ORIGINAL RESEARCH PAPER

Inland wetlands mapping and vulnerability assessment using an integrated geographic information system and remote sensing techniques

C.E. Akumu[1,]*, J. Henry[1], T. Gala[2], S. Dennis[1], C. Reddy[1], F. Tegegne[1], S. Haile[1], R.S. Archer[1]

[1]*Department of Agricultural and Environmental Sciences, College of Agriculture, Tennessee State University, Nashville, Tennessee, USA*

[2]*Department of Geography, Chicago State University, S. King Drive, Chicago, IL, USA*

ABSTRACT: The understanding of inland wetlands' distribution and their level of vulnerability is important to enhance management and conservation efforts. The aim of the study was to map inland wetlands and assess their distribution pattern and vulnerability to natural and human disturbances such as climate change (temperature increase) and human activities by the year 2080. Inland wetland types i.e. forested/shrub, emergent and open water bodies were classified and mapped using maximum likelihood standard algorithm. The spatial distribution pattern of inland wetlands was examined using average nearest neighbor analysis. A weighted geospatial vulnerability analysis was developed using variables such as roads, land cover/ land use (developed and agricultural areas) and climate data (temperature) to predict potentially vulnerable inland wetland types. Inland wetlands were successfully classified and mapped with overall accuracy of about 73 percent. Clustered spatial distribution pattern was found among all inland wetland types with varied degree of clustering. The study found about 13 percent of open water bodies, 11 percent of forested/shrub and 7 percent of emergent wetlands potentially most vulnerable to human and natural stressors. This information could be used to improve wetland planning and management by wetland managers and other stakeholders.

KEYWORDS: *Classification; Distribution pattern; Geospatial; Inland wetlands; Satellite data.*

INTRODUCTION

Wetlands are ecosystems that arise when inundation by water produces soils dominated by anaerobic process and forces the biota, particularly rooted plants to exhibit adaptations to tolerate flooding (Keddy, 2000; Davidson *et al.,* 2018). Wetlands are important ecosystems for the environment as they provide food to migrating birds and habitat for several organisms and plant species. They also protect humans with water quality maintenance, flood and erosion prevention and control (Dugan, 2005, Davidson *et al.,* 2018; Mitsch *et al.,* 2009, Schneider *et al.,*2017). The combination of these functions together with the value placed upon biological diversity and the cultural values of certain wetlands, make these ecosystems invaluable to people all over the world (Dugan, 2005). There are a variety of wetland types including coastal and inland wetlands (Mitsch *et al.,* 2009). Coastal wetlands are mainly influenced by alternate floods and ebbs tides from the ocean whereas, inland wetlands are not affected by the ocean tides and are several miles inland (Mitsch *et al.*, 2009; Phillips, 2018). Inland wetlands are found in most parts of the United States and include peat lands, freshwater swamps and marshes. Peat lands are located mostly in northern states such as Wisconsin, Michigan, Minnesota, Alaska and the glaciated Northeast with deep peat deposits.   Freshwater

✉ *Corresponding Author Email: aclemen1@tnstate.edu*
Tel.: +1 615 963 5616   Fax: +1 615 963 7798

swamps and marshes occur in isolated basins, as fringes around lakes, and along sluggish streams and rivers (Mitsch *et al.*, 2009). The classification and mapping of inland wetlands are important because they are among the world's most productive environments (Ramsar, 1971) and knowing their spatial distribution will greatly enhance conservation and management efforts. Furthermore, understanding inland wetlands' distribution pattern is essential because spatial distribution pattern has profound impacts on population of species, their interactions within ecological communities and the function of ecosystems (Collinge, 2010). For example, inland wetland ecosystems that are clustered in distribution pattern could imply that they consist of plant species that are clumped together and animal species that live in groups. With the potential increase in the earth's temperature and rapid urbanization by the year 2080, significant impact on inland wetland plants and animal species by the end of the century is expected. Therefore, it is imperative to assess the vulnerability of inland wetlands to climate change and human activities. Wetland vulnerability refers to the exposure of a wetland to significant future loss or degradation as a result of anthropogenic or natural factors (Copeland *et al.*, 2010). Assessing the vulnerability of wetlands to natural and human disturbances will enable wetland managers identify wetlands at risk of degradation and loss on the landscape. This will improve wetland management and planning by government agencies and other stakeholders. The rapid evolution of geographic information system (GIS) and remote sensing technology with increasing availability of geospatial datasets such as satellite data provides an opportunity for wetland classification and mapping, distribution pattern and vulnerability analysis. Satellite remote sensing is ideal for mapping and monitoring wetlands because it provides high spatial and temporal resolution datasets at landscape level. It also allows for less time consuming measurements of sensitive sites, without the potential challenges that traditional field methods present (Shuman and Ambrose, 2003). Satellite geospatial approaches have been used to assess wetlands distribution and vulnerability to climate change and human activities (Copeland *et al.,* 2010; Isunju *et al.,* 2016; Matchett and Fleskes, 2017; Rawat and Kumar, 2015; Torbick and Salas, 2014). They successfully assessed and mapped wetlands distribution and found most wetland

complexes vulnerable to disturbances such as land use change and climate change. Nonetheless, little attempts have been made to assess inland wetlands distribution and their vulnerability in Tennessee with significant amount of isolated wetlands that are generally high in species richness (Brose, 2001). The objectives of this study are: 1) to classify and map inland wetland types in middle Tennessee using Landsat 8 Satellite data; 2) to understand the distribution pattern of inland wetland types; and 3) to examine inland wetlands that are potentially most vulnerable to natural and human stressors such as climate change (temperature increase), agricultural expansion and urbanization by the year 2080. This study was carried out in middle Tennessee, USA in 2018.

MATERIALS AND METHODS
Study area

The study area extends around latitude 34°56'14.54'' to 36°36'33.05'' N and longitude 84°56'59.68'' to 87°48'49.75'' W in middle Tennessee, United States of America (Fig. 1). It consists of 38 counties east of the Tennessee River and west of the Eastern Time zone boundary. The communities range from small unincorporated towns to the state's capital city of Nashville (Tennessee Emergency Management Agency, 2017). The study area was selected because the middle Tennessee region has experienced an increase in population in the last 10 years (Mojica, 2018) and this trend is expected to continue in the future. The increase in urban population will lead to increase in residential development and urbanization. This will potentially affect the existence of inland wetlands which play a critical role in flood protection and water quality in the region.

Climate

The region has a moderate climate featuring cool winters and warm summers (Hodges *et al.,* 2018). The mean annual temperature of the region is about 78°F (26°C) in the summer months and 41°F (5°C) in the winter months. The drop in the elevation from east to west causes temperatures to rise significantly in the lower parts of the region. The region receives about 51 inches (1,300 mm) of precipitation a year with precipitation evenly distributed over the seasons (Hodges *et al.,* 2018). Growing season in the area ranges from around 130 days in the eastern mountainous parts (towards city Knoxville) to about

240 days in the western low-lying sections (towards Memphis city) of the state of Tennessee (Hodges *et al.,* 2018).

Vegetation

Due to the variation in elevation within the state of Tennessee, a combination of northern and southern plant species are commonly found in the region (Hodges *et al.,* 2018). There are more than two hundred plant species found in the region with commonly found tree species such as *Gleditsia* (locust), *Populus* (poplar), *Acer* (maple), *Quercus* (oak), *Ulmus* (elm), *Fagus, Pinus* (beech, pine), *Picea* (spruce), *Juglans* (walnut), *Carya* (hickory), and *Platanus* (sycamore).

Geology/ Hydrology

The middle region of Tennessee consists of the Highland Rim and Central Basin (Hodges *et al.,* 2018). The Central Basin is underlain by Ordovician limestone and has alkaline soils, whereas most of the surrounding Highland Rim has acidic soils that are heavily leached (Mitsch *et al.,* 2009). Level plains and fertile land interrupted by rolling hills occupy most of the area with major rivers such as the Tennessee and Cumberland Rivers. The Tennessee River flows southward in the east, northward in the west and drains the southern part of middle Tennessee. The Cumberland River flows southward and drains the upper middle region of Tennessee (Mitsch *et al.*, 2009). The damming of the Tennessee and Cumberland Rivers have controlled flooding and created slack-water lakes within the region. Isolated forested wetlands are found uplands such as the Highland Rim, Central Basin, Cumberland Plateau, and the Blue Ridge Province. Beaver ponds that are typically associated with flood plains are found throughout the state of Tennessee. Fresh water mashes exist along shores of major rivers and lakes such as the Tennessee River and Reelfoot Lake. Many streams in Tennessee have been channelized to enhance drainage of adjacent

Fig. 1: Geographic location of the study area in middle Tennessee, southeastern parts of the United States of America

wetlands for cultivation purposes. This has had significant influence on wetland hydrologic processes in Tennessee by reducing flooding and lowering the water table in upper reaches of streams but increasing downstream deposition of sediment and contribution to downstream flooding (Meador, 1996).

MATERIAL AND METHODS

This involved the classification and delineation of inland wetland types in middle Tennessee using Landsat 8 Satellite data. Furthermore, the study assessed the distribution pattern of the delineated inland wetland types over the entire study area using nearest neighbor analysis technique. This is because average nearest neighbor technique measures the distance between each feature centroid and its nearest neighbor's centroid location. Then, it averages the nearest neighbor distances and compares it to a hypothetical random distribution average to determine the distribution pattern of the feature (Mitchell, 2005). For instance, if the average distance is less than the average for a hypothetical random distribution, then the distribution is considered clustered. If the average distance is greater than a hypothetical random distribution then the distribution is considered dispersed. In addition, a vulnerability assessment of the inland wetland types to temperature increase, urbanization and agricultural

expansion by the year 2018 was performed by GIS modeling and analysis (Fig. 2). This involved the use of input environmental variables such as projected temperature, current landcover/landuse and major road network. With lack of projected landcover/landuse and major road network data for the region by the year 2018, euclidean distances around major roads, and landcover types (urban and agriculture) were generated. The study assumed that projected human activities (urban and agricultural expansion) by the year 2018 are expected to occur within closed distances to current residential, agricultural and road network areas. This is because urban and agricultural expansion are generally expected to occur in closed proximity to current residential, agricultural and road network areas for easier access to human and material resources.

Wetland classification and mapping

Several field visits were carried out to identify the various inland wetland types in middle Tennessee. The geographic locations of the inland wetland types were recorded with the use of a global positioning system (GPS). The GPS locations were imported into GIS environment and overlaid to a Landsat satellite data scene. Digitized wetlands polygons were created around the GPS locations and the polygons
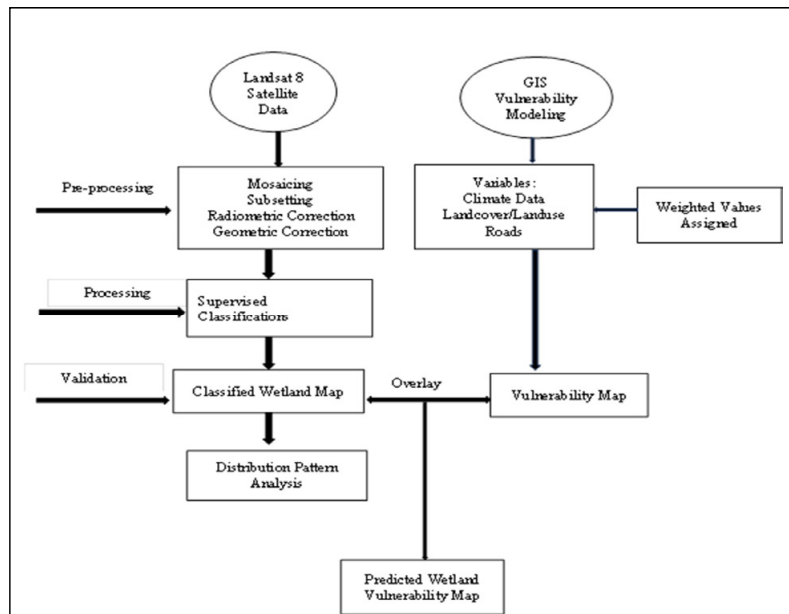

Fig. 2: A schematic representation of the methodological approach used to classify, map and model inland wetlands distribution pattern and vulnerability

were used as training dataset in the delineation and mapping of inland wetland types across the entire study area. Landsat 8 satellite scenes acquired in the months of September 2015 and June 2016 and were used to classify, delineate and map inland wetland types in middle Tennessee. They were the most available cloud free satellite images for the study area taken during the summer/early fall period when inland wetland communities were most visible. Two scenes representing September 2015 and June 2016 acquisition dates were downloaded from the USGIS data repository. They were downloaded as Landsat 8 Level-1 dataset and required preprocessing activities. Landsat 8 satellite consists of 11 spectral bands and the scenes were processed in three phases i.e. pre-processing, processing and validation phases (Fig. 2) in Erdas ER Mapper version 2016. In the Pre-processing phase, Landsat 8 satellite scenes were mosaiced, subsetted, geocoded and radiometric correction performed. Geo-rectification was performed using more than 50 ground control points with a root mean square (RMS) value of less than 1 pixel. Ground control points of more than 50 are acceptable if the root mean square error value is less than one pixel and are unacceptable if the root mean square error value is more than one pixel. Radiometric correction was performed by conversion of digital numbers (DN) to at-surface reflectance using reflectance rescaling coefficients (Eq. 1) derived from NASA, (2018).

$$\rho\lambda\rangle = M_p Q_{cal} + A_p \tag{1}$$

Where:

$\rho\lambda\rangle$ = Top of Atmosphere (TOA) planetary reflectance without correction for solar angle
M_p = Band-specific multiplicative rescaling factor (Reflectance_Mult_Band_*x,* where *x is the band number)*
A_p = Band-specific additive rescaling factor (Reflectance_Add_Band_*x* where *x is the band*

number)
Qcal = digital numbers

The band-specific multiplicative rescaling factor (Reflectance_Mult_Band_x), and additive rescaling factor (Reflectance_Add_Band_*x*) were obtained in the header file of the imageries.

Furthermore, the correction of TOA planetary reflectance for sun angle was performed using Eq. 2 (NASA, 2018).

$$\rho\lambda = \rho\lambda\rangle/\sin(\theta_{SE}) \tag{2}$$

Where:
$\rho\lambda$ =TOA planetary reflectance corrected for sun angle
$\rho\lambda\rangle$ = TOA planetary reflectance without correction for solar angle
θ_{SE} = Local sun elevation angle in degrees provided in the metadata (Sun-Elevation)

Spectral bands in the visible and infrared sections of the spectrum were used in the classification and delineation of inland wetland types (Table 1). In the processing phase, training sites (wetland polygons derived from field visits) were used to extract wetland signatures for supervised classification. Maximum likelihood standard algorithm was used to delineate and classify wetland types. This is because it uses the mean vectors and variance-covariance values of training sites to develop statistical probability for a given pixel. This is then used to classify an unknown pixel by calculating for each class, the probability that it lies in that class. Wetland classification validation was carried out to examine classified inland wetland types on the map to actual wetlands on the ground. This was performed by randomly selecting 90 polygons from the classified inland wetland maps. Ground thruthing and use of Google Earth information was used to validate the inland wetland types derived on the map with that on the ground. The overall accuracy was computed by dividing the total correct (i.e., the sum of the major diagonal in the error matrix table) by the total number

Table 1: Spectral characteristics of Landsat 8 bands used in the classification of inland wetlands (NASA, 2018)

Bands	Wavelength (µm)	Resolution (m)
Band 1 – Ultra Blue (coastal/aerosol)	0.43 – 0.45	30
Band 2 – Blue	0.45 – 0.51	30
Band 3 – Green	0.53 – 0.59	30
Band 4 – Red	0.64 – 0.67	30
Band 5 – Near infrared (NIR)	0.85 – 0.88	30
Band 6 – Shortwave Infrared (SWIR) 1	1.57 – 1.65	30
Band 7 – Shortwave Infrared (SWIR) 2	2.11 – 2.29	30

of pixels in the error matrix table (Congalton, 1991). The kappa statistics was not measured. The digitally classified inland wetland types were later exported into ArcGIS environment version 10.4 for further analysis. The analysis of wetland extents, distribution pattern and vulnerability to temperature increase and urban/agricultural expansion was performed in ArcGIS environment.

Wetlands distribution pattern and vulnerability modeling

The classified wetland types were imported into ArcGIS version 10.4 environments and the raster datasets were converted to vector point datasets. Each classified wetland type (i.e. open water, forested/shrub, and emergent) distribution pattern was assessed by using the average nearest neighbor statistics in ArcGIS. The spatial distribution pattern was assessed based on the z-scores (standard deviation) of average nearest neighbor ratio. A Z-score of less than -1.65 indicates a clustered pattern; Z-score of -1.65 to 1.65 indicates a random pattern and Z-score of greater than 1.65 indicates a dispersed pattern (Environmental Systems Research Institute, 2018). The wetland vulnerability modeling was carried out in ArcGIS version 10.4 environments using the following variables: major roads, landcover/landuse (developed and agricultural) and projected climate dataset (temperature) by year

2080 in Tennessee (Fig. 3a, b and c). The current study examined the potential vulnerability to wetlands by the year 2080 because the available climate data used as major input in the vulnerability modeling was projected to the year 2080. The major roads and landcover/landuse datasets were acquired from the Tennessee GIS Clearinghouse database (Tennessee GIS Clearinghouse, 2017) whereas; the climate data (temperature) was downloaded from the Climate Wizard climate change analysis tool (Girvetz, 2018). These variables were selected because they have been used to assess wetland vulnerability at landscape level and were found to be useful indicators in assessing wetland vulnerability to natural and human stressors (Copeland *et al.*, 2010). Furthermore, there was lack of spatial data for other useful environmental variables such as dam locations, oil pipelines and erosion information.

The input variables were resampled to 30m resolution datasets and weights in the range of 0 to 100% were assigned to the variables based on assumed probability of vulnerability (Table 2). The weights were developed based on extensive experience of scientists working in the field of landuse change and from expert knowledge. The study assigned 80% weight value to major roads and 200m proximity areas from major roads. This is because these areas have a high probability of human activities by the year 2080.
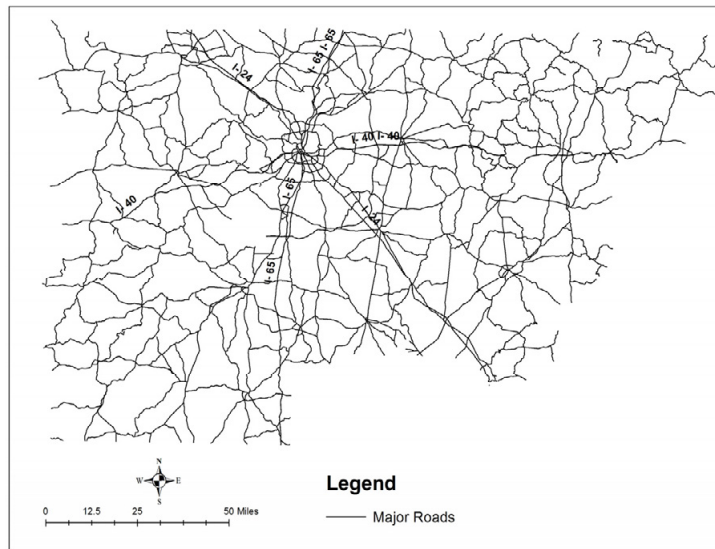

Fig. 3a: Input variable (Major Road) used in modeling inland wetlands' vulnerability to human and natural stressors such as temperature increase and urban/agricultural expansion
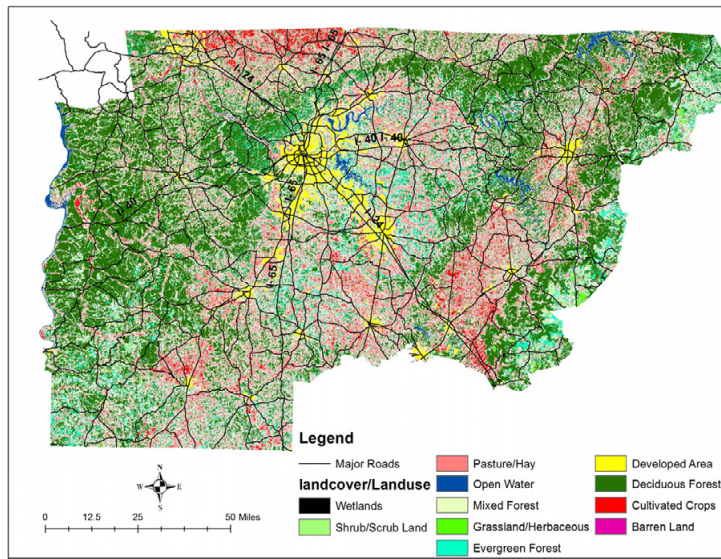
Fig. 3b: Input variable (Landcover/Landuse) used in modeling inland wetlands'
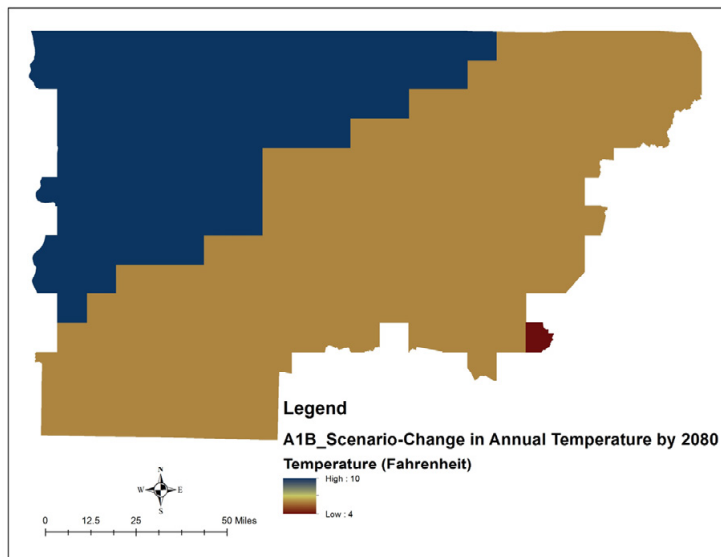vulnerability to human and natural stressors by the year 2080

Fig. 3c: Input variable (Projected Temperature) used in modeling inland wetlands'
vulnerability to human and natural stressors by the year 2080

Furthermore, the study assigned 80% weight value to developed/agricultural areas and 200 m proximity areas from developed/agricultural boundaries. This is because these areas also have a high probability of human activities by the year 2080. Areas beyond 200 m away from major roads, developed/agricultural boundaries were assigned lower weight values (i.e.$\leq$20%). This is because the probability of human activities more than 200m away from current developed and agricultural boundaries is lower. The study also assigned 50% weight value to more than 9°F representing 75th percentile of the projected temperature, 30% weight value for $6-9$ ^{o}F representing the median range of the projected temperature and

20% weight value to less than 6°F representing the 25th percentile of the projected temperature data for the region. This is because it is expected that higher projected temperature would have more impact to inland wetlands than lower temperature. In addition, the study assigned weights to the contribution of each variable to model calibration i.e. 10% for major roads, 30% for developed/agricultural areas and 60% for projected climate change (temperature increase) using Eq. 3. This is because environmental variables have different degree of importance and impact on inland wetland ecosystems. For example, temperature increase is expected to have more impact to inland wetlands than urban/agricultural expansion activities. This is because an increase in temperature can cause intense drought conditions that will cause modification of hydrological regimes in inland wetlands. These will likely lead to possible loss or reduction of species, their composition and distribution. This therefore justifies the highest weight (60%) assigned to projected climate variable (temperature) compare to developed/agricultural variable (30%) obtained from the landcover map (Eq. 3). Furthermore, human activity is expected to have significant impact to inland wetlands and is more likely to occur around developed/agricultural areas than around major roads. Therefore, this justifies the lowest weight (10%) assigned to major road variable relative to developed/agricultural variable (30%) in Eq. 3.

$$(0.1 * \text{ major roads weights}) + (0.3 * \text{developed/agricultural weights}) + (0.6 * \text{projected temperature weights}) \qquad (3)$$

The weighted input variables were then overlaid and the high percentage vulnerability areas (>80%) to inland wetlands extracted. The high percent vulnerability areas were further overlaid to the classified inland wetland map to identify most vulnerable wetlands to human and natural disturbances by year 2080.

RESULTS AND DISCUSSION

Wetland classification and mapping

The classified inland wetland types included: emergent, forested/shrub wetlands and open water bodies (Fig. 4).

The inland wetland types were distributed throughout the study area and were representative of inland wetland classes described by the Federal Geographic Data Committee, (2013). The forested/shrub wetlands were dominated by trees and shrubs such as silk dogwood, red osier dogwood, buttonbush, alder, willow, elderberry, oaks, maples, and ash (Tennessee Wildlife Resources Agency, 2018). The emergent wetlands consisted of persistent emergent plants such as cattail, bulrush, arrowhead, bur reed, blue vervain, swamp milkweed, Joe-Pye weed, jewelweed, and boneset and water plantain (Tennessee Wildlife Resources Agency, 2018). The open water bodies included riverine and lacustrine systems such
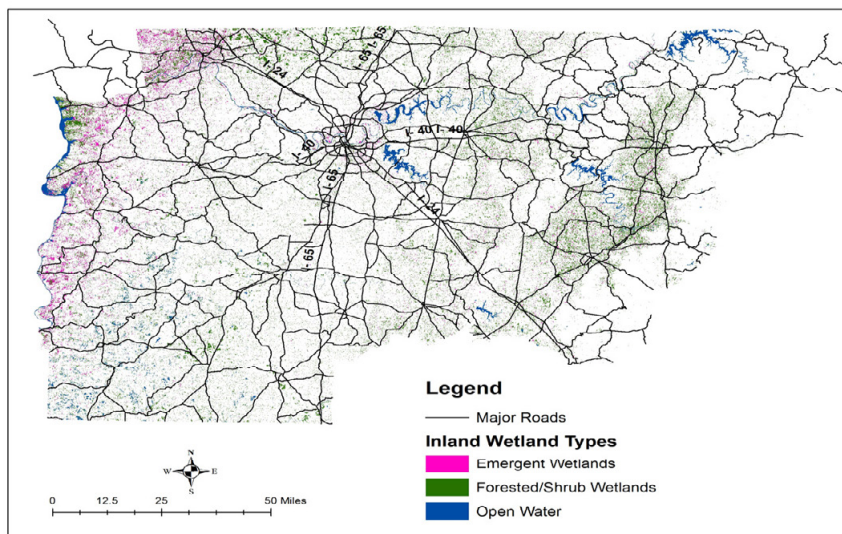

Fig. 4: Classification of inland wetlands derived from Landsat 8 satellite data

Table 2: Weights assigned to input variables used in modeling inland wetland vulnerability

Input variables	Criteria	Weight assigned (%)
	Euclidean distance: 0-200m	80
Major road	Euclidean distance: 200-1000m	20
	Euclidean distance: >1000m	0
Land cover/land use		
	Euclidean distance: 0-200m	80
Developed/agricultural areas	Euclidean distance: 200-1000m	20
	Euclidean distance: >1000m	0
	Temperature (ºF): 0 – 6 ºF	20
A1B climate change scenario	Temperature (ºF): 6 – 9 ºF	30
	Temperature (ºF): > 9 ºF	50

Table 3: Error matrix table of wetland classification

Wetland types	Forested/shrub	Emergent	Open water	Total
Forested/shrub	22	8	0	30
Emergent	7	22	1	30
Open water	8	0	22	30
Total	37	30	23	90
User accuracy	73%	73%	73%	
Producer accuracy	60%	73%	96%	
Total accuracy	73%			

as rivers, streams, lakes and ponds. They consisted of sparsely vegetated floating and submerging plants such as water lily, lotus and pond weed. Forested /shrub wetlands occupied most of the study area i.e. about 235,890 ha whereas; the open water occupied the least of the study area approximately 61,812 ha. The extent of forested/shrub wetlands more than double the extent of open water and emergent wetlands combined. This is probably due to the less gentle topography commonly found in some parts of the region. This is because topography often determines the space available for wetland development and it is a primary indicator of wetland type, frequency and magnitude (Oakley *et al.*, 1985). The extent of open water relative to emergent water was in the ratio of approximately 1:1. Emergent wetlands were dominated in the eastern parts of the region relative to the western parts. The open water bodies were prominent in the eastern parts relative to the western portion of the region. Although forested/shrub wetlands occupied most of the study area (about 63%) whereas, emergent wetlands occupied around 20%, and open water bodies occupied about 17%, species diversity that occurred in the   large forested/shrub wetlands is also found in the small emergent and open water wetlands. A significant amount of the inland wetlands were found to be geographically isolated due to their lack of surface water connection to lakes and rivers. Nonetheless,

they are critical in sustaining a significant degree of landscape functions (Cohen *et al.*, 2016). The user accuracy which implies the probability that map users will have accurately classified inland wetland types on the ground was 75% for all inland wetland types. Therefore, 75% of forested/shrub classified inland wetland type accurately represented forested/shrub inland wetlands on the ground and 25% of forested/shrub on the map inaccurately represented forested/shrub inland wetlands on the ground. This is similar to emergent wetlands and open water bodies where 75% accurately represented emergent wetland and open water bodies on the ground and 25% inaccurately represented emergent wetland and open water bodies on the ground. The producer accuracy which represented how well the classification algorithm predicted the inland wetland types was around 60% for forested/shrub, 73% for emergent, and 96% for open water (Table 3). The wetland classification produced an overall accuracy of about 73% (Table 3). The producer accuracy was about 13% higher for emergent wetlands relative to forested/shrub wetlands. Furthermore, it was around 36% higher for open water bodies relative to forested/shrub wetland types. The lower producer accuracy of forested/shrub wetland type relative to emergent wetland and open water bodies is probably due to mixed pixel of treed/shrub vegetation with other forested landcover types.

The producer accuracy which implies the probability by which the maximum likelihood classifier generated forested/shrub wetland was 60% accurately predicted and 40% inaccurately predicted by the classifier. Furthermore the probability by which the maximum likelihood classifier generated emergent wetland was 73% accurately predicted and 27% inaccurately predicted by the classifier. In addition, the probability by which the maximum likelihood classifier generated open water bodies was 96% accurately predicted and 4% inaccurately predicted by the classifier.

Wetland types distribution pattern and vulnerability modeling

The inland wetland types had a clustered distribution pattern over the entire study area (Table 4). Their Z-score ranged from -966.8 to -1124.1. Open water bodies had the most clustered distribution pattern (Z-score=-1124.1) while emergent wetlands had the least clustered (Z-score= -966.8) distribution pattern.

This was because the average distance between features in the inland wetland types were less than the average for a hypothetical random distribution (Mitchell, 2005). The lower the Z-score value in the negative axis, the higher the degree of clustered distribution pattern whereas, the higher the Z-score value in the negative axis, the lower the degree of clustered distribution pattern. Although, the wetland types had a clustered distribution pattern within the entire study area, the degree of clustered distribution pattern varied among inland wetland types. Open water bodies had the most clustered distribution, followed by forested/shrub and then emergent inland wetlands. This implies there were several schools of fishes in the open water bodies. Furthermore, it suggests that the plant and animal species in the forested/shrub and emergent wetlands were clumped to each other or lived in groups. It also implies that plants in the inland wetland ecosystems drop their seeds straight to the ground and next to each other

Table 4: Distribution pattern of inland wetland types in middle Tennessee

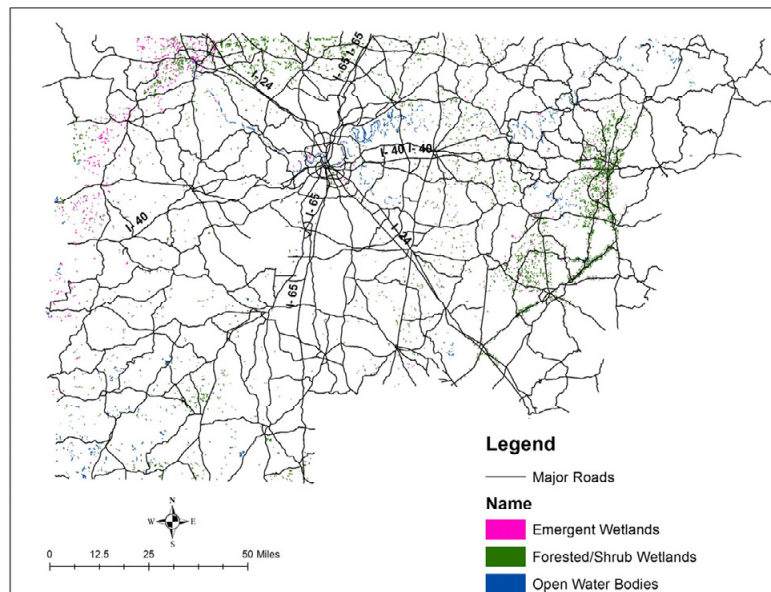| Wetland type	Distribution pattern	P-value	Z-score	Degree of clustering
Emergent	Clustered	0.0	-966.8	Low
Forested/shrub	Clustered	0.0	-1008.2	Medium
Open water	Clustered	0.0	-1124.1	High

Fig. 5: Potentially vulnerable inland wetlands in middle Tennessee as a result of human and natural stressors by the year 2080

thereby generating the clustered distribution pattern. This was more prominent in the forested/shrub inland wetlands than in the emergent inland wetlands. The spatially clustered wetland distribution pattern was similarly found in the Dougherty Plain in Georgia, USA by Martin *et al.* (2012).

A significant amount of inland wetland types were found potentially vulnerable to natural and human stressors (Fig. 5). The potentially vulnerable forested/shrub wetlands were abundantly distributed in the eastern and northern parts of the region. In contrast, the potentially vulnerable emergent wetlands were abundantly found in the western portions of the region. From the total area (about 75459 ha) of emergent wetlands found in the region, approximately 7% were vulnerable to human and natural disturbances (Fig. 6). About 11% of forested/shrub wetlands and about 13% of open water were potentially vulnerable to natural and human stressors such as temperature increase, urban development and agricultural expansion (Fig .6).

Forested/shrub inland wetlands had the most vulnerability to human activities and temperature increase in the region. They covered the largest geographic area compared to the other inland wetland types thereby making them susceptible to human encroachment such as urbanization. More than 5% of inland wetland types in the region were potentially vulnerable to natural and human stressors such as climate change (temperature increase) and urban/agricultural development by the year 2080. Climate change (temperature increase) will challenge the adaptation of species and their composition

in the inland wetland ecosystems. Furthermore, it will likely lead to increase drought conditions and change in precipitation that will affect the hydrologic regimes in inland wetlands (Barrosa and Albernaza, 2014). This will likely have consequences to the human population that depends on inland wetland ecosystems for aspects such as water quality and flood prevention. Adaptive wetland management and planning strategies such as buffering and protection are necessary to curb potential wetland degradation and extinction by the year 2080. Protecting wetlands will also provide recreational and educational opportunities to the society and thereby improving the livelihood of citizens. Furthermore, wetland conservation efforts and climate change adaptation should be enhanced as these might help protect inland wetland ecosystems and their biodiversity. Threat to inland wetlands from urbanization will likely include change in hydrological regimes, decrease ground water discharge and increase in water quality stressors such as nutrients and pollutants (Wright *et al.,* 2006; Liu *et al.,* 2018). Similarly, intensive agriculture is expected to lead to pollution as a result of pesticides and herbicides discharge. This implies active monitoring of inland wetlands is critical to enhance wetland conservation and management in the region. The multi-criteria approach used to assess wetland vulnerability in this study is similar to past studies where multiple environmental variables have been found useful to prioritize threats and impacts on wetlands (Malekmohammadi and Jahanishaki, 2017; Cui *et al.,* 2015; Copeland *et al.,* 2010). Although, inland wetlands are expected to be vulnerable to
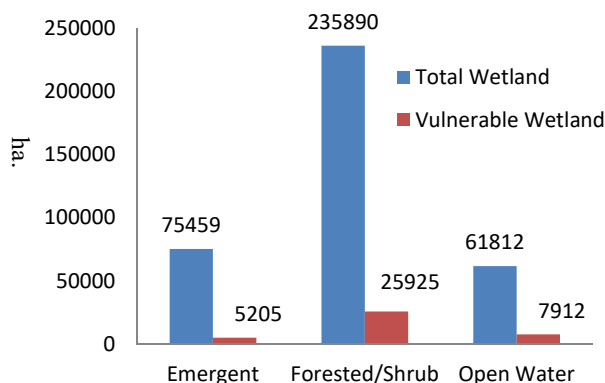

Fig. 6: Total extent of inland wetland types and their respective area potentially vulnerable to urbanization, agricultural expansion and temperature increase by the year 2080 in middle Tennessee, USA

human activities and climate change by the year 2080 according to this study, there were limitations in the input datasets used in the vulnerability modeling. For example the projected climate data (temperature) was very coarse and this affected the modeling outcome due to less variation in projected temperature change in the region by the year 2080. Even though, the projected temperature dataset was resampled in this study, only the cell size was changed and not the pixel values. Furthermore, the weights assigned to the environmental variables in the vulnerability assessment modeling were based on expert opinion and changing the weights values would significantly affect the modeling outcomes. Increasing the number of input variables in the vulnerability modeling could further improve the robustness of the model. However, this is an area of further research. Nonetheless, the study provides a first insight into a quantitative assessment of inland wetland distribution, patterns and vulnerability to human activity and climate change (temperature increase) by the year 2080 in middle Tennessee.

CONCLUSIONS

Satellite remote sensing in combination with GIS has been successfully used to classify and predict inland wetlands, distribution patterns and vulnerability to natural and human stressors in middle Tennessee, USA. The inland wetland types i.e. forested/shrub, emergent wetlands and open water bodies were classified successfully with overall accuracy of around 76%. Forested/shrub inland wetland type had the most extent (235,890 ha) in distribution whereas; open water bodies had the least extent (61,812 ha) in distribution. All inland wetland types had a clustered distribution pattern rather than random or dispersed distribution pattern. This suggested that a significant amount of plant and animal species found in the inland wetland types were clumped together in association and lived in groups. However, the degree of spatial clustering varied among inland wetland types. The open water bodies had the most clustering pattern whereas; the emergent wetlands had the least clustering pattern. About 10% of all inland wetland types in middle Tennessee are expected to be potentially most vulnerable to climate change (temperature increase) and human activities such as urbanization and agricultural expansion by the year 2080. Increasing the number of input

variables in the GIS vulnerability calibration model such as dam locations, oil pipelines distribution could further enhance the spatial prediction of inland wetlands potentially vulnerable to human activities. Nonetheless, this geospatial assessment of inland wetlands classification, distribution pattern and vulnerability study could improve the long term planning and management of inland wetlands at landscape level. Furthermore, this geospatial mapping and modeling approach could be used to easily map, update and assess inland wetlands by scientists in other geographic regions.

CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

ABBREVIATIONS

$°C$	Degree Celsius
DN	Digital number
$Eq.$	Equation
$°F$	Degree Fahrenheit
$Fig.$	Figure
GIS	Geographic information system
ha	Hectare
$i.e.$	That is
m	Meter
mm	Millimeter
N	North
$p\text{-}value$	Probability value
RMS	Root mean square

µm	Micrometer
W	West
Z-Score	Standard score
≤	Less than and equal to
>	Greater than
()	Bracket
%	Percent

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AUTHOR (S) BIOSKETCHES

Akumu, C.E., Ph.D., Assistant Professor, Department of Agricultural and Environmental Sciences, College of Agriculture, Tennessee State University, Nashville, Tennessee, USA. Email: *aclemen1@tnstate.edu*

Henry, J., M.Sc., Department of Agricultural and Environmental Sciences, College of Agriculture, Tennessee State University, Nashville, Tennessee, USA. Email: *jhenry8@my.tnstate.edu*

Gala, T., Ph.D., Associate Professor, Department of Geography, Chicago State University, S. King Drive, Chicago, IL, USA. Email: *tgala@csu.edu*

Dennis, S., Ph.D., Professor, Department of Agricultural and Environmental Sciences, College of Agriculture, Tennessee State University, Nashville, Tennessee, USA. Email: *sdennis@tnstate.edu*

Reddy, C., Ph.D., Professor & Dean, Department of Agricultural and Environmental Sciences, College of Agriculture, Tennessee State University, Nashville, Tennessee, USA. Email: *creddy@tnstate.edu*

Tegegne, F., Ph.D., Professor, Department of Agricultural and Environmental Sciences, College of Agriculture, Tennessee State University, Nashville, Tennessee, USA. Email: *ftegegne@tnstate.edu*

Haile, S., Ph.D., Associate Professor, Department of Agricultural and Environmental Sciences, College of Agriculture, Tennessee State University, Nashville, Tennessee, USA. Email: *shaile@tnstate.edu*

Archer, R.S., Ph.D., Assistant Professor, Department of Agricultural and Environmental Sciences, College of Agriculture, Tennessee State University, Nashville, Tennessee, USA. Email: *rarcher@tnstate.edu*