seasonal change, sun illumination or sun elevation, sun–earth distance, sensor failure or noise, etc. (Caprioli et al. 2006; Paolini et al. 2006). The influences of sun illumination are corrected by division of each pixel value by the sine of solar elevation angle for a particular time and location per spectral band. For the seasonal change, it minimizes radiometric differences between images by relative radiometric normalization process (Lillesand et al. 2008). It is also used for sensor failure or system noise corrected by repetition of neighboring values or averaging the line below and above, whereas geometric distortion is caused mainly by orbital variation, relief variation and projection system. It is necessary to geometrically correct/rectify the imagery in order to prepare two or more satellite images for an accurate change detection comparison (Townshend 1992). The Landsat imageries are geometrically corrected by the providers, and there was no need to correct them for geometric distortion. The Landsat images need to be corrected topographically and radiometrically to better detect land cover changes (Liang et al. 2001; Mahiny and Turner 2007; Zhang and Li 2011; de Mûelenaere et al. 2014). Tomographic correction was not required as the study site is a flat area with no significant topographic effects. As Landsat 8 Level 2 imageries are used, atmospheric correction was not required. The satellite images are atmospherically corrected by the provider (USGS). But these images need to be corrected for local solar angle. Hence, the images were corrected for local solar angle using the following formula (Ihlen 2019):

$$\rho\lambda = \rho\lambda' / \sin\theta\mathrm{SE} \tag{1}$$

where $\rho\lambda$ = TOA planetary reflectance; θSE = local sun elevation angle; the scene center sun elevation angle in degrees is provided in the metadata; θSZ = local solar zenith angle; θSZ = 90°–θSE.

Similarly, haze correction was required to reduce haze effects in the satellite images. For haze corrections, the point spread method (Che-Yen and Chien-Hsiung 2002; Demissie et al. 2015) with a 3 × 3 kernel method was applied because the haze effect is very low in the imagery.

Image Enhancement image spectral enhancement is important to improve the quality of a digitally stored image to make it more interpretable Advanced image enhancement also supports many filters for altering images in various ways. One of the most usual problems related to spectral behaviors of images is the mismatch in brightness. Hence, in this study, the mismatch in the range of values of an image was removed using image spectral filter techniques (linear contrast stretching). Finally, the image was more tonal and clear to interpret and carry out analysis.

Image Classification

Decision Tree Decision tree is one of the inductive learning algorithms that generates classification tree based on the “divide and conquer” strategy using the training data/samples. Otukei and Blaschke (2015) compared decision tree, with other classification techniques for land cover change assessment using Landsat images, and found decision tree methods performing better than others. In addition, decision tree classification is simple and easy to understand, relatively fast and gives similar or better result to the other techniques. It is a predictive model that uses a set of binary rules to calculate a target value. Hence, in this study, the decision tree model was used to clearly separate water hyacinth from other land cover types in the 2013 and 2015 images.

Training the classifier Developing a decision tree requires supervised training data that consist of both explanatory and response variables (de Colstoun et al. 2002; Zhou and Zhang 2013; Rouabeh et al. 2014). Therefore, in this study, training data were taken to define the classification structure using a statistical procedure.

In order to train the classifier, training sets that were formulated from training data were used. Training data (GCPs) collected in 2017 were used for classifying the 2013 and 2015 images using a decision tree technique. The classifiers were trained using the sample training sets, and the signature definition was developed for bands 1 through 7, as spectral value of Landsat images is highly variable in this range of bands. Four training samples for each class were used, and spectral values of each training sample were averaged and used for decision tree classification. The mean spectral signatures for classes, namely water bodies, water hyacinth, bare land/plowing and cultivated lands/shrubs, are shown in Fig. 3. The training data were also used for classifying the 2017 image using a supervised classification technique. Decision tree approach was not required for the 2017 image as the training data are taken in 2017 and can directly be used in a supervised classification technique.

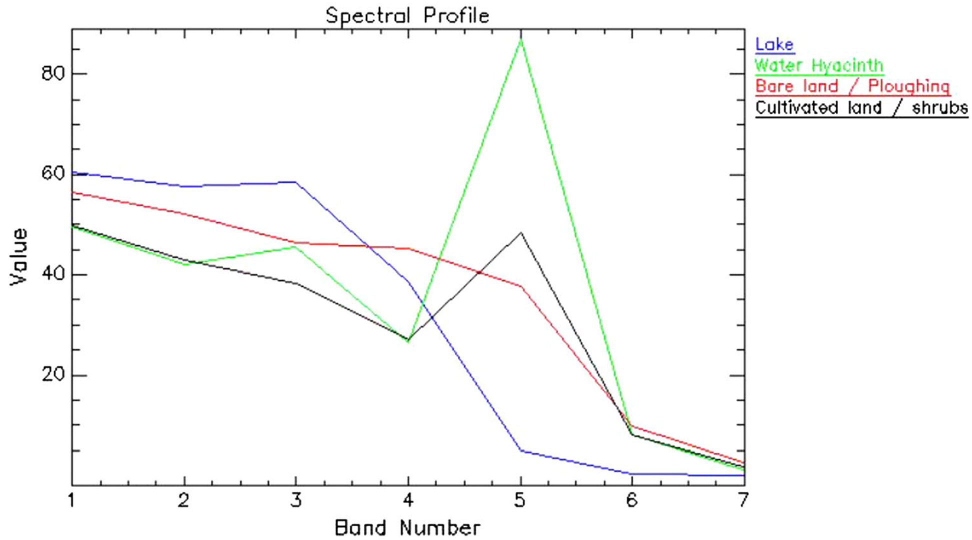

Fig. 3 Spectral signature of each class

Defining class separability class separability was analyzed through spectral value of each class and feature space plot (Gong and Howarth 1989; Chen and Stow 2002). Spectral value of the classes was derived using ENVI 5.3, and based on the result, bands with high separable class value were selected to analyze the classification. Classes with high separability, bands 1 and 5, were used for classification.

Classification in the decision tree the classification has an execution structure (Fig. 4). It starts at the root node, and the decision rule decides to go left or right of the tree branches where the classification process continues through the appropriate branch. The tree consists of rules for taking decision at every node.

B1 (costal) is the band used for initial binary classification of the image, which is subsequently supported by B5 (near infrared) (Fig. 4). In the first node, B1 (costal) is used to segregate plant-covered and non-plant-covered classes. The second node again used B5 (NIR) to segregate the first each two nodes into four independent classes. The plant-covered node was segregated into cultivated/shrubs and water hyacinth covered, whereas the non-plant-covered nodes were segregated into water body and bare lands/plowing areas as a final class.

Decision tree classification approach is helpful for images in which land cover is not well known, but reflectance value of the classes is known using current training (field) data (de Colstoun et al. 2002; Zhou and Zhang 2013; Rouabeh et al. 2014). Using this classification method, spatially similar but different temporal resolution Landsat 8 satellite images were classified following similar approaches. Hence, in this study, the decision tree was used for classifying and analyzing water hyacinth coverage in 2013 and 2015. The two images, i.e., 2013 and 2015, are classified separately following similar approach as the images were taken in two different times. Hence, a single signature definition for each land class (as indicated in Fig. 3) was used for the classification processes

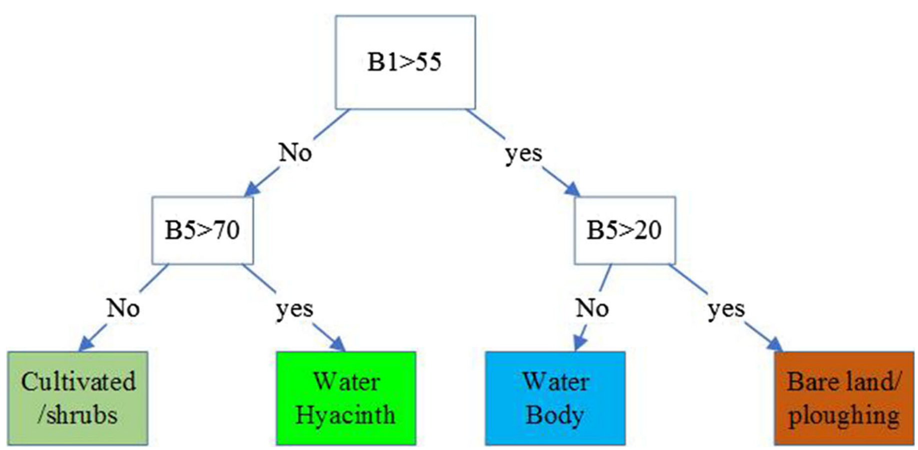

Fig. 4 Structure of the decision tree

Supervised Image Classification Maximum likelihood classifier (MLC) appears to be the most commonly used and accurate algorithm for supervised classification (Dewidar 2004; Ahmad 2012). In supervised classification, training pixels were taken from different land cover classes to determine the classes of unknown pixels. Supervised classification requires the analyst to select training samples from the data which represent the themes to be classified. In supervised classification, the user selects representative samples for each land cover class in the digital image, which is called training sets. Pixels located within these areas, called the training samples, are used to guide the classification algorithm by assigning specific spectral values to a specific class (Srivastava et al. 2012). This classification technique is advantageous because it uses a relatively small number of classes to determine the appropriate land cover for each pixel. Supervised classification technique with maximum MLC was employed to obtain classified map of the year 2017. In maximum likelihood classification, the assumption is that each land cover in each band is normally distributed and calculates the probability that a given pixel belongs to a specific class (Jensen 2015).

Post-Classification and Accuracy Assessment Post-classification is a part of classification which is used as a final step in classification procedures. It helps to know the accuracy or goodness of the classified images to the purpose required (Congalton and Mead 1983; Story and Congalton 1986). Accuracy assessment of the classified maps was done for the classified image of 2017, which have a ground truth data. Accuracy assessment for the 2013 and 2015 was not carried out. It is possible to produce training data for these periods through image subtraction method using the 2017 Landsat image (Annys et al. 2016). But, due to small narrow stripes of the study site where the land cover classes other than the water body are predominantly found, the subtraction method does not work properly to extract unchanged areas. Accuracy assessment is undertaken in ENVI 5.3 software by using "confusion matrix using ground truth ROI" (Congalton and Mead 1983; Story and Congalton 1986). This method was employed by pairing regions of interest (ROIs) with the classes of a classified image to show what percentage of the ROI pixels were or were not contained in a resulting class. Classified image of the year 2017 and ground truth points in the form of ROIs were the inputs for the accuracy assessment result. The overall accuracy was described as follows:

$$\text{Over All Accuracy} = \frac{\text{Total number of correctly classified pixels}}{\text{Total number of pixels}} \times 100, \tag{2}$$

Another measure of classification accuracy is the kappa coefficient. It estimates degree of agreement between test data and the actual land cover classification and yields Khat statistics. The values range between − 1 and +1, where positive values indicate high accuracy of image classification (Afirah et al. 2016):

$$\text{Kappa}(k) = \frac{n\sum_{i=1}^{P} x_{ii} - \sum_{i=1}^{p} x_{io}x_{oi}}{n^2 - \sum_{i=1}^{P} x_{io}x_{oi}}, \tag{3}$$

where n = total number of pixels, P = number of class, $\sum x_{ii}$ = total number of confusion matrix, $\sum x_{io}$ = sum of row i, $\sum x_{oi}$ = sum of column i.

Local Community Discussion

In order to investigate the implication of the water hyacinth invasion to the livelihood of the community living around the lake, focus group discussion was conducted with different stakeholders who have a direct interest in the lake water; focus group discussion was carried out with eleven participants. Fishermen and farmers were participants of the discussion. In the discussion, the discussants were asked about whether or not water hyacinth is affecting their livelihood positively or negatively. They were also asked how invasive weed can be reduced or eliminated.

Results

Lake Water Body and Land Use Coverage in 2013

The classification results show that the proposed method classifies each class correctly. In the year 2013, water hyacinth was having very small coverage, consisting of 112.1 ha (0.17%) of the total study area, which is 67168.3 ha as indicated in Table 2. Whereas most of the area (91.21%) was covered with water body, the peripheries of the lake were covered with the water hyacinth. The

Table 2 Study area coverage in 2013

No.	Class Name	Area (ha)	Percent (%)
1	Water body	61262.35	91.21
2	Water hyacinth	112.14	0.17
3	Cultivated/shrubs/grassland	3462.97	5.16
4	Bareland	2330.81	3.47

other command areas to the water hyacinth around the periphery of the study site were cultivated/shrub/grazing and bareland. The water hyacinth cover in the year 2013 was concentrated only in the northwestern peripheral part of the study site. The rest of the marginal land of the site was dominantly covered with cropland/grass, and bareland as shown in Fig. 5.

Lake Water Body and Land Use Coverage in 2015

In the year 2015, the water hyacinth coverage was estimated as 169 ha, which is 0.25% of the study area (Table 3). As compared to 2013, its coverage increased by 46.6 ha, which is a 50% increment. According to these data, a double water hyacinth cover was recorded in 2 years between 2013 and 2015. This is a very fast increment in a short period. This in turn indicates that such an increase in water hyacinth coverage takes water surface under its control in a very short period of time. Whereas water bodies covered 89.44% of the area of the study site in 2015, a 1.77% decrease in water coverage is observed in the study site. That is, out of the 1185.69 ha decrease in water body, 56.6 ha were taken over by the water hyacinth.

Table 3 Study area coverage in 2015

No.	Class Name	Area (ha)	Percent (%)
1	Water body	60076.66	89.44
2	Water hyacinth	168.75	0.25
3	Cultivated/shrubs/grassland	3471.72	5.17
4	Bare land	3450.53	5.14

The rest was converted to cropland/grassland. In 2015, fast expansion of the water hyacinth was noticed in the eastern part of the lake as can also be recognized in Fig. 6.

Lake and Land Use Coverage in 2017

In the land cover classification of the year 2017, 99.5% of overall accuracy and 98% of kappa coefficient were achieved. As is illustrated in Table 4, water hyacinth covers 1512 ha (2.25% of the entire study site) in 2017. Compared to the water hyacinth cover in 2015, it has shown an increment by 1343.3 ha in 2017, which was 113.3% increment in 2 years period. This expansion of the water hyacinth was mainly at the expense of both water

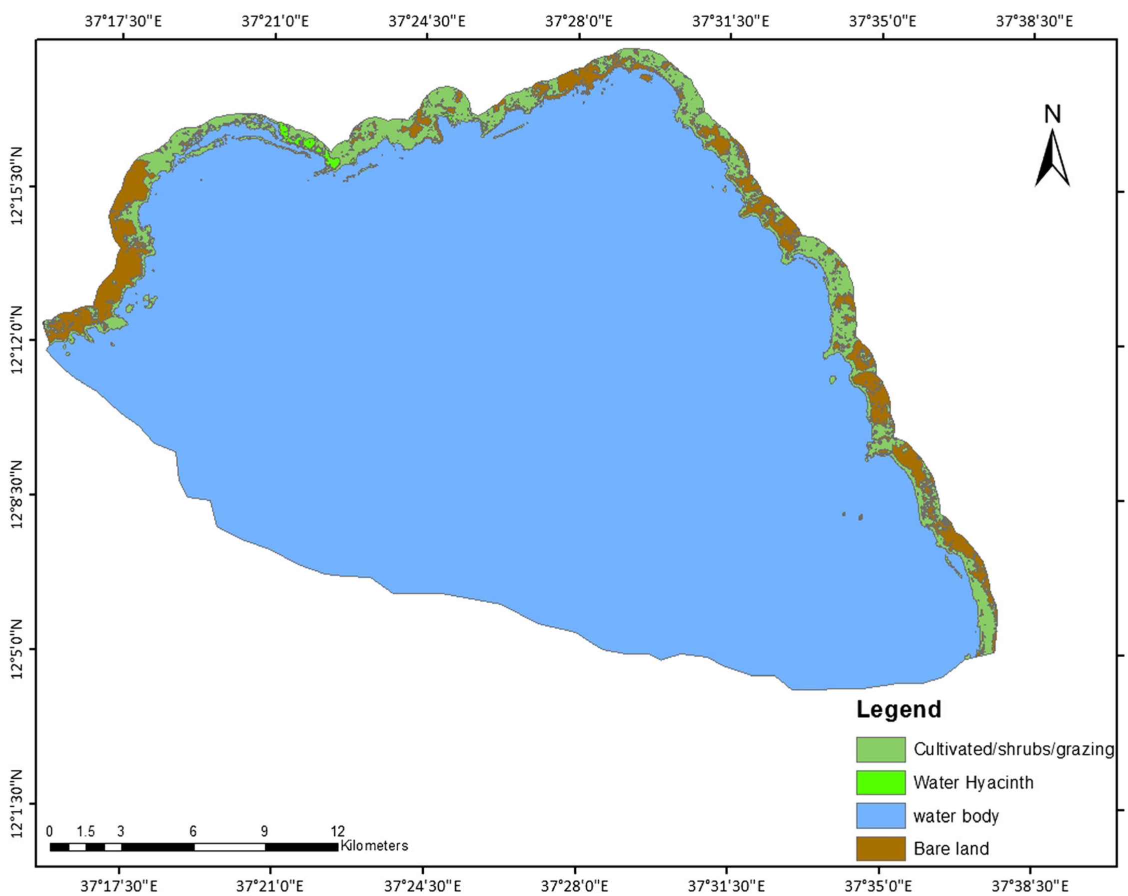

Fig. 5 Water hyacinth coverage in 2013

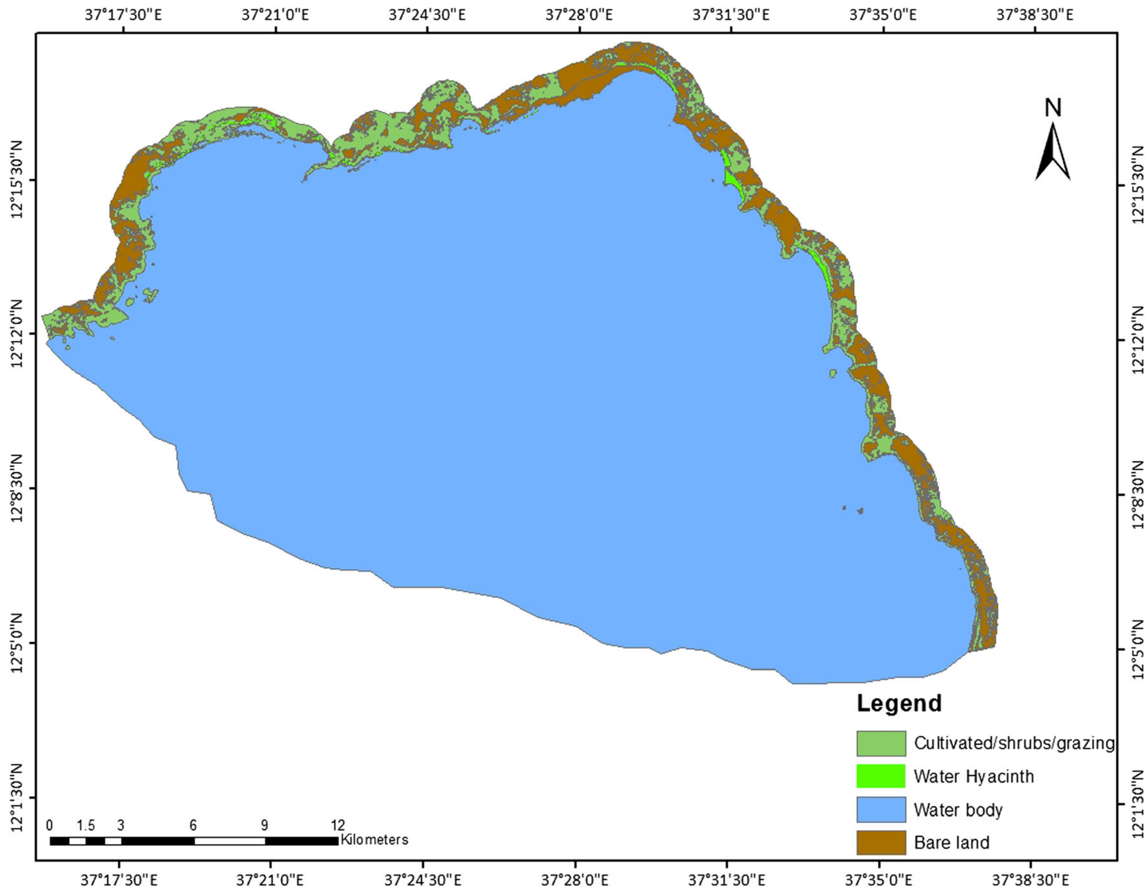

Fig. 6 Water hyacinth coverage in 2015

Table 4 Study area coverage in 2017

No.	Class Name	Area (ha)	Percent (%)
1	Water body	59877.58	89.15
2	Water hyacinth	1511.98	2.25
3	Cultivated/shrubs/grassland	2221.60	3.31
4	Bare land	3555.46	5.29

bodies and cultivated lands. In 2017, high expansion of water hyacinth was detected in almost every part of the study site but more marked in northeastern part of the study area (see Fig. 7).

Spatial Distribution of Water Hyacinth During 2013–2017

In the years between 2013 and 2017, the coverage of the water hyacinth has increased from 112.14 ha to 1511.98 ha (Table 5). This is a fast invasion of the weed over the lake in 4 years. In the 4-year period, it has significantly expanded its coverage by 13.5-fold, which was 1345%, by this it increased its area from 0.08% to 2% of the entire study site. In 2013, the water hyacinth was confined in the northwestern part of the study site. After 2 years again in 2015, new water hyacinth coverage emerged in the eastern part of the lake. Increasing its coverage, in 2017, high expansion was detected in almost every part of the study site with more pronounced invasion in northeastern part of the lake. This expansion depicts expansion of the water hyacinth and a decline in other land cover classes. A decrease in coverage of 2.06% (in the lake) and 1.85% (in cultivated land), and an increase by 2.1% of the water hyacinth coverage were recorded from 2013 to 2017.

Discussion

Detection of the Water Hyacinth

Remote sensing data and techniques (such as decision tree and supervised classification) allowed to separate water hyacinth cover from other land cover types. Even though course resolution satellite images were used because of unavailability of high resolution satellite images, it has been possible to clearly detect the expansion of the water

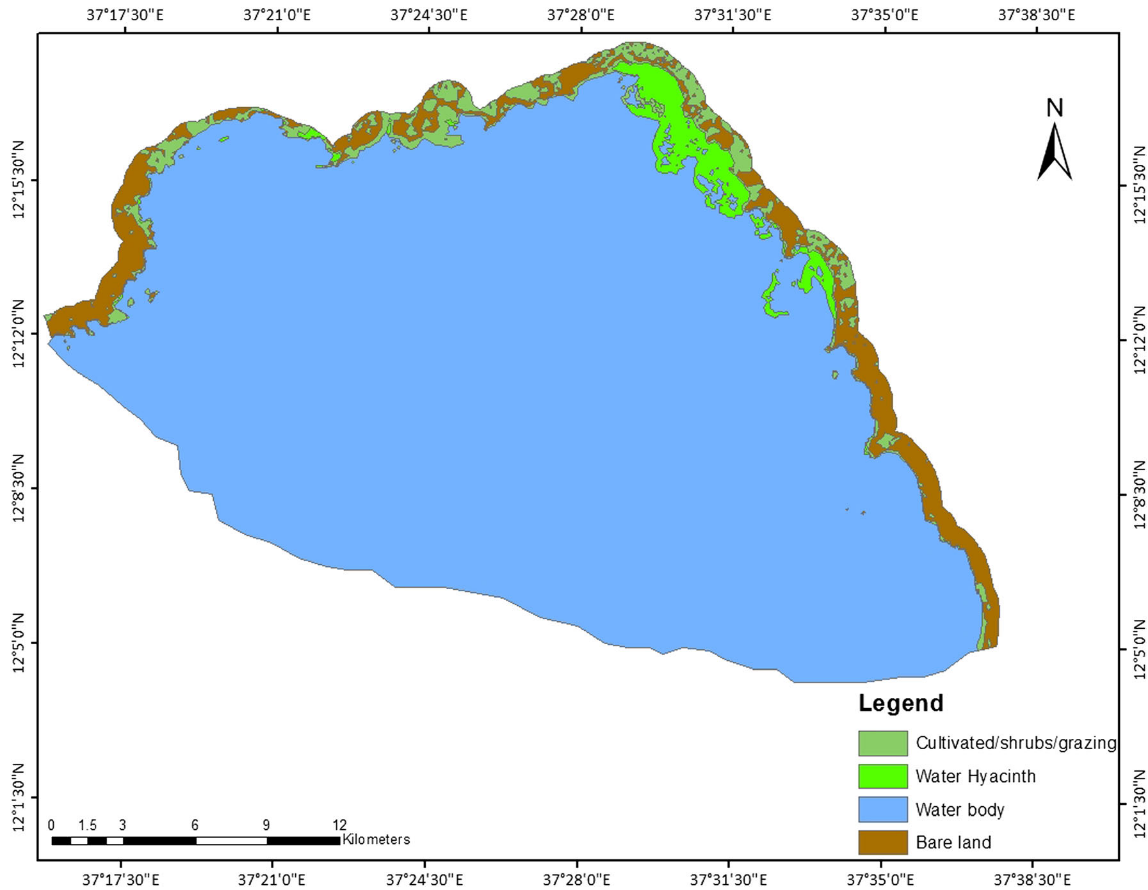

Fig. 7 Water hyacinth coverage in 2017

Table 5 Overall change detection of water hyacinth

No.	Land cover type	2013 to 2015		2015 to 2017		2013 to 2017	
		Area	%	Area	%	Area	%
1	Water body	− 1185.7	− 1.76	− 199.1	− 0.30	− 1384.8	− 2.06
2	Water hyacinth	+ 56.60	+ 0.08	+ 1343	+ 2.0	+ 1400	+ 2.1
3	Cultivated/shrubs/grassland	+ 8.75	+ 0.01	− 1250.1	− 1.86	− 1241.4	− 1.85
4	Bare land	+ 1120	+ 1.67	+ 104.9	+ 0.2	+ 1225	+ 1.8

hyacinth in the lake. This was also achieved due to the fast expansion and large area coverage of the water hyacinth, which in turn makes it easily detectable in course resolution satellite images. The use of the decision tree approach to classify has been a good approach to detect the water hyacinth from other land cover classes. Related to the use of remote sensing data, similar studies were done by Rajapakse et al. (2006) in California Central Valley and water hyacinth was successfully classified using decision tree technique. Another study by Sharma et al. (2013) in India concluded that nonparametric nature and non-sensitivity to outliers classification are based upon proportion of samples within spilt ranges and other properties of decision tree classification methods which give a guarantee for a better result. Land cover classification result of 2017 gave an acceptable accuracy of 99.54%, which was also confirmed by Foody and Mathur (2004); that careful selection of the training samples can help to maximize the supervised classification accuracy. Hence, in the classification, we were certain enough that the water hyacinth was successfully detected clearly and differentiated from other land cover classes, such as grasses, which have close reflectance behavior to water hyacinth.

Water Hyacinth Invasion

When we look at the result, the land cover of 2013 indicated that even if water hyacinth recognizably occurred during 2011 for the first time in Lake Tana, its coverage was small (Asmare 2017). The invasion and expansion were also very slow as was also learned from the local people. Though it may have a polluting impact on the water by allowing remains to settle to the bottom (Clayton 2009; Mangas-Ramírez and Elías-Gutiérrez 2010), the weed could have been controlled using simple preventive mechanisms, such as mechanical clearing of the water hyacinth using human labor (clearing by hand, as it is the cheaper and easily available power) before it gets worse expanding over a large area in the water.

It is noticed that the fast expansion of the water hyacinth was toward cropland and the water body; however, its expansion was more prominent toward the lake, as it ecologically survives floating on water (Barret and Forno 1982). The second land cover that is a good environment for its establishment is cropland. In the study area, recession farming is commonly practiced during the dry season when the water of the lake retreats (Lemma et al. 2017). During the rainy season, the land around the lake is also used for rice production. This area has high moisture content and is used for crop production during the dry season. Hence, this part of the study area was suitable for the expansion of the water hyacinth, leaving the cropland at danger of weed invasion. On the other hand, other land cover areas such as bareland are not affected by the weed, which is unsuitable for the weed invasion. Similar studies were conducted by (Verma et al. 2003) to compare water hyacinth-covered areas on six lakes of India, and similar results were observed: The expansion of the water hyacinth is largely toward water bodies and wetlands or cropland.

The occurrence of the weed was more visible in the northwestern part of the Lake Tana, but later its expansion toward the water was highly distinct in the northeastern part. This is perhaps related to the sediment delivery of the two rivers (Gumara and Rib) in the northern and eastern part of the lake (Lemma et al. 2017) which provides comfortable condition (nutrients washed down from farmlands and other land cover) for the weed in the lake water, the practice of recession agriculture (rice production in the rainy season) and production of other crops (mainly maize) in the northern and eastern part of the lake. The weed is highly prevalent in tropical and sub-tropical water bodies, particularly fresh water bodies as saline water is not suitable for its establishment (Mangas-Ramírez and Elías-Gutiérrez 2010), where water nutrient concentrations are often high due to agricultural runoff, deforestation and insufficient wastewater treatment (Villamagna and Murphy 2010). Moreover, its increasing invasion may also be related to the rise in temperature level due to climate change in the surrounding areas of the lake due to deforestation and human intervention (Rodriguez-Gallego et al. 2004; Hellman et al. 2008; Rahel and Olden 2008). The expansion of the water hyacinth in the northern and eastern part of the lake may also be attributable to its ability to outcompete native vegetation and phytoplankton and the absence of consumers found within its native range such as Neochetina eichhorniae Warner and Neochetina bruchi Hustache (Wilson et al. 2005; Villamagna and Murphy 2010; Tang et al. 2019). However, this requires further investigation.

Water Hyacinth and Implication to Livelihood

Water hyacinth invasion and its fast propagation in Lake Tana have its implication on the livelihoods of the people and ecological community. Incursion and coverage of grazing land or farmland and disruption of boat transport (which in turn reduces fishing) were the most prevalent problems faced by the residents (Fig. 8). Water hyacinth introduces challenges in water conservation and is also causing socioeconomic problems in the surrounding community. It is also a threat in fresh water bodies by adversely affecting water flow, navigation, recreation and mechanical damages to hydroelectric machines (Téllez et al. 2008). It is also responsible for drastic changes in the plant and animal communities of freshwater environments and causes diseases that affect aquatic life in tropical areas. Similarly, it has an adverse effect on fish production as it aggravates a decrease in dissolved oxygen leading to death of fish and other aquatic creatures (Téllez et al. 2008).

There are many ways of clearing water hyacinth from fresh water bodies, such as mechanical techniques using human labor and machineries, and biological techniques (Cilliers 1991; Center et al. 1999; Julien et al. 2001). In Lake Tana, due to the recent invasion of the weed, it is getting wide media coverage. Besides, efforts are in place to remove it. The removal of the weed from the lake is undertaken using mass mobilization by hand and machineries. But this method is not working properly, as the discussants also confirmed, because the expansion of the lake after 2015 (as the result in this study also indicates) is very fast and covers large area in the lake and the surrounding wetland/cropland. Hence, its implication to the livelihood of the farmers and the fisher men is obviously devastating.

If the expansion of the water hyacinth continues, there is no reason for the whole lake to be invaded by the weed. Hence, clear plans of management and monitoring with short-term and long-term strategic actions have to be set. As some authors (e.g., Lu et al. 2007; Martinez-Jimenez and Gomez-Balandra 2007) suggested multi-scale long-term monitoring and research, integration among different control techniques, combination of control with utilization and landscape-level adaptive management techniques are required. Moreover, changing the water hyacinth into economic advantage has to also be thought of as there are

Fig. 8 Expansion of the water hyacinth toward the lake and croplands/wetlands that are used for rice production during the rainy season and other crop production during the dry season

various same experiences worldwide (Gunnarsson and Petersen 2007; Gupta et al. 2012; Ganguly et al. 2012).

Conclusion

It can be concluded that remote sensing is a very useful means for establishing a cheap effective method for the monitoring water body dynamics, such as water hyacinth expansion and distribution. Water hyacinth coverage has shown significant expansion for the years between 2013 and 2017. With 5-year interval, the amount of coverage increased from 112 to 168 ha and then to 1512 ha. Beyond its size of coverage, the weed is spreading toward north-eastern part of the study area. Specifically, the result shows that its coverage and expansion are increasing very fast toward the lake as compared to other coverage types, which is dangerous for sustainability of the lake. Generally, remote sensing images are a vital free source material used to control the spatial and temporal distribution of water hyacinth in northeastern part of Lake Tana. In addition, satellite images are crucial for lake management related to invasive species in order to understand the dynamics of their growth and expansion. Satellite imagery is one of the main resources to monitor change detections, especially, new-generation Earth observation satellites such as Landsat 8 can be obtained freely, and coverage maps can be produced in a good temporal resolution. Temporal and spatial analyses of water hyacinth coverage help water resource planners and decision makers to improve water resource management standards.

Acknowledgements We acknowledge the Amhara Design and Supervision Works Enterprise for funding this study. We also acknowledge Bahir Dar University for the material support during the field work. We acknowledge Mekelle University for materials and laboratory support for this work. Our gratitude goes to Miss. Abrehet Kahsay (Ph.D. researcher) for her technical support during the data collection in the field. We forward our thanks to the community around the lake for their support in giving information particularly during the focus group discussion and interview.

Compliance with Ethical Standards

Conflict of interest Biadgilgn Demissie, Amare Gebremedhin Nigusse and Abraha Geberekidan declare that they do not have any conflict of interest. Tewachew Amare was sponsored by the Amhara Design and Supervision Works Enterprise, Bahir Dar, Ethiopia, to follow his MSc study. He declared that he has reported to the office after completing his study. The Amhara Design and Supervision Works Enterprise does not have any conflict of interest with this article; it is acknowledged in the acknowledgement part of the article.

Human and Animal Rights This article does not have any conflict with human rights as it does not contain any studies connected with human body and interest. This article does not contain any thing connected to animals as subjects of study.

References

Adgo E., Dessie M. & Nyssen J. (2016). *Excursion guide of the TropiLakes2015: Mid-conference excursion*. September 22–24, 2016, Bahir Dar, Ethiopia.

Afirah, T., Sakinah, S., Ahmad, S., & Ahmad, A. (2016). Classification of Landsat 8 satellite data using NDVI thresholds. *Journal of Telecommunication, Electronic and Computer Engineering (JTEC), 9*(4), 37–40.

Ahmad, A. (2012). Analysis of maximum likelihood classification on multispectral data. *Applied Mathematical Sciences, 6*(129), 6425–6436.

Annys, S., Demissie, B., Zenebe, A., & Nyssen, J. (2016). Land cover changes as impacted by rainfall variability in the escarpments of the Ethiopian Rift Valley. *Regional Environmental Change*. https://doi.org/10.1007/s10113-016-1031-2.

Asmare, E. (2017). Current trend of water hyacinth expansion and its consequence on the fisheries around north eastern part of Lake Tana, Ethiopia. *Journal of Biodiversity & Endangered Species, 5*(2), 1–4.

Barret, S. C. H., & Forno, I. W. (1982). Style morph distribution in new world populations of *Eichhornia crassipes* (Mart) Solms-Laubach (water hyacinth). *Aquatic Botany, 13,* 299–306.

Brendonck, L., Maes, J., Rommens, W., Dekeza, N., Nhiwatiwa, T., Barson, M., et al. (2003). The impact of water hyacinth (*Eichhornia crassipes*) in a eutrophic subtropical impoundment (Lake Chivero, Zimbabwe). II. Species diversity. *Archiv fur Hydrobiologie, 158,* 389–405.

Caprioli M, Figorito B, Tarantino E. (2006). Radiometric calibration methods for change detection analysis of satellite data aimed at environmental risk monitoring. *The International Archives of the Photogrametry: Remote Sensing and Spatial Information Sciences, 37*, part B8, Beijing.

Center, T. D., Dray, F. A., Jubinsky, G. P., & Grodowitz, M. J. (1999). Biological Control of water hyacinth under conditions of maintenance management: Can herbicides and insects be integrated? *Environmental Management, 23,* 241–256.

Chen, D., & Stow, D. (2002). The effect of training strategies on supervised classification at different spatial resolutions. *Photogrammetric Engineering and Remote Sensing, 68*(11), 1155–1161.

Che-Yen, W., & Chien-Hsiung, L. (2002). Point spread functions and their applications to forensic image restoration. *Forensic Science Journal, 1,* 15–26.

Cilliers, C. J. (1991). Biological control of water hyacinth, *Eichhornia crassipes* (Pontederiaceae), in South Africa. *Agriculture, Ecosystems & Environment, 37,* 207–217.

Clayton, J. S. (2009). Aquatic weeds and their control in New Zealand Lakes. *Lake and Reservoir Management, 12*(4), 477–486.

Congalton, R. G., & Mead, R. A. (1983). A quantitative method to test for consistency and correctness in photointerpretation. *Photogrammetric Engineering and Remote Sensing, 49*(1), 69–74.

de Colstoun E. B., Story M. H., Thompson C., Smith T. G. & Irons J. R. (2002). Vegetation mapping using multi-temporal ETM + data and a decision tree classifier. In *IEEE international geoscience and remote sensing symposium, 24–28 June 2002*. Toronto, Ontario, Canada. https://ieeexplore.ieee.org/document/1026812.

de Mûelenaere, S., Frankl, A., Haile, M., Poesen, J., Deckers, J., Munro, N., et al. (2014). Historical landscape photographs for calibration of Landsat land use/cover in the Northern Ethiopian Highlands. *Land Degradation and Development, 25,* 319–335. https://doi.org/10.1002/ldr.2142.

Demissie, B., Frankl, A., Haile, M., & Nyssen, J. (2015). Biophysical controlling factors in upper catchments and braided rivers in drylands: The case of a marginal graben of the Ethiopian Rift Valley. *Land Degradation and Development, 26,* 748–758.

Dessie, M., Verhoest, N. E. C., Admasu, T., Pauwels, V. R. N., Poesen, J., Adgo, E., et al. (2014). Effects of the floodplain on river discharge into Lake Tana (Ethiopia). *Hydrology, 519,* 699–710.

Dewidar, K. H. M. (2004). Detection of land use/land cover changes for the Northern part of the Nile delta (Burullus region), Egypt. *International Journal of Remote Sensing, 25*(20), 4079–4089.

Dube, T., Mutanga, O., Sibanda, M., Bangamwabo, V., & Shoko, C. (2017). Testing the detection and discrimination potential of the new Landsat 8 satellite data on the challenging water hyacinth (*Eichhornia crassipes*) in freshwater ecosystems. *Applied Geography, 84,* 11–22.

Foody, G. M., & Mathur, A. (2004). Toward intelligent training of supervised image classifications: directing training data acquisition for SVM classification. *Remote Sensing of Environment, 93*(1–2), 107–117.

Ganguly, A., Chatterjee, P. K., & Dey, A. (2012). Studies on ethanol production from water hyacinth—A review. *Renewable and Sustainable Energy Reviews, 16,* 966–972.

Gong, P., & Howarth, P. (1989). An assessment of some factors influencing multispectral land-cover classification. *Photogrammetric Engineering and Remote Sensing, 56*(5), 597–603.

Goshu, G., Tewabe, D., & Adugna, B. T. (2010). Spatial and temporal distribution of commercially important fish species of Lake Tana. *Ethiopia. Ecohydrology & Hydrobiology, 10*(2–4), 231–240.

Gunnarsson, C. C., & Petersen, C. M. (2007). Water hyacinths as a resource in agriculture and energy production: A literature review. *Waste Management, 27,* 117–129.

Gupta, P., Roy, S., & Mahindrakar, A. B. (2012). Treatment of water using water hyacinth, water lettuce and vetiver grass—A review. *Resources and Environment, 2*(5), 202–215.

Heide, F. Z. (2012). *Feasibility study for a Lake Tana biosphere reserve, Ethiopia* (p. 317). Bonn: BfN-Skripten.

Hellman, J. J., Byers, J. E., Bierwagen, B. G., & Dukes, J. S. (2008). Five potential consequences of climate change for invasive species. *Conservation Biology*, *22*(3), 534–543.

Hestin, E. L., Khanna, S., Andrew, M. E., Santos, M. J., Viers, J. H., Greenberg, J. A., et al. (2008). Identification of invasive vegetation using hyperspectral remote sensing in the California Delta ecosystem. *Remote Sensing of Environment, 112*(11), 4034–4047.

Hsiao, L. H., & Cheng, K. S. (2016). Assessing uncertainty in LULC classification accuracy by using bootstrap resampling. *Remote Sensing, 8*(9), 705–724.

Ihlen V. (2019). Landsat 8 (L8) data users handbook. Department of the InteriorU.S. Geological Survey. LSDS-1574Version 5.0.

Ismail, M. H., Pakhriazad, H. Z., & Shahrin, M. F. (2009). Evaluating supervised and unsupervised techniques for land cover mapping using remote sensing data. *Malaysian Journal of Society and Space*, *5*(1), 1–10.

Jensen, J. (2015). *Introductory digital image processing: A remote sensing perspective*. Upper Saddle River, NJ: Prentice Hall.

Julien M. H., Hill M. P., Center T. D. & Jianqing D. (2001). Biological and integrated control of water hyacinth, *Eichhornia crassipes*. In *Proceedings of the second meeting of the global working group for the biological and integrated control of water hyacinth, 9–12 October 2000* (p. 152). ACIARProceedings No. 102, Beijing, China.

Kebede, S., Travi, Y., Alemayehu, T., & Marc, V. (2006). Water balance of Lake Tana and its sensitivity to fluctuations in rainfall, Blue Nile basin, Ethiopia. *Hydrology, 316*(1–4), 233–247.

Lemma, H., Admasu, T., Dessie, M., Fentie, D., Deckers, J., Frankl, A., et al. (2017). Revisiting lake sediment budgets: How the calculation of lake life time is strongly data and method dependent. *Earth Surface Processes and Landforms, 43,* 593–607.

Liang, S., Fang, H., & Chen, M. (2001). Atmospheric correction of Landsat ETM + land surface imagery—Part I: methods. *IEEE Transactions on Geoscience and Remote Sensing, 39,* 2490–2498.

Ligdi, E. E., ElKahloun, M., & Meire, P. (2010). Ecohydrological status of Lake Tana—A shallow highland lake in the Blue Nile (Abbay) basin in Ethiopia: Review. *Ecohydrology & Hydrobiology, 10*(2–4), 109–122.

Lillesand, T. M., Kiefer, R. W., & Chiman, J. W. (2008). *Remote sensing and image interpretation* (6th ed.). New York: Wiley.

Lu, J. B., Wu, J. G., Fu, Z. H., & Zhu, L. (2007). Water hyacinth in China: A sustainability science-based management framework. *Environmental Management, 40,* 823–830.

Lugo, A., Bravo-Inclán, L. A., Alcocer, J., Gaytán, M. L., Oliva, M. G., Sánchez, M. R., et al. (1998). Effect on the planktonic community of the chemical program used to control water hyacinth (*Eichhornia crassipes*) in Guadalupe Dam, Mexico. *Aquatic Ecosystem Health & Management, 1*(3–4), 333–343.

Mahiny, A. S., & Turner, B. J. (2007). A comparison of four common atmospheric correction methods. *Photogrammetric Engineering and Remote Sensing, 73,* 361–368.

Mangas-Ramírez, E., & Elías-Gutiérrez, M. (2010). Effect of mechanical removal of water hyacinth (*Eichhornia crassipes*) on the water quality and biological communities in a Mexican reservoir. *Aquatic Ecosystem Health & Management, 7*(1), 161–168.

Martinez-Jimenez, M., & Gomez-Balandra, M. A. (2007). Integrated control of *Eichhornia crassipes* by using insects and plant pathogens in Mexico. *Crop Protection, 26,* 1234–1238.

Mather, P., & Koch, M. (2011). *Computer processing of remotely-sensed images: An introduction* (p. 460). New York: Wiley.

McCullough, I. M., Loftin, C. S., & Sader, S. A. (2012). Combining lake and watershed characteristics with Landsat TM data for remote estimation of regional lake clarity. *Remote Sensing of Environment, 123,* 109–115.

Ndimele, P. E., Johnson, C. A., & Anetekhai, M. A. (2011). The invasive aquatic macrophyte water hyacinth {*Eichhornia crassipes* (Mart.) Solm-Laubach: Pontedericeae}: Problems and prospects. *Research Journal of Environmental Science, 5*(6), 509–520.

Otukei, J. R., & Blaschke, T. (2015). Land cover change assessment using decision trees, support vector machines and maximum likelihood classification algorithms. *International Journal of Applied Earth Observation and Geoinformation, 12*(1), 27–31.

Paolini, L., Grings, F., Sobrino, J., Jimenez-Munoz, J. C., & Karszenbaum, H. (2006). Radiometric correction effects in Landsat multi-date/multi-sensor change detection studies. *International Journal of Remote Sensing, 27*(4), 685–704.

Piyaboon, O., Pawongrat, R., & Unartngam, J. (2016). Pathogenicity, host range and activities of a secondary metabolite and enzyme from *Myrothecium roridumon* water hyacinth from Thailand. *Weed Biology and Management, 16,* 132–144.

Poppe, L., Frankl, A., Poesen, J., Admasu, T., Dessie, M., Adgo, E., et al. (2013). Geomorphology of the Lake Tana basin, Ethiopia. *Journal of Maps, 9,* 431–437.

Rahel, F. J., & Olden, J. D. (2008). Assessing the effects of climate change on aquatic invasive species. *Conservation Biology*, *22*(3), 521–533.

Rai, D. N., & Munshi, J. D. (1979). The influence of thick floating vegetation (water hyacinth: *Eichhornia crassipes*) on the physic-chemical environment of a fresh water wetland. *Hydrobiologia, 62,* 65–69.

Rajapakse S.S., Khanna S., Andrew M. E., Ustin S. L. & Lay M. (2006). Identifying and classifying water hyacinth (*Eichhornia crassipes*) using the HyMap sensor. In W. Gao, S. L. Ustin (Eds.), *Proceedings Volume 6298. Remote Sensing and Modeling of Ecosystems for Sustainability III.*

Rodriguez-Gallego, L. R., Mazzeo, N., Gorga, J., Meerhoff, M., Clemente, J., Kruk, C., et al. (2004). Effects of an artificial wetland with free-floating plants on the restoration of a hypertrophic subtropical lake. *Lakes & Reservoirs Research & Management*, *9*(3–4), 203–215.

Rommens, W., Maes, J., Dekeza, N., Inghelbrecht, P., Nhiwatiwa, T., Holsters, E., et al. (2003). The impact of water hyacinth (*Eichhornia crassipes*) in a eutrophic subtropical impoundment (Lake Chivero, Zimbabwe). II. Species diversity. *Archiv für Hydrobiologie, 158*(3), 373–388.

Rouabeh H., Abdelmoula C. & Masmoudi M. (2014). Performance evaluation of decision tree and neural network techniques for road scene image classification task. In *International image processing, applications and systems conference, 5–7 November 2014*, Sfax, Tunisia. https://doi.org/10.1109/ipas.2014.7043274.

Ruelland, D., Tribotte, A., Puech, C., & Dieulin, C. (2011). Comparison of methods for LUCC monitoring over 50 years from aerial photographs and satellite images in a Sahelian catchment. *International Journal of Remote Sensing*, *32*(6), 1747–1777.

Sharma, R., Ghosh, A., & Joshi, P. K. (2013). Decision tree approach for classification of remotely sensed satellite data using open source support. *Journal of Earth System Science, 122*(5), 1237–1247.

Sisay, K., Thurnher, C., & Hasenauer, H. (2016). Daily climate data for the Amhara region in northwestern Ethiopia. *International Journal of Climatology*. https://doi.org/10.1002/joc.4880.

Srivastava, P. K., Han, D., Rico-Ramirez, M. A., Bray, M., & Islam, T. (2012). Selection of classification techniques for land use/land cover change investigation. *Advances in Space Research, 50*(9), 1250–1265.

Story, M., & Congalton, R. G. (1986). Accuracy assessment: A user's perspective. *Photogrammetric Engineering and Remote Sensing, 52*(3), 397–399.

Tang, S., Pan, Y., Wei, C., Li, X., & Lu, S. (2019). Testing of an integrated regime for effective and sustainable control of invasive Crofton weed(*Ageratina adenophora*) comprising the use of natural inhibitor species, activated charcoal, and fungicide. *Weed Biology and Management, 19,* 9–18.

Townshend, J. R. G. (1992). Land cover. *International Journal of Remote Sensing, 13*(6–7), 1319–1328.

UNEP. (2013). Water hyacinth—Can its aggressive invasion be controlled? *Environmental Development, 7,* 139–154.

Verma, R., Singh, S. P., & Raj, K. G. (2003). Assessment of changes in water-hyacinth coverage of water bodies in northern part of Bangalore city using temporal remote sensing data. *Current Science, 84*(6), 795–804.

Vijverberg, J., Sibbing, F. A., & Dejen, E. (2009). Lake Tana: Source of the BlueNile. In H. J. Dumont (Ed.), *Monographiae biologicae 89, the Nile* (pp. 163–192). Dordrecht: Springer.

Villamagna, A. M., & Murphy, B. R. (2010). Ecological and socio-economic impacts of invasive water hyacinth (*Eichhornia crassipes*): A review. *Fresh water Biology, 55*(2), 282–298.

Wilson, J. R., Holst, N., & Rees, M. (2005). Determinants and patterns of population growth in water hyacinth. *Aquatic Botany, 81,* 51–67.

Zhang Y, & Li X. (2011). Topographic normalization of Landsat TM images in rugged terrain based on the high-resolution DEM derived from ASTER. Paper presented at the PIERS 2011 Suzhou, Suzhou, China.

Zhou Z. & Zhang Y. (2013). Integration of association-rule and decision tree for high resolution image classification. In *2013 21st international conference on geoinformatics, 20–22 June 2013*, Kaifeng, China. https://doi.org/10.1109/geoinformatics.2013.6626123.